

Essays on Asset Pricing, Machine Learning and Econometrics

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Abstract

Chapter 2: Recent studies on the performance of machine learning prediction of asset prices base their estimation of trading frictions on break-even transaction cost and control for limits-to-arbitrage by excluding large sections of the sample. Arguably, this approach is misguided as it has ramifications which oppose well-established empirical findings. This chapter overcomes both issues by directly modelling trading frictions as a function of the market microstructure and uses optimisation to adjust for the effects of frictions. The evidence suggests that the success of the neural network model of Gu et al. (2020) is not spurious, but it captures unique pricing information, and this chapter identifies under which conditions this can be realised in the market.

Chapter 3: Neural network models, despite their striking empirical success in asset pricing, are generally considered ‘black boxes’ which obscure the economic foundations of the relationships they identify. This chapter argues that the ‘black box’ notion is a misnomer and shows how to use the methods established in empirical finance to identify the factors which drive the performance of neural networks. Novel results show that the model extracts significant alpha from episodes of investor overreaction, specifically in two scenarios: (a) shorts stocks with recently improved top line when their bottom line fails to improve; and (b) shorts stocks with recently inflated stock prices due to investor overreaction to positive surprises in financial results when their growth fails to be reflected in their fundamentals.

Chapter 4: The validity of the two-pass regression of Fama and Macbeth (1973) depends on the time-dimension, T , being large. When individual assets are used to estimate risk premia the cross-sectional dimension, N , is much larger than T . This chapter explores the levels at which T is small enough to undermine the validity of the two-pass procedure. The investigation employs the asymptotically valid framework of Shanken (1992)–Raponi (2020) and finds that, in univariate regressions the divergence between the two models is statistically significant for time windows up to 10 years in samples containing microcaps and up to 7 years in microcap-free samples. This number is lowered to the 5-year mark in multivariate regressions.

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Hasta la vista!

Abbreviations

AMEX	American Stock Exchange
APT	Arbitrage Pricing Theory
CAPM	Capital Asset Pricing Model
CRSP	Centre for Research in Security Prices
CSR	Corporate Social Responsibility
EIV	Error-in-variables
GLS	Generalised Least Squares
HML	High-minus-Low portfolio
I/B/E/S	Institutional Brokers Estimate System
NASDAQ	National Association of Securities Dealers Automated Quotations
NYSE	New York Stock Exchange
OLS	Ordinary Least Squares
R&D	Research and Development
SDF	Stochastic Discount Factor
SE	Standard Errors
WLS	Weighted Least Squares

Chapter 1

Introduction

Chapter 2: Empirical finance has identified hundreds of factors as explanators of asset prices (e.g., Green et al. 2017; Harvey et al. 2016) raising a fundamental question about which of these factors capture unique sources of risk (Cochrane 2011). The traditional portfolio-sorts approach is, arguably, unable to examine the complete collection of possible explanators simultaneously. In a seminal paper, Gu et al. (2020) illustrates the ability of machine learning methods in digesting a broad predictor set as a natural way to collectively evaluate the vast collection of asset pricing factors. Despite the astounding success of such novel methods, this literature pays little attention to the trading frictions that govern the real world.

Recent studies which focus on machine learning prediction of asset prices (Avramov et al. 2022; Cakici et al. 2023) base their estimation of trading frictions on break-even transaction cost while they control for limits-to-arbitrage by excluding large sections of the sample. It is argued that this approach is misguided as it has ramifications which oppose well-established empirical findings. This chapter applies a realistic trading friction model rooted in the market microstructure fundamentals. This is formulated by combining the spread cost of a trade (Novy-Marx and Velikov 2016) and the trade's market impact (Kyle and Obizhaeva 2020). This model is superior as it naturally incorporates the trading limitations of poor liquidity stocks, and it is directly proportional to the portfolio's turnover.

The friction model is incorporated via a portfolio optimization procedure. The advantage of this approach is that the implied trading frictions are directly incorporated in the portfolio weights alongside volatility and as such, the optimiser avoids positions for which the expected friction impact offsets the expected excess returns and positions of extreme volatility. In this way, the high turnover of the machine learning portfolios is restricted, the microcap bias is controlled without the need to discard large portions of the sample and the attainable predictive signals surface.

Chapter 3: The asset pricing literature has documented hundreds of factors as significant explanators of asset prices (Harvey et al. 2016), a striking realisation that compels contemporary research to distil the truly unique risk premia (Cochrane 2011). The state-of-the-art asset pricing research has been exploring machine learning techniques to address the above limitation of traditional techniques to digest such a broad predictor set (Bagnara 2024). The advantage of such techniques is their flexibility to describe complex relationships which are present in asset pricing. However, these methods are considered as ‘black boxes’ which may obscure the economic foundations of the relationships they describe (Karolyi and Van Nieuwerburgh 2020).

Gu et al. (2020) report that the model is driven predominantly by factors such as short-term reversal, long-term momentum, illiquidity, spread and return volatility. Similarly, Avramov et al. (2022) report that the machine learning predictability is driven by short term signals in distressed stocks. At the same time, Novy-Marx and Velikov (2016) show that after adjusting for transaction costs anomalies with high turnover, such as idiosyncratic volatility and short-run reversal, do not survive statistically. Therefore, it can be argued that to uncover the truly unique risk premia via machine learning techniques one has to consider trading frictions.

This chapter argues that the ‘black box’ notion is a misnomer and shows how to use the intuition already established in the field of asset pricing to identify the factors which drive the exceptional performance generated by the neural network model of Gu et al. (2020). A trading friction model is applied to restrict unrealistic trading strategies and portfolio optimisation is used to choose weights that will maximise expected returns net-of-costs, given the expected volatility. In this way the realisable performance can be measured based on the factor loadings of the neural network portfolio.

Chapter 4: In statistical tests of regression coefficients valid inference depends on two factors: the consistency of the coefficients and the asymptotic normality of their standard errors. This chapter examines the valid inference of the widely used Fama-Macbeth (1973) two-pass regression. When the time dimension is large (large- T model) the risk premia coefficients are consistent however, their standard errors are not asymptotically normal. Shanken (1992) proved the correct formulation for valid standard errors which is used in this chapter. When the time dimension is small, and the test asset dimension is large (large- N model) neither the coefficients, nor their standard errors are valid. Again, Shanken (1992) proved the bias adjustment needed for consistent coefficients whereas, the asymptotically normal standard errors have only recently been proven by Raponi et al. (2020).

When the time dimension is adequately large, both the coefficients and standard errors of the large- T and large- N frameworks are identical. However, when T has not diverged adequately the measures are not equal and thus, the inference becomes invalid. For example, when one uses the large- T model for a short time window (e.g., when performing rolling window regressions) one incurs invalid inference. Specifically, the coefficients computed are biased and their standard errors are smaller than they should. The implication is that the t -statistics are erroneously larger. Based on the recent proof by Raponi et al. (2020) both the large- T and large- N cases can be estimated with validity.

Given the above, the idea explored in this chapter is to estimate the two frameworks across a range of increasing time windows and investigate at which point the inference between the two is statistically different and thus, yield invalid inference. The idea put forward herein is that since the investigation is not restricted to a low number of portfolios, one can use an extended factor-set and thus, the resulting collection of t -statistics can themselves be used to test the inference implications of short time windows. The comparison is quantified via a novel application of Wilcox's (2020) extension of the Pitman (1939)-Morgan (1939) test which evaluates the distribution of t -statistics and measures the statistical significance of the impact of applying the asymptotically valid model.

Chapter 2

An Investigation of the Neural Network Predictability of Asset Prices in Environments with Trading Frictions

2.1 Introduction

Empirical finance has identified hundreds of factors as explainers of asset prices (e.g., Green et al. 2017; Harvey et al. 2016) raising a fundamental question about which of these factors capture unique sources of risk (Cochrane 2011). Modern research challenges the credibility of this plurality of factors and has suggested several possible explanations. Hou et al. (2020) conclude that most anomalies exist in microcaps and Stambaugh et al. (2012) argue that predictability is prominent in the short leg of the spread portfolio. Controlling for these issues is imperative for risk premium measurement. Beyond this evidence, a methodological issue arises, specifically, the limitation of the traditional portfolio sorting approach to examine the complete collection of possible explainers simultaneously. This problem is overcome in the seminal paper of Gu et al. (2020) which illustrates the ability of machine learning methods to digest a broad predictor set as a natural way to evaluate the vast collection of asset pricing factors together. In the same paper, such methods are evidenced to generate impressive performance when used to create portfolios. This naturally raises the question whether this performance can be realised after controlling for the issues discussed above.

Recent studies which focus on scrutinising the performance of machine learning prediction of asset prices, such as Avramov et al. (2022) and Cakici et al. (2023) base their estimation of trading frictions on break-even transaction cost, calculated as the payoff to the long-short portfolio divided by its turnover. It can be argued that this measure, although easy to compute, is potentially misguided such that its validity as a friction measurement is questionable on the basis of both theoretical and empirical considerations. This approach models trading frictions as an inversely proportional function of turnover, a claim which is not supported by empirical evidence which argues in favour of a direct proportionality (Novy-Marx and Velikov 2016). In fact, the ramifications of this misspecification are serious. This is illustrated in Cakici et al. (2023) who, based on this formulation of break-even transaction cost, find that developed markets exhibit higher transaction costs than emerging markets. This conclusion conflicts with both empirical evidence (Domowitz et al. 2001) and the well-established intuition that the more liquid

and informationally efficient developed markets are characterised by lower transaction costs. Given the above, it is argued that the research into scrutinising the asset pricing performance of machine learning methods should be conducted with a more appropriate trading frictions measure.

To overcome these issues, this chapter applies a realistic trading friction model that is rooted in the fundamentals of market microstructure. This is formulated by combining the spread cost of a trade (Novy-Marx and Velikov 2016) with the trade's market impact (Kyle and Obizhaeva 2020). This model is superior to the break-even cost method as it naturally incorporates the trading limitations of poor liquidity stocks, and it is directly proportional to the portfolio's turnover. Thinly traded stocks, such as microcaps, face higher frictions via larger spreads, but also via larger market impact which depends on the volume that the predictive model intends to trade. This friction model is incorporated via a portfolio optimisation procedure. The advantage of this approach is that the implied friction costs are directly incorporated into the portfolio weights alongside volatility, and as such, the optimiser avoids positions of extreme volatility and positions for which the expected friction impact offsets the expected excess returns. In this way, the optimiser naturally controls for the microcap bias without the need to discard large portions of the sample.

This chapter contributes several new findings to the literature, especially on the conditions under which the machine learning predictability is realisable in the market. To begin with, the results show that the equal- and value-weighted approaches to portfolio allocation, commonly reported in the literature (Gu et al. 2020; Avramov et al. 2022) fail to generate positive predictability after adjusting for trading frictions. However, when one uses optimised portfolios and trades with a small initial capital, one is able to extract substantial predictability from the neural network model. This is achieved due to the optimiser considering the expected volatility, a feature that is absent from the equal- and value-weighted methods. Specifically, it avoids positions of extreme volatility, but rather maximises the expected returns given the expected volatility. In this way the high turnover of the machine learning portfolios is controlled. What is more, the optimiser avoids entering positions where the expected friction impact offsets the expected excess returns and thus, the attainable predictive signals surface.

The effect of trading frictions in diminishing the neural network returns is confirmed, statistically, across all forecasting horizons. Importantly, the friction impact is greatest for the equal-weighted portfolio, which indicates that a large portion of the predictability exists in microcaps, as it is also suggested by Avramov et al. (2022). On the contrary, the optimised portfolio exhibits the lowest impact, which indicates how well the optimiser controls for the microcap bias. A considerable portion of the predictability of the neural network portfolio is found to exist in the short leg of the portfolio which is unable to be captured. This indicates that the neural network performance is dependent on difficult-to-trade stocks to some extent. However, it is also found that there is impressive predictability in the long leg, which is more than enough to compensate for the shortcoming of the short leg. Overall, it is concluded that microcaps and other difficult-to-trade stocks make up some portion of the neural network predictability, but these are not large enough to be detrimental.

It is concluded that the success of the neural network model of Gu et al. (2020) is not spurious and this chapter shows under which condition this exceptional predictability can be realised in the market even after adjusting for realistic trading frictions. Controlling for difficult-to-trade stocks reduces the profitability of the machine learning model, but it does not eliminate it completely, as also suggested by Avramov et al. (2022). More importantly, it is found that investors trading a small initial portfolio can extract considerable predictability from the neural network model, however, when the portfolio balance is large enough the predictability diminishes. Introducing the ability to capture non-linear relationships has an incremental value for risk premium measurement as confirmed by the predictability improving with deeper neural network setups and with the addition of interaction terms in the predictor set. Further engineering of the model could potentially uncover more attainable predictability.

2.2 Literature review

2.2.1 Machine learning in asset pricing

Why machine learning?

Hundreds of factors have been documented in the empirical finance literature as significant explanators of asset prices. Given such plurality of factors, the credibility of these discoveries has been challenged by modern research. Some prominent explanations for this phenomenon are as follows: Harvey et al. (2016) consider 296 published factors and report that a large number are false discoveries, McLean and Pontiff (2016) highlight that the out-of-sample performance of asset pricing anomalies is diminished post-publication, Hou et al. (2020) show that 65% of the 452 anomalies they consider are not significant when microcaps are excluded, Avramov et al. (2022; 2013) underline that anomalies tend to concentrate in firms which are financially distressed and around credit rating downgrades, Novy-Marx and Velikov (2016) report that when adjusting for transaction costs, anomalies with high turnover do not survive, statistically.

The ability of traditional techniques to digest such a large predictor set is rather limited. The commonly used portfolio sorting method can only span a small number of predictors, and thus is unable to capture complex predictive patterns. For example, in the leading empirical asset pricing research, Fama and French (2018) suggest a six-factor specification by adding a momentum factor to the Fama and French (2015) five-factor model. Meanwhile, Hou et al. (2021) suggest a five-factor specification that adds an expected growth factor to the Hou et al. (2015) four-factor model. However, they still fail to capture earnings- and momentum-related anomalies, respectively. Exploring larger specifications implies the risk of the portfolios not being sufficiently diversified. Therefore, methods that can simultaneously utilise the high dimensionality of the predictor set are required (Cochrane 2011). The ability of machine learning techniques, such as neural networks, to combine a broad set of possibly weak signals into a meaningful prediction, highlights their potential for empirical success for the asset pricing question.

A further advantage of machine learning methods is the ability to uncover complex patterns given their flexibility and high-dimensional setting (Karolyi and Van Nieuwerburgh 2020). Such patterns are subtle, arise from the interactions between factors, and are often challenging for researchers to predict them a priori. For example, Titman et al. (2004) show that increased capital investment is associated with negative returns, a relationship which is more prominent in firms with lower debt ratios and higher cash flows. Analogously, Stambaugh et al. (2015) find that the idiosyncratic volatility anomaly is positive for underpriced stocks but negative for overpriced stocks. Realising that such interrelations can exist among any of the vast number of factors creates complexity and presents a challenge to traditional researchers to identify these. On the contrary, modelling complex relationships is not only viable for machine learning techniques, but it is likely to be a key reason for the empirical success of these methods (Bianchi et al. 2021; Gu et al. 2020).

Machine learning under trading frictions

The proliferation of machine learning methods in empirical finance to date comes with limited scrutiny of the real frictions that characterize the trading environment. The natural question that arises is whether the superior performance of machine learning prediction is realizable in trading environments, or whether asset pricing research reports illusory performance (Lewellen et al. 2010). This is the focus of this chapter. The most comparable research is the investigation by Avramov et al. (2022) who also start from the neural network model of Gu et al. (2020). As they document, return predictions from machine learning models generate remarkably high turnover in trading portfolios. This implies considerable performance loss to trading frictions. Avramov et al. (2022) model trading costs by the break-even cost and show that, indeed, adjusting for these weakens the performance portfolios constructed from machine learning predictive models. To control for the microcap bias they exclude the entire microcap stock universe along with financially distressed firms and report that the pricing anomalies are concentrated in difficult-to-arbitrage stocks and the predictability is often driven by rather short-lived signals.

Break-even transaction cost is calculated as the payoff to the long-short portfolio divided by its turnover. Whilst providing an initial step forward in assessing the relative success of machine learning portfolios, this approach is not free from criticism as a measure of trading costs. First, the break-even transaction cost is formulated to be inversely proportional to turnover, even though the empirical evidence suggests the opposite. Specifically, Novy-Marx and Velikov (2016) show that the cost of trading low turnover strategies is, on average, less than 0.10% per month, medium turnover strategies between 0.20% and 0.57% per month, and high turnover strategies exceed 1% per month. Trading costs are directly proportional to turnover and modelling them otherwise potentially has serious ramifications. Indeed, these are evident in Cakici et al. (2023) who employ the break-even transaction cost approach and conclude that trading costs are higher in developed markets than in emerging markets. This is also refuted by the empirical evidence, which shows that emerging markets have the higher transaction costs, not developed markets (Domowitz et al. 2001). Given the above, it is arguable that the break-even measure used by Avramov et al. (2022) and Cakici et al. (2023), conflicts well-established empirical results and should be reconsidered.

This chapter responds to this critique and applies a realistic trading cost model. In this approach trading frictions are modelled as a function of two components. First, the spread cost of a trade (Novy-Marx and Velikov 2016) which captures the fact that buying occurs on the bid price and selling occurs on the ask price which is lower. Naturally, more illiquid stocks exhibit larger spread costs. Importantly, this cost component is linear i.e., the percentage spread does not increase when the volume traded increases. Second, the trade's market impact (Kyle and Obizhaeva 2020) captures the fact that when one trades increasingly larger blocks then the execution occurs at increasingly more unfavourable prices. This is a non-linear cost which means that it increases when the capital allocated for a trade increases or when the market price of the stock decreases.

This approach is superior to the method used by Avramov et al. (2022) since both cost components are increasing functions of turnover. What is more, it provides a natural way to control for the effects of microcaps. Specifically, the microcap bias is controlled via wider spreads and higher market impact costs. Whilst controlling for the microcap bias is imperative, it

can be argued that excluding a large portion of the tradable universe, such as in Avramov et al. (2022), potentially misleads the asset pricing inference, given that microcaps are tradable albeit at high cost. Although anomalies congregate in microcaps, there is no theory to suggest that these cannot be captured, the evidence merely suggests that predictability decreases when microcaps are excluded (Hou et al. 2020; Green et al. 2017). Lastly, as opposed to a large extent of the literature which presents the cumulative returns starting from an arbitrary capital, this chapter considers that increasingly larger trades are increasingly more costly to be executed via the market impact. Therefore, this can reveal the levels at which anomalies become saturated and disappear.

Machine learning with portfolio optimisation

Beyond the realistic cost model, this chapter contributes to the existing literature by overlaying the price prediction model with portfolio optimization. Specifically, this chapter applies the neural network setup of Gu et al. (2020) to predict asset returns and subsequently, the predicted returns are penalized by the trading friction cost function. Then, in addition to constructing equal- or value-weighted long-short portfolios consistent with the literature, this chapter extends recent findings by constructing and analysing a long-short portfolio that is optimized. This is a stark improvement compared to the commonly used equal- and value-weighted approaches. The optimisation procedure has the advantage of incorporating the concept of volatility in the portfolio construction, and also restricts positions for which the expected market impact offsets the expected excess returns. As such, the microcap bias can be controlled naturally, the full sample of assets can be retained, and any realisable predictive performance can be measured.

Another novelty used in this chapter is employing predictions over multiperiod horizons, specifically horizons of 1, 3 and 12 months. Subsequently, the portfolio weights are estimated after optimising over the entire investment horizon. For example, for the 3-month horizon the neural network model is tasked to predict three monthly returns ahead and the optimiser computes the optimal monthly trading for the next 3 months, assuming trading occurs monthly. Therefore, the trades which are executed are based on longer-term views of the market. The pioneering investigations, including Gu et al. (2020) and Avramov et al. (2022), predict the one month-

ahead returns, compare these with their realised values, update the model, and then predict the next month-ahead. On the contrary, the evaluation of the multi-period predictions conducted in this chapter has the potential to control the high turnovers reported in the previous literature, however, this comes at the cost of the increased uncertainty associated with longer term predictions. In essence, the optimiser ensures that the predictive model does not enter costly positions only to exit them fully next period, unless the expected profit warrants such action.

On this front, the most comparable investigation is by Jensen et al. (2022) who train their machine learning model to reach the aim portfolio¹ over a multi-period horizon after considering trading costs. Jensen et al. (2022) apply a cost model that only consists of market impact, which is used to penalise the weights of the objective function directly. Instead, this chapter first predicts the expected returns (without altering the objective function) and then applies the cost model, incorporating both market impact and spread cost. A further distinction is that Jensen et al. (2022) employ the stochastic discount factor (SDF) paradigm, whereas this chapter employs the factor model paradigm. The advantage of the latter is that it relates to the wider anomalies' literature, and therefore contributes not only on methodological applications, but also to the empirical finance literature regarding the predictability of asset returns.

2.2.2 Implications of overlooking trading frictions

Numerous empirical investigations have taken on the challenge posed by Cochrane (2011) through the lenses of factor models (Green et al. 2017), the stochastic discount factor (Kozak et al. 2020), or other non-parametric techniques (Freyberger et al. 2020). However, the vast majority of studies pay little regard to the frictions governing the real trading environment. In practice, frictions are realised as trading costs. These can either be direct, in the form of taxes and commissions, or indirect in the form of price spread and market impact (Almgren et al. 2005). While the former are observable and

¹ In portfolio management, the aim portfolio is the portfolio which when achieved the investor ceases to trade. Until that point the investor continually trades in the direction of the aim portfolio. Consequently, the aim portfolio depends on the current and future Markowitz portfolios across the trading path. Interested readers are encouraged to read Jensen et al. (2022) and Gârleanu and Pedersen (2013).

easy to incorporate in a risk model, the latter are notoriously challenging to identify and measure, yet they constitute a significant element of investment performance (Freyre-Sanders et al. 2004). In fact, the majority of trading costs are implicit, they are not expenses, rather they are value lost in trading activity. Arguably, examining the evidence in the asset pricing anomalies literature with respect to this lost value should be a crucial step in tackling Cochrane's (2011) challenge, although it has been largely overlooked in empirical finance research. This chapter aims to fill this void.

Performance measurement

It is rather common in financial research for a strategy to appear good on paper only to fail to match its promise in practice. This is not surprising given that the majority of the asset pricing literature pays little or no attention to trading frictions. It is arguable that ignoring frictions implies that asset pricing factors are not comparable. Consider the three-factor model of Fama and French (1993), which uses the size and value factors under annual rebalancing, compared against the model of Jegadeesh and Titman (1993) that uses momentum and short-term reversal factors under monthly rebalancing. The longer rebalancing period of the first model implies that less intense trading (lower turnover) is required to construct the factors, thus less value lost to microstructure frictions as compared to the latter model. What is more, factors such as short-term reversal are dynamic by nature and thus are always associated with inflated turnovers. In light of these arguments, developing models to consider trading frictions should warrant greater attention to allow performance comparisons of different factors and strategies.

More intense trading activity implies a larger proportion of returns eroded by trading frictions (Amihud and Mendelson 1986). Pertinently, Korajczyk and Sadka (2004) and Lesmond et al. (2004) report that the high turnover of the momentum strategy yields only modest returns after adjusting for trading costs. This is corroborated by Detzel et al. (2023) who find that high turnover strategies cannot be profitably traded after accounting for the effects of frictions. Frequently rebalanced factors exhibit a similar pattern of illusive success on a risk-return basis as well. For example, Hou et al. (2015) and Fama and French (2015) take similar positions in the investment, profitability, size, and market factors. The former is rebalanced monthly,

whereas the latter is rebalanced annually. Comparing the two, Detzel et al. (2023) find that the monthly-rebalanced model exhibits a 40% higher Sharpe ratio than the annually rebalanced model before trading costs. However, this conclusion is reversed after accounting for frictions with the Fama and French (2015) model exhibiting the highest Sharpe ratio.

Inference

The effect of trading frictions on diminishing factor profitability also has direct implications on inference in empirical asset pricing. This resonates with Harvey (2017) who claims that empirical research is biased to publishing statistically successful results and ignoring frictions is certainly feeding that bias. When turnover is considered, Novy-Marx and Velikov (2016) report that most of the low frequency strategies they analyse remain significantly profitable net-of-costs, whereas only two strategies with more than 50% one-sided turnover survive. When considering rebalancing frequency, Detzel et al. (2023) show that factors which are rebalanced monthly have turnover and transaction costs an order of magnitude larger than factors rebalanced annually. Adjusting for the transaction costs results in factor performance diminishing to being not statistically significant. This extends the evidence of Korajczyk and Sadka (2004) and Lesmond et al. (2004) on the significance of high turnover, frequently rebalanced factors, such as momentum. Given the above discussion, it is also argued that overlooking trading frictions potentially leads to incorrect inference in asset pricing studies, with factors being significant on paper, but not in practise.

Accounting for trading costs not only alters the inference of individual anomalies but also impacts the inference of factor models. Detzel et al. (2023) suggest that monthly-rebalanced models exhibit illusory performance, whereas models with less frequent rebalancing actually outperform after adjusting for trading frictions. Specifically, they report that models with more frequent rebalancing, such as Hou et al. (2015) and Barillas and Shanken (2018), exhibit high Sharpe ratios only when transaction costs are ignored. However, when adjusting for these costs, the annually rebalanced Fama and French (2015) model dominates. Furthermore, DeMiguel et al. (2020) find that, surprisingly, adjusting multivariate models for trading costs increases the number of statistically significant factors. The resulting model includes a

broader range of factors and thus presents a more unified view of asset pricing. Following this evidence, it is arguable that adjusting for trading frictions can effectively improve the ability of factor models to price the cross-section of asset returns and inform the current consensus in the literature.

Investor size

It should also be highlighted that the rebalancing frequency and the turnover of an asset pricing factor do not apply equally to every investor, but rather their effects are experienced differently by investors of different sizes. On the one hand, investors with more capital are, theoretically, able to pursue high turnover strategies, given that the fixed costs associated with each trade consume a much smaller proportion of their investment. A trader managing a smaller account can only pursue lower turnover anomalies, as the fixed trading costs would have a relatively large impact on performance. On the other hand, Novy-Marx and Velikov (2016) show that low turnover strategies have higher capacities than high turnover strategies. This means that low turnover anomalies can attract substantially more capital before being saturated and their profitability eroded, thus investors with more capital can only pursue low turnover factors. These arguments imply that strategies comprising different turnover rates may be profitable to investors of different sizes, however, the actual direction of this effect has yet to be explored empirically. This chapter investigates how trading costs affect investors of different sizes and examines the profitability and statistical inference of different factors from the perspective of investor size.

Microcaps

A well-established finding in empirical asset pricing is that the majority of anomalies are present in microcaps (Hou et al. 2020; Green et al. 2017). Therefore, when using equal-weighted portfolios, the inference is skewed towards producing statistically significant anomalies. At the same time, the costs of trading microcaps are more substantial than other stocks due to their relative illiquidity (Jiang 2022). The implication is that, by overlooking trading frictions, one allows the microcap bias to skew the asset pricing inference. This is confirmed empirically by Novy-Marx and Velikov (2016) who report that anomaly spreads are indeed substantially higher for small stocks, but are

eliminated when trading costs are considered. Similarly, microcaps exhibit the highest gross Sharpe ratios compared to other stocks, but these turn severely negative once transaction costs are accounted for (Fama and French 2008).

The importance of adjusting for microcaps is unequivocal, however, the methods that are applied in the literature to control this bias are, at best, open to debate. The most common approach is observed in Green et al. (2017) who compare a sample of assets that includes microcaps with a sub-sample that discards them entirely. This can be misleading since microcaps are tradable, albeit at a high cost. Completely removing them from the analysis could potentially distort the risk premium inference. The second approach, also applied by Green et al. (2017), is to apply a value weighting scheme. A problem then arises as there is no expectation that weighting by value generates an optimal risk-reward performance. Third, some researchers apply a rather superficial trading cost penalty in the form of break-even cost (e.g. Avramov et al. 2022). As previously discussed, the validity of this approach may also be questionable. In response to these limitations, this chapter adjusts the expected returns of each stock with its expected trading cost, given the intensity of trading, arguing that this is not only a valid approach to control for the microcap bias, but is also empirically advantageous.

2.2.3 Modelling trading frictions

Price impact due to the spread

A fundamental element of the market microstructure is the bid-ask spread. This captures the fact that a seller's order is fulfilled at the ask price and a buyer's order is fulfilled at the bid price. On the contrary, the quoted price lies between these two values and does not capture the actual transaction price at which a trade is executed. Naturally, the bid-ask spread seems to be the best measure of the spread element of trading frictions. However, financial empiricists, such as Novy-Marx and Velikov (2016) and others, choose to employ an alternative measure called the effective spread. This measures the deviation between the executed price and the mid-quote price (midpoint between the ask and bid price). Considering this formulation, the effective spread is a more valid measure for the spread cost impact for two reasons. First, it uses the efficient price rather than the quoted market

price, which assumes that trading occurs above and below the price deemed efficient by the market. Second, it uses the mid-quote price which is less volatile and more valid than daily bid-ask price, since orders are not generally executed at exactly the quoted bid or ask prices (Lee and Ready 1991).

Novy-Marx and Velikov (2016) employ the effective spread as the sole element of trading frictions. This choice was criticized by Frazzini et al. (2018) who argue that for large US stocks the effective spread estimates are too small (0.015% on average) to make a significant difference to performance measurement. Although the Frazzini et al. (2018) argument is true, it can also be argued that their conclusion is not generalizable. In fact, it holds only for stocks of large size. Conceptually, the spread reflects the impact of requesting immediate trade execution and so it has long been regarded as a measure of liquidity. Stocks with low liquidity, such as microcaps, generally exhibit low trading volumes and large spreads. Empirical evidence suggests that the spread can exceed 1% for microcaps (Jiang 2022), which is orders of magnitude larger than the average suggested by Frazzini et al. (2018). Ignoring the spread is potentially misleading in asset pricing research, but given that the majority of anomalies are associated with microcaps (Hou et al. 2020; Green et al. 2017), this is imperative to include.

An additional and important argument made by Frazzini et al. (2018) is that the market impact of trading is the more dominant element of trading frictions compared to the effective spread. In fact, this has been evidenced in research on order flow and has been a fundamental factor in some seminal theories of the price impact of trading, such as Kyle's (1985) λ . In this regard, it can be argued that the full nature of transaction costs is not fully captured by Novy-Marx and Velikov (2016), who only incorporate the effective spread. The distinction between the two approaches lies in the fact that the effective spread is a linear impact function, suggesting that trading increasingly large blocks does not have any price impact on the market. On the other hand, the market impact measure describes a non-linear cost model, meaning that trading frictions increase for larger trade sizes.

This chapter argues that a more appropriate model of trading frictions should include both the effective spread and market impact. In this paradigm, thinly traded stocks exhibit higher effective spreads, but also their trading

costs will increase non-linearly with the volume traded. As such, one can adjust for the effect of a large investor attempting to extract arbitrage from thinly traded stocks by applying increased trading costs. The evidence from the market microstructure literature discussed above strongly suggests that investor size is a determinant of limits-to-arbitrage. Modelling frictions in this way introduces the concept of initial capital size into asset pricing studies. This contrasts with the *modus operandi* followed in the literature that starts from an arbitrary capital amount which grows by the cumulative returns of the spread portfolio.

Spread models

To measure the spread impact, one could turn to the quoted end-of-day bid/ask prices. Naturally, this is a valid measure and variables such as the Closing Percent Quoted Spread have proven, empirically, to be relatively accurate proxies for the spread cost incurred (Fong et al. 2017). Despite this evidence, this spread measure has severe limitations. Most importantly, the availability of such quote data is limited. Specifically, the bid-ask data for NASDAQ securities is not reported by CRSP before June 1992. Therefore, investigations which start earlier than that, such as this one, should explore alternative measures. Second, given that trading does not usually occur at the quoted prices, empirical researchers prefer to use an effective spread model instead (Novy-Marx and Velikov 2016). This is based on the actual traded prices rather than the quoted prices, and therefore, it is a preferable measure for real trading frictions. Empirically, the effective spread is lower than the quoted spread on average (Roll 1984), meaning that they may not yield the same empirical results.

Two broad classes of effective spread models are suggested in the literature. The first estimates spreads via regressions of order flow data, such as Glosten and Harris (1988). This approach is not followed in this chapter because order flow data are not easily available. The second uses price data instead. This approach was initiated by Roll (1984), who used the serial covariance of daily returns to infer a measure for the effective spread, with many subsequent papers building on this idea (e.g., Choi, et al. 1988; George et al. 1991). However, the Roll (1984) measure suffers from a substantial limitation as it yields an infeasible negative spread when the first order

autocovariance is positive. Hasbrouck (2009; 2004) developed a Gibbs sampler Bayesian estimation which overcomes this negative spread problem and this was the technique employed by Novy-Marx and Velikov (2016) to compute the effective spread.

Following Roll (1984), more recent research has developed more advantageous models for estimating the effective spread. Corwin and Schultz (2012) design a measure of the effective spread using the daily high and low prices, and more recently Abdi and Rinaldo (2017) develop an estimator using the high, low, and close prices, which aims to overcome the problems of both Roll (1984) and Corwin and Schultz (2012). Unlike in Roll (1984), their measure is independent of the trade direction and can distinguish spreads of different magnitudes. Second, given that high, low, and close prices are used simultaneously means that the spread is computed from a richer information set compared to Roll who only uses closing prices. Third, it does not require ad-hoc adjustments for non-trading days. Empirically, the effective spread estimates generated by the model of Abdi and Rinaldo (2017) yield a cross-sectional correlation with the Daily TAQ effective spreads equal to 0.74 and with the Monthly TAQ spreads equal to 0.86. These are the highest correlations compared to other estimators relying on quote data, including Roll (1984) and Corwin and Schultz (2012). Given the advantages and superior performance offered by Abdi and Rinaldo (2017) their estimator is employed to model the effective spread in this chapter.

Price impact due to the market order

Empirical researchers and practitioners have long identified the phenomenon whereby increasingly large trades are executed at increasingly unfavourable prices. The theoretical underpinning of this phenomenon has been a matter of debate. Kyle (1985) argues that price innovations are a function of their trade size due to players with asymmetric information acting to take advantage of expected price moves. Moro et al. (2009) suggest that market impact is a natural phenomenon with roots in basic economic theory, stock prices react to increasing demand. Regardless of the theoretical justification, market impact has been shown to be a fundamental element of trading frictions. More importantly, Frazzini et al. (2018) demonstrate that the market impact dominates all other costs, including the effective spread.

Unlike the linear nature of the effective spread, market impact is non-linear. The implication is that larger orders have higher cost per unit of stock traded than smaller orders. This also means that trading the same volume of a relatively illiquid stock and a relatively liquid stock, the former will have higher impact cost. Given the above, Frazzini et al. (2018) are justified for criticizing earlier literature, such as Novy-Marx and Velikov (2016), of ignoring the most dominant trading cost driver and focusing only on the spread cost. Furthermore, it is evident how the concept of market capitalisation is incorporated into the cost model. As such, it is argued that this model of trading frictions has the potential to naturally control for the microcap bias without the need to discard large sections of the sample, such as in Avramov et al. (2022) and Green et al. 2017. This is empirically confirmed by Keim and Madhavan (1996) who report that market impact is as high as 4% for small stocks, compared to the broader market for which it ranges between 0.3% and 1% (Chan and Lakonishok 1995). This chapter models the combined effect of effective spread and market impact to represent the trading frictions in the real trading environment.

It should also be noted that two assumptions are adopted. First, as Almgren and Chriss (2001) argue, market impact is a function of two quantities: the speed of execution and a volatility term. For example, when immediate execution is required the market impact is higher, but there is limited drift of the price during execution. On the contrary, if execution is requested without immediacy the market impact may be limited, however the price can drift to levels at which the competitive edge of a trading signal dissipates. For the purposes of this chapter, we assume that immediate execution is always requested, thus there is no possibility of slippage (Almgren 2003). Second, in theory, the market impact could have a permanent and a temporary component, that is price is temporarily inflated due to a large buy trade, but then a portion of that effect is deflated to reveal a longer term permanent effect (Almgren et al. 2005). Since this chapter is concerned about the impact on the trade and not the impact on the market, only the total impact is modelled; in other words, the potential price deflation occurring after a large buy trade does not feature.

The early microstructure literature explored the effectiveness of linear functions to model either the market impact explicitly (e.g. Hausman et al. 1992) or the aggregate price impact, which combines the effect of both spread and market impact (Korajczyk and Sadka 2004; Lesmond et al. 2004). The former found little empirical support, while the latter has been criticised for overstating the true extent of market impact (Frazzini et al. 2018). On the contrary, the notion of a square root relationship between the trade size and market impact, initiated by Kyle (1985), has found long-lasting success. Specifically, Kyle (1985) suggested a relationship between the square root of the dollars traded and market impact. This was later formalised (Torre 1997; Kahn and Grinold, 1999) as $MI \propto \sqrt{Q/V}$, where Q is the executed trade volume and V is the daily traded volume. The theoretical justifications for the square root relationship and its relevance are still being explored, with Gabaix et al. (2006) attributing it to the risk aversion of liquidity providers, Cont and Bouchaud (2000) using it to model herding behaviour and Pohl et al. (2017) using dimensional analysis to argue why this relationship is expected.

While the square root specification has been extensively corroborated empirically (Tóth et al. 2011; Frazzini et al. 2018), researchers have generalised the functional relationship to take a power form, such as $MI \propto (Q/V)^\gamma$ where $0 < \gamma < 1$ is a hyperparameter estimated from the data. In this way the model becomes more adaptive to small deviations from the restrictive square root without changing the fundamental structure of the relationship. Among others, both Bershova and Rakhlin (2013) and Zarinelli et al. (2015) find $\gamma = 0.47$, Tóth et al. (2011) suggest $\gamma = 0.50$, while Bouchaud et al. (2003) report the exponent in the range of $0.52 < \gamma < 0.6$. Considering the extensive findings, it is argued that the square root relationship with $\gamma = 0.5$ is surprisingly accurate and this is the hyperparameter used in this chapter.

2.3 Data and Methodology

2.3.1 Data

The predictor set contains 94 characteristics (Appendix 2A), constructed according to Green et al. (2017). This is the same dataset used in Gu et al. (2020) and Avramov et al. (2022). The creation of this collection of factors is attributed to Green et al. (2017), but for the purposes of this chapter, all factors were reproduced in Python according to their original formulations. The only deviation of this chapter regarding the dataset is that it does not include interaction terms. Specifically, both Gu et al. (2020) and Avramov et al. (2022) interact each of the 94 factors with 8 macroeconomic factors and include the resulting variables in the input dataset. Such interaction terms are not utilised in this chapter purely to limit the computational time required, given that both the prediction and the optimisation procedure are computationally demanding. These are outlined in the next section.

Data were sourced from Compustat, the Centre for Research in Security Prices (CRSP), and Institutional Brokers Estimate System (I/B/E/S). All securities are sourced from CRSP. Firms with common stock (CRSP share code groupings = 1) traded on the NYSE, AMEX or NASDAQ are included in the sample (CRSP exchange Codes = 1, 2 or 3). The sample period spans from December 1959, which is when the first substantial data started to be documented in CRSP and ends in December 2022. The three-month Treasury-bill rate is used as a proxy for the risk-free rate. Monthly stock returns, dividends, and prices are sourced from CRSP and accounting information are collected from the Quarterly and Annual Fundamental Files of the Compustat database. Lastly, all observations reporting monthly returns lower than -100% were deleted.

To avoid a possible look-ahead bias, the excess returns at the end of month m are aligned with the monthly-reported data at month $m - 1$, quarterly reported data at month $m - 3$ and annual-reported data at month $m - 12$. Furthermore, to maximise the usable sample a monthly frequency is applied to the dataset by setting the quarterly-reported factors for month $m - 2$ and

$m - 3$ to equal the factor value at $m - 1$. The annually reported factor values are similarly applied to the last 12 months.

To avoid any influences from extreme values, a winsorizing procedure is applied at the 1st and 99th percentile of the cross-sectional distribution at each monthly period. Subsequently, the values within the monthly cross-sectional distribution are standardised to have a zero mean and unit standard deviation. The scaling scheme ensures that the magnitudes of factors are normalised, and thus the neural network model is not skewed due to large magnitudes. Missing values are replaced by zero, the post-standardised monthly mean. This procedure forces the factors with a high percentage of missing data towards the mean and guarantees that statistically significant characteristics do not result from volatile values due to missing data.

2.3.2 Methodology

Given the discussion in the literature review, this chapter designs a function for trading frictions by combining the price impact due to the spread, s , and the price impact due to the market order, m . The computation of these is described in this section.

Price impact due to the spread

Similar to Roll (1984), the spread model proposed by Abdi and Ranaldo (2017) builds on the assumption that if markets are efficient then the price action on the bid and ask should be equivalent, thus the effective spread should span uniformly in the two directions above and below the efficient price, p^e . Note that the efficient price is unobservable and encapsulates the fundamental value of a security, which is different from the closing price p . Therefore, the deviation of the actual closing ($\log^2$) price, p , from its efficient level is due to the effective spread impact, s , such that

$$p = p^e \pm s/2. \quad (2.1)$$

² All prices in log terms.

Given that the efficient price is not observable, this means that the effective spread, s , cannot be estimated unless a sensible proxy for p^e is used. The innovation in Abdi and Ranaldo (2017) is their argument that the mid-range average of two consecutive days is an effective proxy for the efficient price. Specifically, let η_t be the mid-range estimate for day t , such that³, $\eta_t = (h_t + l_t)/2$, where h and l are the quoted daily high and low prices, respectively. Taking the average of this estimate for two consecutive days, t and $t + 1$, yields a natural estimator for the efficient price, according to

$$E \left[p_t^e - \frac{\eta_t + \eta_{t+1}}{2} \right] = 0. \quad (2.2)$$

The efficient price is assumed to follow geometric Brownian motion, except from non-trading periods, such as weekends, when the efficient-price change is assumed to be zero. The variable $\frac{\eta_t + \eta_{t+1}}{2}$ represents the estimate $\widehat{p}_t^e$ for the efficient value p_t^e .

Abdi and Ranaldo (2017) show that the squared distance between the closing price and the proxy for the efficient price is a function of two components: the effective spread and the efficient price variance. Mathematically this is shown by

$$E \left[\left(p_t - \frac{\eta_t + \eta_{t+1}}{2} \right)^2 \right] = s^2/4 + (1/2 - k_1/8) \sigma_e^2, \quad (2.3)$$

where $k_1 = 4 \ln(2)$ and σ_e^2 is the variance of the efficient price proxy. Given the above discussion, the rational implication is that if the variance component is subtracted from equation (2.3) above then the effective spread will be calculable. Abdi and Ranaldo (2017) compute the variance analytically as

$$E[(\eta_{t+1} - \eta_t)^2] = (2 - k_1/2) \sigma_e^2. \quad (2.4)$$

³ Similar to Corwin and Schultz (2012), Abdi and Ranaldo (2017) assume that the high price is driven by the buying action, thus, $h^e = h + s/2$, whereas the low price is driven by the selling action, $l^e = l - s/2$. Therefore, $\eta = (h^e + l^e)/2 = (h + l)/2$ since the spreads cancel out.

Subtracting equation (2.4) from (2.3) yields the effective spread estimate

$$s = \sqrt{4 E[(p_t - \eta_t)(p_t - \eta_{t+1})]}. \quad (2.5)$$

The expectation within the square root in equation (2.5) may yield a negative number which implies an infeasible spread. The best way to deal with this, among alternatives tested by Abdi and Rinaldo (2017), is the two-day calculated spreads. This dives into the daily frequency of price data and calculates the spread for each pair of consecutive days. When the spread value is infeasible it is replaced by zero. Subsequently, the average spread is calculated across all the entries in a month, and is used as the estimate of the monthly spread impact, $\hat{s}$,

$$\hat{s} = \frac{\Delta P}{P} = \frac{1}{N} \sum_{t=1}^N \sqrt{\max \{4(p_t - \eta_t)(p_t - \eta_{t+1}), 0\}}, \quad (2.6)$$

where N is the number of days in each month.

Price impact due to the market order

As discussed in the literature review, the market impact, $\hat{m}$, formulation is a rather simple, yet powerful measure for this trading cost. Specifically, this is calculated as

$$\hat{m} = \frac{\Delta P}{P} = q \sigma_D \left(\frac{Q}{V} \right)^\gamma, \quad (2.7)$$

where Q is the trade volume executed, V is the daily traded volume, σ_D is the daily volatility, $q \in \{-1, 1\}$, is an indicator taking the value of 1 for buys and -1 for sells, and γ is the power hyperparameter discussed in the literature, $\gamma = 0.5$. ΔP is the price impact, interpreted as the deviation between the price at the start of the trade and the execution price. The daily traded volume, V , is computed as the average daily traded volume of the past 25 trading days. For the purposes of this chapter trading is assumed to happen instantly, so the impact cost is entirely the market impact calculated by equation (2.7) above. This implies that there is no timing risk, defined as the price changing due to the trade being placed over a long period (Almgren et al. 2005).

Portfolio optimisation

The portfolio optimisation framework is developed as outlined in Boyd et al. (2017) and the neural network model is developed exactly as discussed in Gu et al. (2020). The monthly stock price predictions for horizons $H \in \{1, 3, 12\}$ months-ahead are computed from the neural network and are used as the input to the optimisation algorithm. The algorithm applies the cost function described in the previous section and chooses trades that maximise the predicted Sharpe ratio net-of-costs. This creates a zero-cost, long-short portfolio at the beginning of month t . Subsequently, the portfolio holdings are adjusted based on the realised returns of month t . Finally, the simulation continues to the next iteration whereby the portfolio positions at the beginning of month $t + 1$ are chosen based on the neural network predictions for month $t + 1$, the cost function and also, the current portfolio at the end of month t . No look-ahead bias is introduced at any stage of the methodology.

Three simulations are run, one for each of the three investment horizons: monthly, quarterly and annually. It is important to note that in each simulation the entire horizon, H , is considered in the optimisation procedure. For example, when the investment horizon is quarterly ($H = 3$) the optimiser uses the three month-ahead prediction from the neural network and the portfolio is held until the end of month $t + 3$. Subsequently, the holdings are adjusted based on the realised price change from the beginning of month t until the end of month $t + 3$. Then the optimiser is tasked to estimate the new positions that will be held until the end of month $t + 6$, as described in the previous paragraph. This procedure has an interesting property. Specifically, longer investment horizons imply lower trading costs due to the less frequent trading activity, however, the prediction uncertainty is also higher.

The optimisation procedure is described below but readers who wish to gain further intuition about the topic are encouraged to read Diamond and Boyd (2016). The portfolio evolution is simulated to propagate the portfolio weights H periods ahead and deduce the optimal long-short portfolio net of trading costs. Denote the vector $h_t \in \mathbb{R}^{n+1}$ containing the cash values invested in the collection of n assets. The entry $(h_t)_{n+1}$ contains the cash balance of the

investor⁴. The total value of the portfolio at time t is $v_t = \mathbf{1}' h_t$ which is the sum of all the elements in the portfolio. Once the capital is invested the weights of the portfolio $w_t \in \mathbb{R}^{n+1}$ are calculated as $w_t = h_t/v_t$ and the sum of weights equals to 1, $\mathbf{1}' w_t = 1$, by definition.

Trading positions are entered given the predictions of the machine learning model. The vector $u_t \in \mathbb{R}^{n+1}$ contains the cash values of trades. When an entry is positive it implies that the specific asset is bought and when an entry is negative the asset is sold. It should be underlined that the vector u_t is not a prespecified variable but it is the outcome of the optimisation procedure that optimises the trading strategy after considering the price predictions and associated costs over H periods ahead. Assuming that no cash is added or withdrawn from the portfolio, the net of inflows-outflows from the portfolio after transaction costs should equal to 0, i.e.,

$$\mathbf{1}' u_t + \varphi(u) = 0, \quad (2.8)$$

where $\varphi(u)$ is the trading cost function related to the trades u_t . Equation (2.8) suggests that new positions can only be entered when previous positions are sold, or by the use of funds in the cash balance, $(u_t)_{n+1}$. Let $z_t = u_t/v_t$ denote normalised vector, interpreted as the traded value as a proportion of the total portfolio balance, and $\varphi(z) = \varphi(u)/v_t$, then equation (2.8) is normalised as

$$\mathbf{1}' z_t + \varphi(z) = 0, \quad (2.9)$$

Once all trades are placed the portfolio changes to $h_t^p = h_t + u_t$, where h_t^p denotes the post-trade portfolio, and its normalised form is $h_t^p/v_t = w_t + z_t$. It is important to note that trading is assumed to occur at the start of period t . After period t ends the portfolio changes according to the realised asset returns, according to $h_{t+1} = (\mathbf{1} + r_t) \odot h_t^p$, where h_{t+1} is the portfolio at the end of period t and the start of period $t + 1$, r_t is the returns in period t and $\odot$ denotes the Hadamard multiplication. The returns on the cash balance $(r_t)_{n+1}$ are estimated by the 1-month risk-free rate. The total portfolio returns, $R_t^P = (v_{t+1} - v_t)/v_t$, are estimated as

$$R_t^P = r_t' w_{t+1} - \varphi(z). \quad (2.10)$$

⁴ When $(h_t)_{n+1} = 0$ implies that the investor's full capital is invested in the n assets.

Equation (2.10) states that the total portfolio returns are calculated as the sum of the weighted returns on the portfolio weights after the normalised trade vector, z_t , minus the normalised trading costs. As Boyd et al. (2017) argue, when the average per-period returns are small compared to 1 then the next period weights can be estimated as $w_{t+1} = w_t + z_t$, which is used to simulate the evolution of the portfolio into the next period.

The maximisation objective starts from equation (2.10) and follows the paradigm of Markowitz (1952) in forming a convex optimisation problem considering the expected returns, portfolio risk and transaction costs, as described by equation (2.11)

$$\begin{aligned} \text{maximise} \quad & \sum_{\tau=t}^{t+H-1} \left[r_{\tau|t}' w_{\tau+1} - \varphi(z) - \psi(w_{\tau+1}) \right], \\ \text{s. t.} \quad & \mathbf{1}' z_t = 0. \end{aligned} \quad (2.11)$$

Equation (2.11) shows that the objective function aims to maximise the utility of the investor while considering the expected returns from period t until period $t + H$. The expected returns $r_{\tau|t}$ result from the prediction of the neural network model at time t for the next trading period, as well the next H trading periods-ahead i.e., $\tau \in [t : t + H]$. The weights $w_{\tau+1}$ result from the optimisation through the trade vector z which maximises the objective function in equation 2.11. The cost function $\varphi(z)$ is comprised by the spread impact and market impact models described by equations 2.6 and 2.7, respectively. Lastly the volatility function $\psi(w_{\tau+1})$ estimates the weighted volatility of returns and aims to penalise positions of high volatility. The volatility of each stock is calculated as the standard deviation of returns of the last 25 trading days and weighted with $w_{\tau+1}$. It should also be noted that the portfolio optimisation problem in equation 2.11 is convex and solved with CVXPY. This is a python-embedded modelling library for convex optimisation developed at Stanford University by Steven Diamond and Stephen Boyd⁵. All functions and constraints discussed above are convex, thus the problem can reliably be solved using the optimiser.

⁵ Diamond and Boyd (2016)

2.4 Results

2.4.1 Portfolio performance

Tables 2.1 to 2.3 report the performance statistics for the portfolios resulting from the predictions of the neural network (NN) models when the prediction and rebalancing are performed monthly, quarterly, and annually, respectively. The data reported are all calculated as the mean values across all five neural network setups (NN1 - NN5), while the results for the individual NN models are presented in Appendix 2B - 2D. The monthly rebalancing model is the model developed in Gu et al. (2020).

Table 2.1 confirms that the neural network model of Gu et al. (2020) generates a positive out-of-sample R^2 of 0.31%, per month, under the value-weighted scheme. This corroborates the findings of Gu et al. (2020) who report predictive ability in the range of 0.33% to 0.40% per month for value-weighted portfolios. Interestingly, the equal-weighted scheme generates a lower, but still positive, out-of-sample R^2 of 0.16%. Superficially, this is a counterintuitive result given the evidence that anomalies tend to exist in microcaps (Hou et al. 2020). However, this result is confirmed by Gu et al. (2020) who show that the predictive- R^2 of large stocks (ranges from 0.49% to 0.70%) is indeed higher than that of small stocks (ranges from 0.38% to 0.46%). In light of this predictability, one expects that value-weighted NN portfolios would yield higher predictive- R^2 than equal-weighted portfolios given the higher weight placed on large stocks, which explains the evidence in Table 2.1. This is an encouraging result as it highlights that the machine learning predictability is not merely driven by anomalies existing in difficult-to-trade small stocks, but rather it measures a premium that can be captured by active trading.

The above findings are consistent with the profitability of the neural network portfolios. Specifically, the predictions of the neural network models generate a monthly average return of 1.87% under the equal-weighted rebalancing scheme, with a Sharpe ratio of 1.36. Although the value-weighted portfolio generated a larger predictive- R^2 than the equal-weighted, when profitability is considered, it actually generates a lower monthly average

return of 0.63% with a Sharpe ratio of 0.53. Although this again seems counterintuitive, the recent financial machine learning literature has identified the weakness of predictive- R^2 to translate into economic value in the return prediction of complex models such as neural networks. Indeed, Kelly, et al. (2024) discuss how market timing strategies may generate significant profitability with predictive- R^2 metrics that are negative. Rather, they recommend comparing based on economic criteria, such as mean returns, for which the equal-weighted scheme outperforms.

One of the major contributions of this chapter is to examine optimised portfolios compared to the conventional equal- and value-weighted portfolios. When the portfolio weights are optimized, the neural network results are even more impressive, they are enhanced in terms of both predictability and profitability. Specifically, assuming no trading frictions, the out-of-sample R^2 is 1.23%, which is a substantial improvement in the predictive ability compared to the 0.16% of the equal-weighted scheme and the 0.31% of the value-weighted scheme. Similarly, the profitability of the optimised model reaches 3.37% return per month on average with an outstanding Sharpe ratio of 2.51. These are important new findings that highlight substantial predictive and economic value to be extracted from complex machine learning methods, such as neural networks, beyond those reported in the extant literature, which commonly applies equal- and value- weighting schemes.

It should be noted that Gu et al. (2020) find even higher mean returns generated by the neural network models. Specifically, they report that the equal-weighted scheme generates returns in the range of 2.91% to 3.33% (compared to 1.87% in Table 2.1) and the value-weighted scheme from 1.81% to 2.26% (compared to 0.63% in Table 2.1). The same is true for Avramov et al. (2022) who report an equal weighted return for NN3 of 2.47% and a value-weighted return of 1.56%. This is an important discrepancy from this chapter as it highlights the effect of adding interaction terms as predictors. Specifically, both Gu et al. (2020) and Avramov et al. (2022) interact each of the 94 predictors of returns with eight macroeconomic variables generating a predictor set of 920 variables. In contrast, this chapter only uses the 94

original predictors and no interaction terms.⁶ A comparison of the results reveals two things. First, the non-linearities associated with the interaction terms have incremental value for predicting stock returns, which also highlights the effectiveness of neural networks in capturing non-linear relationships. Second, the neural network setup remains an exceptionally good model for predicting expected stock returns since it can achieve high predictability and profitability even without the broader predictor set which includes interaction terms.

To compare findings with the prior literature, the results discussed so far assume trading occurs in a frictionless environment. Table 2.1 presents new results investigating the impact of transactions costs and investor capital. The table shows that when trading frictions are modelled, both the predictability and profitability of neural network portfolios are severely affected. Specifically, in environments with realistic trading frictions, when trading a small portfolio of 1 million USD and a large portfolio of 100 million USD, the monthly out-of-sample R^2 of the equal-weighted portfolio reduces to -1.21% and -1.29% respectively, and the monthly mean returns fall precipitously to -1.92% and -2.33%. Similarly, for the value-weighted portfolio the monthly out-of-sample R^2 drops to -1.33% and -1.41% for the small and large portfolios respectively, and monthly mean returns decline to -0.70% and -1.14%, respectively. These findings are concerning. Despite the success of NN models for return prediction, the two portfolio construction methods commonly applied in the literature to take advantage of it fail to produce positive performance after realistic trading frictions are considered.

To counter this disappointment, optimised portfolios revive the excitement for neural networks. The final column of Table 2.1 highlights that when trading a small portfolio it is, actually, possible to achieve positive predictability and profitability after trading frictions. Specifically, when trading with a small portfolio based on the neural network model, an out-of-sample R^2 of 0.53% can be achieved as well as mean monthly returns of 1.99%. When the initial portfolio size is large however, both out-of-sample R^2 and mean returns dive in the negative (-2.23% and -1.04%, respectively). This is a

⁶ This decision is based on the immense computational load of both the neural network prediction and portfolio optimisation.

major finding since it establishes that the effectiveness of neural network predictions is not as bright as indicated by Gu et al. (2020) but still not as grim as suggested by Avramov et al. (2022). In fact, the truth lies in the middle. When the portfolio is optimised there is significant predictability to be extracted as long as one is not trade with large enough capital that will substantially move the markets. The indication is that considerable predictability stems from thinly traded stocks, but it is still real and tradable.

The effects of optimisation are strikingly evident when the turnover of the neural network portfolio is examined. For the equal- and value-weighted portfolios, turnover is as high as 99% per month, a finding which is corroborated by both Gu et al. (2020) and Avramov et al. (2022). After optimising the portfolio weights the portfolio turnover is much lower, it more than halves to 41%. This is achieved because the optimiser avoids taking extreme positions of high volatility, but rather maximises the expected returns given the expected volatility. Following this procedure the Sharpe ratio is maximised, reaching 2.51 in the setting of a frictionless environment. The incorporation of volatility is absent from the traditional equal- and value-weighted portfolio construction, however, these new results demonstrate that it proves critical when constructing portfolios with high turnover, such as machine learning portfolios. When trading frictions are considered, the optimiser avoids entering positions for which the expected friction impact offsets the expected excess returns. This keeps turnover low, at 42% when trading a small portfolio, and extracts positive returns while limiting risk. However, when managing a large portfolio trading activity is more extensive, which increases the turnover and decreases the profitability to be negative.

On a final note, the neural network portfolios exhibit reasonable downside deviations across the span of the sample as shown by Table 2.1. Specifically, the equal-weighted portfolio exhibits a -18.80% maximum 1-month loss and a -34.47% maximum drawdown, whilst the value-weighted portfolio fares slightly better at -12.60% and -26.26%, respectively. Given that the sample contains major recessions and stock market bubble bursts, it can be argued that the machine learning signal is to some extent independent of the market and can provide diversification benefits. Similar downside deviations are also noted by Gu et al. (2020). When considering transaction costs, however, the excessive trading causes increased 1-month losses and

drawdown to over -95%, which indicates that the portfolios are fully diminished. When overlaying the prediction with portfolio optimization, the results are very different. In optimized portfolios, the 1-month loss and maximum drawdown remain as low as -6.84% and -13.60%, respectively. Given the above, it can be concluded that the neural network of Gu et al. (2020) by itself fails to deliver positive performance in the presence of trading frictions unless it is augmented by an optimisation procedure as proposed herein.

Despite the model's success on the monthly horizon, when quarter-ahead and year-ahead investment horizons are evaluated, the performance of neural networks is disappointing. It is reminded that, for these schemes the neural network predictions are 3-months ahead and 12-months ahead, respectively, and consequently, portfolio rebalancing is conducted on quarterly and annual basis, respectively. Table 2.2 reports the results for the quarterly investment horizon and indicates that both the out-of-sample R^2 and mean returns of the equal-weighted portfolio drop to -1.47% and -1.71% quarterly, respectively. When trading frictions are considered, the performance declines even further. For example, the turnover reaches 104%, which appears higher than the 98% reported for the monthly rebalancing method, however, it is highlighted that in this case the turnover is measured on a quarterly basis. If one could allocate this evenly on a monthly basis⁷, one could understand the dynamic of the monthly horizon prediction in generating high turnovers. The less intensive trading activity of the quarterly investment horizon implies lower trading frictions, yet it fails to capture positive predictability and results in the poor performance noted above. Comparable results are reported for the value-weighted portfolio.

The annual investment horizon results in Table 2.3 exhibit comparable performance. Although the reported turnover is as high as 140%, trading occurs only once a year and thus the actual trading activity is less intensive than both the monthly and quarterly horizons. The performance exhibited is worse than the monthly horizon, however, it is better than the quarterly horizon. Specifically, for the annual horizon and equal-weighted portfolios, the out-of-sample R^2 generated is -3.84% for a 12-month period ahead as

⁷ The performance in Table 2.2 is in the quarterly resolution, thus it would be misguided to report monthly-adjusted values by dividing by 3. Similarly, the performance in Table 2.3 exists in the annual perspective.

compared to -1.47% for a 3-month period in Table 2.2. Similarly, the mean returns are actually positive for a 12-month horizon at 0.91%, compared to -1.71% for the 3-month horizon in Table 2.2.

Based on the evidence, two concluding remarks can be made. First, the neural network model benefits from the plurality of data in the prediction of month-ahead returns, however it proves unable to predict longer term returns. Of course, this is expected since the prediction uncertainty rises the longer in the future one attempts to make a prediction. Second, longer horizons imply less trading activity, thus naturally control for capital loss due to excessive frictions. The quarterly rebalancing results are evidently the worst among the three simulations both in terms of out-of-sample R^2 and mean returns. This indicates that the quarterly horizon is neither short enough to benefit from the dynamic nature of the neural network model, nor is it not long enough to restrict excessive trading. It can also be concluded that the worsening performance of longer horizons suggests that the neural network predictability is dependent on short-lived anomalies.

[Insert Table 2.1]

[Insert Table 2.2]

[Insert Table 2.3]

2.4.2 Model performance

Figure 2.1 illustrates the dispersion of the neural network's profitability according to the mean returns and predictability, as measured by the out-of-sample R^2 , for the five neural network models (NN1 to NN5). The mean monthly returns are shown on the left-hand side and the out-of-sample R^2 on the right-hand side. The major finding illustrated is that both the profitability and predictability measures are mostly in the positive region. Specifically, the entire interquartile range for all weighting schemes is in the positive territory, but there are some extreme negative measurements. Also, the value-weighted scheme, although producing the lowest mean predictability and profitability, generates the least dispersed performance. The complete opposite happens with the optimised portfolios, which exhibit the highest mean performance, but also the most dispersed. This is an interesting finding as it highlights a certain trade-off between mean model performance and dispersion.

[Insert Figure 2.1]

2.4.3 Risk-adjusted performance

Adjusting the neural network portfolio returns for common risk factors reinforces the findings described above. As Table 2.4 shows for the monthly horizon, the risk-adjusted return on the equal-weighted HML portfolio under no trading frictions is significant and positive across all factor models, but it becomes significant and negative after trading frictions are considered. The optimised portfolio's risk-adjusted return is positive and statistically significant at the 1% level across the board in a frictionless environment, but also remains significant and positive under trading frictions with a small portfolio (with the exception of the Fama and French (1993) three factor model augmented with the Pástor and Stambaugh (2003) liquidity factor). This confirms the major finding of this chapter that there is substantial and attainable predictability in the neural network prediction model under certain conditions. When the initial portfolio is large the alphas dive into the negative territory, however, none are statistically significant.

The performance findings on the quarterly and annual investment horizons are also confirmed on a risk-adjusted basis. Table 2.5 shows that the equal weighted portfolio of the quarterly forecast is statistically negative across the board even in an environment without trading frictions. When frictions are considered, the optimised portfolio alphas turn marginally positive in significance when trading a small portfolio, which then evaporates for the large portfolio. For the annual horizon, Table 2.6 reports that the alphas are not significant for the equal-weighted portfolio even without trading frictions and then are significant and negative when frictions are considered. The optimised portfolio alphas are positive and significant in a frictionless environment but turn insignificant when frictions are considered. In summary, these findings confirm that the quarterly forecast is the worst setting among the three different scenarios even on risk-adjusted basis.

[Insert Table 2.4]

[Insert Table 2.5]

[Insert Table 2.6]

2.4.4 Performance across different neural network setups

Table 2.7 reports the portfolio statistics for the individual neural network setups. Panel A shows that for the equal-weighted portfolio without trading frictions, the out-of-sample R^2 increases until NN3, then decreases as 4 and 5 layers are added. For the value-weighted and optimised portfolios, the NN2 to NN5 setups exhibit relatively stable out-of-sample R^2 , whereas the shallowest network, NN1, generates the poorest predictability. Additionally, for the equal- and value-weighted portfolios the impact of trading frictions is greatest for NN1 specification than the deeper models. On the contrary, for the optimised portfolio the impact is more uniform across all models. This is indicative that the deeper neural network models pick up unique pricing signals, whereas the shallowest model, NN1, depends more on the anomalies in microcaps. With regard to mean returns, Panel B shows that for the equal-weighted portfolio the shallow model, NN1 generates the highest performance. However, after optimising the portfolio weights the deeper models again outperform. In fact, the same conclusion is deduced when the Sharpe ratio is considered in Panel C. This confirms the finding discussed, that the deeper networks identify unique information and highlights the incremental effect of nonlinearities in risk premium measurement.

Figures 2.2 and 2.3 illustrate how the individual neural network models perform across rebalancing frequencies in terms of out-of-sample R^2 and mean returns, respectively. Both figures confirm previously stated findings. First, the monthly rebalancing frequency generates the best performance, and the quarterly rebalancing frequency generates the worst. The only exception is the optimised mean return where the annual frequency exhibits the worst performance. Second, both the predictability and profitability of neural networks remain positive after accounting for trading frictions when the initial portfolio is small. When the initial portfolio size is large instead, the performance turns negative. Third, in the optimised portfolio the deeper neural networks generate higher performance. Fourth, the positive predictability of the equal-weighted portfolio does not exist in the longer frequencies, even in a frictionless environment, therefore confirming the effectiveness of the neural networks to make use of high frequency data. Likewise, Figure 2.4 confirms previous findings on risk-adjusted returns. First, the risk-adjusted returns for both equal- and value-weighted portfolios most

often turn negative after applying trading frictions, with the exception of equal-weighted NN1. Second, the optimised portfolio alphas are positive and statistically significant after applying trading frictions related to trading with a small portfolio. Third, when trading the optimised portfolio with a large initial capital, risk-adjusted performance turns negative, but not statistically significantly so across factor models.

[Insert Table 2.7]

[Insert Figure 2.2]

[Insert Figure 2.3]

[Insert Figure 2.4]

2.4.5 Statistical significance of trading friction impact

Tables 2.8 to 2.10 quantify the statistical significance of the trading friction impact. The time series of portfolio's excess returns is compared between a frictionless environment and after the impact of trading frictions. A significant t -statistic indicates that the neural network returns after frictions are smaller in the statistically significant sense, therefore implying that the friction impact is significant. Table 2.8 shows that for all neural network models (NN1 to NN5) trading frictions have a statistically significant effect on portfolio performance. This highlights that it is imperative for investigations into machine learning asset pricing models to control for trading frictions. Another important observation is that the impact of frictions is greatest in the equal-weight portfolio, which indicates that a large portion of the neural network predictability exists in microcaps, as also suggested by Avramov et al. (2022). A new finding is that the impact of trading frictions is lowest on the optimised portfolio, which highlights that the optimiser effectively controls for the microcap bias by avoiding positions for which the expected friction impact offsets the expected returns. Similar findings are seen for the quarterly and annual forecasting horizons in Tables 2.9 and 2.10.

[Insert Table 2.8]

[Insert Table 2.9]

[Insert Table 2.10]

2.4.6 Prediction performance

Table 2.11 evaluates how accurately the neural network model predicts the month-ahead excess returns for all five setups (NN1-NN5). For the equal-weighted portfolio, the prediction is remarkably accurate. For example, in the NN1 model, the spread portfolio is expected to yield 2.95% and actually yields 2.51%. The prediction for the top and bottom legs are also accurate, specifically, -0.89% vs -1.07% for the bottom decile and 2.06% vs 1.44% for the top decile. The prediction accuracy for the optimised portfolios, however, is not accurate on either leg. Most importantly though, the realised return on the long leg outperforms the predicted value by a substantial amount, whereas the predicted return on the short leg underperforms the predicted value. This is quite an interesting result which confirms two findings already discussed. First, a considerable portion of the predictability of the neural network portfolio exists in the short leg and difficult-to-trade stocks as suggested by Avramov et al. (2022). This cannot be captured, thus the realised value underperforms the expectation. Second, there is meaningful predictability to be extracted by the long leg, as suggested by Gu et al. (2020). This is an attainable performance which more than compensates for the shortcoming of the short leg.

[Insert Table 2.11]

2.4.7 Turnover and downside deviation

Figure 2.5 illustrates the turnover across individual neural network models and across rebalancing frequencies. To begin, it is important to note that the annual horizon illustrates turnover when trading occurs once a year, such that if converted to per-month basis, it represents the lowest trading activity. This confirms that having a longer-term horizon is a natural way to control for performance losses due to trading frictions. A second observation is that using the optimised portfolio limits the turnover very effectively due to the advantages of the optimisation method previously discussed. In fact, restricting trading in unfavourable positions brings the turnover down to the about 40%, achieving only the realisable predictability. It is interesting that in every case, the trading activity is roughly constant across all five neural network setups.

Figure 2.6 measures the downside deviation in terms of maximum 1-month loss. The figure illustrates that the downside deviation is relatively low when trading frictions are not present. However, when frictions are applied, portfolios formed based on neural network predictions incur incremental deviations, often exceeding the -40% mark. This indicates that the equal- and value-weighted portfolios from neural network prediction models do not provide the limited downside deviation described in the literature (Gu, et al., 2020) but exhibit serious portfolio risk in a realistic trading environment. On the other hand, the optimised portfolio of the neural network model exhibits substantially lower risk. For example, the maximum 1-month loss when trading a small portfolio remains below 10% even after including trading frictions, which is impressive given that the sample spans serious market downturns. The maximum 1-month loss of the large portfolio, however, ranges from -10% to -30% which represents considerable risk.

The downside deviation is also illustrated in terms of drawdown in Figures 2.7 to 2.9 for the three rebalancing frequencies. Figure 2.7 corroborates that the exceptional monthly performance of the equal- and value-weighted portfolios is only an artefact of ignoring trading frictions. This is evident by the limited drawdown existing only in the frictionless environment, whereas, when frictions are applied, the portfolio balance completely deteriorates. More encouragingly, the optimised portfolio shows rather limited risk, as shown by the drawdown of the small portfolio barely surpassing -10% and recovering, and the large portfolio just reaching -35%, over the span of the sample. Interestingly, for the equal- and value-weighted portfolios, the drawdown in the frictionless environment appears to have been impacted during both the 2000 and 2008 bear markets, however, the optimised portfolio was only impacted during 2008 and 2015 contractions. Similar results are noted in the quarterly and annual rebalancing periods.

[Insert Figure 2.5]

[Insert Figure 2.6]

[Insert Figure 2.7]

[Insert Figure 2.8]

[Insert Figure 2.9]

2.5 Discussion

The success of the neural network model in the prediction of asset prices is not spurious. The major finding in this chapter is that the prediction success of neural networks is not as bright as indicated by Gu et al. (2020) but still not as grim as suggested by Avramov et al. (2022). It is seen that despite the failure of the equal- and value-weighted portfolios to generate predictability after adjusting for trading frictions, when one uses optimised portfolios and trades with a small initial capital, one is able to extract substantial predictability from the neural network model. In fact, this result still holds true after adjusting for common risk factors. When the initial capital is large enough though, the predictability is fully diminished. Optimisation alongside a realistic trading frictions model proves effective in controlling the high turnover of equal- and value-weighted methods (actually halving it) while securing performance with limited volatility. Similarly, it limits the downside deviation over the span of the sample.

The fact that the extractable performance is conditional on the investor size does not mean that it is unreal or unachievable. This chapter shows that it can be perfectly extracted under certain conditions and also, it can be enhanced by further engineering of the financial model, as it can be deduced by the increased performance when the input contains all the interaction terms (Gu et al. 2020; Avramov et al. 2022). Therefore, it is arguable that attempts to control for limits-to-arbitrage by excluding sections of the sample, as in Avramov et al. 2022, are ill-advised given that they discard predictive information that is attainable in trading. To understand the extent of informational loss, consider that Avramov et al. (2022) discard 49% of their sample by excluding microcaps, 78% after excluding nonrated firms and 83% after excluding financially distressed firms. These represent substantial portions of the sample which are lost and with them real and attainable predictive information is lost. On the contrary, by modelling trading frictions as a function of the market microstructure one is able to utilise the whole sample while trading friction implications are directly considered in the trading positions.

A considerable portion of the predictability of the neural network portfolio was found to exist in the short leg which was unable to be captured by the optimiser. This is supportive of the findings in Avramov et al. (2022) that the machine learning performance is driven by distressed and difficult-to-trade stocks. Nonetheless, it was also found that there is considerable predictability in the long leg of the portfolio, as suggested by Gu et al. (2020). In fact, there is extractable performance which more than compensates for the shortcoming of the short leg and highlights the effectiveness of the neural network model to identify unique and tradable signals.

Both Gu et al. (2020) and Avramov et al. (2022) report higher performance from their neural network portfolio than what is reported in this chapter. This discrepancy reveals the added value of using interaction terms which both papers employ. This finding strongly suggests that the nonlinearities associated with the interaction terms have incremental value in asset pricing prediction and introduces the potential to extract further predictability from the optimised neural network portfolio. The positive effect of nonlinearities is also evident when comparing the performance of individual neural network setups. This chapter showed that the shallowest network, NN1, exhibits the highest mean returns only in the equal-weighted portfolio when trading frictions are not considered. When the weights are optimised and frictions are applied, it is seen that the deeper networks, NN2 to NN5, outperform in terms of out-of-sample R^2 , mean returns and Sharpe ratio. Therefore, it can be again argued that the increased nonlinearities captured by the deep neural network models are a value added to risk premium measurement.

The comparison of different forecast horizons reveals that the best results exist in the month-ahead prediction, while the predictive performance deteriorates significantly beyond that. Of course, this is expected as predictive uncertainty naturally rises with the horizon of prediction. At the same time, it was remarked that the relative intensity of the trading activity lowers when the forecasting horizon increases. Longer rebalancing horizons provide a natural way to limit friction losses due to excessive trading activity. The combination of these two findings explains why the quarterly investment horizon exhibits the worst results as this horizon is not short enough to generate exceptional predictability nor it is long enough to incur minimal

trading friction losses. It should be noted that Gu et al. (2020) report contrasting findings. They indicate that the annual forecast generates an impressive out-of-sample R^2 an entire order of magnitude larger than the monthly forecast and based on this finding they suggest that the machine learning models are not merely driven by short-lived inefficiencies. It is suggested that this finding should be taken with a pinch of salt. In fact, the results in Avramov et al. (2022) are strongly suggestive that the machine learning predictability is, indeed, related to short-term inefficiencies. This is supportive of the findings herein as the longer-term horizons are documented to perform more poorly than the monthly horizon.

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Tables

Table 2.1: Portfolio statistics – Monthly investment horizon (mean across all models NN1-NN5)

This table reports portfolio statistics for the neural network portfolios when the investment horizon is one month. The results reported are the average realisations across all five neural network models, NN1-NN5. The individual results for each model are included in Appendix 2B. The left section of the table presents the results after equal weighting the portfolio holdings at each rebalancing period. Similarly, the middle section presents the value-weighted results, and the right section presents the results of the optimised portfolio. For each method, results are reported in three environments: (a) an environment without trading frictions, (b) an environment with trading frictions investing a small initial capital of 1 million USD and (c) an environment with trading frictions investing a large initial capital of 100 million USD. The neural network models are used to predict the stock returns one month ahead, which are then used to create long-short portfolios. The long-short portfolio is constructed by ranking stocks according to the predicted returns and form 10 portfolios, buying the highest quantile portfolio and selling the lowest quintile portfolio. The weights of the holdings in each portfolio vary according to the weighting scheme. The trades are placed, and the portfolio is evaluated at the next period based on the metrics reported. In the first environment no penalties are applied due to trading frictions while in the other two environments penalties are applied simulating realistic trading frictions as a function of the microstructure of individual stocks. Investing horizon is one month and thus, rebalancing of the portfolio is performed monthly based on predicted returns. Mean Returns (%) and R^2_{oos} (%) denote the mean returns and mean out-of-sample R^2 , respectively, across the time series of each portfolio, both reported in percentage basis. Max 1M loss (%) and Max DD (%) denote the Maximum 1-month loss and maximum drawdown, across the time series of each portfolio, both reported in percentage basis. Turnover is the monthly average portfolio turnover and Sharpe ratios are annualised.

Weighting	Equal			Value			Optimised		
	Without TF	With TF Low Capital	With TF High Capital	Without TF	With TF Low Capital	With TF High Capital	Without TF	With TF Low Capital	With TF High Capital
Model	Mean	Mean	Mean	Mean	Mean	Mean	Mean	Mean	Mean
Initial capital (millions)	All	1	100	All	1	100	All	1	100
Horizon (months)	1	1	1	1	1	1	1	1	1
Rebalancing	Monthly	Monthly	Monthly	Monthly	Monthly	Monthly	Monthly	Monthly	Monthly
R^2_{oos} (%)	0.16	-1.21	-1.29	0.31	-1.33	-1.41	1.23	0.53	-2.23
Mean Returns (%)	1.87	-1.92	-2.33	0.63	-0.70	-1.14	3.37	1.99	-1.04
t statistic	9.34	-8.91	-10.37	5.11	-5.30	-6.37	4.67	3.07	-0.87
Sharpe Ratio	1.36	-1.67	-1.90	0.53	-1.18	-1.28	2.51	1.43	-0.54
Sortino Ratio	1.11	-0.35	-0.57	0.27	-0.12	-0.22	5.67	1.43	-0.42
Information Ratio	0.93	-0.75	-0.75	0.01	-0.71	-0.75	0.64	0.02	-0.25
Turnover (%)	98	99	99	98	99	99	41	42	56
Max 1M loss (%)	-18.80	-24.41	-24.93	-12.60	-14.88	-38.12	-4.14	-6.84	-19.64
Max DD (%)	-34.47	-99.98	-100.00	-26.26	-95.41	-99.41	-6.40	-13.60	-38.28
Skewness	0.34	-0.29	-0.30	0.66	-0.16	-4.42	0.29	0.00	-0.68
Excess Kurtosis	2.77	2.41	1.68	4.09	2.73	3.21	-3.45	-3.18	-2.99

Table 2.2: Portfolio statistics – Quarterly investment horizon (mean across all models NN1-NN5)

This table reports portfolio statistics for the neural network portfolios when the investment horizon is three months. The results reported are the average realisations across all five neural network models, NN1-NN5. The individual results for each model are included in Appendix 2C. The left section of the table presents the results after equal weighting the portfolio holdings at each rebalancing period. Similarly, the middle section presents the value-weighted results, and the right section presents the results of the optimised portfolio. For each method, results are reported in three environments: (a) an environment without trading frictions, (b) an environment with trading frictions investing a small initial capital of 1 million USD and (c) an environment with trading frictions investing a large initial capital of 100 million USD. The neural network models are used to predict the stock returns three months ahead, which are then used to create long-short portfolios. The long-short portfolio is constructed by ranking stocks according to the predicted returns and form 10 portfolios, buying the highest quantile portfolio and selling the lowest quintile portfolio. The weights of the holdings in each portfolio vary according to the weighting scheme. The trades are placed, and the portfolio is evaluated at the next period based on the metrics reported. In the first environment no penalties are applied due to trading frictions while in the other two environments penalties are applied simulating realistic trading frictions as a function of the microstructure of individual stocks. Investing horizon is three months and thus, rebalancing of the portfolio is performed quarterly based on predicted returns. Mean Returns (%) and R²oos (%) denote the mean returns and mean out-of-sample R², respectively, across the time series of each portfolio, both reported in percentage basis. Max 1M loss (%) and Max DD (%) denote the Maximum 1-month loss and maximum drawdown, across the time series of each portfolio, both reported in percentage basis. Turnover is the monthly average portfolio turnover and Sharpe ratios are annualised.

Weighting	Equal			Value			Optimised		
	Without TF	With TF Low Capital	With TF High Capital	Without TF	With TF Low Capital	With TF High Capital	Without TF	With TF Low Capital	With TF High Capital
Model	Mean	Mean	Mean	Mean	Mean	Mean	Mean	Mean	Mean
Initial capital (millions)	All	1	100	All	1	100	All	1	100
Horizon (months)	3	3	3	3	3	3	3	3	3
Rebalancing	Quarterly	Quarterly	Quarterly	Quarterly	Quarterly	Quarterly	Quarterly	Quarterly	Quarterly
R²oos (%)	-1.47	-4.12	-4.16	-1.23	-5.54	-5.23	0.67	0.12	-0.77
Mean Returns (%)	-1.71	-4.81	-5.43	-0.13	-1.54	-2.06	2.21	0.72	-2.35
t statistic	-4.21	-11.91	-12.81	-0.76	-9.30	-8.80	2.86	0.90	-1.57
Sharpe Ratio	-1.40	-3.62	-3.87	-0.62	-3.10	-2.84	1.48	0.36	-1.00
Sortino Ratio	-0.24	-0.77	-1.03	-0.07	-0.23	-0.32	2.34	0.30	-0.51
Information Ratio	-0.34	-1.92	-1.98	-0.26	-1.11	-1.21	0.03	-0.73	-0.28
Turnover (%)	104	104	104	104	104	104	42	43	58
Max 1M loss (%)	-19.20	-24.27	-26.34	-5.31	-7.38	-14.18	-7.04	-8.77	-36.55
Max DD (%)	-88.61	-99.82	-99.93	-43.47	-88.25	-94.63	-11.37	-24.00	-59.36
Skewness	0.48	-0.19	-0.28	2.29	0.59	-2.19	0.13	0.06	-1.22
Excess Kurtosis	5.11	1.58	0.95	14.15	4.37	4.84	-3.11	-3.37	-2.08

Table 2.3: Portfolio statistics - Annual investment horizon (mean across all models NN1-NN5)

This table reports portfolio statistics for the neural network portfolios when the investment horizon is twelve months. The results reported are the average realisations across all five neural network models, NN1-NN5. The individual results for each model are included in Appendix 2D. The left section of the table presents the results after equal weighting the portfolio holdings at each rebalancing period. Similarly, the middle section presents the value-weighted results, and the right section presents the results of the optimised portfolio. For each method, results are reported in three environments: (a) an environment without trading frictions, (b) an environment with trading frictions investing a small initial capital of 1 million USD and (c) an environment with trading frictions investing a large initial capital of 100 million USD. The neural network models are used to predict the stock returns twelve months ahead, which are then used to create long-short portfolios. The long-short portfolio is constructed by ranking stocks according to the predicted returns and form 10 portfolios, buying the highest quantile portfolio and selling the lowest quintile portfolio. The weights of the holdings in each portfolio vary according to the weighting scheme. The trades are placed, and the portfolio is evaluated at the next period based on the metrics reported. In the first environment no penalties are applied due to trading frictions while in the other two environments penalties are applied simulating realistic trading frictions as a function of the microstructure of individual stocks. Investing horizon is twelve months and thus, rebalancing of the portfolio is performed annually based on predicted returns. Mean Returns (%) and R²oos (%) denote the mean returns and mean out-of-sample R², respectively, across the time series of each portfolio, both reported in percentage basis. Max 1M loss (%) and Max DD (%) denote the Maximum 1-month loss and maximum drawdown, across the time series of each portfolio, both reported in percentage basis. Turnover is the monthly average portfolio turnover and Sharpe ratios are annualised.

Weighting	Equal			Value			Optimised		
	Without TF	With TF Low Capital	With TF High Capital	Without TF	With TF Low Capital	With TF High Capital	Without TF	With TF Low Capital	With TF High Capital
Model	Mean	Mean	Mean	Mean	Mean	Mean	Mean	Mean	Mean
Initial capital (millions)	All	1	100	All	1	100	All	1	100
Horizon (months)	12	12	12	12	12	12	12	12	12
Rebalancing	Annually	Annually	Annually	Annually	Annually	Annually	Annually	Annually	Annually
R²oos (%)	-3.84	-12.06	-11.03	-1.58	-14.34	-12.12	0.72	0.32	0.35
Mean Returns (%)	0.91	-4.71	-6.90	0.43	-1.81	-2.55	2.25	0.89	-0.14
t statistic	2.66	-12.35	-9.73	1.76	-9.80	-8.82	2.70	1.06	-0.31
Sharpe Ratio	1.19	-7.46	-5.79	0.41	-6.33	-5.53	1.41	0.46	-0.31
Sortino Ratio	3.00	-0.76	-1.31	1.71	-0.51	-0.62	2.43	0.38	0.00
Information Ratio	0.68	-2.92	-3.22	0.13	-1.14	-1.39	-0.22	-0.98	-1.28
Turnover (%)	140	141	141	140	141	141	45	45	64
Max 1M loss (%)	-3.36	-11.66	-23.62	-1.45	-4.72	-9.54	-9.17	-10.76	-13.27
Max DD (%)	-7.87	-81.30	-91.70	-2.59	-46.99	-58.74	-10.55	-20.42	-28.34
Skewness	1.01	-0.59	-1.78	2.21	-0.48	-1.67	-0.29	-0.33	0.39
Excess Kurtosis	-0.62	-1.49	2.79	-2.79	-2.59	-2.10	-3.27	-3.34	-0.85

Table 2.4: Impact of trading frictions on the risk-adjusted returns of the NN portfolios, monthly

This table reports the mean returns and risk-adjusted returns averaged across all five neural network models, NN1-NN5. The individual results for each model are included in Appendix 2D. Panel A reports the results for the equal-weighted rebalancing method and Panel B reports the results for the optimised portfolio. Each panel reports the results for the environment without trading frictions in the top section, the environment with trading frictions investing a small initial capital of 1 million USD in the middle section and the environment with trading frictions investing a large initial capital of 100 million USD in the bottom section. The long-short portfolio is constructed by ranking stocks according to their machine learning predicted returns and form 10 portfolios, buying the highest quintile portfolio and selling the lowest quintile portfolio (HML portfolio). Each section reports the returns for the lowest quintile portfolio (1), the highest quintile portfolio (10) and the High-minus-Low portfolio (HML). Mean returns are adjusted for common factor models, specifically; (a) CAPM, (b) Fama-French-Carhart 4-factor model (FFC), (c) Pástor and Stambaugh liquidity factor model (FFC+PS), (d) Fama-French 5-factor model (FF5), (e) Fama-French 6-factor model (FF6), and Hou et. al., (2015) q-factor model (q). Both mean returns and risk-adjusted returns are expressed in percentage basis. The Newey-West adjusted t statistics are presented in the parentheses. Coefficients denoted with *, **, and *** are statistically significant at the 10%, 5%, and 1% levels, respectively. Investing horizon is one month and thus, rebalancing of the portfolio is performed monthly based on predicted returns.

Panel A: Equal weighted (mean across NN1 to NN5)

No TF							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	-0.668 (-2.06)	-0.767** (-3.02)	-0.696 (-2.61)	-0.727** (-2.89)	-0.674* (-2.70)	-0.665* (-2.75)	-0.451 (-0.71)
10	1.199*** (3.64)	1.119** (2.94)	1.144*** (4.15)	1.106*** (3.35)	1.062*** (3.65)	1.065*** (3.43)	1.494*** (4.60)
HML	1.867*** (9.34)	1.680*** (7.53)	1.631*** (7.44)	1.655*** (7.06)	1.519*** (6.85)	1.511*** (6.81)	1.736*** (5.74)
With TF Small Portfolio							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	1.246*** (3.69)	0.999 (2.61)	0.915 (2.36)	0.825 (2.03)	0.980 (2.51)	0.937 (2.30)	1.174** (2.84)
10	-0.677 (-1.94)	-0.968 (-2.26)	-0.969 (-2.34)	-0.783 (-1.83)	-1.012 (-2.31)	-1.050 (-2.38)	-0.715 (-1.71)
HML	-1.924*** (-8.90)	-2.205*** (-7.31)	-2.119*** (-7.15)	-1.843*** (-5.12)	-2.230*** (-7.45)	-2.223*** (-7.27)	-2.116*** (-7.19)
With TF Large Portfolio							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	1.454*** (4.28)	1.204*** (3.16)	1.119** (2.89)	1.025 (2.53)	1.180*** (3.06)	1.137** (2.83)	1.378*** (3.32)
10	-0.876 (-2.49)	-1.167 (-2.60)	-1.163 (-2.67)	-0.981 (-2.15)	-1.203 (-2.60)	-1.240 (-2.67)	-0.912 (-2.09)
HML	-2.330*** (-10.36)	-2.609*** (-7.64)	-2.517*** (-7.40)	-2.240*** (-5.40)	-2.621*** (-7.78)	-2.612*** (-7.63)	-2.517*** (-7.43)

Panel B: Optimised (mean across NN1 to NN5)

No TF							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	0.032 (0.17)	-0.268 (-2.05)	-0.295* (-2.27)	-0.309* (-2.09)	-0.342* (-2.51)	-0.380** (-3.14)	-0.141 (-1.20)
10	3.405*** (4.01)	2.669*** (4.32)	2.546*** (3.57)	2.185** (2.97)	2.147*** (4.23)	2.075*** (3.90)	3.322*** (3.86)
HML	3.373*** (4.67)	2.719*** (5.20)	2.618*** (4.96)	2.310*** (4.43)	2.261*** (4.13)	2.234*** (4.14)	3.236*** (5.24)
With TF Small Portfolio							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	0.229 (0.94)	-0.076 (-0.59)	-0.102 (-0.78)	-0.108 (-0.88)	-0.151 (-1.14)	-0.196 (-1.51)	0.060 (0.24)
10	2.386** (2.93)	1.687** (3.13)	1.543* (2.58)	1.240 (1.50)	1.229** (3.15)	1.365** (2.82)	2.208* (2.49)
HML	1.991** (3.06)	1.397** (3.12)	1.258** (2.77)	0.974 (1.79)	0.952*** (3.17)	0.931*** (3.24)	1.502* (2.40)
With TF Large Portfolio							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	1.068 (1.32)	1.108 (1.41)	0.905 (1.05)	1.017 (1.47)	0.970 (1.52)	1.266 (1.34)	1.266 (1.34)
10	0.021 (-0.06)	-0.014 (-0.32)	-0.586 (-1.92)	-0.131 (-0.40)	-0.162 (-0.54)	0.295 (0.49)	0.295 (0.49)
HML	-1.264 (-1.19)	-1.340 (-1.43)	-1.667 (-1.68)	-1.374 (-1.59)	-1.351 (-1.51)	-1.194 (-1.07)	-1.194 (-1.07)

Table 2.5: Impact of trading frictions on the risk-adjusted returns of the NN portfolios, quarterly

This table reports the mean returns and risk-adjusted returns averaged across all five neural network models, NN1-NN5. The individual results for each model are included in Appendix 2E. Panel A reports the results for the equal-weighted rebalancing method and Panel B reports the results for the optimised portfolio. Each panel reports the results for the environment without trading frictions in the top section, the environment with trading frictions investing a small initial capital of 1 million USD in the middle section and the environment with trading frictions investing a large initial capital of 100 million USD in the bottom section. The long-short portfolio is constructed by ranking stocks according to their machine learning predicted returns and form 10 portfolios, buying the highest quantile portfolio and selling the lowest quintile portfolio (HML portfolio). Each section reports the returns for the lowest quintile portfolio (1), the highest quintile portfolio (10) and the High-minus-Low portfolio (HML). Mean returns are adjusted for common factor models, specifically; (a) CAPM, (b) Fama-French-Carhart 4-factor model (FFC), (c) Pástor and Stambaugh liquidity factor model (FFC+PS), (d) Fama-French 5-factor model (FF5), (e) Fama-French 6-factor model (FF6), and Hou et. al., (2015) q-factor model (q). Both mean returns and risk-adjusted returns are expressed in percentage basis. The Newey-West adjusted t statistics are presented in the parentheses. Coefficients denoted with *, **, and *** are statistically significant at the 10%, 5%, and 1% levels, respectively. Investing horizon is three months and thus, rebalancing of the portfolio is performed quarterly based on predicted returns.

Panel A: Equal weighted (mean across NN1 to NN5)

No TF							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	1.770*** (3.89)	1.096 (2.13)	1.494*** (3.09)	1.477 (2.64)	1.010 (2.02)	1.030 (2.12)	1.853*** (3.48)
10	0.061 (0.09)	-0.555 (-1.19)	-0.179 (-0.40)	-0.237 (-0.63)	-0.526 (-1.23)	-0.519 (-1.21)	0.084 (0.23)
HML	-1.709*** (-4.21)	-1.697*** (-3.18)	-1.719*** (-3.20)	-1.757*** (-3.09)	-1.582** (-2.94)	-1.595*** (-3.01)	-1.814*** (-3.17)
With TF Small Portfolio							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	3.543*** (7.76)	2.931*** (5.75)	3.217*** (6.91)	3.167*** (5.76)	2.763*** (5.95)	2.798*** (6.19)	3.624*** (6.73)
10	-1.261*** (-3.17)	-1.805*** (-3.79)	-1.544*** (-3.40)	-1.667*** (-3.86)	-1.838*** (-4.14)	-1.833*** (-4.14)	-1.217* (-2.62)
HML	-4.804*** (-11.90)	-4.828*** (-8.93)	-4.853*** (-9.18)	-4.919*** (-8.88)	-4.693*** (-8.82)	-4.722*** (-9.03)	-4.932*** (-8.70)
With TF Large Portfolio							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	3.909*** (8.40)	3.286*** (6.30)	3.584*** (7.19)	3.532*** (6.14)	3.120*** (6.59)	3.153*** (6.80)	3.980*** (6.88)
10	-1.519*** (-3.75)	-2.049*** (-4.04)	-1.802*** (-3.75)	-1.897*** (-4.05)	-2.076*** (-4.31)	-2.070*** (-4.29)	-1.468*** (-3.04)
HML	-5.429*** (-12.81)	-5.428*** (-9.49)	-5.478*** (-9.58)	-5.515*** (-9.22)	-5.286*** (-9.38)	-5.314*** (-9.53)	-5.538*** (-9.14)

Panel B: Optimised (mean across NN1 to NN5)

No TF							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	0.151 (0.53)	-0.161 (-1.00)	-0.231 (-1.84)	-0.204 (-2.15)	-0.204 (-1.50)	-0.204 (-1.60)	-0.039 (-0.39)
10	2.357** (2.89)	1.641 (2.53)	1.605 (1.95)	1.153 (1.10)	1.197 (1.77)	1.181 (1.69)	2.214 (2.20)
HML	2.206** (2.86)	1.584 (2.46)	1.575 (2.58)	1.173 (1.19)	1.174 (2.42)	1.176 (2.37)	2.026 (2.19)
With TF Small Portfolio							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	0.387 (1.43)	0.089 (0.19)	0.017 (0.22)	0.031 (0.59)	0.032 (0.07)	-0.081 (-0.51)	0.206 (0.70)
10	1.110 (1.35)	0.358 (0.64)	0.321 (0.36)	-0.107 (-0.10)	-0.090 (-0.19)	-0.095 (-0.26)	0.971 (0.94)
HML	0.723 (0.89)	0.050 (0.04)	0.118 (-0.04)	-0.322 (-0.44)	-0.353 (-0.78)	-0.235 (-0.57)	0.538 (0.482)
With TF Large Portfolio							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	2.239 (1.85)	1.823 (2.08)	2.110 (2.11)	2.082 (2.03)	2.133 (2.11)	2.007 (1.91)	2.001 (2.34)
10	-0.107 (-0.16)	-0.674 (-1.68)	-0.329 (-0.97)	-0.871*** (-3.32)	-0.881 (-2.08)	-0.680 (-1.51)	-0.277 (-0.87)
HML	-2.347 (-1.57)	-2.716** (-3.09)	-2.663 (-2.05)	-3.137 (-2.21)	-3.241*** (-3.16)	-2.908* (-2.68)	-2.505 (-2.41)

Table 2.6: Impact of trading frictions on the risk-adjusted returns of the NN portfolios, annually

This table reports the mean returns and risk-adjusted returns averaged across all five neural network models, NN1-NN5. The individual results for each model are included in Appendix 2F. Panel A reports the results for the equal-weighted rebalancing method and Panel B reports the results for the optimised portfolio. Each panel reports the results for the environment without trading frictions in the top section, the environment with trading frictions investing a small initial capital of 1 million USD in the middle section and the environment with trading frictions investing a large initial capital of 100 million USD in the bottom section. The long-short portfolio is constructed by ranking stocks according to their machine learning predicted returns and form 10 portfolios, buying the highest quantile portfolio and selling the lowest quantile portfolio (HML portfolio). Each section reports the returns for the lowest quintile portfolio (1), the highest quintile portfolio (10) and the High-minus-Low portfolio (HML). Mean returns are adjusted for common factor models, specifically; (a) CAPM, (b) Fama-French-Carhart 4-factor model (FFC), (c) Pástor and Stambaugh liquidity factor model (FFC+PS), (d) Fama-French 5-factor model (FF5), (e) Fama-French 6-factor model (FF6), and Hou et. al., (2015) q-factor model (q). Both mean returns and risk-adjusted returns are expressed in percentage basis. The Newey-West adjusted t statistics are presented in the parentheses. Coefficients denoted with *, **, and *** are statistically significant at the 10%, 5%, and 1% levels, respectively. Investing horizon is twelve months and thus, rebalancing of the portfolio is performed annually based on predicted returns.

Panel A: Equal weighted (mean across NN1 to NN5)

No TF							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	0.318 (0.78)	1.195 (1.65)	1.268 (1.89)	2.127 (1.77)	1.426 (2.08)	1.462 (2.08)	0.969 (1.28)
10	1.228 (2.54)	2.409*** (3.37)	2.671*** (3.34)	4.097*** (4.24)	2.807*** (3.59)	2.826*** (3.78)	2.048** (2.72)
HML	0.909 (2.66)	-0.237 (-0.22)	-0.111 (-0.06)	0.554 (0.84)	0.038 (0.01)	0.053 (0.01)	-0.357 (-0.27)
With TF Small Portfolio							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	3.310*** (8.20)	3.159*** (13.76)	3.072*** (12.90)	2.769*** (8.05)	3.130*** (11.24)	3.180*** (10.68)	3.010*** (16.80)
10	-1.399*** (-3.11)	-1.609*** (-5.38)	-1.192*** (-4.08)	-1.222*** (-3.56)	-1.225*** (-3.94)	-1.176*** (-3.71)	-1.705*** (-5.65)
HML	-4.709*** (-12.35)	-4.983*** (-12.86)	-4.464*** (-12.88)	-4.180*** (-21.46)	-4.550*** (-13.42)	-4.556*** (-12.78)	-4.930*** (-12.48)
With TF Large Portfolio							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	4.589*** (8.30)	4.391*** (8.59)	4.269*** (8.39)	3.709*** (6.60)	4.194*** (9.40)	4.308*** (9.52)	4.284*** (8.37)
10	-2.314*** (-3.91)	-2.496*** (-4.20)	-2.048*** (-3.83)	-1.782*** (-5.93)	-1.995*** (-3.83)	-1.988*** (-3.71)	-2.620*** (-4.17)
HML	-6.903*** (-9.73)	-7.102*** (-6.57)	-6.518*** (-6.38)	-5.680*** (-10.04)	-6.383*** (-6.98)	-6.496*** (-6.87)	-7.119*** (-6.06)

Panel B: Optimised (mean across NN1 to NN5)

No TF							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	0.298 (0.95)	-0.012 (-0.50)	-0.108 (-0.88)	-0.086 (-1.21)	-0.049 (-0.63)	-0.195 (-1.25)	0.118 (0.08)
10	2.544*** (3.05)	1.813*** (3.66)	1.985* (2.64)	1.551 (1.69)	1.436*** (3.00)	1.542** (2.75)	2.385** (2.92)
HML	2.246 (2.70)	1.607** (3.20)	1.874 (2.41)	1.456 (1.70)	1.259 (2.30)	1.517 (2.26)	2.041 (2.70)
With TF Small Portfolio							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	0.459 (1.34)	0.137 (0.17)	0.022 (-0.26)	0.056 (-0.84)	0.105 (0.02)	-0.070 (-0.55)	0.290 (0.86)
10	1.351 (1.62)	0.598 (1.25)	0.812 (0.97)	0.372 (0.26)	0.230 (0.76)	0.358 (1.40)	1.187 (1.40)
HML	0.891 (1.06)	0.241 (0.43)	0.568 (0.60)	0.135 (-0.10)	-0.101 (-0.31)	0.208 (0.46)	0.672 (0.81)
With TF Large Portfolio							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	0.716 (1.37)	0.341 (1.18)	0.118 (0.51)	0.163 (0.50)	0.052 (1.09)	-0.115 (0.53)	0.560 (1.38)
10	0.572 (0.63)	-0.162 (-0.67)	-0.068 (-0.31)	-0.680 (-1.37)	-0.600 (-2.03)	-0.470 (-1.80)	0.428 (0.44)
HML	-0.144 (-0.30)	-0.722 (-1.98)	-0.410 (-0.73)	-1.028 (-1.53)	-0.880 (-2.12)	-0.776 (-1.73)	-0.358 (-0.94)

Table 2.7: Prediction and profitability statistics – individual models, monthly rebalancing

This table reports portfolio statistics for each of the five neural network setups (NN1-NN5), individually, when the portfolios are rebalanced monthly. Panel A (grey) reports the out-of-sample R^2 in percentage basis, Panel B (green) reports the mean returns in percentage basis, Panel C (blue) reports the annualised Sharpe Ratio and Panel D (orange) reports the annualised Information Ratio. The top section of each panel reports the results for the equal-weighted method, the middle section for the value-weighted method and the bottom section for the optimised-weighted method. Each section reports the results for the five neural network setups across three environments: (a) an environment without trading frictions, (b) an environment with trading frictions, investing a small initial capital of 1 million USD and (c) an environment with trading frictions, investing a large initial capital of 100 million USD. The results are computed at each rebalancing period and then averaged across all periods to generate the table.

Panel A: Out-of-sample R^2 (%)			
Weighting	Equal		
Model	Without TF	With TF Small Portfolio	With TF Large Portfolio
NN1	0.14	-1.58	-1.68
NN2	0.17	-1.24	-1.27
NN3	0.20	-0.99	-1.09
NN4	0.15	-1.08	-1.17
NN5	0.13	-1.16	-1.23

Weighting	Value		
Model	Without TF	With TF Small Portfolio	With TF Large Portfolio
NN1	0.25	-1.54	-1.58
NN2	0.30	-1.35	-1.49
NN3	0.30	-1.38	-1.47
NN4	0.34	-1.23	-1.37
NN5	0.35	-1.15	-1.13

Weighting	Optimised		
Model	Without TF	With TF Small Portfolio	With TF Large Portfolio
NN1	0.89	0.11	-0.60
NN2	1.32	0.74	-3.99
NN3	1.19	0.46	-3.21
NN4	1.30	0.64	-2.81
NN5	1.43	0.72	-0.53

Panel B: Mean Returns (%)			
Weighting	Equal		
Model	Without TF	With TF Small Portfolio	With TF Large Portfolio
NN1	2.51	-1.73	-2.18
NN2	1.49	-2.57	-3.01
NN3	1.98	-1.85	-2.24
NN4	2.02	-1.71	-2.10
NN5	1.34	-1.76	-2.12

Weighting	Value		
Model	Without TF	With TF Small Portfolio	With TF Large Portfolio
NN1	0.92	-0.47	-0.90
NN2	0.58	-0.86	-1.23
NN3	0.61	-0.69	-1.14
NN4	0.53	-0.78	-1.24
NN5	0.50	-0.69	-1.17

Weighting	Optimised		
Model	Without TF	With TF Small Portfolio	With TF Large Portfolio
NN1	3.18	1.75	0.35
NN2	3.34	1.69	-1.15
NN3	3.34	1.97	0.04
NN4	3.49	2.32	-1.58
NN5	3.52	2.23	-2.85

Panel C: Sharpe Ratio			
Weighting	Equal		
Model	Without TF	With TF Small Portfolio	With TF Large Portfolio
NN1	1.99	-1.64	-1.91
NN2	1.04	-2.04	-2.29
NN3	1.45	-1.67	-1.90
NN4	1.45	-1.53	-1.76
NN5	0.88	-1.46	-1.66

Weighting	Value		
Model	Without TF	With TF Small Portfolio	With TF Large Portfolio
NN1	1.00	-1.02	-1.23
NN2	0.49	-1.45	-1.76
NN3	0.49	-1.14	-1.15
NN4	0.38	-1.22	-1.19
NN5	0.31	-1.09	-1.09

Weighting	Optimised		
Model	Without TF	With TF Small Portfolio	With TF Large Portfolio
NN1	2.51	1.29	0.08
NN2	2.15	1.21	-0.21
NN3	2.57	1.45	-0.11
NN4	2.62	1.60	-1.14
NN5	2.72	1.58	-1.30

Panel D: Information Ratio			
Weighting	Equal		
Model	Without TF	With TF Small Portfolio	With TF Large Portfolio
NN1	1.04	-1.05	-1.05
NN2	0.91	-1.01	-1.01
NN3	1.06	-0.62	-0.62
NN4	0.89	-0.56	-0.57
NN5	0.74	-0.51	-0.51

Weighting	Value		
Model	Without TF	With TF Small Portfolio	With TF Large Portfolio
NN1	0.16	-0.59	-0.62
NN2	-0.17	-0.98	-1.08
NN3	0.15	-0.56	-0.59
NN4	-0.11	-0.80	-0.82
NN5	0.01	-0.63	-0.65

Weighting	Optimised		
Model	Without TF	With TF Small Portfolio	With TF Large Portfolio
NN1	0.22	-0.49	-0.42
NN2	0.29	-0.26	-0.38
NN3	0.82	0.24	-0.01
NN4	1.14	0.71	-0.22
NN5	0.72	-0.11	-0.21

Table 2.8: Statistical significance of the impact of trading frictions, monthly rebalancing

This table quantifies the statistical significance of the impact of trading frictions by performing one tailed t-test between the neural network portfolio returns without trading frictions and the returns after trading frictions. The test performed is the dependent t-test for paired samples and tests the null hypothesis that the expected value of returns in a frictionless environment (μ_{NTF}) is lower or equal than the expected value of returns after frictions (μ_{TF}), $H_0: \mu_{NTF} \leq \mu_{TF}$. Panels A to E report the results for the neural network setups starting with the one-layer model (NN1) to the five-layer model (NN5), respectively. Each panel shows the results for the equal-weighted portfolios in the top section, the results for the value-weighted portfolios in the middle section and the results for the optimised portfolios in the bottom section. Each section reports the significance of the impact of trading in an environment with trading frictions, investing a small initial capital of 1 million USD and an environment with trading frictions, investing a large initial capital of 100 million USD. The first column reports the mean returns of the strategy in an environment without trading frictions, the second columns the returns when trading frictions are applied, and t statistic reports the magnitude of statistical significance of the t test. Investing horizon is one month and thus, rebalancing of the portfolio is performed monthly based on predicted returns.

Panel A: NN1				
Weighting	Mean Returns without TF (%)	Mean Returns with TF (%)	t statistic	Compared Portfolio
Equal	2.509	-1.726	41.62	Small
	2.509	-2.179	46.49	Large
Value	0.915	-0.473	14.73	Small
	0.915	-0.903	24.21	Large
Optimised	3.184	1.749	3.40	Small
	3.184	0.345	8.11	Large
Panel B: NN2				
Weighting	Mean Returns without TF (%)	Mean Returns with TF (%)	t statistic	Compared Portfolio
Equal	1.494	-2.570	33.87	Small
	1.494	-3.008	34.82	Large
Value	0.577	-0.860	21.90	Small
	0.577	-1.226	27.53	Large
Optimised	3.341	1.685	5.06	Small
	3.341	-1.153	9.97	Large
Panel C: NN3				
Weighting	Mean Returns without TF (%)	Mean Returns with TF (%)	t statistic	Compared Portfolio
Equal	1.975	-1.853	36.21	Small
	1.975	-2.243	38.94	Large
Value	0.611	-0.688	11.02	Small
	0.611	-1.141	20.98	Large
Optimised	3.335	1.969	6.32	Small
	3.335	0.035	8.41	Large
Panel D: NN4				
Weighting	Mean Returns without TF (%)	Mean Returns with TF (%)	t statistic	Compared Portfolio
Equal	2.017	-1.707	35.40	Small
	2.017	-2.103	37.49	Large
Value	0.532	-0.782	10.64	Small
	0.532	-1.239	20.70	Large
Optimised	3.485	2.322	3.74	Small
	3.485	-1.582	9.87	Large
Panel E: NN5				
Weighting	Mean Returns without TF (%)	Mean Returns with TF (%)	t statistic	Compared Portfolio
Equal	1.344	-1.764	34.76	Small
	1.344	-2.117	33.25	Large
Value	0.496	-0.694	9.63	Small
	0.496	-1.172	19.36	Large
Optimised	3.520	2.230	3.63	Small
	3.520	-2.853	10.52	Large

Table 2.9: Statistical significance of the impact of trading frictions, quarterly rebalancing

This table quantifies the statistical significance of the impact of trading frictions by performing one tailed t-test between the neural network portfolio returns without trading frictions and the returns after trading frictions. The test performed is the dependent t-test for paired samples and tests the null hypothesis that the expected value of returns in a frictionless environment (μ_{NTF}) is lower or equal than the expected value of returns after frictions (μ_{TF}), $H_0: \mu_{NTF} \leq \mu_{TF}$. Panels A to E report the results for the neural network setups starting with the one-layer model (NN1) to the five-layer model (NN5), respectively. Each panel shows the results for the equal-weighted portfolios in the top section, the results for the value-weighted portfolios in the middle section and the results for the optimised portfolios in the bottom section. Each section reports the significance of the impact of trading in an environment with trading frictions, investing a small initial capital of 1 million USD and an environment with trading frictions, investing a large initial capital of 100 million USD. The first column reports the mean returns of the strategy in an environment without trading frictions, the second columns the returns when trading frictions are applied, and t statistic reports the magnitude of statistical significance of the t test. Investing horizon is three months and thus, rebalancing of the portfolio is performed quarterly based on predicted returns.

Panel A: NN1				
Weighting	Mean Returns without TF (%)	Mean Returns with TF (%)	t statistic	Compared Portfolio
Equal	-2.109	-5.115	19.84	Small
	-2.109	-5.677	22.60	Large
Value	-0.147	-1.511	5.74	Small
	-0.147	-2.147	16.55	Large
Optimised	1.470	0.151	1.63	Small
	1.470	-3.726	7.27	Large
Panel B: NN2				
Weighting	Mean Returns without TF (%)	Mean Returns with TF (%)	t statistic	Compared Portfolio
Equal	-3.965	-6.751	16.46	Small
	-3.965	-7.318	16.79	Large
Value	-0.724	-2.133	12.16	Small
	-0.724	-2.632	17.13	Large
Optimised	1.844	0.155	4.31	Small
	1.844	-1.690	7.04	Large
Panel C: NN3				
Weighting	Mean Returns without TF (%)	Mean Returns with TF (%)	t statistic	Compared Portfolio
Equal	-1.109	-4.417	17.67	Small
	-1.109	-5.064	18.86	Large
Value	0.030	-1.413	12.13	Small
	0.030	-1.879	14.43	Large
Optimised	2.415	0.930	4.82	Small
	2.415	-1.832	8.22	Large
Panel D: NN4				
Weighting	Mean Returns without TF (%)	Mean Returns with TF (%)	t statistic	Compared Portfolio
Equal	-0.862	-4.117	17.85	Small
	-0.862	-4.811	19.12	Large
Value	0.042	-1.425	10.88	Small
	0.042	-1.935	14.47	Large
Optimised	2.307	0.882	6.08	Small
	2.307	-2.688	7.95	Large
Panel E: NN5				
Weighting	Mean Returns without TF (%)	Mean Returns with TF (%)	t statistic	Compared Portfolio
Equal	-0.503	-3.623	17.94	Small
	-0.503	-4.276	18.42	Large
Value	0.159	-1.223	11.61	Small
	0.159	-1.711	15.27	Large
Optimised	2.995	1.499	4.31	Small
	2.995	-1.801	7.97	Large

Table 2.10: Statistical significance of the impact of trading frictions, annual rebalancing

This table quantifies the statistical significance of the impact of trading frictions by performing one tailed t-test between the neural network portfolio returns without trading frictions and the returns after trading frictions. The test performed is the dependent t-test for paired samples and tests the null hypothesis that the expected value of returns in a frictionless environment (μ_{NTF}) is lower or equal than the expected value of returns after frictions (μ_{TF}), $H_0: \mu_{NTF} \leq \mu_{TF}$. Panels A to E report the results for the neural network setups starting with the one-layer model (NN1) to the five-layer model (NN5), respectively. Each panel shows the results for the equal-weighted portfolios in the top section, the results for the value-weighted portfolios in the middle section and the results for the optimised portfolios in the bottom section. Each section reports the significance of the impact of trading in an environment with trading frictions, investing a small initial capital of 1 million USD and an environment with trading frictions, investing a large initial capital of 100 million USD. The first column reports the mean returns of the strategy in an environment without trading frictions, the second columns the returns when trading frictions are applied, and t statistic reports the magnitude of statistical significance of the t test. Investing horizon is twelve months and thus, rebalancing of the portfolio is performed annually based on predicted returns.

Panel A: NN1				
Weighting	Mean Returns without TF (%)	Mean Returns with TF (%)	t statistic	Compared Portfolio
Equal	0.582	-4.944	15.10	Small
	0.582	-6.942	21.57	Large
Value	0.065	-2.013	10.40	Small
	0.065	-2.749	17.49	Large
Optimised	1.791	0.358	8.89	Small
	1.791	-0.679	9.91	Large
Panel B: NN2				
Weighting	Mean Returns without TF (%)	Mean Returns with TF (%)	t statistic	Compared Portfolio
Equal	0.234	-5.295	12.86	Small
	0.234	-7.483	20.79	Large
Value	0.337	-1.868	10.45	Small
	0.337	-2.653	13.74	Large
Optimised	1.942	0.610	5.96	Small
	1.942	0.322	11.99	Large
Panel C: NN3				
Weighting	Mean Returns without TF (%)	Mean Returns with TF (%)	t statistic	Compared Portfolio
Equal	1.037	-4.620	7.80	Small
	1.037	-6.984	17.72	Large
Value	0.569	-1.771	6.30	Small
	0.569	-2.777	9.94	Large
Optimised	2.578	1.235	5.82	Small
	2.578	-0.490	8.80	Large
Panel D: NN4				
Weighting	Mean Returns without TF (%)	Mean Returns with TF (%)	t statistic	Compared Portfolio
Equal	1.370	-4.329	10.17	Small
	1.370	-6.768	18.67	Large
Value	0.594	-1.697	10.16	Small
	0.594	-2.346	11.11	Large
Optimised	2.656	1.331	6.64	Small
	2.656	-1.546	9.93	Large
Panel E: NN5				
Weighting	Mean Returns without TF (%)	Mean Returns with TF (%)	t statistic	Compared Portfolio
Equal	1.325	-4.361	15.97	Small
	1.325	-6.341	20.71	Large
Value	0.565	-1.719	9.97	Small
	0.565	-2.240	10.58	Large
Optimised	2.263	0.924	11.54	Small
	2.263	1.671	3.82	Large

Table 2.11: Prediction performance of the neural network portfolios

This table reports the performance of the five neural network setups in predicting month ahead returns. Panels A to E report the predictions for the neural network setups starting with the one-layer model (NN1) to the five-layer model (NN5), respectively. Each panel shows the results for the equal-weighted scheme on the left section and the results for the optimised portfolios on the right section. The panels are also divided in three vertical sections which report the results for simulations of three trading environments: (a) an environment without trading frictions, (b) an environment with trading frictions investing a small initial capital of 1 million USD and (c) an environment with trading frictions investing a large initial capital of 100 million USD. Each section reports the results for the top and bottom deciles, as well as the High-minus-Low 'HML' portfolio. This is the long-short portfolios constructed by ranking stocks according to their machine learning predicted returns and form 10 portfolios, buying the highest quantile portfolio and selling the lowest quintile portfolio. For all setups, investing horizon is one month and thus, rebalancing is performed monthly based on predicted returns. The results for the quarterly rebalancing are presented in Appendix 2H and the results for the annual rebalancing are presented in Appendix 2I. Pred denotes the mean returns predicted by the machine learning model and Avg denotes the mean returns actually realised. Both returns are expressed in percentage basis. SD and SR measure the standard deviation and Sharpe Ratio of the portfolio, respectively, both in annualised basis and expressed in percentage basis.

Panel A: NN1									
	Portfolio	Equal Weighted Portfolios				Optimised Portfolios			
		Pred	Avg	SD	SR	Pred	Avg	SD	SR
Without TF	1	-0.886	-1.072	6.78	-0.67	-0.470	0.086	1.78	-0.28
	10	2.059	1.436	7.02	0.59	1.101	3.270	4.86	2.17
	HML	2.945	2.509	3.96	1.99	1.571	3.184	4.07	2.51
With TF Small Portfolio	1	-0.886	1.156	6.92	0.46	-0.470	0.326	1.87	0.18
	10	2.059	-0.570	7.36	-0.38	1.101	2.075	4.79	1.34
	HML	2.945	-1.726	4.15	-1.64	1.571	1.749	4.10	1.29
With TF Large Portfolio	1	-0.886	1.370	6.95	0.57	-0.470	0.800	3.87	0.51
	10	2.059	-0.809	7.44	-0.49	1.101	1.145	4.01	0.79
	HML	2.945	-2.179	4.38	-1.91	1.571	0.345	5.29	0.08

Panel B: NN2									
	Portfolio	Equal Weighted Portfolios				Optimised Portfolios			
		Pred	Avg	SD	SR	Pred	Avg	SD	SR
Without TF	1	-0.328	-0.380	7.30	-0.29	-0.085	0.058	0.75	-0.78
	10	1.436	1.115	6.83	0.45	1.031	3.399	5.27	2.08
	HML	1.764	1.494	4.20	1.04	1.116	3.341	5.01	2.15
With TF Small Portfolio	1	-0.328	1.796	7.42	0.73	-0.085	0.086	0.86	-0.57
	10	1.436	-0.774	7.20	-0.49	1.031	2.599	3.03	0.39
	HML	1.764	-2.570	4.77	-2.04	1.116	1.685	2.63	1.45
With TF Large Portfolio	1	-0.328	2.050	7.45	0.84	-0.085	1.375	5.08	0.79
	10	1.436	-0.958	7.22	-0.57	1.031	0.222	4.39	0.00
	HML	1.764	-3.008	4.91	-2.29	1.116	-1.153	6.69	-0.71

Panel C: NN3									
	Portfolio	Equal Weighted Portfolios				Optimised Portfolios			
		Pred	Avg	SD	SR	Pred	Avg	SD	SR
Without TF	1	-0.460	-0.780	6.48	-0.54	-0.421	-0.079	1.35	-0.79
	10	1.344	1.195	7.24	0.46	0.736	3.256	5.12	2.05
	HML	1.804	1.975	4.14	1.45	1.157	3.335	4.19	2.57
With TF Small Portfolio	1	-0.459	1.092	6.58	0.45	-0.421	0.197	1.48	-0.07
	10	1.344	-0.761	7.50	-0.46	0.736	2.166	5.01	1.34
	HML	1.803	-1.853	4.32	-1.67	1.157	1.969	4.17	1.45
With TF Large Portfolio	1	-0.459	1.267	6.64	0.54	-0.421	0.506	5.45	0.18
	10	1.344	-0.976	7.54	-0.56	0.736	0.541	2.70	0.40
	HML	1.803	-2.243	4.52	-1.90	1.157	0.035	5.92	-0.11

Panel D: NN4									
	Portfolio	Equal Weighted Portfolios				Optimised Portfolios			
		Pred	Avg	SD	SR	Pred	Avg	SD	SR
Without TF	1	-0.364	-0.734	6.50	-0.52	-0.375	0.017	1.38	-0.53
	10	1.352	1.282	7.31	0.50	0.743	3.502	5.25	2.16
	HML	1.717	2.017	4.24	1.45	1.118	3.485	4.31	2.62
With TF Small Portfolio	1	-0.365	1.079	6.62	0.44	-0.375	0.264	1.53	0.08
	10	1.352	-0.628	7.55	-0.40	0.743	2.587	5.33	1.53
	HML	1.717	-1.707	4.40	-1.53	1.118	2.322	4.55	1.60
With TF Large Portfolio	1	-0.365	1.293	6.72	0.54	-0.375	1.589	4.64	1.02
	10	1.352	-0.810	7.58	-0.48	0.743	0.007	2.92	-0.26
	HML	1.717	-2.103	4.60	-1.76	1.118	-1.582	5.47	-1.14

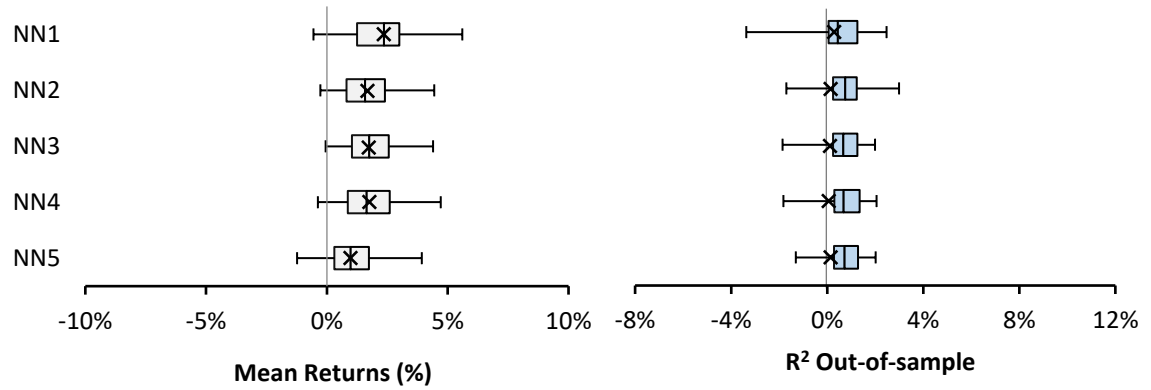
Panel E: NN5									
	Portfolio	Equal Weighted Portfolios				Optimised Portfolios			
		Pred	Avg	SD	SR	Pred	Avg	SD	SR
Without TF	1	-0.135	-0.376	7.10	-0.30	-0.267	0.078	1.24	-0.42
	10	1.317	0.967	6.42	0.39	0.870	3.598	4.93	2.37
	HML	1.453	1.344	4.36	0.88	1.137	3.520	4.19	2.72
With TF Small Portfolio	1	-0.135	1.110	7.33	0.41	-0.267	0.274	1.35	0.12
	10	1.317	-0.654	6.71	-0.46	0.870	2.504	5.00	1.58
	HML	1.453	-1.764	4.75	-1.46	1.137	2.230	4.39	1.58
With TF Large Portfolio	1	-0.135	1.290	7.39	0.49	-0.267	3.142	7.76	1.30
	10	1.317	-0.827	6.72	-0.55	0.870	0.289	3.28	0.07
	HML	1.453	-2.117	4.91	-1.66	1.137	-2.853	8.20	-1.30

Figures

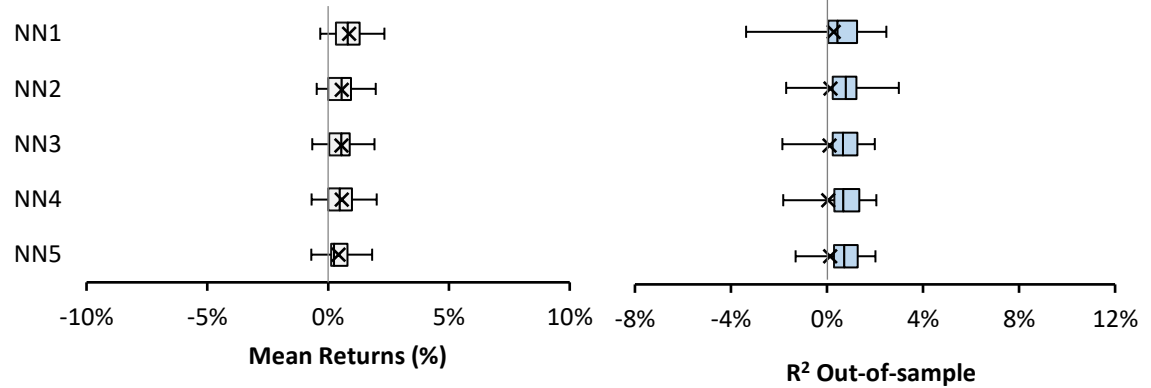
Figure 2.1: Model performance, monthly rebalancing

This figure illustrates the predictive ability of the five neural network setups for the monthly rebalancing frequency. The results for the equal-weighted, value-weighted and optimised portfolios are illustrated in Panels A, B and C, respectively. In each panel, the distribution of mean returns is plotted on the left in white and the distribution of out-of-sample R^2 is plotted on the right in blue. Both are reported in percentage basis.

Panel A: Equal-weighted Portfolios



Panel B: Value-weighted Portfolios



Panel C: Optimised Portfolios

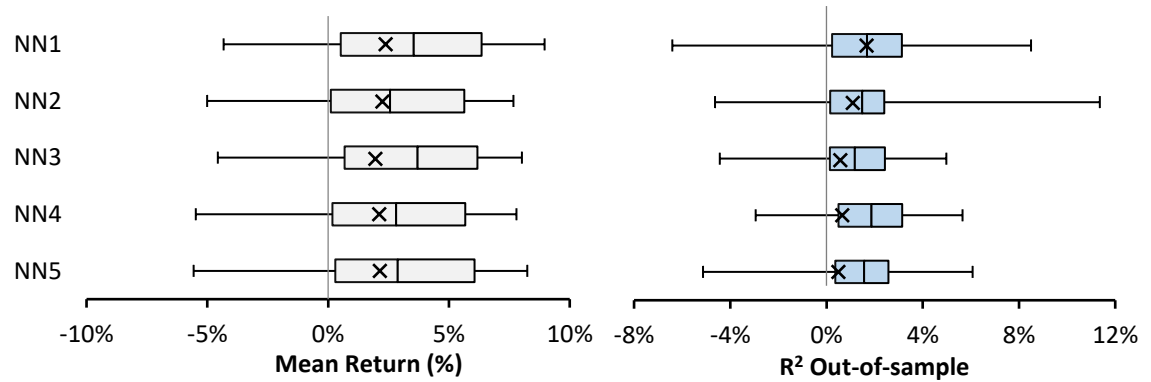


Figure 2.2: Impact of trading frictions on out-of-sample R^2 – individual models, all rebalancing frequencies

This figure illustrates the out-of-sample R^2 (%) for each of the five neural network portfolios (NN1-NN5), individually. Panel A, at the top, illustrates the results of the equal-weighted method and Panel B, at the bottom, illustrates the results of the optimised method. In each panel, the monthly rebalancing simulation results are shown in the left graph, the quarterly rebalancing simulation results are shown in the middle graph and the annual rebalancing simulation results are shown in the right graph. In each graph the simulation of no trading frictions is plotted in green, the simulation of an environment with trading frictions investing a small initial capital of 1 million USD is plotted in light red and the simulation of an environment with trading frictions investing a large initial capital of 100 million USD is plotted in dark red. The results are averaged across all periods and presented in per-month basis.

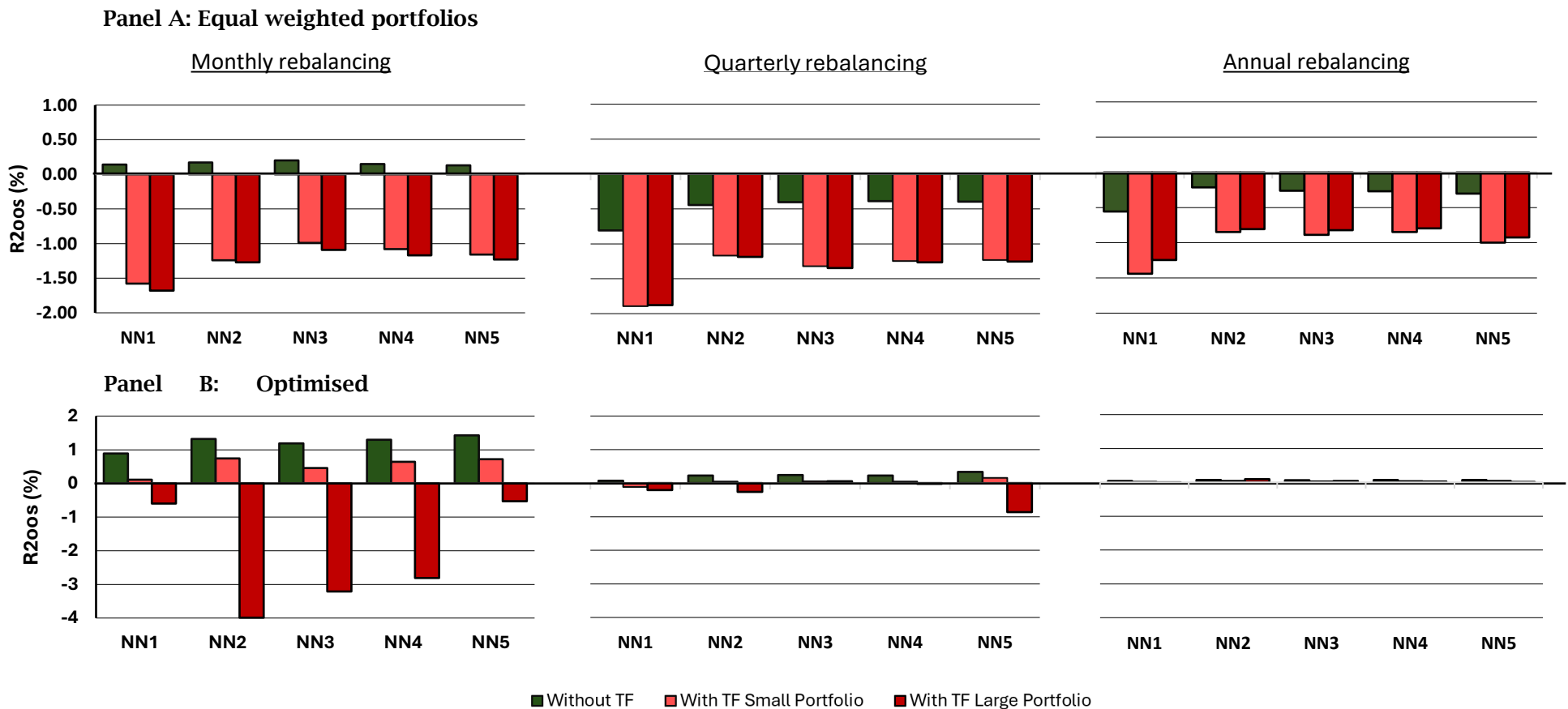


Figure 2.3: Impact of trading frictions on mean returns – individual models, all rebalancing frequencies

This figure illustrates the mean returns (%) for each of the five neural network portfolios (NN1-NN5), individually. Panel A, at the top, illustrates the results of the equal-weighted method and Panel B, at the bottom, illustrates the results of the optimised method. In each panel, the monthly rebalancing simulation results are shown in the left graph, the quarterly rebalancing simulation results are shown in the middle graph and the annual rebalancing simulation results are shown in the right graph. In each graph the simulation of no trading frictions is plotted in green, the simulation of an environment with trading frictions investing a small initial capital of 1 million USD is plotted in light red and the simulation of an environment with trading frictions investing a large initial capital of 100 million USD is plotted in dark red. The results are averaged across all periods and presented in per-month basis.

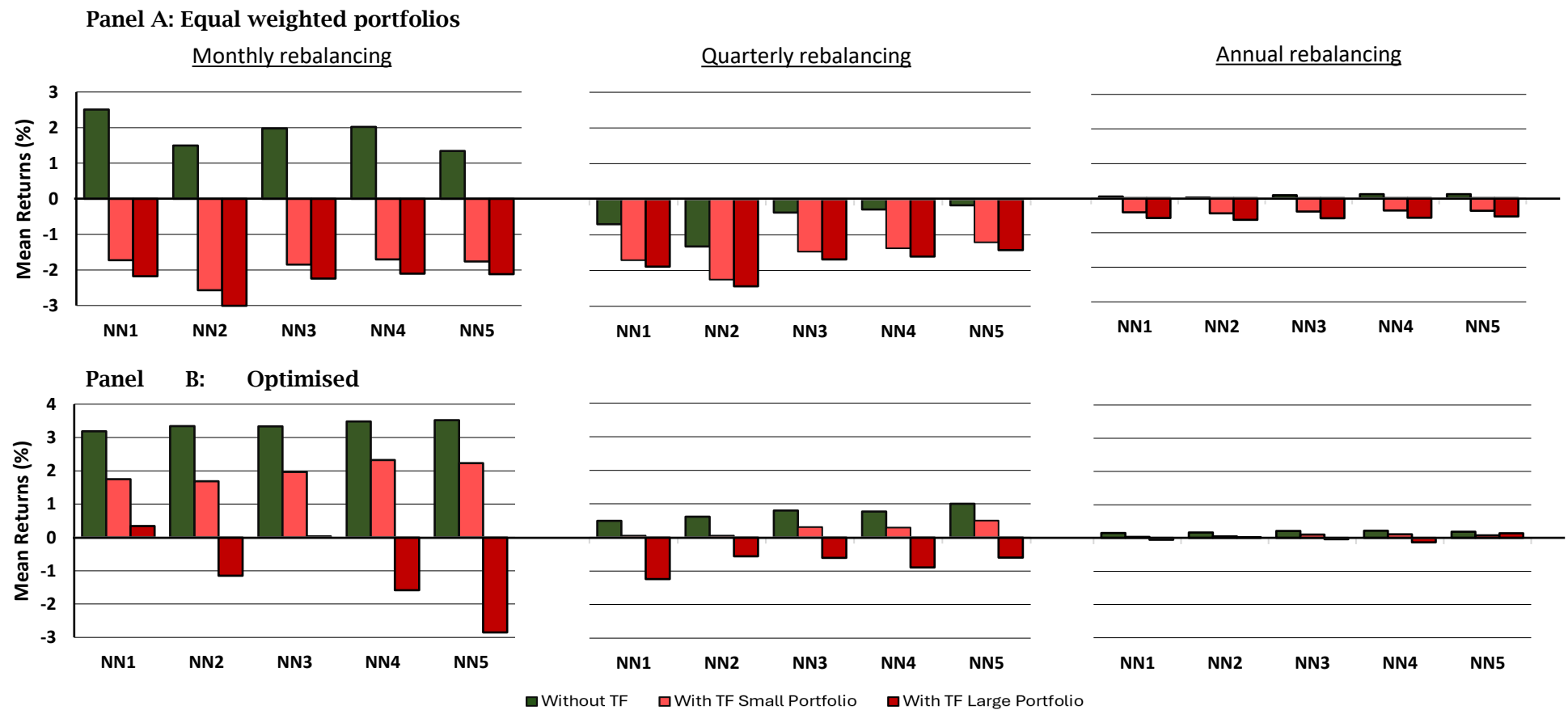
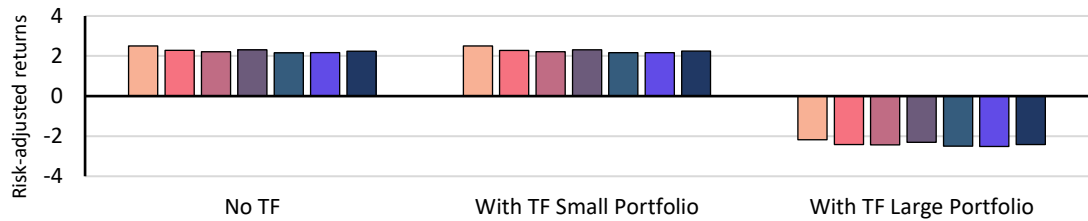


Figure 2.4: Impact of trading frictions on risk-adjusted returns of the NN portfolios, monthly

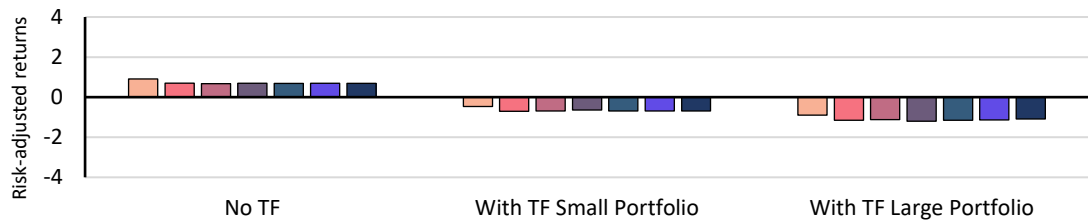
This figure illustrates the risk-adjusted returns for the neural network HML portfolios with monthly rebalancing frequency. Panels A to E report the predictions for the neural network setups starting with the one-layer model (NN1) to the five-layer model (NN5), respectively. Each panel reports the results for the equal-weighted rebalancing method in the top section, the results for the value-weighted rebalancing method in the middle section and the results for the optimised portfolios in the bottom section. Each section illustrates the risk adjusted returns for an environment without trading frictions on the left graph, an environment with trading frictions investing a small initial capital of 1 million USD in the middle graph and an environment with trading frictions investing a large initial capital of 100 million USD on the right graph. Each graph depicts the mean returns adjusted for major common factor models, specifically; (a) CAPM, (b) Fama-French-Carhart 4-factor model (FFC), (c) Pástor and Stambaugh liquidity factor model (FFC+PS), (d) Fama-French 5-factor model (FF5), (e) Fama-French 6-factor model (FF6), and Hou et. al., (2015) q-factor model (q). Risk-adjusted returns which are statistically significant to at least a 10% level are represented by fully filled bars, whereas insignificant risk-adjusted returns are represented by striped filled bars. Investing horizon is one month and thus, rebalancing of the portfolio is performed monthly based on predicted returns. The results for all rebalancing frequencies are included in Appendix 2D to 2F.

Panel A: NN1

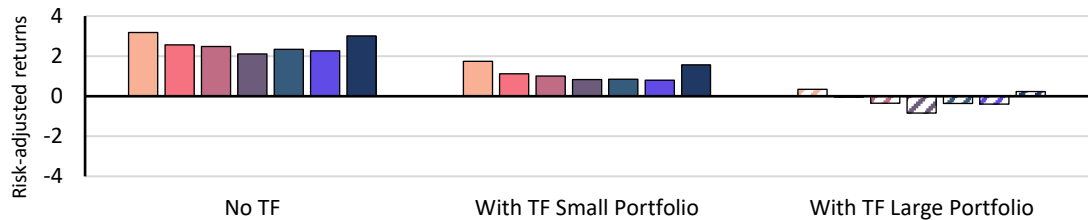
Equal weighted portfolios



Value weighted portfolios



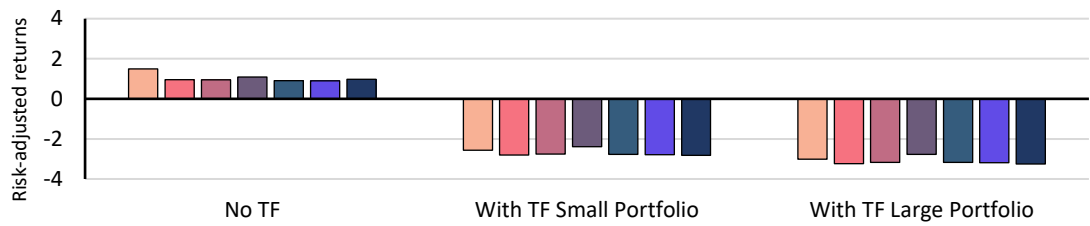
Optimised portfolios



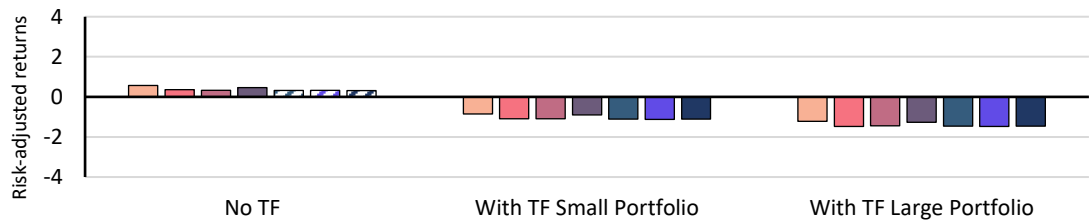
Mean returns CAPM FFC FFC+PS FF5 FF6 q

Panel B: NN2

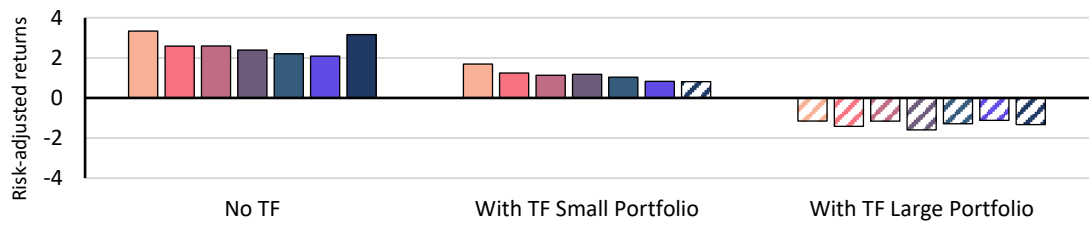
Equal weighted portfolios



Value weighted portfolios

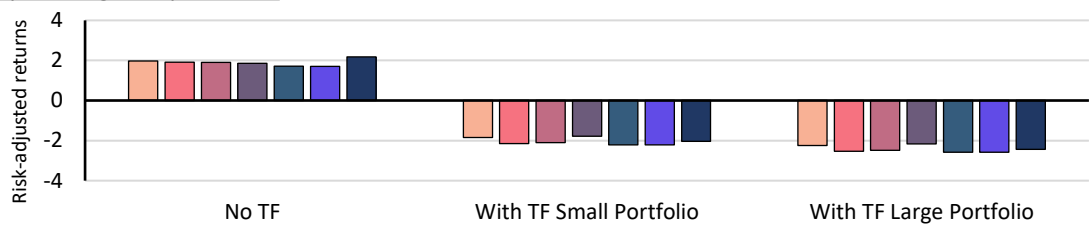


Optimised portfolios

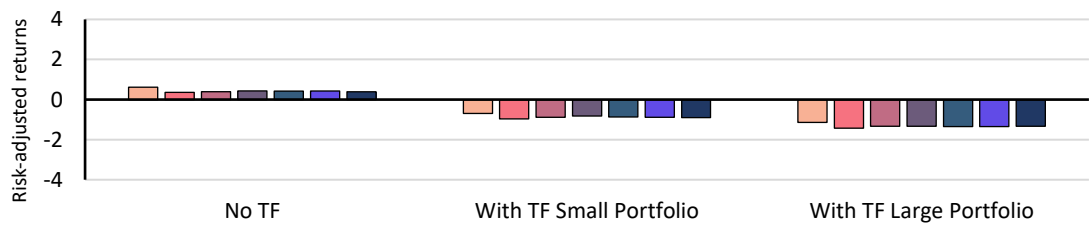


Panel C: NN3

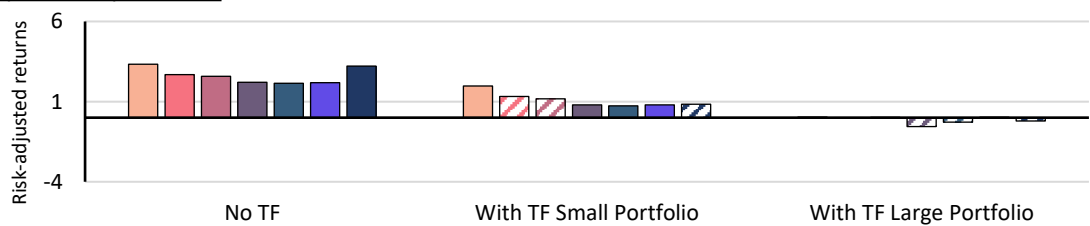
Equal weighted portfolios



Value weighted portfolios



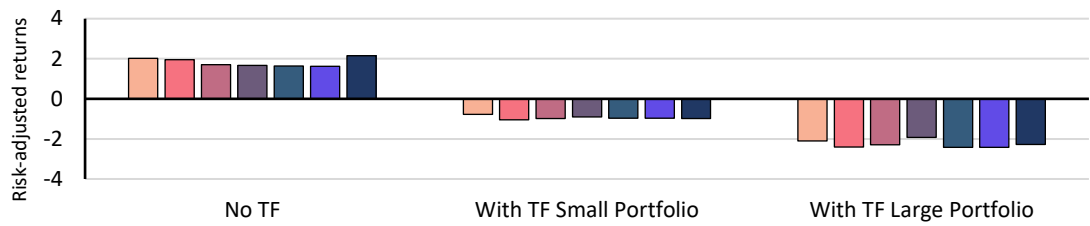
Optimised portfolios



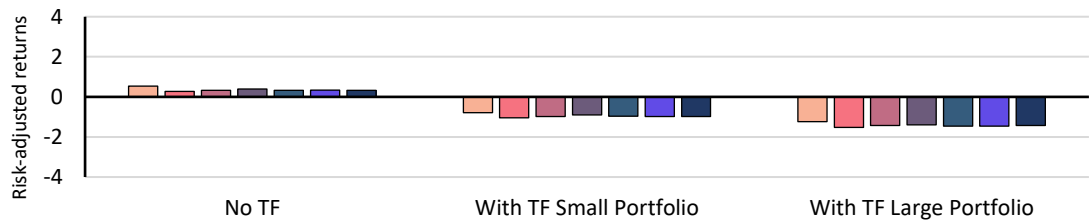
Mean returns CAPM FFC FF3+PS FF5 FF6 q

Panel D: NN4

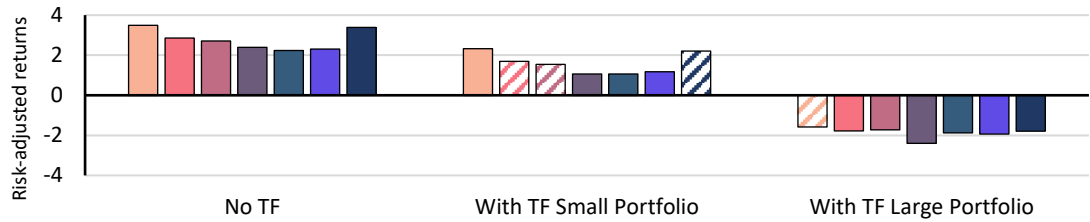
Equal weighted portfolios



Value weighted portfolios

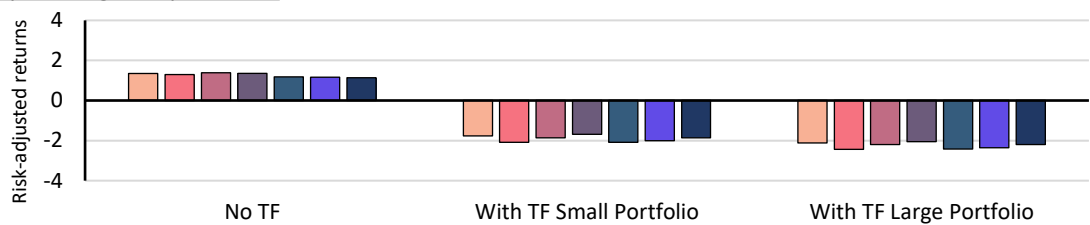


Optimised portfolios

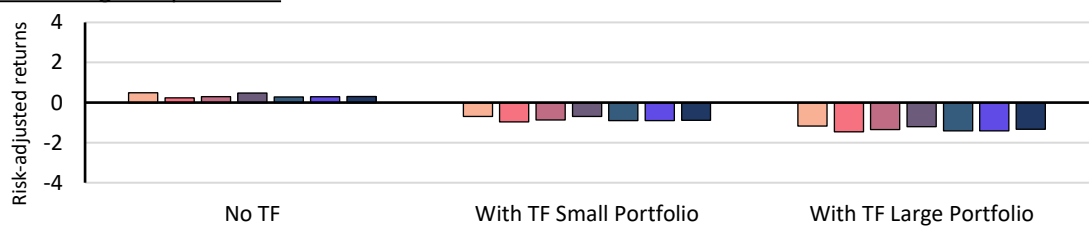


Panel E: NN5

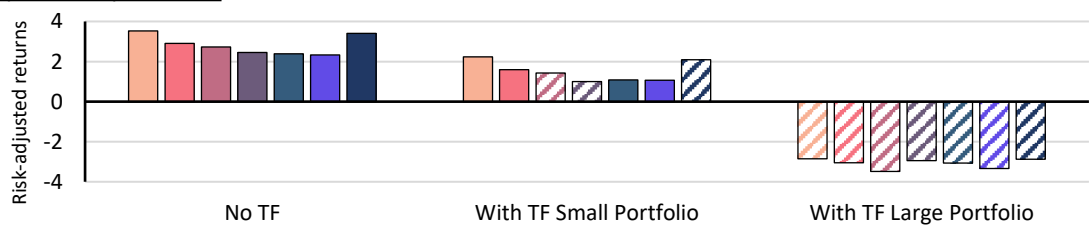
Equal weighted portfolios



Value weighted portfolios



Optimised portfolios

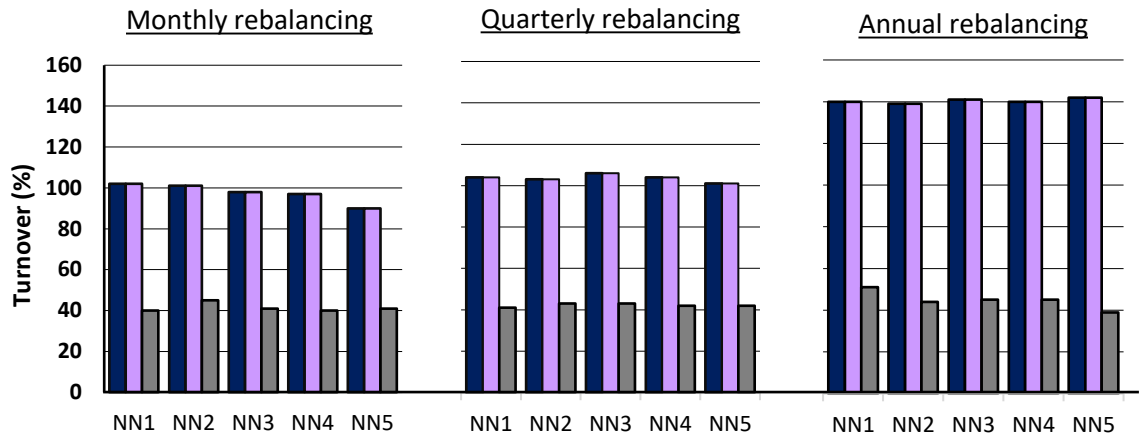


Mean returns CAPM FFC FF3+PS FF5 FF6 q

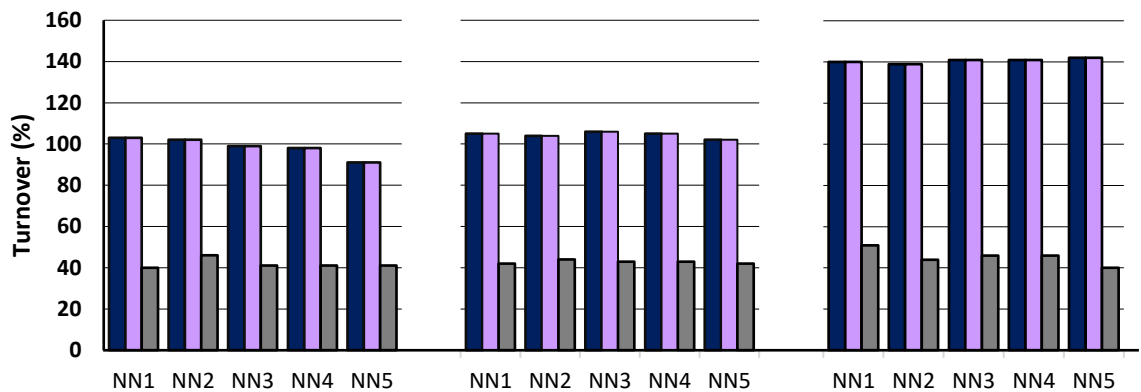
Figure 2.5: Turnover – all rebalancing frequencies

This figure shows the turnover (%) for each of the five neural network portfolios (NN1-NN5), individually. Panel A, at the top, illustrates the results of the simulation of no trading frictions. Panel B, in the middle, illustrates the results of the simulation of an environment with trading frictions investing a small initial capital of 1 million USD. Panel C, at the bottom, illustrates the results of the simulation of an environment with trading frictions investing a large initial capital of 100 million USD. In each panel the monthly rebalancing results are plotted in the left graph, the quarterly rebalancing results are plotted in the middle graph, and the annual rebalancing results are plotted in the right graph. In each graph the equal-weighted measurement is illustrated in dark blue, the value-weighted measurement is illustrated in light purple and the optimised weighted measurement is illustrated in grey. The results are computed at each rebalancing period and then averaged across all periods.

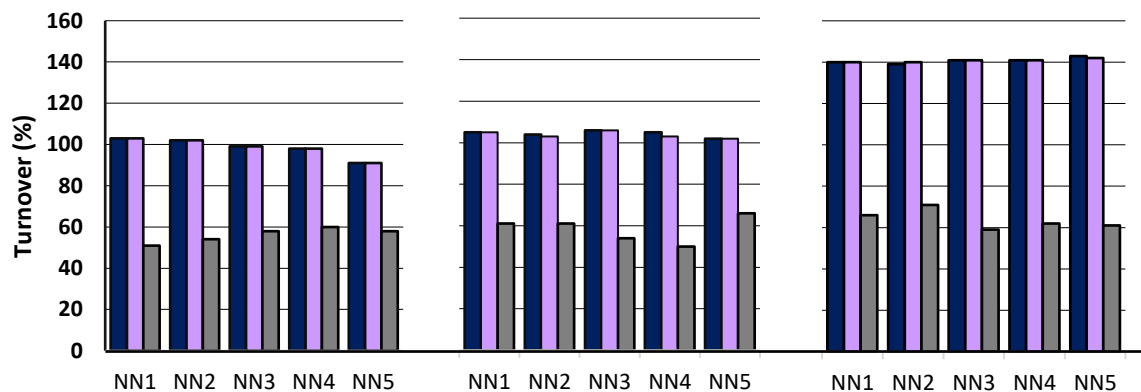
Panel A: Without TF



Panel B: With TF Small Portfolio



Panel C: With TF Large Portfolio



■ Equal ■ Value ■ Optimized

Figure 2.6: Maximum 1-month loss (%) – individual models, all rebalancing frequencies

This figure illustrates the maximum 1-month loss (%) for each of the five neural network portfolios (NN1-NN5), individually. Panel A, at the top, illustrates the results of the simulation of no trading frictions. Panel B, in the middle, illustrates the results of the simulation of an environment with trading frictions investing a small initial capital of 1 million USD. Panel C, at the bottom, illustrates the results of the simulation of an environment with trading frictions investing a large initial capital of 100 million USD. In each panel the monthly rebalancing results are plotted in the left graph, the quarterly rebalancing results are plotted in the middle graph, and the annual rebalancing results are plotted in the right graph. In each graph the equal-weighted measurement is illustrated in dark blue, the value-weighted measurement is illustrated in light purple and the optimised weighted measurement is illustrated in grey. The results are computed at each rebalancing period and then averaged across all periods.

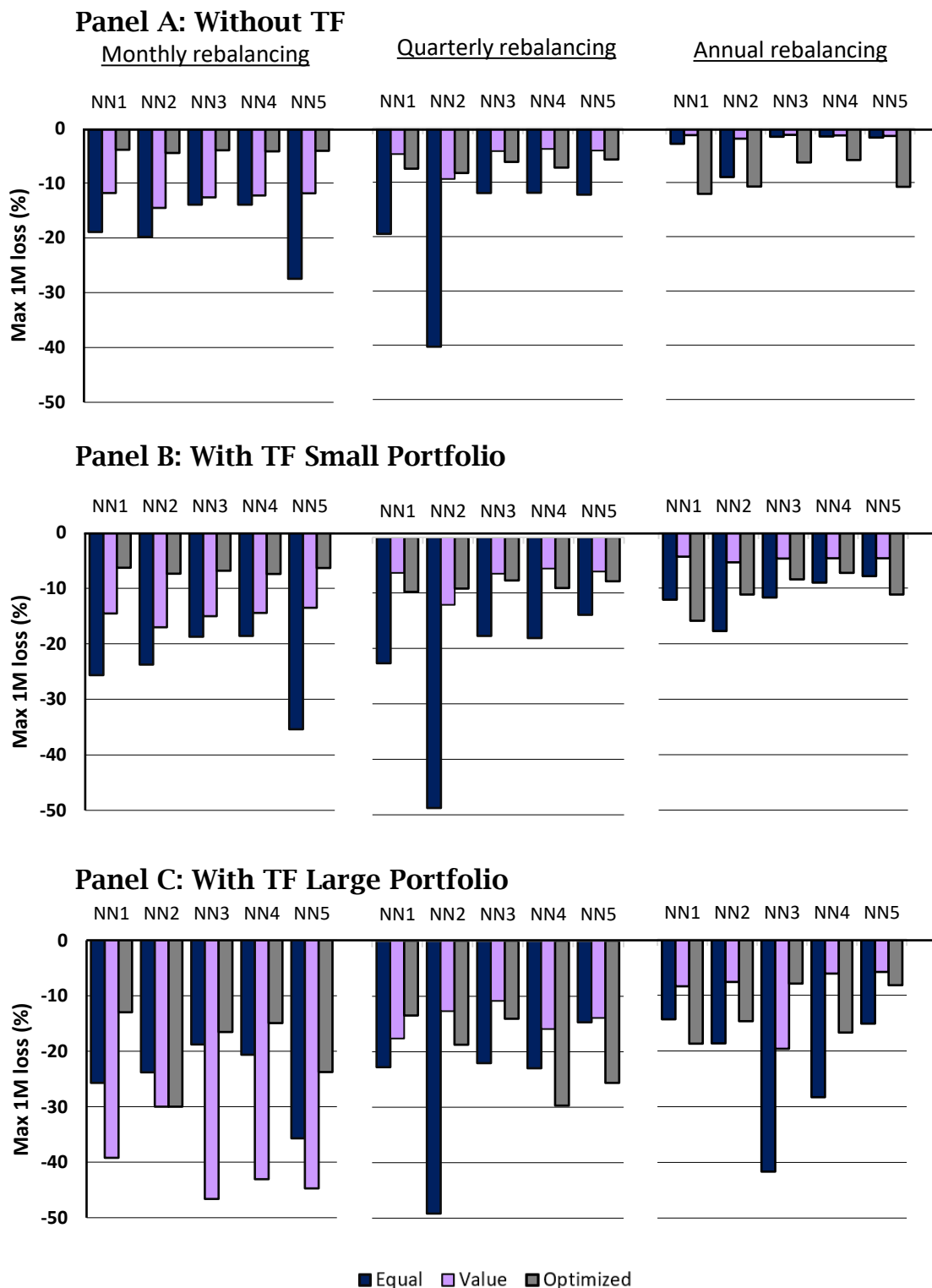
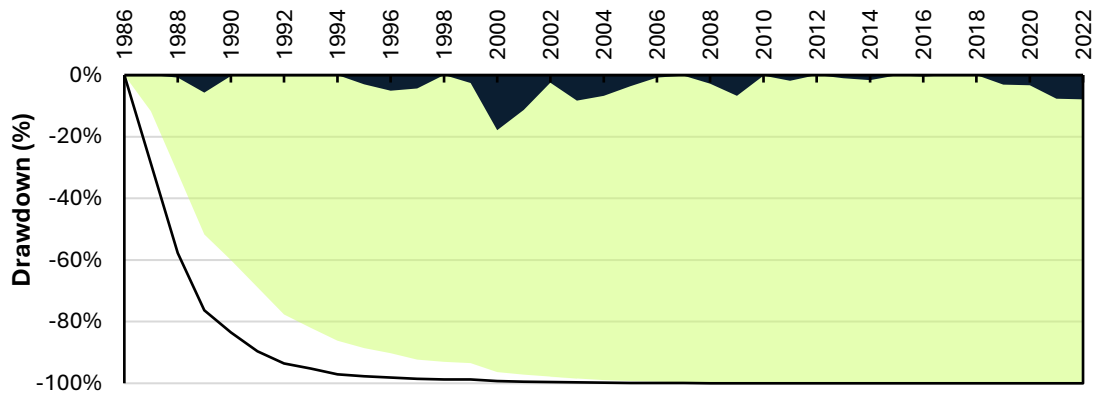


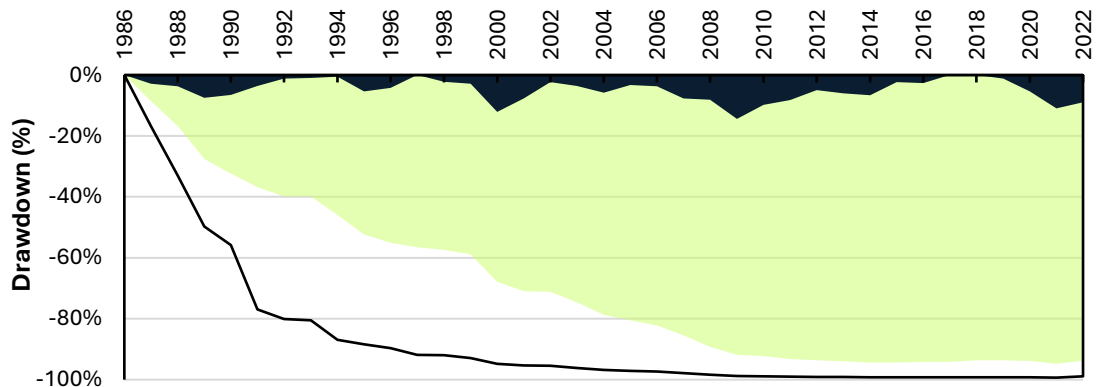
Figure 2.7: Drawdown (%) – Monthly rebalancing, mean across models (NN1-NN5)

This figure illustrates the drawdown (%) realised across the portfolio time series. The results reported are the average realisations across all five neural network models (NN1-NN5) at each time period. For smoothness, one drawdown realisation per year is plotted on the December mark of the specific year and was calculated as the maximum drawdown across the last twelve months. The individual results for each model are included in Appendix 2M. Panel A, at the top, illustrates the results after equal-weighting the portfolio holdings at each rebalancing period. Panel B, in the middle illustrates the results after value-weighting and Panel C, at the bottom illustrates the results after optimising the portfolio at each rebalancing period. Each panel graphs the drawdown realisation in three environments: (a) an environment without trading frictions, demonstrated in dark green, (b) an environment with trading frictions investing a small initial capital of 1 million USD, demonstrated in light green and (c) an environment with trading frictions, investing a large initial capital of 100 million USD, demonstrated by the black line.

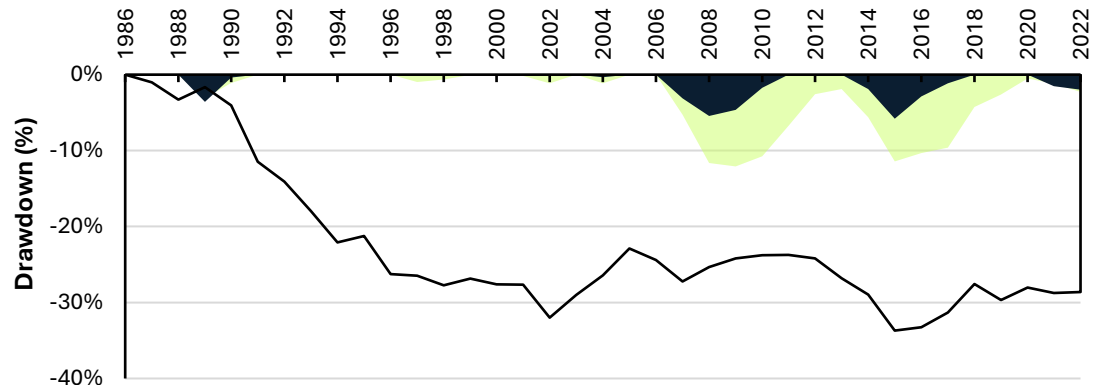
Panel A: Equal-weighted Portfolios



Panel B: Value-weighted Portfolios



Panel C: Optimised Portfolios

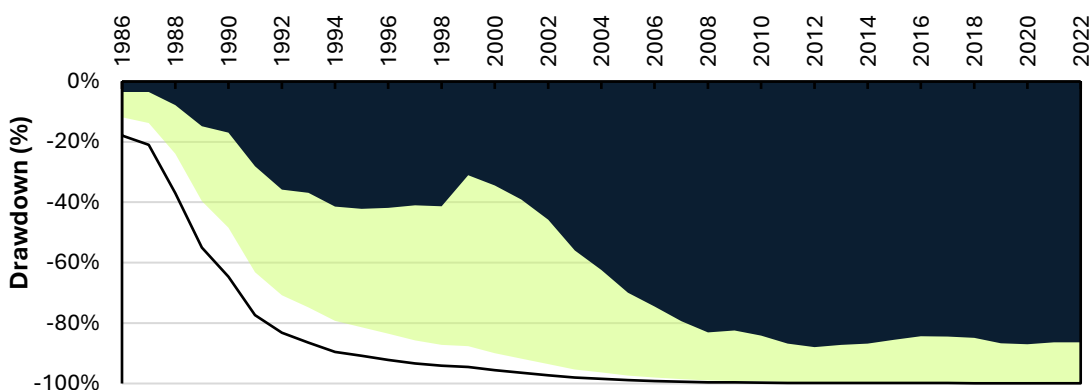


■ No TF Drawdown ■ With TF Small Portfolio Drawdown □ With TF Large Portfolio Drawdown

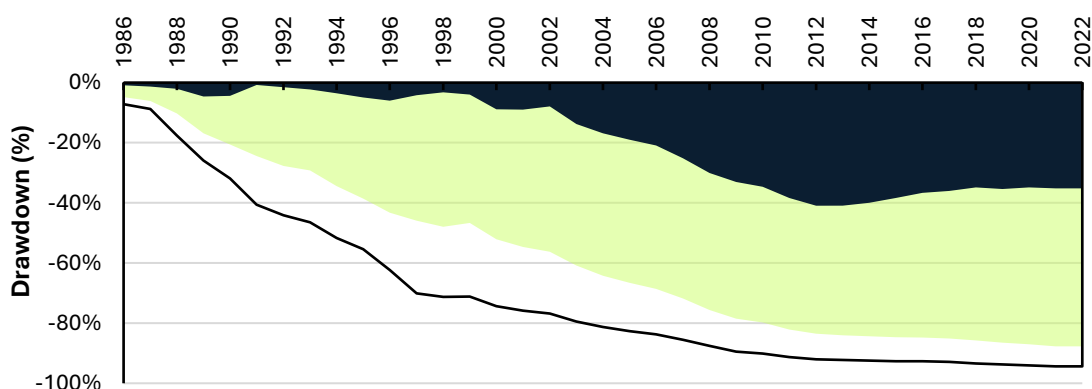
Figure 2.8: Drawdown (%) – Quarterly rebalancing, mean across models (NN1-NN5)

This figure illustrates the drawdown (%) realised across the portfolio time series. The results reported are the average realisations across all five neural network models (NN1-NN5) at each time period. For smoothness, one drawdown realisation per year is plotted on the December mark of the specific year and was calculated as the maximum drawdown across the last twelve months. The individual results for each model are included in Appendix 2N. Panel A, at the top, illustrates the results after equal-weighting the portfolio holdings at each rebalancing period. Panel B, in the middle illustrates the results after value-weighting and Panel C, at the bottom illustrates the results after optimising the portfolio at each rebalancing period. Each panel graphs the drawdown realisation in three environments: (a) an environment without trading frictions, demonstrated in dark green, (b) an environment with trading frictions investing a small initial capital of 1 million USD, demonstrated in light green and (c) an environment with trading frictions, investing a large initial capital of 100 million USD, demonstrated by the black line.

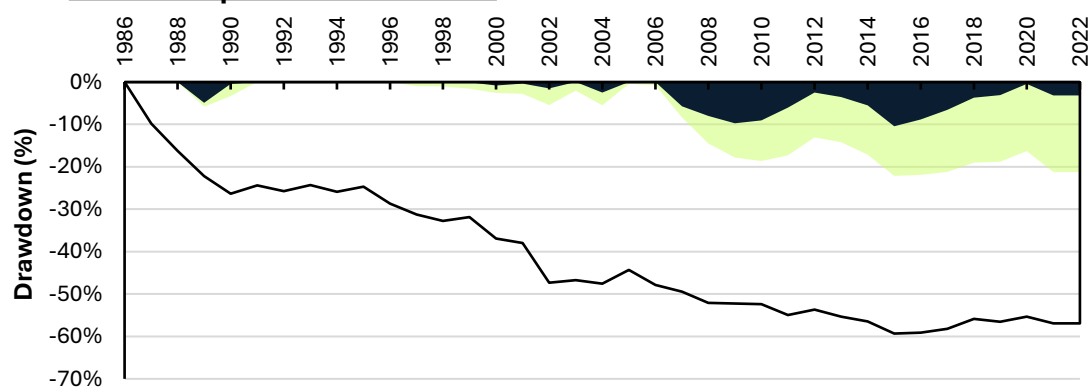
Panel A: Equal-weighted Portfolios



Panel B: Value-weighted Portfolios



Panel C: Optimised Portfolios

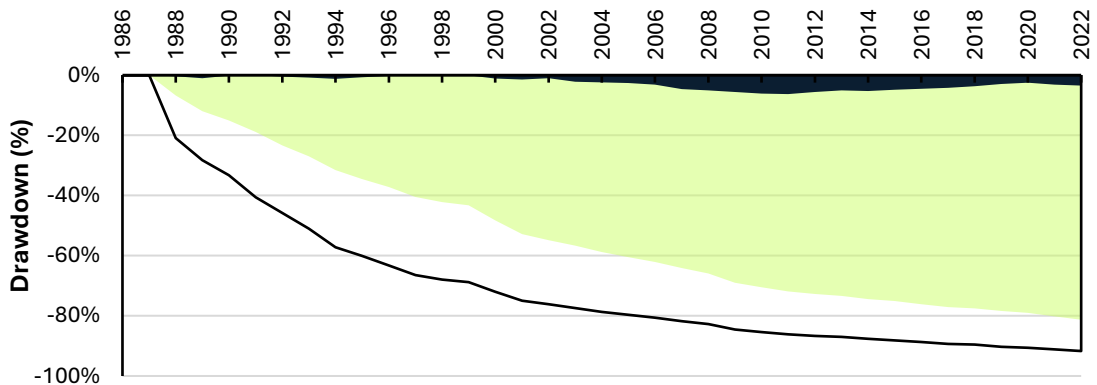


■ No TF Drawdown ■ With TF Small Portfolio Drawdown □ With TF Large Portfolio Drawdown

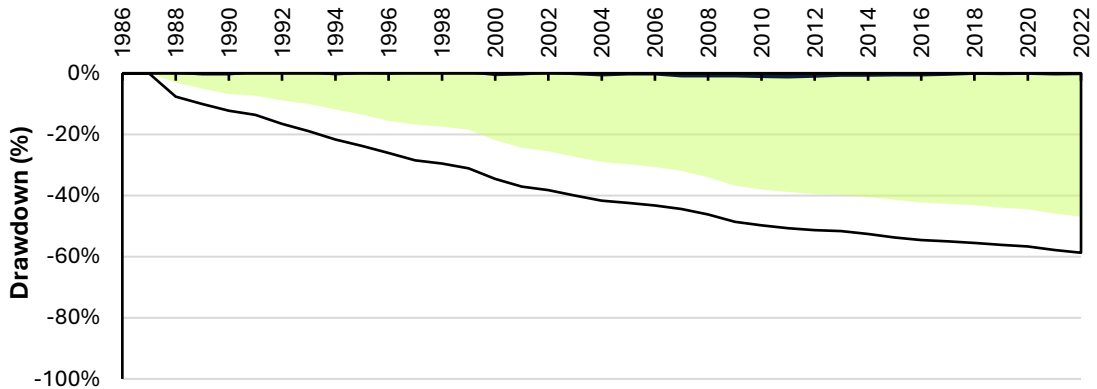
Figure 2.9: Drawdown (%) – Annual rebalancing, mean across models (NN1-NN5)

This figure illustrates the drawdown (%) realised across the portfolio time series. The results reported are the average realisations across all five neural network models (NN1-NN5) at each time period. For smoothness, one drawdown realisation per year is plotted on the December mark of the specific year and was calculated as the maximum drawdown across the last twelve months. The individual results for each model are included in Appendix 2O. Panel A, at the top, illustrates the results after equal-weighting the portfolio holdings at each rebalancing period. Panel B, in the middle illustrates the results after value-weighting and Panel C, at the bottom illustrates the results after optimising the portfolio at each rebalancing period. Each panel graphs the drawdown realisation in three environments: (a) an environment without trading frictions, demonstrated in dark green, (b) an environment with trading frictions investing a small initial capital of 1 million USD, demonstrated in light green and (c) an environment with trading frictions investing a large initial capital of 100 million USD, demonstrated by the black line.

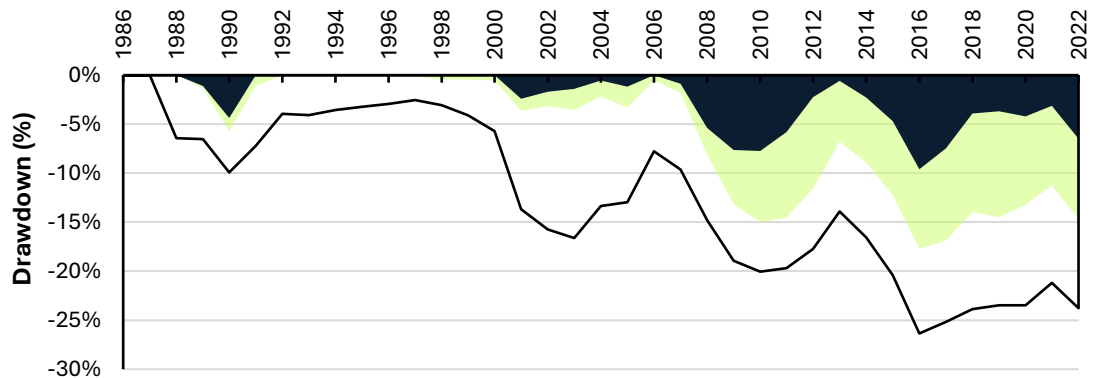
Panel A: Equal-weighted Portfolios



Panel B: Value-weighted Portfolios



Panel C: Optimised Portfolios



■ No TF Drawdown ■ With TF Small Portfolio Drawdown □ With TF Large Portfolio Drawdown

Chapter 3

Tracing the Neural Network Predictability of Asset Prices

3.1 Introduction

The asset pricing literature has documented hundreds of factors as significant explanators of asset prices (Harvey et al. 2016), a striking realisation that compels contemporary research to distil the truly unique risk premia (Cochrane 2011). It becomes necessary to evaluate the complete set of possible factors simultaneously, in order to identify which of them are unique and eliminate the issue of data mining (Harvey 2017). Nonetheless, the traditional econometric techniques, such as portfolio sorts, are unable to digest such a high-dimensional predictor set, thus, the state-of-the-art asset pricing research has been exploring machine learning methods to address these limitations (Bagnara 2024). The advantage of such techniques is their flexibility to capture complex relationships, which are undoubtedly present in asset pricing. However, these methods are considered as ‘black boxes’ which may obscure the economic foundations of the relationships they identify (Karolyi and Van Nieuwerburgh 2020).

This chapter argues that the ‘black box’ notion is a misnomer and shows how to use the methods already established in empirical asset pricing to identify the factors which drive the exceptional performance generated by the neural network model of Gu et al. (2020). Gu et al. (2020) report that their model is driven predominantly by factors such as short-term reversal, long-term momentum, illiquidity, bid-ask spread, and return volatility. However, their findings and interpretations are based on the variance inflation factor which does not identify the direction of the association between risk and return. On the contrary, Avramov et al. (2022) document the realisations of factors on the short and long leg of the machine learning spread portfolio. They find that the long leg contains small and value stocks, with strong profitability measures and strongly follows the short-term reversal and long-term momentum factors. Based on this evidence, they conclude that the machine learning model achieves its performance based on small and difficult-to-arbitrage stocks.

A critical issue which receives limited attention in asset pricing studies is turnover and the value lost to trading frictions. The evidence in Novy-Marx and Velikov (2016) is clear that after adjusting for transaction costs anomalies with high turnover, such as idiosyncratic volatility and short-run reversal, do not survive statistically. This is an especially important issue for neural network models given the exceedingly high turnovers generated by them (Gu et al. 2020; Avramov et al. 2022). Gu et al. (2020) ignore the friction effects entirely, while Avramov et al. (2022) consider frictions only when evaluating portfolio performance and not when evaluating the factor characteristics. Given the above, it is arguable that the unique asset pricing predictors, as confirmed by the neural network model, can only be identified after controlling for the effects of trading frictions.

This chapter applies the realistic friction model described in the previous chapter to distil the realisable, predictive, asset pricing factors captured by the neural network model. Subsequently, the traditional portfolio sorting method is employed to measure the factor realisations chosen by the neural network, effectively shining light inside the ‘black box’. Based on this methodology, the predictive signal generated by the neural network can be evaluated on the basis of individual asset pricing factors, factor categories, industries, in the cross-section and across time. Furthermore, this method proves effective in evaluating the interaction effects among factors and is, thus, able to uncover the complex relationships which drive the remarkable predictive performance of neural networks (Gu et al. 2020).

The findings in this chapter confirm that the neural network achieves predictability by combining signals from most explanators in the dataset (Avramov et al. 2022). However, the resulting signal is highly dependent on predictors relating to momentum, volatility, and stock liquidity, concurring the conclusions of Gu et al. (2020). Novel evidence in this chapter shows that the model invests in small stocks with recently increased volatility measures, which also supports the general conclusions of Avramov et al. (2022). More importantly, the evidence traces the success of the model to episodes of investor overreaction. These include shorting stocks with recently⁸ improved

⁸ Recent effects refer to effects measured in the month before each prediction. The data employed has monthly frequency and consequently, the effects identified occur in the monthly resolution.

top line revenue when their bottom line fails to improve, and stocks with recently inflated stock prices due to investor overreaction to positive surprises in financial results when their growth fails to be reflected in their fundamentals. Furthermore, when considering trading frictions, the optimised-small portfolio does not share the positive market bias of the equal-weighted model of Gu et al. (2020) and focuses on identifying and shorting overpriced stocks, which it does with remarkable effectiveness.

More novel findings in this chapter identify how the neural network signal is distilled by industry. It is reported that the model loads on stocks in the technology, healthcare, and energy industries. Specifically, the equal- and value-weighted models rely heavily on the momentum category with significant dependence on the energy and technology industries. Investment-related factors are also positively related to expected returns in the energy and technology industries, but also in the materials and consumer staples industries. The value vs. growth category focuses on healthcare stocks, whereas the profitability category focuses on stocks in the financial sector. The most novel contribution of this chapter examines the optimisation of machine learning portfolios under transactions costs, and finds dramatic and interesting results. The alpha-generating small-optimised portfolio eliminates all dependence on momentum, but instead executes reversal strategies based on recent improvements in profitability factors, especially for stocks in technology and healthcare industries, yet keeps a positive bias for investment-related factors in those same industries. Lastly, the value vs. growth and intangibles categories are not evidenced to influence the trading behavior of the optimised portfolio.

3.2 Literature review

3.2.1 The necessity of high-dimensional methods

Both theoretically motivated factors, such as the market beta implied by the Capital Asset Pricing Model (CAPM) (Sharpe 1964; Lintner 1965; Mossin 1966), and empirically motivated factors, such as Banz's (1981) size effect and Basu's (1983) value effect, have been proposed as statistically significant explanators of expected returns. Since the asset pricing literature provides no theoretical basis to argue for the precedence of some factors over others, financial research has accumulated over 300 possible explanators all of which coexist and are argued to explain asset prices (Green et al. 2013; Harvey, et al. 2016). Given this extensive collection of evidence, Cochrane (2011) urged the research community to establish which factors are unique explanators of asset prices and which are subsumed by others.

Traditionally, researchers employ a portfolio sorting approach to test asset pricing anomalies, however, this is arguably inadequate to explore the high-dimensional nature of the equity risk premium. The Fama and French (1993) three-factor model has been influential, although it misses the predictability of the profitability and investment factors. These are added in the Fama and French (2015) five-factor model and Hou et al. (2015) four-factor specification. Yet, these models still do not suffice to explain the complete picture of the equity premium as they evidently miss the momentum factor (Barillas and Shanken 2018). Fama and French (2018) then suggested a six-factor model that added a momentum factor, whilst Hou et al. (2020) added an expected growth factor. These modifications are still not sufficient, as they fail to account for earnings-related anomalies and the momentum effects, respectively. Therefore, despite producing some prominent results as discussed above, the low-dimensional asset pricing approach is arguably futile. On the contrary, given the discussion of Cochrane (2011) and the extensive empirical results in the literature, such as Green et al. (2017) and Hou et al. (2020), the necessity arises to start from a high-dimensional setting and work towards a parsimonious model.

This striking factor plurality that characterizes empirical asset pricing convinces contemporary researchers that most findings in the literature are exaggerated. Harvey (2017) traces the cause to an agency problem in the publication process, whereby researchers resort to data mining to identify explanatory factors so that their results can be published. This implies that many published factors resulted from p-hacking. Specifically, a large number of factors being tested individually through trial-and-error, and when one survives statistically, it is then reported in the literature. Thus, such factors are merely statistical manifestations and may have little rationale as fundamental explanators of asset prices.

In response, Harvey (2017) advocates for raising the t -statistic for the establishment of statistical significance, and Lewellen et al. (2010) suggest that asset pricing researchers should fully report confidence intervals. These ideas may have some merit, however, their capacity to eliminate p-hacking is questionable. In contrast, it can be argued that if the asset pricing investigation starts from a high-dimensional predictor set tested simultaneously, then the unique explanators can eventually be distilled while p-hacking can have little effect. The traditional econometrics techniques are, arguably, inadequate to evaluate such high-dimensional input, and thus empirical asset pricing research has shifted recently to machine learning methods (Bagnara 2024).

3.2.2 Introducing the factor categories⁹

(a) *Value vs. Growth*

The value premium has been one of the most influential findings in the financial literature. Early research on asset pricing anomalies conducted by Basu (1977) showed that firms with low price-to-earnings (PE) ratios tend to outperform stocks with high PE ratios. He argues that this relationship is driven by exaggerated investor expectations, and thus it can be predicted that prices will revert towards their natural PE level eventually. Ball (1978) concurs with this finding and suggests that anomalies extend to other value elements, such as expected dividend yields. Litzenberger and Ramaswamy (1982) confirm this suggestion and show that there is a positive and non-linear

⁹ The six-category system of Hou et al. (2020) is used to group factors by functionality.

relationship between returns and expected dividend yields. Furthermore, the size effect was another influential finding in the early literature. As Banz (1981) discovered, smaller firms tend to offer higher risk-adjusted returns than larger firms over long horizons.

These seminal findings raise two important points. First, the value and size effects provided early evidence against the efficient market hypothesis in cross-sectional studies since, in efficient markets, fundamental and market information should not, theoretically, have persistent predictive ability. However, factors such as the size and value effects appear to be statistically significant predictors of asset prices. This leads to the natural question of which other mispricing factors might exist. While these were the earliest discoveries of anomalies, relatively recent research shows that both the value (Eleswarapu and Reinganum 2004) and size (Brennan et al. 2004) effects still remain statistically significant and are often used as common factors to test asset pricing models.

Second, it can be argued that these factors are identified statistically, whereby their creation had no theoretical basis. This relates to the concept of p-hacking discussed above. For example, Litzenberger and Ramaswamy (1982) suggest that the dividend yield effect might possibly be attributed to tax effects, although Ball (1978) admits there is no precise justification for this finding. In fact, both chapters merely identify the statistical significance of the factors without prior theoretical motivation. Similarly, Banz (1981) admits that it is unclear whether the size effect is a risk factor in itself, or just a proxy for some other latent correlated factor. Amihud and Mendelson (1986a) justify the size effect due to investors requiring compensation for assuming the liquidity risk associated with small stocks, but despite this effort, the research community has yet to reach a conclusive justification (Campbell and Vuolteenaho 2004). The upshot of this discussion is that basing the discovery of asset pricing factors on low dimensional models inherently involves the potential for p-hacking and false discoveries, as argued by Harvey (2017).

(b) Investment

Investment-related factors are concerned with how firms finance their capital structure and how this affects their stock prices. To begin with, Titman et al. (2004) report that firms which increase their capital investment tend to achieve negative risk-adjusted returns. This finding is corroborated by Anderson and Garcia-Feijóo (2006) and Cooper et al (2008) for asset growth, among others. On the liability front, Bhandari (1988) reports that the liability-to-equity ratio is positively associated with expected returns. This is corroborated by Valta (2016) who finds that firms with high secured and convertible debt exhibit higher expected returns. Regarding the equity section of the balance sheet, Pontiff and Woodgate (2008) find that net stock issuance exhibits a strong cross-sectional relation with stock returns. The theory behind this finding is that returns are abnormally low after the issuance of new stock and abnormally high after the repurchasing of a firm's stock.

(c) Profitability

The profitability category includes the financial statement ratios, such as the current ratio, quick ratio, and cash flow ratios. In addition, earnings ratios have been shown to predict stock returns. For example, return on equity (Haugen and Baker 1996), return on assets, and gross profit-to-assets (Novy-Marx 2013) have been widely corroborated to be positively correlated with expected returns. Sloan (1996) decomposes earnings into two subcomponents: accruals and cash earnings, and finds that high accruals exhibit lower future returns. This finding is counterintuitive given that accruals are theoretically reflected in earnings, and consequently the implication is that investors may only value cash earnings.

Even though profitability measures are widely used to evaluate a firm's financial performance, the exact mechanism which links them to asset prices is open to debate. For example, an improvement in the current ratio indicates improved liquidity, and thus implies future growth and higher returns. On the other hand, a more illiquid firm should command a higher expected return as compensation for the risk investors bear (Amihud and Mendelson 1986a). Similarly, low liquidity implies a lower debt capacity and more adverse debt renegotiation ability, which has also been shown to be associated with higher expected returns (Valta 2016). Given the above discussion, it is arguable that

individually testing such factors has limited ability to uncover valid inference. On the contrary, the necessity to test all these anomalies simultaneously is evident once again.

(d) Intangibles

Other financial statement variables that are unrelated to size, value, investment, or profitability categories, and whose effect on asset prices is not theoretically derived are included in the intangibles category. For example, Gu (2005) explores the effect of innovation on asset prices by analysing the number of patent citations and finds positive association between them, especially for companies in the technology industry. Similarly, factors quantifying more abstract components of a firm's value proposition are also included, such as organisational capital (Eisfeldt and Papanikolaou 2014) and employee growth rate (Belo et al. 2014). In addition, this category includes the factors relating to corporate social responsibility (CSR), arguing that investors price a diverse spectrum of intangible characteristics such as employee satisfaction (Edmans 2011), environmental performance (Derwall et al. 2005), and ethical behavior (Diltz 1995).

Anomalies related to the research and development (R&D) expense item have also been widely examined. Lev and Sougiannis (1996) report a systematic mispricing of firms with high R&D costs, in which investors underreact to R&D-relevant information. Even though a direct relationship between this cost component and future revenue cannot be found, they report that R&D capital is associated with expected stock prices. Building on this finding, Eberhart et al. (2004) show that increases in R&D expenditure yield significant abnormal operating performance in the long run, concluding that markets are slow to price R&D-relevant information. Lev et al. (2005) observe that early life-cycle firms have high R&D growth and naturally low profitability, whereas mature firms have a low R&D growth rate and higher profitability. They argue that the anomaly fades if both early life-cycle firms and mature firms follow the same accounting standards in reporting their R&D expenditure.

(e) Momentum

Momentum is one of the most widely studied factors in empirical finance. In their seminal paper, Jegadeesh and Titman (1993) show that stocks with high returns over the past three to twelve months (winners) perform better than stocks with low returns over the same period (losers). In the same spirit, Carhart (1997) finds that the addition of a momentum factor (last twelve months winners minus last twelve months losers) to the Fama and French (1993) three-factor model generates an improved pricing model for mutual funds. Interestingly, in longer horizons, the opposite relationship applies. Specifically, De Bondt and Thaler (1985, 1987) provide evidence that stocks exhibit mean-reversion tendencies, given that losers over the past three to five years outperform winners. Similar evidence of mean-reversion is found in very short horizons by Jegadeesh and Titman (1993); at the one-month horizon there is highly significant, negative, first-order, serial correlation in returns.

Momentum-related anomalies are also identified in earnings drift. For example, Bernard and Thomas (1989) report that stocks with unexpectedly high earnings perform better than stocks with low earnings over the following six months. This finding is expanded by Chan et al. (1996) who show that earnings-related momentum is empirically distinct from the price-related momentum described above. Analogously, momentum is found in many other elements of the balance sheet, such as revenue surprise (Kama 2009) and investor reaction to changes in tax expenses (Thomas and Zhang 2011). These discussions show the complex and multifaceted nature of momentum as an asset pricing factor. Due to this complexity, it could be argued that, to capture such inter-relationships, one needs a model which can digest such dimensions and interactions while examining all characteristics simultaneously.

(f) Trading frictions

Due to the abundant data becoming available from the trading environment, the asset pricing literature has identified numerous anomalies related to trading frictions. Ang et al. (2006) find that stocks with high idiosyncratic volatility relative to the Fama and French (1993) model have significantly low average returns. The nature of this risk is still a matter of debate. Bali and Cakici (2008) do not find a relationship between the two in equal-weighted portfolios, while Huang et al. (2010) provide evidence that the idiosyncratic volatility bias might be a manifestation of return reversal.

When considering the volatility in returns, the evidence is less contradictory. Specifically, return volatility has been widely shown to be a predictor of higher expected future returns (Ali et al. 2003). In the same spirit, trading illiquidity is another prominent risk factor. Amihud and Mendelson (1986b) use the bid-ask spread to model illiquidity and find a concave relationship between the spread and asset returns, while they later show that the illiquidity effect is robust to other factors, such as beta and firm size (Amihud and Mendelson 1989). Furthermore, Brunnermeier and Pedersen (2009) discuss how trading liquidity is dependent upon funding liquidity, with bid-ask spreads increasing as margin requirements increase, which might cause liquidity spirals in the markets. Similarly, Chordia et al. (2001) show that not only is liquidity a positive determinant of asset prices, but also the volatility of the liquidity is a determinant too.

3.2.3 Turnover, frequency and transaction costs

A critical factor which is barely discussed in asset pricing studies is turnover. Higher portfolio turnover implies more intense trading activity, which, in turn, implies a larger proportion of returns eroded by trading frictions. For example, Novy-Marx and Velikov (2016) show that the cost of trading low turnover strategies is, on average, less than 0.10% per month, medium turnover strategies is between 0.20% and 0.57% per month, and high turnover strategies exceed 1% per month. In fact, the same paper shows that adjusting for transaction costs, anomalies with high turnover do not survive statistically. Furthermore, Korajczyk and Sadka (2004) and Lesmond et al. (2004) report that the high turnover momentum strategy yields only modest

returns after adjusting for trading costs. This is corroborated by Detzel et al. (2023) who find that high turnover strategies cannot be profitably traded after accounting for the effects of frictions.

The rebalancing frequency of a factor is also important. Frequently rebalanced factors exhibit a similar pattern of illusive success on a risk-return basis. For example, Hou et al. (2015) and Fama and French (2015) take similar positions in the investment, profitability, size, and market factors. The former is rebalanced monthly, whereas the latter is rebalanced annually. Comparing the two, Detzel et al. (2023) find that the monthly-rebalanced model exhibits a 40% higher Sharpe ratio than the annually-rebalanced model before trading costs. However, after accounting for frictions, this is reversed, with the Fama and French (2015) model exhibiting the highest Sharpe ratio. The implication of this discussion is that comparing equal- or value-weighted portfolios with no regard for trading frictions, has the potential to obscure the realizable risk premia and overstate the performance of the spread portfolios. Controlling for unrealizable risk premia should, arguably, be an essential component of empirical asset pricing.

3.2.4 Machine learning as the solution

The most recent empirical literature exhibits widespread applications of machine learning in financial contexts. These range from factor selection (Freyberger et al. 2020) to dimensionality reduction (Kelly et al. 2019), and asset return prediction (Gu et al. 2020). Such novel applications of statistical techniques have shown great promise in tackling the factor plurality that is challenging modern asset pricing and addressing Cochrane's (2011) enquiry about which factors, among the large set of those available and documented, are true explanators of asset prices. Motivated by this promise, Karolyi and Van Nieuwerburgh (2020) encourage researchers to compare machine learning methods consistently and stress the importance for the research to lead to economic interpretations. The purpose of this chapter resonates with this idea. It aims to uncover the asset pricing factors which drive the exceptional predictability of neural networks after adjusting for realistic trading frictions, effectively to shining light in the 'black box'.

The empirical success of machine learning methods was first highlighted in the seminal paper of Gu et al. (2020). They report that using machine learning methods to predict stock returns yields large economic gains. A zero-cost spread portfolio formed on the machine learning predictions realizes monthly returns of around 2%, which is statistically and economically significant. Furthermore, they reveal the effectiveness of neural networks for predicting stock returns by demonstrating that this method outperforms all other machine learning techniques out-of-sample. This outperformance has also been corroborated by Tobek and Hronec (2021) and Cakici et al. (2023) for international samples, while Chen et al. (2023) further enhance the annual Sharpe ratio to an outstanding 2.6 by combining the signals from a collection of networks.

Regarding the unique explainers of asset prices, Gu et al. (2020) identify that the most prominent factors are related to momentum, volatility, and stock liquidity. Specifically, the most prominent factor category identified by the neural network model of Gu et al. (2020) is the momentum category. This includes short-term reversal, 6-, 12- and 36-month momentum, momentum change, and industry momentum. The second most important category is trading frictions. This includes turnover, volatility of turnover, return volatility, idiosyncratic volatility, beta, Amihud illiquidity, bid-ask spread and zero trading days. Third in importance are profitability measures which include earnings-to-price, sales-to-price, and asset growth. The last prominent category is value versus growth, which includes the size effect.

Avramov et al. (2022) find that machine learning models identify factors consistent with most empirical findings. They report that the long leg of the spread portfolio consists of stocks which are small, illiquid, with low analyst coverage, trading at a low price and low beta. Regarding the momentum category, they find that the long leg strongly follows the short-term reversal and 12-month momentum. Regarding the value versus growth category, they find that the neural network model takes long positions in value and old firms. In the profitability category they report that the long leg of the spread portfolio includes firms with high return-on-assets and return-on-equity. Lastly, in the investment category, they find that long positions are taken in firms with low asset growth and high leverage. However, the findings of Avramov et al. (2022) also inconsistent with the literature for certain

factors. For example, their long leg includes stocks with high idiosyncratic volatility which opposes the evidence of Ang et al. (2006), stocks with high credit rating which opposes the findings in Avramov et al. (2013), and stocks with high corporate investment which contradicts the results of Titman et al. (2004).

Despite the impressive performance of the neural network model and the interesting results presented to date, the current literature carries certain limitations. First, the investigations of Gu et al. (2020) are limited by not considering trading frictions. As discussed in the previous section, friction effects can be detrimental to the profitability of spread portfolios. This is especially important for neural network models given the evidence in Avramov et al. (2022) who show that the neural network portfolio yields one-sided turnover in the range of 87% to 98%.

While Avramov et al. (2022) apply certain considerations for the friction effect, such as the breakeven cost and restricted samples, when they evaluate the factors identified by the model, they do so through the standard equal-weighted portfolio under no frictions. In light of this evidence presented above, one understands that the inference about the true, realizable, and unique asset pricing predictors identified by the neural network model could only be evidenced after controlling for friction effects, which has not been addressed by the literature so far.

3.3 Data and methodology

Data and methodology are identical to the previous chapter. Specifically, the dataset includes the 94 predictors compiled by Green et al. (2017). These are the same inputs used by Gu et al. (2020) and Avramov et al. (2022) for the neural network models. As opposed to these papers, the interaction terms between asset pricing factors and macroeconomic variables are not used here for two reasons: due to computational restrictions; and the objective of establishing a benchmark for future research that identifies which individual factors the neural network predictability derives from. For the purposes of this thesis, the 94 factors of Green et al. (2017) have been recomputed from the raw data and were treated as in Gu et al. (2020).

The final dataset spans from January 1957 to December 2022. The training sample spans 12 years and expands by one year at each iteration. The validation sample spans 12 years and rolls forward at each iteration. The remaining sample is used for out-of-sample testing. At each iteration the neural network model is refitted and subsequently predicts the expected returns for twelve monthly periods ahead. This is the same sampling methodology described in more detail by Gu et al. (2020), including the adoption of the same hyperparameters used.

At each iteration the portfolio optimisation procedure generates the spread portfolio which maximizes the expected Sharpe ratio based on the expected returns and the expected volatility. The expected returns are the output of the neural network model, and the expected volatility is calculated from the daily past returns updated by the expected return from the model. One year (252 trading days) of daily return history is required for stocks to be allowed in the portfolio for the volatility estimate to be valid. The expected daily volume is calculated as the average of the last 25 trading days. The three-month T-bill is used as the risk-free rate and common factors are sourced from the websites of Prof. Kenneth French and Prof. Robert Stambaugh.

The spread cost is estimated by equation 2.6 and the impact cost by equation 2.7, described in the previous chapter. The short sale cost is estimated to equal the risk-free rate. The assumption behind this is that investors are borrowing the stock to sell it short and thus, must pay a reasonable interest rate. In this way, selling short a volume of stock is more costly than going long the same volume. The portfolio optimisation is conducted by CVXPY, as described in the previous chapter.

Four simulations are conducted: (a) equal-weighted portfolios, (b) value-weighted portfolios, (c) an environment with trading frictions investing a small initial capital of 1 million USD and (d) an environment with trading frictions investing a large initial capital of 100 million USD. As shown in the previous chapter, the small-optimised portfolio allows the realizable predictability to be extracted from the neural network model, while the large-optimised portfolio demonstrates the inability of large, institutional investors to employ this model.

As described in section 2.3.2, the optimiser constructs the short and long decile portfolios, as well as the resulting spread portfolio, based on the predictions of the neural network model after adjusting for realistic trading frictions. In this chapter the investigation focuses on the stocks which are the constituents of these portfolios. Specifically, the factor realisations of these stocks are evaluated in order to uncover the factors which drive the exceptional predictability of the neural network. The argument put forward in this chapter is that given that the neural network generates positive and significant predictability, if one evaluates the factors that this model is based on, one identifies the predictive relationships between asset pricing factors and expected excess returns by implication. The evaluation is conducted across factor categories, as shown in Appendix 3A, across industries, as well as across time. What is more, the traditional financial method of double sorted portfolios is used to explore the interactions between predictors, an approach which diverges from Gu et al. (2020).

3.4 Results

3.4.1 Which covariates?

Table 3.1 reports the mean characteristic realisation for each individual factor for the low and high portfolio deciles (1 and 10), respectively. It should be noted that in the methodology each characteristic factor was cross-sectionally scaled to the $[-1, 1]$ range at each period, so the expected value is 0. Purely for ease of presentation, the results in Table 3.1 are stated on a percentage basis, meaning the characteristics have been rescaled to the 0% to 100% range. Furthermore, consistent with Gu, et al. (2020) and Avramov, et al. (2022), this chapter does not intend to explain the theoretical underpinnings of various asset pricing predictors, rather it focuses on identifying the factors on which the neural network takes its short and long exposure.

[Insert Table 3.1]

Investment category

For the investment category, the neural network model correctly identifies most asset pricing anomalies from prior literature. Specifically, for the equal-weighted portfolio, increasing capital expenditures and inventory (*invest*) exhibits a negative relationship with expected returns. Similar negative relationships are also observed for the growth in capital expenditure (*grcapx*) and the change in inventories (*chinv*). Moreover, negative associations are also evident for the growth in long-term net operating assets (*grltnoa*) and real estate holdings (*realestate*).

This evidence highlights the capability of neural network models to identify well-known anomalies previously identified in the literature. The above is consistent with the theory that investment in long term assets has a significantly negative impact on monthly expected returns, in full agreement with prior literature. The important finding in this chapter is the discovery of these characteristics as revealed by machine learning prediction models. In theory, long-lived assets are associated with higher risk due to their future use and are vulnerable to negative productivity shocks, thus commanding a higher

risk premium (Tuzel 2010). Similarly, the accumulation of inventory is viewed as a signal of stagnated sales and this negative relationship is identified by the neural network model.

Panel C reports that the optimised-small portfolio, which was previously documented to generate high and attainable alpha, depends heavily on the negative effect of factors associated with investment in assets. In fact, the short leg of the portfolio is loaded with stocks reporting large investment in assets whereas the long leg is loaded with stocks with significantly lower asset investments. Interestingly, the factor that boldly contradicts the literature is asset growth (*agr*) which has a positive association with expected returns according to the neural network. Possibly, although unverified, this juxtaposition arises due to the asset growth factor being constructed on an annual basis whereas the other factors are updated quarterly. Based on this discussion it can be argued that the neural network model captures predictability from the short-lived investor reaction to reports of incremental capital expenditure and long-term assets, but also asset growth is seen as a positive signal in the long term.

On the liability side of the balance sheet, the neural network results generally diverge from the literature. For the equal-weighted portfolio, both the leverage (*lev*) and debt capacity (*tang*) do not have different exposures in machine learning portfolios. Meanwhile, the change in long-term debt (*lgr*) has a negative association with expected returns, as shown by the lower exposure in the top portfolio, rather than the positive relationship found in the literature (e.g., Bhandari 1988). However, the secured debt (*secured*) factor has a positive relationship, as predicted in the literature. When the optimised-small portfolio is examined in Panel C, more interesting observations arise. First, for these three factors (leverage, long-term debt and secured debt), a higher factor realisation is strongly and negatively associated with expected returns, in contradiction to the literature. Second, greater asset tangibility is associated with positive expected returns, thus the short leg of the neural network portfolio is constructed by firms with limited tangibles assets.

The implication is that the neural network identifies firms which take on substantial debt in a short period as short-selling opportunities. On the contrary, according to the theoretical expectation, higher leverage implies riskier firms, which should command a premium for bearing higher risk (Bhandari 1988). Given this contradiction, it is arguable that the neural network is again capturing the short-lived investor reaction to information about a distressed firm and ignores the long-term premium associated with the ownership of riskier equities. Similarly, the asset tangibility finding implies that the neural network identifies firms with limited tangible assets as short opportunities again capturing the investor reaction to the increased risk rather than the long-term premium. Both findings are suggestive that the neural network model naturally captures the short-lived overreaction to the news of financial distress rather than assuming the long-term risk of ownership.

As opposed to liability-related factors, equity-related factors are identified by the neural network model in full agreement with prior literature. Specifically, the model predicts that both the change in shares outstanding (*chcsho*) and growth in common shareholder equity (*egr*) are negatively associated with expected monthly returns. As a matter of fact, the optimised-small portfolio substantially values these two factors by going short firms that issue new shares and buying firms which buy-back shares. This is an interesting observation as it confirms the post-issuance bias which yields negative abnormal returns (Pontiff and Woodgate 2008).

Profitability category - profitability margins and ratios

Improvement in profit margins is theoretically a positive signal for expected stock prices which is also the relationship detected by the neural network model. The results for the equal-weighted portfolio in Panel A of Table 3.1 highlight that the model identifies that both increased gross profitability (*gma*) and increased operating profitability (*operprof*) are associated with higher expected returns. Furthermore, an increase in the % change in gross margin relative to the % change in sales (*pchg_m_pchsale*) also commands a positive risk premium. Similar relationships are also found for the increase in the % change in sales relative to both the % change in inventory (*pchsale_pchinv*) and % change in account receivables

(*pchsale_pchrect*). This reinforces the finding that the neural network model identifies the accumulation of inventory and account receivables as a negative signal for future stock returns, in full agreement with the literature (Abarbanell and Bushee 1998).

The optimised-small portfolio in Panel C generally follows the same patterns, but diverges on some key profitability margins. Specifically, while the operating profitability still seems to be positively associated with expected returns, the portfolio takes short positions in firms which recently reported increased gross margins (*gma*), increased sales growth (*sgr*), increased sales-to-price ratio (*sp*), and increased % change in sales relative to % change in inventory (*pchsale_pchinv*). This finding suggests that the neural network identifies that the top line entails significant alpha-generating information which can be captured by shorting firms that recently reported substantial increases in sales margins. Consistent with the previous section, the neural network seems to capitalize on the overreaction of investors to the positive news of revenue growth and thus, reinforces the idea that the model's success stems from short-lived yet attainable signals.

In contrast to the mixed signals documented in the analysis of profitability margins, profitability ratios are identified as significant and positive explanators of future returns, in full agreement with the literature. Specifically, ratios such as return on assets (*roaq*), return on equity (*roeq*) and return on invested capital (*roic*) are all identified to have a positive association with expected stock returns. Similarly, increased volatility in earnings (*roavol*) is statistically identified as a negative signal as dictated by prior literature. This evidence suggests that the neural network model identifies and trades the positive signal associated with improvements in the bottom line, and also recognizes the increased uncertainty associated with volatile earnings. Indeed, the optimised-small portfolio strongly depends on these profitability ratios, implying that the neural network model extracts significant alpha from the positive overreaction to the news associated with the bottom line.

Profitability category – liquidity ratios

Strong liquidity ratios are associated with healthy firms which grow and mature through their life. In contrast, asset pricing theory suggests that firms which face liquidity issues should command a higher risk premium to compensate investors for the associated incremental risk. The equal-weighted portfolio formed by the neural network does not take positions related to the level of either the current ratio (*currat*), or the quick ratio (*quick*). In addition, a positive % change in the current ratio (*pchcurrat*) and % change in the quick ratio (*pchquick*) are found to be positively associated with expected returns. On the other hand, the alpha-generating optimised-small portfolio has a different viewpoint on liquidity ratios. Specifically, the portfolio takes short positions in firms with strong liquidity as long as there was a recent, strong improvement in liquidity. This evidence is suggestive that the neural network takes a contrarian trading approach whereby it capitalizes on the overreaction of recent positive financial results.

Profitability category – cash and accruals

Revenue accounting affects either the cash or accrual account, depending on whether the sale was made by cash or credit. In theory, increasing accruals are associated with negative future stock returns, whereas low cash levels are associated with higher liquidity risk. The equal-weighted portfolio takes no positions based on the accrual account (*acc*) or the absolute accruals (*absacc*), which is a finding also reported by both Gu et al. (2020) and Avramov et al. (2022). Furthermore, the cash factor is reported in Table 3.1 to be irrelevant as well. This implies that under the equal-weighted portfolio, investors are insensitive to whether profitability is due to cash or credit sales. Regarding the volatility of accruals, once again the neural network finds that investors despise uncertainty. This is concluded due to the equal-weighted portfolio taking short positions in firms with recently increased accrual volatility (*stdacc*) and percent accruals (*pctacc*). On the contrary, the optimised-small portfolio takes long positions in firms with high accruals and high cash levels, and short positions in firms with low absolute accruals. The volatility of accruals still exhibits a strong, in fact the strongest, negative association with expected monthly returns.

Profitability category - Financial statement score

Piotroski (2000) and Mohanram (2005) compiled scoresheets to measure the fundamental and profitability health of firms consisting of 9 and 8 variables, respectively. Both the Piotroski (2000) (*ps*) and Mohanram (2005) (*ms*) models are identified by the equal-weighted model as significant explainers of future returns, whereas, only the Piotroski (2000) model is used by the optimised-small portfolio.

Value vs. growth category

Interestingly, some well-established asset pricing predictors fail to be identified by the equal-weighted portfolio. Specifically, both the book-to-market (*bm*) and size (*mvel1*) factors appear irrelevant in the equal-weighted simulation, as well as their industry-adjusted versions (*bm_ia*, *mve_ia*). On the other hand, the earnings-to-price (*ep*) and cash flow-to-price (*cfp*) ratios are evidenced to have positive associations with expected returns. At the same time, the cash flow volatility (*stdcf*) is confirmed to be significantly negatively associated with future abnormal returns, as it has been documented for all uncertainty measures previously. Regarding growth ratios, only sales-to-inventory (*saleinv*) appears significant, whereas sales-to-receivables (*salerec*) and sales-to-cash (*salecash*) do not seem to be relevant.

On the contrary, the optimised-small portfolio identifies both the book-to-market and size factors, as well as their industry-adjusted versions as significant explainers. The negative association documented for the book-to-market anomaly signifies that the neural network chases the momentum reversal due to the recent overreaction from positive accounting news, which is prevalent in small stocks, as suggested by the negative association of the size factor. Regarding growth ratios, the optimised-small portfolio clearly takes short positions in stocks with high growth ratios, including sales-to-inventory, sales-to-receivables and sales-to-cash. This confirms the earlier finding about the negative association of the top line and expected return and reinforces the idea that the neural network extracts abnormal returns from shorting the overreaction after positive news.

Intangibles category

The equal-weighted portfolio takes long positions in more mature firms (age) in more concentrated industries (*herf*). Firms with high organisational capital (*orgcap*), which reduce their employee numbers (*hire*) are expected to have positive expected returns as firms become leaner and more efficient. The existence of convertible debt (*convind*) is identified as a negative signal due to its effect in diluting stock, whereas the existence of secured debt (*securedind*) is identified as a positive signal due to the existence of tangible assets. Increasing research and development expenses (*rd*) are seen positively by the equal-weighted portfolio, but when sales are not rising as fast as research and development expenses (*rd_sale*), this is considered to be a negative signal.

On the contrary, increasing research and development (R&D) expenses is generally identified as a negative signal by the optimised-small portfolio. Of course, this is not surprising given the fact that R&D generally creates value over a long period, whereas the neural network is trained with monthly data and in that time horizon the R&D benefits are uncertain. Both the organisational capital and the reduction in employee numbers are seen as negative signals. Lastly, the neural network is able to extract alpha by investing in young firms which operate in low concentration industries, in direct contradiction to the behavior of the equal-weighted portfolio.

Trading frictions category

Most trading frictions factors appear to be identified as significant predictors of abnormal future returns according to the machine learning portfolio. To begin with, both the equal-weighted portfolio and the optimised-small portfolio identify that the neural network takes short positions in stocks with high betas (*beta*) and squared beta (*betasq*) and long positions in firms with low betas, as also reported in Avramov et al. (2022). Liquidity appears to be an especially important element of the success of the machine learning portfolio in both portfolio simulations. Specifically, the equal-weighted portfolio takes short positions in stocks with large bid-ask spreads (*baspread*), high share turnover (*turn*), and high volatility of share turnover (*std_turn*). The optimised-small portfolio extracts further performance from volatility factors by taking short positions in stocks with high zero trading days (*zerotrade*) and

illiquidity (*ill*). This indicates that the neural network finds that shorting microcaps, which are naturally characterized by large spreads, low liquidity and low float, is profitable.

Volatility factors are equally critical to the success of the model as liquidity factors. In fact, the machine learning model predicts a non-linear (U-shaped) relationship between volatility measures, such as return volatility (*retvol*), maximum daily return in prior month (*maxret*) and idiosyncratic return volatility (*idiovol*), and future returns. This is highlighted by both the short and the long leg of the spread portfolio being concentrated with stocks of abnormally high volatility. In comparison, the short leg concentrates stocks of higher volatility than the long leg. The implication is that the machine learning model identifies that highly volatile stocks lose value much faster than they gain.

Momentum category

Momentum-related measures appear to be the most important predictors according to the neural network model as evidenced by almost all factors being statistically significant. The short-term reversal factor (*mom1m*) is found to have a strong negative association with expected returns. This is not surprising given the propensity of the neural network to apply reversion trading strategies. Specifically, the model identifies stocks which recently reported improved revenues and higher capital expenses, but unchanged net profitability, and short sells them. This, in effect, is a short-term reversal strategy which is very prevalent in the behavior of the neural network model as evidenced by the 1-month momentum factor.

Similarly, longer-term momentum strategies, such as the 6- (*mom6m*) and 12-month momentum (*mom12m*), exhibit positive association with expected returns, a finding which is further strengthened after adjusting for the industry (*indmom*). This implies that despite the focus on the short-term movements in stock prices, the equal-weighted model still has a long bias to the market. Another facet of momentum which is recognized by the neural network is the momentum due to surprises in financial results. This includes factors such as the earnings announcement return (*ear*), abnormal earnings announcement volume (*aeavol*), number of consecutive earnings increases

(*nincr*) and revenue surprise (*rsup*). In line with the prior literature, the equal-weighted portfolio takes long positions in firms which recently reported a positive momentum-relevant surprise and short positions in firms which reported a negative surprise.

Despite the significant dependence on momentum factors documented for the equal-weighted portfolio, momentum-based trading strategies incur substantial costs. This leads to a very important implication. The optimised-small portfolio, which considers the associated costs before placing trades, exhibits very different behaviour. Specifically, the long bias previously seen is completely dropped and the model solely focuses on extracting alpha from going short high momentum stocks. This is also documented in factors such as abnormal earnings announcement volume (*aeavol*) and number of consecutive earnings increases (*nincr*) given the exhibited negative associations with expected returns. This indicates that the neural network model no longer follows momentum, but rather shorts stocks with exceedingly inflated prices due to investor overreaction to positive surprises in financial results.

3.4.2 Realisations across functional categories

Table 3.2 and Figures 3.1 to 3.6 report the mean factor realizations for each functional category across time. To generate these tables, the factor signs have been set in such a way that an increase in a factor is theoretically expected to yield higher expected returns. For example, the short-term reversal factor, *mom1m*, is theoretically expected to yield lower returns and thus, its sign is reversed. Therefore, an increase in the momentum category implies an increase in its composite factors, each in their theoretically implied direction. Subsequently, the factor realisations of the stocks within each portfolio are averaged across the cross-section, across their functional category and then across time, in this order.

[Insert Table 3.2]

[Insert Figure 3.1]

[Insert Figure 3.2]

[Insert Figure 3.3]

[Insert Figure 3.4]

[Insert Figure 3.5]

[Insert Figure 3.6]

The results in Table 3.2 confirm that the neural network model is heavily dependent on the momentum category when applying the equal-weighted scheme. The investment and profitability categories are the next most important categories. This indicates that under this weighting scheme the neural network is uniformly extracting predictability from both fundamental and market factors. The value-weighted portfolio, shown in Panel B, limits the model's dependence on momentum, but its diminishing effect is rather small. The exposures of the other categories are also limited, with the value vs growth category becoming relatively more important than profitability.

On the other hand, the optimised-small portfolio reported in Panel C exhibits substantially different trading behaviour. Specifically, the overdependence on momentum factors is completely eliminated, as indicated by both the short and long legs of the portfolio having the average momentum exposure. Instead, this model extracts alpha by shorting stocks which recently reported improved profitability factors, as previously observed. Similarly, a negative association is generally exhibited by the trading frictions category, which confirms how successfully the optimiser filters out positions for which trading would have burned more value than it would generate. Lastly, the positive association of the investment and value vs growth categories is confirmed at the same levels as the value-weighted portfolio. This confirms that the machine learning model can extract significant alpha by identifying fundamentally relevant signals.

3.4.3 Realisations across functional categories over time

Figures 3.1 to 3.3 illustrate the exposure of the neural network portfolio across time for the bottom portfolio (short leg), top portfolio (long leg), and the High-minus-Low portfolio (HML), respectively, for the fundamental-related categories (value vs growth, profitability, investment, and intangibles). Figures 3.4 to 3.6 illustrate the results for the market-related factor categories (trading frictions and momentum).

Figures 3.1 to 3.3 show that the equal- and value- weighted models of Gu et al. (2020), effectively combine signals from most predictors in the dataset, which concurs the findings of Avramov et al. (2022). This is seen by the realisations of the four fundamental categories revolving around the mean, thus the HML revolves around 0. Figure 3.3 shows that the HML portfolio exhibits negative expectation (i.e., the short leg is more exposed than the long leg) to the profitability category from 1993 to 2008 and 2011 to 2015. The portfolio exhibits a positive expectation for the investment category across the sampling period, with the magnitude of this relationship being larger in times of market growth such as 2009 to 2016. In combination, these two findings highlight that the neural network performance is linked to periods of high market volatility, as also shown by Avramov et al. (2022). The intangibles category exhibits a minor positive expectation until 2000 and subsequently switches to a minor negative expectation. In contrast, the value vs. growth category does not exhibit any trends over the sampling period.

Figures 3.4 to 3.6 show that the equal- and value- weighted models of Gu et al. (2020) take substantial positive exposure to the momentum category over the sample. Interestingly, this exposure is more prominent in the period between 1997 to 2012, which was a period of high market volatility. On the other hand, the optimised-small portfolio severely restricts the extreme dependence on momentum factors across the sample length. Therefore, this concludes that the neural network model of Gu et al. (2020) owes a substantial extent of its success to momentum strategies. However, these are more expensive to trade than the value they generate. By restricting these positions, the optimiser can yield a significantly positive effect on the neural network profitability. Lastly, the trading frictions category does not exhibit any net exposure in any portfolio simulations.

3.4.4 Realisations across functional categories and industries

Table 3.3 evaluates how the neural network factor realisations are distributed across the 11 S&P industries. The equal-weighted portfolio is evidenced to be dominated by the momentum category across every single industry, but stocks in the energy and technology sectors are especially used by the neural network to execute its momentum strategy. Examining the short and long legs, the momentum positions are uniformly distributed across the two portfolios, with the energy and technology industries being the most prominent. The investment-related positions are evidenced to be more prominent in the energy, technology, materials, and consumer staples industries, while the profitability-related positions are mostly focused on the financial industry. Other interesting observations are noted by the neural network going both short and long in stocks: (a) in the utilities industry if they rank high in the value vs growth category and low in the intangibles category; (b) in the healthcare, technology, and real estate industries when they rank high in investment, intangibles, and trading frictions categories; and (c) in the healthcare industry when they rank low on the value vs. growth category.

On the other hand, Panel C of Table 3.3 finds that the optimised-small portfolio exhibits a very different exposure profile than the equal-weighted portfolio. To begin with, the dependency on the momentum factors is eliminated and both the short and long legs of the portfolio and they have no exposure to momentum positions. Furthermore, the model executes reversal strategies based on recent improvements in profitability factors, especially for stock in technology, healthcare, industrials and real estate industries. A similar negative association is predicted for the trading frictions category across all industries, whereby an increase in trading friction factors is expected to yield lower returns. On the other hand, the model still views improvements in investment-related factors as positive for month-ahead returns across most industries, and most prominently in the technology industry. Finally, the value vs. growth and intangibles categories are not evidenced to influence the trading behavior of the optimised-small portfolio.

[Insert Table 3.3]

3.4.5 Double-sorted portfolios

Table 3.4 presents how the neural network predictive signal is distributed across double-sorted portfolios of commonly used risk factors, specifically, size, book-to-market, market beta, operating profitability, short-term reversal and 12-month momentum. In this way, interactions between the different factors can be uncovered. It should be noted that the table presents the mean return expectation for each of the 25 portfolios, and not the realized returns. Based on this, the interactions between factors can be evaluated and the complexity of the neural network trading behaviour can surface.

[Insert Table 3.4]

For the equal-weighted portfolio, the size x book-to-market sorted portfolios show that expected excess returns increase monotonically with the increase in book-to-market and with the decrease in size. The size effect becomes more prominent in the size x 1-month momentum sorted portfolios. In fact, the equal-weighted scheme exhibits a steep gradient whereby excess returns are predicted to be larger for smaller firms with high predicted momentum reversal. Substantial gradient is also observed in the size (vertical) x 12-months momentum sorted portfolio under the equal-weighted scheme. Specifically, stronger long-term momentum is identified to have a positive association with predicted excess returns and this effect is more intense for smaller stocks. In contrast, when the optimised-small portfolio is considered, the size effect fails to exhibit any association with predicted excess returns, and the effects described above disappear. Similarly, the intersection of size with either operating profitability (Size x operating profitability) and CAPM beta (Size x CAPM beta) eliminates the predictive ability of either factor across both the equal-weighted and the small-optimised portfolio.

Intersecting the book-to-market factor with the momentum factors eliminates most of its predictability, whereas both the 1-month momentum and 12-months momentum still exhibit substantial gradients. The book-to-market factor again fails to be identified as a return predictor when intersected with CAPM beta, whereas the latter exhibits its expected negative association with future returns. On the other hand, book-to-market exhibits a

minor gradient when interacted with operating profitability, with the latter exhibiting a minor positive association as well.

The intersection of the short-term momentum with the long-term momentum (Momentum 1 month x momentum 12 months) for the equal-weighted portfolio generates the steepest profitability gradient observed. This indicates that the neural network model expects that stocks with long-term positive momentum which recently had a month of substantial negative returns present a strong buy signal as their price will correct upwards in the next month. Interestingly, both the 1-month momentum and 12-month momentum limit the effect of the CAPM beta and eliminate the effect of operating profitability.

When considering the optimised-small portfolio, the size factor effect is substantially limited when this is interacted with 1-month momentum, 12-month momentum, CAPM beta, and operating profitability, while it is eliminated when interacting with book-to-market. Furthermore, both momentum factors are eliminated across all interactions. This implies that the neural network as used in Gu et al. (2020) is dependent on momentum effects, both short-run and long-run yet these effects fail to generate any predictability when trading frictions are considered. On the other hand, operating profitability exhibits a minor negative association with expected returns when intersected with size, 1-month momentum, and 12-month momentum factors, but no association when intersected with book-to-market. Finally, CAPM beta does not present any gradient when interacted with any factor except from size.

3.5 Discussion

Evidence from the factor realisations strongly suggests that the neural network extracts significant alpha based on the overreaction of recent positive financial results by shorting firms which recently report substantial improvements in profitability and liquidity ratios. It is interesting to note that there is no evidence that the opposite applies. Indeed, the neural network is not observed to take long positions in firms in recent underreaction scenarios but rather achieves success from the short leg of the spread portfolio. It should be highlighted that the above finding does not imply that low liquidity stocks do not command high risk premium, as suggested by the asset pricing theory. Rather this is the result of the optimiser identifying that shorting the overreaction generally yields positive risk-adjusted returns when training the neural network with monthly data, as opposed to taking long positions in underreaction scenarios whereby a long-term trading strategy is required.

Improvement in the bottom line has been documented to be positively associated with future stock returns, as shown by the long positions taken in stocks which rank high in factors such as return on assets, return on equity and return on invested capital. On the other hand, improvement in the top line has been identified by the neural network as a negative signal. This was evidenced by the small-optimised portfolio shorting stocks which recently reported improvements in top line factors, such as sales growth, sales-to-price ratio and sales relative to % change in inventory. Taking the two findings in conjunction reveals a very interesting result. Specifically, the neural network seems to extract alpha in situations where the top line substantially grows while the bottom line does not. Possibly, it identifies these situations to be associated with firms which either use aggressive earnings smoothing techniques or are inefficient and unable to realize the net profit associated with their increased sales.

It is observed that the neural network model is highly dependent on predictors in the momentum category, as well as the trading frictions category, specifically volatility and stock liquidity measures, which strongly concurs the findings of Gu et al. (2020). The short leg of the spread portfolio

is loaded with highly volatile stocks of low liquidity. This concurs the concept put forward by Avramov et al. (2022) which claims that the predictability of the neural network model is highly dependent on microcaps, in episodes of high market volatility. Combining this with the previous evidence for the profitability factors it becomes obvious that the model extracts alpha from microcaps which recently reported improved revenues but failed to turn this into net profit. Given the above, it is highlighted that the model applies a short-term reversal strategy, which is confirmed by the highly significant 1-month momentum factor.

The findings in this chapter support the general findings of Avramov et al. (2022) who argue that the predictability of the neural network is rooted in anomalies within small stocks. Nonetheless, the results also show that the microcap bias alone does not explain the behavior of the neural network model in any adequacy. A novel finding that is highlighted in this chapter is that the model extracts alpha by shorting situations of investor overreaction. Specifically, the results show negative associations of both book-to-market and size factors, the former being contrary to the literature and the latter being in line with the literature. This suggests that the neural network chases the momentum reversal due to the recent overreaction from positive accounting news, which is prevalent in small stocks. Further evidence to support the above is plentiful, including the negative associations of earnings surprises and other momentum factors with expected returns. Again, this indicates that the model shorts stocks with exceedingly inflated prices due to investor overreaction to positive surprises in financial results.

The optimised large portfolio, on the other hand, values only a limited number of factors overall. This reinforces the idea that the success of the neural network model stems from short-lived signals which cannot be capitalized by large institutional investors. For the profitability category both the financial health scoresheet models of Piotroski (2000) and Mohanram (2005) are identified, which highlights the fact that large investors are largely dependent on fundamental analysis. Other significant fundamental-based factors include the industry-adjusted book-to-market ratios, cash flow-to-price ratio, volatility of cash flow and age. More importantly, while the equal-weighted and optimised-small portfolios largely follow factors related to volatility, stock liquidity and momentum, large investors seem generally

unable to capitalize on these factors. Taken together, the above findings are strongly suggestive that the exceptional profitability of the neural network model is based on short-term reversal signals, associated with high levels of trading frictions. These cannot be captured by large institutional investors, at least based on the current paradigm of the neural network predictive model.

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Tables

Table 3.1: Exposure of individual predictive factors, monthly rebalancing

Table 3.1 reports the mean value of each of the 94 predictive factors for each decile portfolio generated by ranking stocks according to their machine predicted returns. The bottom portfolio is constructed by ranking stocks according to their machine learning predicted returns and form 10 portfolios and selling the lowest quintile portfolio. The top portfolio is constructed by ranking stocks according to their machine learning predicted returns and form 10 portfolios and buying the highest quintile portfolio. The long-short (HML) portfolio is constructed by ranking stocks according to their machine learning predicted returns and form 10 portfolios, buying the highest quintile portfolio and selling the lowest quintile portfolio. The factor realisations corresponding to the stocks chosen for the top and bottom portfolios are averaged to generate the results in the table. Factors were not reordered and thus, reflect the associations based on which they were constructed. At each monthly period the factor input was rescaled to the [0%,100%] range and thus, the expected value for all factors is 50%. The mean values of the lowest and highest deciles are compared based on the null hypothesis $H_0: \mu_{high} = \mu_{low}$ which examines whether the category realisations are significantly different between the two portfolios. The Newey-West adjusted t statistics are presented in the column t stat. The reported results are for the average across the five neural network predictive models (NN1-NN5). The table is divided into four panels, A to D, which report the results for the equal-weighted, value-weighted, optimised portfolio trading a relatively small portfolio of 1 million USD and optimised portfolio trading a relatively large portfolio of 100 million USD, respectively. Investing horizon is one month and thus, rebalancing of the portfolio is performed monthly based on predicted returns. The results for the quarterly and annual rebalancing are presented in Appendix 3C and 3D, respectively.

Category	Factor	Panel A: Equal-weighted Portfolio				Panel B: Value-weighted Portfolio				Panel C: Optimised Small Portfolio				Panel D: Optimised Large Portfolio			
		1	10	HML	t stat	1	10	HML	t stat	1	10	HML	t stat	1	10	HML	t stat
Investment	agr	49.36	54.42	5.05***	9.48	46.87	49.09	2.22***	4.17	41.31	53.58	12.26***	8.22	45.59	48.26	2.67	1.33
	chatoia	49.48	52.22	2.74***	8.97	49.74	50.65	0.91	2.26	46.94	51.24	4.29***	4.08	47.74	51.97	4.23	2.41
	chcsho	54.04	49.08	-4.96***	-12.18	53.72	50.71	-3.01***	-6.15	58.69	46.61	-12.07***	-9.19	55.99	52.22	-3.77	-1.76
	chinv	50.31	46.67	-3.64***	-9.74	52.08	49.54	-2.55***	-5.57	55.06	48.20	-6.85***	-5.16	53.77	51.58	-2.18	-1.35
	cinvest	49.47	50.64	1.17***	5.66	50.06	49.60	-0.46	-0.92	52.09	49.02	-3.07	-1.42	52.73	52.20	-0.52	-0.57
	depr	51.13	53.66	2.53***	5.87	52.55	51.88	-0.66	-1.25	58.45	46.46	-11.99***	-7.52	56.35	52.50	-3.85	-1.98
	egr	48.95	45.78	-3.17***	-6.69	53.50	50.06	-3.44***	-7.10	58.92	46.69	-12.24***	-9.38	55.24	52.84	-2.40	-1.29
	grcapx	50.54	47.48	-3.06***	-9.37	52.34	50.86	-1.48***	-3.17	59.25	46.50	-12.75***	-9.12	56.02	52.84	-3.17	-1.76
	grltnoa	49.79	45.74	-4.05***	-9.82	52.87	49.78	-3.09***	-6.35	58.91	46.88	-12.03***	-11.25	54.86	52.05	-2.80	-1.40
	invest	51.28	46.61	-4.66***	-9.70	53.98	50.30	-3.67***	-7.41	59.62	46.56	-13.06***	-10.59	55.78	52.28	-3.49	-1.80
	lev	46.73	45.98	-0.75	-1.23	51.65	50.35	-1.30	-2.41	59.01	46.46	-12.54***	-10.65	55.89	52.74	-3.14	-1.99
	lgr	51.72	47.02	-4.70***	-11.90	53.54	50.98	-2.56***	-5.05	59.55	46.32	-13.23***	-9.49	56.38	52.48	-3.90	-2.03
	pchcapx_ia	49.12	48.52	-0.59	-1.76	51.06	49.73	-1.32*	-2.62	49.79	50.38	0.60	0.27	49.66	53.37	3.71	1.07
	realestate	49.47	48.49	-0.98***	-3.26	52.07	50.75	-1.32**	-3.16	59.29	46.71	-12.58***	-10.88	55.58	51.67	-3.91	-2.40
	secured	50.60	53.43	2.83***	5.14	52.13	52.84	0.72	1.74	55.44	47.91	-7.53***	-5.03	54.75	53.11	-1.64	-1.39
	tang	52.89	53.52	0.63	1.12	51.86	52.08	0.22	0.34	45.68	51.48	5.79***	7.79	51.92	46.85	-5.06***	-3.28

Table 3.1 continued

Category	Factor	Panel A: Equal-weighted Portfolio				Panel B: Value-weighted Portfolio				Panel C: Optimised Small Portfolio				Panel D: Optimised Large Portfolio			
		1	10	HML	t stat	1	10	HML	t stat	1	10	HML	t stat	1	10	HML	t stat
Profitability	absacc	54.74	54.01	-0.73	-1.70	53.73	52.53	-1.19	-2.46	58.77	46.52	-12.24***	-8.51	56.29	52.34	-3.94	-1.82
	acc	47.74	46.95	-0.78	-1.76	46.64	46.95	0.32	0.57	42.22	52.97	10.75***	9.31	45.56	51.01	5.44*	2.56
	cash	52.83	54.16	1.33	2.02	54.72	53.93	-0.79	-1.77	57.06	47.08	-9.97***	-7.38	55.82	52.46	-3.36	-1.69
	cashdebt	43.91	47.59	3.67***	6.44	47.80	49.21	1.40*	2.61	41.03	53.92	12.88***	8.46	44.73	48.48	3.75	1.94
	chpmia	53.74	45.86	-7.87***	-17.88	52.32	47.85	-4.46***	-7.69	52.57	49.45	-3.12	-1.57	50.90	50.35	-0.55	-0.14
	currat	50.54	51.29	0.75	1.53	52.36	51.28	-1.07	-2.12	58.99	46.55	-12.44***	-8.30	56.26	52.55	-3.71	-2.12
	gma	46.95	51.02	4.07***	8.38	49.54	51.57	2.03***	4.38	53.42	49.22	-4.19***	-4.64	50.88	53.77	2.88	1.70
	ms	45.16	47.70	2.54***	5.77	46.14	47.60	1.45***	3.70	49.06	50.72	1.65	2.17	47.13	52.86	5.73***	5.20
	operprof	43.24	45.99	2.75***	4.81	45.95	47.19	1.24*	2.56	43.76	52.71	8.95***	5.21	45.89	48.55	2.66	1.41
	pchcurrat	47.87	48.84	0.97**	2.96	52.50	51.28	-1.22	-2.49	59.30	46.42	-12.88***	-9.25	56.26	52.46	-3.80	-1.98
	pchdepr	49.96	51.09	1.13***	4.19	52.64	51.48	-1.15	-2.34	59.50	46.37	-13.12***	-9.15	56.45	52.20	-4.25	-2.26
	pchgm_pchsale	47.62	51.77	4.15***	13.42	46.91	49.10	2.19***	4.46	40.77	53.91	13.13***	9.12	44.42	49.02	4.60	2.29
	pchquick	47.62	49.12	1.50***	4.61	52.44	51.34	-1.09	-2.22	59.26	46.43	-12.83***	-9.13	56.24	52.50	-3.74	-1.95
	pchsale_pchinvt	48.15	52.37	4.21***	15.46	47.79	49.65	1.86***	3.93	40.77	53.79	13.01***	9.66	45.26	48.41	3.15	1.67
	pchsale_pchrect	50.14	50.67	0.53**	2.80	47.51	48.75	1.24*	2.51	40.73	53.82	13.09***	9.96	44.83	48.71	3.88	1.91
	pchsale_pchxsga	50.28	50.37	0.09	0.33	52.77	51.42	-1.34**	-2.94	57.85	46.99	-10.86***	-7.58	54.69	53.17	-1.52	-1.12
	pchsaleinv	49.79	51.39	1.59***	5.12	50.86	51.03	0.17	0.55	56.79	47.26	-9.52***	-4.89	55.77	51.46	-4.30	-1.99
	pctacc	53.07	51.44	-1.63***	-3.98	48.75	49.10	0.35	0.68	40.29	53.80	13.51***	10.40	45.04	51.24	6.19	2.44
	ps	42.74	48.65	5.90***	11.63	43.22	47.77	4.54***	10.08	48.13	51.18	3.05***	4.56	46.75	51.52	4.76***	3.64
	quick	50.56	50.73	0.16	0.34	52.40	51.27	-1.13	-2.23	58.89	46.54	-12.35***	-8.10	56.21	52.64	-3.57	-2.04
	roaq	41.84	49.24	7.39***	12.73	44.92	47.85	2.93***	6.23	41.17	53.73	12.56***	8.80	44.34	49.39	5.05	2.34
	roavol	58.05	55.95	-2.10***	-3.59	53.61	51.94	-1.67***	-3.48	58.55	46.41	-12.13***	-7.70	56.72	52.02	-4.69	-2.29
	roeq	43.27	48.36	5.09***	9.29	45.22	47.53	2.31***	4.79	43.84	52.41	8.56***	5.23	47.27	48.43	1.16	0.83
	roic	43.86	47.28	3.42***	5.85	46.48	48.11	1.62**	3.38	41.87	53.74	11.87***	7.18	44.60	48.80	4.20	2.05
	sgr	51.44	48.29	-3.15***	-7.31	53.17	51.23	-1.94***	-4.11	59.21	46.40	-12.81***	-8.52	56.20	52.62	-3.58	-1.89
	sp	46.03	49.98	3.94***	7.02	52.18	51.73	-0.44	-0.82	58.15	47.16	-10.99***	-7.26	55.33	52.79	-2.54	-1.55
	stdacc	55.12	48.95	-6.17***	-14.14	53.88	50.47	-3.41***	-6.82	60.05	45.98	-14.07***	-8.30	57.52	51.83	-5.68**	-2.80
	tb	48.08	47.11	-0.98*	-2.55	50.21	48.79	-1.42**	-2.86	54.66	48.85	-5.81***	-3.17	50.80	52.38	1.58	0.58

Table 3.1 continued																	
Category	Factor	Panel A: Equal-weighted Portfolio				Panel B: Value-weighted Portfolio				Panel C: Optimised Small Portfolio				Panel D: Optimised Large Portfolio			
		1	10	HML	t stat	1	10	HML	t stat	1	10	HML	t stat	1	10	HML	t stat
Value vs growth	bm	46.16	46.99	0.82	2.41	51.59	50.39	-1.20	-2.42	59.48	46.61	-12.86***	-9.09	55.72	53.12	-2.60	-1.60
	bm_ia	51.53	51.98	0.452	1.21	50.55	50.61	0.06	0.22	55.32	47.45	-7.88***	-4.20	57.87	43.65	-14.22***	-6.67
	cashpr	50.34	52.01	1.68***	3.47	51.20	51.12	-0.08	-0.08	54.17	48.23	-5.94**	-2.94	54.14	51.11	-3.03	-1.39
	cfp	42.75	47.24	4.49***	8.55	45.27	47.76	2.49***	4.88	48.50	51.12	2.62	1.82	45.79	54.70	8.91***	3.77
	cfp_ia	46.23	49.01	2.78***	7.12	48.15	49.35	1.20*	2.54	48.04	51.15	3.11	1.80	48.49	52.29	3.80	1.51
	dy	44.71	44.27	-0.44	-0.99	50.08	49.51	-0.57	-0.99	54.30	48.93	-5.37	-2.48	50.56	55.05	4.49	1.38
	ep	42.22	45.21	2.98***	5.02	46.60	47.79	1.19	2.35	41.10	53.77	12.66***	8.09	44.62	48.90	4.28	2.11
	mve_ia	46.71	45.99	-0.71	-1.73	52.40	50.73	-1.66	-2.31	61.13	46.10	-15.02***	-11.64	55.20	53.23	-1.97	-1.39
	mvel1	44.70	44.29	-0.40	-0.75	52.34	50.78	-1.56	-2.02	61.51	46.08	-15.42***	-12.03	54.62	53.64	-0.98	-0.96
	salecash	45.46	46.84	1.37	2.53	52.40	50.46	-1.94***	-3.64	60.02	46.34	-13.67***	-10.45	56.19	52.57	-3.62	-1.92
	saleinv	49.11	48.21	-0.89**	-3.07	51.40	50.83	-0.57	-1.08	59.20	46.46	-12.73***	-8.82	56.04	52.47	-3.57	-1.99
	salerec	49.81	50.10	0.29	0.76	51.64	50.71	-0.93	-2.02	57.52	47.44	-10.08***	-5.38	54.01	53.14	-0.87	-0.91
	stdcf	55.34	49.13	-6.20***	-13.98	53.90	50.50	-3.39***	-6.80	59.97	45.99	-13.98***	-8.27	57.46	51.89	-5.57**	-2.76
Intangibles	age	45.15	48.38	3.23***	5.39	47.41	48.98	1.57	2.21	52.94	49.84	-3.09***	-3.10	49.16	53.97	4.81***	4.33
	chempia	49.77	48.87	-0.91	-2.56	51.27	49.83	-1.44**	-3.11	52.64	49.88	-2.75	-1.30	48.22	53.42	5.20	2.03
	convind	52.16	51.26	-0.90**	-3.04	53.81	51.89	-1.92***	-3.74	58.73	46.76	-11.96***	-10.81	55.22	52.19	-3.02	-1.57
	divi	50.73	50.45	-0.28	-2.45	52.47	50.91	-1.56**	-3.08	59.13	46.51	-12.61***	-9.80	56.09	52.53	-3.56	-1.96
	divo	50.42	50.88	0.45	1.48	52.25	51.44	-0.81	-1.55	59.37	46.45	-12.92***	-9.68	56.20	52.42	-3.78	-2.03
	herf	48.10	51.26	3.16***	6.86	51.50	51.61	0.10	0.45	58.13	46.89	-11.23***	-9.32	55.51	52.41	-3.10	-2.31
	hire	51.17	47.75	-3.42***	-8.00	53.90	50.95	-2.94***	-6.00	59.40	46.40	-13.00***	-9.73	56.19	52.45	-3.73	-1.95
	orgcap	51.00	54.03	3.03***	6.96	52.22	52.08	-0.15	-0.13	57.68	47.02	-10.66***	-7.38	55.78	52.19	-3.58	-2.09
	rd	51.31	55.64	4.33***	9.86	52.59	55.93	3.34***	6.35	56.49	47.56	-8.92***	-8.24	54.75	52.48	-2.27	-1.49
	rd_mve	52.02	51.31	-0.70	-1.90	52.65	51.72	-0.93	-1.76	59.77	46.33	-13.44***	-10.36	56.50	52.22	-4.28	-2.17
	rd_sale	51.52	48.15	-3.37***	-11.15	51.75	51.11	-0.63	-1.27	57.92	47.07	-10.84***	-5.70	55.38	51.43	-3.94	-1.69
	securedind	49.55	53.00	3.44***	5.55	49.54	53.52	3.97***	6.00	49.75	50.45	0.69	1.27	51.12	49.14	-1.98	-1.84
	sin	50.10	50.17	0.07	1.63	52.06	50.75	-1.30	-2.37	59.83	46.31	-13.52***	-9.90	56.27	52.70	-3.57	-1.93

Table 3.1 continued																	
Category	Factor	Equal-weighted Portfolio				Value-weighted Portfolio				Optimised Small Portfolio				Optimised Large Portfolio			
		1	10	HML	t stat	1	10	HML	t stat	1	10	HML	t stat	1	10	HML	t stat
Trading frictions	baspread	62.26	57.37	-4.89***	-6.57	57.01	54.03	-2.98***	-5.84	57.12	47.20	-9.92***	-7.17	56.74	51.82	-4.92	-2.39
	beta	56.94	51.23	-5.71***	-8.54	56.86	52.68	-4.18***	-7.66	57.26	47.78	-9.48***	-8.94	53.45	51.50	-1.94	-1.36
	betasq	56.81	50.92	-5.89***	-8.78	55.42	52.28	-3.14***	-6.67	59.52	46.70	-12.81***	-9.65	55.19	53.27	-1.92	-1.04
	dolvol	46.79	47.30	0.50	0.42	46.87	47.56	0.68	1.36	51.77	50.31	-1.46	-1.22	44.56	50.58	6.01***	3.06
	idiovol	61.33	58.05	-3.28***	-4.62	57.13	55.13	-2.00***	-4.40	56.11	47.63	-8.47***	-6.07	56.43	51.16	-5.27	-2.62
	ill	53.91	53.59	-0.31	-0.31	52.22	50.96	-1.25	-2.40	58.83	46.64	-12.18***	-9.26	56.50	52.39	-4.10	-2.11
	maxret	64.15	52.24	-11.90***	-17.62	57.34	51.21	-6.13***	-12.82	59.20	46.62	-12.57***	-9.47	56.63	51.86	-4.77	-2.41
	retvol	62.95	56.26	-6.69***	-9.44	57.36	53.32	-4.04***	-8.48	58.73	46.89	-11.83***	-9.24	56.64	51.70	-4.94	-2.44
	std_dolvol	53.09	52.98	-0.11	0.08	51.64	52.11	0.46	1.07	50.93	48.89	-2.04	-1.64	57.38	47.38	-9.99***	-5.87
	std_turn	56.21	53.01	-3.19***	-5.95	53.37	51.83	-1.53**	-3.04	60.38	46.23	-14.15***	-10.37	56.33	52.39	-3.93	-1.98
	turn	54.59	51.89	-2.70***	-5.06	53.75	52.16	-1.60***	-3.24	60.90	46.15	-14.75***	-11.32	55.84	52.95	-2.88	-1.33
	zerotrade	45.13	48.60	3.47***	6.24	51.93	50.79	-1.13	-2.45	55.39	47.20	-8.19***	-7.00	56.65	51.22	-5.43	-2.59
Momentum	aeavol	47.80	52.67	4.86***	16.87	51.69	51.92	0.23	0.65	58.47	46.69	-11.77***	-8.56	56.10	52.31	-3.79	-2.06
	chmom	53.69	47.07	-6.61***	-14.10	52.88	48.03	-4.84***	-10.50	47.87	50.88	3.01	2.70	49.26	49.59	0.33	0.35
	chtx	47.56	52.14	4.57***	15.26	49.62	52.42	2.79***	6.48	52.98	49.20	-3.78	-2.55	50.87	53.76	2.89	1.41
	ear	48.11	51.50	3.39***	9.41	49.13	51.57	2.44***	6.90	51.86	49.77	-2.09	-1.71	49.69	53.26	3.57	1.94
	indmom	42.56	58.71	16.14***	24.78	45.01	57.40	12.39***	19.79	50.34	50.06	-0.28	-0.06	48.62	52.69	4.08	1.84
	mom12m	39.93	56.08	16.15***	24.72	47.64	56.67	9.03***	16.08	56.31	47.58	-8.72***	-6.95	54.41	52.57	-1.84	-1.12
	mom1m	61.99	38.33	-23.65***	-29.23	60.77	42.84	-17.92***	-25.92	54.78	48.54	-6.24***	-5.00	52.05	51.71	-0.33	-0.20
	mom36m	47.08	45.69	-1.39	-2.57	52.19	49.89	-2.29***	-4.46	58.10	46.95	-11.16***	-8.70	55.19	52.75	-2.44	-1.48
	mom6m	42.48	54.72	12.24***	20.28	47.60	55.15	7.55***	13.97	53.50	48.63	-4.86***	-4.20	52.16	52.70	0.54	0.04
	nincr	46.57	54.02	7.45***	19.04	50.08	53.70	3.61***	7.49	58.41	46.83	-11.57***	-8.97	54.66	53.34	-1.32	-1.06
	pricedelay	49.74	51.05	1.32***	5.13	50.42	51.00	0.57	1.50	50.50	49.57	-0.93	-0.58	53.76	49.40	-4.36	-2.17
	rsup	46.41	52.20	5.79***	16.58	47.13	50.91	3.78***	8.11	44.73	52.17	7.43***	4.39	46.96	50.08	3.12	1.48

Table 3.2: Realisation of predictive factors by functional category, monthly rebalancing

Table 3.2 reports the mean value for the predictive factors when grouped in their functional category as described in Appendix 3A; Momentum, profitability, trading frictions, value vs. growth, intangibles and investment. Factors were reordered to reflect a positive theoretical association with expected returns. In this way an increase in any factor expects an increase in returns. The long-short portfolio is constructed by ranking stocks according to their machine learning predicted returns and form 10 portfolios, buying the highest quantile portfolio and selling the lowest quintile portfolio (High-minus-Low ‘HML’ portfolio). The factor realisations corresponding to the stocks chosen for the top and bottom portfolios are averaged cross-sectionally into the six categories and then averaged across time to generate the results in the table. The mean values of the lowest and highest deciles are compared based on the null hypothesis $H_0: \mu_{high} = \mu_{low}$ which examines whether the category realisations are significantly different between the two portfolios. The test performed is the two-tailed paired t-test. The mean values are expressed in percentage basis. The Newey-West adjusted t statistics are presented in the parentheses. The reported results are the average across all five neural network models, NN1-NN5. The results for the individual models are included in Appendix 3E. The table is divided into four panels, A to D, which report the results for the equal-weighted, value-weighted, optimised portfolio trading a relatively small portfolio of 1 million USD and optimised portfolio trading a relatively large portfolio of 100 million USD, respectively. Investing horizon is one month and thus, rebalancing of the portfolio is performed monthly based on predicted returns.

Monthly rebalancing – Mean across all models						
Panel A: Equal-weighted Portfolios						
Portfolio	Value vs Growth	Profitability	Investment	Intangibles	Trading frictions	Momentum
1	0.478	0.486	0.497	0.508	0.506	0.466
10	0.494	0.499	0.512	0.516	0.512	0.535
t statistic	1.202	1.293	1.533	0.393	0.900	4.217
Panel B: Value-weighted Portfolios						
Portfolio	Value vs Growth	Profitability	Investment	Intangibles	Trading frictions	Momentum
1	0.495	0.497	0.498	0.507	0.507	0.482
10	0.499	0.499	0.505	0.510	0.512	0.528
t statistic	0.547	0.340	0.896	0.224	0.525	3.420
Panel C: Optimised Small Portfolios						
Portfolio	Value vs Growth	Profitability	Investment	Intangibles	Trading frictions	Momentum
1	0.491	0.512	0.484	0.499	0.512	0.500
10	0.503	0.497	0.505	0.501	0.496	0.500
t statistic	0.487	-0.770	0.890	0.091	-0.572	0.047
Panel D: Optimised Large Portfolios						
Portfolio	Value vs Growth	Profitability	Investment	Intangibles	Trading frictions	Momentum
1	0.496	0.511	0.493	0.524	0.519	0.507
10	0.507	0.496	0.509	0.489	0.493	0.501
t statistic	0.371	-0.640	0.601	-0.998	-0.861	-0.236

Table 3.3: Heatmap of predictive factors by functional category and sector, monthly rebalancing

Table 3.3 reports the mean value for the predictive factors when grouped by functional category (momentum, profitability, trading frictions, value vs. growth, intangibles and investment), as well as the eleven S&P sectors (communication services, consumer discretionary, consumer staples, energy, financials, health care, industrials, information technology, materials, real estate, utilities). The bottom portfolio is constructed by ranking stocks according to their machine learning predicted returns and form 10 portfolios and selling the lowest quintile portfolio. The top portfolio is constructed by ranking stocks according to their machine learning predicted returns and form 10 portfolios and buying the highest quintile portfolio. The long-short (HML) portfolio is constructed by ranking stocks according to their machine learning predicted returns and form 10 portfolios, buying the highest quintile portfolio and selling the lowest quintile portfolio. Factors were reordered to reflect a positive theoretical association with expected returns. In this way an increase in any factor expects an increase in returns. The factor realisations corresponding to the stocks chosen for the top and bottom portfolios are averaged cross-sectionally into the six functional categories and then averaged across the eleven S&P sectors to generate the results in the table. At each monthly period the factor input was rescaled to the [0,1] range and thus, the expected value for all factors is 0.5. For each portfolio, the heatmap illustrates the gradient of predictive factors. The reported results are for the average across the five neural network predictive models (NN1-NN5). The results for the individual models are included in Appendix 3P. The table is divided into four panels, A to D, which report the results for the equal-weighted, value-weighted, optimised portfolio trading a relatively small portfolio of 1 million USD and optimised portfolio trading a relatively large portfolio of 100 million USD, respectively. Investing horizon is one month and thus, rebalancing of the portfolio is performed monthly based on predicted returns.

Method		Panel A: Equal-weighted Portfolio						Panel B: Value-weighted Portfolio					
Portfolio	Sector	Value vs growth	Profitability	Investment	Intangibles	Trading frictions	Momentum	Value vs growth	Profitability	Investment	Intangibles	Trading frictions	Momentum
1	Communication Services	0.476	0.491	0.481	0.494	0.505	0.469	0.482	0.487	0.491	0.495	0.493	0.473
	Consumer Discretionary	0.513	0.488	0.493	0.514	0.505	0.468	0.501	0.505	0.494	0.507	0.516	0.485
	Consumer Staples	0.523	0.499	0.474	0.489	0.487	0.480	0.495	0.508	0.487	0.488	0.496	0.486
	Energy	0.494	0.483	0.468	0.500	0.501	0.459	0.499	0.493	0.484	0.502	0.496	0.468
	Financials	0.485	0.462	0.532	0.501	0.492	0.467	0.498	0.486	0.515	0.501	0.484	0.481
	Health Care	0.416	0.485	0.505	0.514	0.522	0.457	0.483	0.494	0.506	0.514	0.523	0.482
	Industrials	0.512	0.488	0.495	0.520	0.510	0.476	0.497	0.503	0.490	0.509	0.514	0.491
	Technology	0.456	0.502	0.499	0.514	0.513	0.464	0.493	0.502	0.501	0.516	0.515	0.481
	Materials	0.506	0.490	0.467	0.498	0.483	0.469	0.503	0.495	0.487	0.496	0.493	0.476
	Real Estate	0.474	0.467	0.507	0.543	0.515	0.465	0.491	0.503	0.493	0.520	0.518	0.491
	Utilities	0.549	0.470	0.473	0.425	0.463	0.478	0.519	0.468	0.487	0.455	0.424	0.467
10	Communication Services	0.492	0.500	0.493	0.504	0.508	0.532	0.491	0.490	0.490	0.501	0.498	0.520
	Consumer Discretionary	0.530	0.500	0.508	0.522	0.509	0.538	0.507	0.506	0.501	0.511	0.516	0.527
	Consumer Staples	0.536	0.509	0.493	0.497	0.493	0.539	0.501	0.505	0.498	0.492	0.500	0.524
	Energy	0.504	0.495	0.489	0.501	0.503	0.549	0.503	0.493	0.499	0.500	0.496	0.540
	Financials	0.497	0.480	0.542	0.513	0.500	0.537	0.500	0.494	0.516	0.507	0.491	0.526
	Health Care	0.433	0.495	0.511	0.516	0.525	0.519	0.489	0.494	0.511	0.512	0.525	0.523
	Industrials	0.526	0.503	0.509	0.523	0.512	0.542	0.502	0.503	0.499	0.510	0.514	0.530
	Technology	0.468	0.508	0.521	0.527	0.528	0.540	0.496	0.502	0.510	0.522	0.526	0.532
	Materials	0.519	0.500	0.486	0.509	0.489	0.530	0.507	0.493	0.497	0.501	0.499	0.520
	Real Estate	0.481	0.480	0.516	0.548	0.517	0.522	0.494	0.505	0.507	0.527	0.518	0.520
	Utilities	0.550	0.482	0.484	0.431	0.459	0.529	0.519	0.473	0.502	0.458	0.423	0.522
HML	Communication Services	0.016	0.009	0.012	0.009	0.003	0.062	0.009	0.003	-0.001	0.006	0.005	0.046
	Consumer Discretionary	0.018	0.013	0.015	0.007	0.003	0.070	0.006	0.001	0.008	0.004	0.001	0.042
	Consumer Staples	0.013	0.011	0.019	0.008	0.006	0.059	0.006	-0.002	0.011	0.004	0.004	0.039
	Energy	0.010	0.012	0.020	0.000	0.003	0.091	0.004	-0.001	0.016	-0.002	0.000	0.071
	Financials	0.013	0.017	0.010	0.012	0.008	0.070	0.002	0.008	0.001	0.006	0.007	0.045
	Health Care	0.017	0.009	0.007	0.002	0.003	0.062	0.005	0.000	0.004	-0.002	0.002	0.041
	Industrials	0.014	0.015	0.014	0.003	0.002	0.067	0.005	0.000	0.009	0.001	-0.001	0.039
	Technology	0.012	0.006	0.022	0.014	0.015	0.077	0.003	0.001	0.009	0.006	0.011	0.051
	Materials	0.013	0.010	0.019	0.011	0.006	0.061	0.004	-0.002	0.010	0.005	0.006	0.044
	Real Estate	0.007	0.014	0.008	0.005	0.002	0.057	0.003	0.002	0.013	0.007	-0.001	0.029
	Utilities	0.001	0.012	0.012	0.006	-0.004	0.051	0.000	0.005	0.015	0.002	-0.001	0.055

Method		Panel C: Optimised Small Portfolio						Panel D: Optimised Large Portfolio					
Portfolio	Sector	Value vs growth	Profitability	Investment	Intangibles	Trading frictions	Momentum	Value vs growth	Profitability	Investment	Intangibles	Trading frictions	Momentum
1	Communication Services	0.479	0.499	0.470	0.485	0.498	0.491	0.493	0.510	0.481	0.523	0.519	0.505
	Consumer Discretionary	0.499	0.515	0.483	0.500	0.519	0.494	0.501	0.515	0.492	0.520	0.521	0.504
	Consumer Staples	0.493	0.521	0.469	0.487	0.498	0.496	0.496	0.526	0.476	0.510	0.512	0.510
	Energy	0.486	0.507	0.461	0.499	0.507	0.493	0.496	0.509	0.474	0.528	0.516	0.500
	Financials	0.488	0.506	0.493	0.502	0.505	0.501	0.499	0.505	0.504	0.518	0.501	0.510
	Health Care	0.477	0.502	0.491	0.491	0.515	0.488	0.489	0.501	0.500	0.525	0.525	0.498
	Industrials	0.491	0.514	0.473	0.497	0.511	0.495	0.496	0.514	0.484	0.521	0.518	0.507
	Technology	0.483	0.513	0.485	0.501	0.518	0.496	0.493	0.515	0.490	0.525	0.525	0.505
	Materials	0.491	0.516	0.458	0.486	0.504	0.491	0.494	0.515	0.479	0.519	0.515	0.503
	Real Estate	0.478	0.503	0.493	0.522	0.520	0.492	0.488	0.493	0.505	0.524	0.516	0.489
10	Utilities	0.498	0.515	0.463	0.470	0.495	0.513	0.499	0.517	0.473	0.508	0.501	0.519
	Communication Services	0.492	0.506	0.475	0.493	0.493	0.494	0.497	0.497	0.501	0.490	0.505	0.501
	Consumer Discretionary	0.511	0.496	0.500	0.510	0.499	0.494	0.517	0.504	0.518	0.486	0.506	0.497
	Consumer Staples	0.511	0.508	0.494	0.491	0.487	0.502	0.503	0.510	0.496	0.470	0.489	0.502
	Energy	0.500	0.492	0.488	0.494	0.481	0.495	0.502	0.493	0.489	0.501	0.488	0.494
	Financials	0.506	0.491	0.516	0.497	0.485	0.506	0.512	0.480	0.533	0.488	0.480	0.505
	Health Care	0.473	0.491	0.507	0.491	0.506	0.488	0.496	0.501	0.503	0.494	0.505	0.501
	Industrials	0.507	0.496	0.496	0.499	0.487	0.495	0.505	0.502	0.502	0.489	0.493	0.500
	Technology	0.487	0.493	0.510	0.508	0.509	0.491	0.505	0.501	0.509	0.501	0.505	0.500
	Materials	0.501	0.492	0.485	0.501	0.490	0.488	0.511	0.503	0.490	0.490	0.491	0.493
HML	Real Estate	0.489	0.475	0.526	0.529	0.498	0.499	0.494	0.502	0.497	0.513	0.516	0.499
	Utilities	0.522	0.511	0.477	0.452	0.476	0.504	0.523	0.475	0.500	0.460	0.438	0.521
	Communication Services	0.013	0.007	0.006	0.008	-0.005	0.003	0.004	-0.014	0.020	-0.033	-0.014	-0.004
	Consumer Discretionary	0.012	-0.019	0.017	0.010	-0.019	0.000	0.017	-0.011	0.025	-0.035	-0.015	-0.007
	Consumer Staples	0.017	-0.013	0.025	0.004	-0.011	0.006	0.007	-0.016	0.020	-0.041	-0.023	-0.008
	Energy	0.014	-0.015	0.027	-0.005	-0.026	0.001	0.006	-0.016	0.014	-0.027	-0.027	-0.006
	Financials	0.018	-0.015	0.024	-0.005	-0.019	0.005	0.013	-0.025	0.030	-0.030	-0.022	-0.005
	Health Care	-0.004	-0.011	0.016	0.000	-0.009	0.000	0.007	0.000	0.002	-0.031	-0.020	0.003
	Industrials	0.016	-0.018	0.023	0.002	-0.023	0.000	0.009	-0.012	0.018	-0.032	-0.025	-0.007
	Technology	0.004	-0.020	0.024	0.007	-0.010	-0.005	0.012	-0.015	0.018	-0.024	-0.020	-0.005
	Materials	0.010	-0.023	0.027	0.015	-0.014	-0.003	0.017	-0.011	0.010	-0.030	-0.024	-0.010
	Real Estate	0.012	-0.027	0.033	0.007	-0.022	0.007	0.006	0.009	-0.008	-0.011	0.000	0.010
	Utilities	0.023	-0.004	0.014	-0.019	-0.019	-0.009	0.025	-0.042	0.027	-0.048	-0.063	0.001

Table 3.4: Mean machine learning predicted excess returns and out-of-sample R^2 for double-sorted portfolios on predictive factors

Table 3.4 reports the average monthly portfolio predicted excess returns and out-of-sample R^2 for 5x5 bivariate sorted portfolio on certain major factors. At the end of each month all stocks are independently sorted from lowest to highest for the two factors and each is divided in five deciles. Subsequently, stocks are allocated in the 25 portfolios which are created according to their rank in the deciles for the two factors. For each portfolio the machine learning predicted excess returns are calculated at each monthly period and these monthly returns are averaged across time to yield the results in the table. Factors were not reordered and thus, reflect the associations based on which they were constructed. Both mean predicted excess returns and out-of-sample R^2 are presented in percentage basis. The reported results are for the average across the five neural network predictive models (NN1-NN5). The table is divided into four panels, A to D, which report the results for the equal-weighted, value-weighted, optimised portfolio trading a relatively small portfolio of 1 million USD and optimised portfolio trading a relatively large portfolio of 100 million USD, respectively. Investing horizon is one month and thus, rebalancing of the portfolio is performed monthly based on predicted returns.

Size (vertical) x book-to-market (horizontal)

	Mean predicted returns (%)					R ² Out-of-sample (%)					
Portfolio	1	2	3	4	5	1	2	3	4	5	
Equally weighted	1	0.69	0.70	0.72	0.70	0.72	-0.01	0.10	0.08	0.30	0.45
	2	0.66	0.67	0.69	0.70	0.71	-0.08	0.02	0.18	0.37	0.38
	3	0.64	0.67	0.69	0.70	0.68	-0.07	0.11	0.32	0.44	0.34
	4	0.67	0.67	0.69	0.68	0.65	-0.02	0.21	0.35	0.41	0.21
	5	0.67	0.68	0.67	0.65	0.63	0.08	0.06	0.14	0.22	0.17
Value-weighted	1	0.34	0.34	0.35	0.35	0.36	0.07	0.15	0.14	0.13	0.12
	2	0.33	0.33	0.35	0.35	0.35	0.11	0.19	0.21	0.19	0.25
	3	0.32	0.33	0.34	0.35	0.34	0.11	0.17	0.23	0.23	0.30
	4	0.33	0.34	0.35	0.34	0.32	0.12	0.18	0.26	0.31	0.40
	5	0.33	0.34	0.33	0.31	0.30	0.16	0.20	0.30	0.45	0.56
Optimised Small	1	0.02	0.02	0.02	0.04	0.08	1.11	1.11	1.42	1.72	1.77
	2	0.03	0.02	0.02	0.03	0.04	1.00	1.86	1.37	1.35	2.71
	3	0.02	0.02	0.02	0.02	0.02	0.85	1.74	0.83	1.57	1.77
	4	0.02	0.02	0.02	0.02	0.02	0.72	0.17	0.67	1.48	1.20
	5	0.02	0.02	0.01	0.01	0.01	-0.42	-0.01	0.10	0.75	-0.04
Optimised Large	1	-0.05	-0.10	-0.04	-0.10	-0.11	0.93	1.42	0.40	1.06	1.59
	2	-0.10	0.02	-0.09	-0.13	-0.10	0.88	-1.31	-0.88	-0.63	0.06
	3	-0.08	-0.10	-0.06	-0.07	-0.04	-0.38	-1.37	-1.58	-0.57	0.08
	4	-0.12	-0.12	-0.11	-0.08	-0.06	-0.66	-1.89	-0.30	-0.27	-0.05
	5	-0.12	-0.07	-0.06	-0.05	0.01	-2.96	-3.72	-1.43	-1.18	-0.02

Size (vertical) X momentum 1 month (horizontal)

		Mean predicted returns (%)					R ² Out-of-sample (%)				
Portfolio		1	2	3	4	5	1	2	3	4	5
Equally weighted	1	0.95	0.77	0.68	0.60	0.28	0.36	0.07	0.07	0.22	0.17
	2	0.93	0.77	0.69	0.61	0.34	0.15	0.16	0.20	0.27	0.17
	3	0.92	0.77	0.69	0.60	0.37	0.15	0.20	0.36	0.30	0.16
	4	0.91	0.77	0.69	0.61	0.40	0.08	0.34	0.42	0.21	0.15
	5	0.88	0.76	0.68	0.60	0.43	-0.16	0.24	0.44	0.32	-0.11
Value-weighted	1	0.47	0.39	0.35	0.30	0.15	0.08	0.13	0.21	0.23	0.11
	2	0.46	0.39	0.35	0.30	0.17	0.13	0.19	0.27	0.27	0.15
	3	0.46	0.38	0.34	0.30	0.19	0.18	0.21	0.30	0.24	0.13
	4	0.45	0.38	0.34	0.30	0.20	0.23	0.29	0.30	0.22	0.15
	5	0.43	0.37	0.34	0.30	0.22	0.17	0.33	0.29	0.27	0.27
Optimised Small	1	0.05	0.03	0.02	0.03	0.04	0.99	2.20	1.18	1.57	1.92
	2	0.04	0.03	0.02	0.02	0.03	1.67	1.53	1.32	1.50	1.23
	3	0.02	0.02	0.02	0.02	0.03	1.15	1.01	0.98	1.20	1.46
	4	0.01	0.02	0.02	0.02	0.02	1.23	0.55	0.30	0.31	0.93
	5	0.00	0.02	0.01	0.02	0.02	-0.09	0.50	-0.72	-0.72	0.13
Optimised Large	1	-0.11	-0.09	-0.07	-0.06	-0.03	0.82	1.41	1.33	1.71	1.45
	2	-0.06	-0.06	-0.05	-0.11	-0.10	0.53	-0.61	-0.50	-0.50	0.71
	3	-0.06	-0.06	-0.07	-0.04	-0.10	-0.04	-0.45	-1.33	-1.04	0.48
	4	-0.06	-0.03	-0.17	-0.09	-0.10	-0.25	-1.06	-0.35	-1.01	-0.32
	5	-0.01	-0.11	-0.03	-0.05	-0.07	-0.79	-1.70	-3.16	-2.97	-3.32

Size (vertical) X momentum 12 months (horizontal)

		Mean predicted returns (%)					R ² Out-of-sample (%)				
Portfolio		1	2	3	4	5	1	2	3	4	5
Equally weighted	1	0.57	0.68	0.72	0.78	0.94	0.11	0.26	0.29	0.62	0.48
	2	0.50	0.63	0.68	0.74	0.88	-0.07	0.07	0.13	0.60	0.61
	3	0.46	0.60	0.65	0.71	0.85	-0.03	0.08	0.26	0.55	0.37
	4	0.46	0.57	0.64	0.70	0.82	0.01	0.12	0.29	0.30	0.34
	5	0.44	0.56	0.63	0.69	0.79	-0.11	0.10	0.07	0.23	0.27
Value-weighted	1	0.27	0.33	0.35	0.38	0.46	0.03	0.15	0.25	0.48	0.37
	2	0.24	0.31	0.34	0.37	0.44	0.06	0.18	0.21	0.43	0.35
	3	0.23	0.30	0.33	0.36	0.42	0.08	0.17	0.22	0.36	0.25
	4	0.23	0.29	0.32	0.35	0.41	0.15	0.20	0.22	0.28	0.24
	5	0.22	0.28	0.31	0.35	0.39	0.18	0.24	0.25	0.25	0.23
Optimised Small	1	0.05	0.03	0.03	0.02	0.04	1.03	2.21	2.61	1.70	1.98
	2	0.03	0.02	0.02	0.02	0.05	1.14	1.74	0.87	1.49	2.39
	3	0.00	0.01	0.02	0.02	0.04	1.01	0.66	0.51	1.68	1.83
	4	0.01	0.01	0.02	0.02	0.04	1.08	0.52	0.39	0.44	0.98
	5	0.00	0.00	0.02	0.02	0.02	0.54	0.03	-0.81	-1.47	0.63
Optimised Large	1	-0.14	-0.08	-0.02	-0.07	-0.05	0.64	1.62	1.90	2.21	2.92
	2	-0.08	-0.06	-0.06	-0.08	-0.09	-0.35	-0.72	-0.49	0.56	1.20
	3	-0.05	-0.12	0.01	-0.11	-0.04	-1.24	-0.96	-1.65	0.38	1.05
	4	-0.03	-0.05	-0.15	-0.10	-0.11	-0.50	-1.84	-1.64	-1.63	1.33
	5	-0.03	-0.03	-0.04	-0.10	-0.08	-1.71	-2.64	-4.20	-3.34	-0.25

Size (vertical) x CAPM beta (horizontal)

	Mean predicted returns (%)					R ² Out-of-sample (%)					
Portfolio	1	2	3	4	5	1	2	3	4	5	
Equally weighted	1	0.68	0.70	0.66	0.65	0.62	0.25	0.41	0.24	0.35	0.22
	2	0.68	0.68	0.65	0.64	0.59	0.28	0.26	0.22	0.24	0.16
	3	0.68	0.66	0.64	0.64	0.59	0.41	0.45	0.27	0.22	0.11
	4	0.66	0.66	0.64	0.64	0.59	0.40	0.46	0.35	0.24	0.11
	5	0.67	0.64	0.62	0.61	0.58	0.15	0.40	0.12	0.22	0.07
Value-weighted	1	0.34	0.35	0.33	0.32	0.31	0.11	0.21	0.15	0.16	0.12
	2	0.34	0.34	0.33	0.32	0.30	0.27	0.31	0.20	0.20	0.12
	3	0.34	0.33	0.32	0.32	0.30	0.49	0.36	0.20	0.19	0.11
	4	0.33	0.33	0.32	0.32	0.30	0.74	0.39	0.21	0.22	0.12
	5	0.33	0.32	0.30	0.30	0.28	0.65	0.37	0.22	0.25	0.19
Optimised Small	1	0.05	0.04	0.03	0.03	0.02	1.26	1.68	2.23	1.39	1.06
	2	0.04	0.03	0.02	0.02	0.02	0.73	1.67	1.66	1.96	1.38
	3	0.02	0.02	0.02	0.02	0.03	0.80	0.45	0.74	1.25	1.76
	4	0.01	0.01	0.02	0.02	0.03	0.16	0.67	1.09	0.48	1.13
	5	0.01	0.01	0.01	0.02	0.02	-0.25	-1.15	-0.89	-0.01	1.16
Optimised Large	1	-0.11	-0.04	-0.07	-0.09	-0.08	1.04	2.14	1.99	1.53	1.14
	2	-0.11	-0.07	-0.06	-0.07	-0.08	0.70	-0.39	-0.12	1.21	0.85
	3	-0.04	-0.08	-0.09	-0.03	-0.10	1.10	0.17	0.01	-0.08	0.31
	4	-0.10	-0.09	-0.07	-0.05	-0.16	0.16	0.33	-0.20	-0.35	1.19
	5	-0.05	-0.10	-0.05	-0.06	-0.02	-0.43	-0.55	-3.74	-2.78	-0.29

Size (vertical) x operating profitability (horizontal)

	Mean predicted returns (%)					R ² Out-of-sample (%)					
Portfolio	1	2	3	4	5	1	2	3	4	5	
Equally weighted	1	0.70	0.68	0.70	0.70	0.71	0.19	0.17	0.41	0.39	0.34
	2	0.67	0.67	0.70	0.68	0.68	0.12	0.14	0.28	0.36	0.23
	3	0.63	0.65	0.69	0.68	0.67	0.00	0.21	0.33	0.44	0.34
	4	0.61	0.65	0.68	0.68	0.67	0.13	0.24	0.10	0.37	0.23
	5	0.57	0.63	0.66	0.67	0.67	0.08	0.23	-0.08	0.09	0.22
Value-weighted	1	0.35	0.34	0.35	0.35	0.35	0.06	0.07	0.33	0.42	0.47
	2	0.33	0.33	0.35	0.34	0.34	0.11	0.12	0.38	0.34	0.35
	3	0.32	0.32	0.35	0.34	0.34	0.12	0.13	0.34	0.30	0.31
	4	0.30	0.32	0.34	0.34	0.33	0.24	0.15	0.32	0.24	0.25
	5	0.28	0.30	0.32	0.33	0.33	0.66	0.25	0.32	0.20	0.18
Optimised Small	1	0.07	0.05	0.02	0.02	0.02	1.10	1.57	2.41	1.48	1.26
	2	0.05	0.03	0.02	0.02	0.02	2.30	0.96	0.70	0.82	0.82
	3	0.02	0.02	0.02	0.02	0.02	1.57	1.24	-0.06	0.52	0.94
	4	0.01	0.01	0.02	0.02	0.02	1.33	1.40	-1.42	-0.15	0.63
	5	0.00	0.01	0.00	0.02	0.04	1.02	0.58	-0.84	-1.01	-0.50
Optimised Large	1	-0.19	-0.08	-0.04	-0.05	-0.01	1.18	1.07	0.52	0.87	0.96
	2	-0.03	-0.14	-0.11	-0.08	-0.02	1.04	0.03	-1.21	-1.36	-0.85
	3	-0.04	-0.12	-0.07	-0.04	-0.06	0.11	-0.11	-1.79	-1.79	-0.28
	4	-0.01	-0.08	-0.18	-0.06	-0.11	1.38	-0.12	-1.23	-2.16	-0.93
	5	-0.03	-0.01	-0.09	-0.05	-0.10	-0.59	-0.92	-2.72	-2.30	-3.19

Book-to-market (vertical) X momentum 1 month (horizontal)

	Mean predicted returns (%)					R ² Out-of-sample (%)					
Portfolio	1	2	3	4	5	1	2	3	4	5	
Equally weighted	1	0.93	0.77	0.69	0.61	0.32	-0.11	-0.17	0.02	0.16	0.07
	2	0.94	0.77	0.69	0.61	0.38	0.22	0.01	0.10	0.13	0.01
	3	0.95	0.79	0.70	0.62	0.40	0.29	0.23	0.23	0.22	0.05
	4	0.95	0.79	0.70	0.62	0.39	0.39	0.48	0.50	0.34	0.13
	5	0.96	0.80	0.71	0.62	0.35	0.41	0.34	0.42	0.35	0.35
Value-weighted	1	0.44	0.37	0.34	0.30	0.21	0.05	0.16	0.20	0.17	0.09
	2	0.45	0.39	0.35	0.31	0.23	0.06	0.22	0.21	0.16	0.10
	3	0.44	0.38	0.34	0.30	0.22	0.13	0.20	0.23	0.18	0.10
	4	0.44	0.37	0.34	0.29	0.21	0.09	0.20	0.24	0.18	0.10
	5	0.44	0.37	0.32	0.29	0.19	0.12	0.24	0.29	0.25	0.12
Optimised Small	1	0.03	0.02	0.02	0.02	0.04	0.93	1.13	0.27	1.23	0.84
	2	0.02	0.02	0.02	0.02	0.03	1.02	1.54	0.95	0.91	1.66
	3	0.02	0.02	0.02	0.02	0.02	1.26	1.25	0.10	0.43	2.00
	4	0.02	0.03	0.02	0.02	0.02	1.52	1.93	1.19	1.15	1.92
	5	0.03	0.04	0.03	0.02	0.03	1.39	1.90	2.20	2.15	2.54
Optimised Large	1	-0.08	-0.09	-0.05	-0.12	-0.12	0.66	-0.10	-0.69	-0.25	0.33
	2	-0.06	-0.11	-0.09	-0.02	-0.09	-0.12	-0.42	-0.79	-1.54	-1.13
	3	-0.07	-0.04	-0.09	-0.11	-0.05	0.42	-2.05	-0.70	-0.52	-0.50
	4	-0.02	-0.05	-0.13	-0.13	-0.09	-0.36	0.65	0.46	-1.06	0.69
	5	-0.09	-0.08	-0.06	0.02	-0.08	1.05	0.43	-0.22	0.23	2.27

Book-to-market (vertical) X momentum 12 months (horizontal)

	Mean predicted returns (%)					R ² Out-of-sample (%)					
Portfolio	1	2	3	4	5	1	2	3	4	5	
Equally weighted	1	0.51	0.62	0.68	0.73	0.85	-0.10	-0.02	-0.08	0.00	0.12
	2	0.51	0.61	0.67	0.74	0.85	0.07	0.05	0.00	0.22	0.19
	3	0.53	0.62	0.68	0.74	0.87	-0.06	0.14	0.22	0.55	0.45
	4	0.52	0.63	0.67	0.73	0.87	0.12	0.24	0.36	0.78	0.61
	5	0.53	0.65	0.67	0.73	0.89	0.10	0.22	0.27	0.70	0.87
Value-weighted	1	0.23	0.29	0.32	0.35	0.38	0.03	0.10	0.17	0.22	0.13
	2	0.23	0.29	0.32	0.36	0.41	0.03	0.15	0.21	0.23	0.13
	3	0.23	0.28	0.31	0.36	0.41	0.03	0.11	0.15	0.31	0.19
	4	0.22	0.27	0.30	0.34	0.40	0.06	0.14	0.13	0.29	0.22
	5	0.22	0.27	0.30	0.33	0.40	0.03	0.15	0.16	0.21	0.31
Optimised Small	1	0.03	0.02	0.02	0.02	0.04	0.82	1.26	-0.03	0.74	1.40
	2	0.02	0.01	0.02	0.03	0.03	1.04	1.17	1.58	0.48	1.68
	3	0.01	0.02	0.02	0.02	0.03	1.36	1.35	0.82	0.59	1.10
	4	0.02	0.02	0.02	0.02	0.04	1.54	1.42	0.68	1.79	2.23
	5	0.02	0.02	0.04	0.03	0.06	1.25	2.45	2.17	2.34	2.79
Optimised Large	1	-0.12	-0.05	-0.08	-0.13	-0.09	0.37	-0.22	-1.17	0.57	1.14
	2	-0.04	-0.08	-0.04	-0.10	-0.09	-0.31	-1.21	-1.31	-1.89	0.03
	3	-0.05	-0.10	-0.07	-0.05	-0.08	-0.03	-0.63	-1.30	-0.78	-0.52
	4	-0.04	-0.12	-0.05	-0.14	-0.06	0.23	-0.62	-0.95	-1.00	1.71
	5	-0.10	-0.02	-0.04	-0.07	-0.06	0.56	0.35	-0.21	1.95	3.13

Book-to-market (vertical) X CAPM beta (horizontal)

	Mean predicted returns (%)					R ² Out-of-sample (%)					
Portfolio	1	2	3	4	5	1	2	3	4	5	
Equally weighted	1	0.72	0.69	0.66	0.63	0.60	-0.07	0.16	-0.10	0.04	0.02
	2	0.69	0.66	0.66	0.65	0.61	0.14	0.21	0.18	0.24	0.12
	3	0.68	0.67	0.68	0.67	0.62	0.20	0.45	0.24	0.32	0.15
	4	0.67	0.68	0.66	0.65	0.63	0.57	0.54	0.31	0.39	0.28
	5	0.71	0.69	0.64	0.66	0.62	0.40	0.50	0.33	0.37	0.24
Value-weighted	1	0.32	0.33	0.31	0.30	0.30	0.18	0.23	0.15	0.10	0.06
	2	0.35	0.32	0.32	0.31	0.29	0.25	0.21	0.17	0.10	0.07
	3	0.34	0.32	0.32	0.31	0.29	0.19	0.18	0.17	0.17	0.08
	4	0.31	0.32	0.29	0.30	0.29	0.14	0.20	0.09	0.15	0.15
	5	0.32	0.31	0.29	0.29	0.29	0.16	0.22	0.12	0.14	0.14
Optimised Small	1	0.02	0.03	0.02	0.02	0.04	0.66	0.75	1.38	0.99	0.98
	2	0.02	0.02	0.02	0.02	0.03	0.92	1.34	1.53	1.07	1.56
	3	0.02	0.02	0.02	0.02	0.02	1.07	1.00	1.33	1.37	1.24
	4	0.03	0.03	0.02	0.02	0.02	1.46	1.95	0.97	1.50	2.14
	5	0.05	0.03	0.03	0.03	0.02	1.53	2.29	2.24	1.97	1.78
Optimised Large	1	-0.05	-0.11	-0.07	-0.15	-0.11	0.42	0.88	0.86	1.56	0.95
	2	-0.05	-0.06	-0.11	-0.04	-0.11	-0.32	0.38	-0.13	0.32	0.43
	3	-0.09	-0.10	-0.04	-0.06	-0.07	0.62	1.84	-0.31	-0.75	0.44
	4	-0.16	-0.12	-0.09	-0.01	-0.06	0.71	-0.72	-1.22	0.21	1.48
	5	-0.08	-0.01	-0.06	-0.06	-0.09	1.45	0.76	0.99	1.58	0.94

Book-to-market (vertical) X operating profitability (horizontal)

	Mean predicted returns (%)					R ² Out-of-sample (%)					
Portfolio	1	2	3	4	5	1	2	3	4	5	
Equally weighted	1	0.63	0.68	0.67	0.67	0.69	-0.08	0.02	-0.24	-0.03	0.11
	2	0.65	0.66	0.68	0.69	0.68	0.06	0.03	-0.02	0.22	0.25
	3	0.70	0.67	0.70	0.69	0.68	0.12	0.13	0.16	0.39	0.40
	4	0.70	0.68	0.70	0.68	0.70	0.20	0.39	0.51	0.58	0.35
	5	0.72	0.65	0.71	0.72	0.74	0.35	0.32	0.46	0.52	0.59
Value-weighted	1	0.28	0.34	0.31	0.32	0.33	0.08	0.07	0.44	0.25	0.13
	2	0.28	0.31	0.33	0.34	0.34	0.08	0.10	0.24	0.15	0.13
	3	0.33	0.32	0.33	0.33	0.33	0.08	0.12	0.21	0.16	0.23
	4	0.31	0.30	0.33	0.32	0.33	0.16	0.08	0.16	0.17	0.53
	5	0.32	0.29	0.32	0.34	0.35	0.11	0.09	0.17	0.41	1.14
Optimised Small	1	0.04	0.02	0.01	0.01	0.04	1.09	0.91	-1.61	0.22	0.28
	2	0.02	0.01	0.01	0.03	0.04	1.31	1.71	0.68	0.56	0.82
	3	0.02	0.02	0.02	0.03	0.02	1.57	1.58	0.33	0.04	1.02
	4	0.03	0.03	0.03	0.02	0.01	2.12	1.37	0.66	1.01	2.18
	5	0.06	0.05	0.03	0.02	0.01	2.05	1.77	1.43	1.45	1.26
Optimised Large	1	-0.13	-0.10	-0.07	0.00	-0.17	0.77	0.85	-1.51	-2.41	-1.19
	2	-0.03	-0.10	-0.07	-0.10	-0.07	0.49	0.82	-2.25	-2.29	-2.11
	3	-0.04	-0.04	-0.20	-0.03	-0.04	1.49	-0.91	-1.97	-2.31	0.04
	4	-0.04	-0.10	-0.14	-0.11	-0.04	1.37	0.26	-1.56	-1.29	-0.64
	5	-0.07	-0.13	-0.03	-0.06	0.00	1.87	0.44	-0.25	0.44	0.41

Momentum 1 month (vertical) x momentum 12 months (horizontal)

	Mean predicted returns (%)					R ² Out-of-sample (%)					
Portfolio	1	2	3	4	5	1	2	3	4	5	
Equally weighted	1	0.80	0.87	0.91	0.97	1.13	0.08	0.27	0.23	0.49	0.39
	2	0.60	0.70	0.75	0.81	0.94	-0.12	0.13	0.15	0.62	0.43
	3	0.52	0.62	0.67	0.73	0.85	-0.03	0.12	0.39	0.65	0.41
	4	0.43	0.54	0.59	0.65	0.77	0.01	0.12	0.32	0.36	0.58
	5	0.13	0.33	0.38	0.46	0.56	0.10	-0.02	0.06	0.20	0.34
Value-weighted	1	0.35	0.39	0.42	0.45	0.52	0.03	0.04	0.11	0.25	0.14
	2	0.28	0.32	0.36	0.39	0.44	0.05	0.18	0.21	0.29	0.26
	3	0.24	0.29	0.32	0.35	0.40	0.14	0.22	0.18	0.27	0.29
	4	0.20	0.25	0.28	0.32	0.36	0.04	0.17	0.16	0.25	0.24
	5	0.10	0.17	0.21	0.24	0.28	0.05	0.13	0.16	0.18	0.12
Optimised Small	1	0.03	0.01	0.01	0.01	0.05	0.81	1.14	1.92	1.63	2.05
	2	0.01	0.02	0.02	0.03	0.03	1.41	1.47	1.35	1.73	1.66
	3	0.01	0.02	0.02	0.02	0.03	1.03	1.37	-0.18	0.69	1.16
	4	0.01	0.02	0.03	0.02	0.03	1.86	1.66	-0.33	0.23	1.08
	5	0.02	0.02	0.02	0.03	0.05	1.18	1.81	1.14	1.66	1.85
Optimised Large	1	-0.07	-0.07	-0.05	-0.05	-0.06	0.09	0.36	0.54	1.36	2.88
	2	-0.07	-0.09	-0.03	-0.07	-0.08	0.36	-0.71	-0.49	-0.44	0.67
	3	-0.04	-0.10	-0.06	-0.15	-0.06	0.41	-1.08	-1.81	0.14	1.02
	4	-0.10	-0.04	-0.07	-0.05	-0.08	1.28	-0.44	-2.16	-1.56	0.64
	5	-0.06	-0.05	-0.07	-0.14	-0.08	0.54	0.72	-0.70	0.95	1.56

Momentum 1 month (vertical) x CAPM beta (horizontal)

	Mean predicted returns (%)					R ² Out-of-sample (%)					
Portfolio	1	2	3	4	5	1	2	3	4	5	
Equally weighted	1	0.95	0.94	0.92	0.91	0.87	0.59	0.64	0.23	0.35	0.05
	2	0.77	0.76	0.74	0.74	0.70	0.43	0.48	0.21	0.19	-0.01
	3	0.69	0.67	0.66	0.66	0.61	0.11	0.49	0.36	0.29	0.20
	4	0.61	0.59	0.57	0.57	0.52	0.09	0.24	0.29	0.30	0.39
	5	0.37	0.38	0.32	0.32	0.24	-0.02	0.04	0.20	0.18	0.25
Value-weighted	1	0.45	0.43	0.43	0.42	0.42	0.10	0.19	0.09	0.12	0.04
	2	0.38	0.36	0.35	0.35	0.34	0.26	0.27	0.22	0.18	0.16
	3	0.34	0.33	0.32	0.31	0.30	0.23	0.24	0.23	0.17	0.20
	4	0.30	0.29	0.28	0.27	0.25	0.18	0.27	0.17	0.17	0.21
	5	0.22	0.22	0.19	0.19	0.16	0.15	0.17	0.09	0.13	0.09
Optimised Small	1	0.02	0.03	0.02	0.02	0.03	1.29	1.35	2.04	1.24	0.91
	2	0.03	0.03	0.02	0.02	0.02	1.65	2.09	1.33	1.40	1.56
	3	0.03	0.02	0.02	0.02	0.01	0.54	0.75	0.96	1.51	1.36
	4	0.02	0.02	0.02	0.02	0.01	0.47	0.58	1.11	1.14	2.09
	5	0.02	0.02	0.02	0.02	0.05	1.93	1.36	1.34	1.38	1.57
Optimised Large	1	-0.02	-0.06	-0.07	-0.08	-0.08	1.48	2.43	1.75	0.86	0.29
	2	-0.11	-0.06	-0.08	-0.07	-0.05	1.63	1.42	-0.48	0.15	0.17
	3	-0.11	-0.07	-0.06	-0.04	-0.13	0.08	0.07	-0.21	0.47	1.02
	4	-0.08	-0.09	-0.05	-0.07	-0.07	-0.10	-0.76	0.31	0.26	1.33
	5	-0.09	-0.09	-0.09	-0.04	-0.11	0.61	0.49	-0.12	1.16	2.28

Momentum 1 month (vertical) x operating profitability (horizontal)

	Mean predicted returns (%)					R ² Out-of-sample (%)					
Portfolio	1	2	3	4	5	1	2	3	4	5	
Equally weighted	1	0.94	0.92	0.94	0.93	0.92	0.16	0.15	0.39	0.50	0.24
	2	0.76	0.76	0.79	0.78	0.78	-0.03	0.07	0.33	0.59	0.29
	3	0.68	0.67	0.70	0.70	0.69	0.06	0.24	0.41	0.43	0.41
	4	0.59	0.59	0.62	0.61	0.61	0.19	0.29	0.17	0.20	0.42
	5	0.29	0.32	0.41	0.41	0.41	0.20	0.24	-0.07	-0.07	0.05
Value-weighted	1	0.42	0.44	0.44	0.43	0.44	0.06	0.08	0.16	0.02	0.15
	2	0.35	0.36	0.37	0.37	0.38	0.14	0.11	0.24	0.25	0.28
	3	0.31	0.32	0.33	0.34	0.35	0.24	0.16	0.36	0.21	0.26
	4	0.27	0.28	0.30	0.30	0.30	0.18	0.17	0.21	0.21	0.22
	5	0.16	0.19	0.21	0.22	0.22	0.08	0.09	0.16	0.22	0.21
Optimised Small	1	0.05	0.03	0.01	0.02	0.02	0.99	1.44	0.76	1.14	0.95
	2	0.02	0.02	0.02	0.03	0.02	1.89	1.59	0.84	0.87	0.76
	3	0.02	0.02	0.02	0.02	0.02	1.16	1.24	0.14	-0.06	0.81
	4	0.02	0.02	0.02	0.02	0.02	1.90	1.19	-0.25	-0.71	0.27
	5	0.05	0.03	0.02	0.02	0.03	1.91	1.01	0.96	1.05	0.83
Optimised Large	1	-0.08	-0.05	-0.12	-0.01	-0.05	0.80	1.06	-0.70	-0.46	-0.14
	2	-0.06	-0.09	-0.07	-0.06	-0.07	1.07	0.50	-1.90	-1.27	-0.89
	3	-0.02	-0.13	-0.14	-0.09	-0.01	1.13	-1.21	-1.08	-2.10	-0.67
	4	-0.07	-0.08	-0.06	-0.07	-0.07	1.36	-0.85	-1.79	-1.79	-1.16
	5	-0.07	-0.09	-0.08	-0.06	-0.11	1.61	0.77	-0.68	-1.19	-1.57

Momentum 12 months (vertical) x CAPM beta (horizontal)

	Mean predicted returns (%)					R ² Out-of-sample (%)					
Portfolio	1	2	3	4	5	1	2	3	4	5	
Equally weighted	1	0.53	0.53	0.50	0.47	0.44	0.09	0.09	0.10	0.13	0.08
	2	0.61	0.59	0.59	0.58	0.56	-0.04	0.28	0.26	0.24	0.11
	3	0.65	0.64	0.63	0.64	0.62	0.21	0.48	0.24	0.21	0.09
	4	0.71	0.70	0.68	0.69	0.67	0.79	0.76	0.35	0.30	0.28
	5	0.85	0.83	0.82	0.82	0.80	0.58	0.60	0.41	0.54	0.29
Value-weighted	1	0.24	0.23	0.22	0.21	0.20	0.09	0.03	0.07	0.06	0.03
	2	0.29	0.27	0.26	0.26	0.25	0.21	0.15	0.16	0.11	0.08
	3	0.31	0.30	0.29	0.29	0.27	0.27	0.25	0.06	0.18	0.21
	4	0.34	0.33	0.33	0.32	0.31	0.31	0.32	0.17	0.21	0.17
	5	0.38	0.38	0.37	0.38	0.37	0.25	0.34	0.25	0.17	0.11
Optimised Small	1	0.02	0.02	0.01	0.01	0.02	1.17	1.55	1.80	0.95	0.87
	2	0.02	0.02	0.02	0.01	0.01	1.71	1.34	1.62	1.46	1.47
	3	0.03	0.03	0.02	0.02	0.01	0.30	0.87	1.04	1.33	1.70
	4	0.03	0.02	0.02	0.02	0.03	1.08	0.81	0.58	1.29	2.11
	5	0.03	0.03	0.03	0.05	0.05	1.01	1.78	1.66	2.20	2.17
Optimised Large	1	-0.03	-0.05	-0.03	-0.12	-0.12	0.79	1.31	0.23	0.54	0.42
	2	-0.09	-0.07	-0.10	-0.06	-0.04	0.99	0.81	-0.12	-0.25	0.59
	3	-0.04	-0.09	-0.08	-0.01	-0.06	0.24	-0.54	-1.23	0.33	0.75
	4	-0.15	-0.06	-0.09	-0.06	-0.11	-0.07	0.04	0.63	0.86	2.49
	5	-0.09	-0.11	-0.05	-0.05	-0.09	2.19	1.56	1.57	2.26	2.59

Momentum 12 months (vertical) X operating profitability (horizontal)

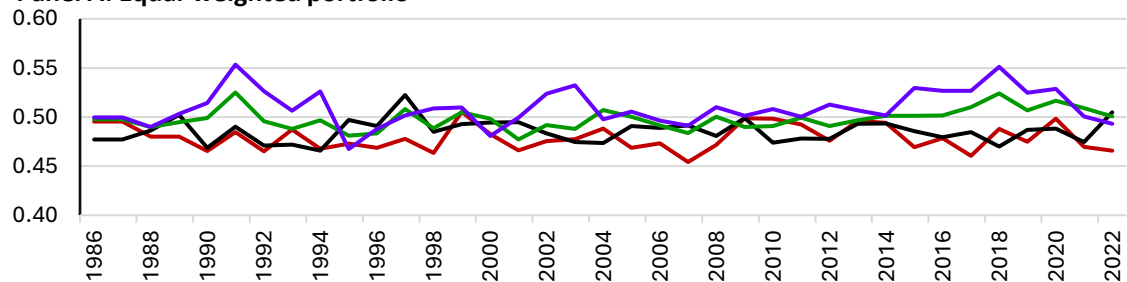
		Mean predicted returns (%)					R ² Out-of-sample (%)				
Portfolio		1	2	3	4	5	1	2	3	4	5
Equally weighted	1	0.51	0.52	0.50	0.50	0.50	0.04	0.04	0.02	0.07	-0.04
	2	0.64	0.62	0.62	0.60	0.60	0.08	0.11	0.16	0.17	0.20
	3	0.69	0.65	0.67	0.66	0.66	0.17	0.19	0.18	0.40	0.34
	4	0.74	0.71	0.74	0.72	0.71	0.32	0.38	0.48	0.65	0.56
	5	0.86	0.84	0.85	0.85	0.84	0.30	0.46	0.54	0.53	0.46
Value-weighted	1	0.20	0.23	0.22	0.23	0.23	0.02	0.02	0.00	0.08	0.07
	2	0.26	0.27	0.27	0.27	0.28	0.08	0.11	0.18	0.15	0.16
	3	0.29	0.30	0.31	0.31	0.32	0.19	0.05	0.23	0.29	0.26
	4	0.31	0.33	0.34	0.35	0.35	0.23	0.17	0.31	0.23	0.29
	5	0.36	0.39	0.39	0.40	0.39	0.14	0.20	0.35	0.19	0.25
Optimised Small	1	0.04	0.02	0.01	0.01	0.01	1.12	0.89	1.00	0.97	0.89
	2	0.02	0.02	0.01	0.01	0.01	1.65	1.70	0.92	0.30	1.05
	3	0.02	0.02	0.02	0.02	0.02	2.07	0.96	0.28	-0.27	0.35
	4	0.02	0.03	0.02	0.02	0.03	1.55	2.25	-0.16	0.08	-0.58
	5	0.06	0.04	0.03	0.04	0.04	2.01	1.81	0.27	1.41	1.29
Optimised Large	1	-0.10	-0.12	-0.06	-0.01	-0.05	0.59	0.27	-0.85	-0.40	-0.59
	2	-0.08	-0.04	-0.11	-0.04	-0.08	0.65	-0.04	-1.26	-1.44	-1.11
	3	-0.04	-0.05	-0.11	-0.04	-0.04	1.58	0.00	-2.10	-3.14	-2.91
	4	-0.03	-0.17	-0.10	-0.09	-0.08	1.70	0.56	-1.35	-2.52	-1.14
	5	-0.05	-0.06	-0.10	-0.10	-0.05	2.50	1.74	-0.82	-0.19	0.29

Figures

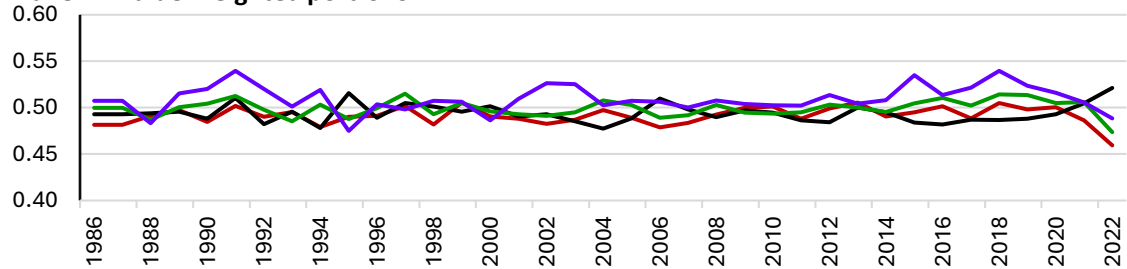
Figure 3.1: Realisation of fundamental-based factors across time, bottom portfolio

Figure 3.1 reports the mean value for fundamental-based predictive factors across time for the bottom portfolio. The bottom portfolio is constructed by ranking stocks according to their machine learning predicted returns and form 10 portfolios and selling the lowest quintile portfolio. The factor realisations corresponding to the stocks chosen in the portfolio are averaged cross-sectionally into four categories of fundamental factors. Factors were reordered to reflect a positive theoretical association with expected returns. In this way an increase in any factor expects an increase in returns. The allocation of factors in their functional category is described in Appendix 3A. In the figure the value vs. growth category is depicted in red, the profitability category is depicted in blue, the investment category is depicted in green, and the intangibles category is depicted in purple. The table is divided into four panels, A to D, which report the results for the equal-weighted, value-weighted, optimised portfolio trading a relatively small portfolio of 1 million USD and optimised portfolio trading a relatively large portfolio of 100 million USD, respectively. Investing horizon is one month and thus, rebalancing of the portfolio is performed monthly based on predicted returns.

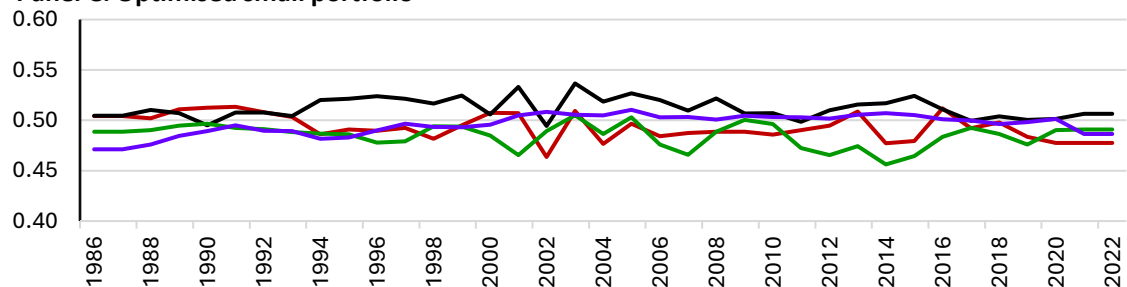
Panel A: Equal-weighted portfolio



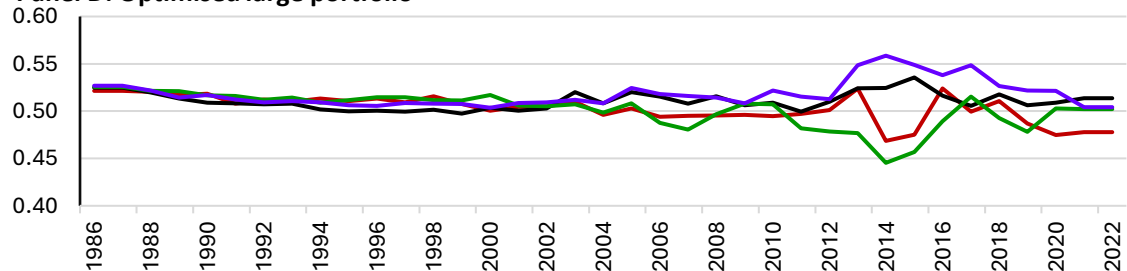
Panel B: Value-weighted portfolio



Panel C: Optimised small portfolio



Panel D: Optimised large portfolio

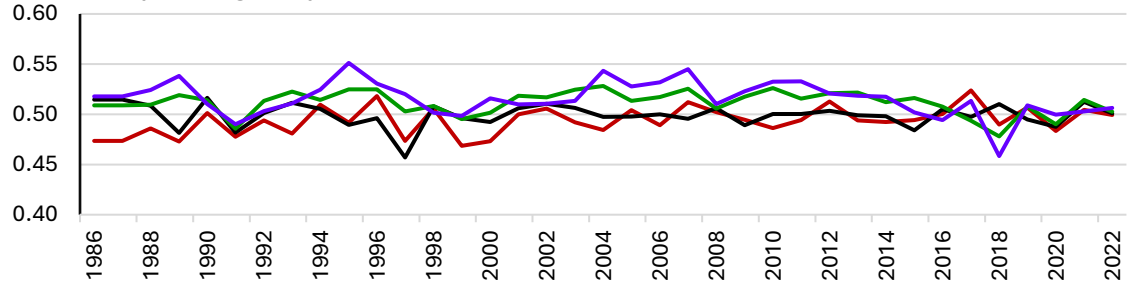


— Value-versus-growth — Profitability — Investment — Intangibles

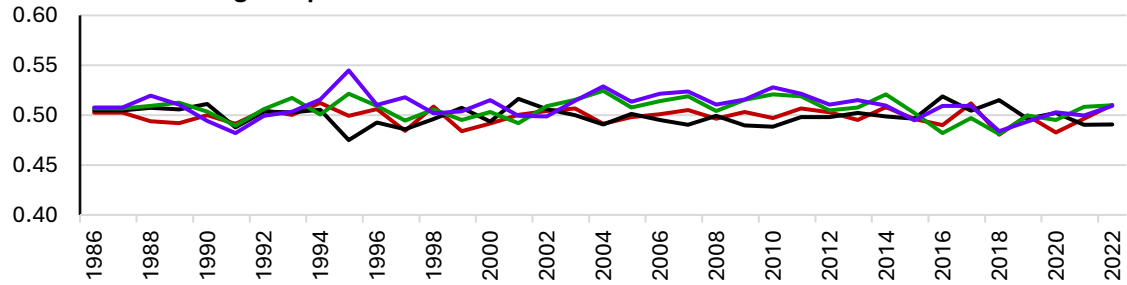
Figure 3.2: Realisation of fundamental-based factors across time, top portfolio

Figure 3.2 reports the mean value for fundamental-based predictive factors across time for the top portfolio. The top portfolio is constructed by ranking stocks according to their machine learning predicted returns and form 10 portfolios and buying the highest quintile portfolio. The factor realisations corresponding to the stocks chosen in the portfolio are averaged cross-sectionally into four categories of fundamental factors. Factors were reordered to reflect a positive theoretical association with expected returns. In this way an increase in any factor expects an increase in returns. The allocation of factors in their functional category is described in Appendix 3A. In the figure the value vs. growth category is depicted in red, the profitability category is depicted in blue, the investment category is depicted in green, and the intangibles category is depicted in purple. The table is divided into four panels, A to D, which report the results for the equal-weighted, value-weighted, optimised portfolio trading a relatively small portfolio of 1 million USD and optimised portfolio trading a relatively large portfolio of 100 million USD, respectively. Investing horizon is one month and thus, rebalancing of the portfolio is performed monthly based on predicted returns.

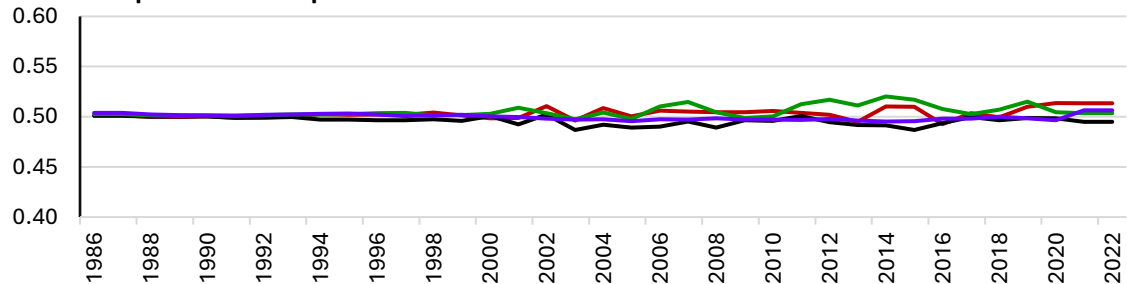
Panel A: Equal-weighted portfolio



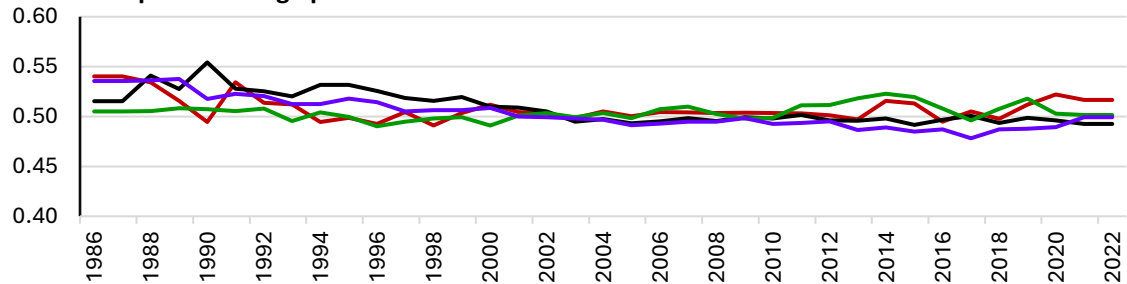
Panel B: Value-weighted portfolio



Panel C: Optimised small portfolio



Panel D: Optimised large portfolio

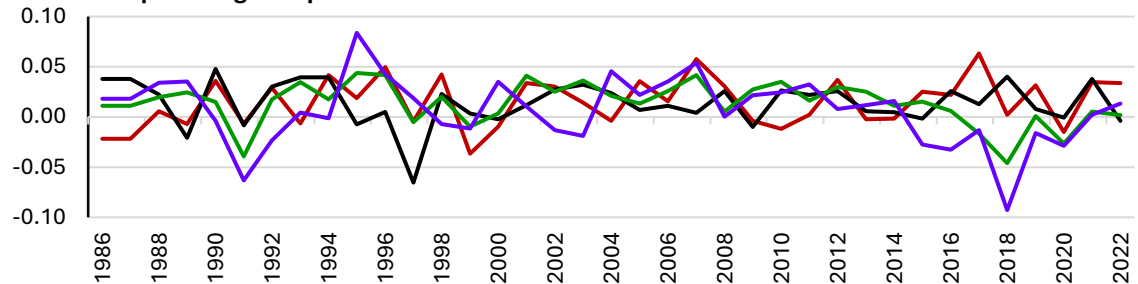


— Value-versus-growth — Profitability — Investment — Intangibles

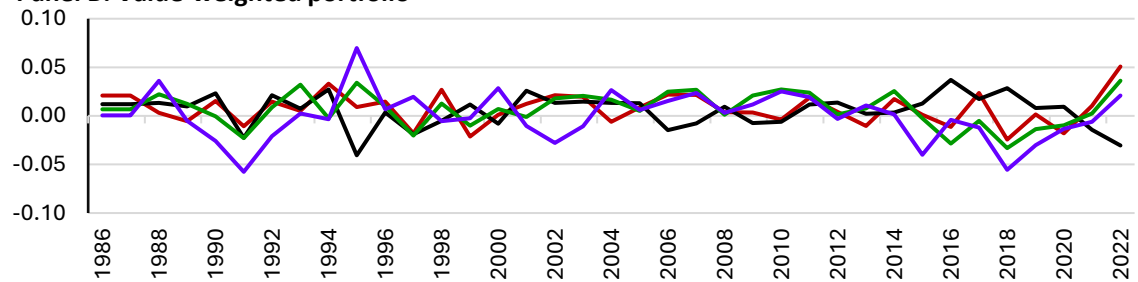
Figure 3.3: Realisation of fundamental-based factors across time, HML portfolio

Figure 3.3 reports the mean value for fundamental-based predictive factors across time for the HML portfolio. The HML portfolio is constructed by ranking stocks according to their machine learning predicted returns and form 10 portfolios, buying the highest quantile portfolio and selling the lowest quintile portfolio. The factor realisations corresponding to the stocks chosen in the portfolio are averaged cross-sectionally into four categories of fundamental factors. Factors were reordered to reflect a positive theoretical association with expected returns. In this way an increase in any factor expects an increase in returns. The allocation of factors in their functional category is described in Appendix 3A. In the figure the value vs. growth category is depicted in red, the profitability category is depicted in blue, the investment category is depicted in green, and the intangibles category is depicted in purple. The table is divided into four panels, A to D, which report the results for the equal-weighted, value-weighted, optimised portfolio trading a relatively small portfolio of 1 million USD and optimised portfolio trading a relatively large portfolio of 100 million USD, respectively. Investing horizon is one month and thus, rebalancing of the portfolio is performed monthly based on predicted returns.

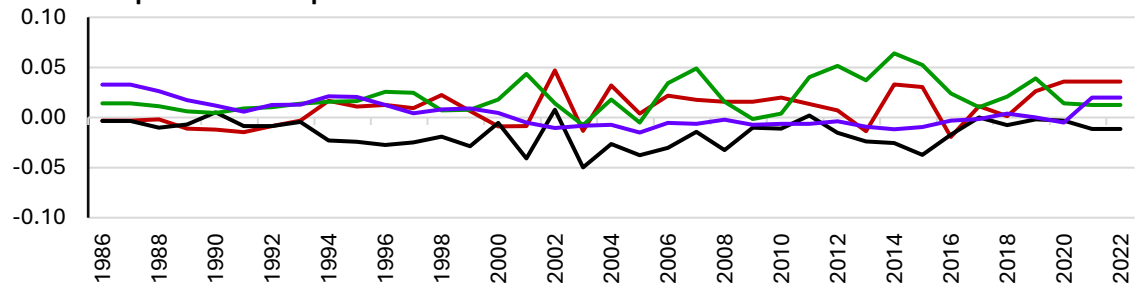
Panel A: Equal-weighted portfolio



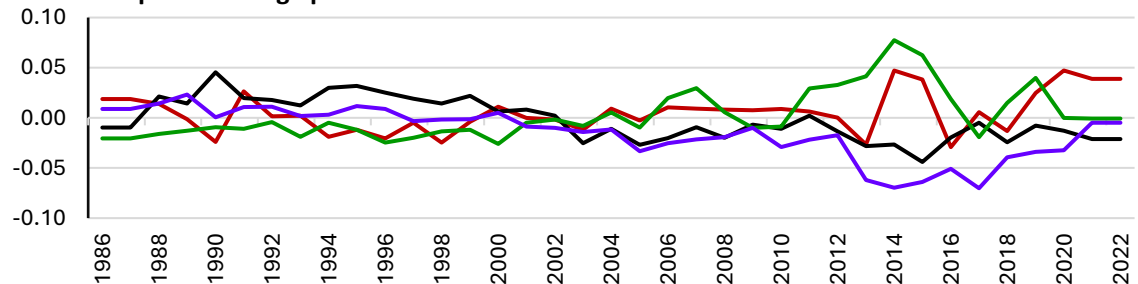
Panel B: Value-weighted portfolio



Panel C: Optimised small portfolio



Panel D: Optimised large portfolio

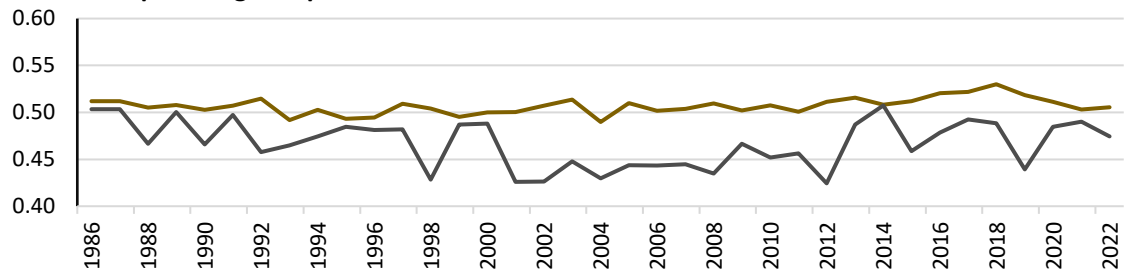


— Value-versus-growth — Profitability — Investment — Intangibles

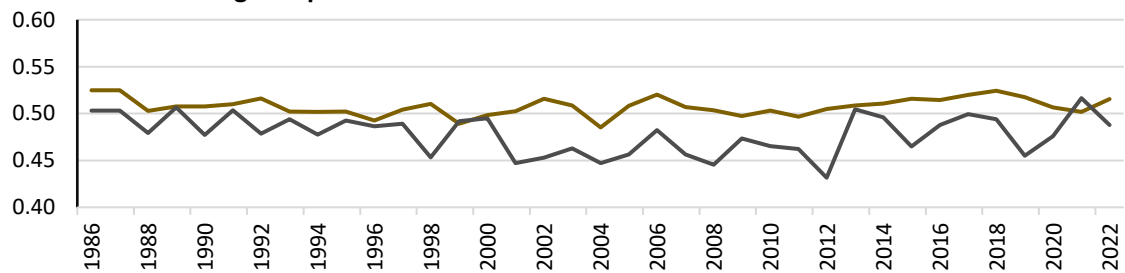
Figure 3.4: Realisation of market-based factors across time, bottom portfolio

Figure 3.4 reports the mean value for market-based predictive factors across time for the bottom portfolio. The bottom portfolio is constructed by ranking stocks according to their machine learning predicted returns and form 10 portfolios and selling the lowest quintile portfolio. The factor realisations corresponding to the stocks chosen in the portfolio are averaged cross-sectionally into four categories of market factors. Factors were reordered to reflect a positive theoretical association with expected returns. In this way an increase in any factor expects an increase in returns. The allocation of factors in their functional category is described in Appendix 3A. In the figure the trading frictions factor is depicted in gold and the momentum factor is depicted in silver. The table is divided into four panels, A to D, which report the results for the equal-weighted, value-weighted, optimised portfolio trading a relatively small portfolio of 1 million USD and optimised portfolio trading a relatively large portfolio of 100 million USD, respectively. Investing horizon is one month and thus, rebalancing of the portfolio is performed monthly based on predicted returns.

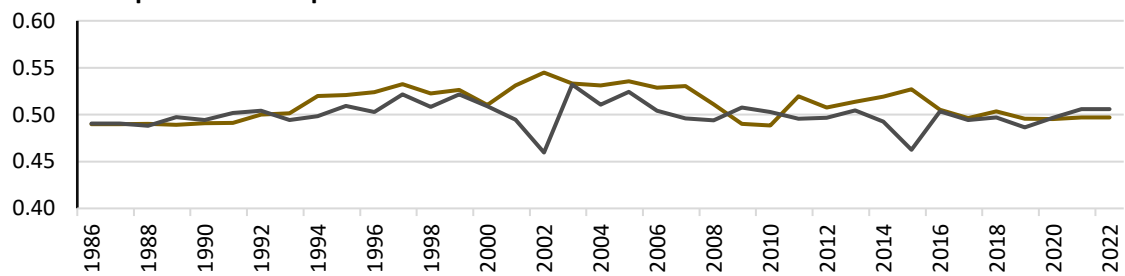
Panel A: Equal-weighted portfolio



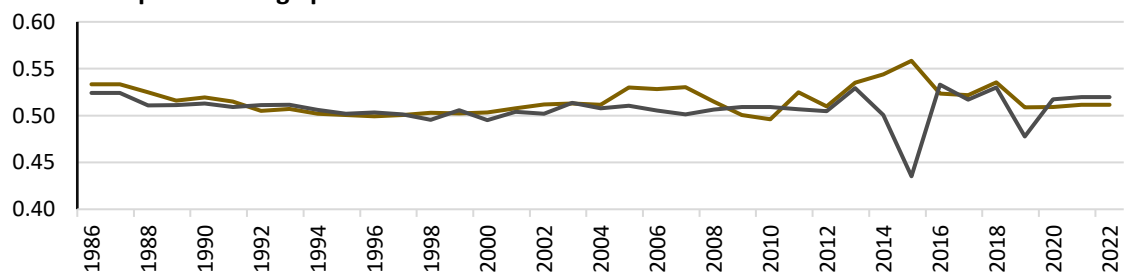
Panel B: Value-weighted portfolio



Panel C: Optimised small portfolio



Panel D: Optimised large portfolio

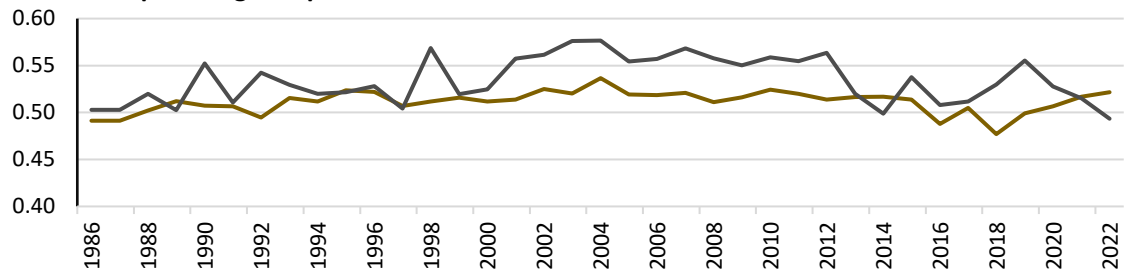


— Trading frictions — Momentum

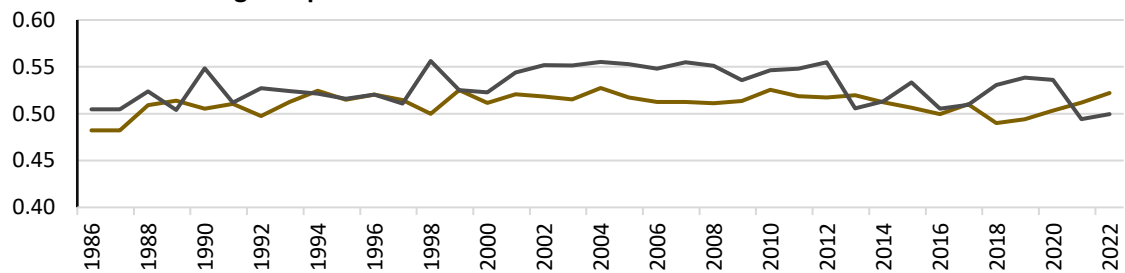
Figure 3.5: Realisation of market-based factors across time, top portfolio

Figure 3.5 reports the mean value for market-based predictive factors across time for the top portfolio. The top portfolio is constructed by ranking stocks according to their machine learning predicted returns and form 10 portfolios and buying the highest quintile portfolio. The factor realisations corresponding to the stocks chosen in the portfolio are averaged cross-sectionally into four categories of market factors. Factors were reordered to reflect a positive theoretical association with expected returns. In this way an increase in any factor expects an increase in returns. The allocation of factors in their functional category is described in Appendix 3A. In the figure the trading frictions factor is depicted in gold and the momentum factor is depicted in silver. The table is divided into four panels, A to D, which report the results for the equal-weighted, value-weighted, optimised portfolio trading a relatively small portfolio of 1 million USD and optimised portfolio trading a relatively large portfolio of 100 million USD, respectively. Investing horizon is one month and thus, rebalancing of the portfolio is performed monthly based on predicted returns.

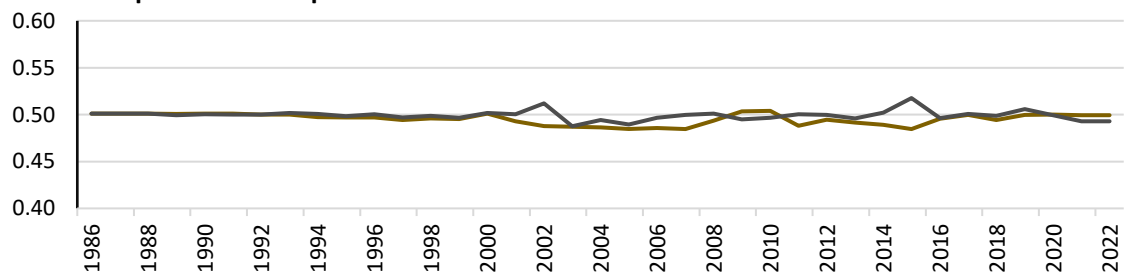
Panel A: Equal-weighted portfolio



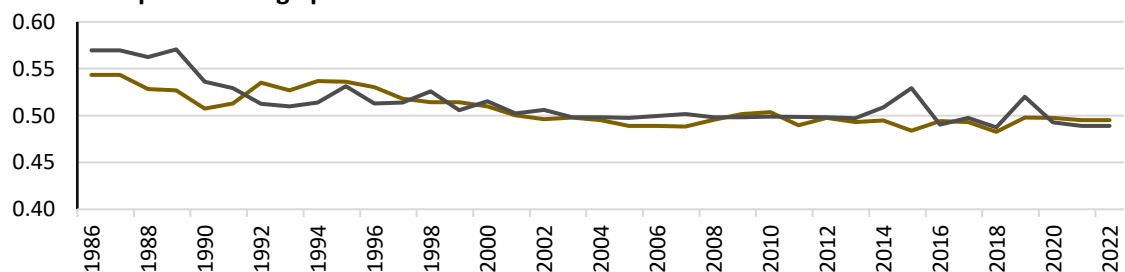
Panel B: Value-weighted portfolio



Panel C: Optimised small portfolio



Panel D: Optimised large portfolio

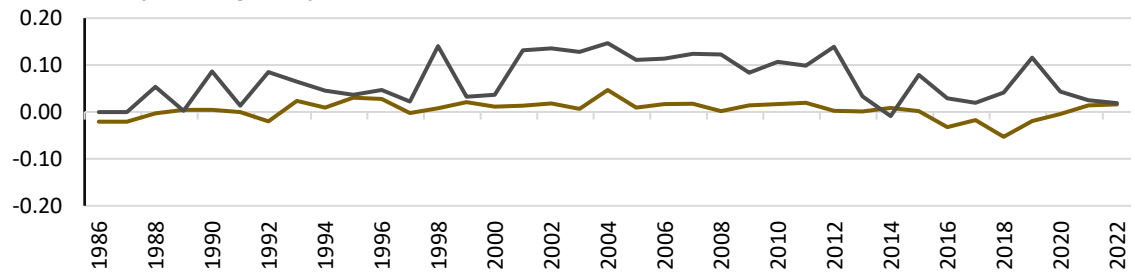


— Trading frictions — Momentum

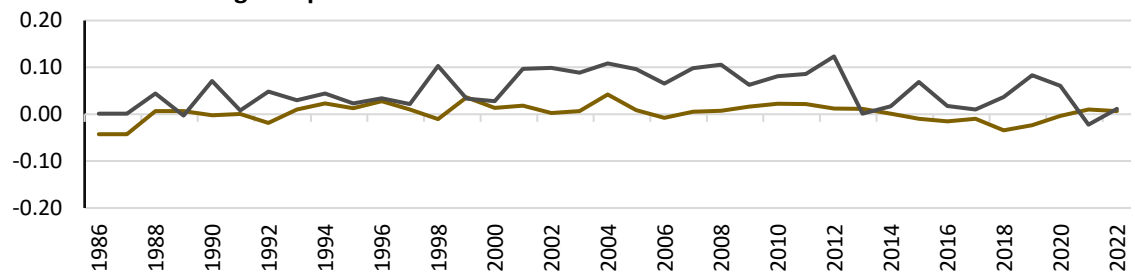
Figure 3.6: Realisation of market-based factors across time, HML portfolio

Figure 3.6 reports the mean value for market-based predictive factors across time for the HML portfolio. The HML portfolio is constructed by ranking stocks according to their machine learning predicted returns and form 10 portfolios, buying the highest quantile portfolio and selling the lowest quintile portfolio. The factor realisations corresponding to the stocks chosen in the portfolio are averaged cross-sectionally into four categories of market factors. Factors were reordered to reflect a positive theoretical association with expected returns. In this way an increase in any factor expects an increase in returns. The allocation of factors in their functional category is described in Appendix 3A. In the figure the trading frictions factor is depicted in gold and the momentum factor is depicted in silver. The table is divided into four panels, A to D, which report the results for the equal-weighted, value-weighted, optimised portfolio trading a relatively small portfolio of 1 million USD and optimised portfolio trading a relatively large portfolio of 100 million USD, respectively. Investing horizon is one month and thus, rebalancing of the portfolio is performed monthly based on predicted returns.

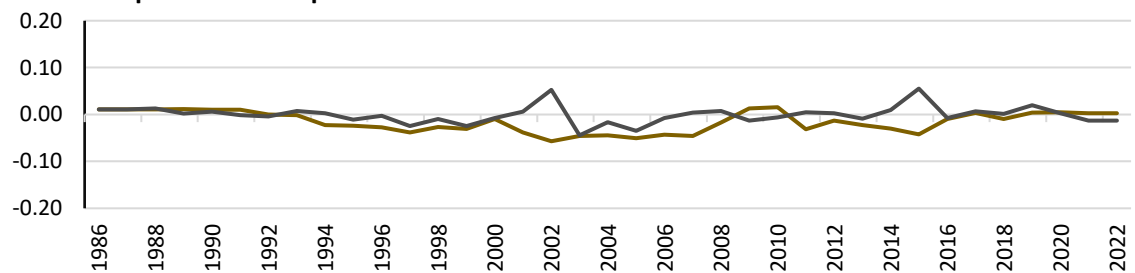
Panel A: Equal-weighted portfolio



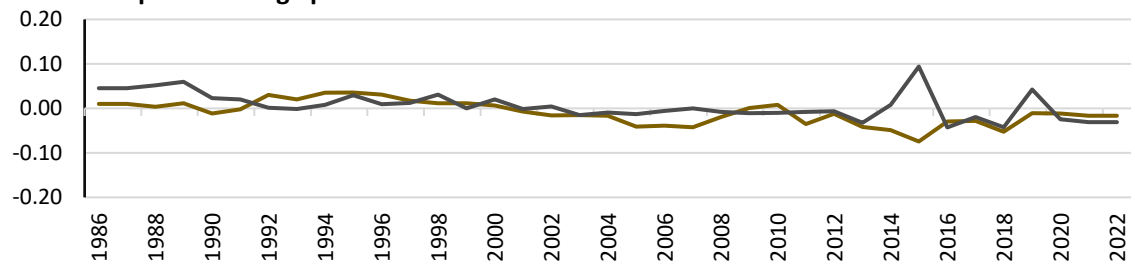
Panel B: Value-weighted portfolio



Panel C: Optimised small portfolio



Panel D: Optimised large portfolio



— Trading frictions — Momentum

Chapter 4

Risk premium estimation in large cross-sections and finite samples

4.1 Introduction

The paradigm of Black et al. (1972) and Fama and Macbeth (1973) of sorting stocks into diversified portfolios according to a chosen characteristic is hardwired in asset pricing studies. The portfolio sorting procedure eliminates the error-in-variables (EIV) bias which is inherent in the estimated betas. Nonetheless, it is also associated with several issues, such as strong factor structure (Lewellen et al. 2010), masking cross-sectional patterns in expected returns and over-rejection of the asset pricing model (Lo and MacKinlay 1990). Potentially, these distort the inference of the asset pricing measurement and possibly, induce empirically favourable results. The econometric setting of this procedure requires the time-series dimension, T , to be much larger than the test asset dimension, N , and the factor dimension, K , given that the number of stocks in the major markets can only be allocated in a low number of well-diversified, orthogonal factor portfolios. Whether this specification is able to capture the complexities in asset pricing is a matter of question.

To circumvent these problems, one might turn to using individual assets instead, given that the two-pass regression is flexible enough to accommodate this. What is more, this setup allows for large factor structures to be examined simultaneously as in Green et al. (2017) and also, allows multiple testing considerations as per Harvey et al. (2016). However, this framework has been challenging for econometricians and empirical researchers alike, which explains why the literature on asset pricing studies via individual assets is rather scarce. In this setting the test asset dimension, N , is larger than the time dimension, T , the latter of which may even be small in absolute terms, as it is frequently seen in investigations applying the rolling regression methodology. The problem lies with the traditional econometric techniques, such as Fama and Macbeth (1973) or Gibbons et al. (1989), which depend on large- T for their validity. This theoretically implies that the inference may be problematic when analysing large cross-sections (large- N) in finite samples (fixed- T), which is the case when considering the real financial data for individual stocks.

The investigation conducted in this chapter focuses on the risk premium measurement in the large cross-section of all available individual stocks. This setting allows for the simultaneous consideration of a broad collection of documented anomalies, as in Green et al. (2017), which is also the approach adopted here. Importantly, the focal research objective of this chapter is to keep the N and K dimensions large and investigate how the risk premium behaves in varied levels of T . Two forms of the two-pass regression are compared; the classic configuration which bases on large- T (large- T , fixed- N) and a framework which is econometrically adjusted by the results of Shanken (1992) and Raponi et al. (2020), and thus is asymptotically valid in finite samples (large- N , fixed- T). The comparison of the two models yields the empirical effects associated with using the traditional two-pass framework and failing to adjust for the size of T . The deviation between the two measurements varies with the varying T and an adapted Pitman-Morgan test is applied to quantify the statistical significance of the divergence.

This chapter makes three contributions to the literature. First, the comparison between the unadjusted two-pass regression and the asymptotically valid Shanken-Raponi framework was quantified via a novel application of the Wilcox's (2020) extension of the Pitman-Morgan test. This methodology enables the investigation into the divergence between the two models and measures the levels at which the time dimension is small enough for the inference to be biased, in a statistically significant sense. This extends the findings of Raponi et al. (2020) as the research question is no longer restricted to measuring the percentage difference between the two sets of results. Rather it evolves into testing hypotheses regarding the inference of the models across the whole spectrum of the time dimension.

Second, the Pitman-Morgan test yielded novel, empirically-relevant findings. There is statistically significant divergence between the asymptotically valid and the unadjusted two-pass models, in the univariate setup, for time windows up to 10 years in the all-stocks sample and up to 7 years in the microcap-free sample. Up to these levels, T is still small enough to raise inference concerns, and thus empirical researchers using such short windows should consider applying the Shanken-Raponi adjustments. Beyond these levels no statistically significant divergence is present. In the multivariate setup, the

deviation between the two models is only apparent up to the 5-year mark, after which it declines rapidly to zero.

Third, the microcap bias is quantified via the application of the Pitman-Morgan test which revealed that when the univariate setup is used, removing microcaps has a statistically significant impact on the risk premium measurement. Interestingly, this impact is not evident at short time windows, however, when the time dimension is large enough the impact of microcaps is distinct. Specifically, the findings show that when microcaps are excluded the resulting *t*-values for the 78 factors move closer to zero. The logical influence is that a major portion of anomalies exist only in microcaps. On the contrary, although the effects of microcaps were observed in the multivariate regression, the impact of the bias cannot be established in the statistical significance sense. This evidence expands on the findings of Green et al. (2017) and Hou et al. (2020) who also identify the same effect, however, their analyses were restricted to counting the number of anomalies before and after removing microcaps.

4.2 Literature review

4.2.1 The three dimensions of asset pricing

The quintessential asset pricing investigation is subject to three dimensions; the time-series dimension, T , the factor dimension, K , and the test asset dimension, N . A combination of these is applied in any given factor model research, often with little regard to how the size of these dimensions impacts the inference of the investigated model. Commonly, researchers adopt the paradigm of Black et al. (1972) and Fama and Macbeth (1973) in grouping stocks into diversified portfolios according to a characteristic of interest. In this configuration, the time dimension is always much larger than both the test asset dimension and the factor dimension since T spans for the decades of historical financial data, while N is usually only as high as 25 portfolios and K is a low number of factors, usually five or six. The advantages and pitfalls of this setup are well-understood by the financial empiricists, however, the understanding of asset pricing inference when the dimensions N and K are large is still limited.

The validity of the traditional econometric techniques relies on T being larger than N and K . For example, in the Gibbons' et al. (1989) test the available degrees-of-freedom decreases rapidly as the dimension N grows to the size of T and the test becomes invalid when $N > T$. Similarly, the inference of the Fama and Macbeth (1973) regression critically depends on T being larger than N as the standard errors of the coefficients tend to zero when N diverges while T is fixed (Raponi et al. 2020). Regarding the factor dimension, the sorted portfolios paradigm can only be applied when K is small, given that there are not enough assets to create a high number of orthogonal factors. If individual stocks are used as test assets K can be large. It should be noted, however, that the probability of Type I error increases with the increasing K . Lastly, K can never be larger than $T - 1$, as this is mathematically invalid.

Recent econometrics research produced interesting mathematical schemes to explore the asset pricing measurement when the dimensions N and K are large. In this setting, valid inference can be achieved in cross-sections where a large number of individual assets are used instead of a low number of portfolios, both when betas are assumed constant (Raponi et al. 2020) or time-varying (Gagliardini et al. 2016). At the same time, alternative ways were developed to treat the EIV issue (Jegadeesh et al. 2019; Kim and Skoulakis 2018) and address the weak identification issue (Kleibergen et al. 2019), which are mathematically prominent when T is not large. Based on these complex schemes a question arises; how large is large (Khalaf 2021) or to put it differently, at what size is T small enough to significantly alter the risk premium inference? This is the question investigated in this chapter.

Research into extending the factor dimension, K , is relatively more mature in the empirical literature and focuses on the use of multiple testing methods to examine the collection of asset pricing factors simultaneously (Harvey et al. 2020; Harvey et al. 2016). This chapter uses a large K factor-set by default, as to investigate how the risk premium measurement varies with T and N , but interested readers are referred to the excellent papers by Green et al. (2017), Hou et al. (2020) and Harvey and Liu (2021). Nevertheless, before expounding complex econometric frameworks the discussion should also address, on a theoretical level, how the large- N framework may ultimately lead to some new knowledge for the study of asset prices. The following section discusses that this setting might not only be econometrically interesting but also has the potential to generate insights for empirical finance.

4.2.2 Why investigate large- N ?

The comparison issue

The portfolio sorting procedure is paradigm in asset pricing studies. Portfolio sorting is advantageous as it eliminates the error-in-variables and generates a clearer signal for the estimation of risk premia. Therefore, it is not surprising that some major empirical findings in the anomalies' literature, such as Banz (1981), Basu (1983) and Fama and French (1993; 2015), flourished from this procedure. In this setting, the time dimension, T , must be much larger than the test asset dimension, N , given that the number of stocks in the major markets can only be divided in a low number of well-diversified, orthogonal factor portfolios. The implication is that portfolio sorting can only allow a comparison of limited asset pricing factors. What is more, the aggregation of data into portfolios, potentially, obscures the underlying risk-generating process and may induce factors to appear statistically significant.

Despite the distinguished empirical success achieved by the low dimensional model, it can be argued that the complexities of asset prices cannot be captured by the large- T , small- N , small- K specification of the portfolio sorting procedure. Notice how the Fama and French (1993) three-factor model, although influential, misses profitability- and investment-related factors. These are added later in Fama and French's (2015) five-factor and Hou et al. (2015) four-factor specifications. Still, these do not suffice to explain the complete picture of the equity premium as they evidently miss the momentum bias (Barillas and Shanken 2018). Fama and French (2018) then suggested a six-factor specification which adds the momentum factor and Hou et al. (2020) adds an expected growth factor. These modifications are arguably still insufficient, as they fail to capture the earnings-related anomaly and the momentum anomaly, respectively. At the same time, it is unlikely that more factors can be added while sufficient diversification is maintained. Given this discussion, it is certainly arguable that this approach does not suffice to capture all the explanators of asset prices even though it is used to its full potential.

On the other hand, allowing N to be large also allows K to be large. In other words, when individual assets are used the investigation can be conducted via a multivariate regression framework, such as in Green et al. (2017). In this setting a large collection of identified anomalies can be examined simultaneously, something which can't be done via the portfolio sorting approach. This is of great importance, given the lively thread in empirical asset pricing aiming to discover which of the hundreds of documented anomalies (Green et al. 2013) are indeed unique explanators of asset prices and which are subsumed by others (Cochrane 2011). Given that Ross' (1976) Arbitrage Pricing Theory (APT) provides no theoretical basis to superimpose one factor over another, the investigation can only be conducted on empirical foundations.

The multivariate investigation allowed by the large- N (thus large- K) framework is, arguably, the only viable route to conduct a comprehensive, comparative investigation of the vast collection of asset pricing factors. Other attempts include Harvey (2017) who advocates for the increase of the t -statistic threshold for the establishment of statistical significance, which was adopted by several leading papers (Green et al. 2017; Hou et al. 2020). Although this decreases the number of accepted anomalies it cannot explain the existence of the plethoric evidence. Alternatively, dimensionality reduction techniques are applied to condense the large factor structure associated with the collection of factors. Examples include shrinkage (Freyberger et al. 2020), regularization (Feng et al. 2020) or a combination of the two (Kozak et al. 2020). Although these achieve improved model performance, the improvement cannot be directly attributed to specific pricing factors. Given the above, the multivariate regression via individual assets is arguably a more realistic option to distinguish among the complete set of anomalies.

Beyond the comparison challenges discussed above, the portfolio sorting approach may be naturally fostering empirically favourable results due to the sorting itself and not due to uncovering an underlying risk-generating process. Lo and MacKinlay (1990) demonstrate that when portfolios are sorted on the basis of a characteristic that empirical research has already found to be related with expected returns (otherwise known as data mining) then the probability of the null hypothesis¹⁰ being rejected in an F -test substantially increases. Not surprisingly, Banz's (1981) size effect and Basu's (1983) value effect became almost standard components of asset pricing models and almost always prove to be statistically significant. The inception of these was not originally based on some theoretical foundation and it is arguable that the research that followed has merely incurred the issue that Lo and MacKinlay (1990) highlight. What is more, given the hundreds of factors that are documented in the literature, it is reasonable to ask why the size and book-to-market factors are specifically used as control factors over any other anomaly.

Ferson et al. (1999) theoretically conceptualize how sorting based on a characteristic as Lo and MacKinlay (1990) describe, inevitably leads to the characteristic appearing to be statistically significant in the two-pass regression. Their explanation hinges on the fact that the return portfolios, R_p , created in the first step of the Fama and Macbeth (1973) procedure are proportional to the attribute. Therefore, regressing R_p against betas in the second step leads to the anomaly being reproduced via the procedure and not actually confirmed by the procedure. This might be the mechanism explaining and supporting Harvey's (2017) critique that most anomalies result from data mining. Conrad et al. (2003) provide empirical evidence in support of this pattern, by sorting portfolios on random firm characteristics and reveal that statistically significant results surface. They argue that up to 50% of the relationships result from their data mining scheme which highlights how the portfolio sorting procedure has a propensity to generate significant results.

¹⁰ $H_0: \alpha_i = 0$ for all assets i

The astounding success of the size and book-to-market factors is also strongly criticized by Lewellen et al. (2010) who wonder whether the factors generate illusory performance. Specifically, they argue how the coefficient of determination, R^2 , can be a highly misleading metric for the performance of an asset pricing model. Their criticism focuses on the observation that the size and book-to-market factors have strong covariance structure with returns. Due to this, a high cross-sectional R^2 is easily achievable given that any factor which is even weakly correlated with the size, or book-to-market variables will line up with expected returns, by implication. Nonetheless, the solutions they suggest are arguably trivial and thus, motivate the investigation into alternative routes; specifically,

- a) The suggestion to include other portfolios as test assets raises a reasonable question, in the spirit of Barillas and Shanken (2017); which portfolios?
- b) The ability to evaluate the magnitudes of the coefficients using guidance from theory is dubious, since the distinct feature of empirically motivated asset pricing anomalies is that they do not usually stem from a fundamental, theoretical background, such as the Capital Asset Pricing Model (CAPM) (Sharpe 1964; Lintner 1965; Mossin 1966) or the Consumption-based CAPM (Lucas 1978; Breeden 1979).
- c) Using Generalised Least Squares (GLS) instead of Ordinary Least Squares (OLS) only makes the problem less severe, as even Lewellen et al. (2010) admit.
- d) Reporting the full confidence intervals instead of the t -values merely provides more information and does not resolve the inference issues.

The above discussion highlights how the portfolio sorting procedure may lead to invalid inference about the significance of factors; through t -values as per Ferson et al. (1999), the significance of the asset pricing model via the F -test as per Lo and MacKinlay (1990), and the explanatory power through the cross-sectional R^2 as per Lewellen et al. (2010). Given these arguments one understands that the sorting procedure is, arguably, fragile and prone to abuse given the a priori knowledge about the anomalies. In light of this discussion, the

existence of hundreds of factors in the literature (Harvey et al. 2016) is not surprising but rather expected. Likewise, the empirical success of the size and book-to-market factors may be considered less like robust evidence for anomalies and more like statistically induced relationships due to portfolio sorts which are manifested through the two-pass regression procedure.

Contrarily, using individual securities in a large- N framework alleviates the requirement of Lewellen's et al. (2010) first suggestion to choose and construct test assets since all available stocks can be used collectively. The classic two-pass estimator is flexible enough to accommodate individual stocks as test assets. At the same time, any worries of extreme factor loadings distorting the risk premium measurement are put to ease by Ang et al. (2020) who show that the increased dispersion in the first stage factor loadings associated with the use of individual stocks, empirically, decreases the variability of the premium estimator in the second stage.

Nonetheless, it should also be underlined that substituting portfolio sorting with individual assets in the two-pass regression is not a plug-and-play operation. As a matter of fact, there are two major inference challenges involved. First, the error-in-variables issue which was otherwise diversified away in the sorted portfolios, is a present danger to the inference of the individual asset model. The evidence regarding the empirical implications of the above is ambivalent, nonetheless. For example, Kim (1995) shows that in the presence of EIV the mean-squared error of models with individual stocks increases, while on the other hand, Kim (1997) does not find any impact due to the EIV on the risk premium measurement for the firm size, book-to-market equity, and earnings-to-price factors. Second, the two-pass estimator is valid only when the time-series dimension, T , is large. When individual assets are used the N dimension is large, in fact, much larger than T , whereas the latter may even be small on absolute terms. The econometric analysis of this configuration proves that both the risk-premium coefficients (Shanken 1992) and their variance (Raponi et al. 2020) are biased and should be adjusted. Yet, recent prominent studies, such as Hou et al. 2020 and Green et al. 2017, do not explicitly consider this issue.

4.2.3 The estimation of large- N

In statistical tests of regression coefficients valid inference depends on two factors: the consistency of the coefficients and the asymptotic normality of their standard errors. This chapter examines the valid inference of the widely used Fama-Macbeth (1973) two-pass regression. When the time dimension is large (large- T model) the risk premia coefficients are consistent however, their standard errors are not asymptotically normal. Shanken (1992) proved the correct formulation for valid standard errors which is used in this chapter. When the time dimension is small, and the test asset dimension is large (large- N model) neither the coefficients, nor their standard errors are valid. Again, Shanken (1992) proved the bias adjustment needed for consistent coefficients whereas, the asymptotically normal standard errors have only recently been proven by Raponi et al. (2020).

When the time dimension is large enough both the coefficients and standard errors of the large- T and large- N frameworks become identical. Nonetheless, when T has not diverged adequately the measures are not equal, and thus the inference becomes invalid. For example, when one uses the large- T model for a short time window (e.g., when performing rolling window regressions) one incurs invalid inference. Specifically, the coefficients computed are biased and their standard errors are smaller than they should. The implication is that the t -statistics are erroneously larger.

After the recent proof by Raponi et al. (2020) both the large- T and large- N frameworks can be estimated with validity. Given the above, the idea explored in this chapter is to estimate the two frameworks across a range of increasing time windows and investigate at which point the inference between the two is statistically different and thus become invalid. The following subsections describe the preliminaries for the Fama-Macbeth regression and then discuss the limiting behavior of the risk premia coefficients and their standard errors.

Preliminaries

Consider an economy with N assets. It is assumed that the returns, $\mathbf{R}_t$, for asset i follow a linear beta-pricing model of the form:

$$\mathbf{R}_t = \boldsymbol{\alpha} + \mathbf{B}\mathbf{F} + \boldsymbol{\varepsilon}_t \quad (4.1)$$

where the asset $i = 1, \dots, N$, the time period $t = 1, \dots, T$, the returns $\mathbf{R}_t = [\mathbf{R}_t^1, \dots, \mathbf{R}_t^N]' \in T \times N$, the asset-specific intercept $\boldsymbol{\alpha} = [\alpha_1, \dots, \alpha_N]' \in N \times 1$, the factor structure $\mathbf{F} \in K \times T$ for factors $k = 1, \dots, K$, the factor loadings of N assets on K factors $\mathbf{B} \in N \times K$ and the random disturbances $\boldsymbol{\varepsilon}_t \in N \times T$. The risk premia are denoted by $\boldsymbol{\Gamma} = [\gamma_0, \boldsymbol{\gamma}']' \in (K + 1) \times 1$ and $\mathbf{X} = [\mathbf{1}_N, \mathbf{B}]$, where $\mathbf{1}_N$ is the N -vector of ones. Note that the uppercase symbols T , N and K are used to denote the fixed sizes of the time, asset and factor dimensions, respectively, whereas the lowercase symbols t , n and k denote the variable case of the three quantities.

Given the no-arbitrage condition, as described in Chamberlain (1983), equation 4.1 above is expected to yield

$$E[\mathbf{R}_t] = \mathbf{X}\boldsymbol{\Gamma} \quad (4.2)$$

where $E[\cdot]$ is the expectation operator, and thus the risk premia are expressed in closed form as

$$\boldsymbol{\Gamma} = (\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}' E[\mathbf{R}_t] \quad (4.3)$$

Empirically, equation 4.1 is computed by the time series average

$$\overline{\mathbf{R}_t} = \boldsymbol{\alpha} + \widehat{\mathbf{B}}\overline{\mathbf{F}} + \overline{\boldsymbol{\varepsilon}_t} \quad (4.4)$$

where $\overline{\mathbf{R}_t} = \frac{1}{T} \sum_1^T \mathbf{R}_t$, $\overline{\boldsymbol{\varepsilon}_t} = \frac{1}{T} \sum_1^T \boldsymbol{\varepsilon}_t$, $\overline{\mathbf{F}} = [\bar{f}_1, \dots, \bar{f}_K]$ and $\widehat{\mathbf{B}}$ is the estimate of $\mathbf{B}$.

This chapter builds on the fact that the two-pass regression framework is valid only when T is large i.e., $t \rightarrow \infty$. The econometric meaning of this is that the risk premium can be estimated in closed form as per equation 4.3. In finite samples, T being large enough suffices for $E[\epsilon_t] = 0$ thus, allowing the valid estimation of the risk premium. In large cross sections, such as when using individual assets, the N dimension dominates the T , the latter of which may even be small in absolute terms. In this framework two econometric implications arise. First, from equation 4.4, one can see that the estimate $\hat{B} = (\hat{F}' \hat{F})^{-1} \hat{F}' (\bar{R}_t - \bar{\epsilon}_t)$. This is the well-known error-in-variables problem, since the $\hat{B} \neq B$ thus, the independent variable in the second stage is estimated with error i.e., $\hat{X} \neq X$. Since $\bar{\epsilon}_t \rightarrow 0$ only when $t \rightarrow \infty$, the implications of the EIV issue may be substantial in large cross-sections, i.e. when $n \rightarrow \infty$. Second, comparing equations 4.2 and 4.4 reveals that the relationship between average returns and risk premia is

$$\bar{R}_t = \gamma_0 \mathbf{1}_N + B(\gamma + \bar{F} - E[F]) + \bar{\epsilon}_t \quad (4.5)$$

When $t \rightarrow \infty$ then $\bar{F} \rightarrow E[F]$ which yields the classic two-pass estimator

$$\hat{\Gamma} = (\hat{X}' \hat{X})^{-1} \hat{X}' \bar{R}_t \quad (4.6)$$

Nonetheless, when $n \rightarrow \infty$ $\bar{F}$ does not converge to its expected value thus, the $\text{plim}_{n \rightarrow \infty}(\hat{\Gamma}) \neq \Gamma$, where $\text{plim}_{n \rightarrow \infty}(\cdot)$ denotes the probability limit when the number of assets tends to infinity.

The limiting behavior of the risk premium coefficients

In the majority of empirical asset pricing investigations, the cross-section of assets is condensed into a small number of portfolios. The condensation into a small cross-section solves the EIV problem since the well-diversified portfolios eliminate the idiosyncratic error $\bar{\varepsilon}_t$ in equation 4.4, which implies $\hat{X} = X$. At the same time, the time dimension T is much larger than the asset dimension N . Given that T is adequately large also implies that $\bar{F} = E[F]$ thus, the risk premium can be consistently estimated by the classic estimator in equation 4.6. On the other hand, when considering large cross-sections in finite samples both n and t converge, but n converges at a much greater rate. For example, Raponi et al. (2020) count that in the period January 1966 to December 2013 there exist an average of 3,435 stocks per month in the major US stock markets. This implies that for every 1-month increment in the T dimension, there is an increment of 3,435 observations in the N dimension, on average. With the N dimension dominating while the T dimension is not adequately large, implies that neither does $\hat{X} \rightarrow X$, nor does $\bar{F} \rightarrow E[F]$ and thus, the estimates for the premia $\hat{\Gamma}$ must be invalid to some level, i.e., $|\hat{\Gamma} - \Gamma| > 0$.

The limiting behavior of the estimator, Γ , when the number of test assets diverges was first considered by Litzenberger and Ramaswamy (1979) who analysed the weighted least squares estimator (WLS). Shanken (1992) solved the more complex case for the ordinary least squares estimator (OLS) in equation 4.6. As previously noted, equation 4.5 implies that the risk premia cannot be estimated when t does not diverge, since neither does $\bar{\varepsilon}_t \rightarrow 0$, nor does $\bar{F} \rightarrow E[F] \Rightarrow \text{plim}_{n \rightarrow \infty}(\hat{\Gamma}) \neq \Gamma$ even if the EIV is resolved. In light of this reality, Shanken (1992) defines the ex-post risk premium quantity

$$\Gamma_P = \left(\gamma + \frac{\gamma_0}{F - E[F]} \right) \quad (4.7)$$

which is to the ex-ante risk premium plus the unexpected factor outcomes. Given that the ex-ante quantity Γ cannot be consistently estimated, empirical research can only turn to the ex-post risk premium parameter, Γ_P . Arguably, the latter is the most favourable parameter for the risk premium estimation in the limit

$n \rightarrow \infty$ due to several attractive properties. Firstly, Γ_P is an unbiased measure of Γ . This means that the investigation conducted herein evaluates comparable quantities; the estimated ex-post premia, $\widehat{\Gamma}_P$, in the large- N case and the estimated ex-ante premia, $\widehat{\Gamma}$, in the large- T case. Secondly, one can see that, when substituting equation 4.7 in equation 4.5, the risk-return specification remains linear, such that

$$\overline{R}_t = \widehat{X} \Gamma_P + \overline{\eta} \quad (4.8)$$

where $\overline{\eta} = \overline{\varepsilon}_t - (\widehat{X} - X) \Gamma_P$. This implies that the ex-post pricing errors, $\overline{\eta}$, can be used to infer the validity of the resulting linear pricing model, in the same way as $\overline{\varepsilon}_t$ can be used to test the ex-ante relationship in 4.5¹¹.

The ex-post quantity, Γ_P , may be consistently estimated in closed form by equation 4.8 only after considering Shanken's (1992) Theorem 5. This suggests that to estimate $\widehat{\Gamma}_P$ in the limit $n \rightarrow \infty$ the $\text{plim}_{n \rightarrow \infty}(\widehat{X}' \overline{R}_t) = X' \overline{R}_t$, however, the $\text{plim}_{n \rightarrow \infty}(\widehat{X}' \widehat{X})$ does not equal to $X'X$, but rather $X'X + \Lambda$ where:

$$\Lambda = \begin{pmatrix} 0 & 0 \\ 0 & \frac{\bar{\sigma}^2}{T} \Sigma_F^{-1} \end{pmatrix}, \quad \bar{\sigma}^2 = \frac{1}{N} \sum_1^N \sigma_{ii}^2 \text{ and } \Sigma_F = E[(F - \bar{F})(F - \bar{F})']$$

Therefore, the unbiased estimator for Γ_P is

$$\widehat{\Gamma}_P = (\widehat{X}' \widehat{X} - \Lambda)^{-1} \widehat{X}' \overline{R}_t \quad (4.9)$$

The bias term, Λ , arises due EIV issue, as the variance of the error terms, $\bar{\sigma}^2$, does not disappear in the limit $n \rightarrow \infty$. Nonetheless, an unbiased estimator of $\widehat{\Gamma}_P$, can still be achieved as per Shanken's theorem described by equation 4.9. One can see that since $\bar{\sigma}^2 > 0$ and Σ_F being positive-definite, then the bias Λ is always positive. Furthermore, as $t \rightarrow \infty, \bar{\sigma}^2 \rightarrow 0 \Rightarrow \Lambda \rightarrow \mathbf{0}$. These imply that when the time window is sufficiently large the risk premium estimation is unbiased, otherwise it should be adjusted according to equation 4.9. Given the

¹¹ Test that the error terms are zero on average

above discussion, this chapter aims to explore the implications on the risk premium measurement at different levels of T , comparing the results before and after the bias is adjusted for. In fact, meta-studies exploring the broad collection of asset pricing anomalies, such as Green et al. (2017) and Chordia et al. (2020), often do not explicitly regard this issue. The expected outcome is that beyond a certain level of T the adjustment, Λ , will have insignificant effect on the premium estimation but the question remains, at which level?

Econometric research has only recently revisited the asymptotic properties of the $n \rightarrow \infty$ case. Bai and Zhou (2015) investigate the behavior of the ex-ante estimator in a joint asymptotic framework where both n and t diverge and show that a bias exist in this setup as well. They provide robust evidence for their estimator's performance after a bias adjustment at various scenarios of N and T . When $t \rightarrow \infty$ their estimator is reduced to the standard OLS estimator of equation 4.6. On the other hand, Raponi et al. (2020) show that the Bai and Zhou (2015) estimator is reduced to a form equivalent to Shanken's adjusted estimator, expressed by equation 4.9, when $n \rightarrow \infty$ and t is fixed.

Gagliardini et al. (2016) consider a joint asymptotic scenario for the weighted least squares in which n and t diverge simultaneously and confirm the requirement for a bias adjustment when T is small. They develop a mathematical scheme for the computation of time-varying risk premia, as opposed to Bai and Zhou (2015) and Shanken (1992) who focus on constant coefficients. More importantly, however, they base their analysis on a different parameter, which is computed as $\Gamma_P - [0, \mathbf{F}]' = \Gamma - [0, E[\mathbf{F}]]'$. On the contrary, Shanken focuses on $\Gamma_P = \Gamma + [0, \mathbf{F} - E[\mathbf{F}]]'$, as expressed by equation 4.7, whereas Bai and Zhou start from Γ which reduces to Shanken's Γ_P if t does not diverge. This chapter focuses on Shanken's ex-post premium estimator, nonetheless, it should be highlighted that all alternatives are mathematically equivalent.

The limiting behavior of the risk premium standard errors

Shanken (1992) analytically showed that the asymptotic standard errors of the Fama-MacBeth (1973) estimator are, in fact, affected by the EIV when $t \rightarrow \infty$. Specifically, Shanken's (1992) estimator, given Jagannathan and Wang (1998) assumption of conditional heteroskedasticity, yields that the asymptotic distribution of $\hat{\Gamma}$ as

$$\sqrt{T}(\hat{\Gamma} - \Gamma) \rightarrow N(\mathbf{0}_{K+1}, V_{\hat{\Gamma}}) \quad (4.10)$$

where $V_{\hat{\Gamma}} = \Sigma_F^* + (1 + \gamma' \Sigma_F^{-1} \gamma) A \Sigma_{\varepsilon} A'$ is the asymptotic variance of the Shanken estimator in the limit $t \rightarrow \infty$, Σ_F^* is the bordered version of Σ_F , $\Sigma_F = E[(F - \bar{F})(F - \bar{F})']$ is the variance-covariance matrix of the factor structure, Σ_{ε} is the variance-covariance matrix of the residuals and $A = (X'X)^{-1}X'$. The matrix $(\gamma' \Sigma_F^{-1} \gamma) A \Sigma_{\varepsilon} A'$ is positive-definite which implies the Fama-MacBeth estimator overstates the precision of the measurement, i.e., generates smaller standard errors if unadjusted.

The mathematical implication of Shanken's (1992) analysis is that if the EIV issue is not accounted for, factors might appear statistically significant, however, the relationship might only be a manifestation of the invalid inference framework. One example emerges from the evidence of Jagannathan and Wang (1998) who build on the Shanken estimator and show that, in the presence of misspecification characteristic factor models generate large t -values. Of course, when stocks are sorted in portfolios the EIV disappears, but when individual securities are used as test assets this inference issue should be accounted for. Shanken's framework implies that one, in fact, does not need portfolios to handle the EIV issue but rather an adjustment to the standard error of the magnitude $(\gamma' \Sigma_F^{-1} \gamma) A \Sigma_{\varepsilon} A'$ suffices to guarantee valid inference.

While the limiting behavior of the risk premium standard errors was completely described by Shanken (1992) when $t \rightarrow \infty$, neither Shanken (1992) nor Bai and Zhou (2015) investigate the asymptotic normality of the estimator in the $n \rightarrow \infty$ case. In fact, this econometric issue has been largely ignored in empirical literature, which applies the large- T standard errors of Fama-MacBeth (1973) on

general principle. The perilous implications of this practice were remarked by Raponi et al. (2020), who analytically proved that the standard errors (SE) of the ex-post risk premia $SE(\widehat{\Gamma}_p) \rightarrow \mathbf{0}$ as $n \rightarrow \infty$. The implication is that by increasing the number of cross-sectional observations when the number of time-series observations is fixed, the $t_{stat}(\widehat{\Gamma}_p) \rightarrow \infty$, thus, the statistical significance of asset pricing factors may be mechanically overstated.

Raponi et al. (2020) analytically derived the asymptotic variance of Shanken's estimator $\widehat{\Gamma}_p$, when n diverges, in which case the asymptotic distribution in the limit $n \rightarrow \infty$ is

$$\sqrt{N}(\widehat{\Gamma}_p - \Gamma_p) \rightarrow N(\mathbf{0}_{K+1}, V_{\widehat{\Gamma}_p}) \quad (4.11)$$

The asymptotic covariance of the estimator is provided in closed form as

$$V_{\widehat{\Gamma}_p} = V + \Sigma_X^{-1} W \Sigma_X^{-1} \quad (4.12)$$

where $V = \sigma^2 / T \left[1 + \gamma_p' \Sigma_F^{-1} \gamma_p \right] (\Sigma_X - \Lambda)^{-1}$ is the variance of the large- T estimator after the ex-post risk premia γ_p are corrected for the EIV issue via the adjustment $\gamma_p' \Sigma_F^{-1} \gamma_p$. The term $\Sigma_X^{-1} W \Sigma_X^{-1}$ captures the variance induced due to the bias adjustment of Shanken (1992) in equation 4.9 and the variance due to the cross-sectional variation among assets, given that the residual variation is not zero when $n \rightarrow \infty$. Based on Raponi's et al. estimator in equation 4.12 one may derive standard errors which are mathematically adjusted for the implications of sampling at fixed T while $n \rightarrow \infty$. Combining this with the coefficient bias-adjustment of Shanken one may compute t -statistics which are not mechanically inflated, as they are constrained by the matrix $\Sigma_X^{-1} W \Sigma_X^{-1}$.

4.3 Data and Methodology

4.3.1 Dataset construction

This chapter explores the risk premium measurement and the implications of the two contrasting models when evaluating a high-dimensional set of potential predictors. The predictor set contains 78 characteristics and is constructed according to Green et al. (2017). They start with 330 asset pricing anomalies reported in Green et al. (2013) and remove all variables which cannot be entirely computed from data provided by Compustat, the Centre for Research in Security Prices (CRSP) or Institutional Brokers Estimate System (I/B/E/S). Subsequently, eight characteristics exhibiting high multicollinearity (variance inflation factor >7) were removed. Finally, all binary variables were discarded since they are non-invertible as required by the methodology. This leaves 78 characteristics in the factor set (Appendix 4A).

All securities are sourced from CRSP. Firms with common stock (CRSP share code groupings = 1) traded on the NYSE, AMEX or NASDAQ (CRSP exchange Codes = 1 or 2 or 3) are included in the sample. The sample period spans from December 1959 which is when the first substantial data started to be documented in CRSP and finishes on December 2021, which yields a sample containing 7360 unique stocks over 62 years. The three-month Treasury-bill rate is used as proxy for the risk-free rate. Monthly stock returns, dividends, and prices are sourced from CRSP, and accounting information is sourced from the Quarterly and Annual Fundamental Files of the Compustat database. Lastly, all observations reporting monthly returns lower than -100% were deleted.

To avoid a possible look-ahead bias, the excess returns at the end of month m are aligned with the monthly-reported data at month $m - 1$, quarterly reported data at month $m - 3$ and annual-reported data at month $m - 12$. Subsequently, to maximise the usable sample data is expressed in monthly frequency by setting the quarterly-reported factors for month $m - 2$ and $m - 3$ to equal the factor value at $m - 1$. Similarly, the annually reported factor values are applied to the last 12 months.

To avoid any influences from extreme values, a winsorizing procedure is applied at the 1st and 99th percentile of the cross-sectional distribution at each monthly period. Subsequently, the values within the monthly cross-sectional distribution are standardized to a zero mean and unit standard deviation. This inherently induces the assumption that characteristic factors are independent and identically distributed random variables, nonetheless, given the diverse magnitudes of the different asset pricing factors a scaling scheme is inevitable. Missing values are then replaced by zero, which is the post-standardized monthly mean. This procedure forces the factors with a high percentage of missing data towards the mean and guarantees that statistically significant characteristics do not result from volatile values due to missing data.

A final consideration is to avoid the bias associated with the influence of micro capitalisation stocks or microcaps. Microcaps are defined as stocks with market capitalisation in the lower 20th percentile of the stock universe. These account for 60% of the total number of stocks, whereas they represent only a 3% of the aggregate market capitalisation. This is problematic for research designs employing equal-weighted returns since it disproportionately weights factors on the characteristics of the minor market capitalisation sample. To control and assess this bias two samples are tested. The first contains all stocks and is thus, is dominated by the influence of microcaps, while the second excludes stocks below the 20th percentile of the NYSE. This is the same data methodology employed by Green et al. (2017). The market capitalisation percentiles are sourced from Kenneth French's website.

4.3.2 Methodology

This study explores asset pricing using individual stocks as an alternative to the portfolio sorting approach. As discussed in the previous section, the individual stock setup is still not free from inference issues since, even after Shanken's (1992) correction for the EIV, the traditional two-pass estimator is invalid when the T dimension is not large. To quantify the empirical implications associated with the size of the time dimension this investigation compares the standard two-pass framework which is valid in the fixed- N , large- T ($t \rightarrow \infty$) case, with the asymptotically valid framework adjusting for the effects of short time windows, fixed- T , large- N ($n \rightarrow \infty$).

Model 1: Fixed- N , large- T ($t \rightarrow \infty$)

The first model applies the classic cross-sectional methodology, traditionally applied in financial research, whereby the time dimension is much greater than the cross-sectional dimension. The risk premium estimates are computed by the well-known formulation

$$\hat{\gamma} = (\hat{B}' \hat{B})^{-1} \hat{B}' \overline{R_t} \quad (4.13)$$

where $\hat{B} = \tilde{F}' (\tilde{F}' \tilde{F})^{-1} R_t$, $\tilde{F} = F - \mathbf{1}_T \bar{f}$, $\bar{f} = \frac{1}{T} \sum_1^T F$, $\overline{R_t} = \frac{1}{T} \sum_1^T R_t$, $\gamma_0 = 0$.

As discussed in section 4.3.2, the EIV issue is present in the standard error estimation in the $t \rightarrow \infty$ case since it is not diversified away through portfolio formation. To neutralise this problem the variance estimation is computed by the asymptotically consistent formulation of Shanken (1992)

$$\hat{V}_{\hat{F}} = \hat{\Sigma}_F + (1 + \hat{\gamma}' \hat{\Sigma}_F^{-1} \hat{\gamma}) \hat{A} \hat{\Sigma}_\varepsilon \hat{A}' \quad (4.14)$$

where $\hat{A} = (\hat{B}' \hat{B})^{-1} \hat{B}'$, $\hat{\Sigma}_F = E[(F - \bar{F})(F - \bar{F})']$, $\hat{\Sigma}_\varepsilon = \begin{cases} \hat{\sigma}_{ii} & i = j \\ 0 & i \neq j \end{cases}$

Given that the Shanken adjustment $\hat{\gamma}' \hat{\Sigma}_F^{-1} \hat{\gamma}$ is always positive, the estimate $\hat{V}_{\hat{F}}$ is larger than its unadjusted equivalent. It should be noted that this adjustment is proportional to the magnitudes of the risk premium estimates and inversely

proportional to the variability of the factors. Finally, the t -statistic for each coefficient is estimated as

$$t(\hat{\gamma}) = \frac{\hat{\gamma}}{\sqrt{\hat{V}_{\hat{\gamma}}}} \quad (4.15)$$

Model 2: Large- N , Fixed- T ($n \rightarrow \infty$)

When the time dimension does not diverge, one cannot estimate the risk premium $\hat{\gamma}$, given that the factor realisation $\bar{F} - E[F]$ cannot be estimated. Due to this, the ex-post risk premium quantity defined by Shanken (1992) is adopted

$$\hat{\gamma}_P = \hat{\gamma} + \bar{F} - E[F]$$

This quantity has certain attractive properties which constitute it the most suitable comparable to the risk premium estimates in equation 4.13. Specifically, it is an unbiased measure of the ex-ante risk premium $\hat{\gamma}$ and also, it can be estimated in a linear fashion i.e., by solving equation 4.9. Importantly, Shanken (1992) shows that in the limit $n \rightarrow \infty$ a bias adjustment, $\hat{\Lambda}$, is required for the valid estimation of risk premia, such that

$$\hat{\gamma}_P = (\hat{B}'\hat{B} - \hat{\Lambda})^{-1} \hat{B}' \bar{R}_t \quad (4.16)$$

where $\hat{\Lambda} = \frac{\bar{\sigma}^2}{T} \Sigma_F^{-1}$, $\bar{\sigma}^2 = \frac{1}{N} \sum_{i=1}^N \hat{\sigma}_{ii}^2$.

The variance of the $\hat{\gamma}_P$ estimator in the $n \rightarrow \infty$ case is derived by Raponi et al. (2020) as

$$\hat{V}_{\hat{\gamma}_P} = \hat{V} + (\hat{\Sigma}_B - \hat{\Lambda})^{-1} \hat{W} (\hat{\Sigma}_B - \hat{\Lambda})^{-1} \quad (4.17)$$

where $\hat{V} = \sigma^2/T \left[1 + \hat{\gamma}_P' \hat{\Sigma}_F^{-1} \hat{\gamma}_P \right] (\hat{\Sigma}_B - \hat{\Lambda})^{-1} \in K \times K$, $\hat{\Sigma}_B = \frac{1}{N} \hat{B}' \hat{B} \in K \times K$,

$$\hat{W} = \hat{Z}' \hat{U}_\varepsilon \hat{Z} \in K \times K, \quad \hat{Z} = \hat{Q} \otimes \hat{P} + \frac{\text{vec}(\hat{M})}{T-K-1} \hat{\gamma}_P' \hat{P}' \hat{P} \in T^2 \times K,$$

$$\hat{Q} = \frac{1_T}{T} - \hat{P} \hat{\gamma}_P \in T \times 1, \quad \hat{P} = \check{F}(\check{F}' \check{F})^{-1} \in T \times K$$

$$\hat{M} = \mathbf{I}_T - \hat{D}(\hat{D}' \hat{D})^{-1} \hat{D}' \in T \times T, \quad \hat{D} = [\mathbf{1}_T, F] \in T \times K + 1$$

$$\hat{\mathbf{U}}_{\varepsilon} = \begin{bmatrix} U_{11} & \cdots & U_{1t} & \cdots & U_{1T} \\ \vdots & \ddots & \vdots & \vdots & \vdots \\ U_{t1} & \cdots & U_{tt} & \cdots & U_{tT} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ U_{T1} & \cdots & U_{Tt} & \cdots & U_{TT} \end{bmatrix} \in T^2 \times T^2$$

$$\hat{\mathbf{U}}_{ii} = \begin{cases} \sigma_4, & i = j, i \neq t \\ 2\sigma_4 + k_4, & i = j = t \\ 0, & i \neq j \end{cases} = \begin{bmatrix} \sigma_4 & 0 & \cdots & 0 \\ 0 & \sigma_4 & 0 & 0 \\ \vdots & 0 & \ddots & 0 \\ 0 & 0 & 0 & 0 \\ 0 & \cdots & \cdots & 2\sigma_4 + k_4 \end{bmatrix} \in T \times T$$

$$\hat{\mathbf{U}}_{is} = \begin{cases} \sigma_4, & i = s, j = t \\ 0, & \text{otherwise} \end{cases} = \begin{bmatrix} 0 & 0 & \cdots & 0 \\ 0 & \ddots & 0 & 0 \\ \vdots & \vdots & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & \cdots & 0 & \sigma_4 \end{bmatrix} \in T \times T$$

$$\sigma_4 = \frac{\sum_1^T \sum_1^N \hat{\varepsilon}_{it}^4}{3N \operatorname{tr}(\hat{\mathbf{M}} \odot \hat{\mathbf{M}})}, \quad k_4 = 0 \quad \text{as per Raponi's et al. (2020).}$$

$\operatorname{vec}(\cdot)$, $\operatorname{tr}(\cdot)$, $\otimes$, $\odot$ denote the vectorization, trace, Kronecker and Hadamard operators, respectively and $\mathbf{I}_T$ is the identity matrix of dimensions $T \times T$. The subscripts i and j denote the row and column position, respectively. Finally, the t -statistic in the ex-post case can be estimated as

$$t(\hat{\mathbf{y}}_p) = \frac{\hat{\mathbf{y}}_p}{\sqrt{\hat{\mathbf{V}}_{\Gamma_P}}} \quad (4.18)$$

A few notes are in order. Equation 4.17 computes the variance of the ex-post estimator $\hat{\mathbf{y}}_p$ as a sum of two components. The first term, $\hat{\mathbf{V}}$, estimates the variance portion as if the error terms converged to zero i.e., this is the same variance calculated by equation 4.14 for the $t \rightarrow \infty$ model. This captures the variance of the classical two-pass regression via $\sigma^2 /_T \hat{\Sigma}_B^{-1}$ which is adjusted for the EIV by the term $\hat{\mathbf{y}}_p' \hat{\Sigma}_F^{-1} \hat{\mathbf{y}}_p$ and for the bias due to the fixed T by the

adjustment $\widehat{\Lambda}$. The second term, through the matrix $\widehat{W}$, adds the variance induced by the cross-sectional variability of the error terms, given that the error terms do not converge to zero unless $t \rightarrow \infty$.

The important implication and focal point of this chapter is that when the time dimension is allowed to diverge not only $\widehat{\Lambda} \rightarrow \mathbf{0}$, but also $\widehat{W} \rightarrow \mathbf{0}$ since the residual variances in $\widehat{U}_\varepsilon \rightarrow \mathbf{0}$ as $t \rightarrow \infty$. Thus, the variance $\widehat{V}_{\widehat{r}_p} \rightarrow \widehat{V}_{\widehat{r}}$ which is the variance of the classic cross-sectional regression of equation 4.14. On the other hand, when the time dimension is not allowed to diverge, such as in the application of rolling regression with fixed windows, there is a distinct and measurable difference between the asymptotically valid variance $\widehat{V}_{\widehat{r}_p}$ and the variance $\widehat{V}_{\widehat{r}}$ of the classic two-pass framework. Therefore, the comparison of models 1 and 2 at different levels of T may, arguably, reveal empirical implications with regard to the level at which the time dimension is large enough to guarantee the valid inference for risk premium measurement and for which time dimensions researchers should apply the fixed- T , large- N adjustments.

Considering that $\widehat{W} > \mathbf{0}$, always, implies that the variance $\widehat{V}_{\widehat{r}_p}$ is always greater than $\widehat{V}$. Moreover, since $\widehat{\Lambda} > \mathbf{0}$, always, implies that $\widehat{V}$ is greater than $\widehat{V}_{\widehat{r}}$, thus, $\widehat{V}_{\widehat{r}_p} > \widehat{V}_{\widehat{r}}$. This means that the standard errors are underestimated in the traditional two-pass regression when the time dimension is not sufficiently large, as it is suggested by Bai and Zhou (2015) and Raponi et al. (2020). Lastly, the ex-post risk premium $\widehat{\gamma}_p > \widehat{\gamma}$, always, due to $\widehat{\Lambda} > \mathbf{0}$ in equation 4.16, therefore, the large- T cross-sectional regression estimates will always underestimate the true risk premium as it is known from Shanken (1992). Since both the numerator and the denominator of the t -statistic increase when the effects of a fixed time window are considered, it is not clear whether the large- N statistic $t(\widehat{\gamma}_p)$ is expected to be larger or lower than its large- T counterpart, $t(\widehat{\gamma})$, a realisation which further motivates the investigation conducted herein.

Regression framework

As discussed, the divergence between the ex-post and ex-ante risk premia (equations 4.13 and 4.16, respectively), as well as their variances (equations 4.14 and 4.17), tends to zero as the time-series dimension gets large. However, when T is small the deviation between the measurements of models 1 and 2 may be substantial and significant. To investigate this effect the two models were run at increasing sizes of T via rolling regressions and the aggregate results were compared. This procedure is illustrated in Figure 4.1 below. When $T = 1$ the regression spans windows of 1 year and rolls forward through the sample, calculating the risk premia, their respective variances and the implied t -statistics according to models 1 and 2. Subsequently, the window is set to 2 years and the same rolling procedure is repeated until the window is as large as the entire time-series dimension, for which case one regression is run. Finally, for each T level the results are aggregated and the comparison between the two models is conducted, given that the only variable is the T dimension.

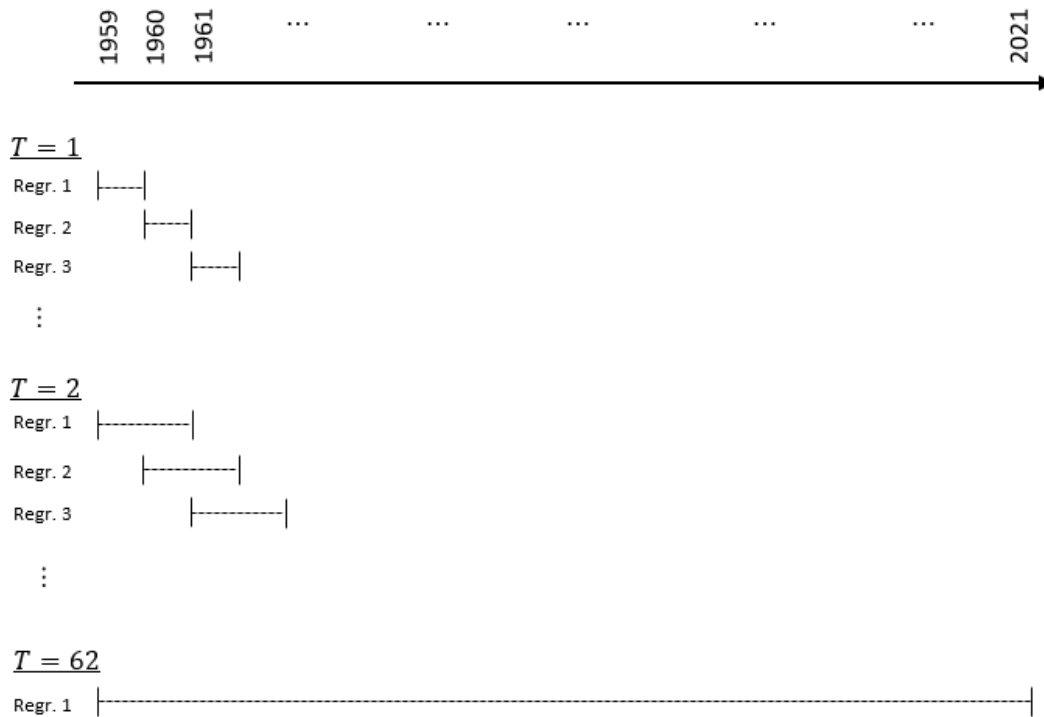


Figure 4.1: Rolling regression procedure

Hypothesis testing

By considering the large cross-section of expected returns and a large set of documented anomalies unlocks the possibility of quantifying the deviation between the ex-ante model 1 and ex-post model 2, whereby the implications regarding the inference of the two models can be statistically tested. The idea put forward in this chapter builds on two concepts. First, for each time window the t -statistics $t(\hat{\gamma})$ and $t(\hat{\gamma}_p)$, for each of the K factors, can be estimated for the ex-ante models 1 and 2, respectively. When a large number of factors are considered, the estimates $t(\hat{\gamma})$ and $t(\hat{\gamma}_p)$ are distributed fairly randomly and uniformly above and below zero, potentially with fat tails¹². Second, the deviation between the estimates $t(\hat{\gamma})$ and $t(\hat{\gamma}_p)$ converges to zero as the time-series dimension increases, given that the ex-post risk premia converge to their ex-ante values, as proved by Shanken (1992), and the ex-post variances converge to their ex-ante values, as proved by Raponi et al. (2020).

The implication of the first concept is that at each time window it is expected that an equal number of factors exhibit t -statistics above and below zero, while the magnitudes of positive and negative values are comparable thus, $E[t(\hat{\gamma})] = E[t(\hat{\gamma}_p)] = 0$. The implication of the second concept is that the magnitude of the divergence¹³ between the two measures $|t(\hat{\gamma}_p) - t(\hat{\gamma})|$ is greater at small T , and tends to zero as T increases. Taking these two implications together, it can be deduced that while the means of the collection of t -statistics are zero at any given time window, the variances of their distributions, $var[t(\hat{\gamma})]$ and $var[t(\hat{\gamma}_p)]$, are equal only when T is large¹⁴. Therefore, the test for the equality of variances becomes the natural test to examine at which levels the time dimension, is small enough to induce statistically significant deviation between models 1 and 2. In layman's terms the question is at what time windows researchers should apply the ex-post model 2

¹² As they are previously identified asset pricing factors after all.

¹³ The magnitude of the divergence is used instead of just the divergence because the t -statistics can have positive or negative values, therefore, the sum of the paired differences is expected to be zero. For this reason, the hypothesis is developed as the test of equality of variances.

¹⁴ Note that this does not discuss about the variance of the risk premia but the variance of the generated t -statistics. The implication discussed is that they follow a normal distribution with fat tails.

due to the inference of the classic two-pass regression being rendered invalid by the effects of small T . Given this discussion, the hypothesis test at each T is formulated as:

$$H_0: \text{var}[t(\hat{\gamma})] = \text{var}[t(\hat{\gamma}_p)] \quad (H1)$$

$$H_A: \text{var}[t(\hat{\gamma})] \neq \text{var}[t(\hat{\gamma}_p)]$$

There are two important considerations for testing the hypothesis $H1$. First, the variables $t(\hat{\gamma})$ and $t(\hat{\gamma}_p)$ are not independent but are, in fact, highly correlated. This is not surprising given that $t(\hat{\gamma}_p)$ is estimated by the ex-post risk premia $\hat{\gamma}_p$ and their variance $\hat{V}_{\hat{\gamma}_p}$, which are essentially derived by imposing adjustments on the ex-ante premia $\hat{\gamma}$ and variance $\hat{V}_{\hat{\gamma}}$, which are the elements in the estimation of $t(\hat{\gamma})$. Given the correlation of tested variables, the Pitman (1939)-Morgan (1939) test is adopted as the most appropriate to test the variance equality hypothesis, given that an F -test would be invalid in this configuration.

The second consideration is that the t -values $t(\hat{\gamma})$ and $t(\hat{\gamma}_p)$ are likely to be distributed with fat tails with the tail values exhibiting high magnitudes, given that the factors considered are documented anomalies. This implies that these tail values might be more strongly affected by the application of the ex-post framework than centre values. In consequence, heteroskedasticity is expected to be present. Given this fact, the Wilcox (2020) extension of the Pitman-Morgan test is the most appropriate test, whereby the heteroskedasticity-consistent estimator HC4 of Cribari-Neto (2004) is extended to test the hypothesis $H1$.

Let $U = t(\hat{\gamma}) + t(\hat{\gamma}_p)$ and $V = t(\hat{\gamma}_p) - t(\hat{\gamma}_p)$, the hypothesis framework above is equivalent to testing the slope of the regression of the standardized vectors U against V , as per Wilcox (2020), such that

$$H_0: b_1 = 0$$

$$H_A: b_1 \neq 0$$

whereby the confidence interval of b_1 is computed by the heteroskedasticity-consistent standard error S_1 from the estimator S

$$\mathbf{S} = \begin{pmatrix} S_0 & 0 \\ 0 & S_1 \end{pmatrix} = \mathbf{A}\mathbf{U}'diag\left[\frac{\mathbf{e}_i^2}{(1 - \mathbf{h}_{ii})^{\delta_i}}\right]\mathbf{U}\mathbf{A} \quad (4.19)$$

where $\mathbf{A} = (\mathbf{U}'\mathbf{U})^{-1}$, $\mathbf{e}_i = \mathbf{V} - b_1\mathbf{U}$, $\mathbf{h}_{ii} = diag(\mathbf{H})$, $\bar{h}_{ii} = \frac{1}{K} \sum \mathbf{h}_{ii}$,

$\mathbf{H} = \mathbf{U}(\mathbf{U}'\mathbf{U})^{-1}\mathbf{U}$, $\delta_i = \min\left\{4, \frac{\mathbf{h}_{ii}}{\bar{h}_{ii}}\right\}$ and $diag(\cdot)$ is the diagonal operator. The confidence interval for the hypothesis test is

$$b_1 \pm tS_1$$

where t is the $1 - \alpha$ quantile of Student's t distribution with $K - 2$ degrees of freedom. It should also be noted that the exponent δ_i serves as a discounting factor for the i -th observation and thereby, tackling the heteroskedasticity issue which might be substantial. What is more, the use of an HC4-type estimator shields against possible inference issues due to sampling from a heavy-tailed distribution. This is arguably a crucial issue given the evidence in Mudholkar et al. (2003) who establish that with such distribution the probability of Type I error exceeds the nominal level when using the traditional Pitman-Morgan test.

The above hypothesis testing framework can also serve as a test for the microcap bias. Even though Green et al. (2017) and Hou et al. (2020) provide unequivocal evidence for the existence and effects of this bias, their analysis is restricted to counting the number of anomalies before and after removing microcaps. Given the statistical test developed above, the set of t -statistics for the microcap dominated sample, $\mathbf{t}(\hat{\mathbf{y}}_M)$, can be effectively compared with the respective statistics of the microcap-free sample $\mathbf{t}(\hat{\mathbf{y}}_{MF})$, which removes the stocks in the lowest 20th percentile of market capitalisation. Hypotheses 2 and 3 test the above for the ex-ante and the ex-post specifications, respectively, as

$$\mathbf{H}_0: var[\mathbf{t}(\hat{\mathbf{y}}_M)] = var[\mathbf{t}(\hat{\mathbf{y}}_{MF})] \quad (H2)$$

$$\mathbf{H}_A: var[\mathbf{t}(\hat{\mathbf{y}}_M)] \neq var[\mathbf{t}(\hat{\mathbf{y}}_{MF})]$$

$$\mathbf{H}_0: var[\mathbf{t}(\hat{\mathbf{y}}_{p_M})] = var[\mathbf{t}(\hat{\mathbf{y}}_{p_{MF}})] \quad (H3)$$

$$\mathbf{H}_A: var[\mathbf{t}(\hat{\mathbf{y}}_{p_M})] \neq var[\mathbf{t}(\hat{\mathbf{y}}_{p_{MF}})]$$

For all hypotheses, testing was performed at each time window for which one t -statistic is computed. A rejection of the null of $H1$ implies that the divergence between the ex-ante (large- T) specification and ex-post (large- N) specification is not only substantial, but also, statistically significant at a given value of T . Hence, the time window should be considered short enough to cause invalid inference if the classic two-pass regression is applied. Similarly, if the nulls of $H2$ and $H3$ are rejected it will provide support for the microcap bias evidence of Green et al. (2017) and Hou et al. (2020), but within a statistical confidence level. Considering the results from the three hypotheses in conjunction is expected to shed light to whether the microcap bias is an influential driver of anomalies or whether the two-pass procedure is erroneously applied when the time series dimension is not large enough.

4.4 Results

4.4.1 Effects due to the ex-post framework¹⁵

Effects on the t-statistic

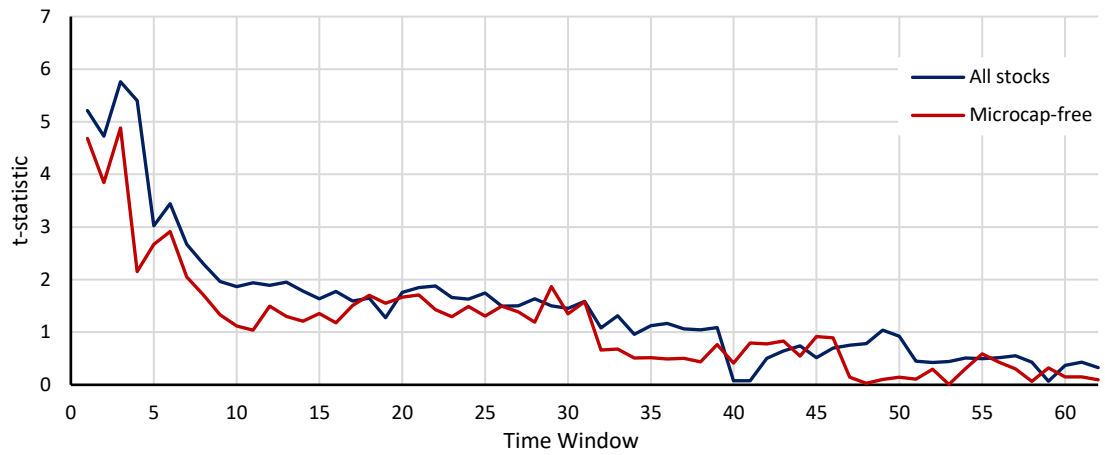


Figure 4.2: Pitman-Morgan test Ex-ante vs. Ex-post, Univariate setup

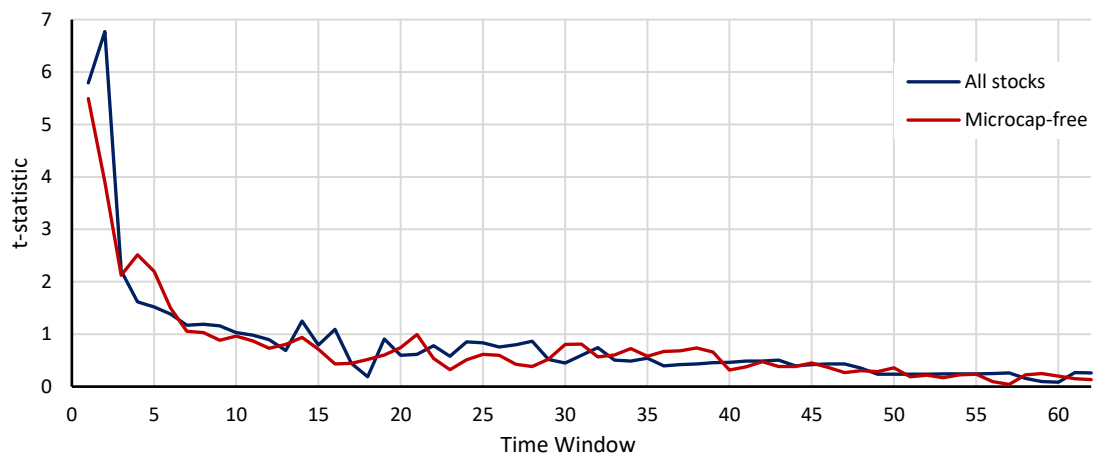


Figure 4.3: Pitman-Morgan test Ex-ante vs. Ex-post, Multivariate setup

¹⁵ In all experiments, results were trimmed at the 90% as to eliminate the top 5% and bottom 5% of extreme values prior to performing the statistical tests. This decision was due to extreme t-values arising in short samples which consequently affected the final measure of the mean t-value.

Figures 4.2 and 4.3 present the results of the Pitman-Morgan test as applied in Hypothesis 1, which examines how the distribution of t -values arising from the ex-ante framework is affected by the application of the ex-post framework, as described by equations 4.16 and 4.17. The top figure illustrates the results of the univariate regression and shows that at short time windows, there is statistically significant impact due to the application of the large- N framework. Specifically, the figure exhibits a significant shift in the cross-section of t -statistics for windows ranging from 1-10 years in the all-stocks sample (blue line). This implies that empirical research using univariate regressions should consider the large- N , fixed- T framework when using time dimensions less than 10 years. This is due to the fact that the statistical significance of the Pitman-Morgan test implies that the variance of the collection of 78 t -values declines upon the application of the ex-post model. Therefore, it can be concluded that at these time levels the asymptotically adjusted model is required to guarantee the valid inference of the two-pass regression.

In comparison, the microcap-free sample yields statistically significant deviation only up to the 7 years mark. This implies that the anomalies' patterns are less volatile when microcaps are excluded which diminishes the overall deviation between the ex-ante and ex-post models faster. Figure 4.2 also indicates that the t -statistics of the factors remain generally unequal until the time window diverges to over 40 and 32 years, for the all-stock and microcap-free samples respectively. Nevertheless, this difference is not statistically significant. Finally, beyond the 40- and 32-year windows the two frameworks yield equivalent inference as the Pitman-Morgan test results are close to zero. This implies that the bias term $\hat{\Lambda}$ and the $\hat{W}$ term converged to zero as the theory expects and thus, the ex-post estimator reduced to the standard OLS estimator of equations 4.6 and 4.10.

Figure 4.3 illustrates the results of the multivariate setup and shows that the ex-ante and ex-post frameworks generally exhibit no inference differences. In this setup, both the all-stocks and microcap-free samples show a Pitman-Morgan t -statistic close to zero for any time window beyond the 5-year mark. This indicates that the distribution of t -values generated by the set of factors is largely unchanged by the application of the ex-post framework. A possible reason for this pattern is that both the coefficients and standard errors exhibit

lower volatility in the multivariate setup. On the contrary, the 1–5-year window in Figure 4.3 shows a distinct divergence between the two frameworks. This might be due to the fact that a lot of factors report null values when the research focuses on the multivariate case of such short time frame. The exclusion of the null values before conducting the regression¹⁶ makes the measurement of the short time window volatile.

Effects on the parameters

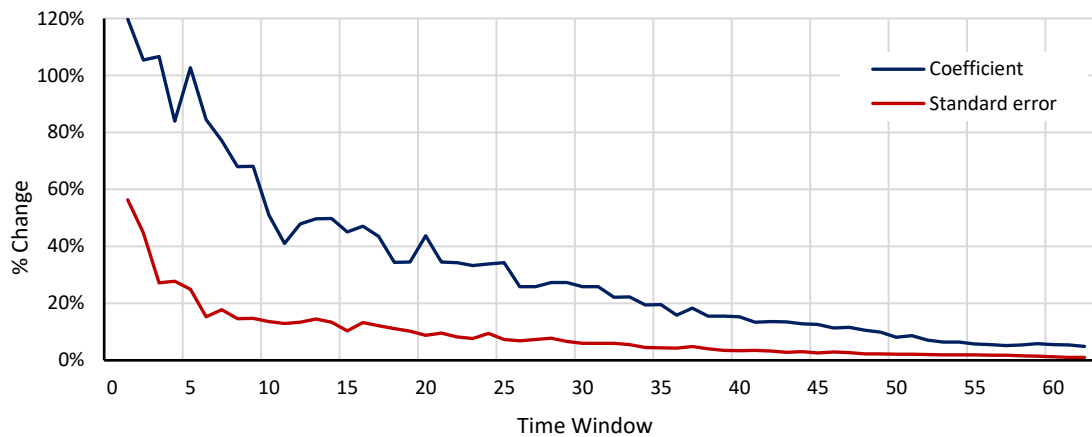


Figure 4.4: % Difference Ex-post vs. Ex-ante, Univariate setup, all stocks sample

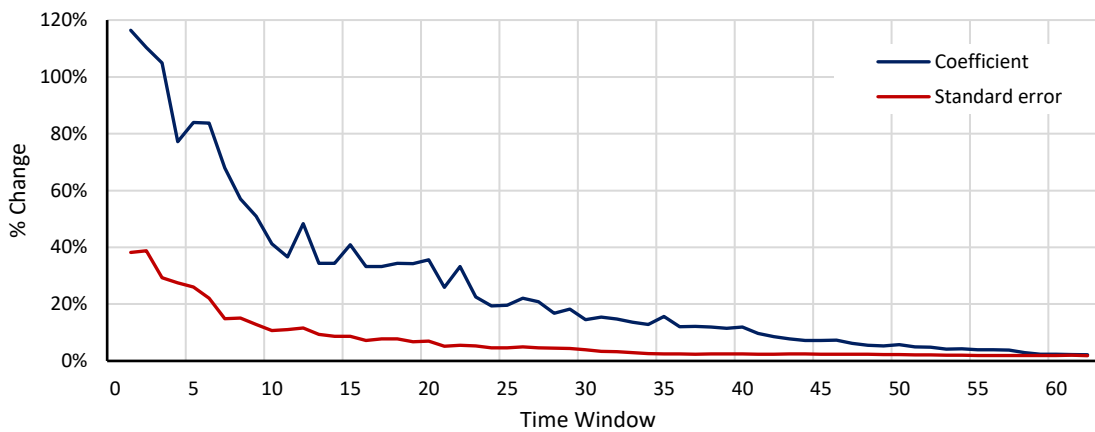


Figure 4.5: % Difference Ex-post vs. Ex-ante, Univariate setup, microcap-free sample

¹⁶ It is reminded that by the methodology the null values are replaced by the cross-sectional average value of zero. At very short time frames of the multivariate setup, however, there are rows in which all factors report null values and are thus, discarded before the regression. This leaves very few observations in the depended variable and makes the measurement volatile. In Green et al. (2017), the missing values issue is noted when discussing the multivariate regression, nonetheless, it does not constitute a problem in their methodology due to the large time windows used.

Figures 4.4 to 4.7 present how the risk premium coefficients and standard errors are affected by the application of the large- N model and provide further insights for the results in figures 4.2 and 4.3 which evaluated the t -statistic. Figures 4.4 and 4.5 report the results for the univariate setup for the all-stocks and microcap-free samples, respectively. These illustrate that the coefficients are strongly affected by the ex-post model which implies that the bias term is substantial, especially at short time windows. On the contrary, the effect of the large- N framework affects the standard errors more mildly which can be seen by comparing the blue and red lines. Interestingly, the impact on the standard errors is not only smaller but also drops to zero faster than the impact on the risk premia. The implication is that the impact of the bias term, $\hat{\Lambda}$, in the risk premium measurement, as expressed in equation 4.16, is the leading driver of the relationships identified in section 4.1.1, i.e., the ex-post t -values are smaller in magnitude due to the numerator (coefficient) being more strongly affected than the denominator (standard error).

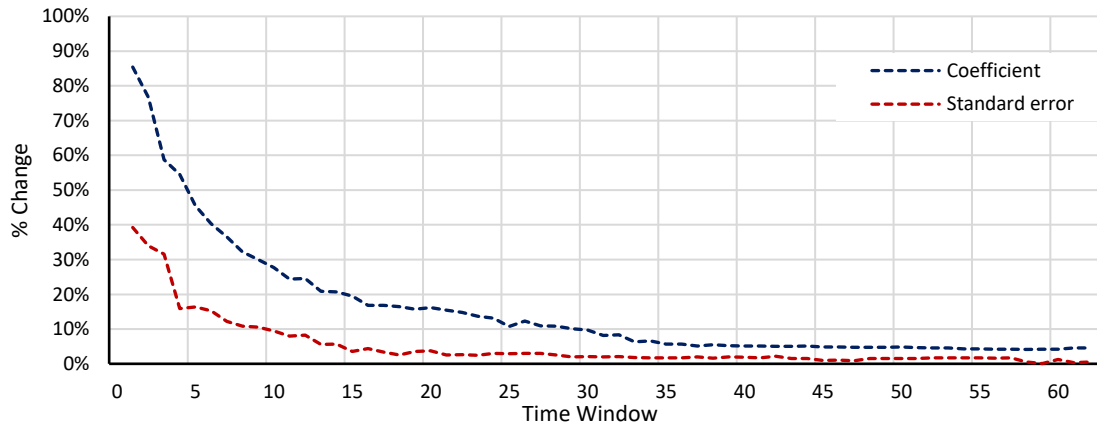


Figure 4.6: % Difference Ex-post vs. Ex-ante, Multivariate setup, all stocks sample

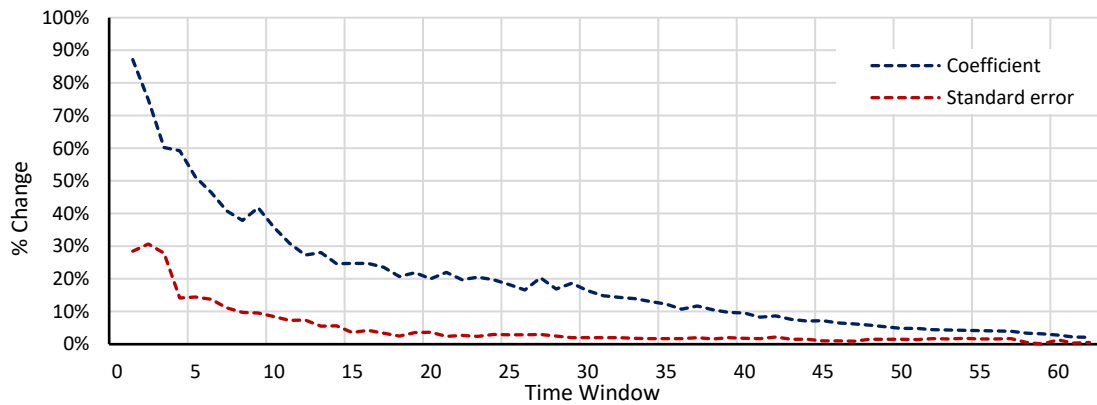


Figure 4.7: % Difference Ex-post vs. Ex-ante, Multivariate setup, microcap-free sample

Figures 4.6 and 4.7 show the results for the multivariate setup. The patterns revealed are equivalent to those of the univariate setup, but in the multivariate case the impact of the ex-post framework seems to be less severe. Comparing Figure 4.4 with 4.6 (all stocks sample) and Figure 4.5 with 4.7 (microcap-free sample) yields the observation that the percentage change of both coefficients and standard errors is lower in the multivariate setup for any given level of T . For example, when the all-stocks sample is used it takes a time window $T = 35$ years for the coefficients to be less than 20% impacted in the univariate setup (Figure 4.4), whereas the 20% level is achieved as fast as $T = 15$ years in the multivariate setup (Figure 4.6). Given this observation the results presented by Figure 4.3 are seen in a richer context and specifically, it can be understood that the large- N model does not significantly affect the inference in the multivariate setup due to both the coefficients and standard errors being less impacted across the time dimension.

The most discernible pattern in all four figures is how the impact of the ex-post model decays with time. This implies that both the bias term, $\hat{\mathbf{A}}$, and the $\hat{\mathbf{W}}$ term converged sufficiently to zero and thus, have insignificant effect on the risk premium estimation reported in section 4.1.1. The implication is that as the time dimension increases, the error-in-variables disappears, and the classic two-pass procedure described by the ex-ante model becomes an unbiased estimator for the risk premium measurement. When the T dimension is small, however, there is a distinct difference between the results obtained by the ex-ante and ex-post models, particularly for the risk premium coefficients.

These findings expand the evidence of Raponi et al. (2020) who reported the risk premia in the cases of $T = 36$ and $T = 120$ months for 2, 5 and 6 factor cases. Specifically, their results show that the percentage difference in risk premia due to the application of the ex-post framework declines when the time window increases. The results presented in figures 4.4 to 4.7 present a richer picture for this pattern by not only considering two specific time dimensions but measure the discrepancy between the two models across the whole spectrum of T . Based on this, it was possible to study how and when the deviation between the models converges to zero, which was not investigated in Raponi et al. (2020). Additionally, evidence in Raponi et al. (2020) indicate that the average

percentage difference between the ex-ante and ex-post models decreases when the number of factors in the regression is increased. This pattern is also seen in brighter light by figures 4.6 and 4.7 which illustrate that the deviation between the models becomes less volatile in the multivariate case.

Bai and Zhou (2015) use a simulation approach to compute the risk premia in the case of $T = 60$ and $T = 120$ months for the univariate setup and from these they calculate the error between the computed and real coefficient values. They find that in the $T = 60$ case, the ex-ante model yields an impressive error in the range of 20%, whereas the ex-post model yields an error in the range of only 5%. When the time dimension is increased to $T = 120$, the error for the ex-ante model drops to 12% and for the ex-post model drops to 2%. Of course, in the empirical realm one does not have real values for the coefficients, nonetheless, the evidence by Bai and Zhou (2015) is still suggestive that the increase in the time dimension leads to substantial improvements for the measurement of risk premia and that the ex-post framework is more impactful at smaller levels of T . Both patterns concur with the findings in this chapter.

Going further, the simulation evidence indicates that the percentage change after the application of the ex-post framework is in the range of 20% for the coefficients in the $T = 60$ case and 11% in the $T = 120$ case. On the contrary, the results of Figure 4.4 show that the change due to the ex-post adjustment is more severe in the empirical evidence and lies at 84% and 51% for the $T = 60$ and $T = 120$ levels, respectively. This is due to the use of factors derived from the real data of individual stocks which are more volatile than the factors generated in the simulation of Bai and Zhou (2015).

On the other hand, Raponi et al. (2020) used the Fama and French (1993) market factor and the Pástor and Stambaugh (2003) liquidity factor and found evidence closer to those in figures 4.6 and 4.7. Specifically, they reported that the market factor is impacted by as much as 64.3% in the $T = 36$ level and 27.2% in the $T = 120$ level, while the liquidity factor is impacted by 41.3% and 54.2%, respectively. Again, it should be noted that factors derived by individual stocks are more volatile than factors derived by portfolio sorts, such as those used by Raponi et al. (2020). Nonetheless, their evidence is along the same lines with figures 4.6 and 4.7.

When the standard errors are compared, the simulation evidence exhibit changes of 15% and 9% for the $T = 60$ and $T = 120$ levels, respectively, whereas the empirical evidence in Figure 4.4 report changes of 24% and 14%, respectively. While the simulation evidence of Bai and Zhou (2015) suggest similar patterns as those reported in the empirical study herein, the empirical evidence is evidently more severe, specifically, when the coefficients are considered.

4.4.2 Full period regression results

Univariate regression																
Factor	All Stocks								Microcap-free							
	Ex-ante			Ex-post			Ex-post with W		Ex-ante			Ex-post			Ex-post with W	
	Coeff	SE	t-stat	Coeff	SE	t-stat	SE	t-stat	Coeff	SE	t-stat	Coeff	SE	t-stat	SE	t-stat
absacc	-0.04	0.036	-1.202	-0.05	0.037	-1.239	0.037	-1.239	-0.03	0.081	-0.423	-0.04	0.082	-0.446	0.084	-0.438
acc	-0.05	0.053	-0.897	-0.05	0.054	-0.925	0.054	-0.925	-0.05	0.098	-0.540	-0.06	0.101	-0.570	0.101	-0.570
aeavol	-0.05	0.054	-0.848	-0.05	0.055	-0.858	0.055	-0.858	-0.00	0.007	-0.448	-0.00	0.007	-0.469	0.007	-0.469
agr	-0.30	0.059	-5.116	-0.31	0.059	-5.255	0.059	-5.256	-0.22	0.052	-4.120	-0.22	0.053	-4.211	0.053	-4.211
baspread	0.11	0.201	0.538	0.11	0.201	0.544	0.201	0.544	-0.15	0.184	-0.794	-0.15	0.187	-0.825	0.189	-0.814
beta	0.14	0.226	0.605	0.14	0.229	0.620	0.229	0.620	0.12	0.229	0.529	0.13	0.231	0.543	0.231	0.543
bm	0.25	0.04	6.119	0.26	0.041	6.341	0.041	6.341	0.14	0.055	2.540	0.15	0.056	2.633	0.056	2.633
bm_ia	-0.01	0.026	-0.472	-0.01	0.026	-0.480	0.026	-0.480	-0.04	0.050	-0.878	-0.04	0.050	-0.888	0.050	-0.884
cash	0.11	0.360	0.312	0.12	0.367	0.330	0.367	0.330	-0.04	0.523	-0.069	-0.04	0.528	-0.071	0.528	-0.071
cashdebt	0.02	0.024	0.960	0.02	0.024	0.984	0.024	0.984	-0.07	0.078	-0.918	-0.08	0.079	-0.949	0.079	-0.949
cashpr	-0.08	0.021	-4.067	-0.09	0.021	-4.209	0.021	-4.209	-0.09	0.046	-2.081	-0.10	0.046	-2.106	0.046	-2.106
cfp	0.11	0.194	0.551	0.11	0.196	0.567	0.196	0.567	0.09	0.077	1.196	0.10	0.079	1.284	0.079	1.284
cfp_ia	0.07	0.136	0.525	0.07	0.138	0.543	0.138	0.543	-0.00	0.003	-0.332	-0.00	0.003	-0.340	0.003	-0.340
chatoia	0.08	0.032	2.650	0.09	0.032	2.697	0.032	2.697	0.08	0.036	2.214	0.08	0.036	2.246	0.036	2.246
chcsho	-0.15	0.026	-6.010	-0.16	0.026	-6.162	0.026	-6.162	-0.13	0.041	-3.131	-0.13	0.041	-3.170	0.041	-3.170
chempia	-0.03	0.009	-3.148	-0.03	0.009	-3.209	0.009	-3.209	-0.02	0.009	-2.128	-0.02	0.009	-2.161	0.009	-2.161
chinv	-0.30	0.082	-3.663	-0.31	0.083	-3.770	0.083	-3.770	-0.16	0.067	-2.380	-0.17	0.067	-2.456	0.068	-2.430
chmom	-0.35	0.099	-3.570	-0.36	0.101	-3.558	0.102	-3.518	-0.27	0.197	-1.385	-0.28	0.199	-1.396	0.211	-1.319
chpmia	0.02	0.067	0.284	0.02	0.068	0.295	0.068	0.295	0.02	0.100	0.021	0.02	1.013	0.022	1.013	0.022
chtx	0.10	0.026	3.840	0.11	0.028	3.909	0.026	4.109	0.06	0.030	1.825	0.06	0.031	1.893	0.031	1.893
cinvest	-0.03	0.040	-0.691	-0.03	0.041	-0.735	0.041	-0.736	-0.04	0.032	-1.250	-0.04	0.033	-1.311	0.033	-1.311
currat	0.01	0.449	0.030	0.01	0.456	0.031	0.456	0.031	-0.06	0.032	-1.766	-0.06	0.032	-1.841	0.032	-1.841

depr	-0.01	0.01	-1.129	-0.01	0.01	-1.177	0.01	-1.177	-0.03	0.160	-0.159	-0.03	0.161	-0.163	0.161	-0.163
dy	-0.05	0.041	-1.153	-0.05	0.041	-1.192	0.041	-1.192	0.01	0.029	0.413	0.01	0.029	0.418	0.029	0.418
ear	0.12	0.026	4.454	0.12	0.027	4.491	0.027	4.491	0.09	0.029	3.099	0.09	0.030	3.189	0.030	3.190
egr	-0.11	0.031	-3.546	-0.11	0.031	-3.645	0.031	-3.645	-0.09	0.029	-3.141	-0.10	0.032	-3.216	0.030	-3.174
ep	-0.00	0.019	-0.173	-0.00	0.019	-0.180	0.019	-0.180	-0.01	0.045	-0.193	-0.01	0.046	-0.201	0.046	-0.201
gma	-0.05	0.062	-0.867	-0.06	0.062	-0.888	0.062	-0.888	-0.04	0.081	-0.516	-0.04	0.082	-0.525	0.082	-0.525
grcapx	-0.09	0.023	-3.820	-0.09	0.023	-3.967	0.023	-3.968	-0.05	0.019	-2.805	-0.06	0.019	-2.965	0.020	-2.911
grltnoa	-0.14	0.034	-4.229	-0.15	0.034	-4.434	0.034	-4.434	-0.12	0.031	-3.736	-0.13	0.032	-3.952	0.032	-3.953
herf	-0.00	0.001	-0.450	-0.00	0.001	-0.457	0.001	-0.457	-0.00	0.003	-0.338	-0.00	0.003	-0.342	0.003	-0.340
hire	-0.01	0.006	-1.477	-0.01	0.006	-1.531	0.006	-1.531	-0.01	0.012	-1.190	-0.01	0.012	-1.210	0.012	-1.210
idiovol	-0.04	0.037	-0.987	-0.04	0.037	-1.014	0.037	-1.014	0.01	0.025	0.599	0.02	0.025	0.639	0.025	0.639
ill	0.26	0.079	3.335	0.27	0.08	3.448	0.080	3.448	0.03	0.016	1.832	0.03	0.016	1.870	0.016	1.870
indmom	0.14	0.045	3.185	0.15	0.045	3.207	0.045	3.207	0.10	0.073	1.430	0.11	0.074	1.438	0.074	1.438
invest	-0.20	0.043	-4.656	-0.21	0.044	-4.796	0.044	-4.796	-0.15	0.049	-3.104	-0.16	0.049	-3.182	0.049	-3.182
lev	-0.04	0.049	-0.732	-0.04	0.05	-0.757	0.050	-0.757	0.00	0.006	0.715	0.00	0.006	0.722	0.006	0.722
mom12m	0.18	0.089	2.033	0.18	0.09	2.060	0.090	2.060	0.10	0.050	1.955	0.10	0.050	1.975	0.050	1.975
mom1m	-0.40	0.073	-5.404	-0.41	0.077	-5.336	0.077	-5.336	-0.25	0.067	-3.787	-0.27	0.07	-3.806	0.073	-3.639
mom36m	-0.19	0.100	-1.891	-0.19	0.102	-1.914	0.102	-1.914	-0.16	0.082	-1.912	-0.16	0.083	-1.914	0.083	-1.914
ms	-0.09	0.101	-0.892	-0.10	0.103	-0.940	0.103	-0.940	-0.07	0.081	-0.855	-0.07	0.082	-0.873	0.082	-0.873
mve_ia	0.02	0.107	0.203	0.02	0.107	0.206	0.107	0.206	0.03	0.087	0.311	0.03	0.087	0.313	0.087	0.313
mvel1	-0.04	0.007	-5.580	-0.04	0.007	-5.701	0.007	-5.701	-0.02	0.008	-2.806	-0.02	0.008	-2.827	0.008	-2.827
nincr	0.01	0.009	1.228	0.01	0.009	1.297	0.009	1.297	0.01	0.01	1.264	0.01	0.010	1.286	0.010	1.279
operprof	0.05	0.015	3.394	0.05	0.015	3.483	0.015	3.483	0.02	0.01	2.343	0.02	0.010	2.397	0.010	2.397
orgcap	0.04	0.023	1.631	0.04	0.023	1.681	0.023	1.681	0.03	0.021	1.586	0.04	0.023	1.615	0.023	1.615
pchcapx_ia	0.00	0.001	0.101	0.00	0.001	0.105	0.001	0.105	0.00	0.004	0.113	0.00	0.004	0.117	0.005	0.116
pchcurrat	-0.06	0.058	-1.110	-0.07	0.058	-1.148	0.058	-1.148	-0.07	0.056	-1.202	-0.07	0.057	-1.254	0.057	-1.254
pchdepr	-0.01	0.100	-0.142	-0.01	0.101	-0.148	0.101	-0.148	0.00	0.048	0.084	0.00	0.049	0.088	0.049	0.088
pchgm_pchsale	0.06	0.023	2.374	0.06	0.024	2.442	0.024	2.443	0.05	0.024	2.079	0.05	0.024	2.146	0.024	2.124

pchsale_pchinvt	0.13	0.063	2.023	0.13	0.064	2.098	0.064	2.098	0.11	0.057	1.839	0.11	0.058	1.893	0.058	1.893
pchsale_pchrect	0.06	0.020	2.764	0.06	0.021	2.859	0.021	2.859	0.03	0.019	1.747	0.03	0.019	1.819	0.019	1.790
pchsale_pchxsga	-0.03	0.017	-1.922	-0.03	0.017	-1.996	0.017	-1.996	-0.03	0.015	-1.854	-0.03	0.015	-1.954	0.015	-1.954
pchsaleinv	0.04	0.025	1.708	0.04	0.025	1.783	0.025	1.783	0.05	0.027	1.782	0.05	0.027	1.850	0.027	1.850
pctacc	-0.09	0.028	-3.230	-0.09	0.028	-3.315	0.028	-3.315	-0.04	0.025	-1.778	-0.05	0.025	-1.851	0.025	-1.851
ps	0.11	0.080	1.348	0.11	0.081	1.382	0.081	1.382	0.07	0.087	0.822	0.07	0.088	0.836	0.088	0.836
rd_mve	0.21	0.094	2.205	0.22	0.095	2.316	0.095	2.316	0.12	0.093	1.268	0.13	0.096	1.392	0.048	2.784
rd_sale	-0.01	0.028	-0.422	-0.01	0.028	-0.445	0.028	-0.445	-0.01	0.019	-0.593	-0.01	0.02	-0.656	0.02	-0.656
realestate	0.01	0.046	0.110	0.01	0.047	0.118	0.047	0.118	0.01	0.050	0.118	0.01	0.053	0.139	0.053	0.139
retvol	-0.15	0.060	-2.471	-0.15	0.061	-2.498	0.061	-2.498	-0.10	0.052	-1.988	-0.11	0.052	-2.040	0.053	-2.022
roaq	0.20	0.106	1.887	0.22	0.109	2.019	0.109	2.019	0.20	0.111	1.794	0.21	0.11	1.887	0.112	1.855
roavol	-0.01	0.017	-0.452	-0.01	0.018	-0.506	0.018	-0.506	-0.01	0.023	-0.332	-0.01	0.024	-0.351	0.024	-0.351
roeq	0.18	0.076	2.380	0.19	0.077	2.524	0.077	2.524	0.14	0.063	2.150	0.14	0.064	2.238	0.064	2.238
roic	0.03	0.082	0.424	0.04	0.082	0.434	0.082	0.434	0.06	0.090	0.650	0.06	0.091	0.671	0.092	0.664
rsup	0.00	0.032	0.114	0.00	0.033	0.121	0.033	0.121	0.01	0.053	0.111	0.01	0.054	0.117	0.054	0.117
salecash	0.00	0.033	0.107	0.00	0.033	0.11	0.033	0.110	0.00	0.028	0.059	0.00	0.028	0.060	0.028	0.060
saleinv	0.04	0.039	0.960	0.04	0.04	0.997	0.040	0.997	0.02	0.038	0.591	0.02	0.039	0.601	0.039	0.598
salerec	0.04	0.057	0.740	0.04	0.058	0.769	0.058	0.769	0.06	0.061	0.959	0.06	0.061	0.979	0.061	0.979
secured	0.00	0.005	0.528	0.00	0.005	-0.585	0.005	-0.585	0.02	0.045	0.493	0.02	0.037	0.602	0.743	0.030
sgr	-0.18	0.047	-3.795	-0.19	0.048	-3.905	0.048	-3.905	-0.11	0.053	-2.014	-0.11	0.054	-2.074	0.054	-2.074
sp	0.25	0.07	3.629	0.26	0.070	3.757	0.070	3.757	0.17	0.059	2.817	0.17	0.060	2.898	0.060	2.898
std_dolvol	0.17	0.049	3.472	0.18	0.050	3.575	0.050	3.575	0.14	0.045	3.132	0.14	0.046	3.169	0.046	3.124
std_turn	-0.11	0.041	-2.661	-0.11	0.042	-2.735	0.042	-2.735	-0.07	0.037	-1.86	-0.07	0.037	-1.885	0.037	-1.885
stdcf	-0.03	0.02	-1.454	-0.03	0.021	-1.656	0.021	-1.656	-0.00	0.001	-1.39	0.00	0.001	1.537	0.001	1.537
tang	-0.00	0.001	-0.665	-0.00	0.001	-0.694	0.001	-0.694	-0.00	0.031	-0.138	-0.00	0.031	-0.142	0.031	-0.142
tb	0.00	0.071	0.757	0.00	0.007	0.776	0.007	0.776	0.00	0.007	0.718	0.00	0.007	0.752	0.007	0.752
turn	-0.30	0.085	-3.571	-0.32	0.086	-3.682	0.086	-3.682	-0.16	0.104	-1.566	-0.17	0.104	-1.585	0.105	-1.579
zerotrade	-0.09	0.032	-2.760	-0.09	0.032	-2.791	0.032	-2.791	-0.06	0.032	-1.813	-0.06	0.033	-1.933	0.033	-1.933

Table 4.1: Univariate regression results for full sample period

This table presents the results of the cross-sectional regressions of monthly stock returns on the 78 characteristics individually in univariate regressions. The left-hand side panel presents the results of the sample containing all stocks, whereas the right-hand side panel presents the results of the sample which excludes microcaps. In each panel three sets of results are shown; A) the ex-ante results which models the classic Fama MacBeth regression, B) the regression in A after considering the bias arising from the finite time dimension of the sample and C) the regression in B after considering the effect of the W matrix arising due to the error terms not diverging to zero in finite time dimensions. Monthly returns for month t are regressed against the previous month characteristics, $t-1$. The data spans the period December 1959 to December 2021. The sample contains all stocks on the NYSE, AMEX and NASDAQ. Missing values are replaced by zeros which is the cross-sectional average after standardizing the characteristics at each period. Microcaps are defined as the stocks with market capitalisation in the lower 20th percentile of the stocks of the NYSE. This was sourced by Kenneth French website. FM coefficients are in % and t-statistics are computed with the Newey-West adjustment of 12 lags, as per Green et. al. (2017). Bold t-statistics indicate factors with statistical significance $t > 3$ or $t < -3$, as in Green et. al. (2017).

Multivariate regression																
Factor	All Stocks								Microcap-free							
	Ex-ante			Ex-post			Ex-post with W		Ex-ante			Ex-post			Ex-post W	
	Coeff	SE	t-stat	Coeff	SE	t-stat	SE	t-stat	Coeff	SE	t-stat	Coeff	SE	t-stat	SE	t-stat
absacc	0.03	0.296	0.115	0.04	0.306	0.120	0.306	0.120	-0.01	0.093	-0.151	-0.01	0.099	-0.146	0.099	-0.146
acc	-0.03	0.074	-0.358	-0.03	0.077	-0.371	0.077	-0.371	-0.04	0.05	-0.709	-0.04	0.055	-0.705	0.055	-0.705
aeavol	0.02	0.065	0.233	0.02	0.065	0.241	0.065	0.241	0.01	0.063	0.216	0.01	0.067	0.220	0.067	0.220
agr	-0.11	0.029	-3.688	-0.11	0.030	-3.736	0.030	-3.736	-0.08	0.027	-3.086	-0.09	0.028	-3.128	0.028	-3.128
baspread	0.18	0.091	2.001	0.19	0.094	2.050	0.094	2.050	0.02	0.058	0.401	0.02	0.060	0.410	0.060	0.410
beta	0.11	0.071	1.513	0.11	0.072	1.539	0.072	1.538	0.05	0.063	0.756	0.05	0.064	0.769	0.064	0.769
bm	0.10	0.032	3.031	0.11	0.035	3.104	0.035	3.104	0.07	0.029	2.479	0.08	0.031	2.609	0.031	2.608
bm_ia	-0.09	0.095	-0.923	-0.09	0.096	-0.930	0.096	-0.930	-0.04	0.066	-0.558	-0.00	0.001	-0.587	0.001	-0.587
cash	0.17	0.046	3.622	0.17	0.046	3.699	0.046	3.699	0.12	0.037	3.095	0.12	0.037	3.254	0.037	3.254
cashdebt	-0.02	0.033	-0.485	-0.02	0.034	-0.496	0.034	-0.496	0.01	0.034	0.295	0.01	0.035	0.303	0.035	0.303
cashpr	-0.02	0.028	-0.837	-0.02	0.029	-0.844	0.029	-0.844	-0.04	0.035	-1.015	-0.04	0.034	-1.023	0.034	-1.023
cfp	0.07	0.029	2.284	0.07	0.03	2.395	0.03	2.395	0.00	0.005	0.036	0.04	0.044	0.904	0.044	0.904
cfp_ia	-0.04	0.134	-0.290	-0.04	0.136	-0.295	0.136	-0.295	-0.00	0.095	-0.017	0.00	0.101	0.018	0.101	0.018
chatoia	0.04	0.016	2.291	0.04	0.016	2.313	0.016	2.313	0.02	0.012	1.487	0.02	0.012	1.501	0.012	1.501
chcsho	-0.04	0.025	-1.696	-0.04	0.025	-1.710	0.025	-1.710	-0.01	0.011	-0.969	-0.02	0.016	-0.977	0.016	-0.977
chempia	-0.01	0.055	-0.207	-0.01	0.056	-0.209	0.056	-0.209	0.02	0.081	0.207	0.19	0.896	0.209	0.896	0.209
chinv	-0.06	0.032	-2.005	-0.07	0.032	-2.047	0.032	-2.047	-0.05	0.044	-1.120	-0.05	0.045	-1.143	0.045	-1.142
chmom	-0.10	0.032	-3.135	-0.10	0.035	-2.986	0.035	-2.986	-0.04	0.023	-1.763	-0.04	0.024	-1.641	0.024	-1.640
chpmia	0.02	0.028	0.755	0.00	0.007	0.775	0.007	0.775	0.03	0.031	0.831	0.03	0.031	0.853	0.031	0.853
chtx	0.01	0.003	3.595	0.01	0.003	3.684	0.003	3.684	0.01	0.004	1.979	0.01	0.005	2.029	0.005	2.029
cinvest	-0.02	0.009	-2.182	-0.02	0.011	-2.252	0.011	-2.252	-0.02	0.009	-2.517	-0.03	0.01	-2.599	0.01	-2.599
currat	-0.03	0.020	-1.428	-0.03	0.020	-1.468	0.020	-1.468	-0.04	0.022	-1.812	-0.04	0.023	-1.863	0.023	-1.863
depr	0.05	0.031	1.629	0.05	0.032	1.656	0.032	1.656	0.04	0.036	1.123	0.04	0.037	1.141	0.037	1.141

dy	-0.05	0.022	-2.149	-0.05	0.022	-2.165	0.022	-2.165	-0.07	0.031	-2.379	-0.07	0.031	-2.398	0.031	-2.398
ear	0.10	0.024	4.268	0.11	0.025	4.343	0.025	4.342	0.07	0.022	3.283	0.07	0.022	3.340	0.022	3.340
egr	-0.01	0.014	-0.723	-0.01	0.015	-0.731	0.015	-0.731	-0.00	0.001	-0.138	-0.00	0.002	-0.242	0.002	-0.242
ep	0.10	0.552	0.188	0.11	0.552	0.193	0.552	0.193	0.05	0.027	1.998	0.06	0.027	2.071	0.027	2.070
gma	0.06	0.034	1.838	0.01	0.003	1.86	0.003	1.86	0.07	0.037	1.926	0.08	0.039	1.953	0.039	1.953
grcapx	0.01	0.026	0.504	0.01	0.026	0.523	0.026	0.523	0.02	0.026	0.756	0.02	0.026	0.785	0.026	0.785
grltnoa	-0.03	0.014	-2.073	-0.03	0.015	-2.153	0.015	-2.153	-0.02	0.013	-1.729	-0.02	0.013	-1.796	0.013	-1.796
herf	-0.02	0.025	-0.922	-0.00	0.001	-0.929	0.001	-0.929	-0.02	0.047	-0.439	-0.02	0.047	-0.442	0.047	-0.442
hire	-0.01	0.039	-0.357	-0.01	0.039	-0.361	0.039	-0.361	0.00	0.009	0.068	0.00	0.011	0.064	0.011	0.064
idiovol	-0.07	0.069	-0.967	-0.07	0.068	-1.010	0.068	-1.010	-0.02	0.042	-0.537	-0.03	0.043	-0.576	0.043	-0.576
ill	0.28	0.061	4.666	0.31	0.091	3.424	0.09	3.458	0.11	0.032	3.589	0.12	0.046	2.633	0.046	2.660
indmom	0.11	0.054	1.955	0.11	0.054	1.954	0.054	1.954	0.09	0.063	1.369	0.09	0.066	1.370	0.066	1.370
invest	-0.02	0.025	-0.823	-0.01	0.012	-0.836	0.012	-0.836	-0.01	0.016	-0.611	-0.01	0.016	-0.621	0.016	-0.621
lev	0.05	0.08	0.583	0.00	0.007	0.586	0.007	0.586	0.06	0.079	0.770	0.06	0.08	0.775	0.08	0.775
mom12m	0.11	0.032	3.039	0.10	0.033	3.043	0.033	3.043	0.07	0.027	2.608	0.07	0.028	2.619	0.028	2.618
mom1m	-0.25	0.044	-5.708	-0.27	0.049	-5.485	0.049	-5.485	-0.17	0.038	-4.425	-0.2	0.044	-4.452	0.044	-4.452
mom36m	-0.02	0.026	-0.830	-0.20	0.243	-0.817	0.243	-0.817	-0.01	0.022	-0.662	-0.01	0.023	-0.655	0.023	-0.655
ms	0.01	0.067	0.209	0.01	0.034	0.212	0.034	0.212	0.03	0.14	0.209	0.03	0.14	0.212	0.14	0.212
mve_ia	0.03	0.021	1.277	0.00	0.002	1.281	0.002	1.281	0.01	0.019	0.785	0.02	0.019	0.788	0.019	0.788
mvel1	-0.47	0.094	-4.971	-0.48	0.096	-4.995	0.436	-4.095	-0.22	0.074	-3.048	-0.23	0.072	-3.155	0.079	-3.605
nincr	0.01	0.02	0.617	0.01	0.02	0.624	0.02	0.624	0.01	0.02	0.586	0.01	0.02	0.593	0.02	0.593
operprof	-0.02	0.034	-0.656	-0.02	0.035	-0.666	0.035	-0.666	-0.02	0.036	-0.591	-0.02	0.036	-0.6	0.036	-0.6
orgcap	0.01	0.021	0.566	0.00	0.002	0.596	0.002	0.596	0.01	0.022	0.477	0.01	0.023	0.503	0.023	0.503
pchcapx_ia	0.05	0.047	1.044	0.05	0.049	1.072	0.049	1.072	0.04	0.043	0.992	0.04	0.043	1.019	0.043	1.019
pchcurrat	0.00	0.009	0.390	0.00	0.013	0.267	0.009	0.401	-0.01	0.049	-0.26	-0.01	0.075	-0.178	0.05	-0.267
pchdepr	-0.04	0.068	-0.597	-0.04	0.07	-0.615	0.07	-0.615	-0.03	0.165	-0.204	-0.04	0.17	-0.21	0.17	-0.21
pchgm_pchsale	-0.03	0.029	-0.878	-0.00	0.001	-0.897	0.001	-0.897	-0.01	0.022	-0.583	-0.01	0.022	-0.594	0.022	-0.594
pchsale_pchinvt	0.02	0.012	1.719	0.02	0.012	1.753	0.012	1.753	0.01	0.007	1.483	0.01	0.007	1.483	0.007	1.481

pchsale_pchrect	0.07	0.037	1.775	0.07	0.038	1.818	0.038	1.818	0.04	0.037	1.065	0.04	0.037	1.091	0.037	1.091
pchsale_pchxsga	0.02	0.072	0.277	0.02	0.075	0.287	0.075	0.287	0.02	0.057	0.267	0.02	0.058	0.267	0.102	0.153
pchsaleinv	-0.02	0.042	-0.561	-0.03	0.044	-0.576	0.044	-0.576	-0.02	0.038	-0.460	-0.02	0.039	-0.474	0.039	-0.474
pctacc	-0.00	0.004	-0.463	-0.00	0.004	-0.475	0.004	-0.475	-0.00	0.004	-0.405	-0.00	0.004	-0.416	0.004	-0.416
ps	0.07	0.048	1.386	0.07	0.049	1.398	0.049	1.398	0.04	0.048	0.831	0.04	0.048	0.839	0.048	0.839
rd_mve	0.16	0.047	3.434	0.18	0.05	3.655	0.05	3.655	0.11	0.037	3.119	0.13	0.039	3.328	0.039	3.328
rd_sale	0.06	0.041	1.395	0.00	0.014	1.492	0.014	1.492	0.03	0.077	0.356	0.03	0.082	0.38	0.082	0.38
realestate	0.02	0.021	1.115	0.03	0.024	1.245	0.024	1.245	0.04	0.029	1.283	0.04	0.027	1.432	0.027	1.432
retvol	-0.24	0.044	-5.349	-0.24	0.045	-5.440	0.045	-5.440	-0.14	0.038	-3.620	-0.17	0.044	-3.776	0.044	-3.776
roaq	0.06	0.032	1.793	0.06	0.032	1.854	0.032	1.854	0.00	0.003	1.411	0.00	0.002	1.560	0.002	1.560
roavol	0.01	0.035	0.327	0.01	0.037	0.340	0.037	0.340	0.01	0.022	0.262	0.01	0.023	0.272	0.023	0.272
roeq	0.00	0.001	1.340	0.00	0.001	1.343	0.001	1.343	0.09	0.039	2.219	0.10	0.043	2.426	0.043	2.426
roic	0.02	0.078	0.280	0.02	0.08	0.286	0.08	0.286	0.01	0.064	0.211	0.01	0.066	0.215	0.066	0.215
rsup	0.29	0.325	0.903	0.31	0.34	0.923	0.34	0.923	0.02	0.028	0.821	0.00	0.004	0.839	0.004	0.839
salecash	-0.03	0.035	-0.919	-0.03	0.036	-0.928	0.036	-0.928	-0.03	0.044	-0.597	-0.03	0.044	-0.603	0.044	-0.603
saleinv	-0.00	0.012	-1.328	-0.00	0.014	-1.477	0.014	-1.436	-0.00	0.005	-0.058	0.00	0.003	0.319	0.003	0.319
salerec	0.00	0.007	0.289	0.00	0.007	0.293	0.007	0.293	0.01	0.043	0.272	0.01	0.043	0.277	0.043	0.277
secured	-0.01	0.043	-0.272	-0.01	0.044	-0.277	0.044	-0.277	-0.00	0.002	-0.263	-0.00	0.002	-0.264	0.002	-0.264
sgr	-0.03	0.036	-0.854	-0.02	0.026	-0.863	0.026	-0.863	-0.04	0.092	-0.463	-0.04	0.095	-0.470	0.095	-0.470
sp	0.00	0.002	0.712	0.00	0.002	0.726	0.002	0.726	0.03	0.049	0.685	0.04	0.048	0.737	0.048	0.737
std_dolvol	-0.14	0.041	-3.472	-0.14	0.042	-3.464	0.042	-3.464	-0.05	0.03	-1.614	-0.05	0.03	-1.610	0.03	-1.610
std_turn	0.34	0.074	4.615	0.07	0.015	4.647	0.020	4.347	0.20	0.062	3.252	0.21	0.063	3.287	0.063	3.286
stdcf	-0.00	0.001	-1.821	-0.00	0.001	-1.947	0.001	-1.947	0.00	0.007	0.028	0.00	0.008	-0.075	0.008	-0.075
tang	-0.00	0.034	-0.126	-0.00	0.035	-0.129	0.035	-0.129	-0.00	0.006	-0.035	-0.00	0.006	-0.051	0.006	-0.051
tb	0.00	0.002	2.189	0.00	0.002	2.257	0.002	2.257	0.00	0.106	0.004	0.00	0.114	0.005	0.114	0.005
turn	-0.36	0.067	-5.426	-0.37	0.068	-5.412	0.068	-5.412	-0.26	0.055	-4.718	-0.26	0.056	-4.706	0.056	-4.706
zerotrade	-0.29	0.071	-4.069	-0.30	0.074	-4.059	0.074	-4.059	-0.02	0.02	-0.827	-0.02	0.021	-0.845	0.021	-0.845

Table 4.2: Multivariate regression results for full sample period

This table presents the results of the cross-sectional regressions of monthly stock returns on the 78 characteristics simultaneously in multivariate regressions. The left-hand side panel presents the results of the sample containing all stocks, whereas the right-hand side panel presents the results of the sample which excludes microcaps. In each panel three sets of results are shown; A) the ex-ante results which models the classic Fama MacBeth regression, B) the regression in A after considering the bias arising from the finite time dimension of the sample and C) the regression in B after considering the effect of the W matrix arising due to the error terms not diverging to zero in finite time dimensions. Monthly returns for month t are regressed against the previous month characteristics, $t-1$. The data spans the period December 1959 to December 2021. The sample contains all stocks on the NYSE, AMEX and NASDAQ. Missing values are replaced by zeros which is the cross-sectional average after standardizing the characteristics at each period. Microcaps are defined as the stocks with market capitalisation in the lower 20th percentile of the stocks of the NYSE. This was sourced by Kenneth French website. FM coefficients are in % and t-statistics are computed with the Newey-West adjustment of 12 lags, as per Green et. al. (2017). Bold t-statistics indicate factors with statistical significance $t > 3$ or $t < -3$, as in Green et. al. (2017)

Impact of the ex-post adjustments

Tables 4.1 and 4.2 report the results for the full period, December 1959 to December 2021, for the univariate and multivariate regressions, respectively. The left panel reports the results for the sample containing all stocks and the right panel reports the results after the exclusion of microcaps. Two distinct observations emerge from these tables. First, comparing the ex-ante and ex-post results, one can observe only a slight impact in the t -values for the collection of factors. Second, comparing the ex-post results before and after the effect of the $\hat{W}$ matrix one observes a trivial, almost non-existent, effect on the t -values. These two observations were mostly expected, particularly in light of the evidence of section 4.4.1 which showed that the effects of the large- N framework diminished to levels near zero when the time dimension becomes large. These observations become apparent in both regressions and across both samples.

Univariate regression

Examining the results in more detail starting from the univariate regression, 23 factors emerged as statistically significant explanators of asset prices in the all-stocks sample; asset growth, book-to-market, cash productivity, change in shares outstanding, industry-adjusted change in employees, change in inventory, change in 6-month momentum, change in tax expense, earnings announcement return, growth in common shareholder equity, growth in capital expenditures, growth in long term net operating assets, illiquidity, industry momentum, capital expenditures and inventory, 1-month momentum, size, operating profitability, percent accruals, sales growth, dollar trading volume, share turnover. However, when microcaps are excluded only 8 factors survive the significance threshold; asset growth, change in shares outstanding, earnings announcement return, Growth in common shareholder equity, growth in long term net operating assets, capital expenditures and inventory, 1-month momentum, dollar trading volume.

These results exhibit similarities to the observations of Green et al. (2017). First, it becomes evident that more factors are univariately significant when microcaps and non-microcaps are equally weighted. Second, factors which are independent determinants in the all-stocks sample are also independent

determinants in microcap-free sample, but not vice versa. This evidence is supportive for the microcap effect since most anomalies are present when the sample is dominated by microcaps but cease to exist when these are excluded. Another observation arising from the comparison of Table 4.1 with the results of Green et al. (2017) is that in the latter a greater number of anomalies survived, specifically, 30 for the all-stocks sample and 12 for the microcap-free sample. This distinct difference arises due to the following reasons: a) factors of binary nature, such as IPO and convertible debt indicator, were used in Green et al. (2017) but excluded in this chapter, as described in section 4.3.2; b) factors constructed with data from the I/B/E/S database, such as number of earnings increases and unexpected quarterly earnings, appearing non-significant due to high number of missing data replaced by zeros; c) factors which are barely below the threshold level, such as industry-adjusted change in asset turnover, arise due to the extended sampling period used in this chapter 1959-2021 as opposed to 1980-2014 in Green et al. (2017).

Multivariate regression

The results for the multivariate regression presented in Table 4.2 reveal only 15 statistically significant anomalies, substantially lower than the 23 discovered by the univariate setup. These are: asset growth, book-to-market, cash holdings, change in tax expense, earnings announcement return, illiquidity, 12-month momentum, 1-month momentum, size, R&D to market capitalisation, return volatility, dollar trading volume, volatility of liquidity, share turnover, zero trading days. When microcaps are excluded however, the number of significant discoveries decreases further to only 10, a pattern also observed in the univariate regression. These are: asset growth, cash holdings, earnings announcement return, illiquidity, size, R&D to market capitalisation, return volatility, volatility of liquidity, share turnover. As it was also observed in the previous section, the anomalies which were discovered for the microcap-free sample were also discovered for the sample containing all stocks, but not vice versa. Additionally, the results for the multivariate setup present a lower number of significant discoveries compared to the evidence of Green et al. (2017) (24 for the all-stocks sample and 12 for the microcap-free sample) due to the same reasons described in the previous section.

4.4.3 Comparison across categories

Comparing across the univariate and multivariate results reveals that three factors are significant in all four cases; asset growth, earnings announcement returns and 1-month momentum, while 6 factors survive in both the univariate and multivariate setups using the all-stocks sample but do not survive in one of their microcap-free counterparts; book-to market, size, change in tax expense, illiquidity, dollar trading volume and shares turnover. Combining these observations generates an interesting dissection of the risk premium puzzle, highlighting that the widely used factors of size and book-to-market survive only in the all-stocks sample, the market beta fails to survive in all cases, whereas the momentum factor survives in every case. The discussion in the literature review posed a question in criticism of some widely used factors, such as book-to-market and size; specifically, why use the specific factors over any other from the hundreds contained in the empirical body of work? The evidence within, make the case for these factors curiouser as they emerge as significant determinants of asset prices, empirically surpassing a large and wide collection of factors.

Categories		Univariate setup		Multivariate setup	
		All stocks	Microcap-free	All stocks	Microcap-free
Fundamental-based	Value-vs-growth	- Book-to-market - Cash productivity - Size - Sales to price		- Book-to-market - Size - Cash holdings	- Size
	Investment	- Asset growth - Change in inventory - Growth in CAPEX - Growth in long term net operating assets - CAPEX & inventory - Change in shares outstanding - Growth in shareholder equity	- Asset growth - Growth in long term net operating assets - CAPEX & inventory - Change in shares outstanding - Growth in shareholder equity	- Asset growth	- Asset growth
	Profitability	- Operating profitability - Percent accruals - Sales growth			
	Intangibles	- Industry-adjusted change in employees		- R&D to market capitalisation	- R&D to market capitalisation
Market-based	Momentum	- 1-month momentum - Change 6-month momentum - Industry momentum - Change in tax expense - Earnings announc. return	- 1-month momentum - Earnings announc. return	- 1-month momentum - 12-month momentum - Earnings announc. return - Change in tax expense	- 1-month momentum - Earnings announc. return
	Trading frictions	- Illiquidity - Dollar trading volume - Share turnover	- Dollar trading volume	- Illiquidity - Dollar trading volume - Return volatility - Volatility of liquidity - Share turnover - Zero trading days	- Illiquidity - Dollar trading volume - Return volatility - Volatility of liquidity - Share turnover

Table 4.3: Classification of empirically identified anomalies

Given the above discussion, Table 4.3 dissects the equity premium further, by allocating the collection of identified anomalies using two classification systems; a) the fundamental-based and market-based categories proposed by McLean and Pontiff (2016) and b) the six-category system used by Hou et al. (2020). A few interesting observations emerge. First, for each of the four tests there is about an equal number of statistically significant discoveries allocated in the fundamental- and the market-based categories. This implies that investors weight equally the information coming from a firm's financial statements with the information coming from the trading environment before making investment decisions. Second, when the all-stocks sample is considered, there exist at least one significant factor in every category in the univariate case, while the same is true for the multivariate case with the exception of the profitability category which is empty. This finding is interesting and shows that there is not one category within most factors are concentrated, but rather anomalies seem to be evenly spread among all categories. Therefore, a strong indication arises that the equity risk premium follows a multifaced risk-generating process whereby the widely used three- and four-factor models do not suffice to capture all aspects of investors' risk perceptions.

Third, factors related to volatility, liquidity and momentum are persistently emerging across all setups which highlights the importance of considering the trading environment in investment decisions. As discussed in the literature review, the Fama and French (2015) five-factor model and Hou, et al. (2015) q-theory model were warmly welcomed by the research community as they firmly re-introduced the profitability and investment factors to the risk premium measurement, however, the evidence emerging from this investigation makes a firm case for the inclusion of the volatility, liquidity and momentum factors. Fourth, a more detailed look at Table 4.3 reveals that investors are certainly focused on the asset-side of the balance sheet, particularly on growth-related factors, whereas no liability-side factor appears to be significant in any setup. This is an interesting finding and might be suggestive that investors exhibit a bias towards the asset column for investment decisions, while they evaluate their downside risk based on factors from the trading environment, such as volatility and liquidity.

4.4.4 Effects due to the microcap bias

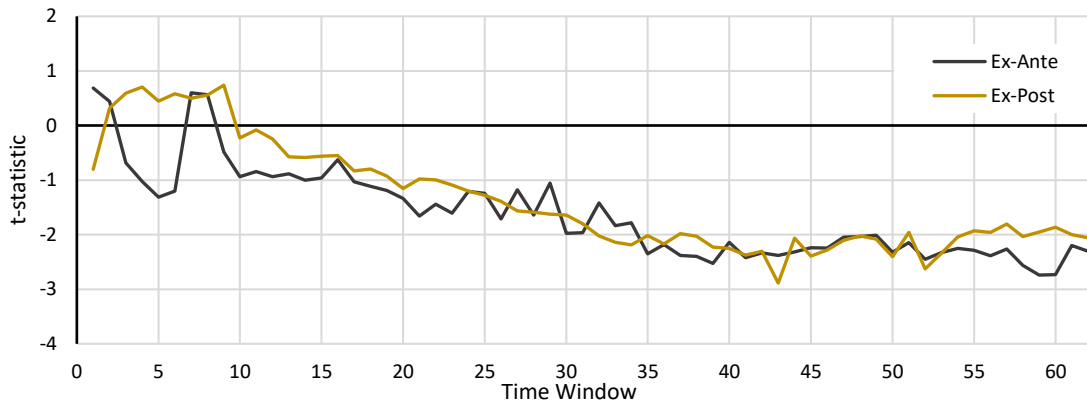


Figure 4.8: Pitman-Morgan test All stocks vs. Microcap-free, univariate setup

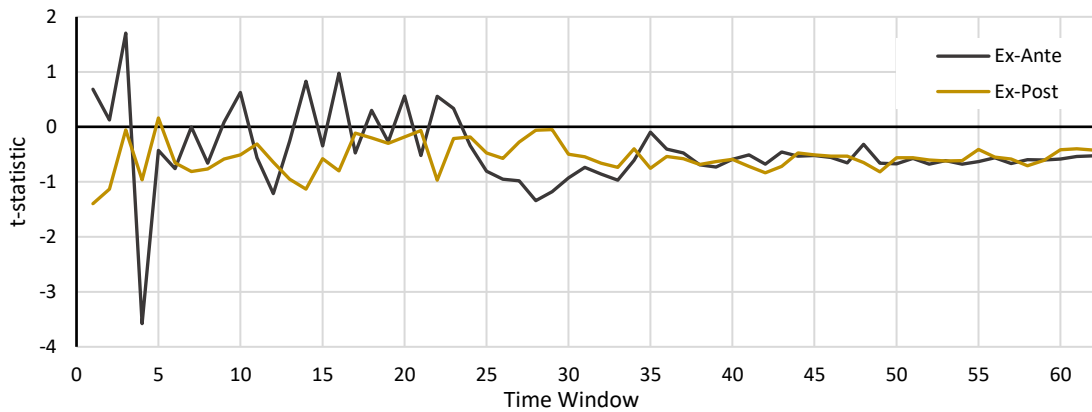


Figure 4.9: Pitman-Morgan test All stocks vs. Microcap-free, multivariate setup

Figures 4.8 and 4.9 present the results for hypotheses 2 and 3 which aim to uncover whether the microcap bias impacts the inference of risk premia in a statistically significant fashion for the ex-ante and ex-post models, respectively. These illustrate the results of the Pitman-Morgan test regarding the distributions of t -values before and after removing microcaps. While the literature presents emphatic evidence that the microcap bias is impactful, these findings have been restricted to counting the number of anomalies before and after removing microcaps, for example Green et al. (2017) and Hou et al. (2020). On the contrary, the t -statistics reported in figures 4.8 and 4.9 effectively measure the strength at which the risk premium inference is impacted when microcaps are removed.

Figure 4.8 shows the results for the univariate setup and illustrates that at low levels of T the exclusion of microcaps does not yield any substantial difference in the distribution of t -values, given that the t -statistic of the Pitman-Morgan test is near zero for both the ex-ante and ex-post models. However, when the time window increases the distinction between the tested variables becomes apparent with the t -statistics reaching statistically significant levels of around -2 . This means that when the microcaps are removed, the variance of the resulting t -values for the collection of asset pricing anomalies is smaller than the respective variance for the all-stocks sample in a statistically significant fashion. The implication is that the exclusion of microcaps does, in fact, bring the collection of t -values closer to zero. Therefore, fewer statistically significant anomalies are expected to arise in a microcap-free sample, a finding which concurs with and expands on the findings of Green et al. (2017) and Hou et al. (2020).

Evidently, the microcap effect is more impactful when the time window becomes sufficiently large. This should not be surprising as the estimates for the coefficients and standard errors converge to their real values as T increases and therefore, the risk premium measurement stabilises. This also explains the volatility observed at low levels of T which arises due to the measurement parameters being volatile given that the time dimension has not adequately converged. The same concept is evident in Figure 4.9 which presents the results for the multivariate regression. Similar to Figure 4.8, the volatility in the Pitman-Morgan t -statistics is high at low levels of T but diminishes when the time window increases. Contrary to Figure 4.8, the t -statistics of the multivariate setup stabilize close to zero which implies that the findings before and after the exclusion of microcaps have equal variance. Based on this, it can be deduced that when the time dimension is sufficiently large, the microcap-bias has no effect on the inference of the multivariate regression setup.

4.5 Discussion

4.5.1 Effects of the fixed- T , large- N framework

Section 4.4.1 evaluated the impact of adjusting the two-pass procedure according to the asymptotically valid framework for finite samples (large- N , fixed- T). Based on the Pitman-Morgan test it was shown that such adjustment is of great importance in the univariate regression setup, given that the distribution of t -values for the collection of 78 anomalies is significantly affected for time windows up to 10 years for the all-stocks sample and up to 7 years for the microcap-free sample. Beyond these, no statistically significant divergence is present and beyond the 40- and 32-year marks, respectively, no substantial difference between the asymptotically valid and the unadjusted two-pass model is even observable. In the multivariate case, the divergence between the two models was only apparent up to the 5-year mark, after which it declines rapidly to zero, nonetheless, it was noted that this volatility in the measurement might have been caused due to entire rows of null values being discarded due to the short timeframe.

This evidence contributes to the literature by extending the results of Raponi et al. (2020) on two major axes. First, the whole spectrum of the time dimension was explored, as opposed to Raponi et al. (2020) who only tested two cases ($T = 36$, $T = 120$), and based on a novel application of the Pitman-Morgan test it became possible to quantify the impact of short-time samples on the risk premium measurement. This testing procedure yielded empirically interesting evidence about when the time dimension should be considered adequately large as to cause no significant impact on the inference. Specifically, empirical researchers should consider the Shanken-Rapioni framework for time windows less than 10 years in univariate regressions of microcap-dominated samples and 7 years in microcap-free samples, whereas this threshold decreases to 5 years in multivariate regressions.

The results of this chapter are also related to Bai and Zhou (2015) who studied the error due to using the unadjusted model for the cases of $T = 60$ and $T = 120$ months. They find that the bias term declines as much as 50% between these two levels, which is concurred by the findings of section 4.1.2 which shows a drop of 40% in the coefficient deviation. Contrary to this chapter, they only tested the univariate setup at only two different time windows, so the findings herein are more detailed about the impact on the measurement.

Second, the application of these two regression setups at factor dimensions $K = 1$ and $K = 78$, respectively, is the second contribution of this chapter. This provides evidence that the error due to applying the invalid, unadjusted model is reduced with the increase in the factor dimension. Raponi et al. (2020) exhibit findings along the same line, however, the maximum number of factors they tested was only six. Pushing this number to $K = 78$ and taking the trimmed mean of the results yielded a much smoother measurement (especially at short time windows), which remedied the volatility of the results in Raponi et al.

4.5.2 Microcap bias

The impact of the microcap bias became apparent in the full period regression results which showed that most anomalies that were significant in the sample containing all stocks did not survive the exclusion of microcaps. This finding confirms the evidence in Green et al. (2017) with the only difference being that the extended sampling period used in this chapter (1959-2021, as opposed to 1980-2014 in Green et al.), pushed most factors constructed from the I/B/E/S dataset to be insignificant. The results in Hou et al. (2020) are also supported by the findings herein, given that the vast majority of anomalies fail to replicate. They report that a failure rate of 82% at a t -value of 2.78 when multiple testing adjustments are made. In this chapter there were no adjustments imposed for multiple testing, nonetheless, 70% of anomalies failed to replicate in the univariate regression and 80% in the multivariate case. Furthermore, they find that almost half of the anomalies do not survive a threshold of 1.97 when microcaps are controlled via value-weighted factor portfolios. The evidence in section 4.4.2 shows that when the threshold is at the more conservative level of 3, the replication failure rate is as high as 90%.

The evidence for the microcap-bias is emphatic given the findings of Green et al. (2017) and Hou et al. (2020), nonetheless, their analysis is restricted to counting the number of anomalies before and after removing microcaps. The results of section 4.4.4 contribute to this literature by quantifying the impact of microcaps using the Pitman-Morgan test. This measured the degree to which the variance of the t -values generated by the collection of anomalies is impacted after microcaps are removed. This testing showed that in the univariate case the distribution of t -values is so strongly affected as to be statistically significant. On the other hand, in the multivariate case the impact of removing microcaps, although evident, cannot be deemed as significant in the statistical sense. Moreover, it was also seen that at small time windows the distribution of t -values is volatile, nonetheless, when the time dimension is allowed to increase the effect of microcaps becomes more apparent. Given this finding, one understands that the strong evidence for the microcap bias in Green et al. (2017) and Hou et al. (2020) is only evident in a large time sample, whereas, if a short time rolling window is used the effects of this bias are not discernible.

4.5.3 Components of risk premium

The full period regression results of section 4.4.2 highlighted that the equity risk premium bases on a multifaced risk structure given that the statistically significant anomalies at each regression setup were evenly spread out among all classification categories. This evidence speaks to the debate on the development of low-dimensional factor models and is suggestive that the widely used three- and four-factor models do not suffice to capture all aspects of investors' risk perceptions. The Fama and French (1993) three-factor model evolved into a five-factor model (Fama and French 2015) by the addition of the investment and profitability factors, similar to the Hou et al. (2015) q-theory model. The critique of Barillas and Shanken (2018) that the Fama and French (2015) and Hou, et al. (2015) specifications miss the momentum factor is substantiated by the evidence in this chapter as the 1-month momentum survives statistical testing across all tests. What is more, factors related to volatility, liquidity and momentum were observed to persistently emerge across all setups, evidence which makes a case for the inclusion of trading environment variables to an updated version of the current five-factor models.

Another interesting finding from section 4.4.3 was that the widely used factors for size and book-to-market survive only when microcaps are included in the sample. Contrarily, the market beta fails to survive in all cases in support of the once controversial evidence by Fama and French (1996), whereas the momentum factor survives in every case highlighting the value of Carhart's (1997) addition. In criticism of the heavy use of factors, such as size and book-to-market, this chapter questioned why use these specific variables as common factors over any other from the hundreds contained in the empirical body of work. Curiously, the evidence from the regressions makes the case for these factors more prominent given that they emerge as explanators of asset prices, empirically surpassing a wide collection of other factors.

4.5.4 Limitations

This investigation has been subject to several limitations. To begin with, the collection of 78 factors used is merely a fraction of the over 300 anomalies identified in empirical literature (Green et al. 2013). The choice of the specific factors was motivated by the idea of establishing comparability with Green et al. (2017) and all other papers which employ their dataset. Furthermore, all the findings in this chapter are relevant to the specific set of 78 factors employed. Although this is a substantial set, the generalizability of the implications cannot be guaranteed from this chapter alone, as a different collection of anomalies might generate different findings. Nonetheless, there is support from the theory about the reported results which indicates that they are on the right line.

Second, even though a large collection of factors was used, no contingencies for multiple testing were made. The recent empirical literature is strongly advocating to control for false discoveries when using large collections of candidate factors (Harvey and Liu 2021; Harvey et al. 2020) as the number of identified anomalies will be statistically overstated. The decision for not using such adjustments was made on the grounds that the investigation should be conducted in an all-else-equal fashion since any adjustments apart from the Shanken-Raponi estimator could have potentially clouded the real impact of short time dimensions.

Third, even though the High Performance Computer achieved a drastic reduction in the computational complexity of the large- N model, the time required to run the experiments reported in section 4.4 was exceedingly high. As an indication, it took about five to six weeks for all parts of the code to run fully once. As a result, the repeatability of this investigation is challenging, which hinders the possibility of running additional experiments to explore new effects and ideas. For example, the findings are suggestive that the number of factors used in the regression affects the sensitivity to the impact of the large- N adjustments. Nonetheless, to investigate the whole spectrum of the factor dimension would be impossible given the time restrictions.

If a researcher wishes to conduct a similar investigation, it is highly recommended that the code should be designed from the beginning based on an architecture for parallel processing. In this way it can take full advantage of the capabilities of a supercomputer and will expedite the required runtime. Besides speed, this will offer agility and flexibility to the researcher who can then explore the concepts more deeply. Unfortunately, when this investigation was conducted access to the supercomputer was granted after most of the code was already written and thus, it was unable to make the efficient use of the advanced computing power.

Chapter 5

Conclusion

Chapter 2: This chapter evaluated the performance of neural networks to predict asset prices after applying a realistic cost function which is rooted in market microstructure. Portfolio weights were optimised based on the implied frictions impact and as such, it was shown how the microcap bias can be controlled without the need to discard large sections of the sample while the attainable predictive signals are able to surface. Controlling for difficult-to-trade stocks reduced the profitability of the machine learning model but it did not eliminate it completely, in part confirming the evidence in Avramov et al. (2022).

It was found that investors trading a small initial portfolio can extract considerable predictability from the neural network model, however, when the portfolio balance is large enough the predictability diminishes. A considerable portion of the predictability was found to exist in the short leg of the High-Minus-Low portfolio, which was not extractable, however, the realisable predictability in the long leg is more than enough to compensate for the shortcoming of the short leg. Moreover, introducing the ability to capture non-linear relationships is evidenced to yield superior predictability as confirmed by the enhanced performance of deeper neural network setups and by the addition of interaction terms in the predictor set. In conclusion, all the evidence is suggestive that the success of the neural network model of Gu et al. (2020) is not spurious, but it captures unique pricing information, and this chapter identifies under which conditions this can be realised in the market. Finally, future research should explore the drivers behind the exceptional performance of the neural network model.

Chapter 3: Neural network models, despite their striking empirical success in asset pricing (Gu et al. 2020), are generally considered ‘black boxes’ which obscure the economic foundations of the predictive relationships they identify. This chapter argued that this notion is a misnomer. State-of-the-art research (Gu et al. 2020; Avramov et al. 2022) has so far hinted at some risk-reward relationships identified by the neural network method. However, the findings so far, have not been scrutinised via the lens of realistic trading frictions as to uncover which of the machine learning signals are practically attainable.

This chapter argued that the intuition already established in the field of asset pricing can be leveraged to fully trace the machine learning predictability to individual risk factors. Furthermore, the use of an optimiser enabled the consideration of trading frictions whereby the truly unique, realizable, risk premia surfaced. The results confirmed that the success of the neural network model of Gu et al. (2020) is dominated by anomalies in the momentum, volatility and stock liquidity categories. However, when trading frictions are considered, the optimiser takes neutral positions in the above factor categories.

Novel results identify that the neural network model extracts significant alpha from episodes of investor overreaction, specifically in two scenarios: (a) shorts stocks with recently improved top line when their bottom line fails to improve; and (b) short stocks with recently inflated stock prices due to investor overreaction to positive surprises in financial results when their growth fails to be reflected in their fundamentals. Lastly, when the neural network signal is distilled by industry, it is observed that the model focuses on stocks in the technology, healthcare and energy industries.

Chapter 4: This chapter examined the idea that the inference of the traditional Fama-Macbeth estimator is invalid when the time dimension is not large enough. Asymptotically valid t -statistics can still be estimated after applying the bias correction term of Shanken (1992) and the variance estimate of Raponi et al. (2020). The idea put forward by this chapter was that by using a large factor set, the distribution of the resulting t -statistics can be used to evaluate the effect of using the asymptotically valid framework. It was argued that the variance of the distributed t -statistics is the same between the asymptotically adjusted and the unadjusted models only when the time dimension is sufficiently large, whereas the variance equality hypothesis is rejected when the time dimension is small. Wilcox (2020) extension of the Pitman-Morgan test was used to test the variance equality hypothesis, while correcting for the heteroskedasticity issue.

The empirical evidence showed that, in univariate regressions the divergence between the two models is statistically significant for time windows up to 10 years in samples containing microcaps and up to 7 years in microcap-free samples. This number was lowered to the 5-year mark in multivariate regressions. The implication is that below these levels T is small enough for the inference to be biased and thus, empirical researchers should consider the large- N framework. The Pitman-Morgan test also showed that removing microcaps has a statistically significant impact on the inference in the univariate setup, which is suggestive that anomalies may arise only in microcap-dominated samples confirming Green et al. (2017) and Hou et al. (2020). The bias was not observable at short timeframes but becomes distinct when T increases.

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Appendix

Appendix 2A – List of factors

Factors	Hou Category	MP Category	Firm characteristic
absacc	Profitability	Fundamental	Absolute accruals
acc	Profitability	Fundamental	Working capital accruals
aeavol	Momentum	Market	Abnormal earnings announcement volume
age	Intangibles	Fundamental	# of years since first Compustat coverage
agr	Investment	Fundamental	Asset growth
baspread	Trading frictions	Market	Bid-ask spread
beta	Trading frictions	Market	Beta
betasq	Trading frictions	Market	Beta squared.
bm	Value/growth	Fundamental	Book-to-market
bm_ia	Value/growth	Fundamental	Industry-adjusted book to market
cash	Value/growth	Fundamental	Cash holdings
cashdebt	Value/growth	Fundamental	Cash flow to debt
cashpr	Value/growth	Fundamental	Cash productivity
cfp	Value/growth	Fundamental	Cash flow to price ratio
cfp_ia	Value/growth	Fundamental	Industry-adjusted cash flow to price ratio
chatoia	Investment	Fundamental	Industry-adjusted change in asset turnover
chcsho	Investment	Fundamental	Change in shares outstanding
chempia	Intangibles	Fundamental	Industry-adjusted change in employees
chinv	Investment	Fundamental	Change in inventory
chmom	Momentum	Market	Change in 6-month momentum
chpmia	Profitability	Fundamental	Industry-adjusted change in profit margin
ctx	Momentum	Market	Change in tax expense
cinvest	Investment	Fundamental	Corporate investment
convind	Intangibles	Fundamental	Convertible debt indicator
currat	Profitability	Fundamental	Current ratio
depr	Investment	Fundamental	Depreciation / PP&E
divi	Intangibles	Fundamental	Dividend initiation
divo	Intangibles	Fundamental	Dividend omission
dolvol	Trading frictions	Market	Dollar trading volume in month t-2
dy	Value/growth	Fundamental	Dividend to price
ear	Momentum	Market	Earnings announcement return
egr	Trading frictions	Market	Growth in common shareholder equity
ep	Value/growth	Fundamental	Earnings to price
gma	Profitability	Fundamental	Gross profitability
grcapx	Investment	Fundamental	Growth in capital expenditures
grltnoa	Investment	Fundamental	Growth in long term net operating assets
herf	Intangibles	Fundamental	Industry sales concentration
hire	Intangibles	Fundamental	Employee growth rate
idiovol	Trading frictions	Market	Idiosyncratic return volatility

ill	Trading frictions	Market	Illiquidity
indmom	Momentum	Market	Industry momentum
invest	Investment	Fundamental	Capital expenditures and inventory
lev	Investment	Fundamental	Leverage
lgr	Investment	Fundamental	Change in long-term debt
maxret	Trading frictions	Market	Maximum daily return in prior month
mom12m	Momentum	Market	12-month momentum
mom1m	Momentum	Market	1-month momentum
mom36m	Momentum	Market	36-month momentum
mom6m	Momentum	Market	6-month momentum
ms	Profitability	Fundamental	Financial statement score
mve_ia	Value/growth	Fundamental	Industry-adjusted size
mvel1	Value/growth	Fundamental	Size
nincr	Momentum	Market	Number of earnings increases
operprof	Profitability	Fundamental	Operating profitability
orgcap	Intangibles	Fundamental	Organizational capital
pchcapx_ia	Investment	Fundamental	Industry adjusted % change in capital expenditures
pchcurrat	Profitability	Fundamental	% change in current ratio
pchdepr	Profitability	Fundamental	% change in depreciation
pchgm_pchsale	Profitability	Fundamental	% change in gross margin - % change in sales
pchquick	Profitability	Fundamental	% change in quick.
pchsale_pchinv	Profitability	Fundamental	% change in sales - % change in inventory
pchsale_pchrect	Profitability	Fundamental	% change in sales - % change in A/R
pchsale_pchxsga	Profitability	Fundamental	% change in sales - % change in SG&A
pchsaleinv	Profitability	Fundamental	% change sales-to-inventory
pctacc	Profitability	Fundamental	Percent accruals
pricedelay	Momentum	Market	Price delay
ps	Profitability	Fundamental	Financial statements score
quick	Profitability	Fundamental	Quick ratio
rd	Intangibles	Fundamental	RD_increase
rd_mve	Intangibles	Fundamental	R&D to market capitalization
rd_sale	Intangibles	Fundamental	R&D to sales
realestate	Investment	Fundamental	Real estate holdings
retvol	Trading frictions	Market	Return volatility
roaq	Profitability	Fundamental	Return on assets
roavol	Profitability	Fundamental	Earnings volatility
roeq	Profitability	Fundamental	Return on equity
roic	Profitability	Fundamental	Return on invested capital
rsup	Momentum	Market	Revenue surprise
salecash	Value/growth	Fundamental	Sales to cash
saleinv	Value/growth	Fundamental	Sales to inventory
salerec	Value/growth	Fundamental	Sales to receivables
secured	Investment	Fundamental	Secured debt

securedind	Intangibles	Fundamental	Secured debt indicator
sgr	Profitability	Fundamental	Sales growth
sin	Intangibles	Fundamental	Sin stock
sp	Value/growth	Fundamental	Sales to price
std_dolvol	Trading frictions	Market	Volatility of liquidity
std_turn	Trading frictions	Market	Volatility of liquidity (share turnover)
stdacc	Profitability	Fundamental	Accrual volatility
stdcf	Value/growth	Fundamental	Cash flow volatility
tang	Investment	Fundamental	Debt capacity/firm tangibility
tb	Profitability	Fundamental	Tax income to book income
turn	Trading frictions	Market	Share turnover
zerotrade	Trading frictions	Market	Zero trading days

Appendix 2B – Portfolio statistics, individual models, monthly rebalancing

This appendix reports portfolio statistics for the neural network portfolios when the investment horizon is one month for the five neural network models, NN1-NN5. The left section of the table presents the results after equal-weighting the portfolio holdings at each rebalancing period. Similarly, the middle section presents the value-weighted results, and the right section presents the results of the optimised portfolio. For each method results are reported in three environments: (a) an environment without trading frictions, (b) an environment with trading frictions, investing a small initial capital of 1 million USD and (c) an environment with trading frictions, investing a large initial capital of 100 million USD. The neural network models are used to predict the stock returns one month ahead, which are then used to create long-short portfolios. The long-short portfolio is constructed by ranking stocks according to the predicted returns and form 10 portfolios, buying the highest quantile portfolio and selling the lowest quintile portfolio. The weights of the holdings in each portfolio vary according to the weighting scheme. The trades are placed, and the portfolio is evaluated at the next period based on the metrics reported. In the first environment no penalties are applied due to trading frictions while the other two environments apply a penalty simulating realistic trading frictions as a function of the microstructure of individual stocks. Investing horizon is one month and thus, rebalancing of the portfolio is performed monthly based on predicted returns. Mean Returns (%) and R2oos (%) denote the mean returns and mean out-of-sample R2, respectively, across the time series of each portfolio, both reported in percentage basis. Max 1M loss (%) and Max DD (%) denote the Maximum 1-month loss and maximum drawdown, across the time series of each portfolio, both reported in percentage basis. Turnover is the monthly average portfolio turnover and Sharpe ratios are annualised. Skewness and Excess Kurtosis illustrate the shape of the distribution of returns yielded by the trading strategy across the sampling period.

NN1 Monthly Rebalancing

Weighting	Equal			Value			Optimized		
	Without TF	With TF Low Capital	With TF High Capital	Without TF	With TF Low Capital	With TF High Capital	Without TF	With TF Low Capital	With TF High Capital
Model	NN1	NN1	NN1	NN1	NN1	NN1	NN1	NN1	NN1
Initial capital (millions)	All	1	100	All	1	100	All	1	100
Horizon	1	1	1	1	1	1	1	1	1
Rebalancing	month	month	month	month	month	month	month	month	month
R2oos (%)	0.14	-1.58	-1.68	0.25	-1.54	-1.58	0.89	0.11	-0.6
Mean Returns (%)	2.509	-1.726	-2.179	0.915	-0.473	-0.903	3.184	1.749	0.345
t statistic	13.15	-8.64	-10.34	8.05	-4.07	-5.84	4.69	2.56	0.39
Sharpe Ratio	1.99	-1.64	-1.91	1	-1.02	-1.23	2.51	1.29	0.08
Sortino Ratio	1.53	-0.36	-0.56	0.58	-0.1	-0.18	5.09	1.42	0.06
Information Ratio	1.04	-1.05	-1.05	0.16	-0.59	-0.62	0.22	-0.49	-0.42
Turnover (%)	102	103	103	102	103	103	40	40	51
Max 1M loss (%)	-18.92	-25.66	-25.72	-11.81	-14.51	-39.19	-3.88	-6.3	-12.96
Max DD (%)	-24.82	-99.97	-100	-20.24	-89.84	-98.53	-6.03	-12.02	-26.06
Skewness	0.37	-0.48	-0.45	0.36	-0.66	-4.41	0.2	-0.06	-0.44
Excess Kurtosis	1.41	1.74	0.77	1.65	1.05	44.05	-3.02	-3.14	-3.42

NN2 Monthly Rebalancing

Weighting	Equal			Value			Optimized		
	Without TF	With TF Low Capital	With TF High Capital	Without TF	With TF Low Capital	With TF High Capital	Without TF	With TF Low Capital	With TF High Capital
Model	NN2	NN2	NN2	NN2	NN2	NN2	NN2	NN2	NN2
Initial capital (millions)	All	1	100	All	1	100	All	1	100
Horizon	1	1	1	1	1	1	1	1	1
Rebalancing	month	month	month	month	month	month	month	month	month
R2oos (%)	0.17	-1.24	-1.27	0.3	-1.35	-1.49	1.32	0.74	-3.99
Mean Returns (%)	1.494	-2.57	-3.008	0.577	-0.86	-1.226	3.341	1.685	-1.153
t statistic	7.39	-11.2	-12.72	4.99	-6.81	-8.85	4.00	3.83	-1.02
Sharpe Ratio	1.04	-2.04	-2.29	0.49	-1.45	-1.76	2.15	1.21	-0.21
Sortino Ratio	1.36	-0.41	-0.84	0.13	-0.13	-0.26	4.93	1.23	-0.71
Information Ratio	0.91	-1.01	-1.01	-0.17	-0.98	-1.08	0.29	-0.26	-0.38
Turnover (%)	101	102	102	101	102	102	45	46	54
Max 1M loss (%)	-19.82	-23.75	-23.81	-14.53	-17	-17.04	-4.48	-7.35	-29.99
Max DD (%)	-41.86	-100	-100	-33.49	-97.95	-99.6	-7.17	-17.52	-25.8
Skewness	-0.35	-0.92	-0.9	0.37	-0.09	-4.35	0.43	-0.23	-0.58
Excess Kurtosis	2.64	1.56	0.89	2.97	2.54	2.28	-3.84	-3.87	-3.98

NN3 Monthly Rebalancing

Weighting	Equal			Value			Optimized		
	Without TF	With TF Low Capital	With TF High Capital	Without TF	With TF Low Capital	With TF High Capital	Without TF	With TF Low Capital	With TF High Capital
Model	NN3	NN3	NN3	NN3	NN3	NN3	NN3	NN3	NN3
Initial capital (millions)	All	1	100	All	1	100	All	1	100
Horizon	1	1	1	1	1	1	1	1	1
Rebalancing	month	month	month	month	month	month	month	month	month
R2oos (%)	0.2	-0.99	-1.09	0.3	-1.38	-1.47	1.19	0.46	-3.21
Mean Returns (%)	1.975	-1.853	-2.243	0.611	-0.688	-1.141	3.335	1.969	0.035
t statistic	9.9	-8.91	-10.31	4.83	-5.09	-5.71	4.78	2.83	0.04
Sharpe Ratio	1.45	-1.67	-1.9	0.49	-1.14	-1.15	2.57	1.45	-0.11
Sortino Ratio	1.05	-0.35	-0.53	0.31	-0.12	-0.24	6.17	1.42	-0.09
Information Ratio	1.06	-0.62	-0.62	0.15	-0.56	-0.59	0.82	0.24	-0.01
Turnover (%)	98	99	99	98	99	99	41	41	58
Max 1M loss (%)	-13.91	-18.69	-18.78	-12.57	-15.02	-46.61	-4.01	-6.83	-16.55
Max DD (%)	-35.47	-99.98	-100	-25.22	-95.87	-99.56	-6.12	-11.99	-32.59
Skewness	1.03	0.42	0.38	0.71	-0.18	-4.65	0.13	-0.13	-0.88
Excess Kurtosis	2.36	1.47	0.79	4.41	3.03	42.3	-3.61	-3.09	-2.05

NN4 Monthly Rebalancing

Weighting	Equal			Value			Optimized		
	Without TF	With TF Low Capital	With TF High Capital	Without TF	With TF Low Capital	With TF High Capital	Without TF	With TF Low Capital	With TF High Capital
Model	NN4	NN4	NN4	NN4	NN4	NN4	NN4	NN4	NN4
Initial capital (millions)	All	1	100	All	1	100	All	1	100
Horizon	1	1	1	1	1	1	1	1	1
Rebalancing	month	month	month	month	month	month	month	month	month
R2oos (%)	0.15	-1.08	-1.17	0.34	-1.23	-1.37	1.3	0.64	-2.81
Mean Returns (%)	2.017	-1.707	-2.103	0.532	-0.782	-1.239	3.485	2.322	-1.582
t statistic	9.88	-8.07	-9.5	4.1	-5.64	-5.98	4.85	3.07	-1.71
Sharpe Ratio	1.45	-1.53	-1.76	0.38	-1.22	-1.19	2.62	1.6	-1.14
Sortino Ratio	1.04	-0.31	-0.45	0.18	-0.14	-0.23	5.63	1.4	-0.52
Information Ratio	0.89	-0.56	-0.57	-0.11	-0.8	-0.82	1.14	0.71	-0.22
Turnover (%)	97	98	98	97	98	98	40	41	60
Max 1M loss (%)	-13.91	-18.57	-20.64	-12.24	-14.41	-43.07	-4.21	-7.42	-14.95
Max DD (%)	-37.78	-99.96	-99.99	-26.23	-97.31	-99.73	-6.21	-14.69	-46.05
Skewness	1.22	0.56	0.45	0.76	0.09	-4.36	0.38	0.21	-0.51
Excess Kurtosis	2.65	1.76	1.36	3.31	2.04	36.3	-3.3	-2.72	-3.01

NN5 Monthly Rebalancing

Weighting	Equal			Value			Optimized		
	Without TF	With TF Low Capital	With TF High Capital	Without TF	With TF Low Capital	With TF High Capital	Without TF	With TF Low Capital	With TF High Capital
Model	NN5	NN5	NN5	NN5	NN5	NN5	NN5	NN5	NN5
Initial capital (millions)	All	1	100	All	1	100	All	1	100
Horizon	1	1	1	1	1	1	1	1	1
Rebalancing	month	month	month	month	month	month	month	month	month
R2oos (%)	0.13	-1.16	-1.23	0.35	-1.15	-1.13	1.43	0.72	-0.53
Mean Returns (%)	1.344	-1.764	-2.117	0.496	-0.694	-1.172	3.52	2.23	-2.853
t statistic	6.4	-7.72	-8.96	3.59	-4.88	-5.45	5.04	3.05	-2.03
Sharpe Ratio	0.88	-1.46	-1.66	0.31	-1.09	-1.09	2.72	1.58	-1.3
Sortino Ratio	0.57	-0.31	-0.46	0.16	-0.12	-0.21	6.53	1.66	-0.84
Information Ratio	0.74	-0.51	-0.51	0.01	-0.63	-0.65	0.72	-0.11	-0.21
Turnover (%)	90	91	91	90	91	91	41	41	58
Max 1M loss (%)	-27.44	-35.4	-35.71	-11.83	-13.48	-44.71	-4.11	-6.31	-23.73
Max DD (%)	-32.4	-99.97	-99.99	-26.1	-96.06	-99.65	-6.49	-11.8	-60.89
Skewness	-0.55	-1.04	-0.98	1.09	0.06	-4.34	0.31	0.2	-0.99
Excess Kurtosis	4.78	5.52	4.59	8.12	5.01	35.4	-3.47	-3.08	-2.47

Appendix 2C – Portfolio statistics, individual models, quarterly rebalancing

This appendix reports portfolio statistics for the neural network portfolios when the investment horizon is one quarter for the five neural network models, NN1-NN5. The left section of the table presents the results after equal-weighting the portfolio holdings at each rebalancing period. Similarly, the middle section presents the value-weighted results, and the right section presents the results of the optimised portfolio. For each method results are reported in three environments: (a) an environment without trading frictions, (b) an environment with trading frictions, investing a small initial capital of 1 million USD and (c) an environment with trading frictions, investing a large initial capital of 100 million USD. The neural network models are used to predict the stock returns three months ahead, which are then used to create long-short portfolios. The long-short portfolio is constructed by ranking stocks according to the predicted returns and form 10 portfolios, buying the highest quantile portfolio and selling the lowest quintile portfolio. The weights of the holdings in each portfolio vary according to the weighting scheme. The trades are placed, and the portfolio is evaluated at the next period based on the metrics reported. In the first environment no penalties are applied due to trading frictions while the other two environments apply a penalty simulating realistic trading frictions as a function of the microstructure of individual stocks. Investing horizon is three months and thus, rebalancing of the portfolio is performed quarterly based on predicted returns. Mean Returns (%) and R2oos (%) denote the mean returns and mean out-of-sample R2, respectively, across the time series of each portfolio, both reported in percentage basis. Max 1M loss (%) and Max DD (%) denote the Maximum 1-month loss and maximum drawdown, across the time series of each portfolio, both reported in percentage basis. Turnover is the monthly average portfolio turnover and Sharpe ratios are annualised. Skewness and Excess Kurtosis illustrate the shape of the distribution of returns yielded by the trading strategy across the sampling period.

NN1 Quarterly Rebalancing

Weighting	Equal			Value			Optimized		
	Without TF	With TF Low Capital	With TF High Capital	Without TF	With TF Low Capital	With TF High Capital	Without TF	With TF Low Capital	With TF High Capital
Model	NN1	NN1	NN1	NN1	NN1	NN1	NN1	NN1	NN1
Initial capital (millions)	All	1	100	All	1	100	All	1	100
Horizon	3	3	3	3	3	3	3	3	3
Rebalancing	quarter	quarter	quarter	quarter	quarter	quarter	quarter	quarter	quarter
R2oos (%)	-2.43	-5.68	-5.64	-1.83	-8.32	-8.07	0.22	-0.34	-0.61
Mean Returns (%)	-2.109	-5.115	-5.677	-0.147	-1.511	-2.147	1.47	0.151	-3.726
t statistic	-6.95	-15.73	-16.41	-1.02	-11.16	-6.02	1.88	0.18	-1.35
Sharpe Ratio	-2.24	-4.76	-4.95	-0.76	-3.73	-1.93	0.92	-0.05	-0.83
Sortino Ratio	-0.31	-0.95	-1.24	-0.09	-0.23	-0.29	0.76	-0.03	-0.64
Information Ratio	-0.25	-2.42	-2.43	-0.09	-0.92	-0.95	0.2	-0.12	-0.13
Turnover (%)	104	105	105	104	105	105	41	42	61
Max 1M loss (%)	-19.51	-22.7	-22.77	-4.81	-6.42	-17.62	-7.51	-9.82	-94.63
Max DD (%)	-96.87	-99.95	-99.98	-43.55	-88.78	-96.2	-17.23	-29.45	-66.97
Skewness	-0.57	-0.7	-0.55	2.84	-0.52	-8.66	-0.14	-0.15	-4.76
Excess Kurtosis	0.32	-0.8	-1.7	18.53	-1.68	8.61	-3.56	-3.53	-4.78

NN2 Quarterly Rebalancing

Weighting	Equal			Value			Optimized		
	Without TF	With TF Low Capital	With TF High Capital	Without TF	With TF Low Capital	With TF High Capital	Without TF	With TF Low Capital	With TF High Capital
Model	NN2	NN2	NN2	NN2	NN2	NN2	NN2	NN2	NN2
Initial capital (millions)	All	1	100	All	1	100	All	1	100
Horizon	3	3	3	3	3	3	3	3	3
Rebalancing	quarter	quarter	quarter	quarter	quarter	quarter	quarter	quarter	quarter
R2oos (%)	-1.33	-3.51	-3.56	-1.25	-5.26	-4.68	0.69	0.16	-0.77
Mean Returns (%)	-3.965	-6.751	-7.318	-0.724	-2.133	-2.632	1.844	0.155	-1.69
t statistic	-7.34	-11.39	-12.36	-4.04	-10.48	-11.35	2.46	0.2	-1.36
Sharpe Ratio	-2.25	-3.41	-3.69	-1.54	-3.36	-3.58	1.24	-0.05	-0.89
Sortino Ratio	-0.5	-1.04	-1.35	-0.13	-0.27	-0.4	2.13	-0.03	-0.31
Information Ratio	-1.23	-2.13	-2.16	-0.71	-1.52	-1.69	-0.02	-1.26	-0.39
Turnover (%)	103	104	104	103	104	103	43	44	61
Max 1M loss (%)	-40.26	-48.76	-49.18	-9.4	-12.15	-12.66	-8.31	-9.22	-18.73
Max DD (%)	-99.77	-100	-100	-70.67	-95.46	-97.83	-9.21	-24.58	-63.83
Skewness	-1.87	-2.05	-2.01	-1.29	-1.48	-1.4	0.1	0.05	-0.05
Excess Kurtosis	3.91	5.26	5.15	-0.42	0.21	-0.5	-2.62	-3.13	-3.01

NN3 Quarterly Rebalancing

Weighting	Equal			Value			Optimized		
	Without TF	With TF Low Capital	With TF High Capital	Without TF	With TF Low Capital	With TF High Capital	Without TF	With TF Low Capital	With TF High Capital
Model	NN3	NN3	NN3	NN3	NN3	NN3	NN3	NN3	NN3
Initial capital (millions)	All	1	100	All	1	100	All	1	100
Horizon	3	3	3	3	3	3	3	3	3
Rebalancing	quarter	quarter	quarter	quarter	quarter	quarter	quarter	quarter	quarter
R2oos (%)	-1.21	-3.96	-4.04	-1.3	-5.49	-5.26	0.73	0.17	0.18
Mean Returns (%)	-1.109	-4.417	-5.064	0.03	-1.413	-1.879	2.415	0.93	-1.832
t statistic	-3.04	-11.51	-12.21	0.19	-9.47	-10	3.23	1.18	-1.71
Sharpe Ratio	-1.06	-3.51	-3.7	-0.37	-3.19	-3.25	1.69	0.51	-1.11
Sortino Ratio	-0.17	-0.74	-1.03	-0.06	-0.23	-0.33	2.33	0.27	-0.51
Information Ratio	-0.13	-1.76	-1.83	-0.09	-0.97	-1.04	-0.02	-1.14	-0.33
Turnover (%)	106	106	106	106	106	106	43	43	54
Max 1M loss (%)	-11.98	-17.78	-22.07	-4.29	-6.56	-10.82	-6.25	-7.78	-14.05
Max DD (%)	-86.24	-99.86	-99.95	-34.35	-86.87	-93.4	-11.29	-24.94	-50.37
Skewness	2.42	0.96	0.58	2.74	0.79	-0.46	0.1	0.06	-0.08
Excess Kurtosis	12.84	3.18	2.13	12.69	2.19	1.2	-3.51	-3.54	-3.37

NN4 Quarterly Rebalancing

Weighting	Equal			Value			Optimized		
	Without TF	With TF Low Capital	With TF High Capital	Without TF	With TF Low Capital	With TF High Capital	Without TF	With TF Low Capital	With TF High Capital
Model	NN4	NN4	NN4	NN4	NN4	NN4	NN4	NN4	NN4
Initial capital (millions)	All	1	100	All	1	100	All	1	100
Horizon	3	3	3	3	3	3	3	3	3
Rebalancing	quarter	quarter	quarter	quarter	quarter	quarter	quarter	quarter	quarter
R2oos (%)	-1.17	-3.74	-3.8	-0.96	-4.57	-4.35	0.69	0.15	-0.07
Mean Returns (%)	-0.862	-4.117	-4.811	0.042	-1.425	-1.935	2.307	0.882	-2.688
t statistic	-2.21	-10.3	-11.19	0.25	-8.84	-8.88	2.85	1.04	-2.17
Sharpe Ratio	-0.81	-3.15	-3.4	-0.33	-2.98	-2.88	1.49	0.44	-1.36
Sortino Ratio	-0.13	-0.61	-0.83	-0.05	-0.23	-0.31	1.91	0.25	-0.54
Information Ratio	0.01	-1.7	-1.8	-0.21	-1.04	-1.16	-0.04	-0.56	-0.16
Turnover (%)	104	105	105	104	105	103	42	43	50
Max 1M loss (%)	-11.95	-18.15	-22.98	-3.88	-5.64	-15.92	-7.29	-9.12	-29.69
Max DD (%)	-86.01	-99.78	-99.92	-37.44	-87.14	-93.99	-13.27	-26.9	-62.77
Skewness	2.07	0.98	0.65	3.11	1.41	-1.08	-0.06	-0.05	-1.04
Excess Kurtosis	9.29	3.26	2.26	14.92	5.06	5.66	-3.54	-3.65	0.86

NN5 Quarterly Rebalancing

Weighting	Equal			Value			Optimized		
	Without TF	With TF Low Capital	With TF High Capital	Without TF	With TF Low Capital	With TF High Capital	Without TF	With TF Low Capital	With TF High Capital
Model	NN5	NN5	NN5	NN5	NN5	NN5	NN5	NN5	NN5
Initial capital (millions)	All	1	100	All	1	100	All	1	100
Horizon	3	3	3	3	3	3	3	3	3
Rebalancing	quarter	quarter	quarter	quarter	quarter	quarter	quarter	quarter	quarter
R2oos (%)	-1.19	-3.7	-3.76	-0.79	-4.05	-3.78	1.01	0.47	-2.59
Mean Returns (%)	-0.503	-3.623	-4.276	0.159	-1.223	-1.711	2.995	1.499	-1.801
t statistic	-1.52	-10.6	-11.89	0.82	-6.56	-7.75	3.88	1.89	-1.26
Sharpe Ratio	-0.64	-3.27	-3.63	-0.11	-2.26	-2.55	2.07	0.93	-0.82
Sortino Ratio	-0.1	-0.53	-0.71	-0.02	-0.21	-0.28	4.55	1.05	-0.56
Information Ratio	-0.12	-1.6	-1.69	-0.19	-1.08	-1.21	0.04	-0.57	-0.41
Turnover (%)	101	102	102	101	102	102	42	42	66
Max 1M loss (%)	-12.31	-13.98	-14.68	-4.17	-6.15	-13.89	-5.83	-7.92	-25.63
Max DD (%)	-74.15	-99.52	-99.81	-31.34	-82.99	-91.71	-5.83	-14.12	-52.85
Skewness	0.36	-0.13	-0.07	4.04	2.74	0.63	0.64	0.4	-0.19
Excess Kurtosis	-0.8	-3.02	-3.11	25.04	16.05	9.21	-2.34	-3	-0.08

Appendix 2D – Portfolio statistics, individual models, annual rebalancing

This appendix reports portfolio statistics for the neural network portfolios when the investment horizon is one year for the five neural network models, NN1-NN5. The left section of the table presents the results after equal-weighting the portfolio holdings at each rebalancing period. Similarly, the middle section presents the value-weighted results, and the right section presents the results of the optimised portfolio. For each method results are reported in three environments: (a) an environment without trading frictions, (b) an environment with trading frictions, investing a small initial capital of 1 million USD and (c) an environment with trading frictions, investing a large initial capital of 100 million USD. The neural network models are used to predict the stock returns twelve months ahead, which are then used to create long-short portfolios. The long-short portfolio is constructed by ranking stocks according to the predicted returns and form 10 portfolios, buying the highest quantile portfolio and selling the lowest quintile portfolio. The weights of the holdings in each portfolio vary according to the weighting scheme. The trades are placed, and the portfolio is evaluated at the next period based on the metrics reported. In the first environment no penalties are applied due to trading frictions while the other two environments apply a penalty simulating realistic trading frictions as a function of the microstructure of individual stocks. Investing horizon is twelve months and thus, rebalancing of the portfolio is performed annually based on predicted returns. Mean Returns (%) and R2oos (%) denote the mean returns and mean out-of-sample R2, respectively, across the time series of each portfolio, both reported in percentage basis. Max 1M loss (%) and Max DD (%) denote the Maximum 1-month loss and maximum drawdown, across the time series of each portfolio, both reported in percentage basis. Turnover is the monthly average portfolio turnover and Sharpe ratios are annualised. Skewness and Excess Kurtosis illustrate the shape of the distribution of returns yielded by the trading strategy across the sampling period.

NN1 Annual Rebalancing

Weighting	Equal			Value			Optimized		
	Without TF	With TF Low Capital	With TF High Capital	Without TF	With TF Low Capital	With TF High Capital	Without TF	With TF Low Capital	With TF High Capital
Model	NN1	NN1	NN1	NN1	NN1	NN1	NN1	NN1	NN1
Initial capital (millions)	All	1	100	All	1	100	All	1	100
Horizon	12	12	12	12	12	12	12	12	12
Rebalancing	annual	annual	annual	annual	annual	annual	annual	annual	annual
R2oos (%)	-6.69	-17.3	-14.95	-3.82	-23.98	-20.71	0.44	0.04	-0.21
Mean Returns (%)	0.582	-4.944	-6.942	0.065	-2.013	-2.749	1.791	0.358	-0.679
t statistic	1.87	-13.33	-12.55	0.5	-11.81	-9.22	1.97	0.38	-0.67
Sharpe Ratio	0.68	-8.03	-7.47	-0.67	-7.55	-5.74	0.99	0.08	-0.52
Sortino Ratio	0.57	-0.76	-1.14	-0.57	-0.52	-0.62	1.55	0.05	-0.29
Information Ratio	0.35	-3.59	-3.01	-0.07	-1.41	-1.56	0.03	-0.45	-0.52
Turnover (%)	140	140	140	140	140	140	51	51	66
Max 1M loss (%)	-2.89	-12.06	-14.35	-1.29	-4.34	-8.41	-12.12	-15.86	-18.71
Max DD (%)	-8.28	-82.67	-91.49	-3.9	-50.27	-60.51	-14.05	-28.19	-36.42
Skewness	0.43	-0.91	-0.69	0.1	-0.23	-1.43	-0.52	-0.74	-0.72
Excess Kurtosis	-3.44	-1.78	-3.4	-3.88	-3.5	-0.66	-2.86	-2.54	-2.13

NN2 Annual Rebalancing

Weighting	Equal			Value			Optimized		
	Without TF	With TF Low Capital	With TF High Capital	Without TF	With TF Low Capital	With TF High Capital	Without TF	With TF Low Capital	With TF High Capital
Model	NN2	NN2	NN2	NN2	NN2	NN2	NN2	NN2	NN2
Initial capital (millions)	All	1	100	All	1	100	All	1	100
Horizon	12	12	12	12	12	12	12	12	12
Rebalancing	annual	annual	annual	annual	annual	annual	annual	annual	annual
R2oos (%)	-2.56	-10.19	-9.68	-0.87	-8.48	-6.45	0.79	0.44	1.14
Mean Returns (%)	0.234	-5.295	-7.483	0.337	-1.868	-2.653	1.942	0.61	0.322
t statistic	0.44	-8.08	-10.03	1.76	-8.18	-8.43	2.25	0.71	0.31
Sharpe Ratio	0.02	-4.85	-5.96	0.37	-5.27	-5.26	1.14	0.26	0.05
Sortino Ratio	0.01	-0.75	-1.17	0.29	-0.49	-0.6	1.85	0.24	0.04
Information Ratio	0.57	-3.27	-3.32	0.24	-1.05	-1.23	0.3	-0.13	-0.35
Turnover (%)	139	139	139	139	139	140	44	44	71
Max 1M loss (%)	-9	-17.74	-18.66	-1.95	-5.36	-7.66	-10.76	-11.14	-14.69
Max DD (%)	-22.82	-85.62	-93.43	-5.01	-48.13	-59.13	-10.76	-16.75	-28.36
Skewness	-0.68	-1.43	-0.81	0.79	-0.61	-0.78	-0.56	-0.54	-0.05
Excess Kurtosis	-2.04	-1.31	-2.93	-1.4	-2.95	-2.89	-3.11	-3.35	-2.72

NN3 Annual Rebalancing

Weighting	Equal			Value			Optimized		
	Without TF	With TF Low Capital	With TF High Capital	Without TF	With TF Low Capital	With TF High Capital	Without TF	With TF Low Capital	With TF High Capital
Model	NN3	NN3	NN3	NN3	NN3	NN3	NN3	NN3	NN3
Initial capital (millions)	All	1	100	All	1	100	All	1	100
Horizon	12	12	12	12	12	12	12	12	12
Rebalancing	annual	annual	annual	annual	annual	annual	annual	annual	annual
R2oos (%)	-3.15	-10.64	-9.86	-1.43	-14.93	-12.59	0.77	0.32	0.5
Mean Returns (%)	1.037	-4.62	-6.984	0.569	-1.771	-2.777	2.578	1.235	-0.49
t statistic	3.61	-13.72	-6.45	2.11	-10.19	-5.31	3.23	1.47	-0.61
Sharpe Ratio	1.65	-8.29	-3.84	0.76	-6.6	-3.3	1.7	0.69	-0.52
Sortino Ratio	4.69	-0.81	-1.75	3.14	-0.52	-0.76	3.23	0.53	-0.33
Information Ratio	0.84	-2.55	-2.95	0.07	-1.21	-1.67	-0.87	-2.21	-1.35
Turnover (%)	141	141	141	141	141	141	45	46	59
Max 1M loss (%)	-1.61	-11.67	-41.67	-1.23	-4.67	-19.65	-6.31	-8.41	-7.95
Max DD (%)	-1.7	-80.86	-92.56	-1.23	-46.43	-63.23	-8.45	-19.86	-28.42
Skewness	1.61	-1.21	-4.38	3.65	-0.41	-4.45	0.06	0.01	0.1
Excess Kurtosis	0.06	-0.03	17.94	-2.82	-2.31	-1.86	-3.56	-3.6	-3.97

NN4 Annual Rebalancing

Weighting	Equal			Value			Optimized		
	Without TF	With TF Low Capital	With TF High Capital	Without TF	With TF Low Capital	With TF High Capital	Without TF	With TF Low Capital	With TF High Capital
Model	NN4	NN4	NN4	NN4	NN4	NN4	NN4	NN4	NN4
Initial capital (millions)	All	1	100	All	1	100	All	1	100
Horizon	12	12	12	12	12	12	12	12	12
Rebalancing	annual	annual	annual	annual	annual	annual	annual	annual	annual
R2oos (%)	-3.21	-10.19	-9.57	-0.63	-12.82	-10.75	0.79	0.33	0.31
Mean Returns (%)	1.37	-4.329	-6.768	0.594	-1.697	-2.346	2.656	1.331	-1.546
t statistic	3.86	-13.5	-8.18	2.21	-9.59	-11.06	3.36	1.62	-1.69
Sharpe Ratio	1.88	-8.18	-4.87	0.81	-6.24	-6.97	1.77	0.78	-1.12
Sortino Ratio	6.94	-0.75	-1.42	3.08	-0.5	-0.55	3.49	0.63	-0.75
Information Ratio	0.87	-2.64	-3.57	0.14	-1.13	-1.49	-0.83	-1.99	-2.8
Turnover (%)	140	141	141	140	141	141	45	46	62
Max 1M loss (%)	-1.56	-9.01	-28.31	-1.33	-4.62	-6.13	-5.86	-7.24	-16.74
Max DD (%)	-1.8	-78.63	-91.42	-1.33	-44.9	-56.24	-8.67	-19.28	-35.83
Skewness	2.11	-0.05	-2.56	3.42	-0.56	-0.72	0.02	0.02	-0.12
Excess Kurtosis	2.08	-1.87	5.28	-2.94	-2.29	-2.6	-3.75	-3.84	-2.09

NN5 Annual Rebalancing

Weighting	Equal			Value			Optimized		
	Without TF	With TF Low Capital	With TF High Capital	Without TF	With TF Low Capital	With TF High Capital	Without TF	With TF Low Capital	With TF High Capital
Model	NN5	NN5	NN5	NN5	NN5	NN5	NN5	NN5	NN5
Initial capital (millions)	All	1	100	All	1	100	All	1	100
Horizon	12	12	12	12	12	12	12	12	12
Rebalancing	annual	annual	annual	annual	annual	annual	annual	annual	annual
R2oos (%)	-3.61	-11.97	-11.08	-1.13	-11.47	-10.11	0.81	0.49	0.01
Mean Returns (%)	1.325	-4.361	-6.341	0.565	-1.719	-2.24	2.263	0.924	1.671
t statistic	3.53	-13.14	-11.45	2.2	-9.22	-10.07	2.71	1.12	1.12
Sharpe Ratio	1.71	-7.96	-6.83	0.79	-5.99	-6.37	1.43	0.5	0.56
Sortino Ratio	2.8	-0.74	-1.06	2.6	-0.5	-0.55	2.01	0.43	1.31
Information Ratio	0.79	-2.55	-3.24	0.27	-0.9	-1	0.29	-0.13	-1.38
Turnover (%)	142	142	143	142	142	142	39	40	61
Max 1M loss (%)	-1.73	-7.82	-15.1	-1.46	-4.62	-5.84	-10.81	-11.16	-8.24
Max DD (%)	-4.73	-78.74	-89.62	-1.46	-45.21	-54.57	-10.81	-18.02	-12.67
Skewness	1.59	0.67	-0.48	3.11	-0.58	-0.96	-0.45	-0.42	2.74
Excess Kurtosis	0.26	-2.44	-2.95	-2.92	-1.91	-2.48	-3.05	-3.38	6.64

Appendix 2E: Impact of trading frictions on risk-adjusted returns of the NN portfolios, monthly

This appendix reports the mean returns and risk-adjusted returns for the neural network predictive models NN1- NN2. Panel A reports the results for the equal-weighted rebalancing method and Panel B reports the results for the value weighted portfolio and Panel C for the optimised portfolio. Each panel reports the results for the environment without trading frictions in the top section, the environment with trading frictions investing a small initial capital of 1 million USD in the middle section and the environment with trading frictions investing a large initial capital of 100 million USD in the bottom section. The long-short portfolio is constructed by ranking stocks according to their machine learning predicted returns and form 10 portfolios, buying the highest quantile portfolio and selling the lowest quintile portfolio (HML portfolio). Each section reports the returns for the lowest quintile portfolio (1), the highest quintile portfolio (10) and the High-minus-Low portfolio (HML). Mean returns are adjusted for common factor models, specifically; (a) CAPM, (b) Fama-French-Carhart 4-factor model (FFC), (c) Pástor and Stambaugh liquidity factor model (FFC+PS), (d) Fama-French 5-factor model (FF5), (e) Fama-French 6-factor model (FF6), and Hou et. al., (2015) q-factor model (q). Both mean returns and risk-adjusted returns are expressed in percentage basis. The Newey-West adjusted t statistics are presented in the parentheses. Coefficients denoted with *, **, and *** are statistically significant at the 10%, 5%, and 1% levels, respectively. Investing horizon is one month and thus, rebalancing of the portfolio is performed monthly based on predicted returns.

Panel A: Equally weighted (NN1)

No TF							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	-1.072** (-3.29)	-1.356*** (-3.86)	-1.348*** (-3.71)	-1.344*** (-3.5)	-1.329*** (-3.56)	-1.365*** (-3.52)	-1.095** (-3.07)
10	1.436*** (4.25)	1.166** (3.04)	1.1** (3.11)	1.2** (2.81)	1.069** (2.82)	1.041* (2.79)	1.373*** (3.65)
HML	2.509*** (13.15)	2.284*** (8.88)	2.213*** (9.17)	2.309*** (7.93)	2.16*** (9.19)	2.17*** (8.85)	2.241*** (9.21)
With TF Small Portfolio							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	1.156*** (3.47)	0.888 (2.41)	0.855 (2.23)	0.825 (1.95)	0.901 (2.33)	0.861 (2.13)	1.104** (2.87)
10	-0.57 (-1.61)	-0.846 (-1.86)	-0.897 (-2.13)	-0.772 (-1.73)	-0.918 (-2.02)	-0.975 (-2.18)	-0.649 (-1.48)
HML	-1.726*** (-8.64)	-1.971*** (-7.14)	-1.987*** (-7.0)	-1.832*** (-5.72)	-2.057*** (-7.31)	-2.071*** (-7.0)	-1.98*** (-7.21)
With TF Large Portfolio							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	1.37*** (4.1)	1.102** (3.0)	1.066* (2.81)	1.038 (2.49)	1.115** (2.92)	1.073* (2.69)	1.313*** (3.42)
10	-0.809 (-2.26)	-1.084 (-2.19)	-1.13 (-2.44)	-1.032 (-2.0)	-1.144 (-2.3)	-1.198 (-2.45)	-0.882 (-1.86)
HML	-2.179*** (-10.34)	-2.424*** (-6.99)	-2.431*** (-6.92)	-2.305*** (-5.49)	-2.496*** (-7.21)	-2.506*** (-7.08)	-2.423*** (-7.05)

Panel B: Value weighted (NN1)

No TF							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	-0.367* (-2.66)	-0.63*** (-4.16)	-0.594*** (-3.89)	-0.597*** (-3.78)	-0.614*** (-4.16)	-0.608*** (-3.98)	-0.494*** (-3.44)
10	0.548*** (3.87)	0.305 (2.09)	0.314 (2.46)	0.332 (2.5)	0.31 (2.08)	0.32 (2.12)	0.422*** (3.36)
HML	0.915*** (8.05)	0.698*** (5.12)	0.673*** (4.86)	0.694*** (4.21)	0.686*** (4.98)	0.693*** (4.73)	0.689*** (5.39)
With TF Small Portfolio							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	0.494*** (3.71)	0.238 (1.88)	0.258 (1.87)	0.267 (1.75)	0.244 (1.86)	0.253 (1.81)	0.351* (2.65)
10	0.021 (0.14)	-0.229 (-1.33)	-0.202 (-1.36)	-0.139 (-0.96)	-0.213 (-1.21)	-0.209 (-1.18)	-0.113 (-0.78)
HML	-0.473*** (-4.07)	-0.705*** (-4.64)	-0.695*** (-4.5)	-0.641*** (-3.76)	-0.694*** (-4.34)	-0.697*** (-4.09)	-0.691*** (-4.79)
With TF Large Portfolio							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	0.836*** (5.09)	0.594** (3.15)	0.599*** (3.3)	0.72** (3.12)	0.617** (3.1)	0.617** (3.07)	0.672*** (3.76)
10	-0.066 (-0.44)	-0.317 (-1.68)	-0.288 (-1.74)	-0.239 (-1.33)	-0.293 (-1.52)	-0.287 (-1.48)	-0.194 (-1.22)
HML	-0.903*** (-5.84)	-1.149*** (-5.58)	-1.122*** (-5.51)	-1.193*** (-4.56)	-1.147*** (-5.17)	-1.139*** (-5.05)	-1.093*** (-5.79)

Panel C: Optimized (NN1)							
No TF							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	0.086 (0.29)	-0.239 (-1.72)	-0.285 (-1.55)	-0.239 (-1.15)	-0.427*** (-1.43)	-0.465*** (-4.65)	-0.059 (-0.35)
10	3.27*** (4.03)	2.543*** (5.05)	2.42*** (3.61)	2.055** (3.06)	2.142*** (3.59)	2.022*** (3.54)	3.178*** (3.02)
HML	3.184*** (4.69)	2.563*** (4.99)	2.482*** (4.43)	2.11** (3.2)	2.341*** (3.19)	2.266*** (3.12)	3.01*** (3.62)
With TF Small Portfolio							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	0.326 (1.04)	-0.001 (-0.0)	-0.05 (-0.25)	-0.004 (-0.02)	-0.195 (-1.55)	-0.234 (-1.82)	0.186 (1.25)
10	2.075 (2.6)	1.338** (2.99)	1.181 (1.92)	0.813 (1.02)	0.88*** (3.69)	0.779*** (3.51)	1.98 (2.42)
HML	1.749* (2.56)	1.12* (2.58)	1.008* (2.51)	0.833* (2.8)	0.848*** (3.39)	0.792*** (3.5)	1.567* (2.36)
With TF Large Portfolio							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	0.8 (1.24)	0.381 (0.84)	0.575 (0.88)	0.493 (0.95)	0.383 (0.88)	0.28 (0.58)	0.571 (0.9)
10	1.145 (1.71)	0.553 (1.29)	0.448 (0.96)	-0.164 (-0.29)	0.25 (0.69)	0.108 (0.27)	1.032 (1.69)
HML	0.345 (0.39)	-0.046 (-0.08)	-0.349 (-0.47)	-0.841 (-1.39)	-0.361 (-0.5)	-0.393 (-0.48)	0.234 (0.42)

Panel A: Equally weighted (NN2)

No TF							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	-0.38 (-1.08)	-0.664 (-2.01)	-0.684 (-2.12)	-0.655 (-2.0)	-0.680 (-2.12)	-0.680 (-2.12)	-0.635 (-1.93)
10	1.115*** (3.79)	1.088*** (3.54)	1.081*** (3.53)	1.095*** (3.15)	1.077*** (3.67)	1.0778*** (3.69)	1.0789*** (3.36)
HML	1.494*** (7.39)	0.956*** (4.92)	0.95*** (4.89)	1.089*** (5.01)	0.907*** (4.85)	0.899*** (4.84)	0.976*** (4.92)
With TF Small Portfolio							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	1.796*** (5.03)	1.52*** (3.62)	1.462*** (3.37)	1.356** (2.91)	1.48*** (3.46)	1.456** (3.22)	1.766*** (3.84)
10	-0.774 (-2.24)	-1.046 (-2.41)	-1.056* (-2.63)	-0.798 (-1.93)	-1.053 (-2.4)	-1.091 (-2.5)	-0.828 (-2.01)
HML	-2.57*** (-11.2)	-2.804*** (-7.34)	-2.752*** (-7.34)	-2.388*** (-5.54)	-2.77*** (-7.21)	-2.782*** (-7.02)	-2.822*** (-7.66)
With TF Large Portfolio							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	2.05*** (5.72)	1.776*** (4.27)	1.71*** (3.97)	1.593*** (3.46)	1.732*** (4.1)	1.703*** (3.82)	2.012*** (4.4)
10	-0.958* (-2.76)	-1.227* (-2.72)	-1.234** (-2.95)	-0.941 (-2.26)	-1.21* (-2.63)	-1.25* (-2.74)	-1.013 (-2.37)
HML	-3.008*** (-12.72)	-3.24*** (-8.34)	-3.178*** (-8.22)	-2.769*** (-6.31)	-3.179*** (-8.15)	-3.188*** (-7.96)	-3.253*** (-8.57)

Panel B: Value weighted (NN2)

No TF							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	-0.143 (-0.98)	-0.41 (-2.43)	-0.357 (-2.12)	-0.408 (-2.18)	-0.393 (-2.26)	-0.372 (-2.06)	-0.25 (-1.58)
10	0.433** (3.17)	0.188 (1.23)	0.208 (1.57)	0.289 (2.05)	0.167 (1.09)	0.189 (1.2)	0.292 (2.28)
HML	0.577*** (4.99)	0.361*** (3.07)	0.329* (2.71)	0.463** (2.90)	0.322 (2.34)	0.326 (2.11)	0.315 (2.39)
With TF Small Portfolio							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	0.753*** (5.23)	0.496** (3.28)	0.523** (3.28)	0.458 (2.44)	0.495** (3.12)	0.518** (3.05)	0.629*** (4.18)
10	-0.107 (-0.74)	-0.366 (-1.89)	-0.334 (-1.94)	-0.21 (-1.17)	-0.372 (-1.91)	-0.365 (-1.86)	-0.248 (-1.46)
HML	-0.86*** (-6.81)	-1.099*** (-5.87)	-1.092*** (-5.71)	-0.903*** (-4.13)	-1.104*** (-5.7)	-1.118*** (-5.36)	-1.103*** (-6.09)
With TF Large Portfolio							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	1.031*** (6.9)	0.783*** (5.27)	0.796*** (5.16)	0.742*** (4.08)	0.78*** (5.19)	0.799*** (4.94)	0.891*** (6.1)
10	-0.195 (-1.32)	-0.451 (-2.22)	-0.418 (-2.3)	-0.286 (-1.56)	-0.447 (-2.2)	-0.441 (-2.16)	-0.34 (-1.88)
HML	-1.226*** (-8.85)	-1.471*** (-7.34)	-1.449*** (-7.07)	-1.262*** (-5.42)	-1.464*** (-7.14)	-1.476*** (-6.79)	-1.458*** (-7.35)

Panel C: Optimized (NN2)

No TF							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	0.058 (0.46)	-0.207 (-1.96)	-0.219 (-2.0)	-0.233 (-1.86)	-0.276* (-2.75)	-0.28** (-3.01)	-0.136 (-2.15)
10	3.399*** (3.87)	2.599*** (4.26)	2.596* (2.67)	2.341 (1.74)	2.152*** (7.24)	2.028*** (6.44)	3.252** (3.12)
HML	3.341*** (4.0)	2.587*** (3.57)	2.593* (3.64)	2.389 (3.53)	2.201*** (3.21)	2.087*** (3.06)	3.161** (4.11)
With TF Small Portfolio							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	0.086 (0.6)	-0.186 (-1.83)	-0.184 (-1.89)	-0.209 (-1.73)	-0.228 (-2.05)	-0.246 (-2.43)	-0.109 (-1.69)
10	2.599*** (3.59)	2.018*** (3.01)	2.001*** (2.97)	2.298*** (2.92)	2.03*** (2.95)	2.848* (2.62)	2.024* (2.69)
HML	1.685*** (3.83)	1.251** (2.95)	1.139** (2.93)	1.173** (2.93)	1.029** (2.94)	0.823* (2.69)	0.812 (2.53)
With TF Large Portfolio							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	1.375 (1.6)	0.971 (1.12)	0.727 (1.13)	0.533 (0.57)	0.749 (1.23)	0.572 (1.29)	1.177 (1.1)
10	0.222 (0.3)	-0.229 (-0.55)	-0.215 (-0.93)	-0.89* (-2.69)	-0.314 (-0.76)	-0.33 (-0.87)	0.069 (0.19)
HML	-1.153 (-1.02)	-1.418 (-1.22)	-1.157 (-1.71)	-1.595 (-1.41)	-1.288 (-1.44)	-1.12 (-1.61)	-1.33 (-1.17)

Panel A: Equally weighted (NN3)

No TF							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	-0.780 (-2.5)	-0.708 (-2.6)	-0.552 (-2.08)	-0.618 (-2.67)	-0.602 (-2.36)	-0.518 (-2.46)	-0.032 (-0.09)
10	1.195*** (3.43)	1.205 (0.47)	1.35*** (6.14)	1.238*** (4.18)	1.111*** (4.87)	1.185*** (3.85)	2.145*** (5.8)
HML	1.975*** (9.90)	1.912*** (9.07)	1.902*** (8.21)	1.856*** (7.85)	1.713*** (7.23)	1.703*** (7.81)	2.177*** (5.89)
With TF Small Portfolio							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	1.092*** (3.45)	0.856 (2.34)	0.795 (2.21)	0.688 (1.83)	0.859 (2.32)	0.821 (2.17)	1.007* (2.58)
10	-0.761 (-2.11)	-1.058 (-2.55)	-1.066* (-2.58)	-0.861 (-2.05)	-1.112 (-2.57)	-1.153* (-2.62)	-0.804 (-1.95)
HML	-1.853*** (-8.91)	-2.151*** (-8.02)	-2.096*** (-8.12)	-1.783*** (-5.55)	-2.209*** (-8.51)	-2.209*** (-8.46)	-2.038*** (-7.87)
With TF Large Portfolio							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	1.267*** (3.97)	1.026* (2.81)	0.968* (2.68)	0.858 (2.26)	1.024* (2.8)	0.987* (2.63)	1.182** (3.0)
10	-0.976* (-2.69)	-1.274** (-2.9)	-1.275** (-2.89)	-1.073 (-2.37)	-1.326** (-2.87)	-1.366** (-2.92)	-1.022 (-2.33)
HML	-2.243*** (-10.31)	-2.538*** (-8.05)	-2.479*** (-7.96)	-2.165*** (-5.59)	-2.587*** (-8.43)	-2.588*** (-8.39)	-2.431*** (-7.69)

Panel B: Value weighted (NN3)

No TF							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	-0.077 (-0.58)	-0.326 (-2.34)	-0.313 (-2.38)	-0.308 (-2.23)	-0.36* (-2.58)	-0.341 (-2.38)	-0.193 (-1.53)
10	0.534*** (3.44)	0.271 (1.8)	0.314 (2.25)	0.358 (2.26)	0.3 (1.94)	0.322 (2.05)	0.424** (3.22)
HML	0.611*** (4.83)	0.360*** (3.77)	0.393** (3.17)	0.432* (2.73)	0.423*** (3.31)	0.428*** (3.35)	0.39** (3.27)
With TF Small Portfolio							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	0.62*** (4.62)	0.389** (3.08)	0.378** (3.22)	0.393** (3.22)	0.355* (2.8)	0.374** (2.84)	0.493*** (4.29)
10	-0.068 (-0.43)	-0.332 (-1.88)	-0.278 (-1.73)	-0.2 (-1.16)	-0.282 (-1.61)	-0.268 (-1.5)	-0.178 (-1.2)
HML	-0.688*** (-5.09)	-0.958*** (-6.13)	-0.89*** (-6.19)	-0.827*** (-5.04)	-0.875*** (-5.92)	-0.877*** (-5.82)	-0.898*** (-6.64)
With TF Large Portfolio							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	0.933*** (4.67)	0.718* (2.7)	0.679** (2.91)	0.739** (2.85)	0.68* (2.62)	0.698* (2.66)	0.794*** (3.33)
10	-0.208 (-1.28)	-0.477 (-2.39)	-0.419 (-2.25)	-0.351 (-1.7)	-0.43 (-2.11)	-0.417 (-2.01)	-0.313 (-1.79)
HML	-1.141*** (-5.71)	-1.432*** (-5.15)	-1.333*** (-5.17)	-1.324*** (-4.4)	-1.348*** (-4.94)	-1.35*** (-4.92)	-1.334*** (-5.23)

Panel C: Optimized (NN3)

No TF							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	-0.079 (-0.35)	-0.401** (-3.1)	-0.397** (-3.06)	-0.443*** (-2.91)	-0.372*** (-2.92)	-0.446*** (-2.86)	-0.258 (-1.52)
10	3.256*** (3.81)	2.503*** (3.17)	2.406*** (3.21)	1.948** (2.96)	2.0*** (2.92)	1.957*** (3.33)	3.186*** (4.25)
HML	3.335*** (4.78)	2.685*** (5.78)	2.58*** (5.39)	2.207*** (5.19)	2.145*** (5.12)	2.182*** (5.39)	3.217*** (5.98)
With TF Small Portfolio							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	0.197 (0.8)	-0.135 (-0.82)	-0.121 (-0.78)	-0.166 (-1.6)	-0.107 (-0.74)	-0.183 (-1.23)	0.022 (0.12)
10	2.166 (2.59)	1.406** (3.01)	1.277 (1.77)	0.815 (0.92)	0.86*** (3.15)	0.838*** (2.62)	2.087 (2.39)
HML	1.969* (2.83)	1.322** (3.25)	1.175 (1.83)	0.796 (0.93)	0.739*** (3.41)	0.801*** (3.69)	0.838 (2.53)
With TF Large Portfolio							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	0.506 (0.56)	-0.018 (-0.04)	0.065 (0.11)	0.321 (0.5)	0.252 (0.38)	0.003 (0.01)	0.381 (0.62)
10	0.541 (1.2)	0.172 (0.38)	0.3 (0.71)	-0.051 (-0.15)	0.199 (0.36)	0.252 (0.42)	0.399 (1.22)
HML	0.035 (0.04)	-0.029 (-0.06)	0.012 (0.02)	-0.557 (-0.6)	-0.28 (-0.44)	0.028 (0.04)	-0.208 (-0.31)

Panel A: Equally weighted (NN4)

No TF							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	-0.734 (-2.35)	-0.766*** (-4.62)	-0.533** (-2.95)	-0.552*** (-3.48)	-0.445** (-2.96)	-0.446*** (-2.93)	0.047 (0.13)
10	1.282*** (3.64)	1.188 (3.81)	1.172*** (3.77)	1.117*** (3.44)	1.193*** (3.79)	1.178*** (3.77)	2.199*** (5.46)
HML	2.017*** (9.88)	1.954*** (8.43)	1.705*** (8.22)	1.669*** (7.96)	1.639*** (7.68)	1.624*** (7.41)	2.152*** (5.33)
With TF Small Portfolio							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	1.079*** (3.39)	0.841 (2.34)	0.747 (2.11)	0.606 (1.65)	0.816 (2.25)	0.78 (2.1)	0.997 (2.56)
10	-0.628 (-1.73)	-0.927 (-2.22)	-0.923 (-2.19)	-0.682 (-1.53)	-0.983 (-2.26)	-1.024 (-2.32)	-0.659 (-1.57)
HML	-1.707*** (-8.07)	-2.006*** (-7.11)	-1.905*** (-6.72)	-1.522*** (-3.87)	-2.036*** (-7.0)	-2.039*** (-7.12)	-1.883*** (-6.5)
With TF Large Portfolio							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	1.293*** (4.0)	1.05** (2.9)	0.957* (2.67)	0.809 (2.16)	1.016** (2.82)	0.981* (2.66)	1.209** (3.04)
10	-0.81 (-2.22)	-1.111* (-2.59)	-1.102 (-2.54)	-0.875 (-1.89)	-1.167* (-2.6)	-1.208* (-2.65)	-0.84 (-1.95)
HML	-2.103*** (-9.5)	-2.398*** (-7.38)	-2.294*** (-6.95)	-1.918*** (-4.31)	-2.42*** (-7.34)	-2.424*** (-7.43)	-2.276*** (-6.74)

Panel B: Value weighted (NN4)

No TF							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	-0.026 (-0.19)	-0.269 (-1.78)	-0.272 (-1.87)	-0.276 (-1.67)	-0.294 (-1.9)	-0.282 (-1.81)	-0.155 (-1.09)
10	0.506** (3.2)	0.243 (1.52)	0.291 (1.99)	0.351 (2.13)	0.271 (1.68)	0.291 (1.76)	0.399* (2.8)
HML	0.532*** (4.1)	0.274** (2.98)	0.328** (2.91)	0.393** (2.87)	0.328* (2.27)	0.338* (2.35)	0.327* (2.29)
With TF Small Portfolio							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	0.668*** (4.98)	0.435** (3.25)	0.421** (3.2)	0.422* (2.75)	0.406** (2.9)	0.422** (2.97)	0.535*** (4.17)
10	-0.114 (-0.7)	-0.376 (-2.01)	-0.321 (-1.92)	-0.243 (-1.39)	-0.327 (-1.74)	-0.318 (-1.68)	-0.224 (-1.44)
HML	-0.782*** (-5.64)	-1.048*** (-6.32)	-0.976*** (-6.16)	-0.9*** (-4.65)	-0.97*** (-5.83)	-0.975*** (-5.82)	-0.987*** (-6.5)
With TF Large Portfolio							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	1.046*** (5.04)	0.829* (2.68)	0.787** (2.81)	0.823* (2.7)	0.798 (2.57)	0.811* (2.62)	0.897** (3.2)
10	-0.193 (-1.18)	-0.461 (-2.42)	-0.404 (-2.35)	-0.34 (-1.88)	-0.417 (-2.14)	-0.41 (-2.09)	-0.297 (-1.87)
HML	-1.239*** (-5.98)	-1.527*** (-4.96)	-1.425*** (-4.93)	-1.397*** (-4.29)	-1.453*** (-4.66)	-1.457*** (-4.69)	-1.421*** (-5.01)

Panel C: Optimized (NN4)

No TF							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	0.017 (0.08)	-0.285 (-2.11)	-0.316** (-3.23)	-0.378*** (-3.35)	-0.326*** (-3.5)	-0.385*** (-2.97)	-0.161 (-1.05)
10	3.502*** (4.0)	2.789*** (4.15)	2.616*** (3.86)	2.199*** (3.4)	2.137*** (3.61)	2.141*** (3.39)	3.453*** (4.42)
HML	3.485*** (4.85)	2.856*** (5.75)	2.709*** (5.74)	2.392*** (5.69)	2.235*** (4.98)	2.306*** (5.10)	3.387*** (5.87)
With TF Small Portfolio							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	0.264 (1.04)	-0.043 (-0.23)	-0.081 (-0.63)	-0.115 (-0.88)	-0.096 (-0.71)	-0.165 (-1.18)	0.093 (0.5)
10	2.587* (2.91)	1.869** (3.74)	1.684 (3.13)	1.14 (1.31)	1.199*** (3.06)	1.231*** (3.12)	2.525 (2.5)
HML	2.322** (3.07)	1.692* (3.68)	1.542 (3.54)	1.07 (1.19)	1.068*** (3.26)	1.175*** (3.62)	2.206 (2.4)
With TF Large Portfolio							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	1.589 (2.03)	1.213*** (3.4)	1.098*** (3.56)	1.248 (2.21)	1.158*** (3.56)	1.191*** (4.24)	1.407** (2.81)
10	0.007 (0.01)	-0.348 (-1.34)	-0.412 (-1.7)	-0.98*** (-3.47)	-0.494 (-1.52)	-0.525 (-1.77)	-0.164 (-1.05)
HML	-1.582 (-1.71)	-1.779*** (-3.37)	-1.725*** (-3.55)	-2.399*** (-3.39)	-1.877*** (-4.26)	-1.935*** (-4.0)	-1.793** (-3.04)

Panel A: Equally weighted (NN5)

No TF							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	-0.376 (-1.1)	-0.342 (-2.05)	-0.365 (-2.23)	-0.466* (-2.82)	-0.316 (-2.52)	-0.317 (-2.76)	-0.542 (1.38)
10	0.967** (3.13)	0.948*** (3.88)	1.02*** (4.21)	0.884** (3.18)	0.864*** (3.14)	0.846*** (3.08)	0.678*** (4.76)
HML	1.344*** (6.4)	1.295*** (6.35)	1.385*** (6.71)	1.354*** (6.57)	1.180*** (5.32)	1.163*** (5.15)	1.137*** (3.38)
With TF Small Portfolio							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	1.11** (3.15)	0.89 (2.35)	0.716 (1.88)	0.653 (1.82)	0.844 (2.19)	0.77 (1.92)	0.996 (2.38)
10	-0.654 (-2.03)	-0.965 (-2.26)	-0.904 (-2.21)	-0.806 (-1.91)	-0.997 (-2.31)	-1.009 (-2.3)	-0.636 (-1.58)
HML	-1.764*** (-7.72)	-2.093*** (-6.95)	-1.855*** (-6.58)	-1.693*** (-4.94)	-2.078*** (-7.26)	-2.014*** (-6.75)	-1.859*** (-6.72)
With TF Large Portfolio							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	1.29*** (3.63)	1.068** (2.82)	0.894 (2.33)	0.827 (2.28)	1.014* (2.67)	0.941 (2.37)	1.174* (2.76)
10	-0.827 (-2.56)	-1.14* (-2.61)	-1.076 (-2.56)	-0.986 (-2.25)	-1.171* (-2.64)	-1.181* (-2.62)	-0.804 (-1.96)
HML	-2.117*** (-8.96)	-2.445*** (-7.44)	-2.204*** (-6.98)	-2.047*** (-5.32)	-2.423*** (-7.79)	-2.358*** (-7.3)	-2.205*** (-7.14)

Panel B: Value weighted (NN5)

No TF							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	-0.034 (-0.23)	-0.285 (-1.72)	-0.28 (-1.73)	-0.345 (-1.98)	-0.302 (-1.81)	-0.286 (-1.67)	-0.151 (-0.96)
10	0.463** (2.84)	0.189 (1.17)	0.251 (1.64)	0.366 (2.13)	0.216 (1.34)	0.241 (1.45)	0.38* (2.61)
HML	0.496*** (3.59)	0.237** (2.92)	0.296** (2.94)	0.476** (2.96)	0.281** (2.93)	0.292** (2.96)	0.303* (2.38)
With TF Small Portfolio							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	0.605*** (4.16)	0.364 (2.45)	0.346 (2.39)	0.296 (2.01)	0.338 (2.17)	0.355 (2.22)	0.479*** (3.42)
10	-0.09 (-0.55)	-0.364 (-1.86)	-0.295 (-1.69)	-0.159 (-0.91)	-0.325 (-1.68)	-0.314 (-1.59)	-0.175 (-1.07)
HML	-0.694*** (-4.88)	-0.965*** (-5.84)	-0.876*** (-5.79)	-0.69*** (-3.98)	-0.9*** (-5.64)	-0.904*** (-5.53)	-0.881*** (-6.25)
With TF Large Portfolio							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	1.012*** (4.59)	0.788 (2.3)	0.74 (2.38)	0.727 (2.21)	0.762 (2.22)	0.774 (2.26)	0.866* (2.78)
10	-0.16 (-0.97)	-0.44 (-2.22)	-0.37 (-2.08)	-0.249 (-1.38)	-0.407 (-2.05)	-0.398 (-1.96)	-0.239 (-1.44)
HML	-1.172*** (-5.45)	-1.466*** (-4.39)	-1.345*** (-4.36)	-1.21*** (-3.56)	-1.407*** (-4.23)	-1.407*** (-4.27)	-1.333*** (-4.44)

Panel C: Optimized (NN5)

No TF							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	0.078 (0.38)	-0.211 (-1.39)	-0.259 (-1.52)	-0.253 (-1.19)	-0.309 (-1.98)	-0.324 (-2.24)	-0.091 (-0.94)
10	3.598*** (4.38)	2.913*** (5.0)	2.692*** (4.51)	2.384*** (3.71)	2.305*** (3.81)	2.227*** (2.82)	3.541*** (4.53)
HML	3.52*** (5.04)	2.906*** (5.91)	2.728*** (5.61)	2.453*** (4.57)	2.387*** (4.16)	2.33*** (4.05)	3.406*** (6.64)
With TF Small Portfolio							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	0.274 (1.22)	-0.016 (-0.09)	-0.078 (-0.39)	-0.05 (-0.21)	-0.13 (-0.69)	-0.155 (-0.89)	0.112 (1.06)
10	2.504** (3.0)	1.805** (2.92)	1.573 (3.11)	1.136 (1.36)	1.178*** (2.93)	1.133*** (2.23)	2.428 (2.45)
HML	2.23** (3.05)	1.602* (3.17)	1.428 (3.08)	1.001 (1.11)	1.08** (2.87)	1.066*** (2.7)	2.09 (2.18)
With TF Large Portfolio							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	3.142 (2.36)	2.795 (1.28)	3.075 (1.37)	1.931 (1.04)	2.544 (1.3)	2.805 (1.5)	2.797 (1.31)
10	0.289 (0.51)	-0.04 (-0.09)	-0.195 (-0.65)	-0.847** (-3.0)	-0.298 (-0.78)	-0.315 (-0.75)	0.142 (0.44)
HML	-2.853 (-2.03)	-3.052 (-1.23)	-3.484 (-1.44)	-2.945 (-1.63)	-3.067 (-1.34)	-3.338 (-1.53)	-2.874 (-1.28)

Appendix 2F: Impact of trading frictions on risk-adjusted returns of the NN portfolios, quarterly

This appendix reports the mean returns and risk-adjusted returns for the neural network predictive models NN1- NN2. Panel A reports the results for the equal-weighted rebalancing method and Panel B reports the results for the value weighted portfolio and Panel C for the optimised portfolio. Each panel reports the results for the environment without trading frictions in the top section, the environment with trading frictions investing a small initial capital of 1 million USD in the middle section and the environment with trading frictions investing a large initial capital of 100 million USD in the bottom section. The long-short portfolio is constructed by ranking stocks according to their machine learning predicted returns and form 10 portfolios, buying the highest quantile portfolio and selling the lowest quintile portfolio (HML portfolio). Each section reports the returns for the lowest quintile portfolio (1), the highest quintile portfolio (10) and the High-minus-Low portfolio (HML). Mean returns are adjusted for common factor models, specifically; (a) CAPM, (b) Fama-French-Carhart 4-factor model (FFC), (c) Pástor and Stambaugh liquidity factor model (FFC+PS), (d) Fama-French 5-factor model (FF5), (e) Fama-French 6-factor model (FF6), and Hou et. al., (2015) q-factor model (q). Both mean returns and risk-adjusted returns are expressed in percentage basis. The Newey-West adjusted t statistics are presented in the parentheses. Coefficients denoted with *, **, and *** are statistically significant at the 10%, 5%, and 1% levels, respectively. Investing horizon is three months and thus, rebalancing of the portfolio is performed quarterly based on predicted returns.

Panel A: Equally weighted (NN1)

No TF							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	2.01*** (4.71)	1.649** (3.27)	1.659*** (3.93)	1.349 (2.11)	1.407** (3.1)	1.477*** (3.36)	2.029*** (3.56)
10	-0.099 (-0.27)	-0.456 (-1.06)	-0.519 (-1.37)	-0.708 (-1.91)	-0.734 (-2.09)	-0.709 (-2.04)	-0.004 (-0.01)
HML	-2.109*** (-6.95)	-2.335*** (-3.65)	-2.408*** (-3.82)	-2.268** (-3.07)	-2.368*** (-3.65)	-2.413*** (-3.8)	-2.261** (-3.22)
With TF Small Portfolio							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	3.825*** (8.55)	3.462*** (6.33)	3.479*** (7.94)	3.145*** (4.78)	3.216*** (6.82)	3.305*** (7.49)	3.875*** (6.22)
10	-1.29** (-3.35)	-1.654*** (-3.62)	-1.744*** (-3.88)	-1.969*** (-4.54)	-1.945*** (-4.93)	-1.949*** (-5.06)	-1.202* (-2.69)
HML	-5.115*** (-15.73)	-5.346*** (-8.1)	-5.453*** (-8.43)	-5.326*** (-7.17)	-5.388*** (-7.9)	-5.481*** (-8.63)	-5.304*** (-7.34)
With TF Large Portfolio							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	4.145*** (9.18)	3.778*** (6.84)	3.8*** (8.33)	3.433*** (5.2)	3.53*** (7.51)	3.62*** (8.21)	4.185*** (6.43)
10	-1.532*** (-3.86)	-1.894*** (-3.49)	-1.992*** (-3.77)	-2.187*** (-4.06)	-2.182*** (-4.44)	-2.188*** (-4.52)	-1.44** (-2.81)
HML	-5.677*** (-16.41)	-5.901*** (-7.87)	-6.022*** (-8.2)	-5.831*** (-7.04)	-5.938*** (-7.7)	-6.035*** (-8.31)	-5.853*** (-7.27)

Panel B: Value weighted (NN1)

No TF							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	0.315 (2.32)	0.034 (0.21)	0.104 (0.61)	-0.049 (-0.2)	0.03 (0.19)	0.045 (0.28)	0.164 (0.86)
10	0.168 (1.01)	-0.124 (-0.88)	-0.092 (-0.47)	-0.208 (-1.29)	-0.176 (-1.21)	-0.17 (-1.15)	0.06 (0.31)
HML	-0.147 (-1.02)	-0.387 (-1.78)	-0.427 (-1.89)	-0.37 (-1.44)	-0.433 (-1.99)	-0.442 (-2.03)	-0.331 (-1.44)
With TF Small Portfolio							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	1.124*** (7.87)	0.844*** (4.71)	0.926*** (4.97)	0.788** (2.98)	0.837*** (4.6)	0.865*** (4.96)	0.98*** (4.53)
10	-0.387 (-2.6)	-0.675*** (-4.77)	-0.657** (-3.22)	-0.716*** (-4.49)	-0.73*** (-4.61)	-0.738*** (-4.71)	-0.504* (-2.65)
HML	-1.511*** (-11.16)	-1.748*** (-7.02)	-1.814*** (-7.22)	-1.716*** (-6.21)	-1.793*** (-6.68)	-1.83*** (-7.23)	-1.712*** (-6.72)
With TF Large Portfolio							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	1.675*** (4.59)	1.393** (3.19)	1.514** (2.96)	1.557 (2.11)	1.379** (3.18)	1.419** (3.2)	1.51** (3.23)
10	-0.473** (-3.12)	-0.76*** (-4.85)	-0.744*** (-3.52)	-0.791*** (-4.53)	-0.813*** (-4.69)	-0.822*** (-4.81)	-0.588** (-3.02)
HML	-2.147*** (-6.02)	-2.383*** (-4.88)	-2.488*** (-4.77)	-2.559*** (-3.4)	-2.419*** (-4.85)	-2.468*** (-4.97)	-2.325*** (-4.99)

Panel C: Optimized (NN1)							
No TF							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	0.301 (0.87)	-0.039 (-0.15)	-0.236 (-1.1)	-0.169 (-0.52)	-0.118 (-0.62)	-0.119 (-0.66)	0.128 (0.33)
10	1.771 (2.15)	1.007 (1.58)	1.199 (1.44)	0.859 (0.91)	0.656 (1.24)	0.749 (1.23)	1.645 (1.74)
HML	1.47 (1.88)	0.828 (1.69)	1.213 (1.84)	0.844 (1.33)	0.546 (1.62)	0.507 (1.58)	1.29 (1.89)
With TF Small Portfolio							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	0.485 (1.23)	0.144 (0.49)	-0.096 (-0.43)	-0.033 (-0.1)	0.065 (0.28)	-0.23 (-1.17)	0.319 (0.75)
10	0.636 (0.75)	-0.165 (-0.29)	-0.119 (-1.29)	-0.265 (-0.28)	-0.489 (-1.74)	-0.437 (-1.69)	0.514 (0.53)
HML	0.151 (0.18)	-0.527 (-1.04)	-0.058 (-0.68)	-0.416 (-0.61)	-0.78 (-2.11)	-0.428 (-1.39)	-0.031 (-0.04)
With TF Large Portfolio							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	3.203 (1.21)	2.508 (1.27)	3.401 (1.0)	4.313 (1.11)	4.179 (1.12)	3.758 (1.08)	2.96 (1.18)
10	-0.523 (-0.71)	-1.105 (-2.08)	-1.105 (-2.45)	-1.468*** (-4.69)	-1.509* (-2.61)	-1.386 (-2.24)	-0.612 (-1.86)
HML	-3.726 (-1.35)	-3.832 (-1.57)	-4.728 (-1.27)	-5.966 (-1.56)	-5.916 (-1.39)	-5.365 (-1.32)	-3.799 (-1.4)

Panel A: Equally weighted (NN2)

No TF							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	3.259*** (5.55)	2.375*** (3.79)	3.026*** (5.42)	3.399*** (5.85)	2.303*** (3.89)	2.312*** (4.04)	3.466*** (5.74)
10	-0.705 (-2.04)	-1.331* (-2.7)	-0.897 (-1.83)	-1.134* (-2.75)	-1.17 (-2.47)	-1.17 (-2.47)	-0.765 (-1.49)
HML	-3.965*** (-7.34)	-3.705*** (-6.49)	-3.922*** (-7.25)	-4.533*** (-8.61)	-3.473*** (-6.36)	-3.482*** (-6.51)	-4.232*** (-7.23)
With TF Small Portfolio							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	4.999*** (8.12)	4.088*** (5.93)	4.743*** (7.81)	5.098*** (8.0)	3.984*** (6.25)	3.992*** (6.43)	5.211*** (7.73)
10	-1.752*** (-4.75)	-2.368*** (-4.65)	-1.943*** (-3.74)	-2.185*** (-5.14)	-2.192*** (-4.41)	-2.192*** (-4.4)	-1.79*** (-3.35)
HML	-6.751*** (-11.39)	-6.455*** (-10.58)	-6.686*** (-11.56)	-7.283*** (-13.14)	-6.176*** (-10.66)	-6.184*** (-10.83)	-7.001*** (-11.08)
With TF Large Portfolio							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	5.337*** (8.61)	4.412*** (6.48)	5.087*** (8.2)	5.438*** (8.09)	4.329*** (6.84)	4.336*** (6.99)	5.54*** (8.11)
10	-1.981*** (-5.31)	-2.576*** (-5.03)	-2.173*** (-4.22)	-2.382*** (-5.62)	-2.389*** (-4.78)	-2.389*** (-4.77)	-2.009*** (-3.8)
HML	-7.318*** (-12.36)	-6.988*** (-11.51)	-7.26*** (-12.42)	-7.82*** (-13.71)	-6.717*** (-11.62)	-6.725*** (-11.76)	-7.549*** (-11.91)

Panel B: Value weighted (NN2)

No TF							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	0.598*** (3.41)	0.318 (1.4)	0.352 (1.61)	0.272 (0.9)	0.251 (1.01)	0.281 (1.15)	0.483 (2.5)
10	-0.126 (-0.83)	-0.419** (-3.18)	-0.353 (-1.63)	-0.46** (-2.81)	-0.422** (-3.14)	-0.427** (-3.15)	-0.306 (-1.32)
HML	-0.724*** (-4.04)	-0.966*** (-3.56)	-0.936** (-3.18)	-0.942*** (-3.41)	-0.9** (-3.26)	-0.935*** (-3.51)	-1.017*** (-3.84)
With TF Small Portfolio							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	1.418*** (7.8)	1.145*** (5.01)	1.185*** (5.72)	1.103*** (3.83)	1.082*** (4.51)	1.125*** (4.94)	1.304*** (6.75)
10	-0.715*** (-4.36)	-1.01*** (-6.54)	-0.947*** (-4.04)	-1.052*** (-5.6)	-0.996*** (-6.52)	-1.015*** (-6.77)	-0.897*** (-3.45)
HML	-2.133*** (-10.48)	-2.384*** (-7.91)	-2.362*** (-7.28)	-2.366*** (-7.86)	-2.305*** (-7.73)	-2.367*** (-8.71)	-2.428*** (-8.18)
With TF Large Portfolio							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	1.757*** (8.51)	1.485*** (7.52)	1.528*** (8.24)	1.427*** (5.84)	1.422*** (7.08)	1.457*** (7.6)	1.632*** (8.97)
10	-0.875*** (-5.11)	-1.165*** (-6.15)	-1.106*** (-4.47)	-1.173*** (-5.71)	-1.137*** (-6.32)	-1.162*** (-6.62)	-1.064*** (-3.93)
HML	-2.632*** (-11.35)	-2.88*** (-9.4)	-2.865*** (-9.09)	-2.812*** (-9.58)	-2.786*** (-9.49)	-2.846*** (-10.69)	-2.923*** (-9.96)

Panel C: Optimized (NN2)

No TF							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	0.347 (1.25)	-0.02 (-0.14)	-0.046 (-0.5)	0.201 (0.58)	-0.077 (-0.61)	-0.059 (-0.46)	0.131 (0.62)
10	2.191* (2.98)	1.581 (2.56)	1.402 (2.01)	0.914 (1.1)	1.152** (1.84)	1.081* (1.66)	2.033 (2.31)
HML	1.844 (2.46)	1.382 (2.08)	1.033 (2.67)	0.53 (0.86)	1.002 (2.2)	0.919 (1.97)	1.675 (2.07)
With TF Small Portfolio							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	0.725 (2.18)	0.411 (1.13)	0.447 (1.31)	0.634 (1.41)	0.275 (1.18)	0.238 (1.12)	0.54 (1.64)
10	0.88 (1.22)	0.244 (0.43)	0.123 (0.17)	-0.425 (-0.47)	-0.185 (-0.53)	-0.217 (-0.6)	0.725 (0.84)
HML	0.155 (0.2)	-0.386 (-0.54)	-0.547 (-0.78)	-1.244 (-1.72)	-0.687 (-1.5)	-0.676 (-1.48)	-0.042 (-0.05)
With TF Large Portfolio							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	1.858 (2.35)	1.665 (2.3)	1.89* (2.66)	1.344*** (4.43)	1.839** (3.15)	1.737* (2.8)	1.609 (2.42)
10	0.168 (0.17)	-0.702 (-1.49)	0.094 (0.08)	-0.119 (-0.1)	-0.732 (-1.55)	-0.609 (-1.3)	-0.039 (-0.04)
HML	-1.69 (-1.36)	-2.585*** (-3.65)	-2.019 (-1.29)	-1.647 (-1.68)	-2.798*** (-4.53)	-2.567*** (-3.5)	-1.874 (-1.46)

Panel A: Equally weighted (NN3)

No TF							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	1.274** (3.34)	0.565 (1.4)	1.003 (2.29)	0.938 (1.88)	0.527 (1.28)	0.533 (1.32)	1.333** (2.88)
10	0.165 (0.39)	-0.525 (-1.22)	-0.019 (-0.05)	0.022 (0.05)	-0.413 (-0.95)	-0.41 (-0.93)	0.196 (0.47)
HML	-1.109** (-3.04)	-1.09 (-2.62)	-1.022 (-2.33)	-0.916 (-1.83)	-0.94 (-2.23)	-0.943 (-2.25)	-1.136 (-2.41)
With TF Small Portfolio							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	3.095*** (7.86)	2.381*** (5.88)	2.809*** (6.7)	2.769*** (5.97)	2.315*** (6.05)	2.319*** (6.12)	3.127*** (6.84)
10	-1.322** (-3.12)	-2.0*** (-4.37)	-1.519*** (-3.45)	-1.508*** (-3.37)	-1.897*** (-4.13)	-1.892*** (-4.0)	-1.263** (-2.95)
HML	-4.417*** (-11.51)	-4.38*** (-10.25)	-4.328*** (-10.16)	-4.277*** (-9.35)	-4.212*** (-10.18)	-4.211*** (-10.12)	-4.39** (-9.78)
With TF Large Portfolio							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	3.432*** (8.44)	2.703*** (6.34)	3.15*** (6.72)	3.124*** (6.12)	2.636*** (6.46)	2.639*** (6.48)	3.453*** (6.84)
10	-1.632*** (-3.78)	-2.28*** (-4.49)	-1.827*** (-3.8)	-1.752*** (-3.63)	-2.164*** (-4.33)	-2.159*** (-4.22)	-1.573*** (-3.33)
HML	-5.064*** (-12.21)	-4.984*** (-10.83)	-4.977*** (-10.52)	-4.876*** (-9.75)	-4.8*** (-10.79)	-4.798*** (-10.7)	-5.026*** (-10.17)

Panel B: Value weighted (NN3)

No TF							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	0.224 (1.61)	-0.062 (-0.41)	0.002 (0.01)	-0.133 (-0.58)	-0.074 (-0.44)	-0.059 (-0.34)	0.093 (0.46)
10	0.254 (1.39)	-0.037 (-0.22)	-0.012 (-0.08)	-0.072 (-0.49)	-0.109 (-0.8)	-0.091 (-0.66)	0.134 (0.78)
HML	0.03 (0.19)	-0.204 (-0.85)	-0.245 (-1.07)	-0.15 (-0.59)	-0.261 (-1.18)	-0.259 (-1.15)	-0.186 (-0.78)
With TF Small Portfolio							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	0.932*** (6.73)	0.652*** (5.0)	0.712*** (4.56)	0.583* (2.79)	0.634*** (4.38)	0.661*** (4.74)	0.802*** (4.86)
10	-0.481** (-2.88)	-0.772*** (-4.04)	-0.767*** (-3.98)	-0.796*** (-4.68)	-0.836*** (-4.75)	-0.838*** (-4.87)	-0.603*** (-3.37)
HML	-1.413*** (-9.47)	-1.653*** (-6.73)	-1.71*** (-7.38)	-1.59*** (-6.33)	-1.696*** (-6.88)	-1.726*** (-7.41)	-1.633*** (-7.46)
With TF Large Portfolio							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	1.096*** (7.22)	0.818*** (6.42)	0.872*** (5.68)	0.686*** (3.48)	0.799*** (6.04)	0.824*** (6.34)	0.959*** (5.58)
10	-0.783*** (-4.08)	-1.066*** (-3.9)	-1.08*** (-4.26)	-1.058*** (-4.51)	-1.12*** (-4.49)	-1.126*** (-4.56)	-0.901*** (-3.82)
HML	-1.879*** (-10.0)	-2.113*** (-6.63)	-2.183*** (-6.93)	-1.955*** (-6.42)	-2.146*** (-6.79)	-2.177*** (-7.12)	-2.088*** (-7.06)

Panel C: Optimized (NN3)

No TF							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	-0.095 (-0.52)	-0.381 (-2.24)	-0.429*** (-4.45)	-0.502*** (-7.38)	-0.363*** (-3.48)	-0.362*** (-3.05)	-0.297 (-1.62)
10	2.32* (2.81)	1.581 (1.99)	1.519 (1.51)	0.951 (0.69)	1.098 (1.3)	1.09 (1.27)	2.156 (1.85)
HML	2.415** (3.23)	1.744 (2.5)	1.726 (2.8)	1.268 (0.96)	1.234* (2.62)	1.331** (2.54)	2.227 (2.15)
With TF Small Portfolio							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	0.139 (0.73)	-0.143 (-0.81)	-0.208 (-1.66)	-0.264*** (-3.31)	-0.124 (-0.83)	-0.239 (-1.6)	-0.055 (-0.3)
10	1.069 (1.27)	0.296 (0.36)	0.238 (0.21)	-0.338 (-0.23)	-0.202 (-0.41)	-0.187 (-0.41)	0.902 (0.72)
HML	0.93 (1.18)	0.221 (0.28)	0.223 (0.2)	-0.258 (-0.17)	-0.305 (-0.57)	-0.169 (-0.35)	0.73 (0.61)
With TF Large Portfolio							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	1.708 (1.93)	1.172 (2.05)	1.468 (2.39)	1.645 (1.48)	1.203 (1.82)	1.102 (1.58)	1.484* (2.63)
10	-0.124 (-0.18)	-0.511 (-1.54)	0.009 (0.03)	-0.649*** (-3.49)	-0.57 (-1.47)	-0.183 (-0.41)	-0.346 (-1.05)
HML	-1.832 (-1.71)	-1.902*** (-3.98)	-1.682 (-2.46)	-2.478 (-2.14)	-2.0*** (-3.64)	-1.505** (-2.87)	-2.057** (-3.12)

Panel A: Equally weighted (NN4)

No TF							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	1.255** (3.22)	0.555 (1.28)	0.978 (2.08)	0.933 (1.79)	0.488 (1.06)	0.495 (1.1)	1.316* (2.71)
10	0.394 (0.91)	-0.331 (-0.68)	0.214 (0.45)	0.267 (0.57)	-0.203 (-0.41)	-0.2 (-0.4)	0.431 (0.9)
HML	-0.862 (-2.21)	-0.886 (-1.96)	-0.764 (-1.63)	-0.665 (-1.22)	-0.692 (-1.47)	-0.695 (-1.5)	-0.885 (-1.81)
With TF Small Portfolio							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	3.048*** (7.59)	2.342*** (5.55)	2.748*** (6.14)	2.713*** (5.44)	2.228*** (5.21)	2.233*** (5.33)	3.085*** (6.48)
10	-1.069 (-2.45)	-1.784*** (-3.7)	-1.267* (-2.66)	-1.223* (-2.65)	-1.679*** (-3.41)	-1.674*** (-3.32)	-0.999 (-2.19)
HML	-4.117*** (-10.3)	-4.126*** (-9.25)	-4.015*** (-8.8)	-3.936*** (-8.09)	-3.907*** (-8.62)	-3.908*** (-8.65)	-4.085*** (-8.67)
With TF Large Portfolio							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	3.504*** (8.28)	2.777*** (6.18)	3.204*** (6.18)	3.185*** (5.49)	2.66*** (5.71)	2.664*** (5.78)	3.535*** (6.52)
10	-1.306** (-2.96)	-2.006*** (-4.1)	-1.507** (-3.16)	-1.453** (-3.08)	-1.904*** (-3.82)	-1.899*** (-3.72)	-1.226* (-2.73)
HML	-4.811*** (-11.19)	-4.782*** (-10.28)	-4.711*** (-9.34)	-4.638*** (-8.56)	-4.563*** (-9.52)	-4.562*** (-9.5)	-4.76*** (-9.25)

Panel B: Value weighted (NN4)

No TF							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	0.264 (1.82)	-0.026 (-0.17)	0.037 (0.18)	-0.09 (-0.37)	-0.037 (-0.21)	-0.027 (-0.15)	0.137 (0.67)
10	0.306 (1.65)	0.023 (0.11)	0.038 (0.19)	-0.024 (-0.13)	-0.05 (-0.27)	-0.038 (-0.21)	0.177 (0.82)
HML	0.042 (0.25)	-0.18 (-0.64)	-0.229 (-0.84)	-0.146 (-0.48)	-0.24 (-0.9)	-0.239 (-0.87)	-0.187 (-0.66)
With TF Small Portfolio							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	0.969*** (6.48)	0.679*** (4.52)	0.758*** (4.29)	0.625* (2.59)	0.678*** (4.08)	0.703*** (4.34)	0.855*** (4.59)
10	-0.456* (-2.68)	-0.742*** (-3.43)	-0.737*** (-3.35)	-0.75*** (-3.61)	-0.791*** (-3.86)	-0.803*** (-4.04)	-0.584* (-2.66)
HML	-1.425*** (-8.84)	-1.651*** (-5.58)	-1.726*** (-6.15)	-1.587*** (-4.57)	-1.696*** (-5.62)	-1.733*** (-6.02)	-1.667*** (-5.93)
With TF Large Portfolio							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	1.216*** (6.6)	0.928*** (5.61)	0.993*** (5.14)	0.778*** (3.36)	0.919*** (5.42)	0.941*** (5.53)	1.094*** (5.04)
10	-0.719*** (-3.69)	-1.005*** (-3.71)	-1.014*** (-3.82)	-1.049*** (-3.93)	-1.055*** (-4.03)	-1.075*** (-4.21)	-0.848*** (-3.35)
HML	-1.935*** (-8.88)	-2.163*** (-5.94)	-2.239*** (-6.31)	-2.039*** (-4.86)	-2.201*** (-5.91)	-2.242*** (-6.21)	-2.17*** (-6.26)

Panel C: Optimized (NN4)

No TF							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	0.113 (0.56)	-0.171 (-1.32)	-0.253 (-2.0)	-0.281 (-1.81)	-0.209 (-1.44)	-0.312 (-2.13)	-0.062 (-0.58)
10	2.42 (2.71)	1.623 (2.3)	1.677 (1.74)	1.075 (0.88)	1.138** (1.67)	1.172** (1.58)	2.292 (2.01)
HML	2.307* (2.85)	1.575 (2.31)	1.708 (2.75)	1.172 (0.93)	1.119 (2.75)	1.263** (2.79)	2.127 (2.01)
With TF Small Portfolio							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	0.303 (1.38)	0.019 (0.11)	-0.07 (-0.41)	-0.096 (-0.52)	-0.003 (-0.02)	-0.126 (-0.7)	0.134 (0.95)
10	1.185 (1.3)	0.361 (0.53)	0.444 (0.43)	-0.154 (-0.12)	-0.176 (-0.45)	-0.092 (-0.27)	1.062 (0.9)
HML	0.882 (1.04)	0.123 (0.17)	0.291 (0.27)	-0.242 (-0.18)	-0.4 (-0.81)	-0.187 (-0.44)	0.702 (0.61)
With TF Large Portfolio							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	2.524 (2.28)	2.007* (2.78)	2.348* (2.72)	2.394 (2.21)	2.119** (2.99)	2.155* (2.76)	2.271** (3.21)
10	-0.164 (-0.25)	-0.593 (-2.02)	-0.141 (-0.55)	-0.976*** (-4.34)	-0.7 (-2.06)	-0.328 (-0.82)	-0.375 (-1.37)
HML	-2.688 (-2.17)	-2.819*** (-4.17)	-2.712** (-2.91)	-3.555*** (-3.38)	-3.046*** (-4.05)	-2.703*** (-3.48)	-2.873*** (-3.69)

Panel A: Equally weighted (NN5)

No TF							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	1.053* (2.65)	0.338 (0.91)	0.805 (1.77)	0.769 (1.59)	0.329 (0.78)	0.335 (0.79)	1.123 (2.51)
10	0.55 (1.46)	-0.135 (-0.31)	0.325 (0.77)	0.364 (0.86)	-0.112 (-0.26)	-0.108 (-0.24)	0.566 (1.32)
HML	-0.503 (-1.52)	-0.473 (-1.22)	-0.48 (-1.0)	-0.405 (-0.72)	-0.441 (-1.03)	-0.442 (-1.03)	-0.558 (-1.19)
With TF Small Portfolio							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	2.75*** (6.69)	2.384*** (5.09)	2.307*** (5.97)	2.11*** (4.64)	2.074*** (5.42)	2.141*** (5.61)	2.822*** (6.38)
10	-0.873 (-2.21)	-1.223* (-2.65)	-1.247** (-3.27)	-1.454*** (-3.62)	-1.481*** (-3.86)	-1.458*** (-3.92)	-0.833 (-1.92)
HML	-3.623*** (-10.6)	-3.835*** (-6.47)	-3.785*** (-6.97)	-3.775*** (-6.66)	-3.782*** (-6.74)	-3.826*** (-6.92)	-3.883*** (-6.65)
With TF Large Portfolio							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	3.131*** (7.5)	2.764*** (5.7)	2.681*** (6.54)	2.484*** (5.82)	2.445*** (6.47)	2.51*** (6.56)	3.187*** (6.5)
10	-1.144* (-2.85)	-1.492** (-3.12)	-1.512*** (-3.84)	-1.715*** (-3.86)	-1.742*** (-4.2)	-1.716*** (-4.26)	-1.092 (-2.54)
HML	-4.276*** (-11.89)	-4.485*** (-6.99)	-4.423*** (-7.45)	-4.411*** (-7.08)	-4.414*** (-7.31)	-4.453*** (-7.42)	-4.506*** (-7.11)

Panel B: Value weighted (NN5)

No TF							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	0.186 (1.26)	-0.105 (-0.73)	-0.022 (-0.12)	-0.173 (-0.77)	-0.11 (-0.7)	-0.081 (-0.52)	0.068 (0.37)
10	0.344 (1.66)	0.064 (0.29)	0.052 (0.28)	0.051 (0.26)	-0.056 (-0.35)	-0.061 (-0.38)	0.216 (0.95)
HML	0.159 (0.82)	-0.061 (-0.24)	-0.157 (-0.73)	0.012 (0.04)	-0.173 (-0.82)	-0.207 (-1.02)	-0.079 (-0.32)
With TF Small Portfolio							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	0.887*** (5.88)	0.597*** (5.12)	0.663*** (4.22)	0.53** (3.12)	0.569*** (4.52)	0.599*** (4.91)	0.766*** (4.6)
10	-0.337 (-1.73)	-0.618* (-2.65)	-0.632** (-3.15)	-0.624*** (-3.46)	-0.726*** (-3.9)	-0.744*** (-4.12)	-0.462 (-1.92)
HML	-1.223*** (-6.56)	-1.445*** (-5.88)	-1.525*** (-7.62)	-1.366*** (-5.35)	-1.521*** (-6.94)	-1.57*** (-7.77)	-1.456*** (-6.1)
With TF Large Portfolio							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	1.118*** (6.31)	0.831*** (5.83)	0.887*** (4.99)	0.703*** (4.25)	0.802*** (5.91)	0.827*** (6.0)	0.985*** (4.87)
10	-0.592* (-2.76)	-0.872** (-3.24)	-0.895*** (-3.91)	-0.948*** (-3.8)	-0.969*** (-4.19)	-0.99*** (-4.37)	-0.713** (-2.86)
HML	-1.711*** (-7.75)	-1.933*** (-6.75)	-2.013*** (-7.85)	-1.862*** (-5.75)	-1.998*** (-7.59)	-2.044*** (-8.12)	-1.925*** (-7.09)

Panel C: Optimized (NN5)

No TF							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	0.092 (0.5)	-0.197 (-1.15)	-0.192 (-1.15)	-0.271 (-1.64)	-0.256 (-1.39)	-0.27 (-1.7)	-0.095 (-0.72)
10	3.086*** (3.84)	2.414*** (4.26)	2.229** (3.06)	1.969 (1.92)	1.943*** (2.82)	1.815*** (2.73)	2.947** (3.09)
HML	2.995*** (3.88)	2.392*** (3.75)	2.199** (2.84)	2.055 (1.89)	1.972*** (2.95)	1.863*** (2.98)	2.815** (2.85)
With TF Small Portfolio							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	0.283 (1.67)	0.016 (0.07)	0.016 (0.07)	-0.086 (-0.43)	-0.051 (-0.24)	-0.049 (-0.24)	0.093 (0.48)
10	1.782 (2.21)	1.058 (2.2)	0.923 (1.15)	0.645 (0.58)	0.582 (2.17)	0.454 (1.67)	1.655 (1.73)
HML	1.499 (1.89)	0.823 (1.34)	0.684 (0.78)	0.546 (0.46)	0.406 (1.09)	0.282 (0.78)	1.335 (1.28)
With TF Large Portfolio							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	1.905 (1.48)	1.763 (2.02)	1.447 (1.78)	0.714 (0.94)	1.325 (1.48)	1.286 (1.37)	1.682 (2.3)
10	0.104 (0.15)	-0.463 (-1.3)	-0.505 (-1.99)	-1.145*** (-3.99)	-0.896* (-2.73)	-0.897* (-2.78)	-0.016 (-0.07)
HML	-1.801 (-1.26)	-2.445 (-2.09)	-2.174 (-2.33)	-2.043 (-2.33)	-2.448 (-2.19)	-2.404 (-2.25)	-1.924 (-2.4)

Appendix 2G: Impact of trading frictions on risk-adjusted returns of the NN portfolios, annually

This appendix reports the mean returns and risk-adjusted returns for the neural network predictive models NN1- NN2. Panel A reports the results for the equal-weighted rebalancing method and Panel B reports the results for the value weighted portfolio and Panel C for the optimised portfolio. Each panel reports the results for the environment without trading frictions in the top section, the environment with trading frictions investing a small initial capital of 1 million USD in the middle section and the environment with trading frictions investing a large initial capital of 100 million USD in the bottom section. The long-short portfolio is constructed by ranking stocks according to their machine learning predicted returns and form 10 portfolios, buying the highest quantile portfolio and selling the lowest quintile portfolio (HML portfolio). Each section reports the returns for the lowest quintile portfolio (1), the highest quintile portfolio (10) and the High-minus-Low portfolio (HML). Mean returns are adjusted for common factor models, specifically; (a) CAPM, (b) Fama-French-Carhart 4-factor model (FFC), (c) Pástor and Stambaugh liquidity factor model (FFC+PS), (d) Fama-French 5-factor model (FF5), (e) Fama-French 6-factor model (FF6), and Hou et. al., (2015) q-factor model (q). Both mean returns and risk-adjusted returns are expressed in percentage basis. The Newey-West adjusted t statistics are presented in the parentheses. Coefficients denoted with *, **, and *** are statistically significant at the 10%, 5%, and 1% levels, respectively. Investing horizon is twelve months and thus, rebalancing of the portfolio is performed annually based on predicted returns.

Panel A: Equally weighted (NN1)

No TF							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	0.431 (1.15)	0.248 (0.88)	0.446 (1.76)	0.267 (1.04)	0.481 (1.7)	0.52 (1.67)	0.162 (0.64)
10	1.013 (2.4)	0.806** (3.17)	1.025*** (4.16)	0.656 (2.15)	0.977*** (3.78)	1.047*** (3.93)	0.724** (3.06)
HML	0.582 (1.87)	0.344 (1.06)	0.379 (1.51)	0.2 (1.35)	0.302 (1.12)	0.327 (1.2)	0.348 (1.13)
With TF Small Portfolio							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	3.486*** (7.82)	3.34*** (13.45)	3.378*** (12.34)	2.962*** (8.11)	3.454*** (10.81)	3.497*** (10.32)	3.168*** (14.23)
10	-1.458** (-3.31)	-1.675*** (-6.15)	-1.328*** (-5.59)	-1.334*** (-4.29)	-1.376*** (-5.55)	-1.325*** (-5.01)	-1.793*** (-6.64)
HML	-4.944*** (-13.33)	-5.23*** (-19.56)	-4.906*** (-17.28)	-4.484*** (-21.97)	-5.024*** (-16.73)	-5.022*** (-16.39)	-5.176*** (-17.03)
With TF Large Portfolio							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	4.716*** (8.39)	4.552*** (9.9)	4.573*** (8.78)	4.267*** (6.75)	4.593*** (8.5)	4.674*** (8.39)	4.34*** (10.53)
10	-2.226*** (-4.16)	-2.413*** (-4.46)	-2.037*** (-4.0)	-1.723*** (-5.97)	-1.999*** (-4.44)	-1.98*** (-4.1)	-2.583*** (-4.08)
HML	-6.942*** (-12.55)	-7.179*** (-8.7)	-6.81*** (-7.63)	-6.178*** (-9.35)	-6.786*** (-8.22)	-6.854*** (-8.05)	-7.138*** (-7.82)

Panel B: Value weighted (NN1)

No TF							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	0.256 (1.81)	0.02 (0.13)	0.143 (1.11)	0.067 (0.8)	0.124 (1.2)	0.144 (1.18)	0.081 (0.68)
10	0.321 (2.23)	0.083 (0.83)	0.284*** (3.72)	0.216 (2.46)	0.238* (2.69)	0.266** (3.13)	0.109 (1.11)
HML	0.065 (0.5)	-0.152 (-1.87)	-0.059 (-0.86)	-0.04 (-0.71)	-0.081 (-1.02)	-0.077 (-0.93)	-0.187 (-2.31)
With TF Small Portfolio							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	1.421*** (9.39)	1.201*** (18.44)	1.251*** (15.82)	1.091*** (11.07)	1.256*** (13.99)	1.264*** (14.69)	1.211*** (18.9)
10	-0.593*** (-3.6)	-0.829*** (-5.44)	-0.598*** (-4.7)	-0.508*** (-5.42)	-0.631*** (-4.95)	-0.612*** (-4.72)	-0.815*** (-5.88)
HML	-2.013*** (-11.81)	-2.245*** (-11.89)	-2.05*** (-10.66)	-1.787*** (-14.86)	-2.082*** (-10.26)	-2.076*** (-10.37)	-2.242*** (-11.73)
With TF Large Portfolio							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	1.909*** (7.93)	1.686*** (9.17)	1.695*** (11.19)	1.643*** (6.97)	1.687*** (9.9)	1.717*** (9.23)	1.668*** (9.99)
10	-0.84*** (-3.66)	-1.061*** (-4.11)	-0.84** (-3.25)	-0.585*** (-6.13)	-0.835*** (-3.79)	-0.833*** (-3.58)	-1.08*** (-3.79)
HML	-2.749*** (-9.22)	-2.962*** (-6.73)	-2.735*** (-6.58)	-2.416*** (-8.08)	-2.717*** (-6.8)	-2.749*** (-6.58)	-2.962*** (-6.55)

Panel C: Optimized (NN1)							
No TF							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	0.567 (1.23)	0.222 (0.81)	-0.147 (-0.83)	-0.13 (-0.72)	0.133 (0.55)	-0.237 (-1.04)	0.43 (1.1)
10	2.357 (2.71)	1.547* (2.6)	1.922 (2.2)	1.689 (1.62)	1.219*** (3.54)	1.399*** -3.04	2.214 (2.49)
HML	1.791 (1.97)	1.106 (2.28)	1.847 (2.27)	1.634 (1.82)	0.859 (1.98)	1.415*** -1.92	1.557 (2.19)
With TF Small Portfolio							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	0.817 (1.51)	0.464 (1.35)	0.008 (0.04)	0.029 (0.16)	0.349 (1.17)	-0.084 (-0.3)	0.697 (1.47)
10	1.175 (1.34)	0.341 (0.62)	0.665 (0.74)	0.396 (0.37)	-0.055 (-0.18)	0.12 (0.41)	1.034 (1.13)
HML	0.358 (0.38)	-0.342 (-0.69)	0.434 (0.5)	0.184 (0.2)	-0.632 (-1.39)	-0.017 (-0.04)	0.111 (0.13)
With TF Large Portfolio							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	1.357 (1.94)	1.01 (2.55)	0.239 (1.08)	0.473 (0.96)	0.683** (3.02)	0.138 (0.6)	1.262 (1.79)
10	0.678 (0.78)	-0.092 (-0.2)	-0.005 (-0.01)	-0.322 (-0.36)	-0.512 (-2.12)	-0.304 (-2.11)	0.576 (0.85)
HML	-0.679 (-0.67)	-1.321*** (-3.61)	-0.467 (-0.93)	-0.979 (-1.71)	-1.423*** (-3.79)	-1.663 (-3.98)	-0.913 (-1.95)

Panel A: Equally weighted (NN2)

No TF							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	0.742 (1.45)	2.68* (2.67)	2.626* (2.65)	2.469 (1.71)	2.925** (2.82)	2.963* (2.68)	2.416 (1.9)
10	0.976 (2.46)	2.563** (3.25)	3.19** (3.14)	3.609*** (4.65)	3.17*** (3.55)	3.275*** (3.7)	2.319 (2.5)
HML	0.234 (0.44)	0.042 (0.04)	0.154 (0.18)	1.094 (0.87)	0.451 (0.4)	0.466 (0.41)	0.048 (0.04)
With TF Small Portfolio							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	3.876*** (6.69)	3.786*** (11.75)	3.501*** (9.29)	3.152*** (6.42)	3.674*** (7.82)	3.739*** (7.49)	3.598*** (11.53)
10	-1.419** (-3.5)	-1.652*** (-7.8)	-1.146*** (-4.53)	-0.881** (-3.03)	-1.248*** (-3.87)	-1.198*** (-4.32)	-1.793*** (-8.6)
HML	-5.295*** (-8.08)	-5.652*** (-12.84)	-4.847*** (-9.37)	-4.221*** (-8.84)	-5.116*** (-7.31)	-5.137*** (-7.53)	-5.605*** (-12.54)
With TF Large Portfolio							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	5.339*** (7.07)	5.164*** (9.66)	4.857*** (8.94)	4.548*** (5.34)	4.826*** (9.96)	4.991*** (9.0)	5.08*** (8.42)
10	-2.144*** (-4.76)	-2.35*** (-6.78)	-1.871*** (-5.91)	-1.345*** (-4.92)	-1.905*** (-5.34)	-1.877*** (-5.67)	-2.521*** (-7.13)
HML	-7.483*** (-10.03)	-7.729*** (-9.03)	-6.928*** (-8.6)	-6.082*** (-6.97)	-6.926*** (-8.81)	-7.068*** (-8.56)	-7.816*** (-8.39)

Panel B: Value weighted (NN2)

No TF							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	0.164 (0.95)	-0.061 (-0.47)	0.06 (0.43)	-0.034 (-0.23)	0.034 (0.25)	0.066 (0.42)	-0.016 (-0.12)
10	0.501* (2.74)	0.248 (2.51)	0.475*** (3.99)	0.453*** (3.65)	0.389** (2.94)	0.425*** (3.73)	0.281 (2.22)
HML	0.337 (1.76)	0.094 (0.64)	0.214 (1.16)	0.299 (1.7)	0.16 (0.79)	0.159 (0.78)	0.082 (0.47)
With TF Small Portfolio							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	1.424*** (7.86)	1.223*** (12.1)	1.225*** (10.8)	1.016*** (6.94)	1.238*** (8.51)	1.256*** (8.48)	1.215*** (13.31)
10	-0.443 (-2.52)	-0.676*** (-4.32)	-0.399** (-3.2)	-0.3 (-2.47)	-0.445** (-3.01)	-0.422** (-3.11)	-0.703*** (-4.86)
HML	-1.868*** (-8.18)	-2.113*** (-8.43)	-1.824*** (-7.63)	-1.505*** (-6.78)	-1.878*** (-6.66)	-1.878*** (-6.77)	-2.134*** (-8.98)
With TF Large Portfolio							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	2.0*** (7.42)	1.779*** (9.71)	1.821*** (7.51)	1.591*** (5.2)	1.78*** (8.09)	1.834*** (7.72)	1.805*** (8.04)
10	-0.652** (-3.23)	-0.877*** (-4.06)	-0.605*** (-3.31)	-0.426** (-3.03)	-0.625*** (-3.55)	-0.613*** (-3.49)	-0.92*** (-4.4)
HML	-2.653*** (-8.43)	-2.871*** (-6.54)	-2.626*** (-5.69)	-2.205*** (-5.42)	-2.599*** (-6.34)	-2.647*** (-6.06)	-2.939*** (-6.17)

Panel C: Optimized (NN2)

No TF							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	0.279 (0.97)	-0.069 (-0.52)	0.048 (0.15)	0.099 (0.22)	-0.123 (-0.89)	-0.139 (-0.96)	0.045 (0.21)
10	2.221 (2.68)	1.483*** (3.73)	1.62** (2.87)	1.065 (1.96)	1.088*** (3.31)	1.169*** (3.08)	2.09** (3.19)
HML	1.942 (2.25)	1.333** (3.1)	1.35 (2.57)	0.782 (2.09)	0.985** (2.49)	1.087*** (2.48)	1.819** (3.16)
With TF Small Portfolio							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	0.38 (1.2)	0.02 (0.14)	0.162 (0.46)	0.222 (0.45)	-0.023 (-0.16)	-0.042 (-0.27)	0.144 (0.62)
10	0.99 (1.22)	0.223 (0.6)	0.46 (0.69)	-0.128 (-0.19)	-0.11 (-0.51)	0.002 (0.01)	0.842 (1.23)
HML	0.61 (0.71)	-0.016 (-0.04)	0.075 (0.13)	-0.534 (-1.31)	-0.314 (-0.93)	-0.176 (-0.53)	0.472 (0.79)
With TF Large Portfolio							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	0.396 (1.56)	0.149 (0.95)	0.014 (0.11)	-0.031 (-0.18)	0.013 (0.12)	0.018 (0.14)	0.185 (0.91)
10	0.718 (0.7)	-0.287 (-0.86)	0.489 (0.43)	0.031 (0.02)	-0.644 (-1.97)	-0.266 (-0.84)	0.5 (0.52)
HML	0.322 (0.31)	-0.655 (-1.97)	0.252 (0.24)	-0.123 (-0.1)	-0.884 (-2.45)	-0.505 (-1.42)	0.089 (0.1)

Panel A: Equally weighted (NN3)

No TF							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	0.136 (0.44)	1.234 (1.61)	0.94 (1.58)	2.241 (2.13)	1.186 (2.0)	1.176 (1.89)	0.919 (1.38)
10	1.174 (2.41)	2.396*** (3.32)	2.543* (2.81)	5.01*** (4.12)	2.883* (2.64)	2.9** (2.85)	1.85** (2.81)
HML	1.037*** (3.61)	-0.71 (-1.19)	-0.725 (-1.46)	0.549 (0.7)	-0.717 (-1.72)	-0.712 (-1.9)	-0.795 (-1.2)
With TF Small Portfolio							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	3.021*** (8.85)	2.85*** (13.29)	2.824*** (13.95)	2.553*** (9.24)	2.84*** (12.26)	2.883*** (11.6)	2.712*** (17.27)
10	-1.599** (-3.43)	-1.8*** (-4.24)	-1.423*** (-3.73)	-1.265*** (-3.31)	-1.384*** (-4.18)	-1.364*** (-3.81)	-1.89*** (-4.08)
HML	-4.62*** (-13.72)	-4.865*** (-9.7)	-4.447*** (-11.01)	-4.006*** (-31.91)	-4.418*** (-15.82)	-4.447*** (-14.42)	-4.817*** (-9.84)
With TF Large Portfolio							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	3.946*** (10.05)	3.749*** (8.87)	3.734*** (9.06)	3.201*** (7.52)	3.667*** (10.29)	3.754*** (10.76)	3.631*** (9.34)
10	-3.038* (-2.98)	-3.158* (-2.71)	-2.672* (-2.62)	-1.869*** (-6.6)	-2.383** (-3.07)	-2.466** (-3.08)	-3.365 (-2.42)
HML	-6.984*** (-6.45)	-7.122*** (-4.53)	-6.606*** (-4.61)	-5.258*** (-14.73)	-6.243*** (-5.76)	-6.419*** (-5.84)	-7.21*** (-4.0)

Panel B: Value weighted (NN3)

No TF							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	0.147 (1.05)	-0.066 (-0.48)	0.081 (0.71)	0.096 (0.94)	0.075 (0.79)	0.12 (1.11)	-0.07 (-0.57)
10	0.716 (2.34)	0.438*** (3.99)	0.624*** (4.28)	0.54 (2.48)	0.488*** (4.65)	0.55*** (4.82)	0.524* (2.74)
HML	0.569 (2.11)	0.289 (2.23)	0.344 (2.27)	0.256 (2.12)	0.219 (2.5)	0.23 (2.41)	0.38 (1.96)
With TF Small Portfolio							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	1.201*** (9.8)	0.998*** (14.83)	1.074*** (15.82)	1.001*** (11.52)	1.09*** (17.16)	1.12*** (15.5)	0.979*** (15.68)
10	-0.57* (-2.93)	-0.822*** (-4.78)	-0.605*** (-3.72)	-0.48*** (-4.42)	-0.672*** (-4.44)	-0.64*** (-4.13)	-0.785*** (-4.43)
HML	-1.771*** (-10.19)	-2.035*** (-11.11)	-1.879*** (-9.63)	-1.67*** (-11.55)	-1.956*** (-10.49)	-1.96*** (-10.63)	-1.979*** (-9.85)
With TF Large Portfolio							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	1.536*** (9.51)	1.325*** (18.2)	1.449*** (18.59)	1.152*** (11.52)	1.444*** (17.34)	1.479*** (17.65)	1.321*** (17.03)
10	-1.241 (-2.44)	-1.441** (-2.85)	-1.192 (-2.42)	-0.641*** (-4.35)	-1.119** (-3.22)	-1.123** (-3.12)	-1.49 (-2.49)
HML	-2.777*** (-5.31)	-2.981*** (-5.54)	-2.841*** (-5.26)	-1.981*** (-8.63)	-2.757*** (-6.74)	-2.802*** (-6.93)	-3.026*** (-4.74)

Panel C: Optimized (NN3)

No TF							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	0.281 (0.93)	-0.037 (-0.17)	-0.124 (-0.47)	-0.083 (-0.25)	-0.034 (-0.11)	-0.209 (-0.81)	0.128 (0.9)
10	2.859** (3.51)	2.095*** (3.46)	2.299* (2.66)	1.878 (1.49)	1.728*** (3.01)	1.825*** (2.47)	2.68** (2.89)
HML	2.578** (3.23)	1.914* (2.73)	2.2 (2.25)	1.777 (1.24)	1.535* (2.16)	1.813*** (2.15)	2.326 (2.5)
With TF Small Portfolio							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	0.484 (1.3)	0.148 (0.51)	0.046 (0.14)	0.11 (0.25)	0.165 (0.42)	-0.049 (-0.15)	0.349 (1.91)
10	1.719 (2.08)	0.928 (1.74)	1.173 (1.33)	0.802 (0.63)	0.555 (1.83)	0.678 (2.5)	1.537 (1.7)
HML	1.235 (1.47)	0.562 (0.81)	0.905 (0.87)	0.508 (0.33)	0.162 (0.26)	0.506 (0.98)	0.961 (1.01)
With TF Large Portfolio							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	0.65 (1.54)	0.265 (0.91)	0.069 (0.24)	0.211 (0.83)	0.137 (0.32)	-0.138 (-0.33)	0.516* (2.64)
10	0.16 (0.21)	-0.569 (-2.0)	-0.443 (-0.84)	-1.226 (-1.73)	-0.865*** (-3.87)	-0.725*** (-4.04)	-0.007 (-0.02)
HML	-0.49 (-0.61)	-1.052* (-2.65)	-0.734 (-1.14)	-1.622 (-2.32)	-1.229** (-2.85)	-0.808 (-2.09)	-0.75 (-1.65)

Panel A: Equally weighted (NN4)

No TF							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	0.108 (0.35)	0.869 (1.42)	0.649 (1.18)	1.896 (1.67)	0.902 (1.72)	0.891 (1.68)	0.574 (1.11)
10	1.478* (2.8)	2.963*** (3.3)	3.023** (2.96)	5.023*** (4.35)	3.373*** (3.39)	3.373*** (3.95)	2.363 (2.46)
HML	1.37*** (3.86)	-0.248 (-0.36)	-0.208 (-0.27)	0.215 (0.25)	0.08 (0.12)	0.071 (0.1)	-0.501 (-0.62)
With TF Small Portfolio							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	3.055*** (8.85)	2.88*** (13.66)	2.765*** (13.54)	2.473*** (8.09)	2.77*** (11.81)	2.819*** (10.96)	2.754*** (20.29)
10	-1.274* (-2.84)	-1.487*** (-4.6)	-0.996** (-3.15)	-1.318*** (-3.79)	-1.034** (-2.99)	-0.978* (-2.72)	-1.53*** (-4.75)
HML	-4.329*** (-13.5)	-4.582*** (-11.52)	-3.961*** (-14.89)	-3.979*** (-29.14)	-3.998*** (-15.69)	-3.997*** (-14.67)	-4.498*** (-12.41)
With TF Large Portfolio							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	4.701*** (6.44)	4.441*** (5.97)	4.26*** (6.34)	3.145*** (6.56)	4.007*** (8.24)	4.164*** (8.8)	4.439*** (5.05)
10	-2.067*** (-3.99)	-2.28*** (-3.53)	-1.777** (-3.23)	-1.935*** (-6.81)	-1.795** (-3.15)	-1.769** (-2.9)	-2.296*** (-3.66)
HML	-6.768*** (-8.18)	-6.936*** (-4.89)	-6.236*** (-5.11)	-5.268*** (-9.91)	-5.996*** (-5.88)	-6.133*** (-5.91)	-6.95*** (-4.51)

Panel B: Value weighted (NN4)

No TF							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	0.195 (1.59)	-0.028 (-0.34)	0.09 (1.0)	0.109 (0.95)	0.067 (0.98)	0.109 (1.14)	0.003 (0.05)
10	0.789 (2.52)	0.51*** (4.08)	0.751*** (4.18)	0.531** (2.95)	0.599*** (4.58)	0.665*** (4.83)	0.604** (3.02)
HML	0.594 (2.21)	0.323* (2.68)	0.46** (3.05)	0.234** (3.14)	0.337** (3.03)	0.357** (3.14)	0.386 (2.26)
With TF Small Portfolio							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	1.224*** (10.16)	1.006*** (19.31)	1.048*** (12.3)	1.006*** (7.45)	1.042*** (10.51)	1.071*** (9.47)	1.031*** (18.85)
10	-0.472 (-2.49)	-0.731*** (-5.71)	-0.479*** (-4.33)	-0.51*** (-4.67)	-0.574*** (-4.36)	-0.529*** (-4.11)	-0.676*** (-5.2)
HML	-1.697*** (-9.59)	-1.952*** (-10.46)	-1.727*** (-9.86)	-1.704*** (-6.93)	-1.81*** (-8.38)	-1.8*** (-8.57)	-1.922*** (-9.8)
With TF Large Portfolio							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	1.567*** (10.4)	1.338*** (21.28)	1.358*** (16.03)	1.173*** (7.72)	1.335*** (13.91)	1.365*** (12.2)	1.385*** (16.64)
10	-0.78*** (-4.0)	-1.033*** (-4.57)	-0.842*** (-3.59)	-0.691*** (-4.23)	-0.927*** (-4.01)	-0.877*** (-3.79)	-0.978*** (-4.48)
HML	-2.346*** (-11.06)	-2.586*** (-7.88)	-2.4*** (-7.5)	-2.053*** (-6.21)	-2.456*** (-7.37)	-2.442*** (-7.46)	-2.577*** (-7.67)

Panel C: Optimized (NN4)

No TF							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	0.322 (1.15)	0.012 (0.05)	-0.068 (-0.24)	-0.006 (-0.02)	0.01 (0.03)	-0.136 (-0.5)	0.161 (1.04)
10	2.978*** (3.7)	2.212*** (3.76)	2.424* (2.8)	2.016 (1.58)	1.854*** (2.4)	1.935*** (2.76)	2.799** (3.03)
HML	2.656** (3.36)	1.981* (2.77)	2.27 (2.3)	1.838 (1.25)	1.617* (2.17)	1.851*** (2.08)	2.411 (2.52)
With TF Small Portfolio							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	0.51 (1.47)	0.183 (0.61)	0.087 (0.25)	0.169 (0.37)	0.197 (0.5)	0.01 (0.03)	0.368 (1.91)
10	1.842 (2.28)	1.055 (1.99)	1.314 (1.46)	0.949 (0.73)	0.693 (2.24)	0.801** (2.85)	1.663 (1.8)
HML	1.331 (1.62)	0.653 (0.91)	1.004 (0.94)	0.596 (0.38)	0.269 (0.43)	0.57 (1.05)	1.068 (1.08)
With TF Large Portfolio							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	1.463 (2.06)	0.883 (2.13)	1.203 (1.88)	1.418 (1.86)	0.98** (2.86)	0.907** (3.14)	1.287 (2.07)
10	-0.082 (-0.11)	-0.652 (-1.54)	-0.449 (-1.3)	-1.375*** (-3.44)	-1.07 (-2.4)	-0.768 (-1.47)	-0.258 (-0.76)
HML	-1.546 (-1.69)	-1.754** (-2.92)	-1.874 (-2.44)	-2.978*** (-3.9)	-2.277*** (-2.46)	-1.896*** (-1.93)	-1.772 (-2.44)

Panel A: Equally weighted (NN5)

No TF							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	0.176 (0.54)	0.946 (1.7)	1.679 (2.31)	3.764 (2.3)	1.636 (2.16)	1.761 (2.52)	0.778 (1.4)
10	1.500 (2.63)	3.321*** (3.84)	3.577*** (3.63)	6.19*** (5.95)	3.636*** (4.59)	3.535*** (4.49)	2.986* (2.79)
HML	1.325** (3.53)	-0.614 (-0.68)	-0.155 (-0.3)	0.716 (1.05)	0.075 (0.12)	0.115 (0.15)	-0.886 (-0.74)
With TF Small Portfolio							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	3.116*** (8.79)	2.94*** (16.65)	2.895*** (15.41)	2.709*** (8.4)	2.915*** (13.52)	2.966*** (13.03)	2.82*** (20.71)
10	-1.245 (-2.51)	-1.431*** (-4.13)	-1.068*** (-3.41)	-1.314*** (-3.39)	-1.087** (-3.12)	-1.015* (-2.71)	-1.521*** (-4.19)
HML	-4.361*** (-13.14)	-4.586*** (-10.71)	-4.163*** (-11.87)	-4.212*** (-15.46)	-4.196*** (-11.56)	-4.181*** (-10.9)	-4.556*** (-10.62)
With TF Large Portfolio							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	4.245*** (9.58)	4.05*** (8.58)	3.924*** (8.86)	3.386*** (6.84)	3.877*** (10.05)	3.958*** (10.66)	3.931*** (8.51)
10	-2.096*** (-3.7)	-2.283*** (-3.54)	-1.887*** (-3.39)	-2.039*** (-5.39)	-1.894** (-3.18)	-1.851** (-2.84)	-2.338*** (-3.58)
HML	-6.341*** (-11.45)	-6.548*** (-5.74)	-6.011*** (-5.96)	-5.614*** (-9.25)	-5.966*** (-6.25)	-6.008*** (-6.02)	-6.484*** (-5.61)

Panel B: Value weighted (NN5)

No TF							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	0.205 (1.48)	-0.026 (-0.25)	0.106 (1.25)	0.088 (1.11)	0.084 (1.37)	0.124 (1.39)	0.021 (0.26)
10	0.771 (2.4)	0.505*** (4.12)	0.797*** (4.4)	0.57* (2.68)	0.655*** (4.27)	0.741*** (5.49)	0.579** (2.91)
HML	0.565 (2.2)	0.316* (2.59)	0.491** (2.96)	0.294 (2.39)	0.376 (2.45)	0.418** (2.84)	0.344 (2.25)
With TF Small Portfolio							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	1.24*** (9.05)	1.028*** (20.06)	1.042*** (15.37)	0.936*** (9.4)	1.037*** (13.61)	1.071*** (11.52)	1.028*** (21.87)
10	-0.479 (-2.29)	-0.723*** (-4.13)	-0.424*** (-3.35)	-0.506** (-3.06)	-0.513** (-2.86)	-0.442* (-2.79)	-0.685*** (-4.09)
HML	-1.719*** (-9.22)	-1.966*** (-8.23)	-1.665*** (-8.11)	-1.63*** (-7.46)	-1.744*** (-6.77)	-1.713*** (-6.78)	-1.928*** (-8.43)
With TF Large Portfolio							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	1.528*** (9.43)	1.31*** (11.38)	1.276*** (11.12)	1.134*** (8.57)	1.251*** (11.27)	1.291*** (10.71)	1.315*** (9.85)
10	-0.711** (-3.4)	-0.957*** (-4.11)	-0.687*** (-3.64)	-0.661*** (-3.35)	-0.776*** (-3.55)	-0.707*** (-3.35)	-0.919*** (-4.01)
HML	-2.24*** (-10.07)	-2.482*** (-6.58)	-2.164*** (-6.16)	-1.983*** (-6.52)	-2.221*** (-6.24)	-2.198*** (-6.0)	-2.449*** (-6.48)

Panel C: Optimized (NN5)

No TF							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	0.043 (0.51)	-0.19* (-2.71)	-0.253** (-3.02)	-0.311*** (-5.3)	-0.235* (-2.76)	-0.255** (-2.95)	-0.171** (-2.84)
10	2.305 (2.67)	1.731*** (4.77)	1.664* (2.7)	1.111 (1.81)	1.292*** (2.45)	1.384*** (2.42)	2.144** (3.03)
HML	2.263 (2.71)	1.703*** (5.14)	1.703* (2.7)	1.251 (2.11)	1.303*** (2.72)	1.421*** (2.87)	2.094** (3.16)
With TF Small Portfolio							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	0.107 (1.26)	-0.126 (-1.74)	-0.189 (-2.23)	-0.247*** (-5.46)	-0.163 (-1.83)	-0.189 (-2.07)	-0.107 (-1.59)
10	1.031 (1.21)	0.444 (1.34)	0.45 (0.65)	-0.155 (-0.23)	0.068 (0.43)	0.19 (1.23)	0.862 (1.18)
HML	0.924 (1.12)	0.352 (1.17)	0.425 (0.59)	-0.079 (-0.12)	0.006 (0.04)	0.16 (0.85)	0.748 (1.08)
With TF Large Portfolio							
Portfolio	Mean	CAPM	FFC	FF3+PS	FF5	FF6	q
1	-0.283 (-0.22)	-0.598 (-0.63)	-0.931 (-0.72)	-1.254 (-0.96)	-1.55 (-0.86)	-1.502 (-0.88)	-0.449 (-0.51)
10	1.387 (1.58)	0.79 (1.23)	0.064 (0.13)	-0.511 (-1.35)	0.09 (0.18)	-0.288 (-0.54)	1.332 (1.65)
HML	1.671 (1.12)	1.17 (1.21)	0.772 (0.62)	0.559 (0.38)	1.413 (0.97)	0.993 (0.76)	1.554 (1.23)

Appendix 2H: Performance of the neural network portfolios, monthly rebalancing

This appendix reports the performance of the five neural network setups in predicting month ahead returns. Panels A to E report the predictions for the neural network setups starting with the one-layer model (NN1) to the five layer model (NN5), respectively. Each panel shows the results for the equal-weighted weighting scheme on the left section and the results for the optimised portfolios on the right section. The panels are also divided in three vertical sections which report the results for simulations of three trading environments: (a) an environment without trading frictions, (b) an environment with trading frictions investing a small initial capital of 1 million USD and (c) an environment with trading frictions investing a large initial capital of 100 million USD. Each section reports the results for the top and bottom deciles, as well as the High-minus-Low 'HML' portfolio. This is the long-short portfolios constructed by ranking stocks according to their machine learning predicted returns and form 10 portfolios, buying the highest quantile portfolio and selling the lowest quintile portfolio. For all setups, investing horizon is one month and thus, rebalancing is performed monthly based on predicted returns. Pred denotes the mean returns predicted by the machine learning model and Avg denotes the mean returns actually realised. Both returns are expressed in percentage basis. SD and SR measure the standard deviation and Sharpe Ratio of the portfolio, respectively, both in annualised basis and expressed in percentage basis.

Model	Panel A: NN1												
	Portfolio	Equally Weighted Portfolios				Value Weighted Portfolios				Optimized Portfolios			
		Pred	Avg	SD	SR	Pred	Avg	SD	SR	Pred	Avg	SD	SR
Without TF	1	-0.886	-1.072	6.78	-0.67	-0.540	-0.367	2.87	-0.73	-0.470	0.086	1.78	-0.28
	10	2.059	1.436	7.02	0.59	1.024	0.548	2.95	0.37	1.101	3.270	4.86	2.17
	HML	2.945	2.509	3.96	1.99	1.564	0.915	2.36	1.00	1.571	3.184	4.07	2.51
With TF Small Portfolio	1	-0.886	1.156	6.92	0.46	-0.541	0.494	2.77	0.32	-0.470	0.326	1.87	0.18
	10	2.059	-0.570	7.36	-0.38	1.024	0.021	3.05	-0.24	1.101	2.075	4.79	1.34
	HML	2.945	-1.726	4.15	-1.64	1.564	-0.473	2.41	-1.02	1.571	1.749	4.10	1.29
With TF Large Portfolio	1	-0.886	1.370	6.95	0.57	-0.541	0.836	3.41	0.61	-2.251	0.800	3.87	0.51
	10	2.059	-0.809	7.44	-0.49	1.024	-0.066	3.12	-0.34	1.154	1.145	4.01	0.79
	HML	2.945	-2.179	4.38	-1.91	1.564	-0.903	3.21	-1.23	3.405	0.345	5.29	0.08

Model	Panel B: NN2												
	Portfolio	Equally Weighted Portfolios				Value Weighted Portfolios				Optimized Portfolios			
		Pred	Avg	SD	SR	Pred	Avg	SD	SR	Pred	Avg	SD	SR
Without TF	1	-0.328	-0.380	7.30	-0.29	-0.235	-0.143	3.05	-0.43	-0.085	0.058	0.75	-0.78
	10	1.436	1.115	6.83	0.45	0.700	0.433	2.84	0.24	1.031	3.399	5.27	2.08
	HML	1.764	1.494	4.20	1.04	0.935	0.577	2.40	0.49	1.116	3.341	5.01	2.15
With TF Small Portfolio	1	-0.328	1.796	7.42	0.73	-0.234	0.753	2.99	0.60	-0.085	0.086	0.86	-0.57
	10	1.436	-0.774	7.20	-0.49	0.700	-0.107	3.03	-0.39	1.031	2.599	3.03	0.39
	HML	1.764	-2.570	4.77	-2.04	0.935	-0.860	2.63	-1.45	1.116	1.685	2.63	1.45
With TF Large Portfolio	1	-0.328	2.050	7.45	0.84	-0.234	1.031	3.10	0.89	-1.257	1.375	5.08	0.79
	10	1.436	-0.958	7.22	-0.57	0.700	-0.195	3.07	-0.49	0.702	0.222	4.39	0.00
	HML	1.764	-3.008	4.91	-2.29	0.935	-1.226	2.88	-1.76	1.959	-1.153	6.69	-0.71

Model	Panel C: NN3												
	Portfolio	Equally Weighted Portfolios				Value Weighted Portfolios				Optimized Portfolios			
		Pred	Avg	SD	SR	Pred	Avg	SD	SR	Pred	Avg	SD	SR
Without TF	1	-0.460	-0.780	6.48	-0.54	-0.273	-0.077	2.78	-0.39	-0.421	-0.079	1.35	-0.79
	10	1.344	1.195	7.24	0.46	0.675	0.534	3.23	0.32	0.736	3.256	5.12	2.05
	HML	1.804	1.975	4.14	1.45	0.948	0.611	2.63	0.49	1.157	3.335	4.19	2.57
With TF Small Portfolio	1	-0.459	1.092	6.58	0.45	-0.271	0.620	2.79	0.48	-0.421	0.197	1.48	-0.07
	10	1.344	-0.761	7.50	-0.46	0.675	-0.068	3.29	-0.32	0.736	2.166	5.01	1.34
	HML	1.803	-1.853	4.32	-1.67	0.946	-0.688	2.81	-1.14	1.157	1.969	4.17	1.45
With TF Large Portfolio	1	-0.459	1.267	6.64	0.54	-0.271	0.933	4.15	0.58	-3.438	0.506	5.45	0.18
	10	1.344	-0.976	7.54	-0.56	0.675	-0.208	3.38	-0.46	0.781	0.541	2.70	0.40
	HML	1.803	-2.243	4.52	-1.90	0.946	-1.141	4.15	-1.15	4.219	0.035	5.92	-0.11

Model	Panel D: NN4												
	Portfolio	Equally Weighted Portfolios				Value Weighted Portfolios				Optimized Portfolios			
		Pred	Avg	SD	SR	Pred	Avg	SD	SR	Pred	Avg	SD	SR
Without TF	1	-0.364	-0.734	6.50	-0.52	-0.213	-0.026	2.83	-0.32	-0.375	0.017	1.38	-0.53
	10	1.352	1.282	7.31	0.50	0.671	0.506	3.28	0.29	0.743	3.502	5.25	2.16
	HML	1.717	2.017	4.24	1.45	0.884	0.532	2.70	0.38	1.118	3.485	4.31	2.62
With TF Small Portfolio	1	-0.365	1.079	6.62	0.44	-0.214	0.668	2.79	0.54	-0.375	0.264	1.53	0.08
	10	1.352	-0.628	7.55	-0.40	0.671	-0.114	3.38	-0.36	0.743	2.587	5.33	1.53
	HML	1.717	-1.707	4.40	-1.53	0.885	-0.782	2.88	-1.22	1.118	2.322	4.55	1.60
With TF Large Portfolio	1	-0.365	1.293	6.72	0.54	-0.214	1.046	4.31	0.65	-2.977	1.589	4.64	1.02
	10	1.352	-0.810	7.58	-0.48	0.671	-0.193	3.39	-0.44	0.703	0.007	2.92	-0.26
	HML	1.717	-2.103	4.60	-1.76	0.885	-1.239	4.31	-1.19	3.680	-1.582	5.47	-1.14

Model	Panel E: NN5												
	Portfolio	Equally Weighted Portfolios				Value Weighted Portfolios				Optimized Portfolios			
		Pred	Avg	SD	SR	Pred	Avg	SD	SR	Pred	Avg	SD	SR
Without TF	1	-0.135	-0.376	7.10	-0.30	-0.137	-0.034	3.01	-0.31	-0.267	0.078	1.24	-0.42
	10	1.317	0.967	6.42	0.39	0.646	0.463	3.39	0.23	0.870	3.598	4.93	2.37
	HML	1.453	1.344	4.36	0.88	0.782	0.496	2.87	0.31	1.137	3.520	4.19	2.72
With TF Small Portfolio	1	-0.135	1.110	7.33	0.41	-0.135	0.605	3.02	0.42	-0.267	0.274	1.35	0.12
	10	1.317	-0.654	6.71	-0.46	0.646	-0.090	3.41	-0.33	0.870	2.504	5.00	1.58
	HML	1.453	-1.764	4.75	-1.46	0.781	-0.694	2.96	-1.09	1.137	2.230	4.39	1.58
With TF Large Portfolio	1	-0.135	1.290	7.39	0.49	-0.135	1.012	4.58	0.59	-2.538	3.142	7.76	1.30
	10	1.317	-0.827	6.72	-0.55	0.646	-0.160	3.42	-0.40	0.659	0.289	3.28	0.07
	HML	1.453	-2.117	4.91	-1.66	0.781	-1.172	4.47	-1.09	3.196	-2.853	8.20	-1.30

Appendix 2I: Performance of the neural network portfolios, quarterly rebalancing

This appendix reports the performance of the five neural network setups in predicting three months ahead returns. Panels A to E report the predictions for the neural network setups starting with the one-layer model (NN1) to the five-layer model (NN5), respectively. Each panel shows the results for the equal-weighted weighting scheme on the left section and the results for the optimised portfolios on the right section. The panels are also divided in three vertical sections which report the results for simulations of three trading environments: (a) an environment without trading frictions, (b) an environment with trading frictions investing a small initial capital of 1 million USD and (c) an environment with trading frictions investing a large initial capital of 100 million USD. Each section reports the results for the top and bottom deciles, as well as the High-minus-Low 'HML' portfolio. This is the long-short portfolios constructed by ranking stocks according to their machine learning predicted returns and form 10 portfolios, buying the highest quantile portfolio and selling the lowest quintile portfolio. For all setups, investing horizon is three months and thus, rebalancing is performed quarterly based on predicted returns. Pred denotes the mean returns predicted by the machine learning model and Avg denotes the mean returns actually realised. Both returns are expressed in percentage basis. SD and SR measure the standard deviation and Sharpe Ratio of the portfolio, respectively, both in annualised basis and expressed in percentage basis.

Model	Panel A: NN1												
	Portfolio	Equally Weighted Portfolios				Value Weighted Portfolios				Optimized Portfolios			
		Pred	Avg	SD	SR	Pred	Avg	SD	SR	Pred	Avg	SD	SR
Without TF	1	-0.559	2.010	5.11	1.21	-0.293	0.315	1.62	0.18	-0.441	0.301	2.07	0.12
	10	1.926	-0.099	4.44	-0.26	0.941	0.168	1.99	-0.11	1.495	1.771	4.93	1.08
	HML	2.485	-2.109	3.63	-2.24	1.234	-0.147	1.71	-0.76	1.936	1.470	4.70	0.92
With TF Small Portfolio	1	-0.559	3.825	5.35	2.33	-0.293	1.124	1.71	1.81	-0.441	0.485	2.37	0.38
	10	1.926	-1.290	4.61	-1.14	0.941	-0.387	1.78	-1.20	1.495	0.636	5.08	0.28
	HML	2.485	-5.115	3.89	-4.76	1.234	-1.511	1.62	-3.73	1.936	0.151	4.99	-0.05
With TF Large Portfolio	1	-0.559	4.145	5.40	2.51	-0.293	1.675	4.36	1.15	-2.820	3.203	15.87	0.65
	10	1.926	-1.532	4.74	-1.29	0.941	-0.473	1.81	-1.34	1.320	-0.523	4.44	-0.59
	HML	2.485	-5.677	4.14	-4.95	1.234	-2.147	4.26	-1.93	4.140	-3.726	16.55	-0.83

Model	Panel B: NN2												
	Portfolio	Equally Weighted Portfolios				Value Weighted Portfolios				Optimized Portfolios			
		Pred	Avg	SD	SR	Pred	Avg	SD	SR	Pred	Avg	SD	SR
Without TF	1	-0.111	3.259	7.02	1.50	-0.093	0.598	2.10	0.61	-0.260	0.347	1.67	0.25
	10	1.371	-0.705	4.13	-0.78	0.669	-0.126	1.83	-0.68	1.078	2.191	4.41	1.54
	HML	1.482	-3.965	6.46	-2.25	0.762	-0.724	2.14	-1.54	1.338	1.844	4.50	1.24
With TF Small Portfolio	1	-0.111	4.999	7.36	2.24	-0.093	1.418	2.17	1.89	-0.260	0.725	2.00	0.86
	10	1.371	-1.752	4.41	-1.56	0.669	-0.715	1.96	-1.67	1.078	0.880	4.35	0.52
	HML	1.481	-6.751	7.09	-3.41	0.762	-2.133	2.44	-3.36	1.338	0.155	4.67	-0.05
With TF Large Portfolio	1	-0.111	5.337	7.41	2.39	-0.093	1.757	2.47	2.14	-1.191	1.858	4.74	1.19
	10	1.371	-1.981	4.46	-1.72	0.669	-0.875	2.05	-1.87	1.304	0.168	5.98	-0.03
	HML	1.481	-7.318	7.08	-3.69	0.762	-2.632	2.77	-3.58	2.495	-1.690	7.44	-0.89

Model	Panel C: NN3												
	Portfolio	Equally Weighted Portfolios				Value Weighted Portfolios				Optimized Portfolios			
		Pred	Avg	SD	SR	Pred	Avg	SD	SR	Pred	Avg	SD	SR
Without TF	1	-0.289	1.274	4.57	0.79	-0.144	0.224	1.67	-0.01	-0.423	-0.095	1.09	-1.02
	10	1.252	0.165	5.02	-0.05	0.611	0.254	2.18	0.04	0.967	2.320	4.95	1.46
	HML	1.541	-1.109	4.37	-1.06	0.755	0.030	1.87	-0.37	1.389	2.415	4.49	1.69
With TF Small Portfolio	1	-0.289	3.095	4.71	2.11	-0.144	0.932	1.65	1.47	-0.423	0.139	1.14	-0.27
	10	1.252	-1.322	5.06	-1.06	0.612	-0.481	2.00	-1.23	0.967	1.069	5.07	0.58
	HML	1.541	-4.417	4.59	-3.51	0.756	-1.413	1.78	-3.19	1.389	0.930	4.72	0.51
With TF Large Portfolio	1	-0.289	3.432	4.86	2.28	-0.144	1.096	1.82	1.65	-3.388	1.708	5.31	0.97
	10	1.252	-1.632	5.17	-1.25	0.612	-0.783	2.29	-1.53	1.015	-0.124	4.08	-0.30
	HML	1.541	-5.064	4.96	-3.70	0.756	-1.879	2.25	-3.25	4.403	-1.832	6.43	-1.11

Model	Panel D: NN4												
	Portfolio	Equally Weighted Portfolios				Value Weighted Portfolios				Optimized Portfolios			
		Pred	Avg	SD	SR	Pred	Avg	SD	SR	Pred	Avg	SD	SR
Without TF	1	-0.203	1.255	4.66	0.76	-0.101	0.264	1.73	0.07	-0.408	0.113	1.21	-0.33
	10	1.266	0.394	5.17	0.11	0.617	0.306	2.22	0.12	0.980	2.420	5.35	1.42
	HML	1.469	-0.862	4.66	-0.81	0.718	0.042	2.00	-0.33	1.387	2.307	4.85	1.49
With TF Small Portfolio	1	-0.203	3.048	4.80	2.03	-0.102	0.969	1.79	1.43	-0.408	0.303	1.32	0.20
	10	1.266	-1.069	5.21	-0.86	0.617	-0.456	2.03	-1.17	0.980	1.185	5.48	0.61
	HML	1.469	-4.117	4.78	-3.15	0.719	-1.425	1.93	-2.98	1.387	0.882	5.11	0.44
With TF Large Portfolio	1	-0.203	3.504	5.06	2.24	-0.102	1.216	2.20	1.55	-3.037	2.524	6.64	1.20
	10	1.266	-1.306	5.27	-1.01	0.617	-0.719	2.33	-1.41	0.780	-0.164	3.89	-0.35
	HML	1.469	-4.811	5.14	-3.40	0.719	-1.935	2.60	-2.88	3.817	-2.688	7.42	-1.36

Model	Panel E: NN5												
	Portfolio	Equally Weighted Portfolios				Value Weighted Portfolios				Optimized Portfolios			
		Pred	Avg	SD	SR	Pred	Avg	SD	SR	Pred	Avg	SD	SR
Without TF	1	-0.003	1.053	4.76	0.60	-0.028	0.186	1.76	-0.09	-0.154	0.092	1.10	-0.43
	10	1.259	0.550	4.52	0.24	0.615	0.344	2.47	0.16	1.038	3.086	4.82	2.06
	HML	1.263	-0.503	3.95	-0.64	0.644	0.159	2.30	-0.11	1.192	2.995	4.63	2.07
With TF Small Portfolio	1	-0.003	2.750	4.92	1.78	-0.026	0.887	1.80	1.26	-0.154	0.283	1.02	0.19
	10	1.259	-0.873	4.72	-0.81	0.616	-0.337	2.32	-0.85	1.038	1.782	4.84	1.11
	HML	1.263	-3.623	4.09	-3.27	0.642	-1.223	2.23	-2.26	1.192	1.499	4.75	0.93
With TF Large Portfolio	1	-0.003	3.131	4.99	2.01	-0.026	1.118	2.12	1.45	-2.738	1.905	7.74	0.75
	10	1.259	-1.144	4.80	-0.99	0.616	-0.592	2.57	-1.11	0.822	0.104	4.17	-0.10
	HML	1.263	-4.276	4.30	-3.63	0.642	-1.711	2.64	-2.55	3.560	-1.801	8.58	-0.82

Appendix 2J: Performance of the neural network portfolios, annual rebalancing

This appendix reports the performance of the five neural network setups in predicting twelve months ahead returns. Panels A to E report the predictions for the neural network setups starting with the one-layer model (NN1) to the five-layer model (NN5), respectively. Each panel shows the results for the equal-weighted weighting scheme on the left section and the results for the optimised portfolios on the right section. The panels are also divided in three vertical sections which report the results for simulations of three trading environments: (a) an environment without trading frictions, (b) an environment with trading frictions investing a small initial capital of 1 million USD and (c) an environment with trading frictions investing a large initial capital of 100 million USD. Each section reports the results for the top and bottom deciles, as well as the High-minus-Low 'HML' portfolio. This is the long-short portfolios constructed by ranking stocks according to their machine learning predicted returns and form 10 portfolios, buying the highest quantile portfolio and selling the lowest quintile portfolio. For all setups, investing horizon is twelve months and thus, rebalancing is performed annual based on predicted returns. Pred denotes the mean returns predicted by the machine learning model and Avg denotes the mean returns actually realised. Both returns are expressed in percentage basis. SD and SR measure the standard deviation and Sharpe Ratio of the portfolio, respectively, both in annualised basis and expressed in percentage basis.

Model	Panel A: NN1												
	Portfolio	Equally Weighted Portfolios				Value Weighted Portfolios				Optimized Portfolios			
		Pred	Avg	SD	SR	Pred	Avg	SD	SR	Pred	Avg	SD	SR
Without TF	1	-0.249	0.431	2.25	0.33	-0.103	0.256	0.85	0.17	-0.320	0.567	2.76	0.42
	10	1.883	1.013	2.53	1.09	0.922	0.321	0.86	0.42	1.589	2.357	5.21	1.41
	HML	2.132	0.582	1.86	0.68	1.024	0.065	0.78	-0.67	1.909	1.791	5.44	0.99
With TF Small Portfolio	1	-0.249	3.486	2.67	4.24	-0.103	1.421	0.91	4.60	-0.320	0.817	3.24	0.63
	10	1.883	-1.458	2.64	-2.19	0.922	-0.593	0.99	-2.83	1.589	1.175	5.26	0.62
	HML	2.132	-4.944	2.23	-8.03	1.025	-2.013	1.02	-7.55	1.909	0.358	5.69	0.08
With TF Large Portfolio	1	-0.249	4.716	3.37	4.62	-0.103	1.909	1.44	4.06	-0.827	1.357	4.19	0.93
	10	1.883	-2.226	3.21	-2.63	0.922	-0.840	1.38	-2.65	1.719	0.678	5.23	0.30
	HML	2.132	-6.942	3.32	-7.47	1.025	-2.749	1.79	-5.74	2.546	-0.679	6.07	-0.52

Model	Panel B: NN2												
	Portfolio	Equally Weighted Portfolios				Value Weighted Portfolios				Optimized Portfolios			
		Pred	Avg	SD	SR	Pred	Avg	SD	SR	Pred	Avg	SD	SR
Without TF	1	0.034	0.742	3.07	0.59	0.015	0.164	1.03	-0.17	-0.107	0.279	1.72	0.10
	10	1.293	0.976	2.38	1.10	0.634	0.501	1.10	0.90	1.225	2.221	4.97	1.39
	HML	1.260	0.234	3.20	0.02	0.619	0.337	1.15	0.37	1.332	1.942	5.19	1.14
With TF Small Portfolio	1	0.035	3.876	3.47	3.65	0.017	1.424	1.09	3.85	-0.107	0.380	1.90	0.28
	10	1.293	-1.419	2.43	-2.33	0.634	-0.443	1.06	-2.16	1.225	0.990	4.88	0.54
	HML	1.259	-5.295	3.93	-4.85	0.617	-1.868	1.37	-5.27	1.332	0.610	5.13	0.26
With TF Large Portfolio	1	0.035	5.339	4.53	3.92	0.017	2.000	1.62	3.82	-0.596	0.396	1.52	0.38
	10	1.293	-2.144	2.70	-3.03	0.634	-0.652	1.21	-2.48	1.527	0.718	6.14	0.28
	HML	1.259	-7.483	4.48	-5.96	0.617	-2.653	1.89	-5.26	2.123	0.322	6.21	0.05

Model	Panel C: NN3												
	Portfolio	Equally Weighted Portfolios				Value Weighted Portfolios				Optimized Portfolios			
		Pred	Avg	SD	SR	Pred	Avg	SD	SR	Pred	Avg	SD	SR
Without TF	1	-0.089	0.136	1.88	-0.15	-0.033	0.147	0.84	-0.28	-0.299	0.281	1.81	0.10
	10	1.189	1.174	2.92	1.13	0.577	0.716	1.84	0.94	1.024	2.859	4.89	1.87
	HML	1.278	1.037	1.72	1.65	0.611	0.569	1.62	0.76	1.323	2.578	4.79	1.70
With TF Small Portfolio	1	-0.088	3.021	2.05	4.75	-0.032	1.201	0.74	4.64	-0.299	0.484	2.23	0.40
	10	1.189	-1.599	2.80	-2.25	0.577	-0.570	1.17	-2.33	1.024	1.719	4.95	1.04
	HML	1.277	-4.620	2.02	-8.29	0.610	-1.771	1.04	-6.60	1.323	1.235	5.06	0.69
With TF Large Portfolio	1	-0.088	3.946	2.36	5.48	-0.032	1.536	0.97	4.72	-1.326	0.650	2.54	0.58
	10	1.189	-3.038	6.13	-1.84	0.577	-1.241	3.06	-1.65	0.926	0.160	4.54	-0.05
	HML	1.277	-6.984	6.50	-3.84	0.610	-2.777	3.14	-3.30	2.252	-0.490	4.80	-0.52

Model	Panel D: NN4												
	Portfolio	Equally Weighted Portfolios				Value Weighted Portfolios				Optimized Portfolios			
		Pred	Avg	SD	SR	Pred	Avg	SD	SR	Pred	Avg	SD	SR
Without TF	1	-0.023	0.108	1.84	-0.20	0.000	0.195	0.74	-0.10	-0.280	0.322	1.68	0.19
	10	1.206	1.478	3.16	1.38	0.585	0.789	1.88	1.06	1.034	2.978	4.82	1.98
	HML	1.229	1.370	2.13	1.88	0.585	0.594	1.61	0.81	1.314	2.656	4.75	1.77
With TF Small Portfolio	1	-0.024	3.055	2.07	4.75	0.000	1.224	0.72	4.83	-0.280	0.510	2.09	0.47
	10	1.206	-1.274	2.70	-1.91	0.585	-0.472	1.14	-2.09	1.034	1.842	4.85	1.15
	HML	1.230	-4.329	1.92	-8.18	0.584	-1.697	1.06	-6.24	1.314	1.331	4.93	0.78
With TF Large Portfolio	1	-0.024	4.701	4.38	3.55	0.000	1.567	0.90	5.18	-2.546	1.463	4.25	1.01
	10	1.206	-2.067	3.11	-2.54	0.585	-0.780	1.17	-2.95	0.929	-0.082	4.46	-0.24
	HML	1.230	-6.768	4.96	-4.87	0.584	-2.346	1.27	-6.97	3.475	-1.546	5.49	-1.12

Model	Panel E: NN5												
	Portfolio	Equally Weighted Portfolios				Value Weighted Portfolios				Optimized Portfolios			
		Pred	Avg	SD	SR	Pred	Avg	SD	SR	Pred	Avg	SD	SR
Without TF	1	0.118	0.176	1.94	-0.07	0.072	0.205	0.83	-0.04	-0.050	0.043	0.50	-1.25
	10	1.242	1.500	3.42	1.30	0.611	0.771	1.93	1.00	1.267	2.305	5.11	1.41
	HML	1.124	1.325	2.25	1.71	0.539	0.565	1.54	0.79	1.317	2.263	4.93	1.43
With TF Small Portfolio	1	0.117	3.116	2.13	4.72	0.072	1.240	0.82	4.32	-0.050	0.107	0.50	-0.80
	10	1.242	-1.245	2.98	-1.70	0.611	-0.479	1.26	-1.92	1.267	1.031	5.04	0.56
	HML	1.125	-4.361	1.99	-7.96	0.539	-1.719	1.12	-5.99	1.317	0.924	4.88	0.50
With TF Large Portfolio	1	0.117	4.245	2.66	5.25	0.072	1.528	0.97	4.68	-1.760	-0.283	7.64	-0.23
	10	1.242	-2.096	3.40	-2.36	0.611	-0.711	1.26	-2.56	1.037	1.387	5.26	0.76
	HML	1.125	-6.341	3.32	-6.83	0.539	-2.240	1.33	-6.37	2.797	1.671	8.99	0.56

Appendix 2K: Performance of the neural network portfolios, monthly rebalancing, all deciles

This appendix reports the performance of the five neural network setups in predicting month ahead returns. Panels A to E report the predictions for the neural network setups starting with the one-layer model (NN1) to the five-layer model (NN5), respectively. Each panel shows the results for the equal-weighted weighting scheme in the left section, the results for the value-weighted weighting scheme in the middle section and the results for the optimised portfolios on the right section. The long-short portfolio is constructed by ranking stocks according to their machine learning predicted returns and form 10 portfolios, buying the highest quantile portfolio and selling the lowest quintile portfolio (High-minus-Low 'HML' portfolio). The table reports the results of the 10 deciles, as well as the HML portfolio. For all setups, investing horizon is one month and thus, rebalancing is performed monthly based on predicted returns. The results for the quarterly rebalancing are presented in Pred denotes the mean returns predicted by the machine learning model and Avg denotes the mean returns actually realised. Both returns are expressed in percentage basis. SD and SR measure the standard deviation and Sharpe Ratio of the portfolio, respectively, both in annualised basis and expressed in percentage basis.

Panel A: NN1								
portfolio	Equally Weighted - Without TF				Value Weighted - Without TF			
	Pred	Avg	SD	SR	Pred	Avg	SD	SR
1	-0.886	-1.072	6.78	-0.67	-0.540	-0.367	2.87	-0.73
2	0.113	0.372	6.17	0.08	0.058	0.334	2.72	0.12
3	0.379	0.641	5.72	0.25	0.190	0.366	2.44	0.18
4	0.568	0.706	5.51	0.30	0.285	0.326	2.40	0.13
5	0.728	0.898	5.40	0.43	0.365	0.389	2.29	0.23
6	0.881	0.898	5.48	0.42	0.440	0.446	2.28	0.32
7	1.040	0.994	5.61	0.47	0.520	0.397	2.38	0.23
8	1.223	0.943	5.75	0.43	0.612	0.330	2.45	0.13
9	1.469	1.052	6.19	0.46	0.734	0.398	2.59	0.22
10	2.059	1.436	7.02	0.59	1.024	0.548	2.95	0.37
HML	2.945	2.509	3.96	1.99	1.564	0.915	2.36	1.00

Panel B: NN2								
portfolio	Equally Weighted - Without TF				Value Weighted - Without TF			
	Pred	Avg	SD	SR	Pred	Avg	SD	SR
1	-0.328	-0.380	7.30	-0.29	-0.235	-0.143	3.05	-0.43
2	0.224	0.374	6.30	0.08	0.115	0.276	2.80	0.05
3	0.396	0.587	5.76	0.21	0.199	0.308	2.53	0.10
4	0.517	0.655	5.51	0.26	0.259	0.312	2.40	0.11
5	0.620	0.790	5.35	0.36	0.310	0.374	2.36	0.20
6	0.716	0.861	5.40	0.40	0.358	0.402	2.35	0.24
7	0.815	0.914	5.47	0.43	0.407	0.361	2.39	0.18
8	0.930	0.964	5.78	0.44	0.465	0.385	2.40	0.22
9	1.084	0.992	6.06	0.43	0.540	0.411	2.56	0.24
10	1.436	1.115	6.83	0.45	0.700	0.433	2.84	0.24
HML	1.764	1.494	4.20	1.04	0.935	0.577	2.40	0.49

Panel C: NN3								
portfolio	Equally Weighted - Without TF				Value Weighted - Without TF			
	Pred	Avg	SD	SR	Pred	Avg	SD	SR
1	-0.460	-0.780	6.48	-0.54	-0.273	-0.077	2.78	-0.39
2	0.282	0.521	5.95	0.17	0.141	0.337	2.56	0.14
3	0.419	0.726	5.60	0.30	0.210	0.311	2.38	0.11
4	0.518	0.759	5.45	0.33	0.259	0.341	2.32	0.16
5	0.605	0.739	5.45	0.32	0.303	0.445	2.36	0.31
6	0.688	0.811	5.53	0.36	0.344	0.397	2.44	0.23
7	0.776	0.885	5.66	0.40	0.388	0.414	2.51	0.25
8	0.878	0.974	5.85	0.44	0.438	0.373	2.52	0.19
9	1.015	1.030	6.26	0.44	0.505	0.430	2.71	0.25
10	1.344	1.195	7.24	0.46	0.675	0.534	3.23	0.32
HML	1.804	1.975	4.14	1.45	0.948	0.611	2.63	0.49

Panel D: NN4								
portfolio	Equally Weighted - Without TF				Value Weighted - Without TF			
	Pred	Avg	SD	SR	Pred	Avg	SD	SR
1	-0.364	-0.734	6.50	-0.52	-0.213	-0.026	2.83	-0.32
2	0.302	0.450	5.95	0.12	0.151	0.354	2.56	0.16
3	0.438	0.648	5.58	0.26	0.219	0.303	2.39	0.10
4	0.536	0.740	5.46	0.32	0.268	0.349	2.33	0.17
5	0.622	0.698	5.47	0.29	0.311	0.397	2.33	0.24
6	0.705	0.808	5.56	0.36	0.352	0.382	2.39	0.21
7	0.793	0.885	5.65	0.40	0.396	0.432	2.52	0.27
8	0.894	0.975	5.82	0.44	0.446	0.365	2.47	0.18
9	1.030	1.108	6.23	0.48	0.513	0.431	2.74	0.25
10	1.352	1.282	7.31	0.50	0.671	0.506	3.28	0.29
HML	1.717	2.017	4.24	1.45	0.884	0.532	2.70	0.38

Panel E: NN5								
portfolio	Equally Weighted - Without TF				Value Weighted - Without TF			
	Pred	Avg	SD	SR	Pred	Avg	SD	SR
1	-0.135	-0.376	7.10	-0.30	-0.137	-0.034	3.01	-0.31
2	0.424	0.548	6.37	0.17	0.213	0.314	2.88	0.09
3	0.542	0.693	6.00	0.26	0.271	0.293	2.76	0.07
4	0.627	0.752	5.63	0.32	0.314	0.308	2.67	0.09
5	0.700	0.754	5.54	0.32	0.350	0.426	2.55	0.26
6	0.770	0.813	5.51	0.36	0.385	0.373	2.56	0.19
7	0.843	0.857	5.50	0.39	0.421	0.412	2.60	0.23
8	0.929	0.906	5.63	0.41	0.463	0.379	2.64	0.19
9	1.046	0.947	5.86	0.42	0.521	0.417	2.85	0.22
10	1.317	0.967	6.42	0.39	0.646	0.463	3.39	0.23
HML	1.453	1.344	4.36	0.88	0.782	0.496	2.87	0.31

Appendix 2L: Performance of the neural network portfolios, quarterly rebalancing, all deciles

This appendix reports the performance of the five neural network setups in predicting three months ahead returns. Panels A to E report the predictions for the neural network setups starting with the one-layer model (NN1) to the five-layer model (NN5), respectively. Each panel shows the results for the equal-weighted weighting scheme in the left section, the results for the value-weighted weighting scheme in the middle section and the results for the optimised portfolios on the right section. The long-short portfolio is constructed by ranking stocks according to their machine learning predicted returns and form 10 portfolios, buying the highest quantile portfolio and selling the lowest quintile portfolio (High-minus-Low 'HML' portfolio). The table reports the results of the 10 deciles, as well as the HML portfolio. For all setups, investing horizon is three months and thus, rebalancing is performed quarterly based on predicted returns. The results for the quarterly rebalancing are presented in Pred denotes the mean returns predicted by the machine learning model and Avg denotes the mean returns actually realised. Both returns are expressed in percentage basis. SD and SR measure the standard deviation and Sharpe Ratio of the portfolio, respectively, both in annualised basis and expressed in percentage basis.

Panel A: NN1								
portfolio	Equally Weighted - Without TF				Value Weighted - Without TF			
	Pred	Avg	SD	SR	Pred	Avg	SD	SR
1	-0.559	2.010	5.11	1.21	-0.293	0.315	1.62	0.18
2	0.211	1.852	4.00	1.40	0.106	0.584	1.61	0.76
3	0.443	1.541	3.73	1.22	0.222	0.462	1.47	0.55
4	0.609	1.155	3.56	0.90	0.306	0.411	1.41	0.44
5	0.751	0.940	3.46	0.71	0.376	0.346	1.39	0.29
6	0.887	0.682	3.48	0.45	0.444	0.302	1.34	0.18
7	1.030	0.512	3.56	0.27	0.515	0.190	1.28	-0.11
8	1.196	0.287	3.66	0.05	0.599	0.184	1.35	-0.12
9	1.418	0.111	3.87	-0.11	0.709	0.133	1.45	-0.23
10	1.926	-0.099	4.44	-0.26	0.941	0.168	1.99	-0.11
HML	2.485	-2.109	3.63	-2.24	1.234	-0.147	1.71	-0.76

Panel B: NN2								
portfolio	Equally Weighted - Without TF				Value Weighted - Without TF			
	Pred	Avg	SD	SR	Pred	Avg	SD	SR
1	-0.111	3.259	7.02	1.50	-0.093	0.598	2.10	0.61
2	0.328	2.075	4.75	1.35	0.167	0.533	1.66	0.63
3	0.470	1.506	3.94	1.12	0.236	0.474	1.50	0.56
4	0.573	1.129	3.50	0.89	0.287	0.419	1.46	0.45
5	0.662	0.882	3.46	0.65	0.331	0.339	1.41	0.27
6	0.745	0.509	3.40	0.28	0.373	0.169	1.47	-0.14
7	0.830	0.394	3.43	0.16	0.414	0.193	1.42	-0.09
8	0.930	0.109	3.35	-0.13	0.465	0.049	1.40	-0.45
9	1.065	-0.145	3.58	-0.36	0.532	0.070	1.44	-0.39
10	1.371	-0.705	4.13	-0.78	0.669	-0.126	1.83	-0.68
HML	1.482	-3.965	6.46	-2.25	0.762	-0.724	2.14	-1.54

Panel C: NN3								
portfolio	Equally Weighted - Without TF				Value Weighted - Without TF			
	Pred	Avg	SD	SR	Pred	Avg	SD	SR
1	-0.289	1.274	4.57	0.79	-0.144	0.224	1.67	-0.01
2	0.330	1.633	4.07	1.19	0.165	0.437	1.44	0.50
3	0.446	1.351	3.75	1.04	0.223	0.448	1.33	0.57
4	0.532	1.127	3.55	0.88	0.267	0.296	1.39	0.16
5	0.608	0.934	3.56	0.68	0.304	0.304	1.32	0.19
6	0.683	0.794	3.51	0.56	0.341	0.247	1.40	0.04
7	0.761	0.674	3.51	0.44	0.380	0.226	1.38	-0.01
8	0.851	0.542	3.69	0.29	0.425	0.223	1.39	-0.02
9	0.971	0.502	4.12	0.23	0.484	0.194	1.65	-0.08
10	1.252	0.165	5.02	-0.05	0.611	0.254	2.18	0.04
HML	1.541	-1.109	4.37	-1.06	0.755	0.030	1.87	-0.37

Panel D: NN4								
portfolio	Equally Weighted - Without TF				Value Weighted - Without TF			
	Pred	Avg	SD	SR	Pred	Avg	SD	SR
1	-0.203	1.255	4.66	0.76	-0.101	0.264	1.73	0.07
2	0.351	1.510	3.96	1.12	0.175	0.460	1.42	0.56
3	0.466	1.253	3.70	0.96	0.233	0.449	1.35	0.56
4	0.551	1.032	3.53	0.79	0.276	0.277	1.39	0.12
5	0.626	0.823	3.43	0.60	0.313	0.323	1.27	0.25
6	0.700	0.777	3.59	0.53	0.350	0.227	1.38	-0.01
7	0.778	0.698	3.57	0.45	0.389	0.226	1.35	-0.01
8	0.868	0.613	3.71	0.36	0.433	0.282	1.41	0.13
9	0.987	0.639	4.13	0.34	0.492	0.174	1.55	-0.13
10	1.266	0.394	5.17	0.11	0.617	0.306	2.22	0.12
HML	1.469	-0.862	4.66	-0.81	0.718	0.042	2.00	-0.33

Panel E: NN5								
portfolio	Equally Weighted - Without TF				Value Weighted - Without TF			
	Pred	Avg	SD	SR	Pred	Avg	SD	SR
1	-0.003	1.053	4.76	0.60	-0.028	0.186	1.76	-0.09
2	0.477	1.195	4.14	0.81	0.239	0.280	1.76	0.10
3	0.580	1.098	3.84	0.78	0.289	0.364	1.61	0.29
4	0.654	0.980	3.57	0.73	0.327	0.236	1.59	0.01
5	0.718	0.918	3.59	0.66	0.359	0.337	1.48	0.25
6	0.780	0.899	3.53	0.65	0.390	0.236	1.46	0.01
7	0.846	0.811	3.50	0.57	0.423	0.227	1.46	-0.01
8	0.922	0.721	3.58	0.47	0.461	0.232	1.46	0.00
9	1.024	0.770	3.89	0.48	0.511	0.232	1.58	0.00
10	1.259	0.550	4.52	0.24	0.615	0.344	2.47	0.16
HML	1.263	-0.503	3.95	-0.64	0.644	0.159	2.30	-0.11

Appendix 2M: Performance of the neural network portfolios, annual rebalancing, all deciles

This appendix reports the performance of the five neural network setups in predicting twelve months ahead returns. Panels A to E report the predictions for the neural network setups starting with the one-layer model (NN1) to the five-layer model (NN5), respectively. Each panel shows the results for the equal-weighted weighting scheme in the left section, the results for the value-weighted weighting scheme in the middle section and the results for the optimised portfolios on the right section. The long-short portfolio is constructed by ranking stocks according to their machine learning predicted returns and form 10 portfolios, buying the highest quantile portfolio and selling the lowest quintile portfolio (High-minus-Low 'HML' portfolio). The table reports the results of the 10 deciles, as well as the HML portfolio. For all setups, investing horizon is twelve months and thus, rebalancing is performed annually based on predicted returns. The results for the quarterly rebalancing are presented in Pred denotes the mean returns predicted by the machine learning model and Avg denotes the mean returns actually realised. Both returns are expressed in percentage basis. SD and SR measure the standard deviation and Sharpe Ratio of the portfolio, respectively, both in annualised basis and expressed in percentage basis.

Panel A: NN1								
portfolio	Equally Weighted - Without TF				Value Weighted - Without TF			
	Pred	Avg	SD	SR	Pred	Avg	SD	SR
1	-0.249	0.431	2.25	0.33	-0.103	0.256	0.85	0.17
2	0.278	0.745	2.11	0.87	0.138	0.399	0.83	0.77
3	0.486	0.880	1.99	1.15	0.242	0.367	0.97	0.54
4	0.637	0.868	1.92	1.18	0.317	0.387	0.73	0.82
5	0.768	0.921	1.82	1.34	0.383	0.379	0.69	0.82
6	0.895	0.925	1.88	1.31	0.448	0.539	1.24	0.90
7	1.030	0.807	1.87	1.10	0.516	0.252	0.73	0.17
8	1.190	0.875	1.95	1.17	0.595	0.351	0.77	0.61
9	1.402	0.905	2.13	1.12	0.698	0.356	0.77	0.63
10	1.883	1.013	2.53	1.09	0.922	0.321	0.86	0.42
HML	2.132	0.582	1.86	0.68	1.024	0.065	0.78	-0.67

Panel B: NN2								
portfolio	Equally Weighted - Without TF				Value Weighted - Without TF			
	Pred	Avg	SD	SR	Pred	Avg	SD	SR
1	0.034	0.742	3.07	0.59	0.015	0.164	1.03	-0.17
2	0.369	0.725	2.57	0.69	0.187	0.254	0.98	0.13
3	0.490	0.766	2.26	0.84	0.244	0.247	0.82	0.13
4	0.580	0.823	2.01	1.04	0.290	0.364	0.81	0.64
5	0.656	0.878	1.85	1.24	0.329	0.362	0.75	0.67
6	0.727	0.844	1.75	1.24	0.364	0.343	0.87	0.51
7	0.804	0.841	1.73	1.25	0.402	0.336	0.78	0.53
8	0.892	0.851	1.83	1.20	0.445	0.339	0.78	0.55
9	1.012	0.927	2.11	1.17	0.507	0.422	0.77	0.93
10	1.293	0.976	2.38	1.10	0.634	0.501	1.10	0.90
HML	1.260	0.234	3.20	0.02	0.619	0.337	1.15	0.37

Panel C: NN3								
portfolio	Equally Weighted - Without TF				Value Weighted - Without TF			
	Pred	Avg	SD	SR	Pred	Avg	SD	SR
1	-0.089	0.136	1.88	-0.15	-0.033	0.147	0.84	-0.28
2	0.377	0.840	2.44	0.88	0.186	0.424	0.91	0.79
3	0.496	0.942	2.12	1.18	0.249	0.404	0.82	0.80
4	0.573	0.933	1.95	1.28	0.287	0.353	0.71	0.67
5	0.639	0.873	1.84	1.24	0.320	0.348	0.66	0.70
6	0.700	0.803	1.70	1.20	0.349	0.367	0.76	0.69
7	0.765	0.821	1.83	1.15	0.382	0.344	0.78	0.57
8	0.844	0.878	1.95	1.17	0.421	0.335	0.80	0.52
9	0.950	0.964	2.18	1.19	0.475	0.363	0.84	0.60
10	1.189	1.174	2.92	1.13	0.577	0.716	1.84	0.94
HML	1.278	1.037	1.72	1.65	0.611	0.569	1.62	0.76

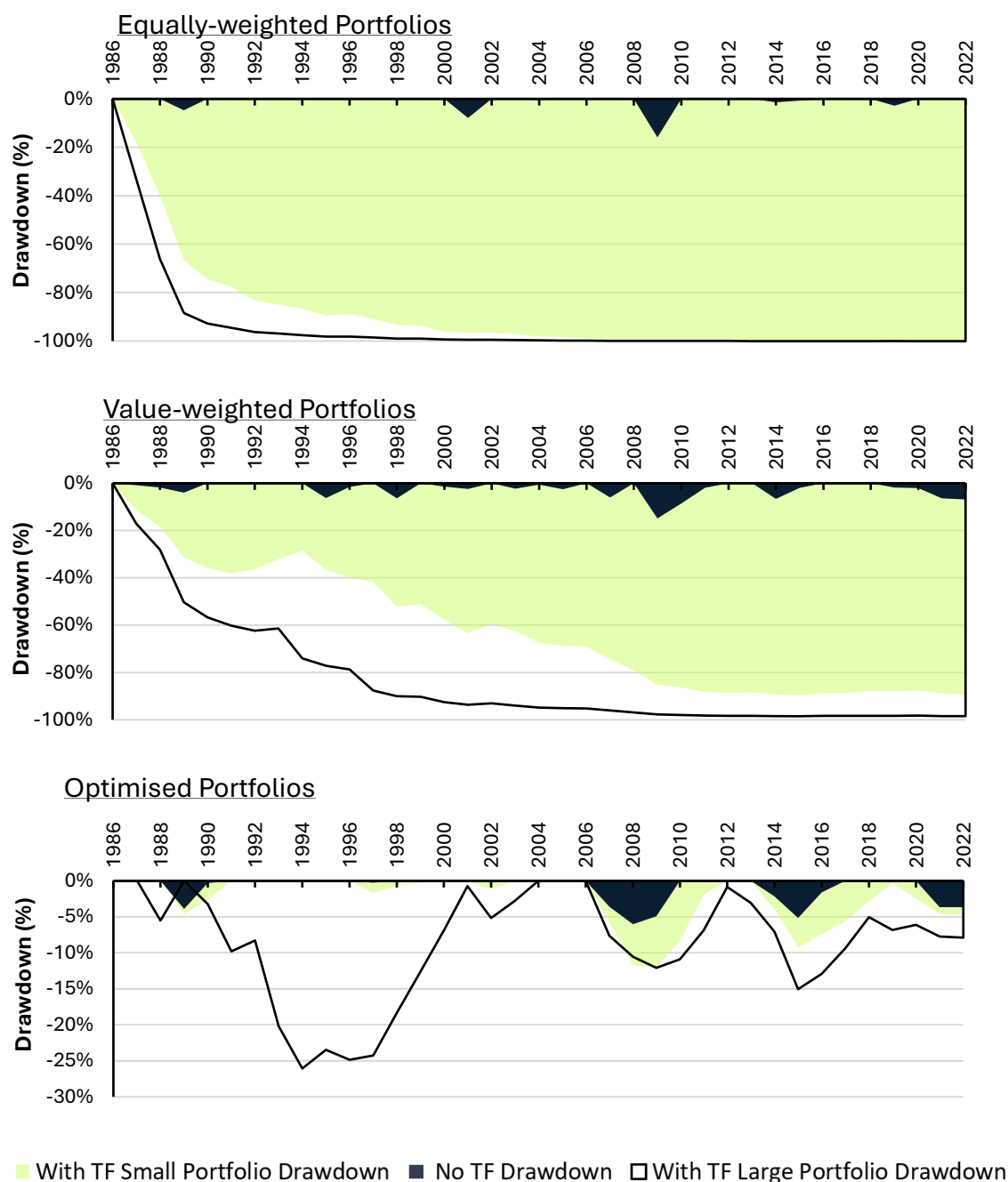
Panel D: NN4								
portfolio	Equally Weighted - Without TF				Value Weighted - Without TF			
	Pred	Avg	SD	SR	Pred	Avg	SD	SR
1	-0.023	0.108	1.84	-0.20	0.000	0.195	0.74	-0.10
2	0.413	0.594	2.12	0.62	0.206	0.298	0.89	0.32
3	0.519	0.815	2.08	1.00	0.261	0.416	0.90	0.77
4	0.595	0.790	1.85	1.08	0.298	0.337	0.70	0.60
5	0.659	0.808	1.80	1.14	0.330	0.341	0.68	0.64
6	0.720	0.790	1.79	1.11	0.360	0.316	0.68	0.51
7	0.785	0.801	1.75	1.15	0.392	0.363	0.75	0.68
8	0.863	1.008	2.14	1.28	0.432	0.352	0.80	0.59
9	0.968	1.173	2.23	1.48	0.485	0.399	0.85	0.74
10	1.206	1.478	3.16	1.38	0.585	0.789	1.88	1.06
HML	1.229	1.370	2.13	1.88	0.585	0.594	1.61	0.81

Panel E: NN5								
portfolio	Equally Weighted - Without TF				Value Weighted - Without TF			
	Pred	Avg	SD	SR	Pred	Avg	SD	SR
1	0.118	0.176	1.94	-0.07	0.072	0.205	0.83	-0.04
2	0.531	0.474	2.02	0.44	0.265	0.270	0.86	0.22
3	0.619	0.750	1.87	0.99	0.310	0.298	0.85	0.33
4	0.685	0.724	1.71	1.03	0.343	0.228	0.79	0.05
5	0.742	0.804	1.76	1.16	0.371	0.329	0.76	0.51
6	0.797	0.798	1.74	1.16	0.398	0.302	0.73	0.41
7	0.856	0.905	1.84	1.29	0.428	0.422	0.76	0.94
8	0.927	1.089	2.15	1.41	0.464	0.356	0.80	0.61
9	1.022	1.145	2.24	1.44	0.511	0.454	0.84	0.98
10	1.242	1.500	3.42	1.30	0.611	0.771	1.93	1.00
HML	1.124	1.325	2.25	1.71	0.539	0.565	1.54	0.79

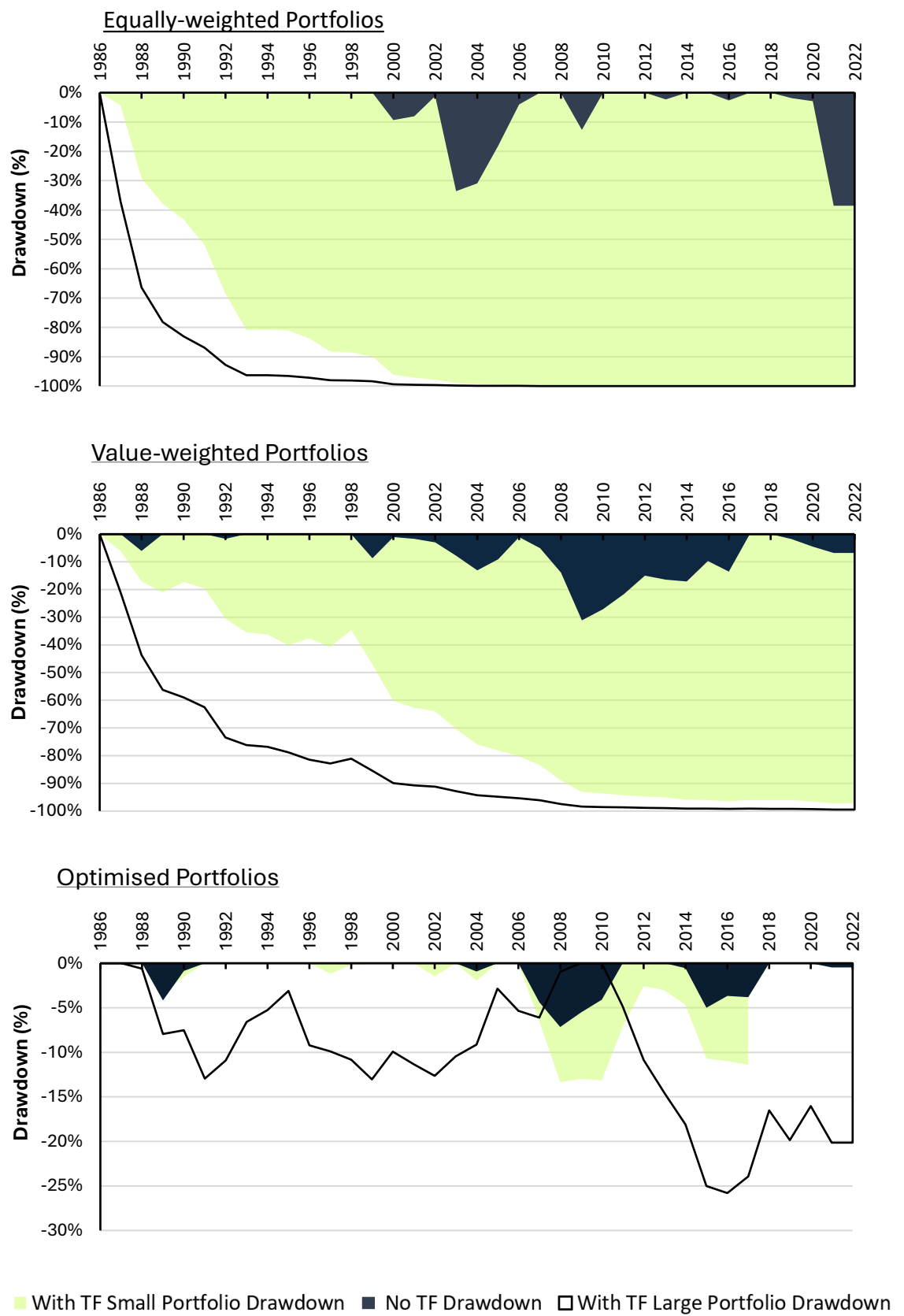
Appendix 2N - Drawdown (%), individual models, monthly rebalancing

This appendix illustrates the drawdown (%) realised across the portfolio time series. Panel A, at the top, illustrates the results after equal-weighting the portfolio holdings at each rebalancing period. Panel B, in the middle illustrates the results after value-weighting and Panel C, at the bottom illustrates the results after optimising the portfolio at each rebalancing period. Each panel graphs the drawdown realisation in three environments: (a) an environment without trading frictions, demonstrated in dark green, (b) an environment with trading frictions investing a small initial capital of 1 million USD, demonstrated in light green and (c) an environment with trading frictions, investing a large initial capital of 100 million USD, demonstrated by the black line.

NN1

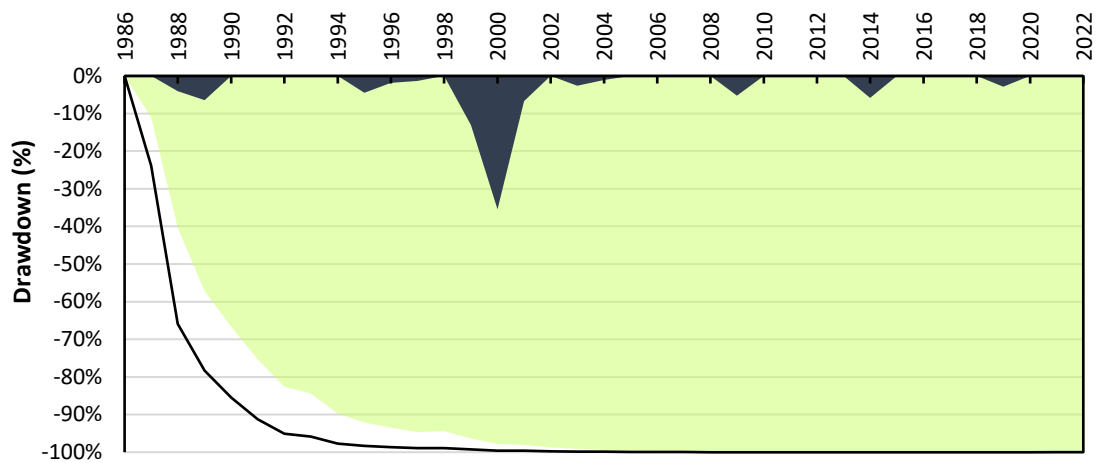


NN2

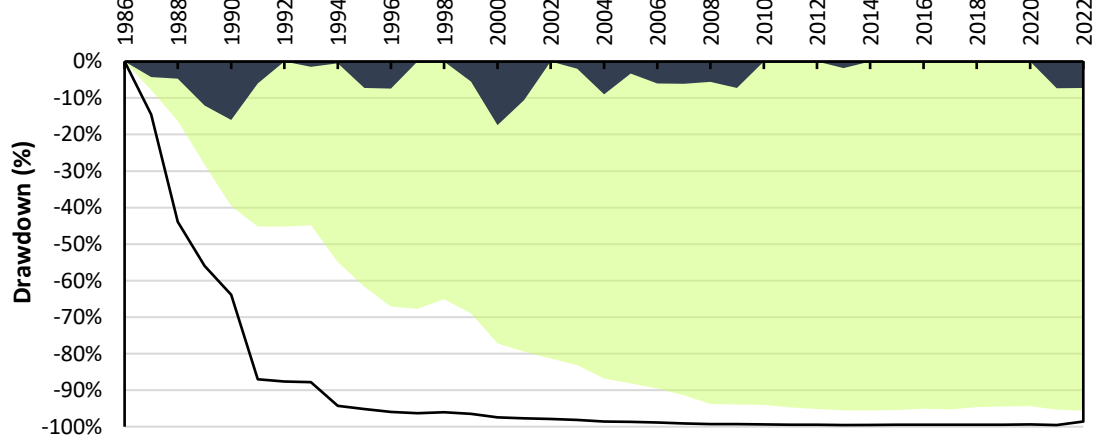


NN3

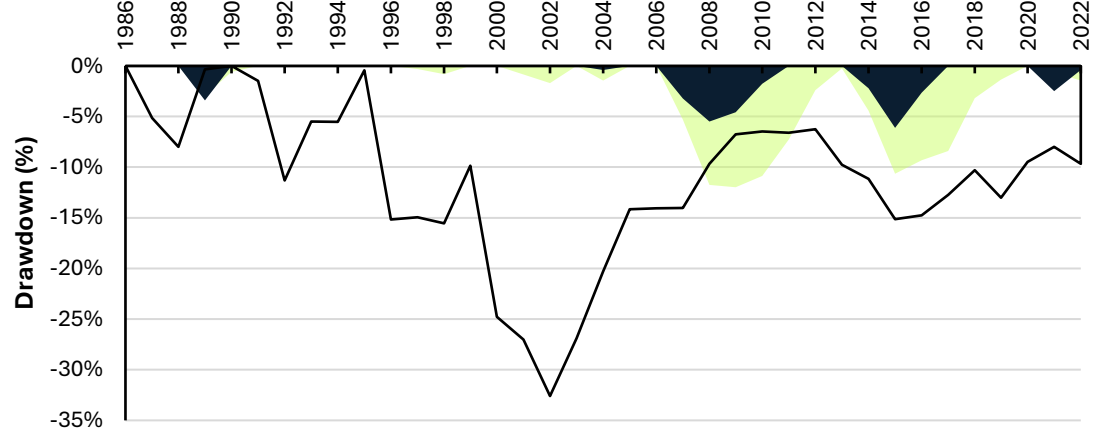
Equally-weighted Portfolios



Value-weighted Portfolios



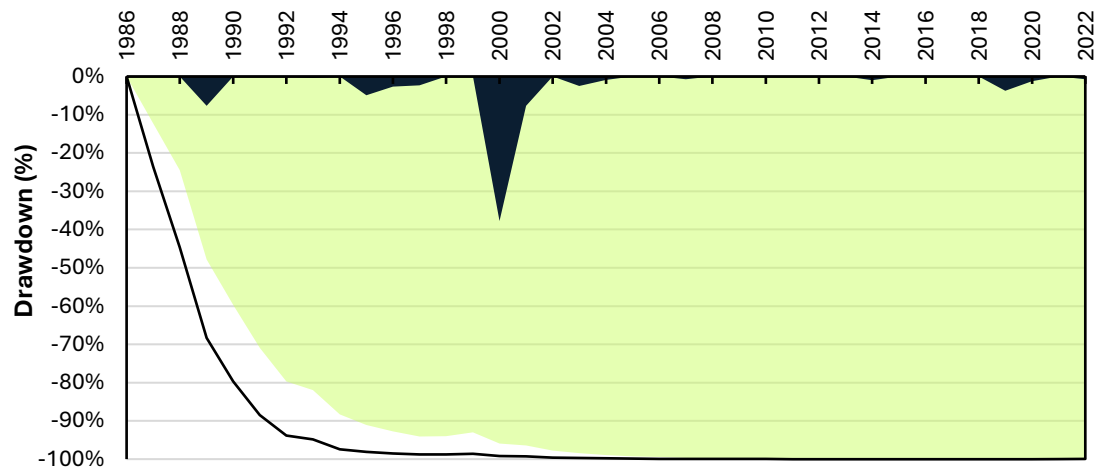
Optimised Portfolios



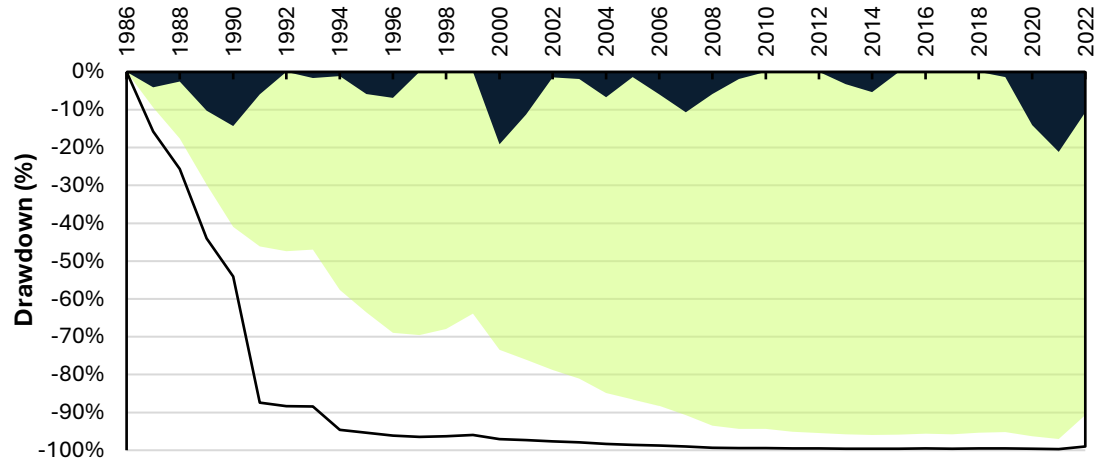
With TF Small Portfolio Drawdown No TF Drawdown With TF Large Portfolio Drawdown

NN4

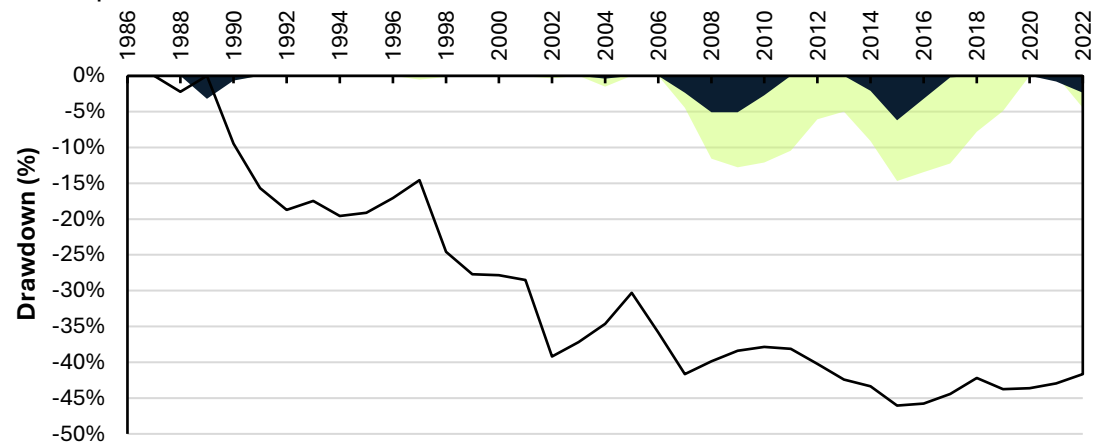
Equally-weighted Portfolios



Value-weighted Portfolios



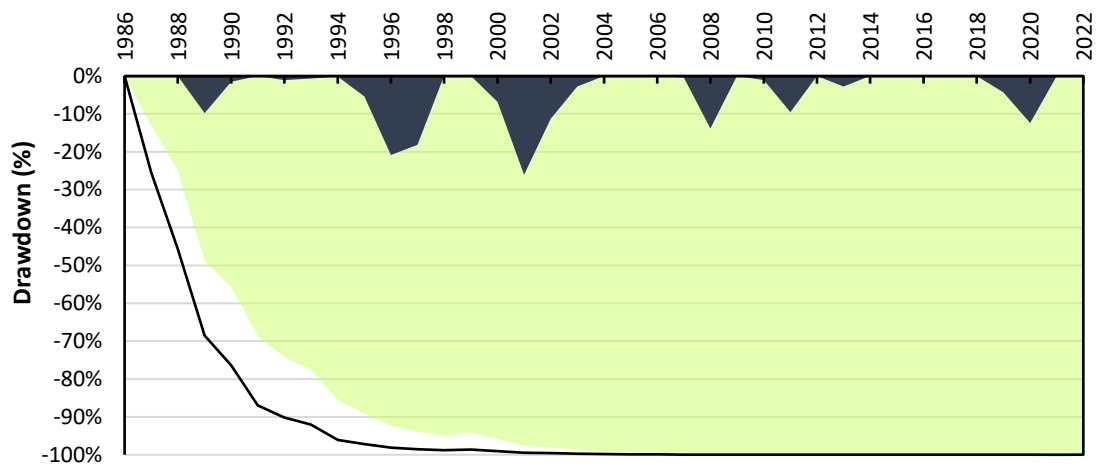
Optimised Portfolios



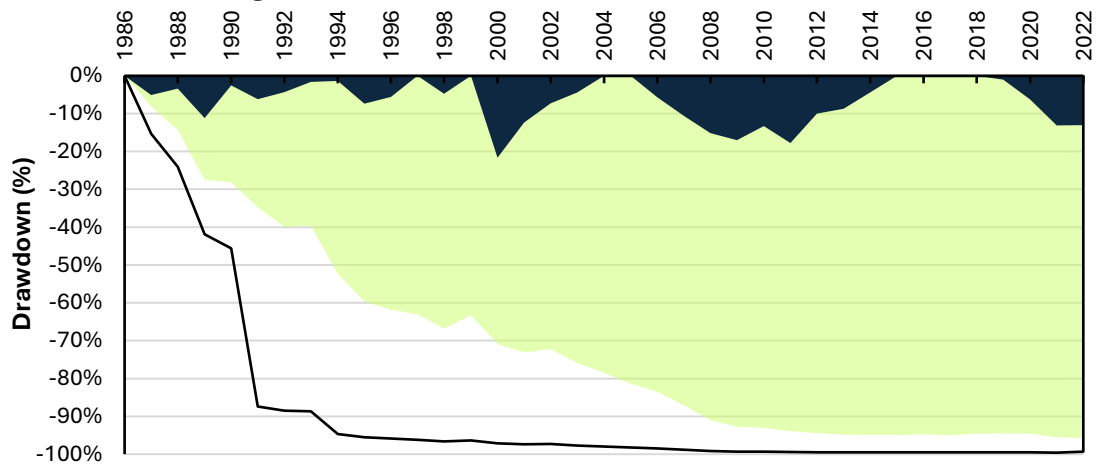
With TF Small Portfolio Drawdown No TF Drawdown With TF Large Portfolio Drawdown

NN5

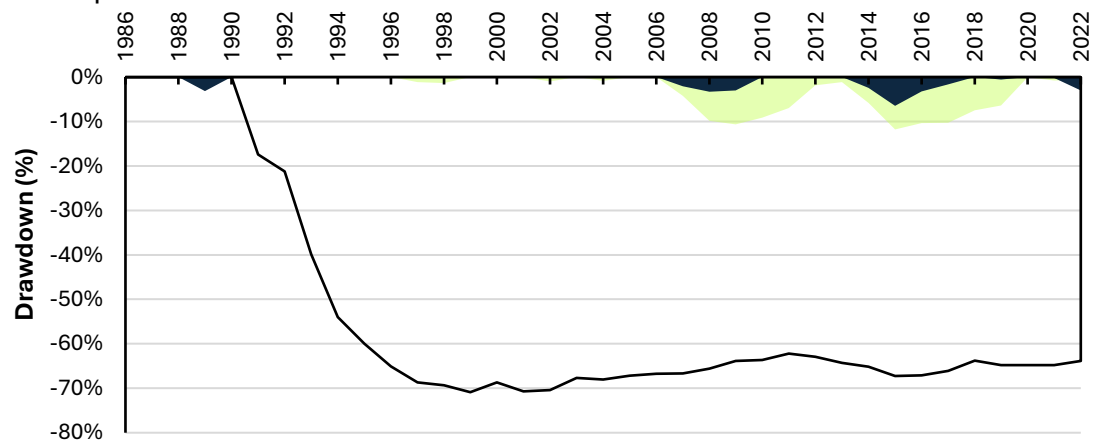
Equally-weighted Portfolios



Value-weighted Portfolios



Optimised Portfolios

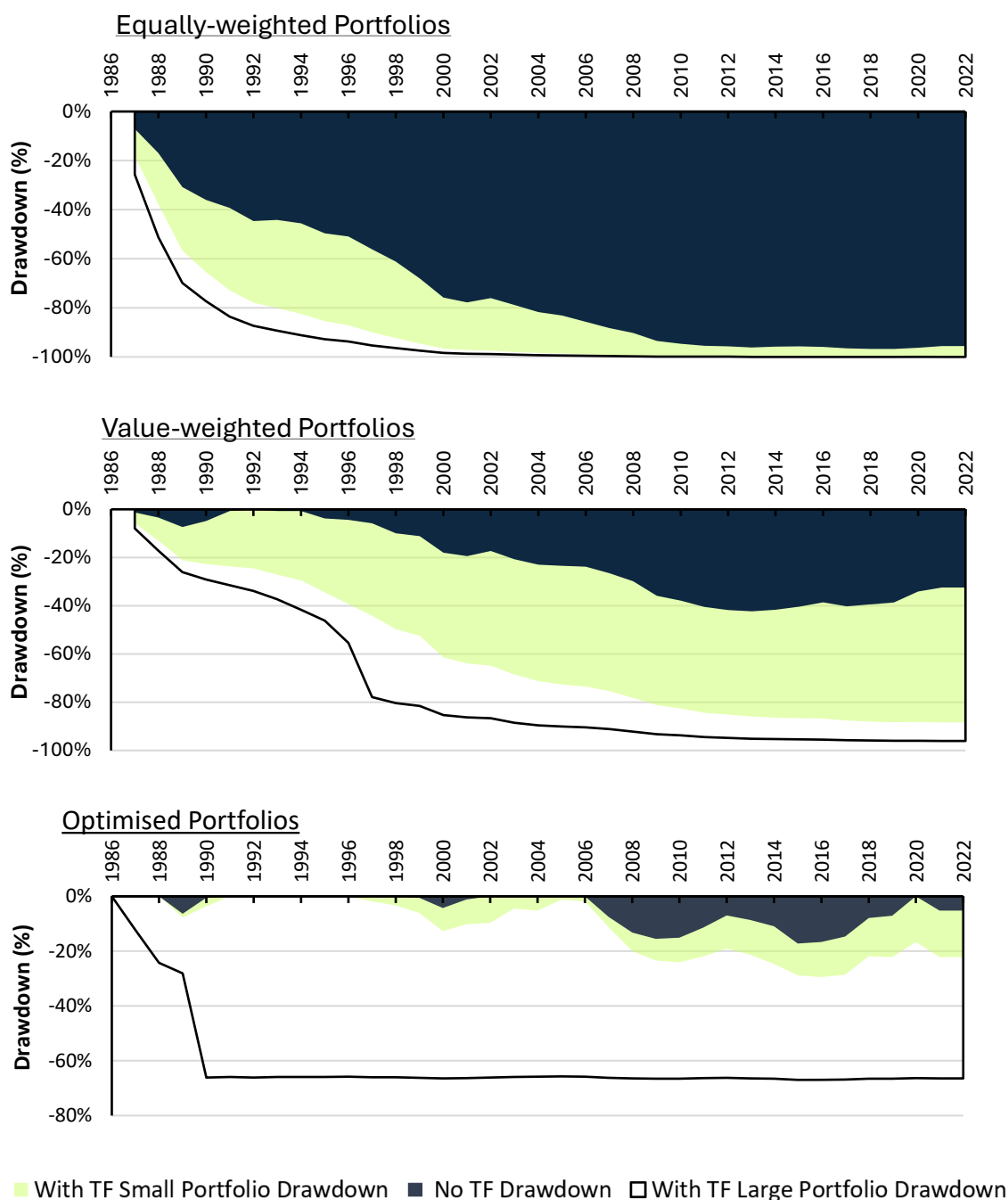


With TF Small Portfolio Drawdown No TF Drawdown With TF Large Portfolio Drawdown

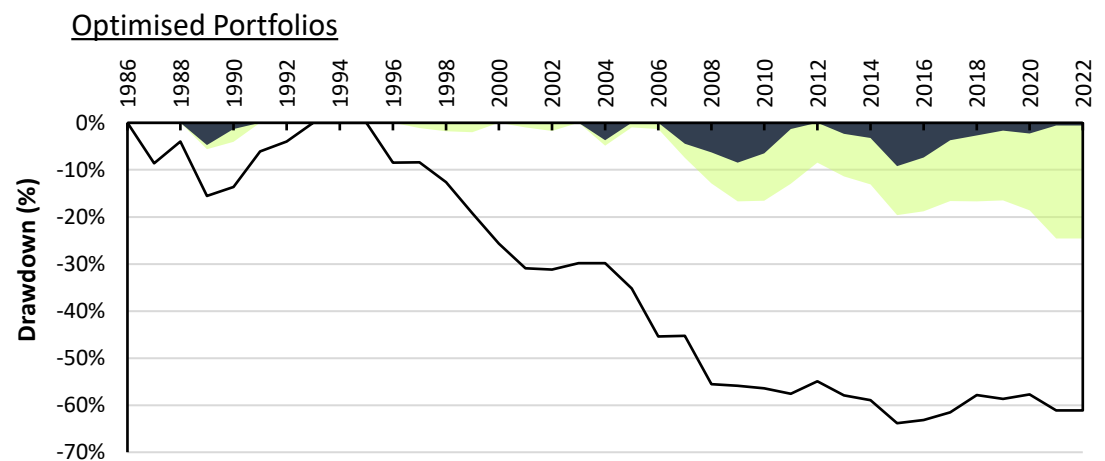
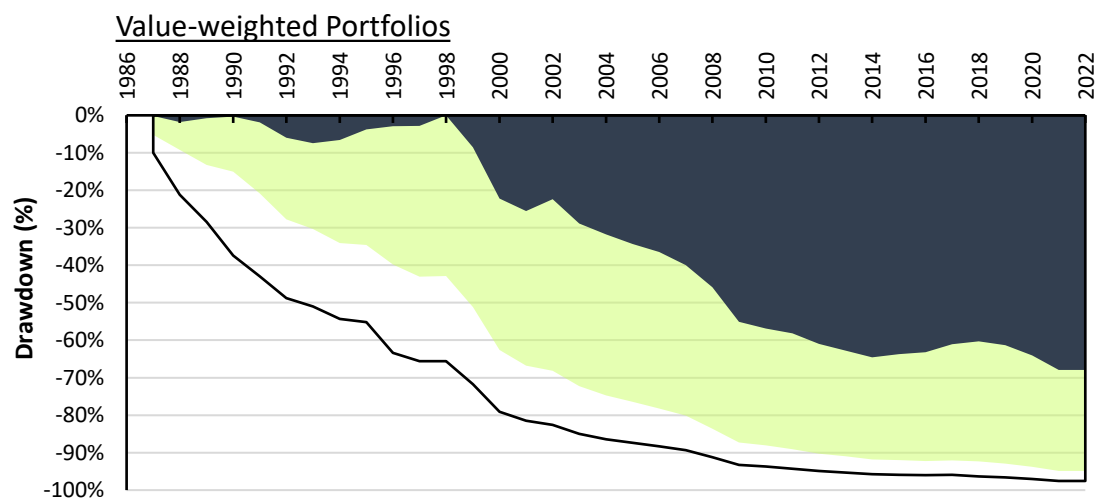
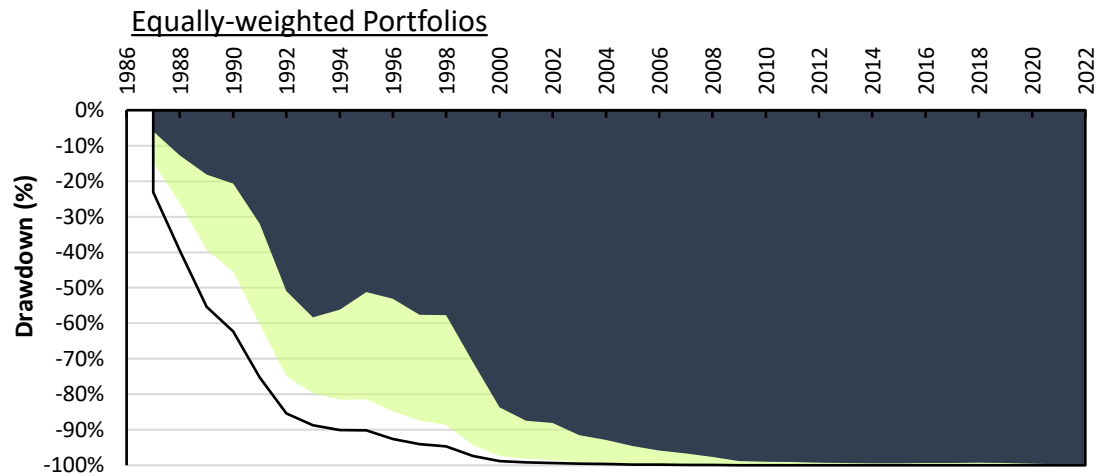
Appendix 2O – Drawdown (%), individual models, quarterly rebalancing

This appendix illustrates the drawdown (%) realised across the portfolio time series. Panel A, at the top, illustrates the results after equal-weighting the portfolio holdings at each rebalancing period. Panel B, in the middle illustrates the results after value-weighting and Panel C, at the bottom illustrates the results after optimising the portfolio at each rebalancing period. Each panel graphs the drawdown realisation in three environments: (a) an environment without trading frictions, demonstrated in dark green, (b) an environment with trading frictions investing a small initial capital of 1 million USD, demonstrated in light green and (c) an environment with trading frictions, investing a large initial capital of 100 million USD, demonstrated by the black line.

NN1



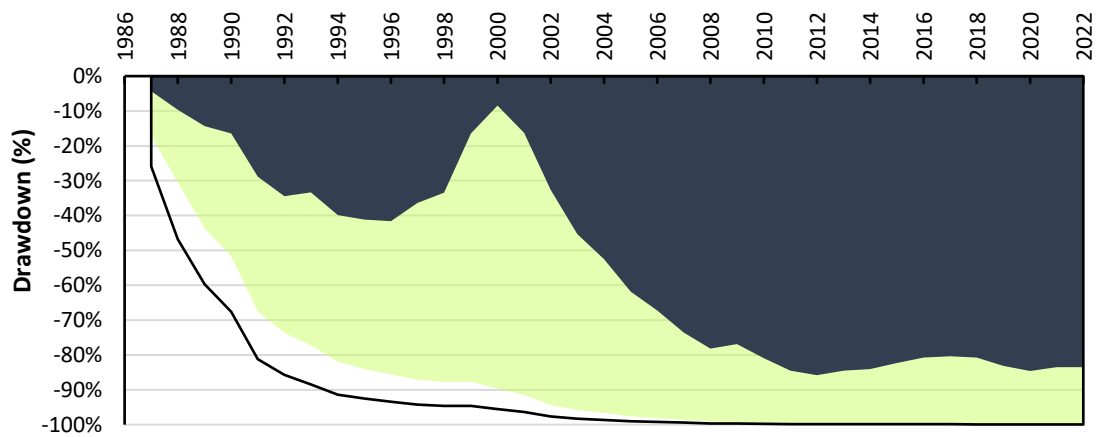
NN2



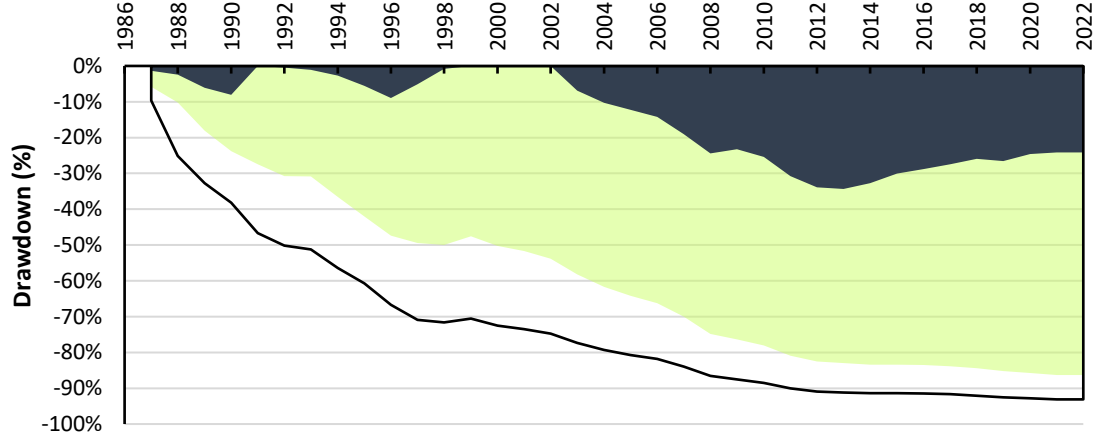
With TF Small Portfolio Drawdown No TF Drawdown With TF Large Portfolio Drawdown

NN3

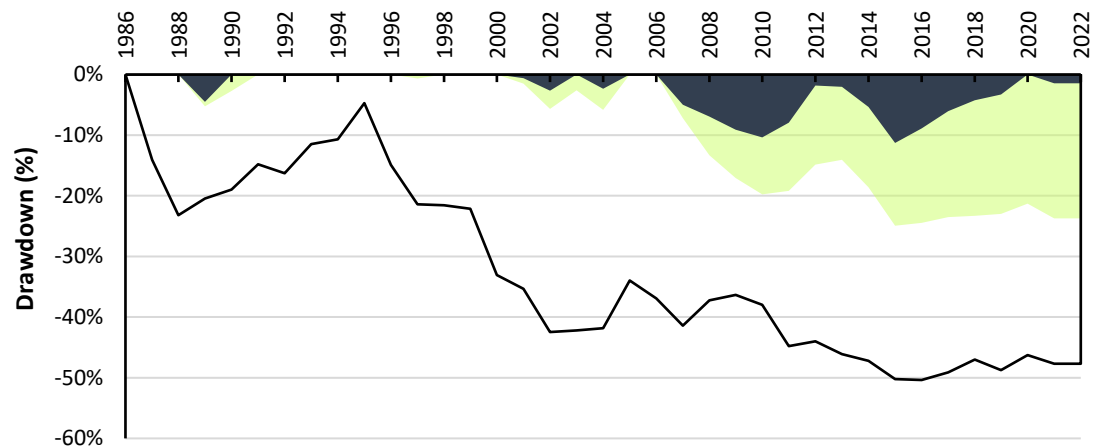
Equally-weighted Portfolios



Value-weighted Portfolios

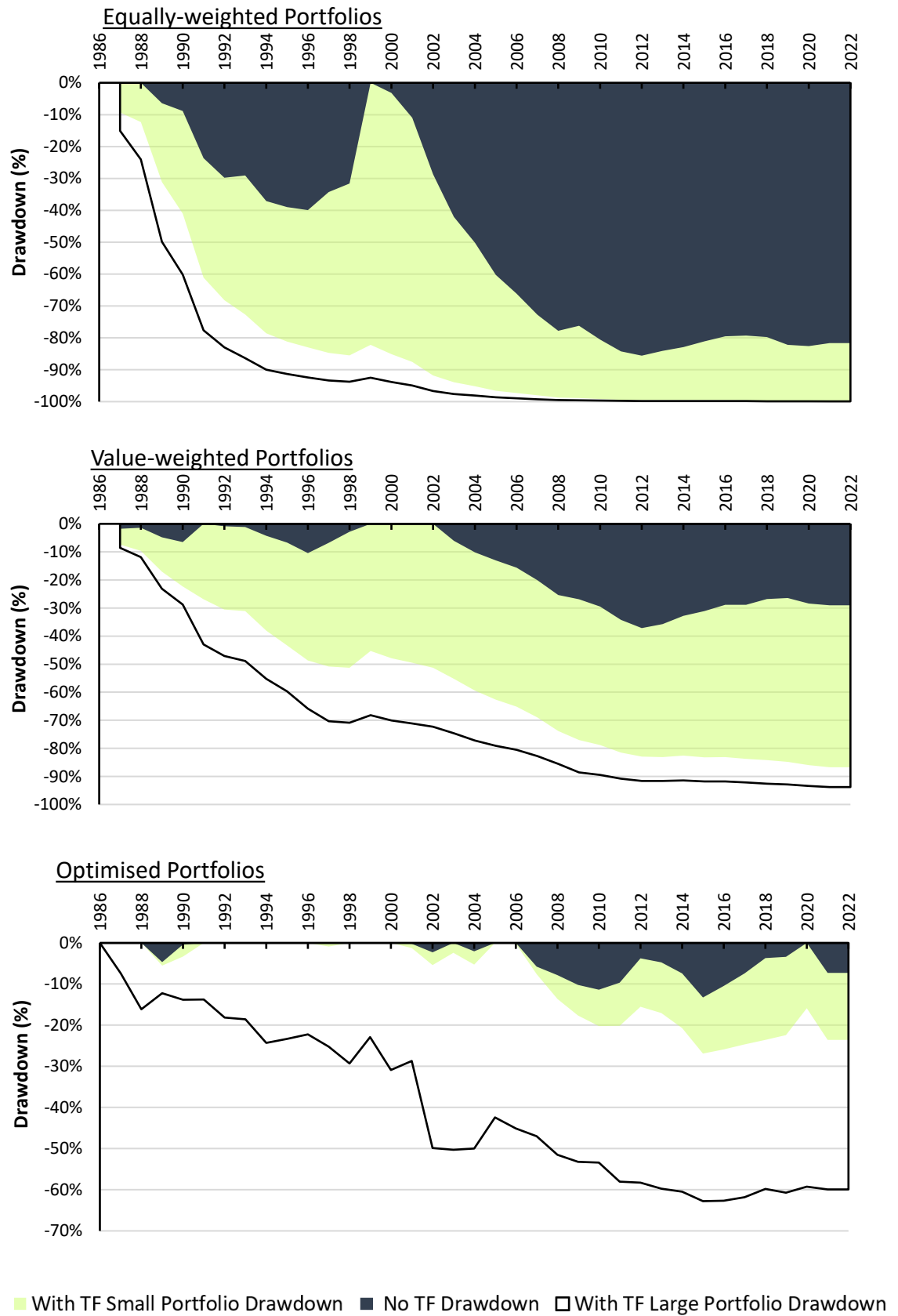


Optimised Portfolios

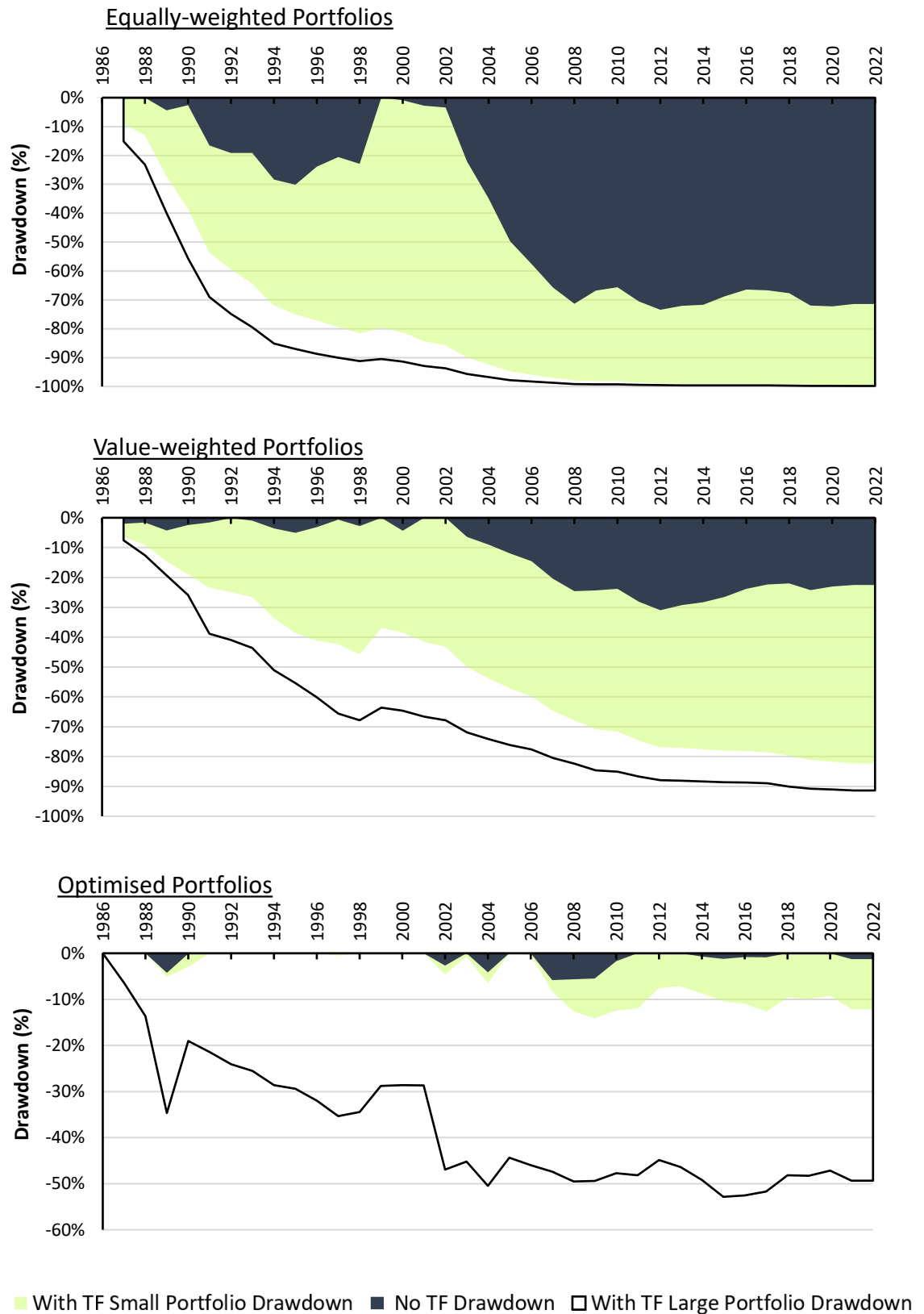


With TF Small Portfolio Drawdown No TF Drawdown With TF Large Portfolio Drawdown

NN4



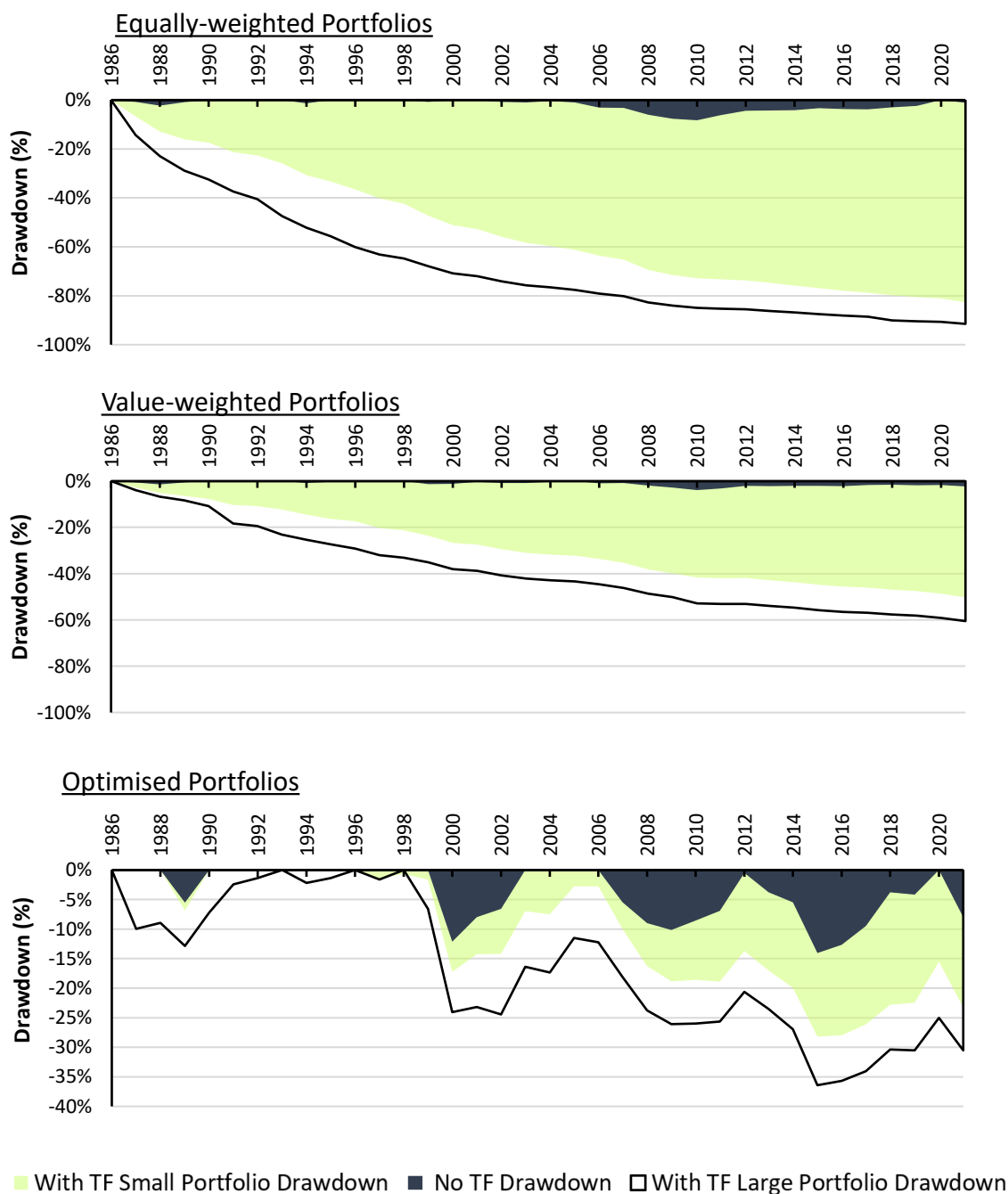
NN5



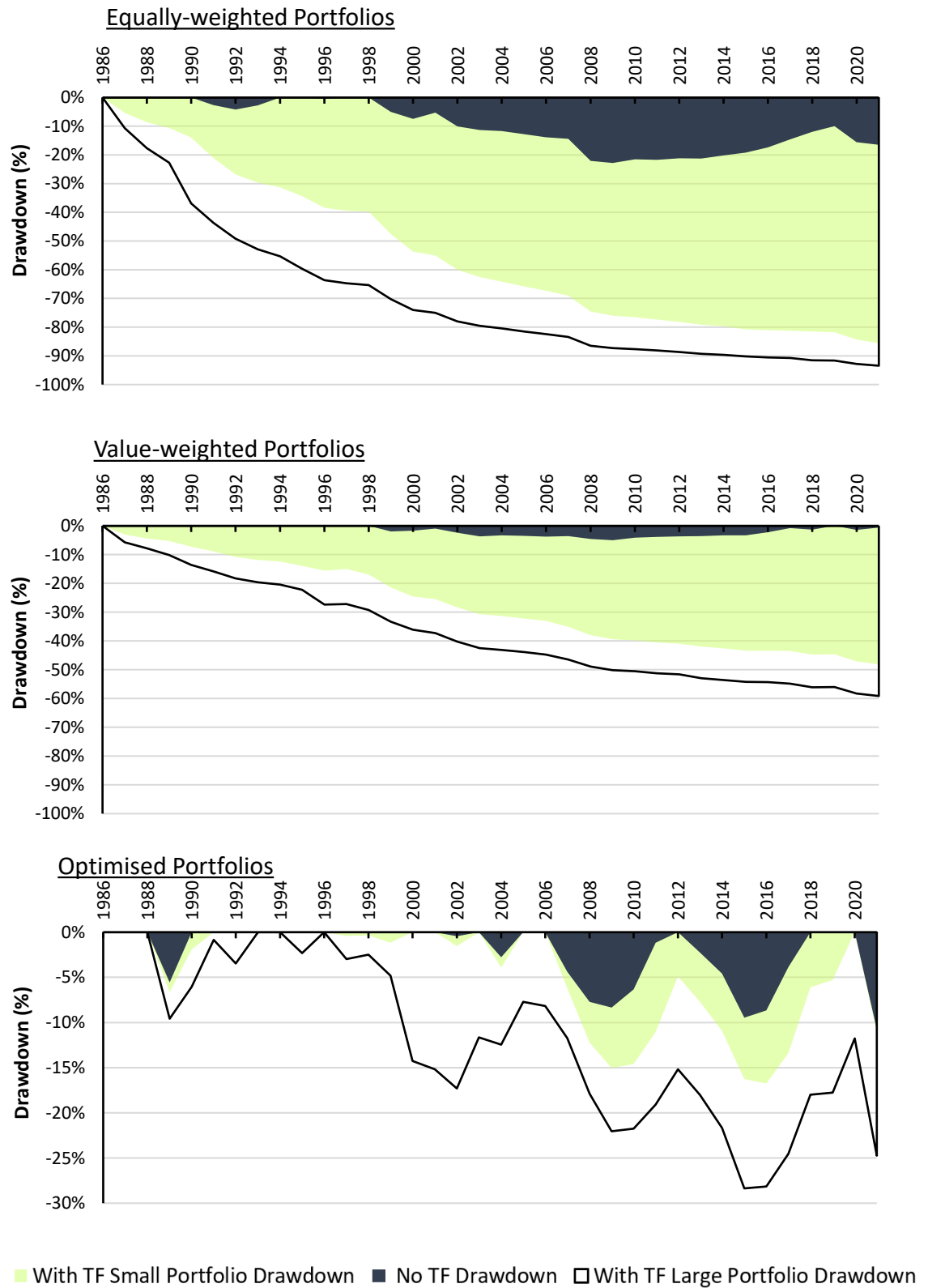
Appendix 2P - Drawdown (%), individual models, annual rebalancing

This appendix illustrates the drawdown (%) realised across the portfolio time series. Panel A, at the top, illustrates the results after equal-weighting the portfolio holdings at each rebalancing period. Panel B, in the middle illustrates the results after value-weighting and Panel C, at the bottom illustrates the results after optimising the portfolio at each rebalancing period. Each panel graphs the drawdown realisation in three environments: (a) an environment without trading frictions, demonstrated in dark green, (b) an environment with trading frictions investing a small initial capital of 1 million USD, demonstrated in light green and (c) an environment with trading frictions, investing a large initial capital of 100 million USD, demonstrated by the black line.

NN1

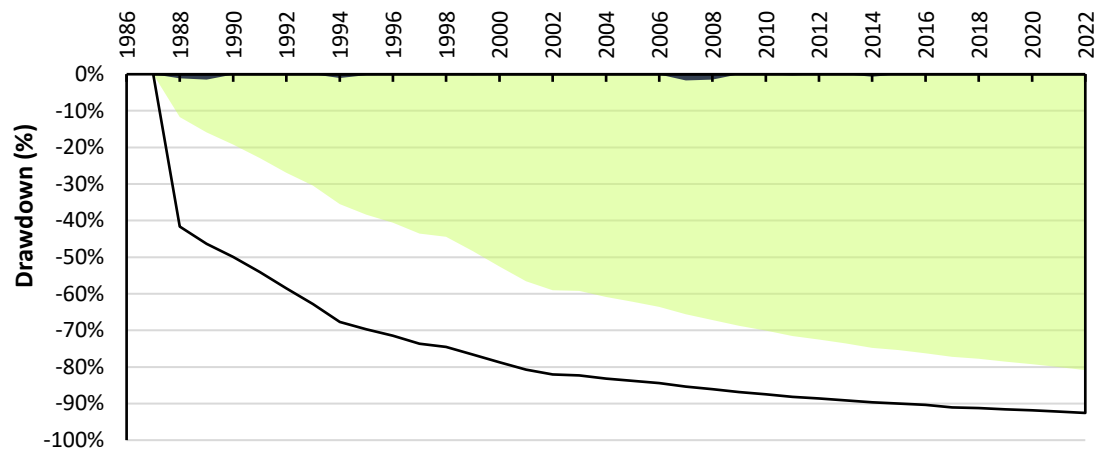


NN2

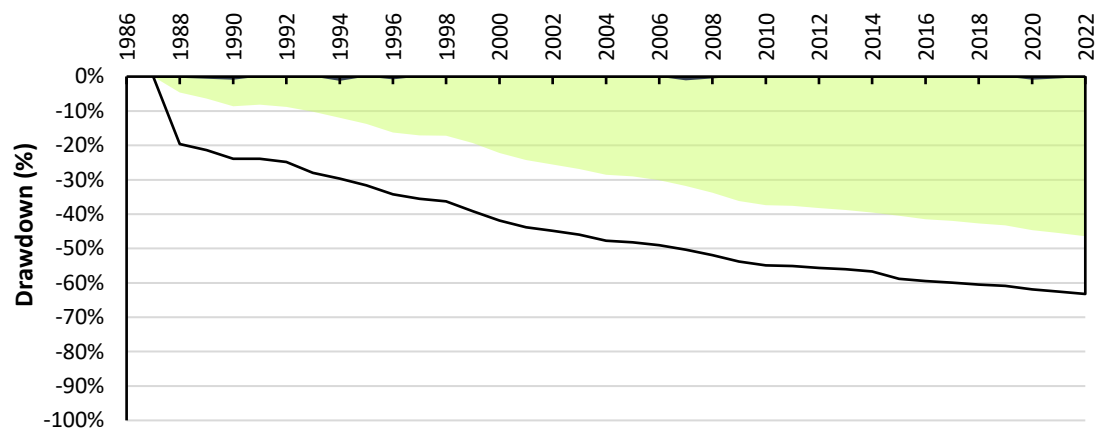


NN3

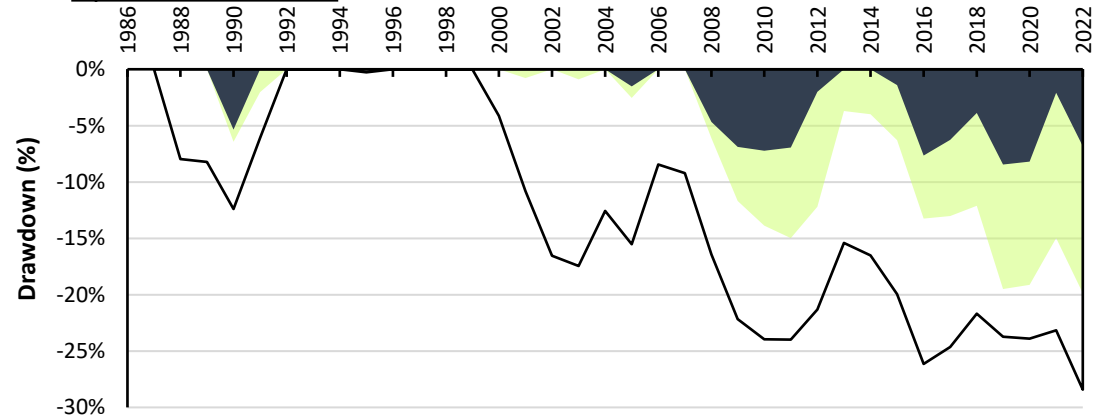
Equally-weighted Portfolios



Value-weighted Portfolios



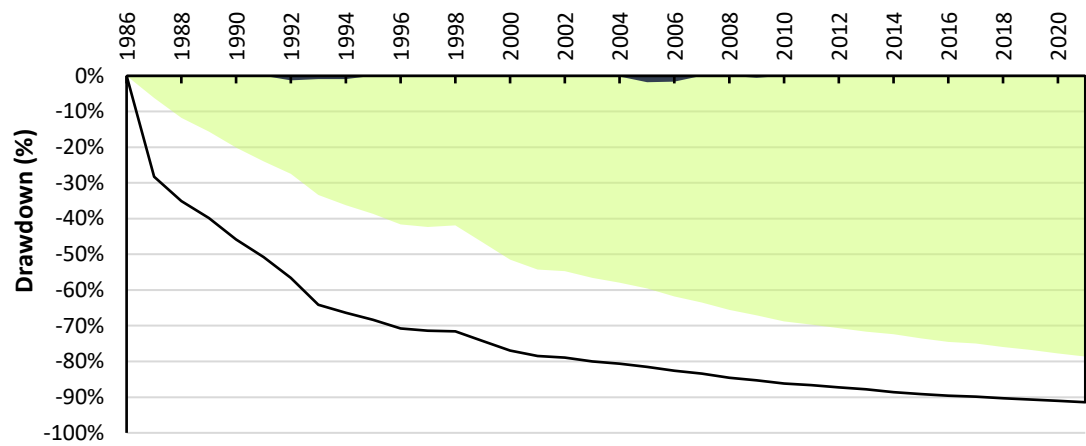
Optimised Portfolios



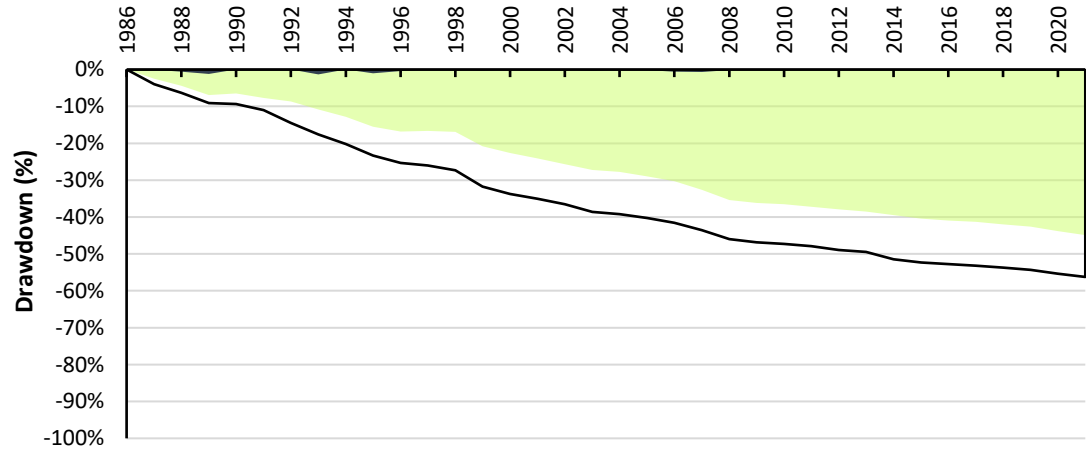
■ With TF Small Portfolio Drawdown
 ■ No TF Drawdown
 ■ With TF Large Portfolio Drawdown

NN4

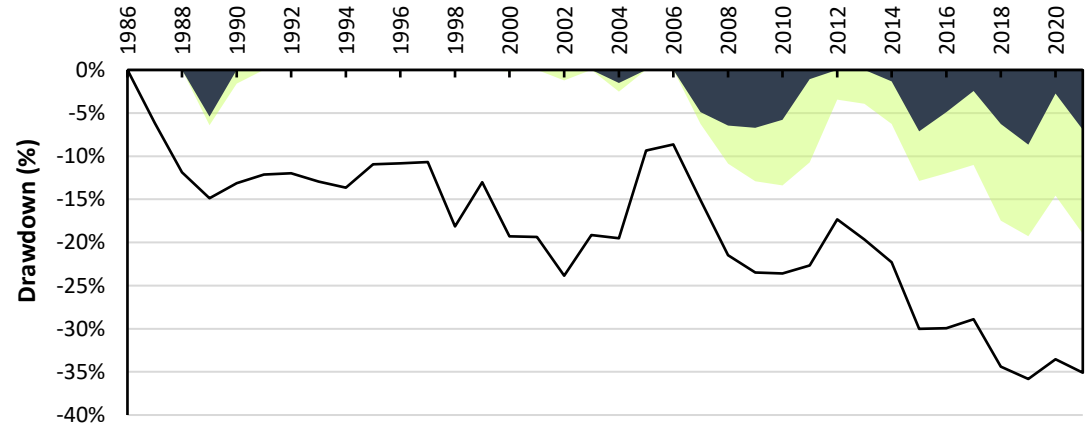
Equally-weighted Portfolios



Value-weighted Portfolios

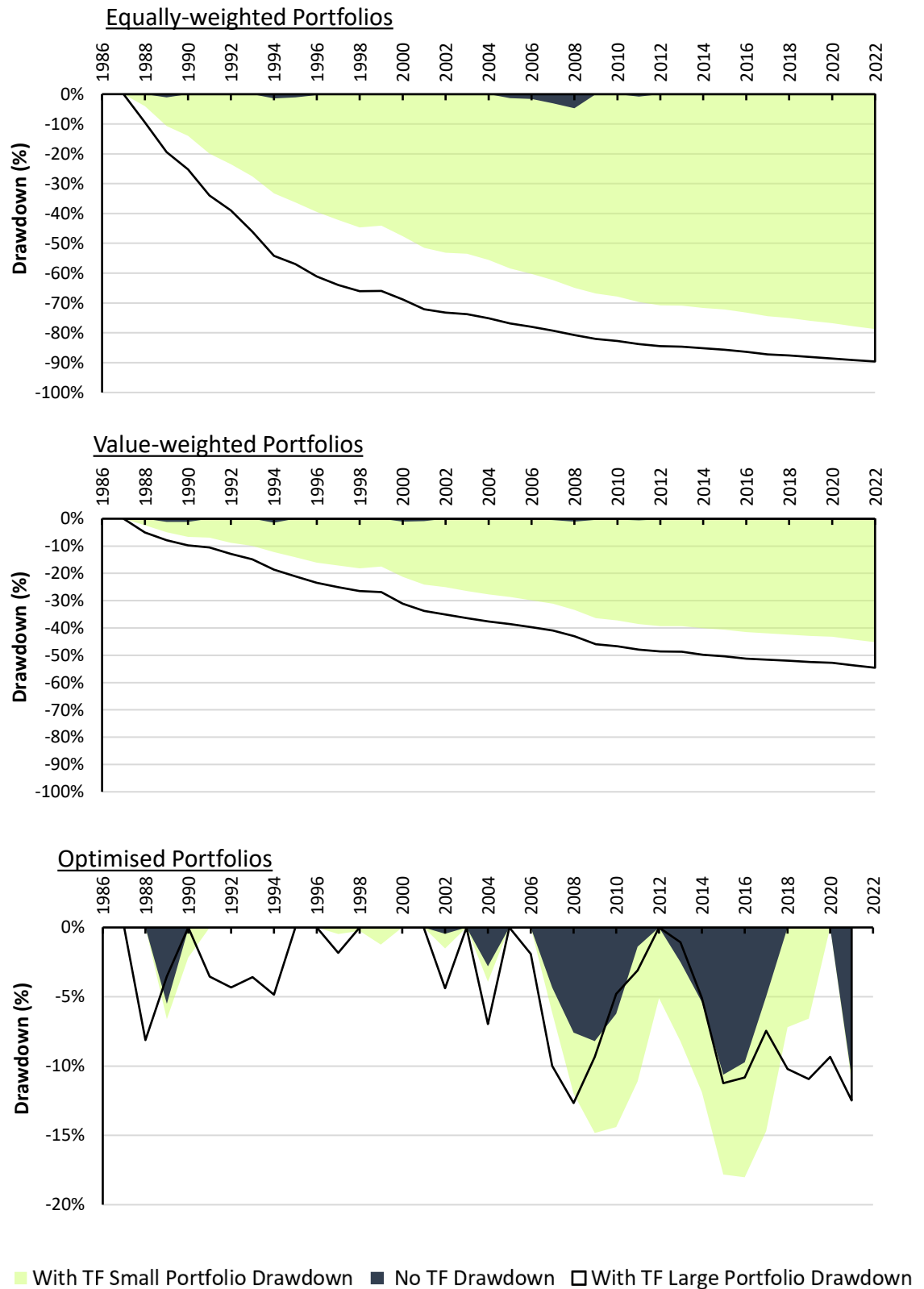


Optimised Portfolios



With TF Small Portfolio Drawdown No TF Drawdown With TF Large Portfolio Drawdown

NN5



Appendix 3A – List of factors

Factors	Hou Category	MP Category	Firm characteristic
absacc	Profitability	Fundamental	Absolute accruals
acc	Profitability	Fundamental	Working capital accruals
aeavol	Momentum	Market	Abnormal earnings announcement volume
age	Intangibles	Fundamental	# of years since first Compustat coverage
agr	Investment	Fundamental	Asset growth
baspread	Trading frictions	Market	Bid-ask spread
beta	Trading frictions	Market	Beta
betasq	Trading frictions	Market	Beta squared.
bm	Value/growth	Fundamental	Book-to-market
bm_ia	Value/growth	Fundamental	Industry-adjusted book to market
cash	Value/growth	Fundamental	Cash holdings
cashdebt	Value/growth	Fundamental	Cash flow to debt
cashpr	Value/growth	Fundamental	Cash productivity
cfp	Value/growth	Fundamental	Cash flow to price ratio
cfp_ia	Value/growth	Fundamental	Industry-adjusted cash flow to price ratio
chatoia	Investment	Fundamental	Industry-adjusted change in asset turnover
chcsho	Investment	Fundamental	Change in shares outstanding
chempia	Intangibles	Fundamental	Industry-adjusted change in employees
chinv	Investment	Fundamental	Change in inventory
chmom	Momentum	Market	Change in 6-month momentum
chpmia	Profitability	Fundamental	Industry-adjusted change in profit margin
ctx	Momentum	Market	Change in tax expense
cinvest	Investment	Fundamental	Corporate investment
convind	Intangibles	Fundamental	Convertible debt indicator
currat	Profitability	Fundamental	Current ratio
depr	Investment	Fundamental	Depreciation / PP&E
divi	Intangibles	Fundamental	Dividend initiation
divo	Intangibles	Fundamental	Dividend omission
dolvol	Trading frictions	Market	Dollar trading volume in month t-2
dy	Value/growth	Fundamental	Dividend to price
ear	Momentum	Market	Earnings announcement return
egr	Trading frictions	Market	Growth in common shareholder equity
ep	Value/growth	Fundamental	Earnings to price
gma	Profitability	Fundamental	Gross profitability
grcapx	Investment	Fundamental	Growth in capital expenditures
grltnoa	Investment	Fundamental	Growth in long term net operating assets
herf	Intangibles	Fundamental	Industry sales concentration
hire	Intangibles	Fundamental	Employee growth rate

idiovol	Trading frictions	Market	Idiosyncratic return volatility
ill	Trading frictions	Market	Illiquidity
indmom	Momentum	Market	Industry momentum
invest	Investment	Fundamental	Capital expenditures and inventory
lev	Investment	Fundamental	Leverage
lgr	Investment	Fundamental	Change in long-term debt
maxret	Trading frictions	Market	Maximum daily return in prior month
mom12m	Momentum	Market	12-month momentum
mom1m	Momentum	Market	1-month momentum
mom36m	Momentum	Market	36-month momentum
mom6m	Momentum	Market	6-month momentum
ms	Profitability	Fundamental	Financial statement score
mve_ia	Value/growth	Fundamental	Industry-adjusted size
mvel1	Value/growth	Fundamental	Size
nincr	Momentum	Market	Number of earnings increases
operprof	Profitability	Fundamental	Operating profitability
orgcap	Intangibles	Fundamental	Organizational capital
pchcapx_ia	Investment	Fundamental	Industry adjusted % change in capital expenditures
pchcurrat	Profitability	Fundamental	% change in current ratio
pchdepr	Profitability	Fundamental	% change in depreciation
pchgm_pchsale	Profitability	Fundamental	% change in gross margin - % change in sales
pchquick	Profitability	Fundamental	% change in quick.
pchsale_pchinv	Profitability	Fundamental	% change in sales - % change in inventory
pchsale_pchrect	Profitability	Fundamental	% change in sales - % change in A/R
pchsale_pchxsga	Profitability	Fundamental	% change in sales - % change in SG&A
pchsaleinv	Profitability	Fundamental	% change sales-to-inventory
pctacc	Profitability	Fundamental	Percent accruals
pricedelay	Momentum	Market	Price delay
ps	Profitability	Fundamental	Financial statements score
quick	Profitability	Fundamental	Quick ratio
rd	Intangibles	Fundamental	RD_increase
rd_mve	Intangibles	Fundamental	R&D to market capitalization
rd_sale	Intangibles	Fundamental	R&D to sales
realestate	Investment	Fundamental	Real estate holdings
retvol	Trading frictions	Market	Return volatility
roaq	Profitability	Fundamental	Return on assets
roavol	Profitability	Fundamental	Earnings volatility
roeq	Profitability	Fundamental	Return on equity
roic	Profitability	Fundamental	Return on invested capital
rsup	Momentum	Market	Revenue surprise
salecash	Value/growth	Fundamental	Sales to cash
saleinv	Value/growth	Fundamental	Sales to inventory
salerec	Value/growth	Fundamental	Sales to receivables

secured	Investment	Fundamental	Secured debt
securedind	Intangibles	Fundamental	Secured debt indicator
sgr	Profitability	Fundamental	Sales growth
sin	Intangibles	Fundamental	Sin stock
sp	Value/growth	Fundamental	Sales to price
std_dolvol	Trading frictions	Market	Volatility of liquidity
std_turn	Trading frictions	Market	Volatility of liquidity (share turnover)
stdacc	Profitability	Fundamental	Accrual volatility
stdcf	Value/growth	Fundamental	Cash flow volatility
tang	Investment	Fundamental	Debt capacity/firm tangibility
tb	Profitability	Fundamental	Tax income to book income
turn	Trading frictions	Market	Share turnover
zerotrade	Trading frictions	Market	Zero trading days

Appendix 3B: Exposure of individual predictive factors, monthly rebalancing

Appendix 3B reports the mean value of each of the 94 predictive factors for each decile portfolio generated by ranking stocks according to their machine predicted returns. The bottom portfolio is constructed by ranking stocks according to their machine learning predicted returns and form 10 portfolios and selling the lowest quintile portfolio. The top portfolio is constructed by ranking stocks according to their machine learning predicted returns and form 10 portfolios and buying the highest quintile portfolio. The long-short (HML) portfolio is constructed by ranking stocks according to their machine learning predicted returns and form 10 portfolios, buying the highest quintile portfolio and selling the lowest quintile portfolio. The factor realisations corresponding to the stocks chosen for the top and bottom portfolios are averaged to generate the results in the table. At each monthly period the factor input was rescaled to the [0%,100%] range and thus, the expected value for all factors is 50%. The mean values of the lowest and highest deciles are compared based on the null hypothesis $H_0: \mu_{high} = \mu_{low}$ which examines whether the category realisations are significantly different between the two portfolios. The Newey-West adjusted t statistics are presented in the column t stat. The reported results are for the average across the five neural network predictive models (NN1-NN5). The table is divided into four panels, A to D, which report the results for the equal-weighted, value-weighted, optimised portfolio trading a relatively small portfolio of 1 million USD and optimised portfolio trading a relatively large portfolio of 100 million USD, respectively. Investing horizon is one month and thus, rebalancing of the portfolio is performed monthly based on predicted returns.

Category	Factor	Panel A: Equal-weighted Portfolio				Panel B: Value-weighted Portfolio				Panel C: Optimised Small Portfolio				Panel D: Optimised Large Portfolio			
		1	10	HML	t stat	1	10	HML	t stat	1	10	HML	t stat	1	10	HML	t stat
Investment	agr	49.36	54.42	5.05***	9.48	46.87	49.09	2.22***	4.17	41.31	53.58	12.26***	8.22	45.59	48.26	2.67	1.33
	chatoia	49.48	52.22	2.74***	8.97	49.74	50.65	0.91	2.26	46.94	51.24	4.29***	4.08	47.74	51.97	4.23	2.41
	chcsho	54.04	49.08	-4.96***	-12.18	53.72	50.71	-3.01***	-6.15	58.69	46.61	-12.07***	-9.19	55.99	52.22	-3.77	-1.76
	chinv	50.31	46.67	-3.64***	-9.74	52.08	49.54	-2.55***	-5.57	55.06	48.20	-6.85***	-5.16	53.77	51.58	-2.18	-1.35
	cinvest	49.47	50.64	1.17***	5.66	50.06	49.60	-0.46	-0.92	52.09	49.02	-3.07	-1.42	52.73	52.20	-0.52	-0.57
	depr	51.13	53.66	2.53***	5.87	52.55	51.88	-0.66	-1.25	58.45	46.46	-11.99***	-7.52	56.35	52.50	-3.85	-1.98
	egr	48.95	45.78	-3.17***	-6.69	53.50	50.06	-3.44***	-7.10	58.92	46.69	-12.24***	-9.38	55.24	52.84	-2.40	-1.29
	grcapx	50.54	47.48	-3.06***	-9.37	52.34	50.86	-1.48***	-3.17	59.25	46.50	-12.75***	-9.12	56.02	52.84	-3.17	-1.76
	grltnoa	49.79	45.74	-4.05***	-9.82	52.87	49.78	-3.09***	-6.35	58.91	46.88	-12.03***	-11.25	54.86	52.05	-2.80	-1.40
	invest	51.28	46.61	-4.66***	-9.70	53.98	50.30	-3.67***	-7.41	59.62	46.56	-13.06***	-10.59	55.78	52.28	-3.49	-1.80
	lev	46.73	45.98	-0.75	-1.23	51.65	50.35	-1.30	-2.41	59.01	46.46	-12.54***	-10.65	55.89	52.74	-3.14	-1.99
	lgr	51.72	47.02	-4.70***	-11.90	53.54	50.98	-2.56***	-5.05	59.55	46.32	-13.23***	-9.49	56.38	52.48	-3.90	-2.03
	pchcapx_ia	49.12	48.52	-0.59	-1.76	51.06	49.73	-1.32*	-2.62	49.79	50.38	0.60	0.27	49.66	53.37	3.71	1.07
	realestate	49.47	48.49	-0.98***	-3.26	52.07	50.75	-1.32**	-3.16	59.29	46.71	-12.58***	-10.88	55.58	51.67	-3.91	-2.40
	secured	50.60	53.43	2.83***	5.14	52.13	52.84	0.72	1.74	55.44	47.91	-7.53***	-5.03	54.75	53.11	-1.64	-1.39
	tang	52.89	53.52	0.63	1.12	51.86	52.08	0.22	0.34	45.68	51.48	5.79***	7.79	51.92	46.85	-5.06***	-3.28

Appendix 3B continued																	
Category	Factor	Panel A: Equal-weighted Portfolio				Panel B: Value-weighted Portfolio				Panel C: Optimised Small Portfolio				Panel D: Optimised Large Portfolio			
		1	10	HML	t stat	1	10	HML	t stat	1	10	HML	t stat	1	10	HML	t stat
Profitability	absacc	54.74	54.01	-0.73	-1.70	53.73	52.53	-1.19	-2.46	58.77	46.52	-12.24***	-8.51	56.29	52.34	-3.94	-1.82
	acc	47.74	46.95	-0.78	-1.76	46.64	46.95	0.32	0.57	42.22	52.97	10.75***	9.31	45.56	51.01	5.44*	2.56
	cash	52.83	54.16	1.33	2.02	54.72	53.93	-0.79	-1.77	57.06	47.08	-9.97***	-7.38	55.82	52.46	-3.36	-1.69
	cashdebt	43.91	47.59	3.67***	6.44	47.80	49.21	1.40*	2.61	41.03	53.92	12.88***	8.46	44.73	48.48	3.75	1.94
	chpmia	53.74	45.86	-7.87***	-17.88	52.32	47.85	-4.46***	-7.69	52.57	49.45	-3.12	-1.57	50.90	50.35	-0.55	-0.14
	currat	50.54	51.29	0.75	1.53	52.36	51.28	-1.07	-2.12	58.99	46.55	-12.44***	-8.30	56.26	52.55	-3.71	-2.12
	gma	46.95	51.02	4.07***	8.38	49.54	51.57	2.03***	4.38	53.42	49.22	-4.19***	-4.64	50.88	53.77	2.88	1.70
	ms	45.16	47.70	2.54***	5.77	46.14	47.60	1.45***	3.70	49.06	50.72	1.65	2.17	47.13	52.86	5.73***	5.20
	operprof	43.24	45.99	2.75***	4.81	45.95	47.19	1.24*	2.56	43.76	52.71	8.95***	5.21	45.89	48.55	2.66	1.41
	pchcurrat	47.87	48.84	0.97**	2.96	52.50	51.28	-1.22	-2.49	59.30	46.42	-12.88***	-9.25	56.26	52.46	-3.80	-1.98
	pchdepr	49.96	51.09	1.13***	4.19	52.64	51.48	-1.15	-2.34	59.50	46.37	-13.12***	-9.15	56.45	52.20	-4.25	-2.26
	pchgm_pchsale	47.62	51.77	4.15***	13.42	46.91	49.10	2.19***	4.46	40.77	53.91	13.13***	9.12	44.42	49.02	4.60	2.29
	pchquick	47.62	49.12	1.50***	4.61	52.44	51.34	-1.09	-2.22	59.26	46.43	-12.83***	-9.13	56.24	52.50	-3.74	-1.95
	pchsale_pchinvt	48.15	52.37	4.21***	15.46	47.79	49.65	1.86***	3.93	40.77	53.79	13.01***	9.66	45.26	48.41	3.15	1.67
	pchsale_pchrect	50.14	50.67	0.53**	2.80	47.51	48.75	1.24*	2.51	40.73	53.82	13.09***	9.96	44.83	48.71	3.88	1.91
	pchsale_pchxsga	50.28	50.37	0.09	0.33	52.77	51.42	-1.34**	-2.94	57.85	46.99	-10.86***	-7.58	54.69	53.17	-1.52	-1.12
	pchsaleinv	49.79	51.39	1.59***	5.12	50.86	51.03	0.17	0.55	56.79	47.26	-9.52***	-4.89	55.77	51.46	-4.30	-1.99
	pctacc	53.07	51.44	-1.63***	-3.98	48.75	49.10	0.35	0.68	40.29	53.80	13.51***	10.40	45.04	51.24	6.19	2.44
	ps	42.74	48.65	5.90***	11.63	43.22	47.77	4.54***	10.08	48.13	51.18	3.05***	4.56	46.75	51.52	4.76***	3.64
	quick	50.56	50.73	0.16	0.34	52.40	51.27	-1.13	-2.23	58.89	46.54	-12.35***	-8.10	56.21	52.64	-3.57	-2.04
	roaq	41.84	49.24	7.39***	12.73	44.92	47.85	2.93***	6.23	41.17	53.73	12.56***	8.80	44.34	49.39	5.05	2.34
	roavol	58.05	55.95	-2.10***	-3.59	53.61	51.94	-1.67***	-3.48	58.55	46.41	-12.13***	-7.70	56.72	52.02	-4.69	-2.29
	roeq	43.27	48.36	5.09***	9.29	45.22	47.53	2.31***	4.79	43.84	52.41	8.56***	5.23	47.27	48.43	1.16	0.83
	roic	43.86	47.28	3.42***	5.85	46.48	48.11	1.62**	3.38	41.87	53.74	11.87***	7.18	44.60	48.80	4.20	2.05
	sgr	51.44	48.29	-3.15***	-7.31	53.17	51.23	-1.94***	-4.11	59.21	46.40	-12.81***	-8.52	56.20	52.62	-3.58	-1.89
	sp	46.03	49.98	3.94***	7.02	52.18	51.73	-0.44	-0.82	58.15	47.16	-10.99***	-7.26	55.33	52.79	-2.54	-1.55
	stdacc	55.12	48.95	-6.17***	-14.14	53.88	50.47	-3.41***	-6.82	60.05	45.98	-14.07***	-8.30	57.52	51.83	-5.68**	-2.80
	tb	48.08	47.11	-0.98*	-2.55	50.21	48.79	-1.42**	-2.86	54.66	48.85	-5.81***	-3.17	50.80	52.38	1.58	0.58

Appendix 3B continued																	
Category	Factor	Panel A: Equal-weighted Portfolio				Panel B: Value-weighted Portfolio				Panel C: Optimised Small Portfolio				Panel D: Optimised Large Portfolio			
		1	10	HML	t stat	1	10	HML	t stat	1	10	HML	t stat	1	10	HML	t stat
Value vs growth	bm	46.16	46.99	0.82	2.41	51.59	50.39	-1.20	-2.42	59.48	46.61	-12.86***	-9.09	55.72	53.12	-2.60	-1.60
	bm_ia	51.53	51.98	0.452	1.21	50.55	50.61	0.06	0.22	55.32	47.45	-7.88***	-4.20	57.87	43.65	-14.22***	-6.67
	cashpr	50.34	52.01	1.68***	3.47	51.20	51.12	-0.08	-0.08	54.17	48.23	-5.94**	-2.94	54.14	51.11	-3.03	-1.39
	cfp	42.75	47.24	4.49***	8.55	45.27	47.76	2.49***	4.88	48.50	51.12	2.62	1.82	45.79	54.70	8.91***	3.77
	cfp_ia	46.23	49.01	2.78***	7.12	48.15	49.35	1.20*	2.54	48.04	51.15	3.11	1.80	48.49	52.29	3.80	1.51
	dy	44.71	44.27	-0.44	-0.99	50.08	49.51	-0.57	-0.99	54.30	48.93	-5.37	-2.48	50.56	55.05	4.49	1.38
	ep	42.22	45.21	2.98***	5.02	46.60	47.79	1.19	2.35	41.10	53.77	12.66***	8.09	44.62	48.90	4.28	2.11
	mve_ia	46.71	45.99	-0.71	-1.73	52.40	50.73	-1.66	-2.31	61.13	46.10	-15.02***	-11.64	55.20	53.23	-1.97	-1.39
	mvel1	44.70	44.29	-0.40	-0.75	52.34	50.78	-1.56	-2.02	61.51	46.08	-15.42***	-12.03	54.62	53.64	-0.98	-0.96
	salecash	45.46	46.84	1.37	2.53	52.40	50.46	-1.94***	-3.64	60.02	46.34	-13.67***	-10.45	56.19	52.57	-3.62	-1.92
	saleinv	49.11	48.21	-0.89**	-3.07	51.40	50.83	-0.57	-1.08	59.20	46.46	-12.73***	-8.82	56.04	52.47	-3.57	-1.99
	salerec	49.81	50.10	0.29	0.76	51.64	50.71	-0.93	-2.02	57.52	47.44	-10.08***	-5.38	54.01	53.14	-0.87	-0.91
	stdcf	55.34	49.13	-6.20***	-13.98	53.90	50.50	-3.39***	-6.80	59.97	45.99	-13.98***	-8.27	57.46	51.89	-5.57**	-2.76
Intangibles	age	45.15	48.38	3.23***	5.39	47.41	48.98	1.57	2.21	52.94	49.84	-3.09***	-3.10	49.16	53.97	4.81***	4.33
	chempia	49.77	48.87	-0.91	-2.56	51.27	49.83	-1.44**	-3.11	52.64	49.88	-2.75	-1.30	48.22	53.42	5.20	2.03
	convind	52.16	51.26	-0.90**	-3.04	53.81	51.89	-1.92***	-3.74	58.73	46.76	-11.96***	-10.81	55.22	52.19	-3.02	-1.57
	divi	50.73	50.45	-0.28	-2.45	52.47	50.91	-1.56**	-3.08	59.13	46.51	-12.61***	-9.80	56.09	52.53	-3.56	-1.96
	divo	50.42	50.88	0.45	1.48	52.25	51.44	-0.81	-1.55	59.37	46.45	-12.92***	-9.68	56.20	52.42	-3.78	-2.03
	herf	48.10	51.26	3.16***	6.86	51.50	51.61	0.10	0.45	58.13	46.89	-11.23***	-9.32	55.51	52.41	-3.10	-2.31
	hire	51.17	47.75	-3.42***	-8.00	53.90	50.95	-2.94***	-6.00	59.40	46.40	-13.00***	-9.73	56.19	52.45	-3.73	-1.95
	orgcap	51.00	54.03	3.03***	6.96	52.22	52.08	-0.15	-0.13	57.68	47.02	-10.66***	-7.38	55.78	52.19	-3.58	-2.09
	rd	51.31	55.64	4.33***	9.86	52.59	55.93	3.34***	6.35	56.49	47.56	-8.92***	-8.24	54.75	52.48	-2.27	-1.49
	rd_mve	52.02	51.31	-0.70	-1.90	52.65	51.72	-0.93	-1.76	59.77	46.33	-13.44***	-10.36	56.50	52.22	-4.28	-2.17
	rd_sale	51.52	48.15	-3.37***	-11.15	51.75	51.11	-0.63	-1.27	57.92	47.07	-10.84***	-5.70	55.38	51.43	-3.94	-1.69
	securedind	49.55	53.00	3.44***	5.55	49.54	53.52	3.97***	6.00	49.75	50.45	0.69	1.27	51.12	49.14	-1.98	-1.84
	sin	50.10	50.17	0.07	1.63	52.06	50.75	-1.30	-2.37	59.83	46.31	-13.52***	-9.90	56.27	52.70	-3.57	-1.93

Appendix 3B continued																	
Category	Factor	Equal-weighted Portfolio				Value-weighted Portfolio				Optimised Small Portfolio				Optimised Large Portfolio			
		1	10	HML	t stat	1	10	HML	t stat	1	10	HML	t stat	1	10	HML	t stat
Trading frictions	baspread	62.26	57.37	-4.89***	-6.57	57.01	54.03	-2.98***	-5.84	57.12	47.20	-9.92***	-7.17	56.74	51.82	-4.92	-2.39
	beta	56.94	51.23	-5.71***	-8.54	56.86	52.68	-4.18***	-7.66	57.26	47.78	-9.48***	-8.94	53.45	51.50	-1.94	-1.36
	betasq	56.81	50.92	-5.89***	-8.78	55.42	52.28	-3.14***	-6.67	59.52	46.70	-12.81***	-9.65	55.19	53.27	-1.92	-1.04
	dolvol	46.79	47.30	0.50	0.42	46.87	47.56	0.68	1.36	51.77	50.31	-1.46	-1.22	44.56	50.58	6.01***	3.06
	idiovol	61.33	58.05	-3.28***	-4.62	57.13	55.13	-2.00***	-4.40	56.11	47.63	-8.47***	-6.07	56.43	51.16	-5.27	-2.62
	ill	53.91	53.59	-0.31	-0.31	52.22	50.96	-1.25	-2.40	58.83	46.64	-12.18***	-9.26	56.50	52.39	-4.10	-2.11
	maxret	64.15	52.24	-11.90***	-17.62	57.34	51.21	-6.13***	-12.82	59.20	46.62	-12.57***	-9.47	56.63	51.86	-4.77	-2.41
	retvol	62.95	56.26	-6.69***	-9.44	57.36	53.32	-4.04***	-8.48	58.73	46.89	-11.83***	-9.24	56.64	51.70	-4.94	-2.44
	std_dolvol	53.09	52.98	-0.11	0.08	51.64	52.11	0.46	1.07	50.93	48.89	-2.04	-1.64	57.38	47.38	-9.99***	-5.87
	std_turn	56.21	53.01	-3.19***	-5.95	53.37	51.83	-1.53**	-3.04	60.38	46.23	-14.15***	-10.37	56.33	52.39	-3.93	-1.98
	turn	54.59	51.89	-2.70***	-5.06	53.75	52.16	-1.60***	-3.24	60.90	46.15	-14.75***	-11.32	55.84	52.95	-2.88	-1.33
	zerotrade	45.13	48.60	3.47***	6.24	51.93	50.79	-1.13	-2.45	55.39	47.20	-8.19***	-7.00	56.65	51.22	-5.43	-2.59
Momentum	aeavol	47.80	52.67	4.86***	16.87	51.69	51.92	0.23	0.65	58.47	46.69	-11.77***	-8.56	56.10	52.31	-3.79	-2.06
	chmom	53.69	47.07	-6.61***	-14.10	52.88	48.03	-4.84***	-10.50	47.87	50.88	3.01	2.70	49.26	49.59	0.33	0.35
	chtx	47.56	52.14	4.57***	15.26	49.62	52.42	2.79***	6.48	52.98	49.20	-3.78	-2.55	50.87	53.76	2.89	1.41
	ear	48.11	51.50	3.39***	9.41	49.13	51.57	2.44***	6.90	51.86	49.77	-2.09	-1.71	49.69	53.26	3.57	1.94
	indmom	42.56	58.71	16.14***	24.78	45.01	57.40	12.39***	19.79	50.34	50.06	-0.28	-0.06	48.62	52.69	4.08	1.84
	mom12m	39.93	56.08	16.15***	24.72	47.64	56.67	9.03***	16.08	56.31	47.58	-8.72***	-6.95	54.41	52.57	-1.84	-1.12
	mom1m	61.99	38.33	-23.65***	-29.23	60.77	42.84	-17.92***	-25.92	54.78	48.54	-6.24***	-5.00	52.05	51.71	-0.33	-0.20
	mom36m	47.08	45.69	-1.39	-2.57	52.19	49.89	-2.29***	-4.46	58.10	46.95	-11.16***	-8.70	55.19	52.75	-2.44	-1.48
	mom6m	42.48	54.72	12.24***	20.28	47.60	55.15	7.55***	13.97	53.50	48.63	-4.86***	-4.20	52.16	52.70	0.54	0.04
	nincr	46.57	54.02	7.45***	19.04	50.08	53.70	3.61***	7.49	58.41	46.83	-11.57***	-8.97	54.66	53.34	-1.32	-1.06
	pricedelay	49.74	51.05	1.32***	5.13	50.42	51.00	0.57	1.50	50.50	49.57	-0.93	-0.58	53.76	49.40	-4.36	-2.17
	rsup	46.41	52.20	5.79***	16.58	47.13	50.91	3.78***	8.11	44.73	52.17	7.43***	4.39	46.96	50.08	3.12	1.48

Appendix 3C: Exposure of individual predictive factors, quarterly rebalancing

Appendix 3C reports the mean value of each of the 94 predictive factors for each decile portfolio generated by ranking stocks according to their machine predicted returns. The bottom portfolio is constructed by ranking stocks according to their machine learning predicted returns and form 10 portfolios and selling the lowest quintile portfolio. The top portfolio is constructed by ranking stocks according to their machine learning predicted returns and form 10 portfolios and buying the highest quintile portfolio. The long-short (HML) portfolio is constructed by ranking stocks according to their machine learning predicted returns and form 10 portfolios, buying the highest quintile portfolio and selling the lowest quintile portfolio. The factor realisations corresponding to the stocks chosen for the top and bottom portfolios are averaged to generate the results in the table. At each monthly period the factor input was rescaled to the [0%,100%] range and thus, the expected value for all factors is 50%. The mean values of the lowest and highest deciles are compared based on the null hypothesis $H_0: \mu_{high} = \mu_{low}$ which examines whether the category realisations are significantly different between the two portfolios. The Newey-West adjusted t statistics are presented in the column t stat. The reported results are for the average across the five neural network predictive models (NN1-NN5). The table is divided into four panels, A to D, which report the results for the equal-weighted, value-weighted, optimised portfolio trading a relatively small portfolio of 1 million USD and optimised portfolio trading a relatively large portfolio of 100 million USD, respectively. Investing horizon is three months and thus, rebalancing of the portfolio is performed quarterly based on predicted returns.

Category	Factor	Panel A: Equal-weighted Portfolio				Panel B: Value-weighted Portfolio				Panel C: Optimised Small Portfolio				Panel D: Optimised Large Portfolio			
		1	10	HML	t stat	1	10	HML	t stat	1	10	HML	t stat	1	10	HML	t stat
Investment	agr	48.48	55.13	6.64***	7.39	44.91	49.55	4.64***	5.47	36.59	54.76	18.16***	10.17	46.33	51.91	5.58	2.23
	chatoia	49.33	52.57	3.23***	6.31	49.23	50.83	1.596	2.32	47.81	51.49	3.69*	2.60	48.78	50.85	2.07	1.50
	chcsho	54.24	47.95	-6.28***	-9.13	55.39	50.27	-5.11***	-6.45	62.99	45.45	-17.53***	-11.14	55.11	48.18	-6.92***	-3.24
	chinv	50.90	45.97	-4.92***	-7.64	53.43	49.13	-4.29***	-5.63	58.73	47.47	-11.26***	-7.26	52.15	49.37	-2.78	-1.33
	cinvest	49.02	50.95	1.94***	5.06	49.64	49.78	0.148	0.15	54.36	48.74	-5.62	-2.01	50.73	49.61	-1.11	-0.39
	depr	50.21	53.24	3.03***	3.99	53.85	51.54	-2.30**	-2.90	63.20	45.24	-17.95***	-9.98	55.19	48.22	-6.96***	-3.14
	egr	49.70	45.45	-4.25***	-5.42	55.01	49.57	-5.43***	-6.86	62.89	45.58	-17.31***	-10.37	54.49	48.57	-5.92**	-2.74
	grcapx	50.86	46.89	-3.97***	-6.93	54.04	50.58	-3.46***	-4.46	63.88	45.11	-18.76***	-10.65	54.83	48.29	-6.53***	-3.02
	grltnoa	50.64	45.27	-5.37***	-7.79	54.57	49.22	-5.35***	-6.56	62.08	45.89	-16.19***	-10.33	54.28	48.46	-5.81***	-3.29
	invest	51.92	45.89	-6.04***	-7.36	55.69	49.83	-5.85***	-7.17	63.47	45.45	-18.02***	-11.08	55.02	48.17	-6.84***	-3.32
	lev	47.24	46.37	-0.864	-0.81	53.19	50.25	-2.94***	-3.46	63.39	45.20	-18.19***	-10.89	54.83	48.28	-6.55***	-3.15
	lgr	52.32	46.19	-6.13***	-9.39	55.21	50.57	-4.636***	-5.68	64.00	44.95	-19.04***	-10.95	55.37	48.08	-7.30***	-3.39
	pchcapx_ia	49.22	48.36	-0.86	-1.41	51.39	49.96	-1.44	-1.69	53.68	49.97	-3.71	-1.39	49.06	50.62	1.56	0.70
	realestate	49.72	48.60	-1.126	-2.24	53.23	50.49	-2.74***	-3.69	61.85	46.01	-15.84***	-10.23	54.19	48.51	-5.67***	-3.36
	secured	50.27	53.04	2.77**	2.98	52.91	52.30	-0.608	-0.62	62.08	46.44	-15.64***	-8.05	53.26	49.09	-4.17	-2.12
	tang	52.43	53.28	0.856	0.94	50.78	51.73	0.952	1.02	43.71	51.67	7.95***	6.03	51.96	49.12	-2.83**	-2.73

Appendix 3C continued																	
Category	Factor	Panel A: Equal-weighted Portfolio				Panel B: Value-weighted Portfolio				Panel C: Optimised Small Portfolio				Panel D: Optimised Large Portfolio			
		1	10	HML	t stat	1	10	HML	t stat	1	10	HML	t stat	1	10	HML	t stat
Profitability	absacc	54.06	53.35	-0.722	-0.95	54.90	52.17	-2.72***	-3.49	63.46	45.37	-18.08***	-10.42	55.46	48.05	-7.41***	-3.52
	acc	48.57	47.00	-1.566	-1.95	46.05	47.31	1.252	1.59	40.37	53.53	13.15***	7.98	45.67	52.14	6.47***	3.44
	cash	51.97	53.64	1.68	1.53	54.96	53.38	-1.582	-2.02	62.07	46.17	-15.89***	-9.43	54.96	48.28	-6.67***	-3.85
	cashdebt	44.20	48.43	4.23***	4.36	46.23	49.45	3.21***	3.77	36.06	55.34	19.28***	10.34	45.03	52.33	7.29**	3.10
	chpmia	54.25	45.43	-8.82***	-11.16	53.18	46.82	-6.35***	-6.14	52.72	48.89	-3.83	-1.52	50.85	49.82	-1.02	-0.46
	currat	49.89	50.86	0.976	1.14	53.87	51.05	-2.82***	-3.54	63.62	45.17	-18.45***	-10.40	55.15	48.15	-7.00***	-3.22
	gma	46.20	51.13	4.92***	5.82	49.91	51.50	1.582	1.99	56.45	48.74	-7.71***	-5.74	49.52	50.86	1.34	0.90
	ms	45.60	48.40	2.80***	3.79	46.58	48.28	1.71	2.50	48.83	50.77	1.95	2.08	47.63	51.71	4.07***	3.85
	operprof	43.95	47.01	3.052**	2.96	44.92	47.80	2.87***	3.54	37.98	54.10	16.12***	8.42	46.49	51.81	5.32	2.35
	pchcurrat	47.65	49.08	1.438*	2.65	53.94	51.06	-2.87***	-3.65	63.84	45.08	-18.75***	-10.72	55.33	48.08	-7.25***	-3.34
	pchdepr	49.56	50.99	1.42**	3.18	53.99	51.23	-2.76***	-3.54	63.69	45.19	-18.49***	-10.15	55.31	48.11	-7.20***	-3.27
	pchgm_pchsale	47.63	52.40	4.77***	8.90	45.32	49.43	4.12***	5.16	36.13	55.06	18.93***	10.70	44.95	52.38	7.42***	3.33
	pchquick	47.32	49.41	2.08***	3.76	53.89	51.14	-2.75***	-3.48	63.77	45.07	-18.69***	-10.50	55.32	48.08	-7.24***	-3.29
	pchsale_pchinvt	47.66	53.01	5.35***	10.65	45.95	50.05	4.10***	5.21	36.26	54.88	18.61***	10.78	45.75	52.12	6.37**	2.99
	pchsale_pchrect	50.01	50.94	0.922	2.61	46.02	49.05	3.03***	3.90	36.61	54.97	18.35***	10.76	45.37	52.19	6.81***	3.12
	pchsale_pchxsga	50.05	50.30	0.252	0.52	54.07	51.16	-2.91***	-3.86	62.54	45.66	-16.87***	-9.21	54.67	48.46	-6.21***	-3.24
	pchsaleinv	49.36	51.46	2.10***	3.82	51.90	50.88	-1.02	-1.14	59.97	46.21	-13.76***	-5.58	54.20	48.61	-5.59	-2.42
	pctacc	53.36	51.15	-2.21***	-3.15	47.27	49.38	2.11*	2.52	37.45	54.68	17.23***	8.67	44.86	52.78	7.92***	3.21
	ps	42.71	49.89	7.17***	8.40	42.81	48.74	5.93***	7.76	46.34	51.56	5.22***	8.51	47.39	51.73	4.33***	4.04
	quick	50.01	50.29	0.282	0.31	53.90	51.05	-2.85***	-3.58	63.62	45.18	-18.43***	-10.36	55.15	48.16	-6.99***	-3.20
	roaq	42.47	50.00	7.54***	8.00	44.12	48.48	4.36***	5.68	36.48	54.91	18.43***	10.60	44.45	52.67	8.21***	3.67
	roavol	56.83	54.66	-2.174	-2.06	54.84	51.59	-3.24***	-4.20	63.81	44.99	-18.82***	-10.43	55.78	47.87	-7.91***	-3.65
	roeq	43.92	49.15	5.22***	5.68	44.56	48.41	3.84***	4.92	38.42	53.64	15.22***	7.78	46.49	51.65	5.16	2.30
	roic	44.17	48.26	4.08***	4.05	45.15	48.47	3.32***	4.23	36.44	55.14	18.70***	10.32	44.73	52.53	7.80***	3.60
	sgr	51.79	47.65	-4.14***	-5.59	54.90	50.89	-4.01***	-5.13	64.01	45.08	-18.92***	-10.64	54.92	48.22	-6.70***	-3.16
	sp	45.39	50.43	5.04***	5.30	53.38	51.58	-1.80	-2.22	62.26	46.12	-16.14***	-8.45	54.11	48.68	-5.43	2.23
	stdacc	55.65	48.35	-7.30***	-9.49	55.39	50.22	-5.17***	-6.28	64.55	44.50	-20.04***	-10.69	56.47	47.56	-8.91***	-3.78
	tb	48.21	47.37	-0.846	-1.27	51.07	48.95	-2.11*	-2.54	56.86	48.43	-8.43***	-3.49	50.73	50.23	-0.49	0.06

Appendix 3C continued																	
Category	Factor	Panel A: Equal-weighted Portfolio				Panel B: Value-weighted Portfolio				Panel C: Optimised Small Portfolio				Panel D: Optimised Large Portfolio			
		1	10	HML	t stat	1	10	HML	t stat	1	10	HML	t stat	1	10	HML	t stat
Value vs growth	bm	45.92	47.40	1.48	2.35	53.03	50.21	-2.82***	-3.43	63.72	45.30	-18.42***	-9.80	54.42	48.50	-5.92**	-2.72
	bm_ia	51.11	51.99	0.878	1.35	50.87	50.43	-0.446	-0.48	48.00	48.02	0.01	0.02	55.47	47.33	-8.14***	-4.90
	cashpr	50.20	51.69	1.492	1.67	52.33	50.99	-1.338	-1.49	57.48	47.47	-10.01***	-4.06	52.71	49.15	-3.55	-1.34
	cfp	42.90	48.36	5.46***	6.08	45.54	48.76	3.22***	3.71	49.21	51.31	2.10	1.17	46.49	52.17	5.68**	3.01
	cfp_ia	46.17	49.58	3.41***	4.98	48.24	49.88	1.646	2.03	48.32	51.22	2.90	1.29	47.09	51.44	4.35	1.93
	dy	45.47	45.03	-0.438	-0.61	50.78	49.73	-1.042	-1.12	59.40	47.98	-11.41***	-4.38	48.73	50.87	2.12	1.16
	ep	43.01	46.38	3.36***	3.20	45.45	48.16	2.71***	3.37	36.43	54.80	18.37***	10.06	44.95	52.38	7.44***	3.31
	mve_ia	47.07	46.42	-0.654	-0.90	54.22	50.76	-3.45**	-2.90	63.97	45.18	-18.79***	-10.33	54.70	48.30	-6.40**	-2.77
	mvel1	44.93	45.98	1.048	0.72	54.15	51.02	-3.136	-2.45	63.93	45.41	-18.52***	-10.18	54.30	48.51	-5.79*	-2.64
	salecash	45.42	47.19	1.776	1.95	53.92	50.24	-3.67***	-4.33	63.92	44.98	-18.94***	-10.68	55.19	48.17	-7.02***	-3.12
	saleinv	49.08	48.20	-0.872	-1.70	53.03	50.65	-2.37**	-2.89	63.57	45.21	-18.36***	-10.38	54.70	48.27	-6.42***	-3.08
	salerec	49.28	49.94	0.656	1.00	52.99	50.35	-2.63***	-3.33	62.05	46.18	-15.87***	-7.49	53.14	49.08	-4.05	-1.48
	stdcf	55.84	48.47	-7.36***	-9.42	55.41	50.24	-5.16***	-6.28	64.48	44.55	-19.93***	-10.66	56.38	47.61	-8.76***	-3.77
Intangibles	age	45.48	49.69	4.20***	4.00	48.99	49.99	1.00	0.81	54.03	49.01	-5.01***	-5.13	48.83	51.15	2.31**	2.81
	chempia	50.26	48.65	-1.60*	-2.56	51.95	49.65	-2.29**	-2.79	55.95	49.09	-6.86*	-2.68	48.62	51.23	2.60	1.36
	convind	52.19	51.23	-0.952	-1.85	55.10	51.70	-3.39***	-3.98	61.58	45.85	-15.72***	-11.48	54.48	48.52	-5.96**	-3.01
	divi	50.68	50.43	-0.252	-1.34	53.93	50.66	-3.27***	-4.06	63.46	45.19	-18.27***	-10.84	55.12	48.20	-6.91***	-3.12
	divo	50.41	50.83	0.414	2.45	53.73	51.16	-2.57**	-3.15	63.68	45.14	-18.54***	-10.74	55.26	48.11	-7.14***	-3.29
	herf	47.63	51.52	3.89***	4.74	52.80	51.63	-1.17	-1.27	61.94	45.94	-16.00***	-9.21	54.15	48.56	-5.58**	-2.96
	hire	51.64	47.11	-4.52***	-6.36	55.55	50.47	-5.08***	-6.40	63.87	45.17	-18.70***	-10.97	55.08	48.19	-6.89***	-3.19
	orgcap	49.83	53.92	4.09***	5.29	53.18	51.88	-1.296	-1.63	61.81	45.81	-15.99***	-9.13	54.17	48.61	-5.55*	-2.65
	rd	50.93	55.83	4.91***	6.45	53.29	55.95	2.65**	2.91	59.89	46.94	-12.95***	-8.33	53.45	48.86	-4.59	-2.41
	rd_mve	51.84	51.24	-0.592	-0.90	53.99	51.44	-2.55**	-3.15	63.86	45.08	-18.78***	-10.53	55.29	48.15	-7.14***	-3.23
	rd_sale	52.14	47.91	-4.22***	-7.80	53.17	50.87	-2.29**	-2.80	60.81	45.76	-15.04***	-6.17	54.44	48.45	-5.99	-2.38
	securedind	49.22	52.98	3.75***	3.43	49.14	53.44	4.30***	3.71	49.32	50.46	1.14	1.50	50.79	49.86	-0.93	-0.93
	sin	50.11	50.19	0.082	0.90	53.64	50.54	-3.09***	-3.56	64.07	44.98	-19.09***	-10.82	55.25	48.14	-7.11***	-3.14

Appendix 3C continued																	
Category	Factor	Equal-weighted Portfolio				Value-weighted Portfolio				Optimised Small Portfolio				Optimised Large Portfolio			
		1	10	HML	t stat	1	10	HML	t stat	1	10	HML	t stat	1	10	HML	t stat
Trading frictions	baspread	60.62	54.90	-5.72***	-4.43	56.95	52.66	-4.29***	-5.11	62.15	45.83	-16.32***	-9.11	56.03	47.73	-8.31***	-3.77
	beta	56.65	50.25	-6.40***	-5.74	57.02	51.77	-5.24***	-5.76	59.34	47.21	-12.13***	-9.09	53.64	48.62	-5.01***	-4.00
	betasq	56.48	49.86	-6.62***	-5.93	56.43	51.60	-4.82***	-6.14	63.43	45.67	-17.75***	-10.21	54.59	48.31	-6.28***	-4.01
	dolvol	47.60	48.08	0.476	0.20	46.91	48.06	1.138	1.35	45.24	51.96	6.72***	5.58	45.82	52.03	6.21***	3.12
	idiovol	60.37	56.39	-3.97***	-3.13	57.51	54.23	-3.28***	-4.08	60.60	46.57	-14.03***	-8.98	55.15	47.90	-7.24***	-4.01
	ill	53.48	52.39	-1.09	-0.81	53.66	50.64	-3.02***	-3.65	63.54	45.05	-18.48***	-10.11	55.51	48.03	-7.47***	-3.22
	maxret	59.71	52.64	-7.06***	-6.73	56.03	51.11	-4.91***	-6.44	63.74	45.37	-18.38***	-10.93	55.76	47.86	-7.90***	-3.73
	retvol	60.14	53.98	-6.15***	-5.25	56.55	51.96	-4.59***	-5.94	63.32	45.66	-17.65***	-10.54	55.91	47.81	-8.09***	-3.89
	std_dolvol	50.95	51.89	0.942	1.27	50.97	51.49	0.524	0.75	51.98	48.08	-3.90***	-3.98	55.42	47.83	-7.59***	-4.27
	std_turn	54.31	51.74	-2.57***	-3.06	54.22	51.04	-3.18***	-3.91	64.46	45.03	-19.43***	-11.09	55.44	48.01	-7.42***	-3.32
	turn	53.84	51.37	-2.47**	-2.79	54.98	51.68	-3.30***	-3.98	64.42	45.25	-19.16***	-11.17	55.21	48.22	-6.98***	-3.51
	zerotrade	46.07	49.11	3.03***	3.35	53.09	50.51	-2.57***	-3.32	59.59	45.77	-13.81***	-10.66	55.69	47.90	-7.78***	-3.68
Momentum	aeavol	47.75	52.14	4.39***	10.38	53.03	51.38	-1.65	-2.02	63.15	45.43	-17.72***	-10.14	54.98	48.23	-6.74***	-3.05
	chmom	49.52	50.01	0.486	0.62	49.23	49.76	0.536	0.72	46.38	51.30	4.92***	3.41	49.21	50.61	1.41	0.90
	chtx	47.67	52.36	4.68***	9.87	50.47	52.69	2.22**	3.10	57.37	48.63	-8.73***	-4.46	50.22	50.58	0.36	0.29
	ear	47.83	51.89	4.06***	8.49	49.28	51.86	2.58***	4.67	54.99	49.18	-5.80***	-3.80	49.82	50.44	0.62	0.76
	indmom	41.79	60.38	18.59***	16.18	44.62	58.89	14.26***	12.98	51.05	50.32	-0.73	-0.41	49.04	50.50	1.46	0.80
	mom12m	39.45	57.89	18.43***	16.71	48.86	57.29	8.43***	8.95	60.33	46.79	-13.54***	-8.37	53.11	49.06	-4.05	-2.09
	mom1m	51.62	46.62	-4.99***	-6.08	53.14	48.16	-4.98***	-6.17	56.05	48.17	-7.88***	-5.22	51.35	49.80	-1.55	-1.01
	mom36m	47.59	45.96	-1.638	-1.88	53.71	49.59	-4.11***	-4.95	62.55	45.62	-16.92***	-10.46	54.04	48.72	-5.32*	-2.62
	mom6m	41.33	56.43	15.09***	14.98	47.56	56.21	8.64***	9.35	56.69	48.26	-8.42***	-5.40	51.15	49.98	-1.17	-0.43
	nincr	46.98	54.29	7.30***	12.59	51.60	53.53	1.93*	2.53	62.71	46.07	-16.64***	-9.33	53.55	48.98	-4.57	-2.49
	pricedelay	49.72	51.01	1.29***	3.30	50.66	50.80	0.144	0.23	51.32	49.29	-2.03	-1.25	52.98	49.07	-3.91	-1.72
	rsup	46.65	52.03	5.38***	8.99	46.56	51.18	4.61***	5.88	42.35	52.97	10.62***	4.91	46.95	51.33	4.38	1.83

Appendix 3D: Exposure of individual predictive factors, annual rebalancing

Appendix 3D reports the mean value of each of the 94 predictive factors for each decile portfolio generated by ranking stocks according to their machine predicted returns. The bottom portfolio is constructed by ranking stocks according to their machine learning predicted returns and form 10 portfolios and selling the lowest quintile portfolio. The top portfolio is constructed by ranking stocks according to their machine learning predicted returns and form 10 portfolios and buying the highest quintile portfolio. The long-short (HML) portfolio is constructed by ranking stocks according to their machine learning predicted returns and form 10 portfolios, buying the highest quintile portfolio and selling the lowest quintile portfolio. The factor realisations corresponding to the stocks chosen for the top and bottom portfolios are averaged to generate the results in the table. At each monthly period the factor input was rescaled to the [0%,100%] range and thus, the expected value for all factors is 50%. The mean values of the lowest and highest deciles are compared based on the null hypothesis $H_0: \mu_{high} = \mu_{low}$ which examines whether the category realisations are significantly different between the two portfolios. The Newey-West adjusted t statistics are presented in the column t stat. The reported results are for the average across the five neural network predictive models (NN1-NN5). The table is divided into four panels, A to D, which report the results for the equal-weighted, value-weighted, optimised portfolio trading a relatively small portfolio of 1 million USD and optimised portfolio trading a relatively large portfolio of 100 million USD, respectively. Investing horizon is twelve months and thus, rebalancing of the portfolio is performed annually based on predicted returns.

Category	Factor	Panel A: Equal-weighted Portfolio				Panel B: Value-weighted Portfolio				Panel C: Optimised Small Portfolio				Panel D: Optimised Large Portfolio			
		1	10	HML	t stat	1	10	HML	t stat	1	10	HML	t stat	1	10	HML	t stat
Investment	agr	48.10	55.51	7.40***	4.40	45.90	49.35	3.45	2.02	36.18	56.24	20.05***	12.50	38.02	52.82	14.79***	7.09
	chatoia	49.76	51.65	1.89	2.52	49.57	50.29	0.71	0.49	47.58	51.92	4.34*	3.03	45.35	51.15	5.80***	3.62
	chcsho	53.57	47.28	-6.29***	-4.70	54.33	50.07	-4.25*	-2.57	63.51	43.79	-19.72***	-14.85	63.15	47.22	-15.93***	-9.38
	chinv	50.97	46.41	-4.55***	-4.28	52.98	49.50	-3.48	-2.35	58.81	46.48	-12.33***	-8.53	57.43	48.55	-8.87***	-5.45
	cinvest	49.56	50.86	1.29	2.28	49.91	51.23	1.31	0.87	55.94	48.05	-7.89**	-2.85	53.61	48.86	-4.74	-1.72
	depr	49.64	52.88	3.25	2.11	53.04	51.74	-1.29	-0.79	63.93	43.65	-20.27***	-13.51	63.82	47.18	-16.64***	-8.91
	egr	50.91	44.76	-6.15***	-4.10	53.81	49.44	-4.36*	-2.67	63.30	44.05	-19.25***	-13.29	62.00	47.46	-14.53***	-7.84
	grcapx	50.98	47.35	-3.63***	-3.54	53.40	50.93	-2.47	-1.54	64.56	43.54	-21.01***	-13.66	63.44	47.20	-16.24***	-9.04
	grltnoa	50.81	45.36	-5.45***	-4.42	53.54	49.41	-4.13	-2.44	61.61	44.48	-17.13***	-12.91	61.64	47.39	-14.24***	-9.83
	invest	51.78	46.20	-5.57***	-3.83	54.37	49.88	-4.49*	-2.64	63.82	43.83	-19.99***	-14.92	62.97	47.20	-15.77***	-9.66
	lev	47.47	46.82	-0.65	-0.32	52.69	50.66	-2.03	-1.18	63.95	43.55	-20.40***	-13.76	63.22	47.23	-15.99***	-9.15
	lgr	52.11	46.19	-5.92***	-5.19	53.90	50.80	-3.10	-1.81	64.76	43.30	-21.45***	-14.88	64.19	47.04	-17.15***	-9.64
	pchcapx_ia	49.76	48.62	-1.13	-1.03	51.41	50.53	-0.87	-0.49	54.94	49.37	-5.56	-2.05	50.97	49.87	-1.10	-0.39
	realestate	50.26	48.74	-1.51	-1.44	52.81	50.97	-1.84	-1.17	62.29	44.66	-17.62***	-12.74	61.37	47.56	-13.80***	-9.74
	secured	50.28	52.90	2.62	1.44	52.27	52.21	-0.06	-0.03	62.02	45.26	-16.76***	-9.35	59.60	48.35	-11.25***	-7.90
	tang	52.50	52.71	0.20	0.14	50.94	50.72	-0.22	-0.09	42.96	52.53	9.56***	6.73	46.19	50.45	4.26***	4.02

Appendix 3D continued																	
Category	Factor	Panel A: Equal-weighted Portfolio				Panel B: Value-weighted Portfolio				Panel C: Optimised Small Portfolio				Panel D: Optimised Large Portfolio			
		1	10	HML	t stat	1	10	HML	t stat	1	10	HML	t stat	1	10	HML	t stat
Profitability	absacc	52.59	52.59	-0.00	-0.11	53.56	52.12	-1.44	-0.90	64.13	43.65	-20.47***	-14.21	63.72	47.24	-16.48***	-8.83
	acc	49.36	47.48	-1.88	-1.27	47.31	47.88	0.56	0.39	41.16	54.71	13.55***	8.81	39.68	52.21	12.53***	7.38
	cash	51.75	52.95	1.20	0.55	53.95	53.44	-0.51	-0.29	62.03	44.77	-17.26***	-11.93	61.44	47.73	-13.71***	-8.01
	cashdebt	46.12	48.22	2.08	0.97	46.89	49.19	2.30	1.33	35.00	57.01	22.01***	14.41	35.35	53.25	17.89***	9.40
	chpmia	53.24	47.60	-5.64***	-4.06	53.50	47.11	-6.39***	-3.24	51.98	48.70	-3.28	-1.25	51.04	49.53	-1.50	-0.57
	currat	50.45	50.82	0.37	0.19	53.14	51.37	-1.77	-1.10	64.47	43.48	-20.98***	-13.59	63.68	47.19	-16.49***	-8.58
	gma	46.65	50.82	4.16	2.41	49.74	51.10	1.35	0.80	55.76	48.31	-7.44***	-5.95	52.60	49.90	-2.70*	-2.69
	ms	47.03	47.91	0.87	0.51	47.48	47.81	0.33	0.24	48.50	51.26	2.75*	3.16	46.70	51.03	4.33***	4.24
	operprof	46.23	46.75	0.50	0.11	46.12	47.92	1.80	1.08	37.35	55.59	18.24***	10.19	39.12	52.28	13.16***	6.46
	pchcurrat	48.98	48.36	-0.62	-0.80	53.23	51.00	-2.23	-1.36	64.47	43.28	-21.19***	-13.80	64.09	47.12	-16.96***	-9.43
	pchdepr	49.92	50.96	1.03	1.27	53.28	51.25	-2.03	-1.27	64.30	43.48	-20.81***	-13.60	64.10	47.14	-16.95***	-9.53
	pchgm_pchsale	48.87	51.55	2.68*	2.56	46.33	49.22	2.88	1.75	35.38	56.84	21.46***	14.41	35.96	53.19	17.22***	9.31
	pchquick	48.82	48.52	-0.29	-0.37	53.18	50.99	-2.19	-1.33	64.43	43.28	-21.15***	-13.51	64.17	47.13	-17.04***	-9.67
	pchsale_pchinvt	48.61	52.40	3.79***	4.85	46.81	49.63	2.82	1.74	35.69	56.53	20.84***	14.55	36.96	53.07	16.11***	9.32
	pchsale_pchrect	49.85	51.15	1.30	2.06	46.83	49.20	2.37	1.47	35.96	56.55	20.58***	14.36	36.77	53.10	16.32***	8.91
	pchsale_pchxsga	50.54	49.33	-1.20	-1.25	53.40	50.94	-2.45	-1.58	63.26	43.99	-19.26***	-11.56	62.03	47.68	-14.35***	-7.39
	pchsaleinv	50.06	50.72	0.66	0.76	52.64	50.41	-2.22	-1.40	60.02	45.14	-14.88***	-5.99	60.78	47.81	-12.96***	-5.65
	pctacc	52.22	50.77	-1.45	-1.18	47.90	49.14	1.24	0.73	38.48	56.00	17.52***	8.30	37.03	53.59	16.55***	8.64
	ps	45.79	48.98	3.18	2.09	45.65	48.06	2.41	1.73	45.32	52.38	7.05***	10.55	44.96	51.52	6.56***	6.95
	quick	50.65	50.01	-0.63	-0.42	53.21	51.36	-1.84	-1.14	64.48	43.46	-21.02***	-13.56	63.74	47.21	-16.53***	-8.62
	roaq	45.07	48.78	3.71	1.79	45.67	47.96	2.29	1.42	36.00	56.65	20.64***	14.00	36.40	53.04	16.64***	9.20
	roavol	54.74	53.88	-0.86	-0.38	53.76	51.66	-2.09	-1.28	64.62	43.31	-21.31***	-14.57	64.23	47.04	-17.19***	-9.41
	roeq	46.25	47.98	1.71	0.77	46.04	48.00	1.95	1.19	38.29	55.09	16.79***	9.17	40.36	51.92	11.56***	5.90
	roic	45.88	48.19	2.30	1.01	45.99	48.24	2.24	1.40	35.47	56.85	21.38***	13.96	36.10	53.21	17.11***	9.16
	sgr	52.07	46.91	-5.16***	-3.60	53.95	51.17	-2.78	-1.68	64.50	43.46	-21.03***	-13.78	63.47	47.17	-16.30***	-9.01
	sp	45.17	50.77	5.60*	2.74	52.42	51.75	-0.66	-0.38	62.62	44.57	-18.04***	-10.08	62.23	47.74	-14.48***	-7.20
	stdacc	55.49	47.85	-7.63***	-4.48	54.52	50.48	-4.03	-2.38	65.44	42.81	-22.62***	-14.78	65.88	46.68	-19.19***	-11.09
	tb	48.32	48.02	-0.30	-0.30	51.20	48.87	-2.33	-1.44	55.50	47.92	-7.58**	-2.98	54.61	49.56	-5.05	-2.29

Appendix 3D continued																	
Category	Factor	Panel A: Equal-weighted Portfolio				Panel B: Value-weighted Portfolio				Panel C: Optimised Small Portfolio				Panel D: Optimised Large Portfolio			
		1	10	HML	t stat	1	10	HML	t stat	1	10	HML	t stat	1	10	HML	t stat
Value vs growth	bm	46.31	48.39	2.07	1.39	52.60	50.48	-2.12	-1.25	64.34	43.60	-20.74***	-12.29	63.01	47.47	-15.53***	-8.60
	bm_ia	50.32	51.95	1.63	1.18	50.93	50.12	-0.80	-0.51	48.35	48.49	0.14	0.08	54.89	47.86	-7.03*	-2.62
	cashpr	50.76	51.40	0.63	0.33	52.16	51.07	-1.09	-0.60	57.57	46.43	-11.14***	-4.61	58.11	48.29	-9.81***	-4.12
	cfp	44.78	48.47	3.69	2.00	47.16	48.96	1.80	1.08	48.92	51.68	2.76	1.28	46.22	51.80	5.58*	2.57
	cfp_ia	47.49	49.55	2.06	1.61	49.36	49.11	-0.24	-0.27	48.44	51.36	2.92	1.24	47.87	51.26	3.38	1.31
	dy	46.91	45.91	-0.99	-0.67	51.40	50.21	-1.19	-0.66	59.37	46.96	-12.40***	-4.72	54.33	49.67	-4.66	-1.63
	ep	45.67	46.49	0.82	0.29	46.58	47.93	1.35	0.83	35.68	56.57	20.89***	13.68	36.16	53.03	16.87***	9.13
	mve_ia	47.67	46.92	-0.75	-0.59	53.53	51.34	-2.18	-0.92	64.28	43.60	-20.67***	-13.80	63.66	47.09	-16.57***	-9.60
	mvel1	46.91	45.88	-1.02	-0.55	53.53	51.72	-1.81	-0.72	63.85	43.80	-20.04***	-13.25	63.21	47.20	-16.01***	-9.51
	salecash	46.08	47.58	1.50	0.73	53.13	50.65	-2.48	-1.45	64.58	43.36	-21.22***	-14.28	64.10	47.10	-16.99***	-9.30
	saleinv	49.70	47.77	-1.93	-2.02	52.66	50.90	-1.76	-1.04	64.20	43.51	-20.68***	-13.69	63.60	47.17	-16.42***	-9.11
	salerec	49.08	49.99	0.91	0.58	52.53	50.06	-2.47	-1.44	62.51	44.76	-17.74***	-9.04	61.40	47.91	-13.48***	-6.30
	stdcf	55.55	47.94	-7.61***	-4.40	54.54	50.51	-4.03	-2.39	65.38	42.85	-22.52***	-14.69	65.79	46.72	-19.07***	-11.02
Intangibles	age	46.26	50.13	3.86	1.71	48.95	50.71	1.75	0.63	53.68	48.63	-5.04***	-5.08	53.71	49.57	-4.14***	-3.92
	chempia	50.37	48.30	-2.07	-1.86	51.76	49.79	-1.97	-1.22	54.46	48.84	-5.62	-2.11	49.15	50.80	1.65	0.57
	convind	51.44	51.22	-0.22	-0.17	53.79	52.24	-1.55	-0.83	61.51	44.68	-16.83***	-15.81	62.17	47.41	-14.75***	-9.43
	divi	50.24	50.28	0.03	0.19	52.86	50.71	-2.14	-1.29	64.20	43.58	-20.62***	-14.10	63.98	47.18	-16.80***	-9.50
	divo	50.25	50.51	0.26	1.19	53.01	51.14	-1.86	-1.08	64.28	43.56	-20.72***	-13.92	64.08	47.16	-16.92***	-9.47
	herf	47.17	51.74	4.56	2.43	52.01	52.01	0.00	0.01	62.68	44.35	-18.33***	-12.28	62.48	47.50	-14.98***	-8.92
	hire	51.93	46.84	-5.09***	-3.97	54.28	50.40	-3.88	-2.39	64.28	43.65	-20.63***	-14.24	63.51	47.13	-16.37***	-9.39
	orgcap	49.19	53.67	4.48**	2.83	52.46	51.75	-0.70	-0.44	62.28	44.50	-17.78***	-11.82	61.03	47.85	-13.18***	-7.22
	rd	50.35	55.00	4.65***	3.64	52.40	55.38	2.98	1.67	59.81	45.96	-13.84***	-9.82	59.72	48.24	-11.48***	-7.14
	rd_mve	51.00	50.95	-0.05	-0.02	53.09	51.61	-1.47	-0.90	64.31	43.35	-20.95***	-13.72	63.96	47.19	-16.77***	-9.11
	rd_sale	52.42	47.62	-4.80***	-4.23	52.86	51.42	-1.44	-0.84	60.62	44.52	-16.11***	-6.51	61.40	47.71	-13.68***	-5.83
	securedind	49.10	53.04	3.94	1.85	49.14	53.31	4.16	1.79	48.30	50.78	2.48	2.45	50.51	49.97	-0.53	-0.58
	sin	50.03	50.20	0.17	1.13	52.93	50.80	-2.13	-1.21	64.65	43.40	-21.25***	-13.88	64.48	47.06	-17.41***	-9.62

Appendix 3D continued																	
Category	Factor	Equal-weighted Portfolio				Value-weighted Portfolio				Optimised Small Portfolio				Optimised Large Portfolio			
		1	10	HML	t stat	1	10	HML	t stat	1	10	HML	t stat	1	10	HML	t stat
Trading frictions	baspread	57.34	53.86	-3.48	-1.29	54.82	52.42	-2.40	-1.40	63.09	44.24	-18.84***	-12.24	62.43	47.45	-14.98***	-8.64
	beta	54.02	49.85	-4.16	-1.75	54.62	51.72	-2.89	-1.52	57.47	46.65	-10.81***	-10.12	56.27	48.41	-7.85***	-5.82
	betasq	53.97	49.48	-4.48	-1.90	54.52	51.73	-2.79	-1.73	63.07	44.36	-18.71***	-12.10	61.58	47.47	-14.11***	-8.16
	dolvol	48.85	47.32	-1.52	-0.80	47.81	47.59	-0.22	-0.20	42.83	53.25	10.42***	8.29	42.26	51.66	9.39***	5.21
	idiovol	57.02	55.12	-1.89	-0.70	55.62	53.69	-1.93	-1.08	61.39	44.98	-16.41***	-12.05	60.49	47.65	-12.84***	-7.48
	ill	51.80	52.93	1.12	0.61	52.97	50.93	-2.04	-1.21	64.35	43.40	-20.95***	-13.54	64.07	47.14	-16.93***	-9.11
	maxret	55.90	53.10	-2.81	-1.36	54.02	51.52	-2.49	-1.57	63.99	43.73	-20.25***	-13.83	63.44	47.26	-16.18***	-8.99
	retvol	56.82	53.37	-3.44	-1.42	54.52	51.82	-2.70	-1.70	63.62	43.98	-19.63***	-13.39	62.94	47.38	-15.56***	-8.65
	std_dolvol	49.48	52.11	2.62	1.64	50.39	51.45	1.06	0.68	53.68	47.41	-6.27***	-7.11	57.56	48.16	-9.39***	-4.64
	std_turn	52.91	50.64	-2.26	-1.25	53.37	50.94	-2.42	-1.47	64.68	43.48	-21.20***	-14.12	64.44	47.05	-17.38***	-9.23
	turn	52.67	50.05	-2.62	-1.33	54.02	51.54	-2.47	-1.40	64.23	43.77	-20.45***	-14.06	63.66	47.14	-16.52***	-9.21
zerotrade	47.06	50.09	3.03	1.51	52.68	50.69	-1.98	-1.26	61.63	44.21	-17.41***	-16.02	62.70	47.31	-15.39***	-8.13	
Momentum	aeavol	48.31	50.81	2.49**	3.11	52.58	51.11	-1.47	-0.91	63.78	43.83	-19.95***	-13.30	63.56	47.23	-16.33***	-9.28
	chmom	47.13	52.27	5.14***	4.72	46.95	51.43	4.47**	3.34	45.83	51.81	5.97**	4.15	47.81	50.65	2.83	1.82
	ctx	48.74	50.92	2.17	2.39	50.77	52.21	1.44	0.91	56.91	47.85	-9.05***	-5.03	54.28	49.72	-4.56	-2.47
	ear	48.49	51.16	2.66***	4.64	49.12	51.38	2.26	2.26	54.70	48.77	-5.92***	-4.04	51.64	50.10	-1.54	-1.26
	indmom	43.63	57.33	13.70***	6.65	45.51	56.44	10.93***	5.46	50.73	50.34	-0.38	-0.20	49.53	50.57	1.04	0.52
	mom12m	43.45	54.66	11.20***	5.99	49.91	55.13	5.22**	2.87	60.75	45.58	-15.16***	-10.27	59.91	48.20	-11.71***	-6.97
	mom1m	47.26	50.93	3.66**	3.12	49.65	51.78	2.13	1.52	55.68	47.73	-7.95***	-5.68	55.17	49.21	-5.96***	-4.12
	mom36m	49.57	46.11	-3.46	-1.97	53.23	49.85	-3.38	-2.02	62.97	44.11	-18.86***	-13.94	61.67	47.53	-14.13***	-9.12
	mom6m	43.26	54.84	11.57***	6.39	47.45	55.39	7.94***	4.26	56.94	47.56	-9.38***	-6.19	56.05	49.05	-6.99***	-4.46
	nincr	47.66	51.95	4.29***	5.06	51.39	52.54	1.14	0.73	62.70	44.69	-18.01***	-11.81	61.60	47.75	-13.85***	-8.69
	pricedelay	49.96	51.03	1.06	1.64	51.07	50.67	-0.39	-0.32	52.66	48.67	-3.98	-2.32	55.27	49.03	-6.23**	-3.04
	rsup	47.73	50.77	3.03*	2.54	47.73	51.45	3.71	2.34	41.84	53.98	12.13***	5.74	40.74	51.89	11.14***	5.29

Appendix 3E: Realisation of predictive factors by functional category, monthly rebalancing

Appendix 3E reports the mean value for the predictive factors when grouped in their functional category as described in Appendix 3A; Momentum, profitability, trading frictions, value vs. growth, intangibles and investment. The long-short portfolio is constructed by ranking stocks according to their machine learning predicted returns and form 10 portfolios, buying the highest quantile portfolio and selling the lowest quintile portfolio (High-minus-Low 'HML' portfolio). The factor realisations corresponding to the stocks chosen for the top and bottom portfolios are averaged cross-sectionally into the six categories and then averaged across time to generate the results in the table. The mean values of the lowest and highest deciles are compared based on the null hypothesis $H_0: \mu_{high} = \mu_{low}$ which examines whether the category realisations are significantly different between the two portfolios. The mean values are expressed in percentage basis. The Newey-West adjusted t statistics are presented in the parentheses. The results report the five neural network models, NN1-NN5, individually. The table is divided into four panels, A to D, which report the results for the equal-weighted, value-weighted, optimised portfolio trading a relatively small portfolio of 1 million USD and optimised portfolio trading a relatively large portfolio of 100 million USD, respectively. Investing horizon is one month and thus, rebalancing of the portfolio is performed monthly based on predicted returns.

NN1 Monthly rebalancing						
Panel A: Equal-weighted Portfolios						
Portfolio	Value vs Growth	Profitability	Investment	Intangibles	Trading frictions	Momentum
1	0.474	0.482	0.495	0.508	0.508	0.461
10	0.496	0.505	0.514	0.514	0.510	0.541
t statistic	1.77	2.30	1.81	0.24	0.34	3.99
Panel B: Value-weighted Portfolios						
Portfolio	Value vs Growth	Profitability	Investment	Intangibles	Trading frictions	Momentum
1	0.493	0.496	0.497	0.507	0.510	0.479
10	0.499	0.504	0.506	0.509	0.510	0.532
t statistic	0.74	0.84	0.99	0.12	0.00	3.33
Panel C: Optimised Small Portfolios						
Portfolio	Value vs Growth	Profitability	Investment	Intangibles	Trading frictions	Momentum
1	0.490	0.515	0.483	0.501	0.518	0.505
10	0.504	0.495	0.507	0.499	0.493	0.498
t statistic	0.43	-0.83	0.78	-0.06	-0.77	-0.28
Panel D: Optimised Large Portfolios						
Portfolio	Value vs Growth	Profitability	Investment	Intangibles	Trading frictions	Momentum
1	0.493	0.516	0.486	0.527	0.527	0.506
10	0.503	0.497	0.505	0.494	0.494	0.500
t statistic	0.31	-0.72	0.62	-0.88	-0.99	-0.24

NN2 Monthly rebalancing						
Panel A: Equal-weighted Portfolios						
Portfolio	Value vs Growth	Profitability	Investment	Intangibles	Trading frictions	Momentum
1	0.477	0.482	0.500	0.517	0.507	0.458
10	0.497	0.502	0.510	0.509	0.512	0.545
t statistic	1.42	1.91	1.22	-0.31	0.57	4.20
Panel B: Value-weighted Portfolios						
Portfolio	Value vs Growth	Profitability	Investment	Intangibles	Trading frictions	Momentum
1	0.497	0.490	0.502	0.512	0.505	0.471
10	0.500	0.501	0.505	0.507	0.511	0.534
t statistic	0.50	1.85	0.73	-0.39	0.79	4.06
Panel C: Optimised Small Portfolios						
Portfolio	Value vs Growth	Profitability	Investment	Intangibles	Trading frictions	Momentum
1	0.488	0.514	0.478	0.501	0.516	0.499
10	0.503	0.498	0.505	0.500	0.497	0.500
t statistic	0.49	-0.64	0.87	-0.02	-0.59	0.06
Panel D: Optimised Large Portfolios						
Portfolio	Value vs Growth	Profitability	Investment	Intangibles	Trading frictions	Momentum
1	0.495	0.511	0.498	0.527	0.519	0.512
10	0.516	0.495	0.514	0.481	0.490	0.499
t statistic	0.64	-0.59	0.52	-1.11	-0.82	-0.44

NN3 Monthly rebalancing						
Panel A: Equal-weighted Portfolios						
Portfolio	Value vs Growth	Profitability	Investment	Intangibles	Trading frictions	Momentum
1	0.478	0.488	0.495	0.504	0.504	0.470
10	0.493	0.496	0.515	0.523	0.516	0.532
t statistic	1.13	0.88	1.86	0.91	1.46	3.96
Panel B: Value-weighted Portfolios						
Portfolio	Value vs Growth	Profitability	Investment	Intangibles	Trading frictions	Momentum
1	0.494	0.499	0.497	0.504	0.506	0.487
10	0.501	0.496	0.507	0.513	0.514	0.525
t statistic	0.76	-0.44	1.24	0.65	0.78	2.93
Panel C: Optimised Small Portfolios						
Portfolio	Value vs Growth	Profitability	Investment	Intangibles	Trading frictions	Momentum
1	0.492	0.509	0.488	0.498	0.508	0.498
10	0.503	0.497	0.505	0.501	0.497	0.501
t statistic	0.56	-0.78	0.92	0.17	-0.51	0.19
Panel D: Optimised Large Portfolios						
Portfolio	Value vs Growth	Profitability	Investment	Intangibles	Trading frictions	Momentum
1	0.497	0.508	0.492	0.519	0.514	0.502
10	0.504	0.499	0.506	0.495	0.497	0.502
t statistic	0.33	-0.54	0.68	-0.95	-0.76	-0.03

NN4 Monthly rebalancing						
Panel A: Equal-weighted Portfolios						
Portfolio	Value vs Growth	Profitability	Investment	Intangibles	Trading frictions	Momentum
1	0.479	0.489	0.495	0.504	0.504	0.467
10	0.493	0.495	0.514	0.522	0.514	0.534
t statistic	1.10	0.62	1.84	0.87	1.30	4.32
Panel B: Value-weighted Portfolios						
Portfolio	Value vs Growth	Profitability	Investment	Intangibles	Trading frictions	Momentum
1	0.495	0.499	0.497	0.503	0.506	0.484
10	0.500	0.496	0.506	0.513	0.512	0.527
t statistic	0.59	-0.51	1.15	0.71	0.62	3.56
Panel C: Optimised Small Portfolios						
Portfolio	Value vs Growth	Profitability	Investment	Intangibles	Trading frictions	Momentum
1	0.492	0.510	0.487	0.499	0.509	0.498
10	0.503	0.497	0.505	0.501	0.497	0.501
t statistic	0.50	-0.77	0.83	0.10	-0.56	0.18
Panel D: Optimised Large Portfolios						
Portfolio	Value vs Growth	Profitability	Investment	Intangibles	Trading frictions	Momentum
1	0.497	0.511	0.489	0.524	0.516	0.505
10	0.503	0.496	0.507	0.491	0.495	0.500
t statistic	0.24	-0.63	0.65	-0.96	-0.71	-0.23

NN5 Monthly rebalancing						
Panel A: Equal-weighted Portfolios						
Portfolio	Value vs Growth	Profitability	Investment	Intangibles	Trading frictions	Momentum
1	0.483	0.489	0.500	0.508	0.505	0.472
10	0.489	0.495	0.507	0.513	0.510	0.525
t statistic	0.59	0.75	0.93	0.26	0.83	4.62
Panel B: Value-weighted Portfolios						
Portfolio	Value vs Growth	Profitability	Investment	Intangibles	Trading frictions	Momentum
1	0.495	0.500	0.498	0.507	0.507	0.489
10	0.496	0.500	0.502	0.508	0.512	0.520
t statistic	0.16	-0.05	0.37	0.04	0.44	3.22
Panel C: Optimised Small Portfolios						
Portfolio	Value vs Growth	Profitability	Investment	Intangibles	Trading frictions	Momentum
1	0.492	0.512	0.482	0.495	0.508	0.499
10	0.502	0.497	0.505	0.502	0.498	0.500
t statistic	0.46	-0.83	1.05	0.28	-0.43	0.09
Panel D: Optimised Large Portfolios						
Portfolio	Value vs Growth	Profitability	Investment	Intangibles	Trading frictions	Momentum
1	0.500	0.511	0.498	0.523	0.520	0.508
10	0.509	0.494	0.512	0.485	0.489	0.502
t statistic	0.33	-0.73	0.53	-1.10	-1.03	-0.24

Appendix 3F: Realisation of predictive factors by functional category, quarterly rebalancing

Appendix 3F reports the mean value for the predictive factors when grouped in their functional category as described in Appendix 3A; Momentum, profitability, trading frictions, value vs. growth, intangibles and investment. The long-short portfolio is constructed by ranking stocks according to their machine learning predicted returns and form 10 portfolios, buying the highest quantile portfolio and selling the lowest quintile portfolio (High-minus-Low 'HML' portfolio). The factor realisations corresponding to the stocks chosen for the top and bottom portfolios are averaged cross-sectionally into the six categories and then averaged across time to generate the results in the table. The mean values of the lowest and highest deciles are compared based on the null hypothesis $H_0: \mu_{high} = \mu_{low}$ which examines whether the category realisations are significantly different between the two portfolios. The mean values are expressed in percentage basis. The Newey-West adjusted t statistics are presented in the parentheses. The results report the five neural network models, NN1-NN5, individually. The table is divided into four panels, A to D, which report the results for the equal-weighted, value-weighted, optimised portfolio trading a relatively small portfolio of 1 million USD and optimised portfolio trading a relatively large portfolio of 100 million USD, respectively. Investing horizon is three month and thus, rebalancing of the portfolio is performed quarterly based on predicted returns.

NN1 Quarterly rebalancing						
Panel A: Equal-weighted Portfolios						
Portfolio	Value vs Growth	Profitability	Investment	Intangibles	Trading frictions	Momentum
1	0.471	0.481	0.493	0.510	0.507	0.466
10	0.498	0.507	0.514	0.509	0.509	0.539
t statistic	2.16	2.66	1.89	-0.05	0.26	4.84
Panel B: Value-weighted Portfolios						
Portfolio	Value vs Growth	Profitability	Investment	Intangibles	Trading frictions	Momentum
1	0.491	0.500	0.493	0.509	0.513	0.485
10	0.500	0.503	0.506	0.507	0.508	0.531
t statistic	0.70	0.29	0.98	-0.10	-0.36	3.47
Panel C: Optimised Small Portfolios						
Portfolio	Value vs Growth	Profitability	Investment	Intangibles	Trading frictions	Momentum
1	0.493	0.510	0.487	0.501	0.512	0.501
10	0.504	0.494	0.508	0.499	0.492	0.499
t statistic	0.41	-0.76	0.76	-0.06	-0.69	-0.12
Panel D: Optimised Large Portfolios						
Portfolio	Value vs Growth	Profitability	Investment	Intangibles	Trading frictions	Momentum
1	0.495	0.508	0.497	0.516	0.515	0.507
10	0.503	0.498	0.502	0.496	0.496	0.499
t statistic	0.47	-0.70	0.34	-1.02	-1.06	-0.65

NN2 Quarterly rebalancing						
Panel A: Equal-weighted Portfolios						
Portfolio	Value vs Growth	Profitability	Investment	Intangibles	Trading frictions	Momentum
1	0.476	0.480	0.498	0.518	0.506	0.462
10	0.498	0.504	0.512	0.503	0.512	0.544
t statistic	1.67	2.28	1.60	-0.64	0.73	4.71
Panel B: Value-weighted Portfolios						
Portfolio	Value vs Growth	Profitability	Investment	Intangibles	Trading frictions	Momentum
1	0.495	0.494	0.498	0.512	0.506	0.478
10	0.500	0.502	0.506	0.504	0.511	0.534
t statistic	0.84	1.02	1.33	-0.64	0.56	4.79
Panel C: Optimised Small Portfolios						
Portfolio	Value vs Growth	Profitability	Investment	Intangibles	Trading frictions	Momentum
1	0.491	0.513	0.482	0.505	0.515	0.502
10	0.504	0.495	0.507	0.498	0.494	0.499
t statistic	0.42	-0.68	0.80	-0.21	-0.61	-0.09
Panel D: Optimised Large Portfolios						
Portfolio	Value vs Growth	Profitability	Investment	Intangibles	Trading frictions	Momentum
1	0.494	0.512	0.500	0.523	0.519	0.512
10	0.502	0.496	0.500	0.491	0.493	0.495
t statistic	0.44	-0.95	0.00	-1.26	-1.37	-1.14

NN3 Quarterly rebalancing						
Panel A: Equal-weighted Portfolios						
Portfolio	Value vs Growth	Profitability	Investment	Intangibles	Trading frictions	Momentum
1	0.478	0.487	0.493	0.502	0.502	0.472
10	0.496	0.498	0.517	0.521	0.515	0.534
t statistic	1.58	1.24	2.08	1.06	1.67	5.22
Panel B: Value-weighted Portfolios						
Portfolio	Value vs Growth	Profitability	Investment	Intangibles	Trading frictions	Momentum
1	0.494	0.501	0.495	0.503	0.505	0.488
10	0.502	0.497	0.508	0.511	0.513	0.526
t statistic	0.82	-0.49	1.27	0.62	0.71	3.64
Panel C: Optimised Small Portfolios						
Portfolio	Value vs Growth	Profitability	Investment	Intangibles	Trading frictions	Momentum
1	0.490	0.509	0.484	0.501	0.506	0.495
10	0.504	0.496	0.507	0.499	0.497	0.502
t statistic	0.59	-0.65	0.93	-0.09	-0.35	0.31
Panel D: Optimised Large Portfolios						
Portfolio	Value vs Growth	Profitability	Investment	Intangibles	Trading frictions	Momentum
1	0.496	0.511	0.497	0.520	0.518	0.505
10	0.504	0.497	0.504	0.494	0.495	0.500
t statistic	0.36	-0.89	0.36	-1.08	-1.14	-0.35

NN4 Quarterly rebalancing						
Panel A: Equal-weighted Portfolios						
Portfolio	Value vs Growth	Profitability	Investment	Intangibles	Trading frictions	Momentum
1	0.479	0.487	0.493	0.503	0.502	0.470
10	0.496	0.497	0.516	0.518	0.513	0.536
t statistic	1.60	1.24	2.05	0.88	1.37	5.08
Panel B: Value-weighted Portfolios						
Portfolio	Value vs Growth	Profitability	Investment	Intangibles	Trading frictions	Momentum
1	0.494	0.500	0.495	0.503	0.506	0.486
10	0.500	0.497	0.506	0.511	0.511	0.528
t statistic	0.70	-0.44	1.14	0.58	0.49	3.93
Panel C: Optimised Small Portfolios						
Portfolio	Value vs Growth	Profitability	Investment	Intangibles	Trading frictions	Momentum
1	0.488	0.511	0.482	0.501	0.508	0.496
10	0.505	0.495	0.507	0.499	0.495	0.501
t statistic	0.62	-0.73	0.91	-0.09	-0.43	0.17
Panel D: Optimised Large Portfolios						
Portfolio	Value vs Growth	Profitability	Investment	Intangibles	Trading frictions	Momentum
1	0.498	0.508	0.498	0.518	0.516	0.504
10	0.503	0.498	0.504	0.493	0.495	0.501
t statistic	0.33	-0.80	0.41	-1.24	-1.26	-0.24

NN5 Quarterly rebalancing						
Panel A: Equal-weighted Portfolios						
Portfolio	Value vs Growth	Profitability	Investment	Intangibles	Trading frictions	Momentum
1	0.481	0.489	0.499	0.507	0.504	0.475
10	0.491	0.495	0.508	0.511	0.510	0.525
t statistic	1.06	0.89	1.36	0.28	0.95	4.97
Panel B: Value-weighted Portfolios						
Portfolio	Value vs Growth	Profitability	Investment	Intangibles	Trading frictions	Momentum
1	0.493	0.503	0.496	0.507	0.509	0.492
10	0.497	0.500	0.501	0.506	0.512	0.520
t statistic	0.31	-0.28	0.43	-0.03	0.23	2.65
Panel C: Optimised Small Portfolios						
Portfolio	Value vs Growth	Profitability	Investment	Intangibles	Trading frictions	Momentum
1	0.488	0.509	0.482	0.496	0.503	0.493
10	0.504	0.496	0.506	0.501	0.498	0.501
t statistic	0.64	-0.63	1.00	0.17	-0.22	0.33
Panel D: Optimised Large Portfolios						
Portfolio	Value vs Growth	Profitability	Investment	Intangibles	Trading frictions	Momentum
1	0.496	0.514	0.493	0.531	0.523	0.511
10	0.506	0.494	0.508	0.486	0.491	0.499
t statistic	0.33	-0.73	0.50	-1.15	-0.94	-0.49

Quarterly rebalancing – Mean across all models						
Panel A: Equal-weighted Portfolios						
Portfolio	Value vs Growth	Profitability	Investment	Intangibles	Trading frictions	Momentum
1	0.477	0.485	0.495	0.508	0.504	0.469
10	0.496	0.500	0.513	0.512	0.512	0.536
t statistic	1.614	1.662	1.796	0.308	0.997	4.966
Panel B: Value-weighted Portfolios						
Portfolio	Value vs Growth	Profitability	Investment	Intangibles	Trading frictions	Momentum
1	0.493	0.500	0.495	0.507	0.508	0.486
10	0.500	0.500	0.505	0.508	0.511	0.528
t statistic	0.674	0.020	1.030	0.087	0.324	3.694
Panel C: Optimised Small Portfolios						
Portfolio	Value vs Growth	Profitability	Investment	Intangibles	Trading frictions	Momentum
1	0.490	0.510	0.483	0.501	0.509	0.497
10	0.504	0.495	0.507	0.499	0.495	0.500
t statistic	0.536	-0.690	0.878	-0.057	-0.460	0.121
Panel D: Optimised Large Portfolios						
Portfolio	Value vs Growth	Profitability	Investment	Intangibles	Trading frictions	Momentum
1	0.496	0.511	0.497	0.522	0.518	0.508
10	0.504	0.497	0.504	0.492	0.494	0.499
t statistic	0.385	-0.814	0.323	-1.150	-1.154	-0.572

Appendix 3G: Realisation of predictive factors by functional category, annual rebalancing

Appendix 3G reports the mean value for the predictive factors when grouped in their functional category as described in Appendix 3A; Momentum, profitability, trading frictions, value vs. growth, intangibles and investment. The long-short portfolio is constructed by ranking stocks according to their machine learning predicted returns and form 10 portfolios, buying the highest quantile portfolio and selling the lowest quintile portfolio (High-minus-Low 'HML' portfolio). The factor realisations corresponding to the stocks chosen for the top and bottom portfolios are averaged cross-sectionally into the six categories and then averaged across time to generate the results in the table. The mean values of the lowest and highest deciles are compared based on the null hypothesis $H_0: \mu_{high} = \mu_{low}$ which examines whether the category realisations are significantly different between the two portfolios. The mean values are expressed in percentage basis. The Newey-West adjusted t statistics are presented in the parentheses. The results report the five neural network models, NN1-NN5, individually. The table is divided into four panels, A to D, which report the results for the equal-weighted, value-weighted, optimised portfolio trading a relatively small portfolio of 1 million USD and optimised portfolio trading a relatively large portfolio of 100 million USD, respectively. Investing horizon is twelve month and thus, rebalancing of the portfolio is performed annually based on predicted returns.

NN1 Annual rebalancing						
Panel A: Equal-weighted Portfolios						
Portfolio	Value vs Growth	Profitability	Investment	Intangibles	Trading frictions	Momentum
1	0.471	0.487	0.492	0.503	0.506	0.473
10	0.499	0.504	0.511	0.509	0.507	0.525
t statistic	2.46	2.03	1.66	0.32	0.13	4.08
Panel B: Value-weighted Portfolios						
Portfolio	Value vs Growth	Profitability	Investment	Intangibles	Trading frictions	Momentum
1	0.492	0.498	0.496	0.505	0.510	0.486
10	0.498	0.503	0.503	0.508	0.506	0.523
t statistic	0.72	0.60	0.83	0.24	-0.44	3.47
Panel C: Optimised Small Portfolios						
Portfolio	Value vs Growth	Profitability	Investment	Intangibles	Trading frictions	Momentum
1	0.494	0.510	0.488	0.505	0.513	0.503
10	0.505	0.494	0.508	0.497	0.492	0.499
t statistic	0.45	-0.84	0.79	-0.32	-0.81	-0.20
Panel D: Optimised Large Portfolios						
Portfolio	Value vs Growth	Profitability	Investment	Intangibles	Trading frictions	Momentum
1	0.491	0.513	0.487	0.514	0.515	0.502
10	0.505	0.494	0.507	0.494	0.494	0.500
t statistic	0.53	-0.88	0.78	-0.65	-0.75	-0.13

NN2 Annual rebalancing						
Panel A: Equal-weighted Portfolios						
Portfolio	Value vs Growth	Profitability	Investment	Intangibles	Trading frictions	Momentum
1	0.476	0.486	0.499	0.511	0.504	0.471
10	0.502	0.502	0.510	0.503	0.510	0.529
t statistic	2.17	1.81	1.36	-0.42	0.70	3.90
Panel B: Value-weighted Portfolios						
Portfolio	Value vs Growth	Profitability	Investment	Intangibles	Trading frictions	Momentum
1	0.495	0.498	0.499	0.509	0.507	0.486
10	0.500	0.501	0.505	0.503	0.511	0.524
t statistic	0.71	0.40	0.81	-0.57	0.47	3.53
Panel C: Optimised Small Portfolios						
Portfolio	Value vs Growth	Profitability	Investment	Intangibles	Trading frictions	Momentum
1	0.493	0.515	0.484	0.510	0.518	0.507
10	0.504	0.492	0.509	0.494	0.490	0.496
t statistic	0.33	-0.86	0.74	-0.43	-0.80	-0.35
Panel D: Optimised Large Portfolios						
Portfolio	Value vs Growth	Profitability	Investment	Intangibles	Trading frictions	Momentum
1	0.493	0.519	0.486	0.520	0.523	0.508
10	0.503	0.497	0.505	0.498	0.497	0.500
t statistic	0.32	-0.84	0.64	-0.64	-0.79	-0.32
NN3 Annual rebalancing						
Panel A: Equal-weighted Portfolios						
Portfolio	Value vs Growth	Profitability	Investment	Intangibles	Trading frictions	Momentum
1	0.485	0.494	0.496	0.499	0.499	0.481
10	0.496	0.495	0.514	0.521	0.514	0.522
t statistic	1.19	0.17	1.79	1.66	1.95	4.53
Panel B: Value-weighted Portfolios						
Portfolio	Value vs Growth	Profitability	Investment	Intangibles	Trading frictions	Momentum
1	0.498	0.503	0.497	0.501	0.504	0.492
10	0.500	0.495	0.507	0.510	0.514	0.520
t statistic	0.23	-1.35	1.31	1.01	1.11	3.50
Panel C: Optimised Small Portfolios						
Portfolio	Value vs Growth	Profitability	Investment	Intangibles	Trading frictions	Momentum
1	0.491	0.513	0.485	0.504	0.511	0.502
10	0.505	0.494	0.508	0.498	0.495	0.499
t statistic	0.51	-0.86	0.84	-0.19	-0.53	-0.09
Panel D: Optimised Large Portfolios						
Portfolio	Value vs Growth	Profitability	Investment	Intangibles	Trading frictions	Momentum
1	0.492	0.517	0.486	0.514	0.517	0.506
10	0.503	0.498	0.504	0.499	0.498	0.501
t statistic	0.39	-0.84	0.67	-0.49	-0.63	-0.22

NN4 Annual rebalancing						
Panel A: Equal-weighted Portfolios						
Portfolio	Value vs Growth	Profitability	Investment	Intangibles	Trading frictions	Momentum
1	0.485	0.493	0.497	0.500	0.499	0.481
10	0.497	0.492	0.514	0.521	0.513	0.521
t statistic	1.17	-0.11	1.78	1.48	1.85	4.36
Panel B: Value-weighted Portfolios						
Portfolio	Value vs Growth	Profitability	Investment	Intangibles	Trading frictions	Momentum
1	0.497	0.503	0.498	0.502	0.503	0.491
10	0.499	0.494	0.504	0.511	0.512	0.520
t statistic	0.24	-1.28	0.81	0.96	1.17	3.36
Panel C: Optimised Small Portfolios						
Portfolio	Value vs Growth	Profitability	Investment	Intangibles	Trading frictions	Momentum
1	0.490	0.513	0.485	0.505	0.512	0.502
10	0.505	0.494	0.508	0.498	0.495	0.499
t statistic	0.53	-0.82	0.80	-0.22	-0.55	-0.10
Panel D: Optimised Large Portfolios						
Portfolio	Value vs Growth	Profitability	Investment	Intangibles	Trading frictions	Momentum
1	0.491	0.509	0.483	0.505	0.508	0.496
10	0.502	0.499	0.504	0.500	0.499	0.501
t statistic	0.56	-0.63	1.01	-0.25	-0.38	0.26
NN5 Annual rebalancing						
Panel A: Equal-weighted Portfolios						
Portfolio	Value vs Growth	Profitability	Investment	Intangibles	Trading frictions	Momentum
1	0.486	0.496	0.498	0.499	0.501	0.486
10	0.491	0.495	0.508	0.513	0.509	0.514
t statistic	0.67	-0.38	1.39	1.23	1.50	4.52
Panel B: Value-weighted Portfolios						
Portfolio	Value vs Growth	Profitability	Investment	Intangibles	Trading frictions	Momentum
1	0.495	0.507	0.496	0.504	0.507	0.497
10	0.497	0.500	0.501	0.507	0.512	0.517
t statistic	0.15	-0.64	0.35	0.19	0.40	1.74
Panel C: Optimised Small Portfolios						
Portfolio	Value vs Growth	Profitability	Investment	Intangibles	Trading frictions	Momentum
1	0.493	0.516	0.484	0.511	0.521	0.508
10	0.504	0.492	0.509	0.494	0.489	0.496
t statistic	0.32	-0.84	0.73	-0.43	-0.82	-0.37
Panel D: Optimised Large Portfolios						
Portfolio	Value vs Growth	Profitability	Investment	Intangibles	Trading frictions	Momentum
1	0.496	0.518	0.489	0.517	0.521	0.510
10	0.502	0.497	0.504	0.498	0.497	0.500
t statistic	0.22	-0.88	0.55	-0.63	-0.79	-0.44

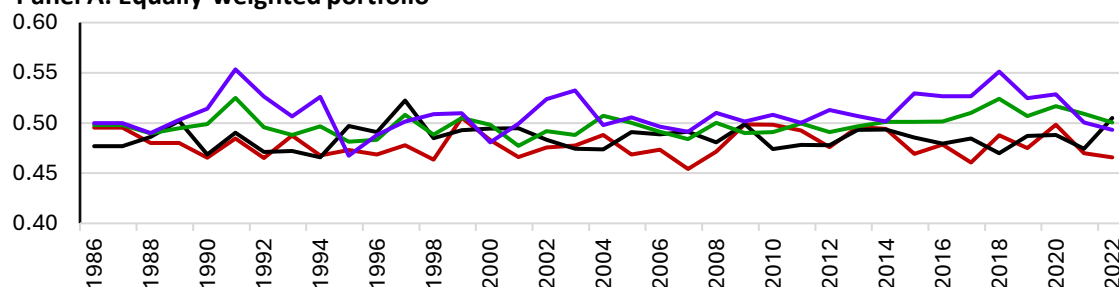
Panel C: Annual rebalancing – Mean across all models						
Panel A: Equal-weighted Portfolios						
Portfolio	Value vs Growth	Profitability	Investment	Intangibles	Trading frictions	Momentum
1	0.481	0.491	0.496	0.502	0.502	0.478
10	0.497	0.498	0.511	0.513	0.511	0.522
t statistic	1.533	0.704	1.598	0.852	1.224	4.276
Panel B: Value-weighted Portfolios						
Portfolio	Value vs Growth	Profitability	Investment	Intangibles	Trading frictions	Momentum
1	0.495	0.502	0.497	0.504	0.506	0.490
10	0.499	0.499	0.504	0.508	0.511	0.521
t statistic	0.410	-0.453	0.822	0.365	0.543	3.119
Panel C: Optimised Small Portfolios						
Portfolio	Value vs Growth	Profitability	Investment	Intangibles	Trading frictions	Momentum
1	0.492	0.513	0.485	0.507	0.515	0.504
10	0.505	0.493	0.508	0.496	0.492	0.498
t statistic	0.427	-0.845	0.777	-0.317	-0.702	-0.223
Panel D: Optimised Large Portfolios						
Portfolio	Value vs Growth	Profitability	Investment	Intangibles	Trading frictions	Momentum
1	0.493	0.515	0.486	0.514	0.517	0.504
10	0.503	0.497	0.505	0.498	0.497	0.500
t statistic	0.403	-0.815	0.731	-0.533	-0.668	-0.171

Appendix 3H: Realisation of fundamental-based factors across time, monthly rebalancing

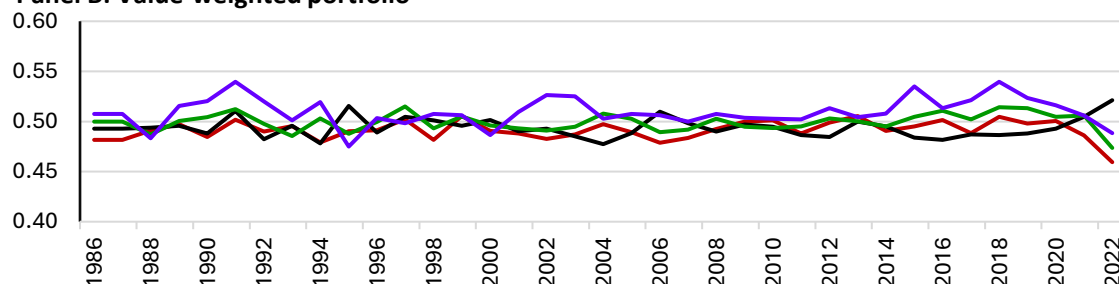
Appendix 3H reports the mean value for fundamental-based predictive factors across time. Stocks are ranked according to their machine learning predicted returns and form 10 portfolios. The bottom portfolio is constructed by selling the lowest quintile, the top portfolio is constructed by buying the highest quintile and the HML portfolio is constructed by buying the highest quintile portfolio and selling the lowest quintile portfolio. The factor realisations corresponding to the stocks chosen in the portfolio are averaged cross-sectionally into four categories of fundamental factors. The allocation of factors in their functional category is described in Appendix 3A. In the figure the value vs. growth category is depicted in red, the profitability category is depicted in blue, the investment category is depicted in green, and the intangibles category is depicted in purple. The table is divided into four panels, A to D, which report the results for the equal-weighted, value-weighted, optimised portfolio trading a relatively small portfolio of 1 million USD and optimised portfolio trading a relatively large portfolio of 100 million USD, respectively. Investing horizon is one month and thus, rebalancing of the portfolio is performed monthly based on predicted returns.

Bottom portfolio

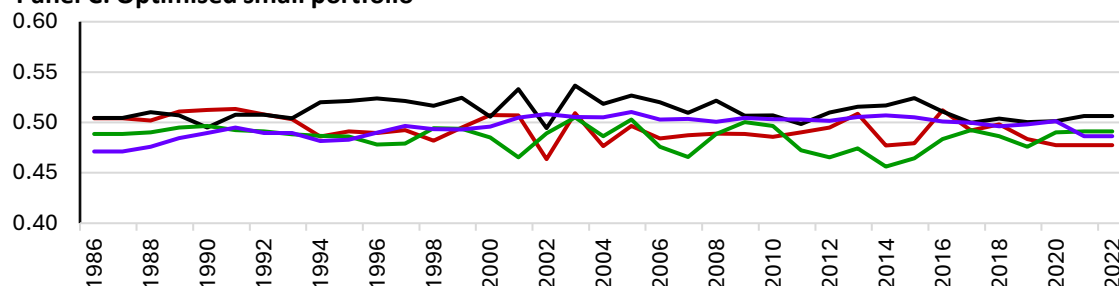
Panel A: Equally-weighted portfolio



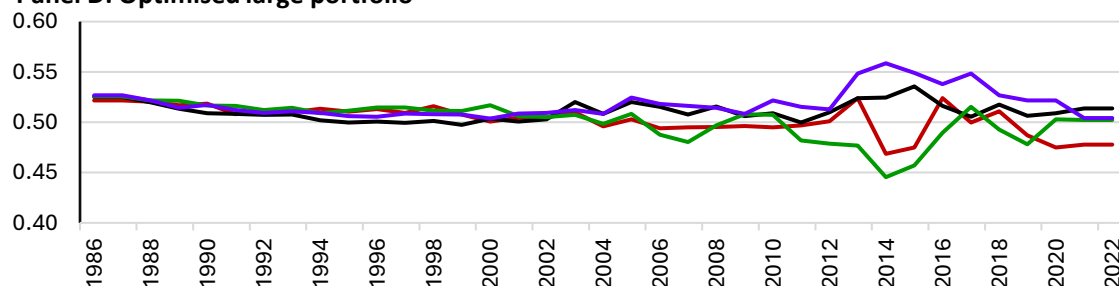
Panel B: Value-weighted portfolio



Panel C: Optimised small portfolio



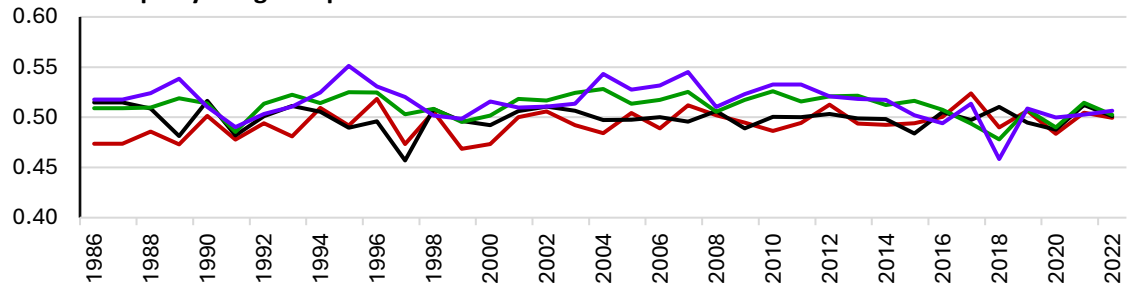
Panel D: Optimised large portfolio



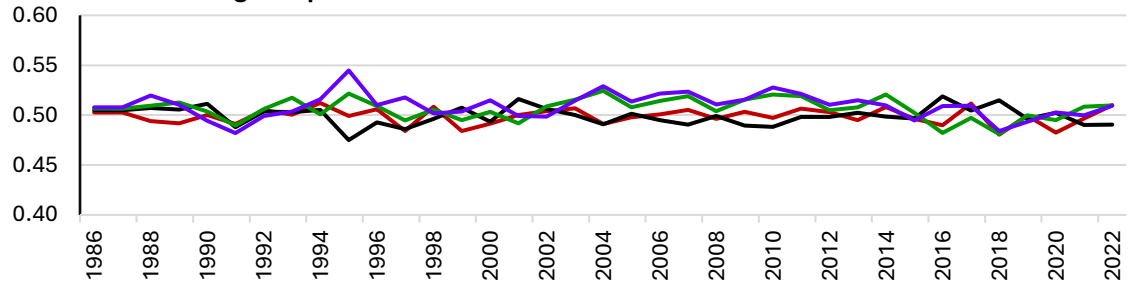
— Value-versus-growth — Profitability — Investment — Intangibles

Top portfolio

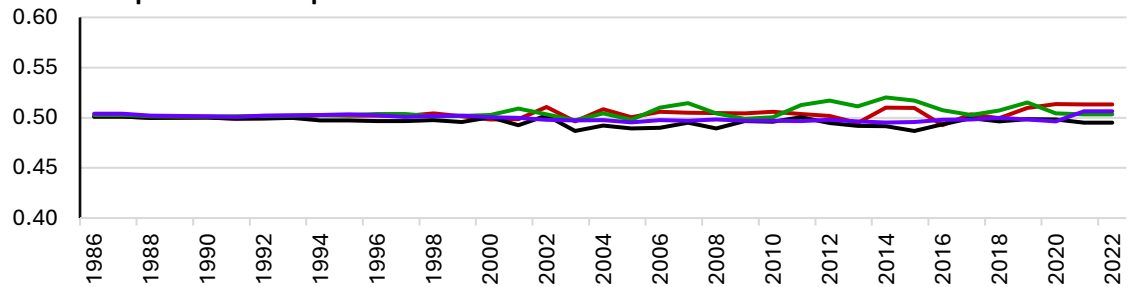
Panel A: Equally-weighted portfolio



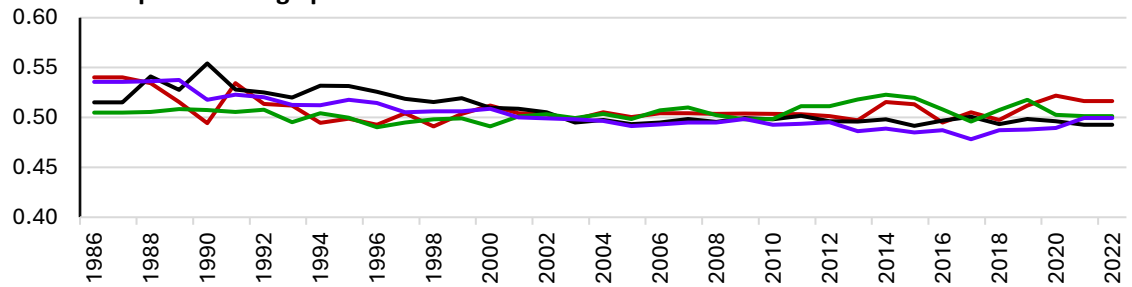
Panel B: Value-weighted portfolio



Panel C: Optimised small portfolio



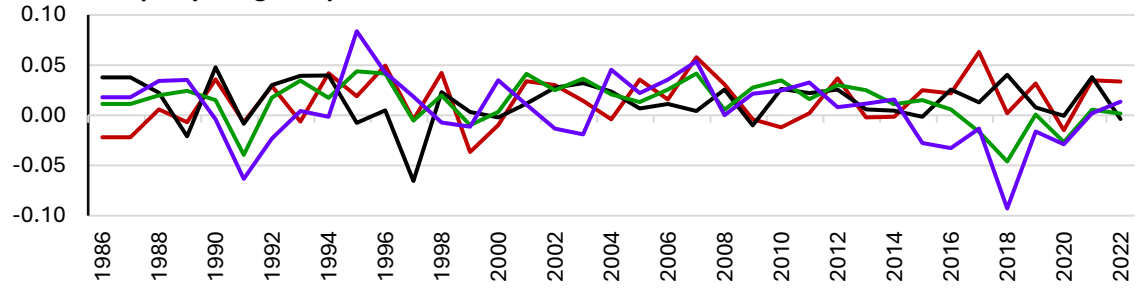
Panel D: Optimised large portfolio



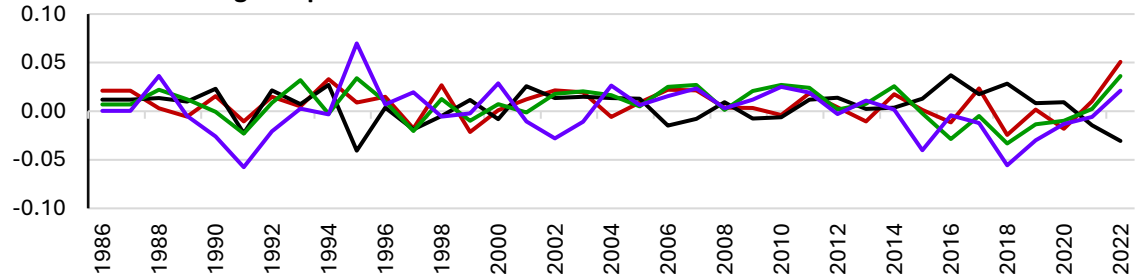
Value-versus-growth Profitability Investment Intangibles

HML portfolio

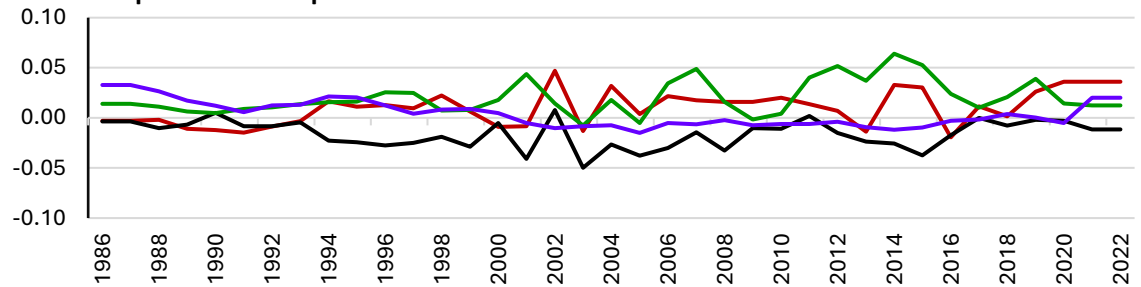
Panel A: Equally-weighted portfolio



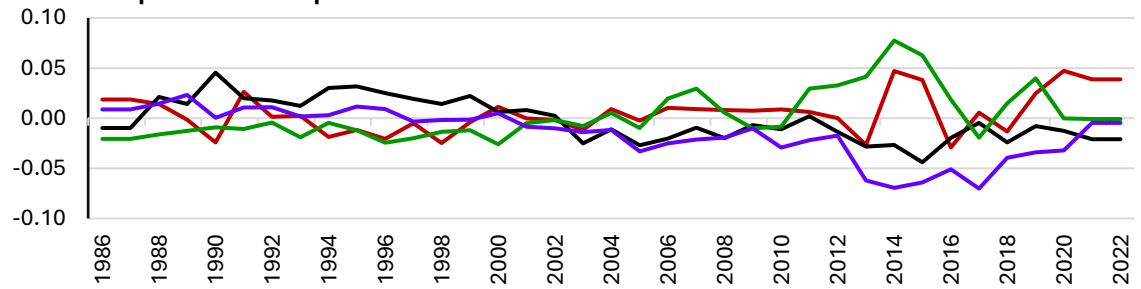
Panel B: Value-weighted portfolio



Panel C: Optimised small portfolio



Panel D: Optimised small portfolio



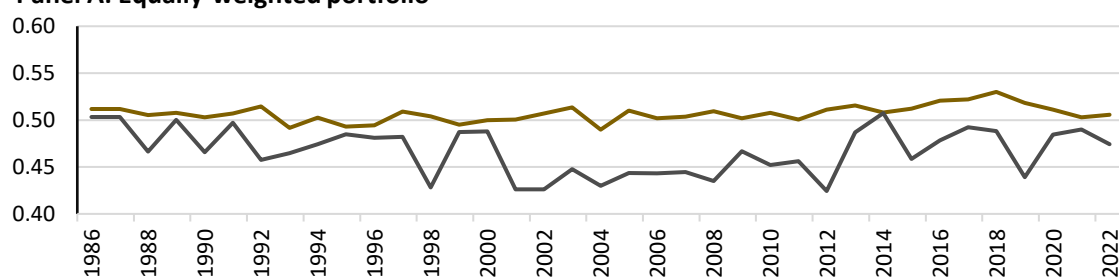
Value-versus-growth Profitability Investment Intangibles

Appendix 3I: Realisation of market-based factors across time, monthly rebalancing

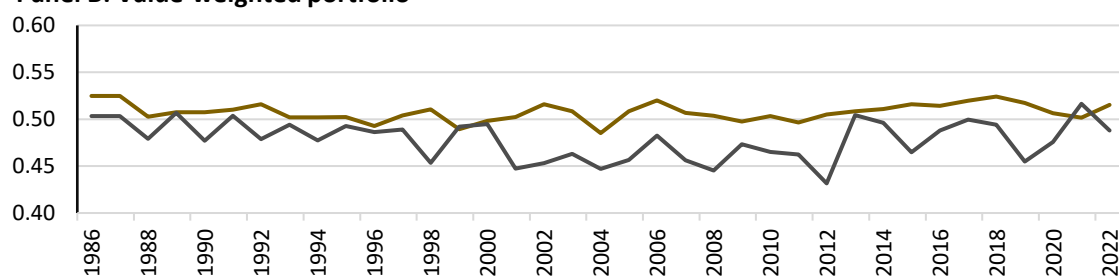
Appendix 3I reports the mean value for market-based predictive factors across time. Stocks are ranked according to their machine learning predicted returns and form 10 portfolios. The bottom portfolio is constructed by selling the lowest quintile, the top portfolio is constructed by buying the highest quintile and the HML portfolio is constructed by buying the highest quantile portfolio and selling the lowest quintile portfolio. The factor realisations corresponding to the stocks chosen in the portfolio are averaged cross-sectionally into four categories of market factors. The allocation of factors in their functional category is described in Appendix 3A. In the figure the trading frictions factor is depicted in gold and the momentum factor is depicted in silver. The table is divided into four panels, A to D, which report the results for the equal-weighted, value-weighted, optimised portfolio trading a relatively small portfolio of 1 million USD and optimised portfolio trading a relatively large portfolio of 100 million USD, respectively. Investing horizon is one month and thus, rebalancing of the portfolio is performed monthly based on predicted returns.

Bottom portfolio

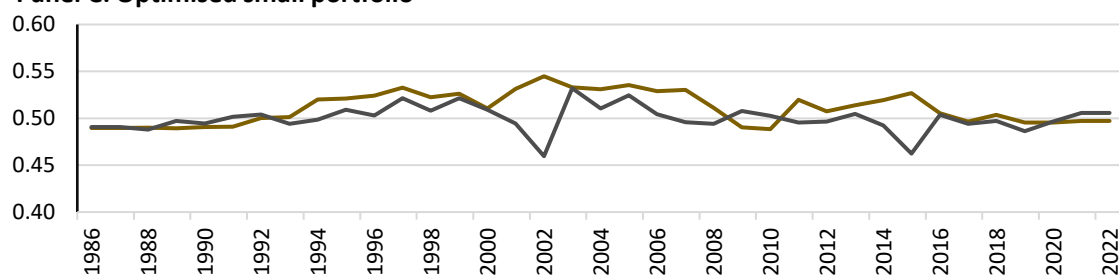
Panel A: Equally-weighted portfolio



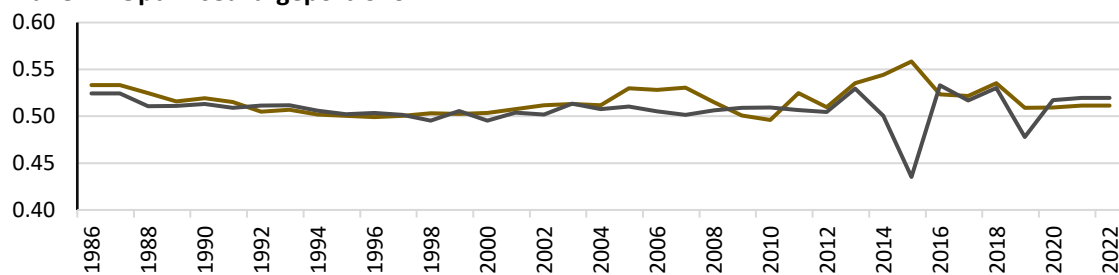
Panel B: Value-weighted portfolio



Panel C: Optimised small portfolio



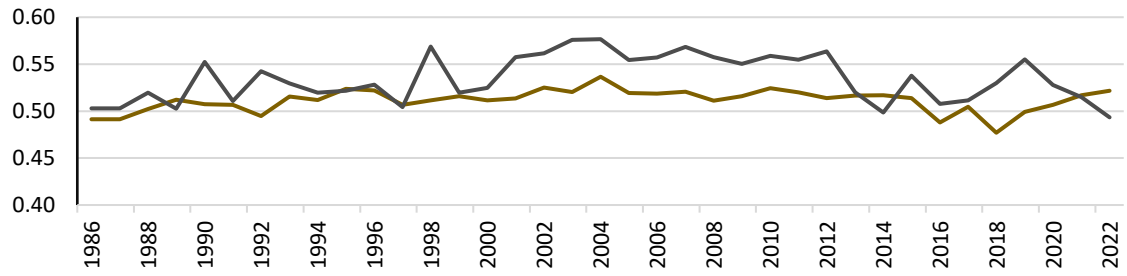
Panel D: Optimised largeportfolio



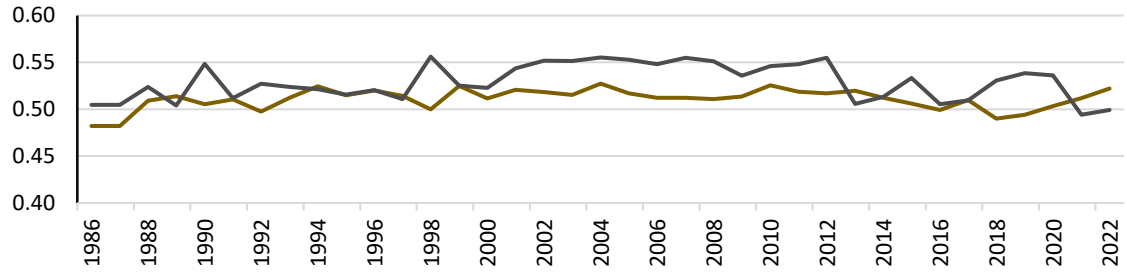
— Trading frictions — Momentum

Top portfolio

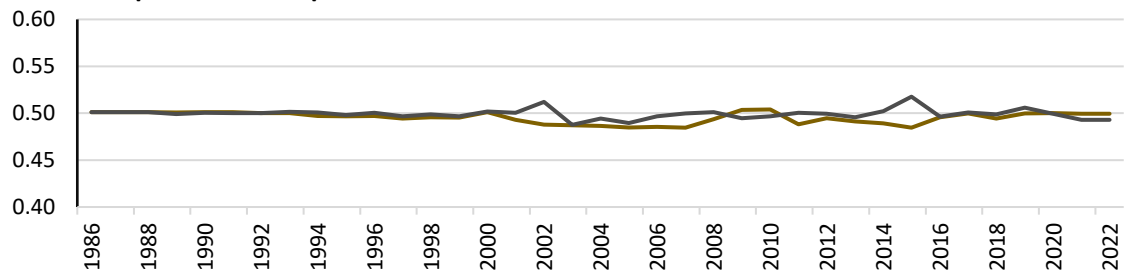
Panel A: Equally-weighted portfolio



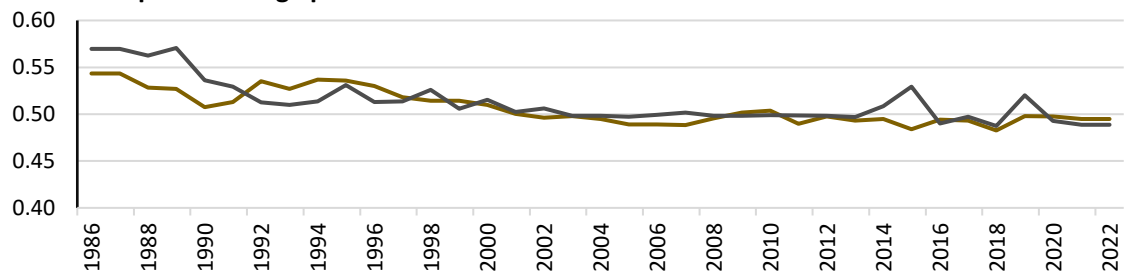
Panel B: Value-weighted portfolio



Panel C: Optimised small portfolio



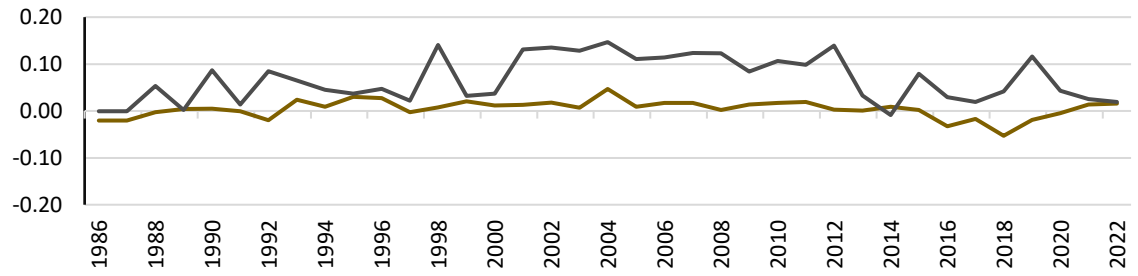
Panel D: Optimised large portfolio



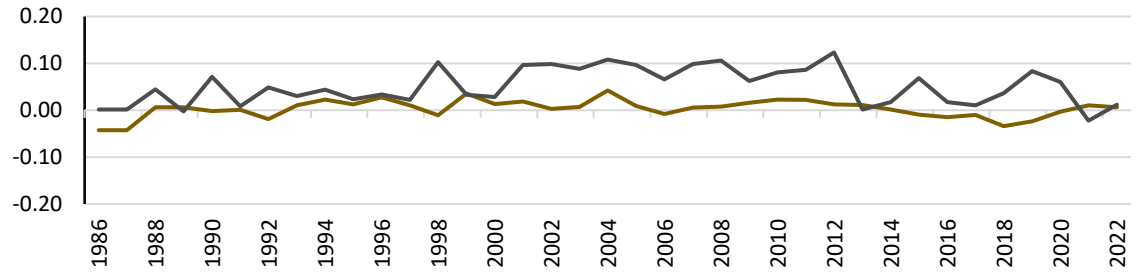
— Trading frictions — Momentum

HML portfolio

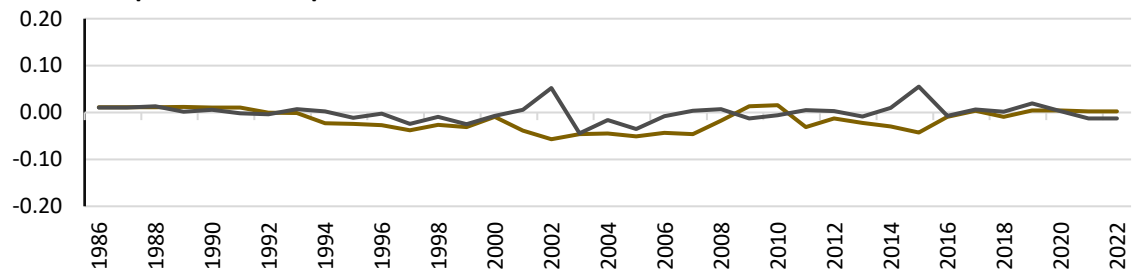
Panel A: Equally-weighted portfolio



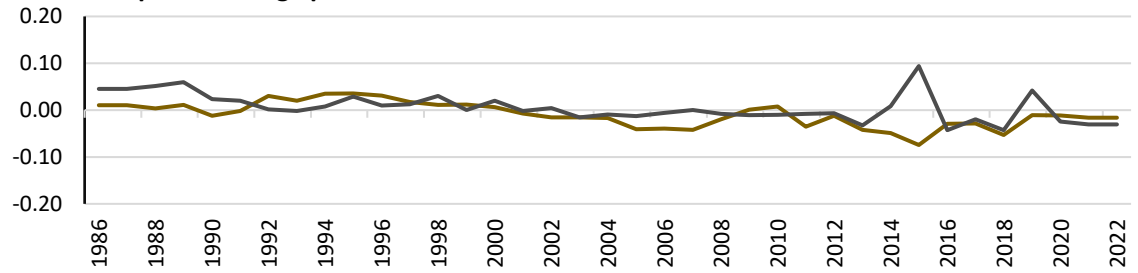
Panel B: Value-weighted portfolio



Panel C: Optimised small portfolio



Panel D: Optimised large portfolio



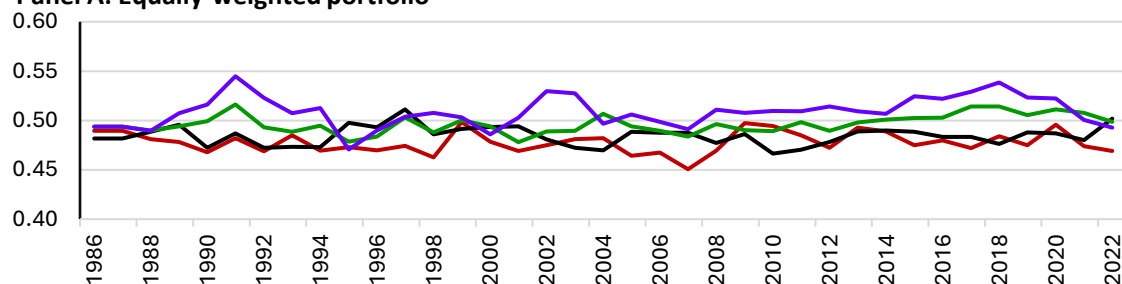
— Trading frictions — Momentum

Appendix 3J: Realisation of fundamental-based factors across time, quarterly rebalancing

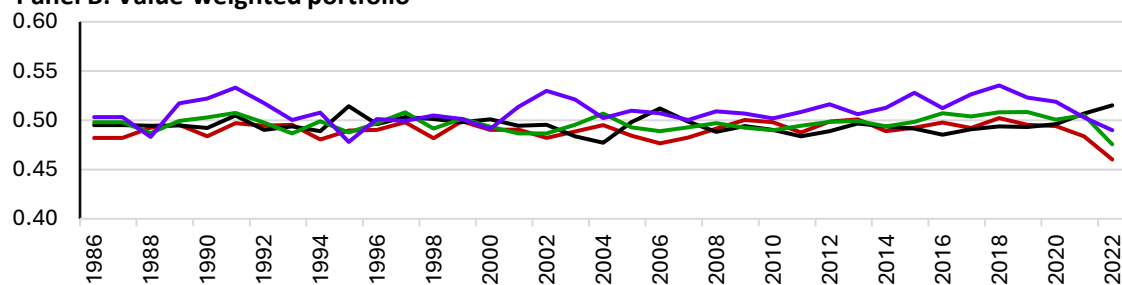
Appendix 3J reports the mean value for fundamental-based predictive factors across time. Stocks are ranked according to their machine learning predicted returns and form 10 portfolios. The bottom portfolio is constructed by selling the lowest quintile, the top portfolio is constructed by buying the highest quintile and the HML portfolio is constructed by buying the highest quintile portfolio and selling the lowest quintile portfolio. The factor realisations corresponding to the stocks chosen in the portfolio are averaged cross-sectionally into four categories of fundamental factors. The allocation of factors in their functional category is described in Appendix 3A. In the figure the value vs. growth category is depicted in red, the profitability category is depicted in blue, the investment category is depicted in green, and the intangibles category is depicted in purple. The table is divided into four panels, A to D, which report the results for the equal-weighted, value-weighted, optimised portfolio trading a relatively small portfolio of 1 million USD and optimised portfolio trading a relatively large portfolio of 100 million USD, respectively. Investing horizon is three months and thus, rebalancing of the portfolio is performed quarterly based on predicted returns.

Bottom portfolio

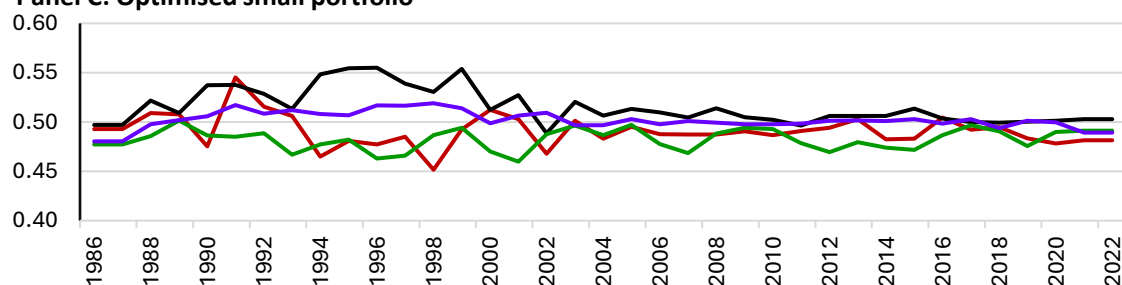
Panel A: Equally-weighted portfolio



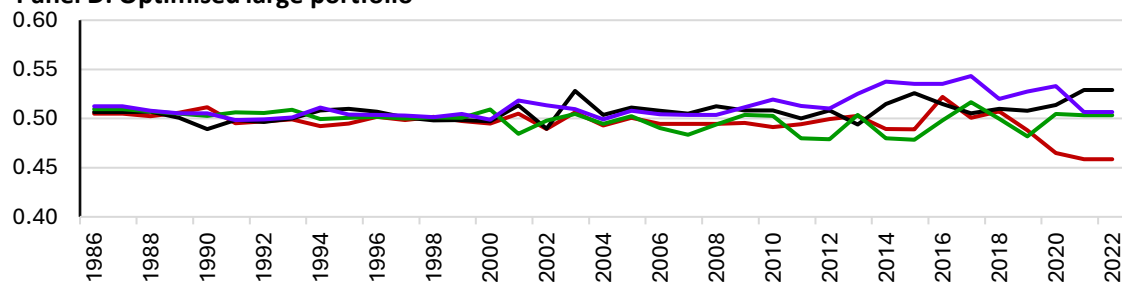
Panel B: Value-weighted portfolio



Panel C: Optimised small portfolio



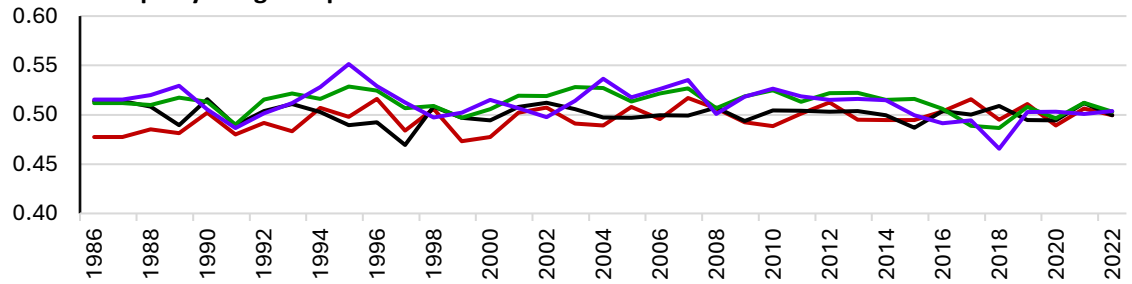
Panel D: Optimised large portfolio



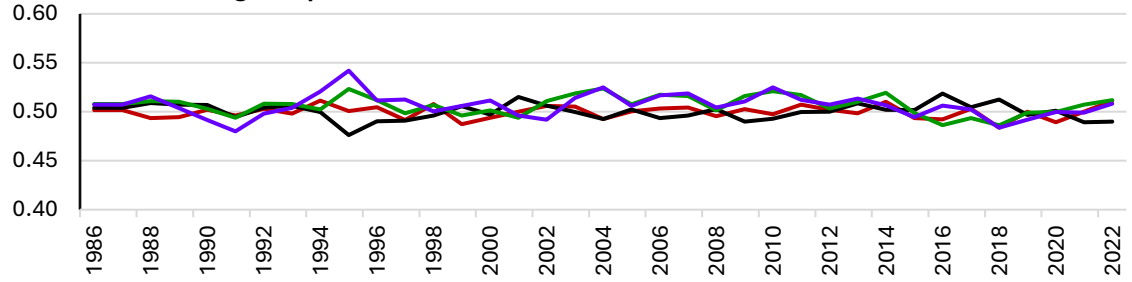
— Value-versus-growth — Profitability — Investment — Intangibles

Top portfolio

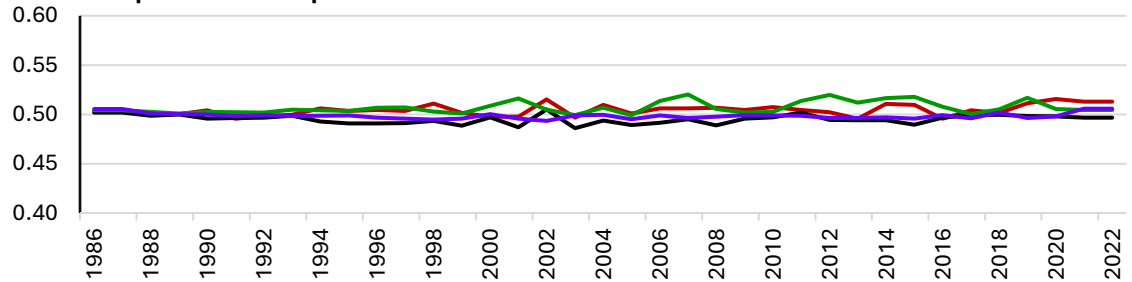
Panel A: Equally-weighted portfolio



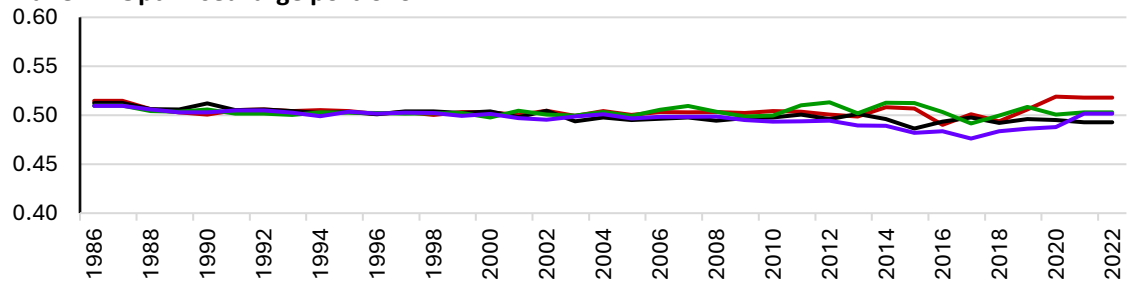
Panel B: Value-weighted portfolio



Panel C: Optimised small portfolio



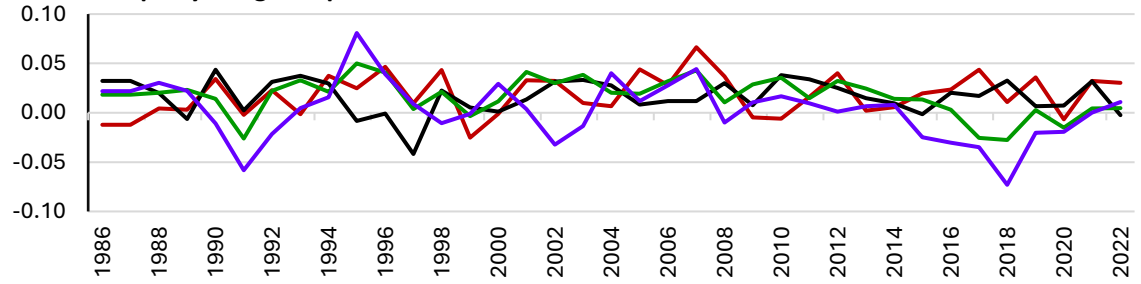
Panel D: Optimised large portfolio



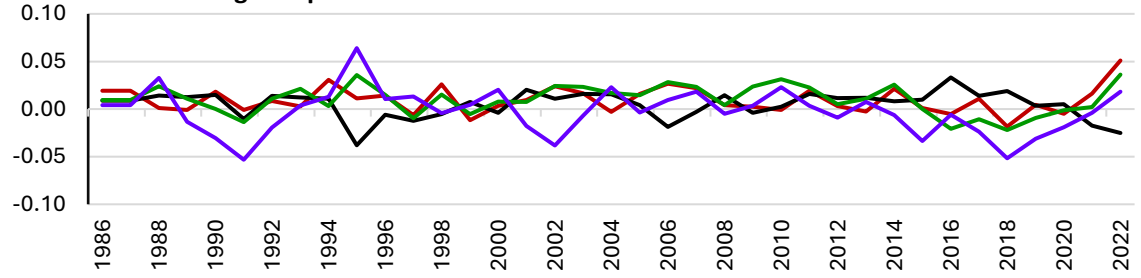
Value-versus-growth Profitability Investment Intangibles

HML portfolio

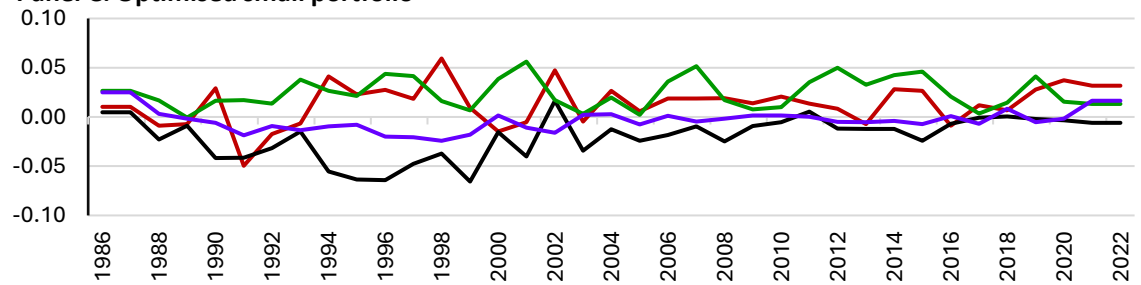
Panel A: Equally-weighted portfolio



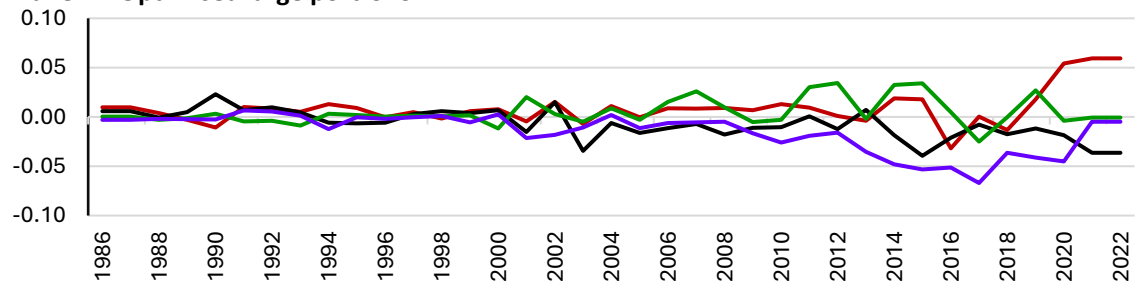
Panel B: Value-weighted portfolio



Panel C: Optimised small portfolio



Panel D: Optimised large portfolio



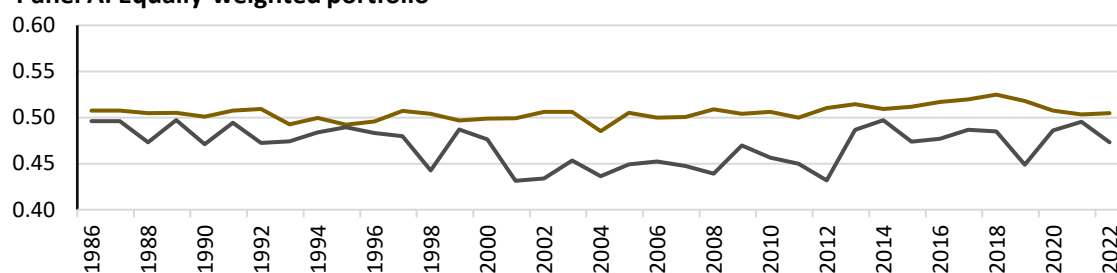
Value-versus-growth Profitability Investment Intangibles

Appendix 3K: Realisation of market-based factors across time, quarterly rebalancing

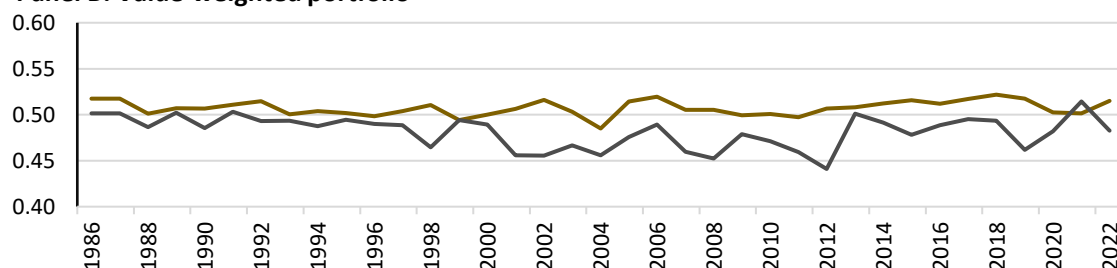
Appendix 3K reports the mean value for market-based predictive factors across time. Stocks are ranked according to their machine learning predicted returns and form 10 portfolios. The bottom portfolio is constructed by selling the lowest quintile, the top portfolio is constructed by buying the highest quintile and the HML portfolio is constructed by buying the highest quantile portfolio and selling the lowest quintile portfolio. The factor realisations corresponding to the stocks chosen in the portfolio are averaged cross-sectionally into four categories of market factors. The allocation of factors in their functional category is described in Appendix 3A. In the figure the trading frictions factor is depicted in gold and the momentum factor is depicted in silver. The table is divided into four panels, A to D, which report the results for the equal-weighted, value-weighted, optimised portfolio trading a relatively small portfolio of 1 million USD and optimised portfolio trading a relatively large portfolio of 100 million USD, respectively. Investing horizon is three month and thus, rebalancing of the portfolio is performed quarterly based on predicted returns.

Bottom portfolio

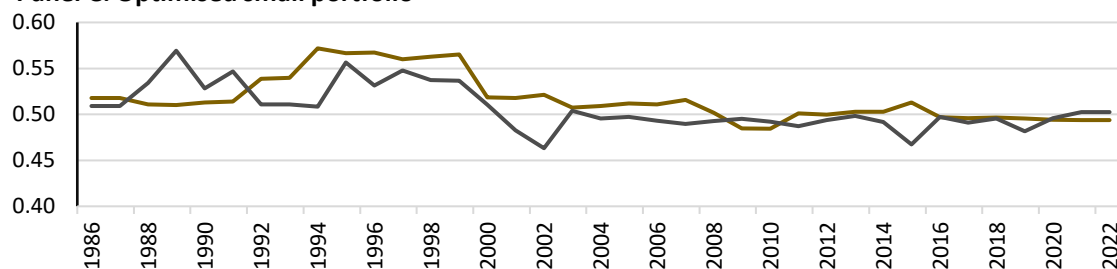
Panel A: Equally-weighted portfolio



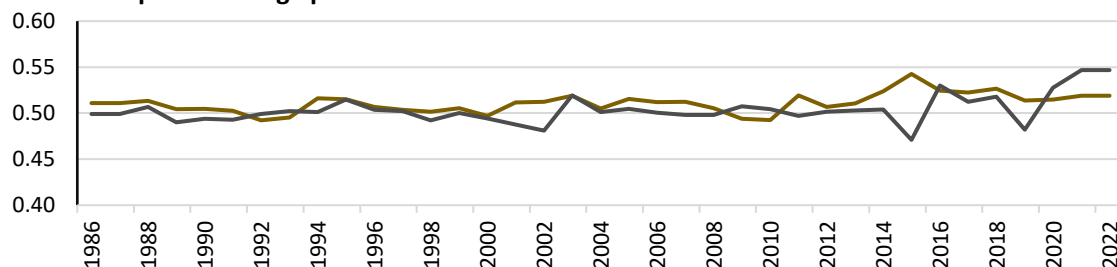
Panel B: Value-weighted portfolio



Panel C: Optimised small portfolio



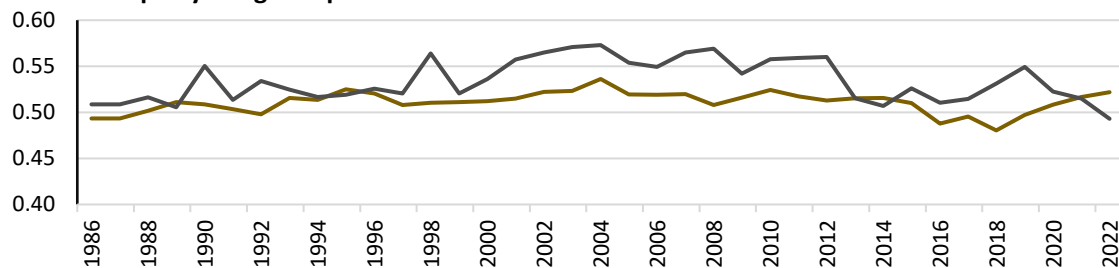
Panel D: Optimised large portfolio



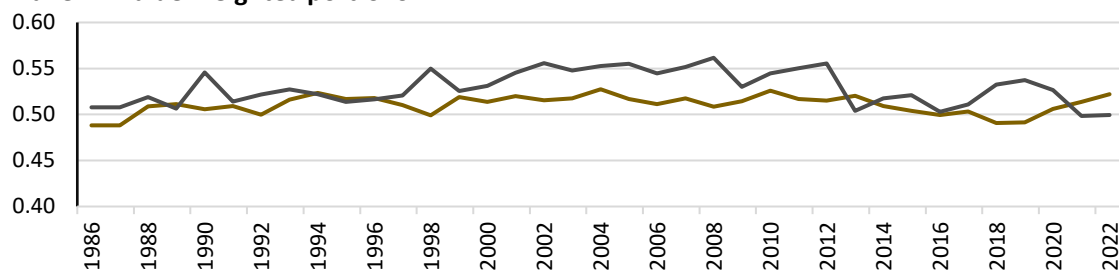
— Trading frictions — Momentum

Top portfolio

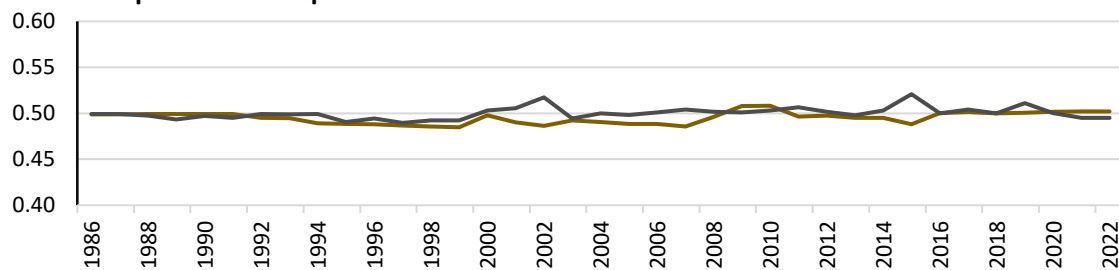
Panel A: Equally-weighted portfolio



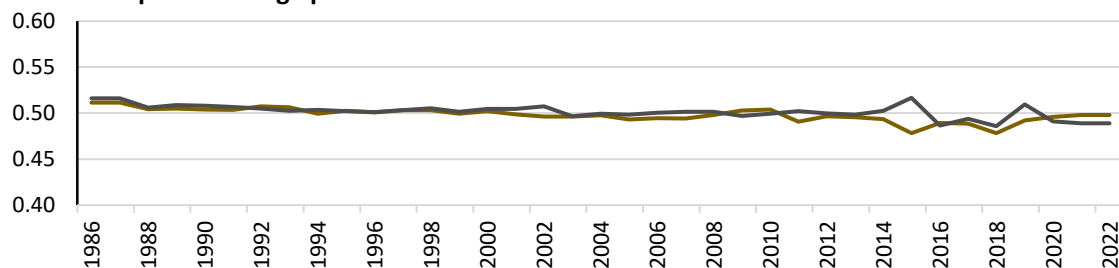
Panel B: Value-weighted portfolio



Panel C: Optimised small portfolio



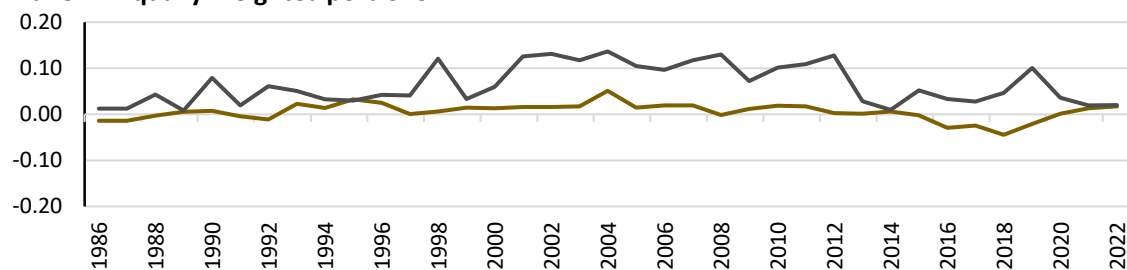
Panel D: Optimised large portfolio



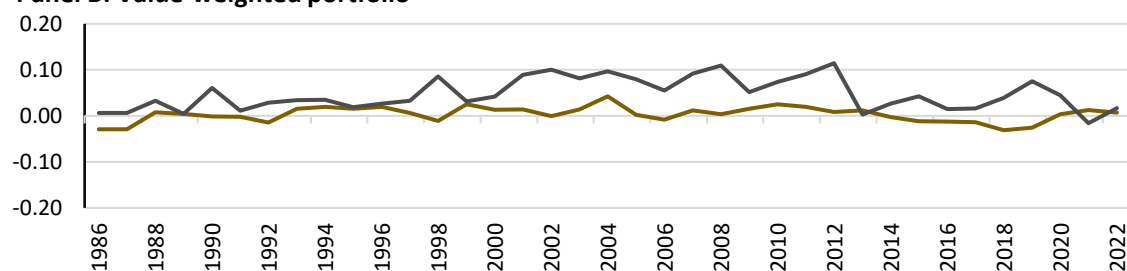
— Trading frictions — Momentum

HML portfolio

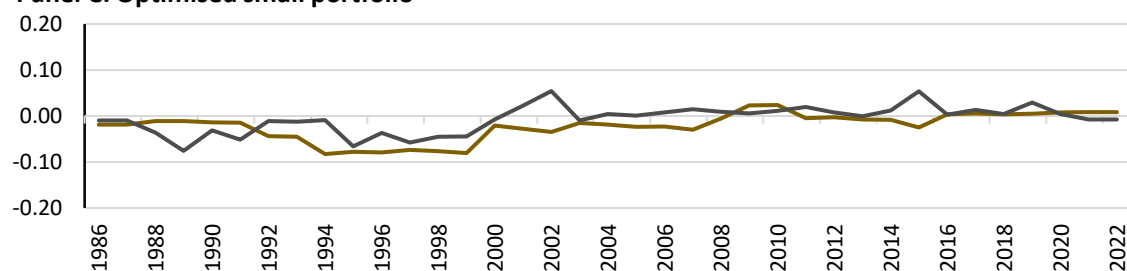
Panel A: Equally-weighted portfolio



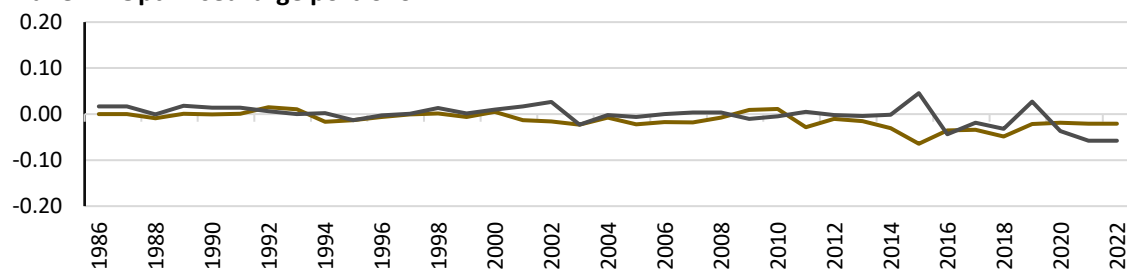
Panel B: Value-weighted portfolio



Panel C: Optimised small portfolio



Panel D: Optimised large portfolio



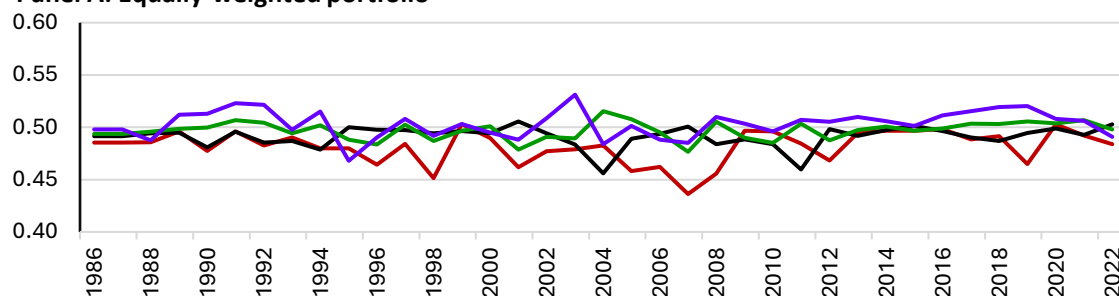
— Trading frictions — Momentum

Appendix 3L: Realisation of fundamental-based factors across time, annual rebalancing

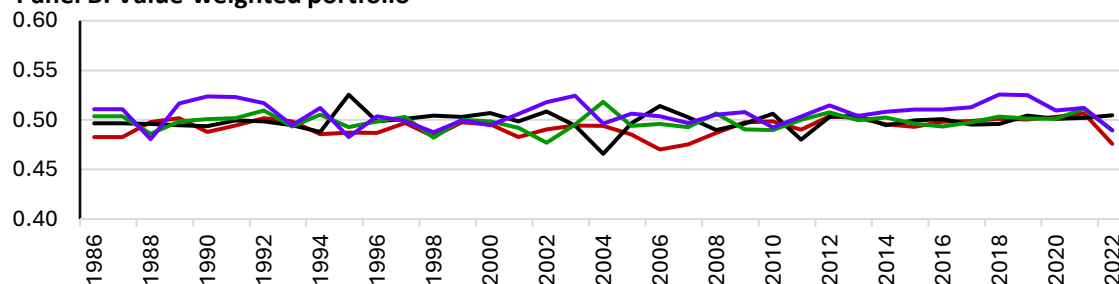
Appendix 3L reports the mean value for fundamental-based predictive factors across time. Stocks are ranked according to their machine learning predicted returns and form 10 portfolios. The bottom portfolio is constructed by selling the lowest quintile, the top portfolio is constructed by buying the highest quintile and the HML portfolio is constructed by buying the highest quintile portfolio and selling the lowest quintile portfolio. The factor realisations corresponding to the stocks chosen in the portfolio are averaged cross-sectionally into four categories of fundamental factors. The allocation of factors in their functional category is described in Appendix 3A. In the figure the value vs. growth category is depicted in red, the profitability category is depicted in blue, the investment category is depicted in green, and the intangibles category is depicted in purple. The table is divided into four panels, A to D, which report the results for the equal-weighted, value-weighted, optimised portfolio trading a relatively small portfolio of 1 million USD and optimised portfolio trading a relatively large portfolio of 100 million USD, respectively. Investing horizon is twelve months and thus, rebalancing of the portfolio is performed annually based on predicted returns.

Bottom portfolio

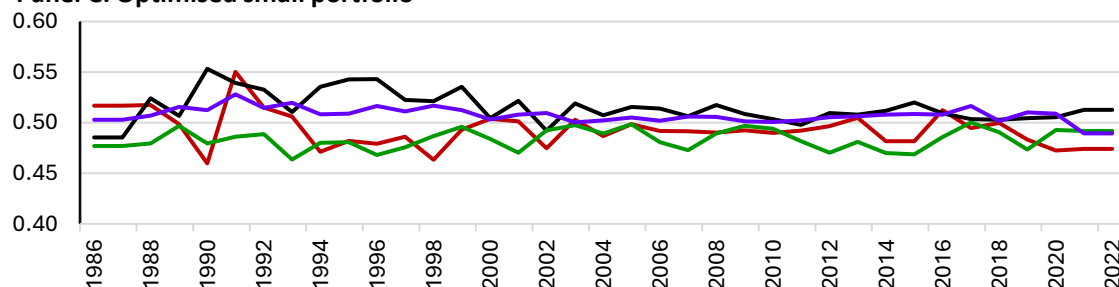
Panel A: Equally-weighted portfolio



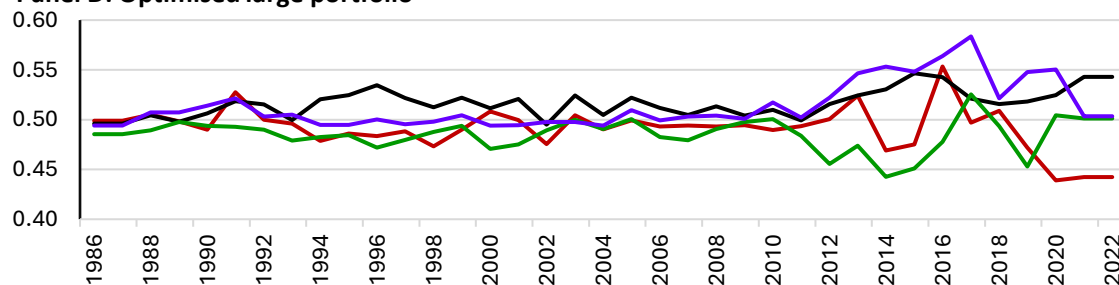
Panel B: Value-weighted portfolio



Panel C: Optimised small portfolio



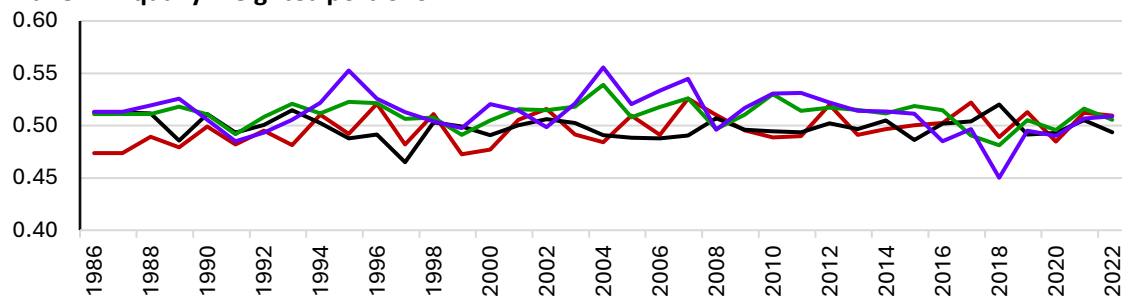
Panel D: Optimised large portfolio



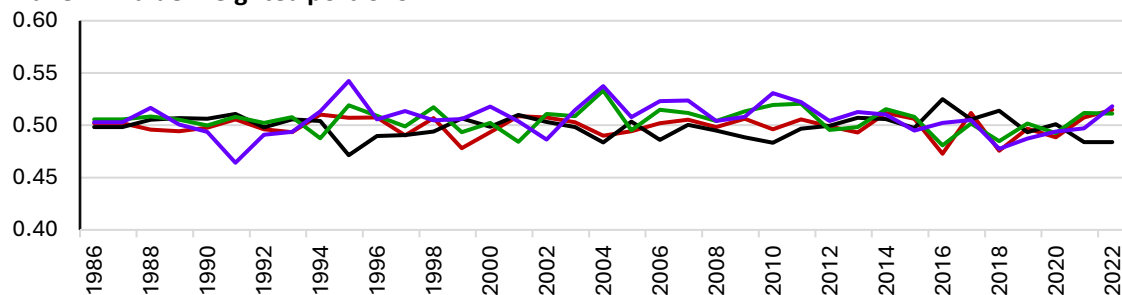
— Value-versus-growth — Profitability — Investment — Intangibles

Top portfolio

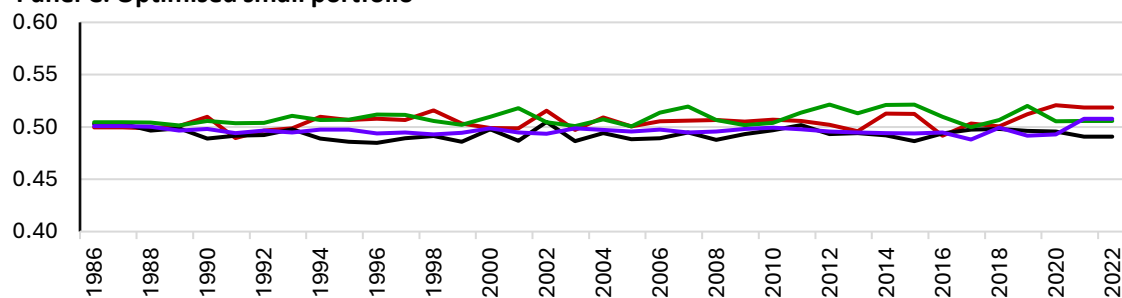
Panel A: Equally-weighted portfolio



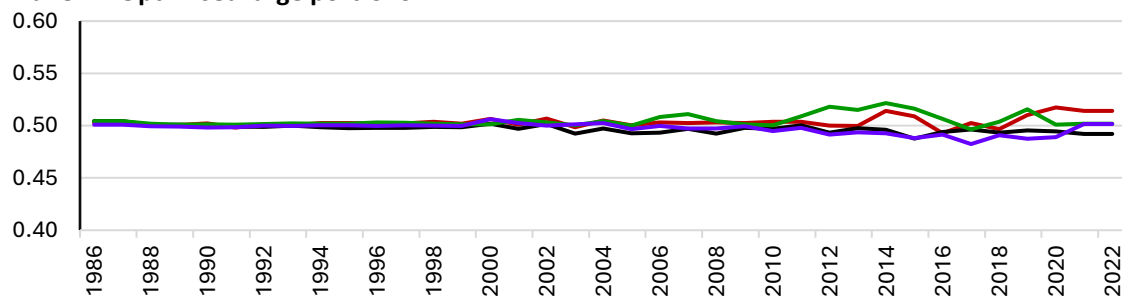
Panel B: Value-weighted portfolio



Panel C: Optimised small portfolio



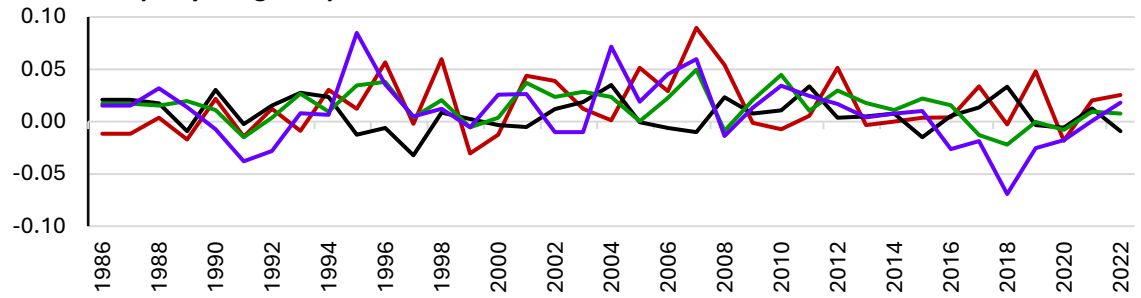
Panel D: Optimised large portfolio



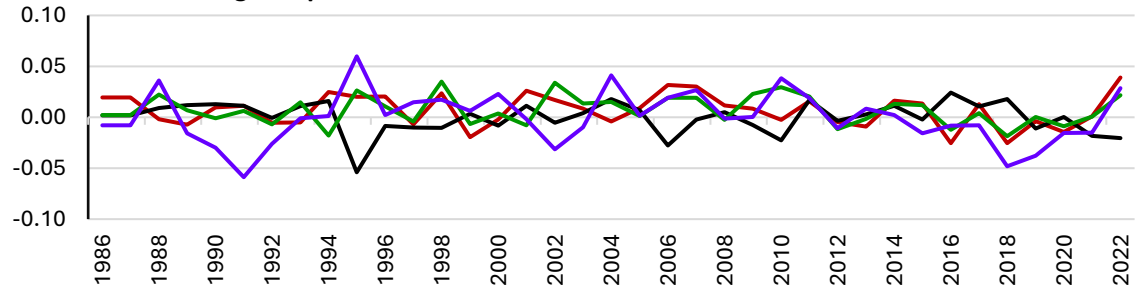
Value-versus-growth Profitability Investment Intangibles

HML portfolio

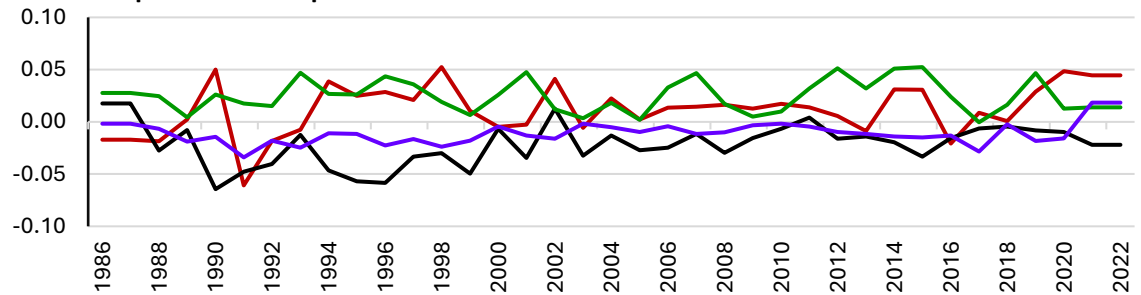
Panel A: Equally-weighted portfolio



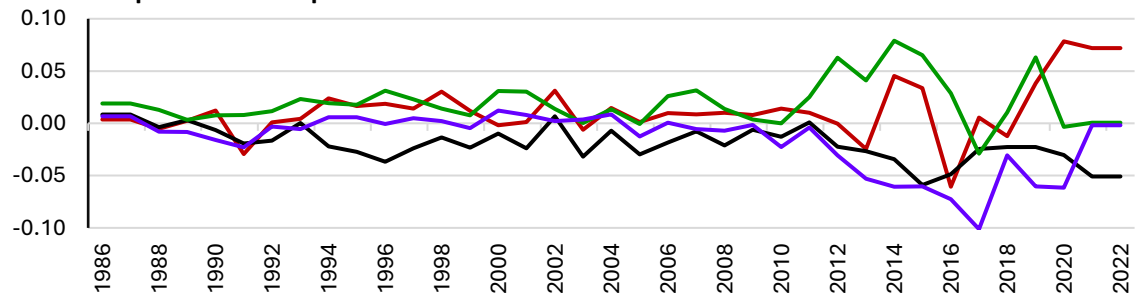
Panel B: Value-weighted portfolio



Panel C: Optimised small portfolio



Panel C: Optimised small portfolio



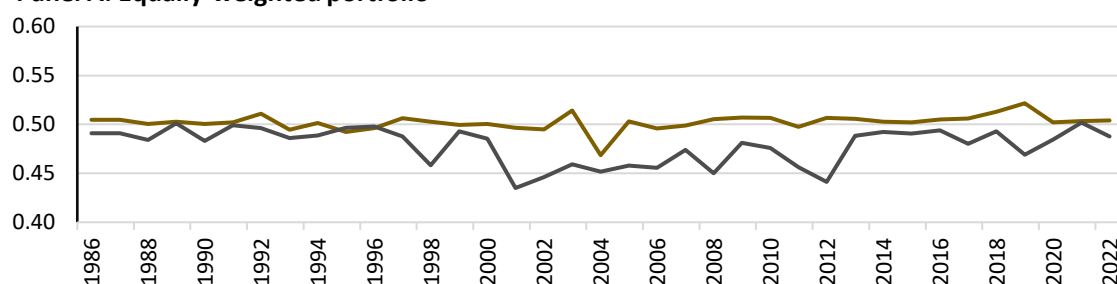
Value-versus-growth Profitability Investment Intangibles

Appendix 3M: Realisation of market-based factors across time, annual rebalancing

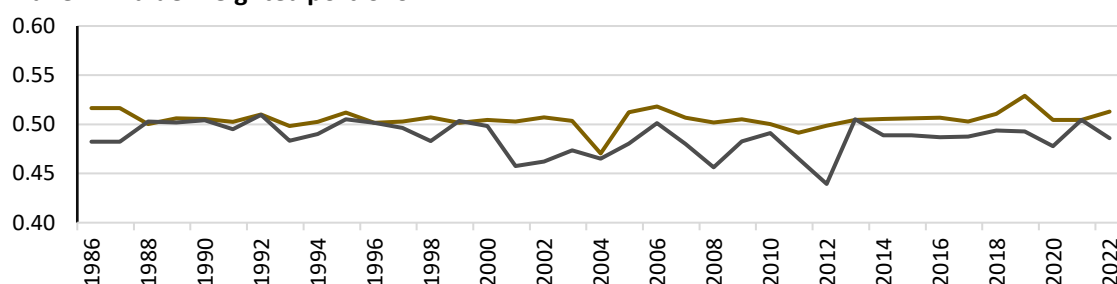
Appendix 3M reports the mean value for market-based predictive factors across time. Stocks are ranked according to their machine learning predicted returns and form 10 portfolios. The bottom portfolio is constructed by selling the lowest quintile, the top portfolio is constructed by buying the highest quintile and the HML portfolio is constructed by buying the highest quantile portfolio and selling the lowest quintile portfolio. The factor realisations corresponding to the stocks chosen in the portfolio are averaged cross-sectionally into four categories of market factors. The allocation of factors in their functional category is described in Appendix 3A. In the figure the trading frictions factor is depicted in gold and the momentum factor is depicted in silver. The table is divided into four panels, A to D, which report the results for the equal-weighted, value-weighted, optimised portfolio trading a relatively small portfolio of 1 million USD and optimised portfolio trading a relatively large portfolio of 100 million USD, respectively. Investing horizon is twelve month and thus, rebalancing of the portfolio is performed annually based on predicted returns.

Bottom portfolio

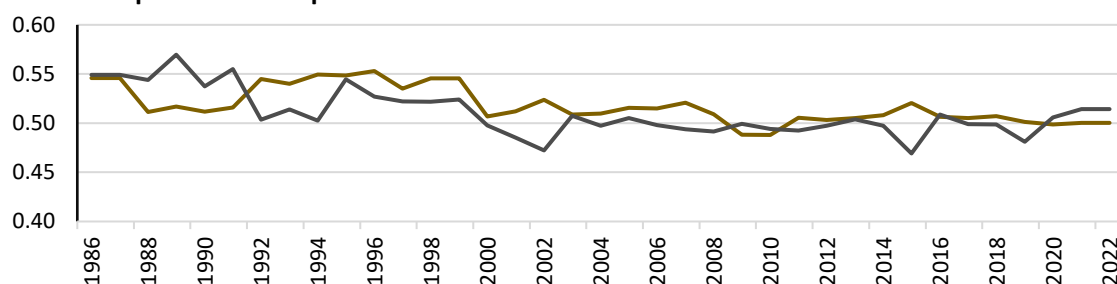
Panel A: Equally-weighted portfolio



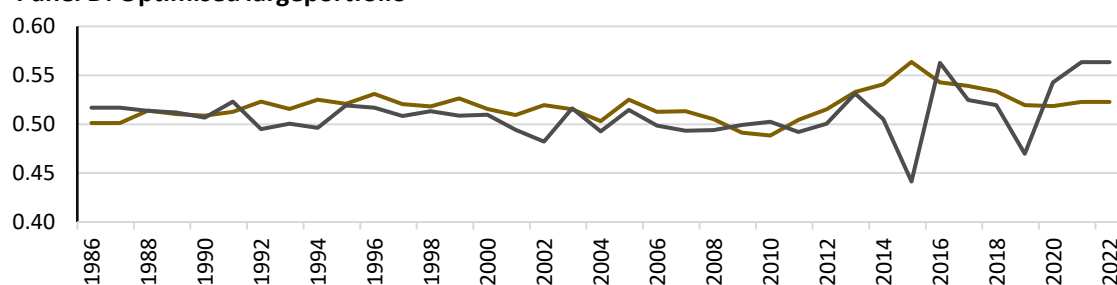
Panel B: Value-weighted portfolio



Panel C: Optimised small portfolio



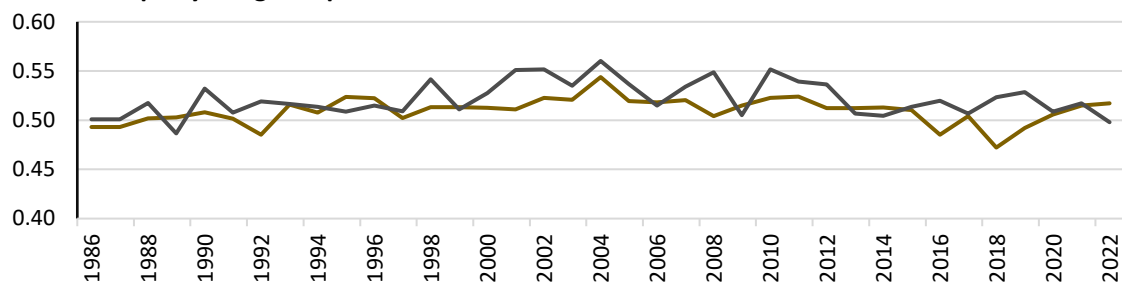
Panel D: Optimised largeportfolio



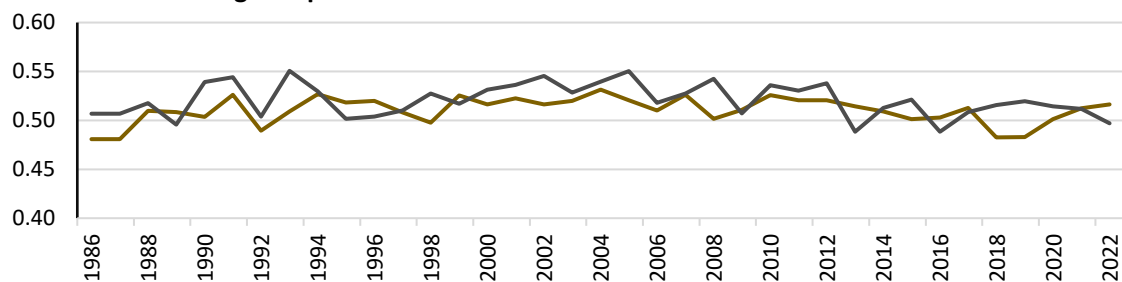
— Trading frictions — Momentum

Top portfolio

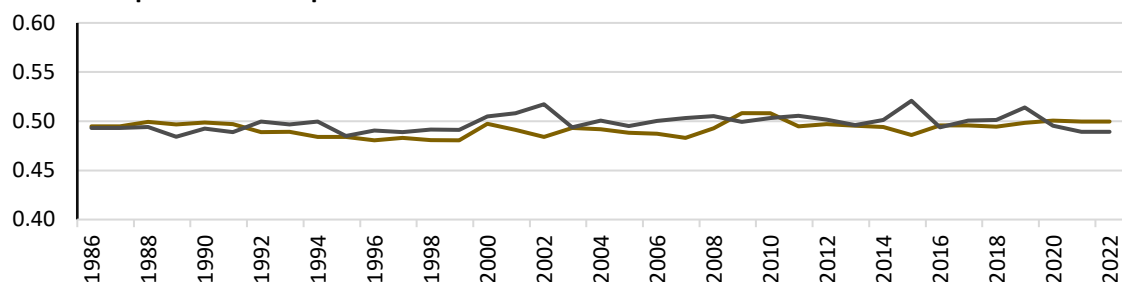
Panel A: Equally-weighted portfolio



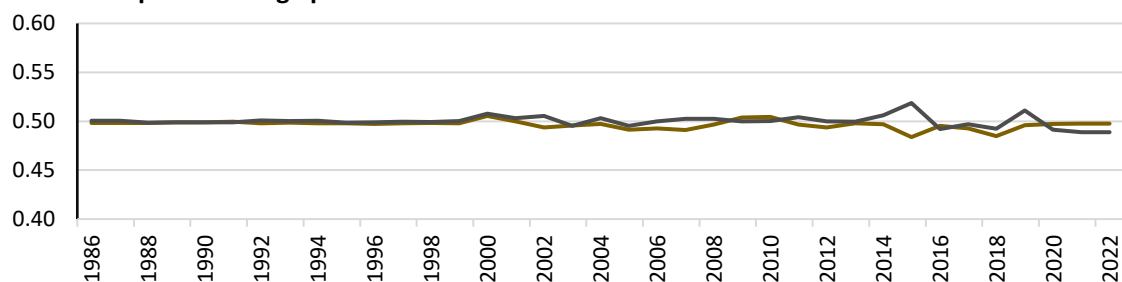
Panel B: Value-weighted portfolio



Panel C: Optimised small portfolio



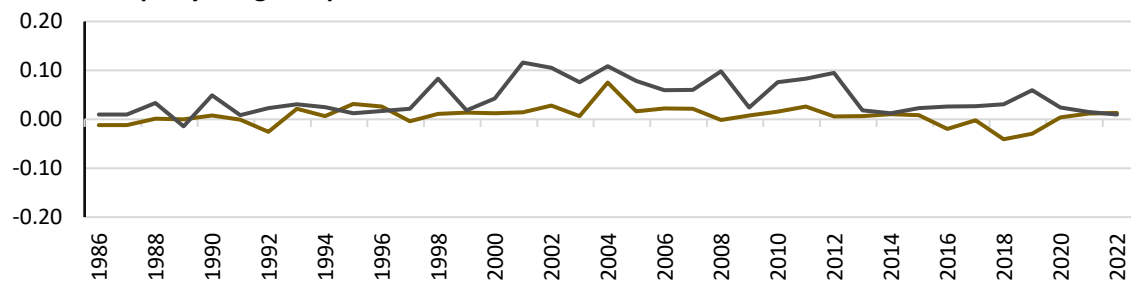
Panel D: Optimised large portfolio



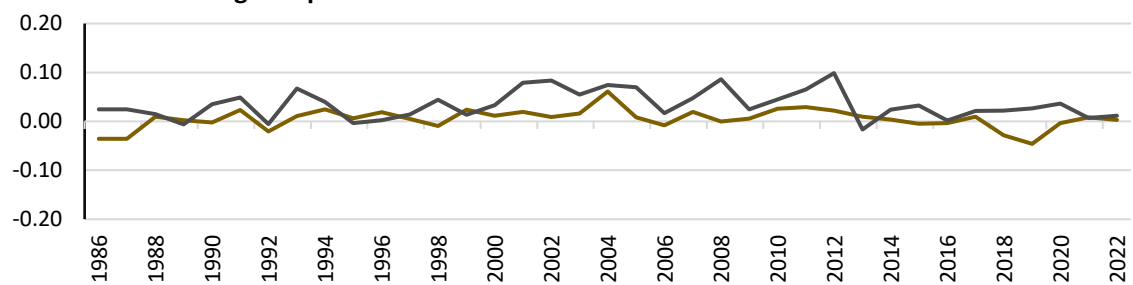
— Trading frictions — Momentum

HML portfolio

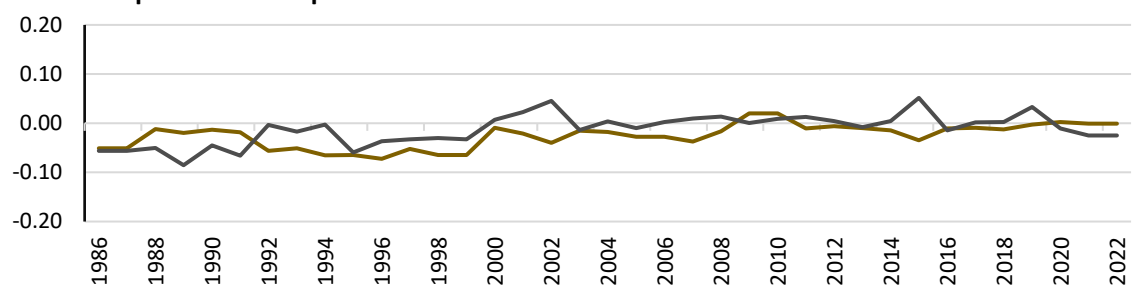
Panel A: Equally-weighted portfolio



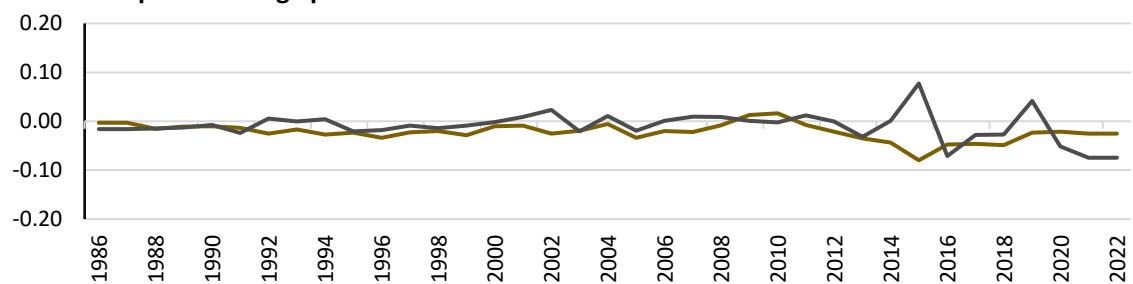
Panel B: Value-weighted portfolio



Panel C: Optimised small portfolio



Panel D: Optimised large portfolio



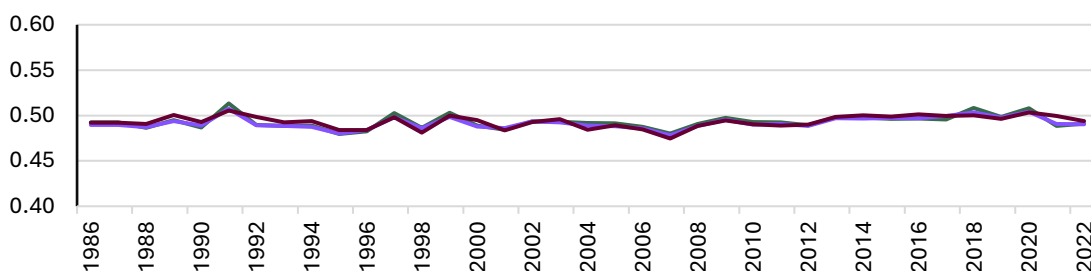
— Trading frictions — Momentum

Appendix 3N: Realisation of fundamental-based factors across rebalancing frequencies

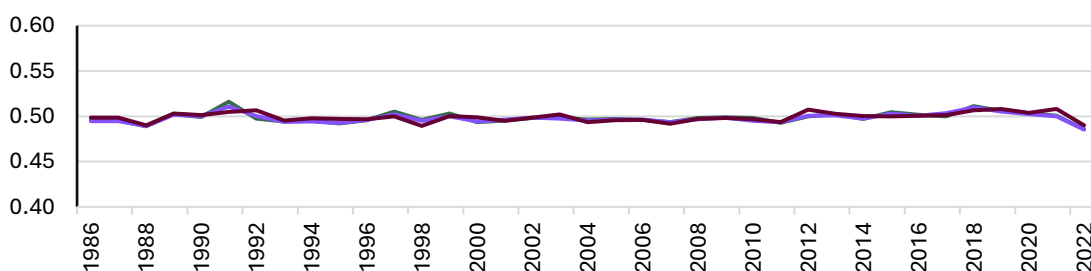
Appendix 3N reports the mean value for the fundamental-based factors across rebalancing frequencies. Stocks are ranked according to their machine learning predicted returns and form 10 portfolios. The bottom portfolio is constructed by selling the lowest quintile, the top portfolio is constructed by buying the highest quintile and the HML portfolio is constructed by buying the highest quintile portfolio and selling the lowest quintile portfolio. The factor realisations corresponding to the stocks chosen in the portfolio are averaged cross-sectionally into two thematic categories: fundamental-based factors and market-based factors. The allocation of factors in their functional category is described in Appendix 3A. The table is divided into four panels, A to D, which report the results for the equal-weighted, value-weighted, optimised portfolio trading a relatively small portfolio of 1 million USD and optimised portfolio trading a relatively large portfolio of 100 million USD, respectively. Monthly rebalancing frequency is depicted in green, quarterly rebalancing frequency is depicted in purple and annual rebalancing frequency is depicted in red.

Bottom portfolio

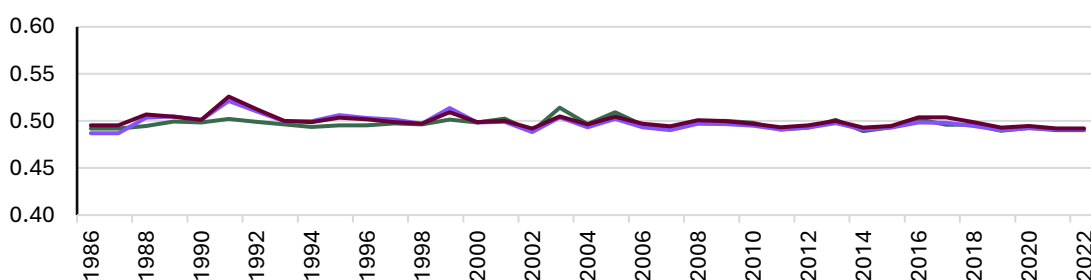
Panel A: Equally-weighted portfolio



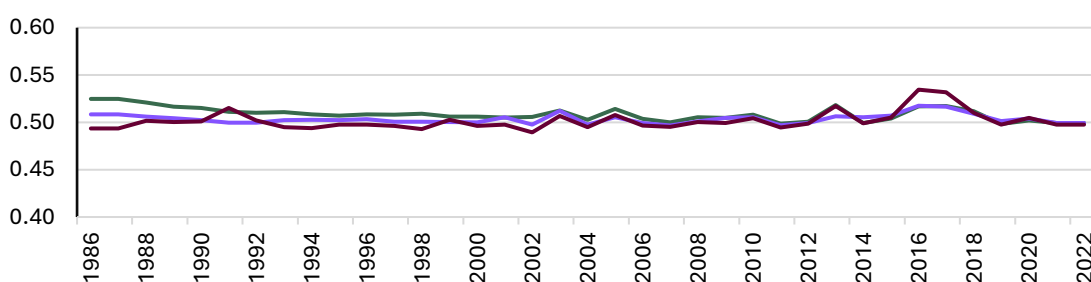
Panel B: Value-weighted portfolio



Panel C: Optimised small portfolio



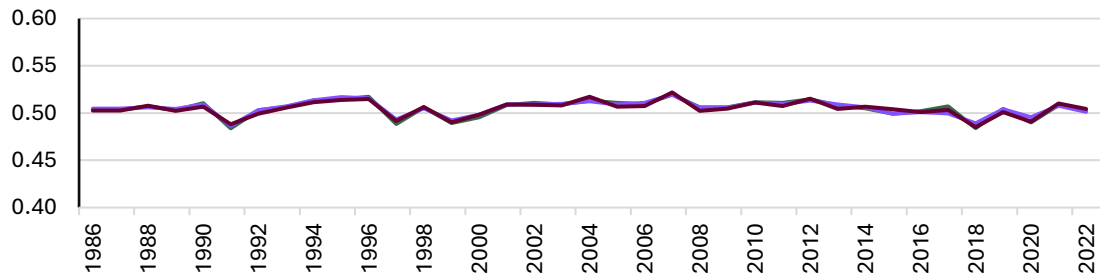
Panel D: Optimised large portfolio



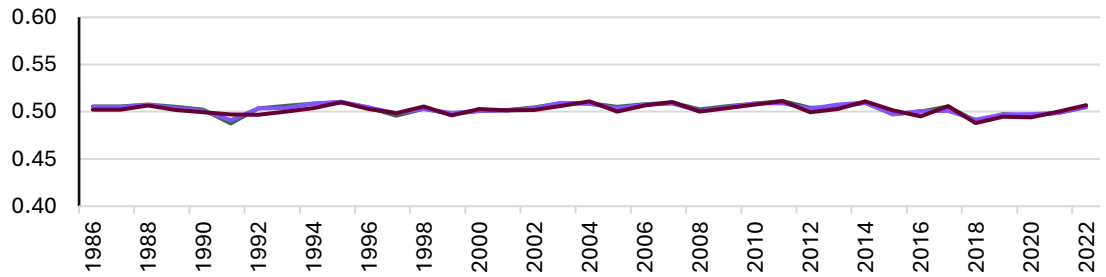
— Monthly rebalancing — Quarterly rebalancing — Annual rebalancing

Top portfolio

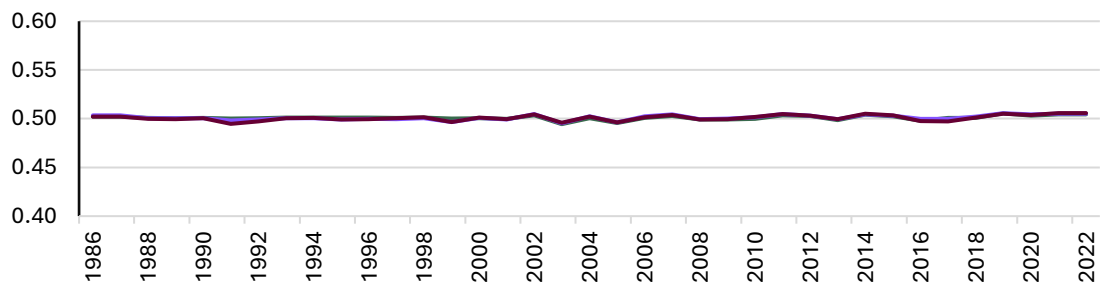
Panel A: Equally-weighted portfolio



Panel B: Value-weighted portfolio



Panel C: Optimised small portfolio



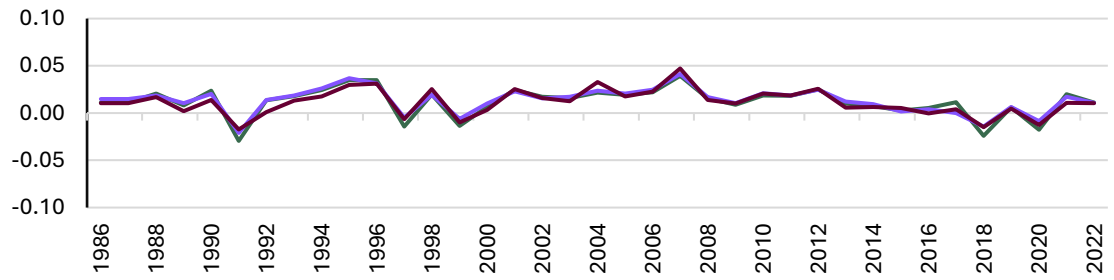
Panel D: Optimised large portfolio



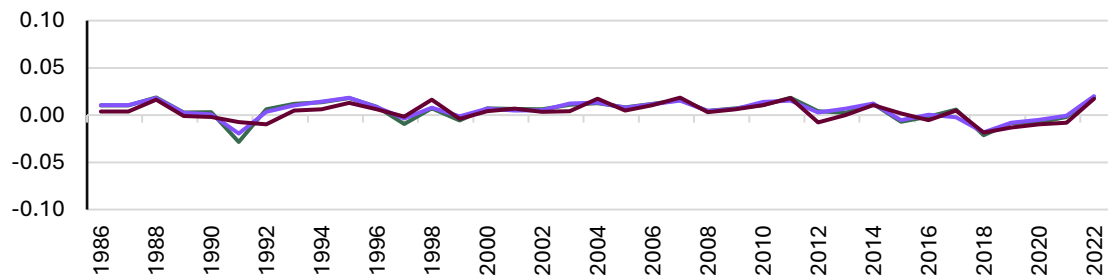
— Monthly rebalancing — Quarterly rebalancing — Annual rebalancing

HML portfolio

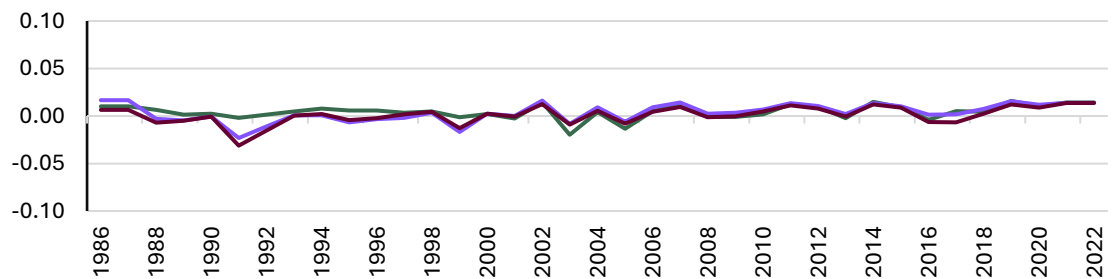
Panel A: Equally-weighted portfolio



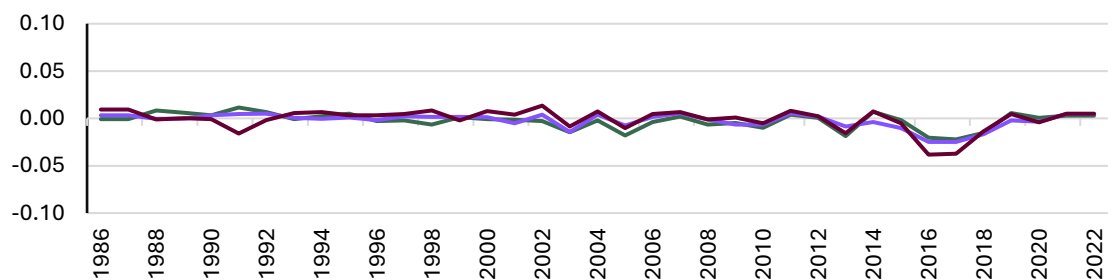
Panel B: Value-weighted portfolio



Panel C: Optimised small portfolio



Panel D: Optimised large portfolio



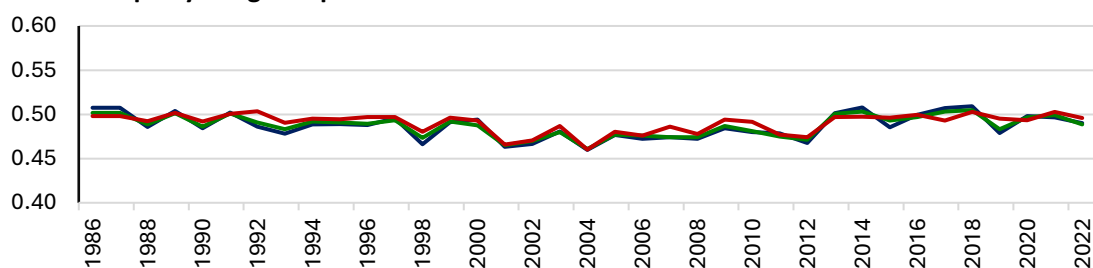
— Monthly rebalancing — Quarterly rebalancing — Annual rebalancing

Appendix 3O: Realisation of market-based factors across rebalancing frequencies

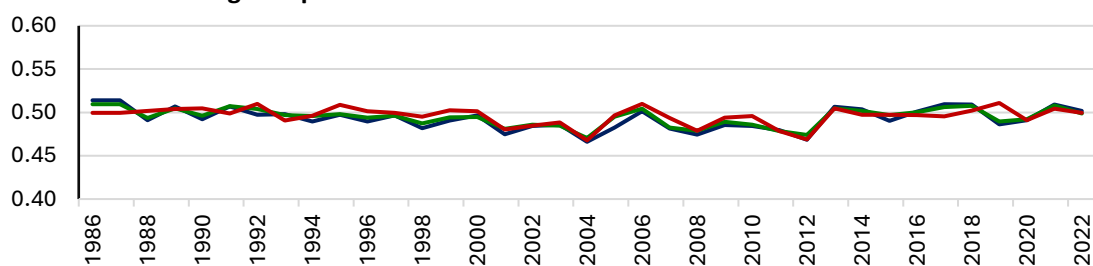
Appendix 3O reports the mean value for the market-based factors across rebalancing frequencies. Stocks are ranked according to their machine learning predicted returns and form 10 portfolios. The bottom portfolio is constructed by selling the lowest quintile, the top portfolio is constructed by buying the highest quintile and the HML portfolio is constructed by buying the highest quintile portfolio and selling the lowest quintile portfolio. The factor realisations corresponding to the stocks chosen in the portfolio are averaged cross-sectionally into two thematic categories: fundamental-based factors and market-based factors. The allocation of factors in their functional category is described in Appendix 3A. The table is divided into four panels, A to D, which report the results for the equal-weighted, value-weighted, optimised portfolio trading a relatively small portfolio of 1 million USD and optimised portfolio trading a relatively large portfolio of 100 million USD, respectively. Monthly rebalancing frequency is depicted in blue, quarterly rebalancing frequency is depicted in green and annual rebalancing frequency is depicted in red.

Bottom portfolio

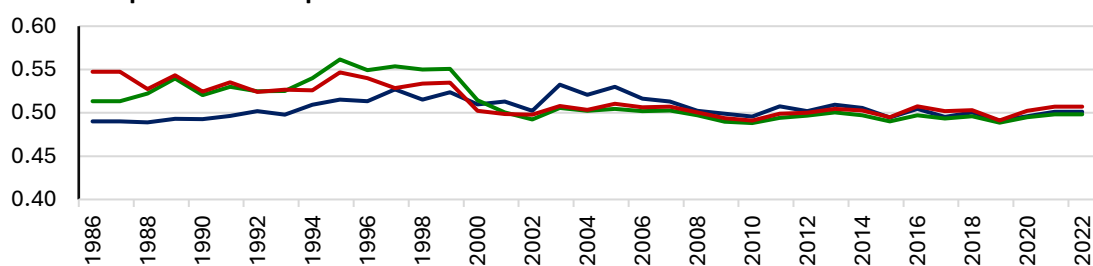
Panel A: Equally-weighted portfolio



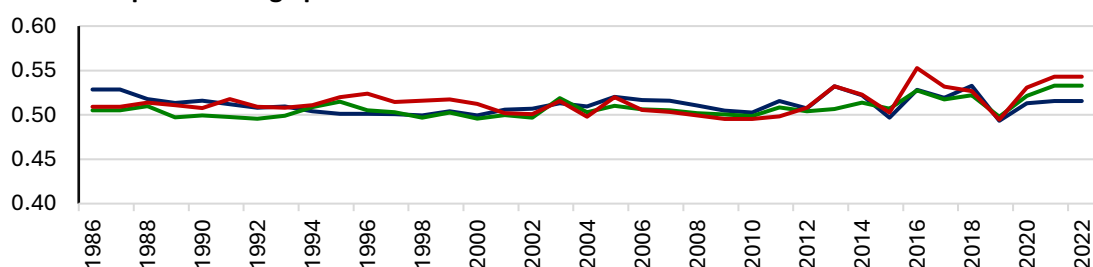
Panel B: Value-weighted portfolio



Panel C: Optimised small portfolio



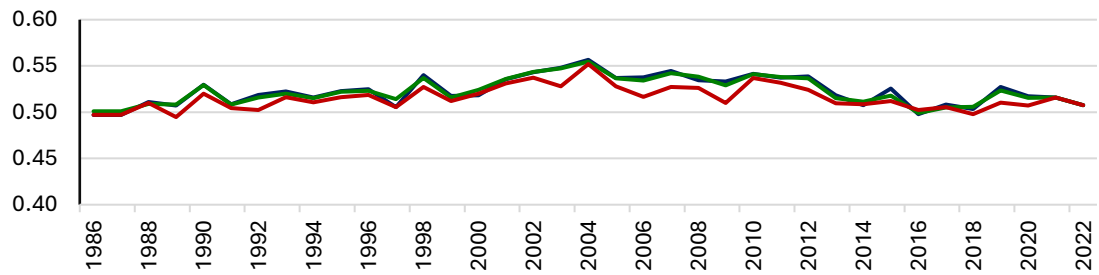
Panel D: Optimised large portfolio



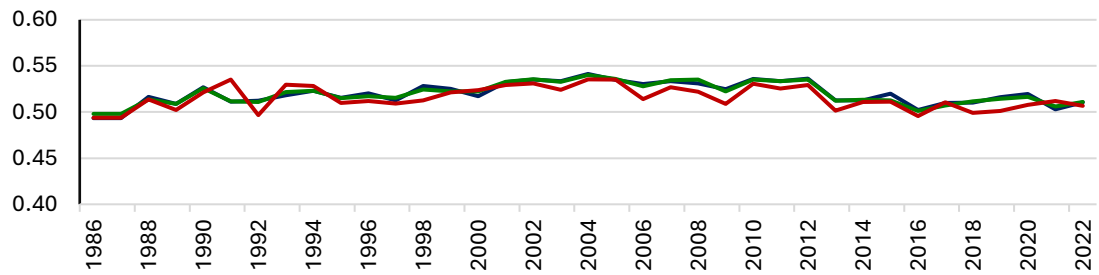
— Monthly rebalancing — Quarterly rebalancing — Annual rebalancing

Top portfolio

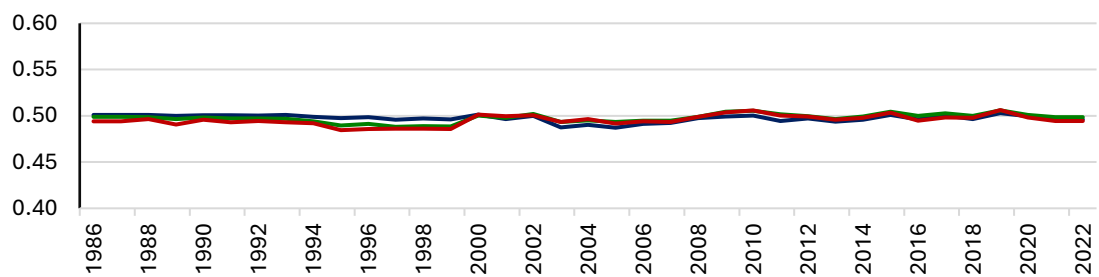
Panel A: Equally-weighted portfolio



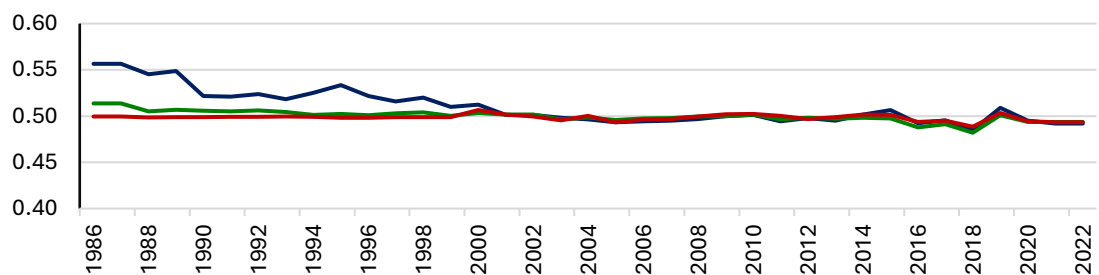
Panel B: Value-weighted portfolio



Panel C: Optimised small portfolio



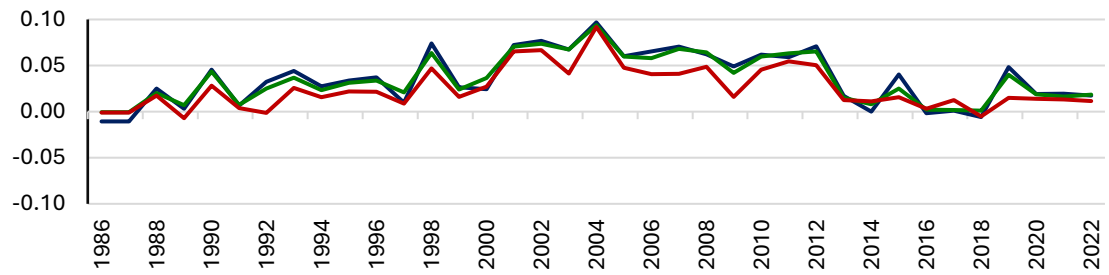
Panel D: Optimised large portfolio



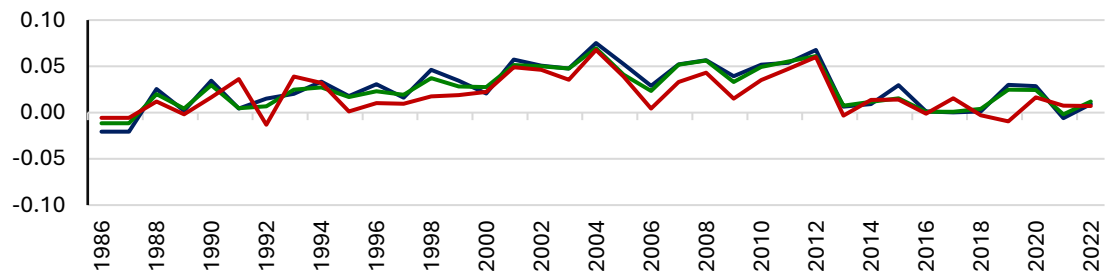
— Monthly rebalancing — Quarterly rebalancing — Annual rebalancing

HML portfolio

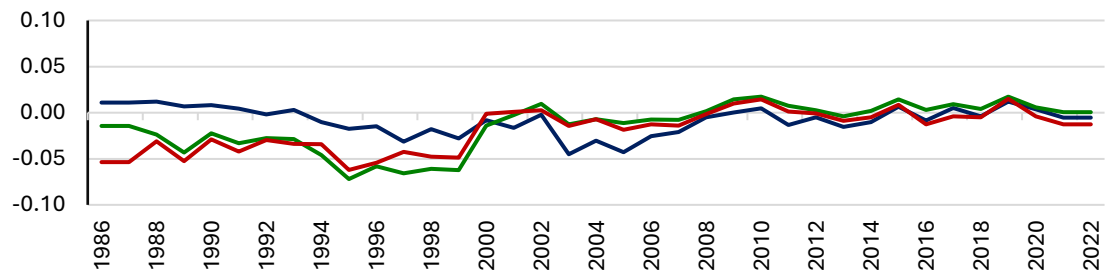
Panel A: Equally-weighted portfolio



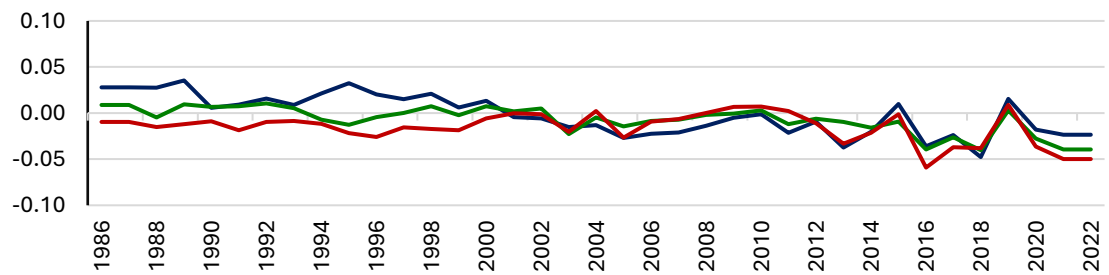
Panel B: Value-weighted portfolio



Panel C: Optimised small portfolio



Panel D: Optimised large portfolio



— Monthly rebalancing — Quarterly rebalancing — Annual rebalancing

Appendix 3P: Means of predictive factors by functional category and sector, monthly rebalancing

Appendix 3P reports the mean value for the predictive factors when grouped by functional category (momentum, profitability, trading frictions, value vs. growth, intangibles and investment), as well as the eleven S&P sectors (communication services, consumer discretionary, consumer staples, energy, financials, health care, industrials, information technology, materials, real estate, utilities). The bottom portfolio is constructed by ranking stocks according to their machine learning predicted returns and form 10 portfolios and selling the lowest quintile portfolio. The top portfolio is constructed by ranking stocks according to their machine learning predicted returns and form 10 portfolios and buying the highest quintile portfolio. The long-short (HML) portfolio is constructed by ranking stocks according to their machine learning predicted returns and form 10 portfolios, buying the highest quantile portfolio and selling the lowest quintile portfolio. The factor realisations corresponding to the stocks chosen for the top and bottom portfolios are averaged cross-sectionally into the six functional categories and then averaged across the eleven S&P sectors to generate the results in the table. At each monthly period the factor input was rescaled to the [0,1] range and thus, the expected value for all factors is 0.5. For each portfolio, the heatmap illustrates the gradient of predictive factors. The reported results the five neural network predictive models, NN1-NN5, respectively. The table is divided into four panels, A to D, which report the results for the equal-weighted, value-weighted, optimised portfolio trading a relatively small portfolio of 1 million USD and optimised portfolio trading a relatively large portfolio of 100 million USD, respectively. Investing horizon is one month and thus, rebalancing of the portfolio is performed monthly based on predicted returns.

NN1

Method		Equal-weighted Portfolio						Value-weighted Portfolio					
Portfolio	Sector	Value vs growth	Profitability	Investment	Intangibles	Trading frictions	Momentum	Value vs growth	Profitability	Investment	Intangibles	Trading frictions	Momentum
1	Communication Services	0.476	0.489	0.476	0.49	0.505	0.464	0.48	0.487	0.488	0.494	0.492	0.467
	Consumer Discretionary	0.509	0.482	0.49	0.515	0.506	0.462	0.499	0.504	0.491	0.508	0.518	0.481
	Consumer Staples	0.517	0.492	0.472	0.493	0.491	0.476	0.494	0.507	0.485	0.492	0.502	0.484
	Energy	0.492	0.476	0.468	0.504	0.502	0.457	0.498	0.493	0.481	0.504	0.5	0.471
	Financials	0.484	0.463	0.528	0.499	0.496	0.467	0.496	0.484	0.513	0.501	0.486	0.479
	Health Care	0.415	0.483	0.504	0.513	0.522	0.454	0.483	0.494	0.508	0.513	0.524	0.48
	Industrials	0.506	0.482	0.493	0.521	0.512	0.471	0.495	0.503	0.488	0.511	0.519	0.489
	Technology	0.451	0.497	0.495	0.508	0.512	0.453	0.491	0.501	0.498	0.514	0.515	0.472
	Materials	0.498	0.481	0.47	0.504	0.488	0.469	0.5	0.493	0.487	0.5	0.5	0.479
	Real Estate	0.472	0.45	0.505	0.555	0.514	0.464	0.489	0.5	0.49	0.53	0.519	0.49
10	Utilities	0.542	0.47	0.47	0.429	0.469	0.478	0.508	0.475	0.488	0.464	0.445	0.479
	Communication Services	0.496	0.504	0.5	0.504	0.508	0.538	0.492	0.495	0.496	0.499	0.499	0.526
	Consumer Discretionary	0.534	0.507	0.51	0.519	0.509	0.544	0.507	0.509	0.502	0.511	0.517	0.532
	Consumer Staples	0.535	0.516	0.495	0.49	0.492	0.544	0.5	0.505	0.502	0.487	0.493	0.527
	Energy	0.505	0.502	0.492	0.496	0.501	0.558	0.501	0.494	0.501	0.498	0.49	0.545
	Financials	0.499	0.484	0.543	0.512	0.498	0.541	0.502	0.491	0.521	0.507	0.485	0.529
	Health Care	0.437	0.499	0.513	0.514	0.521	0.524	0.486	0.503	0.507	0.512	0.525	0.529
	Industrials	0.529	0.511	0.51	0.519	0.51	0.547	0.504	0.507	0.5	0.508	0.511	0.532
	Technology	0.47	0.516	0.521	0.523	0.525	0.547	0.496	0.51	0.508	0.52	0.526	0.538
	Materials	0.519	0.505	0.483	0.506	0.485	0.535	0.507	0.495	0.496	0.501	0.494	0.523
	Real Estate	0.482	0.478	0.514	0.551	0.522	0.527	0.49	0.51	0.499	0.529	0.52	0.528
	Utilities	0.552	0.484	0.491	0.433	0.461	0.537	0.516	0.472	0.5	0.456	0.417	0.524

Method		Optimised - Low capital portfolio						Optimised - High capital portfolio					
Portfolio	Sector	Value vs growth	Profitability	Investment	Intangibles	Trading frictions	Momentum	Value vs growth	Profitability	Investment	Intangibles	Trading frictions	Momentum
1	Communication Services	0.473	0.509	0.467	0.482	0.514	0.492	0.49	0.512	0.481	0.518	0.529	0.495
	Consumer Discretionary	0.495	0.517	0.479	0.503	0.526	0.5	0.492	0.516	0.484	0.526	0.532	0.499
	Consumer Staples	0.488	0.53	0.468	0.489	0.511	0.508	0.484	0.527	0.47	0.518	0.521	0.506
	Energy	0.49	0.516	0.457	0.501	0.52	0.502	0.495	0.516	0.467	0.526	0.53	0.512
	Financials	0.488	0.502	0.497	0.502	0.504	0.503	0.489	0.511	0.49	0.53	0.516	0.508
	Health Care	0.476	0.507	0.488	0.49	0.516	0.492	0.488	0.509	0.49	0.525	0.534	0.498
	Industrials	0.488	0.519	0.471	0.501	0.517	0.503	0.493	0.518	0.481	0.517	0.521	0.507
	Technology	0.486	0.518	0.484	0.512	0.532	0.5	0.494	0.518	0.488	0.534	0.536	0.501
	Materials	0.497	0.516	0.469	0.501	0.517	0.505	0.496	0.519	0.48	0.526	0.519	0.5
	Real Estate	0.477	0.498	0.482	0.519	0.534	0.483	0.482	0.467	0.523	0.523	0.523	0.461
	Utilities	0.503	0.521	0.469	0.477	0.507	0.523	0.507	0.519	0.48	0.513	0.511	0.518
10	Communication Services	0.486	0.507	0.478	0.49	0.492	0.49	0.494	0.502	0.499	0.498	0.513	0.503
	Consumer Discretionary	0.512	0.495	0.504	0.505	0.496	0.491	0.514	0.505	0.516	0.492	0.509	0.499
	Consumer Staples	0.503	0.505	0.492	0.488	0.484	0.498	0.499	0.511	0.492	0.473	0.489	0.5
	Energy	0.496	0.487	0.492	0.494	0.478	0.494	0.5	0.501	0.484	0.507	0.497	0.501
	Financials	0.505	0.485	0.52	0.496	0.483	0.5	0.503	0.484	0.529	0.502	0.486	0.503
	Health Care	0.474	0.491	0.504	0.492	0.504	0.488	0.492	0.508	0.494	0.498	0.511	0.502
	Industrials	0.508	0.494	0.497	0.496	0.479	0.491	0.502	0.502	0.498	0.494	0.493	0.498
	Technology	0.49	0.491	0.51	0.507	0.504	0.49	0.503	0.503	0.505	0.502	0.51	0.501
	Materials	0.506	0.491	0.488	0.498	0.477	0.481	0.511	0.499	0.489	0.494	0.492	0.488
	Real Estate	0.483	0.486	0.511	0.537	0.516	0.504	0.502	0.493	0.498	0.499	0.522	0.493
	Utilities	0.52	0.504	0.475	0.456	0.472	0.502	0.517	0.483	0.494	0.467	0.452	0.517

NN2

Method		Equal-weighted Portfolio						Value-weighted Portfolio					
Portfolio	Sector	Value vs growth	Profitability	Investment	Intangibles	Trading frictions	Momentum	Value vs growth	Profitability	Investment	Intangibles	Trading frictions	Momentum
1	Communication Services	0.487	0.492	0.487	0.508	0.507	0.462	0.49	0.485	0.495	0.503	0.495	0.464
	Consumer Discretionary	0.514	0.487	0.495	0.519	0.504	0.458	0.504	0.499	0.497	0.508	0.511	0.471
	Consumer Staples	0.516	0.493	0.477	0.5	0.492	0.473	0.497	0.501	0.49	0.493	0.496	0.478
	Energy	0.492	0.483	0.476	0.508	0.501	0.46	0.504	0.489	0.488	0.506	0.493	0.464
	Financials	0.486	0.455	0.534	0.512	0.489	0.46	0.501	0.479	0.519	0.509	0.479	0.473
	Health Care	0.413	0.482	0.508	0.521	0.525	0.449	0.486	0.485	0.512	0.519	0.522	0.47
	Industrials	0.509	0.484	0.498	0.531	0.512	0.467	0.498	0.498	0.493	0.516	0.513	0.481
	Technology	0.454	0.493	0.502	0.526	0.519	0.455	0.491	0.493	0.504	0.524	0.514	0.469
	Materials	0.498	0.484	0.472	0.508	0.487	0.461	0.504	0.486	0.491	0.499	0.489	0.463
	Real Estate	0.476	0.471	0.505	0.543	0.511	0.467	0.492	0.499	0.496	0.521	0.509	0.486
	Utilities	0.554	0.47	0.475	0.43	0.465	0.471	0.516	0.472	0.492	0.459	0.429	0.471
10	Communication Services	0.494	0.506	0.491	0.493	0.507	0.538	0.489	0.493	0.493	0.495	0.5	0.523
	Consumer Discretionary	0.535	0.505	0.508	0.515	0.51	0.552	0.506	0.509	0.502	0.508	0.519	0.536
	Consumer Staples	0.542	0.515	0.49	0.487	0.494	0.549	0.502	0.509	0.497	0.487	0.5	0.53
	Energy	0.509	0.501	0.484	0.489	0.503	0.562	0.503	0.495	0.501	0.495	0.494	0.548
	Financials	0.5	0.482	0.542	0.51	0.501	0.547	0.5	0.492	0.518	0.506	0.488	0.534
	Health Care	0.432	0.495	0.508	0.508	0.521	0.523	0.492	0.496	0.51	0.51	0.523	0.526
	Industrials	0.532	0.507	0.508	0.518	0.514	0.554	0.502	0.506	0.499	0.508	0.516	0.539
	Technology	0.471	0.513	0.522	0.521	0.527	0.549	0.497	0.505	0.51	0.52	0.525	0.539
	Materials	0.527	0.507	0.483	0.499	0.487	0.54	0.509	0.495	0.494	0.496	0.499	0.528
	Real Estate	0.488	0.483	0.519	0.544	0.51	0.53	0.494	0.509	0.503	0.527	0.525	0.526
	Utilities	0.566	0.484	0.483	0.426	0.464	0.531	0.53	0.473	0.5	0.455	0.421	0.518

Method		Optimised - Low capital portfolio						Optimised - High capital portfolio					
Portfolio	Sector	Value vs growth	Profitability	Investment	Intangibles	Trading frictions	Momentum	Value vs growth	Profitability	Investment	Intangibles	Trading frictions	Momentum
1	Communication Services	0.483	0.47	0.482	0.494	0.484	0.496	0.504	0.514	0.493	0.525	0.517	0.517
	Consumer Discretionary	0.5	0.513	0.486	0.5	0.519	0.496	0.505	0.519	0.497	0.523	0.525	0.515
	Consumer Staples	0.504	0.521	0.476	0.486	0.491	0.484	0.5	0.528	0.48	0.513	0.507	0.512
	Energy	0.486	0.505	0.462	0.499	0.509	0.485	0.5	0.509	0.492	0.533	0.515	0.505
	Financials	0.486	0.515	0.48	0.504	0.518	0.5	0.507	0.512	0.509	0.526	0.507	0.521
	Health Care	0.466	0.507	0.478	0.496	0.517	0.487	0.487	0.503	0.507	0.534	0.527	0.508
	Industrials	0.484	0.514	0.463	0.496	0.514	0.494	0.498	0.515	0.49	0.527	0.522	0.516
	Technology	0.473	0.5	0.479	0.499	0.51	0.494	0.493	0.517	0.495	0.523	0.523	0.518
	Materials	0.478	0.518	0.446	0.472	0.496	0.488	0.496	0.513	0.49	0.523	0.525	0.511
	Real Estate	0.474	0.511	0.496	0.52	0.52	0.492	0.493	0.51	0.499	0.539	0.521	0.519
	Utilities	0.493	0.521	0.456	0.479	0.503	0.505	0.506	0.519	0.476	0.506	0.502	0.52
10	Communication Services	0.49	0.503	0.47	0.491	0.491	0.49	0.51	0.491	0.512	0.48	0.5	0.501
	Consumer Discretionary	0.51	0.497	0.499	0.515	0.501	0.495	0.524	0.501	0.525	0.477	0.503	0.494
	Consumer Staples	0.51	0.51	0.495	0.493	0.489	0.5	0.515	0.509	0.497	0.476	0.492	0.496
	Energy	0.498	0.495	0.485	0.493	0.48	0.498	0.502	0.49	0.494	0.495	0.482	0.49
	Financials	0.506	0.493	0.514	0.497	0.489	0.507	0.524	0.475	0.539	0.476	0.472	0.502
	Health Care	0.473	0.494	0.505	0.49	0.508	0.488	0.497	0.509	0.497	0.498	0.51	0.505
	Industrials	0.509	0.496	0.498	0.498	0.484	0.496	0.517	0.497	0.513	0.476	0.489	0.499
	Technology	0.486	0.492	0.512	0.506	0.508	0.491	0.519	0.498	0.521	0.482	0.498	0.503
	Materials	0.503	0.489	0.485	0.496	0.488	0.484	0.521	0.506	0.491	0.486	0.491	0.497
	Real Estate	0.491	0.472	0.529	0.532	0.502	0.501	0.487	0.52	0.486	0.522	0.53	0.506
	Utilities	0.519	0.513	0.476	0.452	0.482	0.503	0.537	0.475	0.494	0.463	0.438	0.508

NN3

Method		Equal-weighted Portfolio						Value-weighted Portfolio					
Portfolio	Sector	Value vs growth	Profitability	Investment	Intangibles	Trading frictions	Momentum	Value vs growth	Profitability	Investment	Intangibles	Trading frictions	Momentum
1	Communication Services	0.473	0.492	0.479	0.489	0.504	0.474	0.48	0.488	0.492	0.49	0.491	0.478
	Consumer Discretionary	0.512	0.489	0.491	0.511	0.505	0.473	0.5	0.508	0.492	0.505	0.516	0.492
	Consumer Staples	0.526	0.501	0.472	0.484	0.484	0.486	0.494	0.511	0.486	0.485	0.495	0.49
	Energy	0.493	0.486	0.464	0.493	0.5	0.458	0.498	0.494	0.483	0.498	0.494	0.468
	Financials	0.485	0.462	0.531	0.497	0.491	0.468	0.498	0.489	0.513	0.499	0.485	0.485
	Health Care	0.416	0.485	0.504	0.511	0.521	0.461	0.482	0.496	0.504	0.512	0.522	0.487
	Industrials	0.513	0.49	0.491	0.515	0.509	0.48	0.497	0.505	0.488	0.506	0.514	0.495
	Technology	0.459	0.507	0.498	0.508	0.509	0.472	0.495	0.504	0.501	0.512	0.512	0.489
	Materials	0.51	0.495	0.462	0.492	0.479	0.474	0.503	0.499	0.485	0.493	0.492	0.482
	Real Estate	0.473	0.47	0.506	0.533	0.516	0.468	0.493	0.503	0.491	0.514	0.52	0.493
10	Utilities	0.542	0.465	0.466	0.419	0.462	0.474	0.516	0.466	0.485	0.452	0.424	0.461
	Communication Services	0.493	0.497	0.495	0.514	0.512	0.529	0.494	0.488	0.489	0.507	0.5	0.519
	Consumer Discretionary	0.53	0.497	0.512	0.528	0.51	0.534	0.509	0.502	0.505	0.513	0.516	0.523
	Consumer Staples	0.537	0.505	0.499	0.511	0.497	0.535	0.505	0.502	0.501	0.5	0.503	0.521
	Energy	0.501	0.492	0.49	0.509	0.506	0.545	0.504	0.489	0.5	0.505	0.498	0.536
	Financials	0.497	0.48	0.542	0.516	0.502	0.535	0.501	0.494	0.514	0.508	0.493	0.524
	Health Care	0.434	0.494	0.515	0.521	0.529	0.518	0.491	0.489	0.515	0.514	0.528	0.52
	Industrials	0.524	0.5	0.512	0.529	0.514	0.539	0.505	0.499	0.502	0.513	0.514	0.526
	Technology	0.467	0.504	0.524	0.536	0.533	0.536	0.496	0.499	0.512	0.526	0.528	0.528
	Materials	0.516	0.497	0.49	0.517	0.495	0.525	0.507	0.491	0.5	0.504	0.502	0.515
	Real Estate	0.48	0.482	0.517	0.55	0.518	0.516	0.496	0.501	0.514	0.526	0.513	0.512
	Utilities	0.542	0.48	0.482	0.443	0.459	0.53	0.521	0.47	0.501	0.462	0.429	0.527

Method		Optimised - Low capital portfolio						Optimised - High capital portfolio					
Portfolio	Sector	Value vs growth	Profitability	Investment	Intangibles	Trading frictions	Momentum	Value vs growth	Profitability	Investment	Intangibles	Trading frictions	Momentum
1	Communication Services	0.476	0.497	0.472	0.491	0.492	0.479	0.487	0.5	0.473	0.528	0.517	0.499
	Consumer Discretionary	0.498	0.516	0.484	0.494	0.518	0.493	0.498	0.511	0.497	0.517	0.516	0.498
	Consumer Staples	0.487	0.521	0.464	0.485	0.494	0.497	0.499	0.528	0.479	0.506	0.511	0.511
	Energy	0.483	0.5	0.459	0.493	0.495	0.488	0.494	0.511	0.461	0.526	0.514	0.498
	Financials	0.489	0.502	0.499	0.503	0.5	0.501	0.501	0.495	0.513	0.51	0.492	0.505
	Health Care	0.479	0.495	0.499	0.49	0.516	0.485	0.491	0.497	0.503	0.527	0.524	0.495
	Industrials	0.493	0.514	0.473	0.499	0.507	0.493	0.5	0.515	0.482	0.522	0.515	0.501
	Technology	0.487	0.512	0.491	0.503	0.522	0.496	0.495	0.509	0.497	0.52	0.524	0.499
	Materials	0.49	0.511	0.464	0.479	0.497	0.483	0.49	0.509	0.482	0.508	0.502	0.503
	Real Estate	0.484	0.493	0.499	0.525	0.51	0.488	0.499	0.478	0.518	0.488	0.504	0.464
	Utilities	0.512	0.505	0.466	0.456	0.475	0.513	0.495	0.51	0.473	0.505	0.491	0.516
10	Communication Services	0.497	0.505	0.483	0.504	0.495	0.496	0.492	0.497	0.501	0.495	0.511	0.499
	Consumer Discretionary	0.511	0.495	0.498	0.505	0.497	0.492	0.517	0.509	0.515	0.493	0.513	0.498
	Consumer Staples	0.516	0.508	0.495	0.489	0.488	0.503	0.494	0.512	0.495	0.467	0.49	0.506
	Energy	0.502	0.49	0.49	0.497	0.481	0.495	0.498	0.499	0.482	0.508	0.494	0.499
	Financials	0.506	0.492	0.515	0.498	0.485	0.507	0.507	0.487	0.527	0.498	0.489	0.506
	Health Care	0.475	0.492	0.508	0.491	0.506	0.49	0.498	0.493	0.509	0.494	0.502	0.498
	Industrials	0.506	0.498	0.495	0.499	0.491	0.496	0.5	0.505	0.499	0.497	0.499	0.501
	Technology	0.486	0.492	0.509	0.509	0.509	0.492	0.501	0.504	0.505	0.51	0.511	0.502
	Materials	0.495	0.499	0.483	0.503	0.496	0.494	0.508	0.504	0.488	0.494	0.494	0.494
	Real Estate	0.493	0.482	0.519	0.52	0.493	0.496	0.5	0.516	0.491	0.516	0.514	0.504
	Utilities	0.522	0.512	0.476	0.456	0.478	0.503	0.516	0.478	0.504	0.465	0.444	0.532

NN4

Method		Equal-weighted Portfolio						Value-weighted Portfolio					
Portfolio	Sector	Value vs growth	Profitability	Investment	Intangibles	Trading frictions	Momentum	Value vs growth	Profitability	Investment	Intangibles	Trading frictions	Momentum
1	Communication Services	0.472	0.491	0.478	0.49	0.504	0.47	0.48	0.487	0.491	0.49	0.492	0.475
	Consumer Discretionary	0.512	0.49	0.491	0.511	0.506	0.471	0.501	0.507	0.493	0.505	0.516	0.488
	Consumer Staples	0.526	0.503	0.473	0.485	0.485	0.481	0.495	0.51	0.486	0.485	0.495	0.487
	Energy	0.493	0.485	0.464	0.497	0.501	0.455	0.498	0.494	0.482	0.5	0.496	0.465
	Financials	0.484	0.463	0.533	0.497	0.491	0.465	0.499	0.487	0.515	0.498	0.484	0.482
	Health Care	0.417	0.488	0.502	0.51	0.52	0.459	0.483	0.496	0.504	0.512	0.522	0.484
	Industrials	0.515	0.492	0.492	0.515	0.509	0.478	0.499	0.505	0.489	0.506	0.514	0.492
	Technology	0.459	0.509	0.496	0.508	0.509	0.466	0.494	0.506	0.5	0.51	0.514	0.485
	Materials	0.509	0.495	0.462	0.491	0.48	0.47	0.505	0.498	0.485	0.492	0.491	0.477
	Real Estate	0.48	0.47	0.514	0.542	0.516	0.464	0.49	0.507	0.494	0.518	0.521	0.493
	Utilities	0.546	0.47	0.47	0.424	0.462	0.48	0.523	0.462	0.484	0.45	0.417	0.46
10	Communication Services	0.49	0.495	0.494	0.512	0.509	0.531	0.495	0.487	0.489	0.507	0.497	0.52
	Consumer Discretionary	0.53	0.496	0.511	0.527	0.508	0.535	0.507	0.502	0.503	0.512	0.514	0.526
	Consumer Staples	0.538	0.504	0.497	0.507	0.494	0.537	0.504	0.503	0.5	0.497	0.501	0.524
	Energy	0.504	0.493	0.489	0.505	0.505	0.55	0.505	0.49	0.5	0.502	0.496	0.541
	Financials	0.498	0.477	0.541	0.517	0.5	0.535	0.5	0.494	0.514	0.509	0.491	0.525
	Health Care	0.432	0.491	0.515	0.522	0.528	0.52	0.488	0.489	0.514	0.515	0.527	0.523
	Industrials	0.524	0.498	0.511	0.528	0.512	0.541	0.503	0.499	0.5	0.513	0.512	0.528
	Technology	0.466	0.502	0.523	0.534	0.531	0.539	0.496	0.498	0.511	0.526	0.526	0.531
	Materials	0.519	0.497	0.49	0.515	0.491	0.529	0.507	0.491	0.5	0.504	0.498	0.519
	Real Estate	0.477	0.479	0.515	0.55	0.517	0.522	0.496	0.499	0.513	0.526	0.512	0.517
	Utilities	0.547	0.48	0.483	0.435	0.459	0.528	0.519	0.473	0.504	0.46	0.423	0.525

Method		Optimised - Low capital portfolio						Optimised - High capital portfolio					
Portfolio	Sector	Value vs growth	Profitability	Investment	Intangibles	Trading frictions	Momentum	Value vs growth	Profitability	Investment	Intangibles	Trading frictions	Momentum
1	Communication Services	0.486	0.509	0.468	0.489	0.494	0.489	0.491	0.515	0.473	0.528	0.52	0.51
	Consumer Discretionary	0.5	0.512	0.485	0.499	0.515	0.489	0.506	0.512	0.496	0.523	0.518	0.502
	Consumer Staples	0.489	0.513	0.468	0.491	0.5	0.492	0.497	0.525	0.473	0.509	0.513	0.512
	Energy	0.484	0.506	0.462	0.502	0.504	0.494	0.494	0.505	0.47	0.534	0.514	0.496
	Financials	0.488	0.504	0.497	0.506	0.503	0.501	0.499	0.497	0.506	0.511	0.492	0.505
	Health Care	0.485	0.501	0.5	0.488	0.514	0.486	0.49	0.503	0.499	0.52	0.523	0.499
	Industrials	0.496	0.516	0.477	0.497	0.51	0.494	0.495	0.512	0.485	0.524	0.516	0.505
	Technology	0.483	0.51	0.49	0.493	0.516	0.493	0.493	0.517	0.489	0.529	0.523	0.502
	Materials	0.499	0.51	0.461	0.489	0.502	0.484	0.49	0.521	0.469	0.526	0.517	0.504
	Real Estate	0.492	0.501	0.51	0.525	0.507	0.499	0.479	0.509	0.494	0.546	0.523	0.51
	Utilities	0.493	0.513	0.462	0.465	0.491	0.512	0.498	0.513	0.473	0.506	0.5	0.522
10	Communication Services	0.49	0.509	0.475	0.486	0.493	0.498	0.495	0.497	0.497	0.495	0.508	0.501
	Consumer Discretionary	0.512	0.496	0.499	0.512	0.499	0.496	0.514	0.504	0.516	0.487	0.506	0.496
	Consumer Staples	0.515	0.508	0.495	0.493	0.486	0.506	0.499	0.509	0.494	0.468	0.491	0.502
	Energy	0.503	0.492	0.488	0.493	0.482	0.495	0.497	0.493	0.487	0.504	0.487	0.49
	Financials	0.506	0.494	0.514	0.498	0.487	0.508	0.51	0.48	0.531	0.485	0.48	0.506
	Health Care	0.476	0.488	0.512	0.49	0.504	0.487	0.496	0.494	0.51	0.493	0.502	0.498
	Industrials	0.506	0.496	0.495	0.501	0.491	0.497	0.5	0.502	0.499	0.494	0.495	0.5
	Technology	0.489	0.493	0.51	0.508	0.51	0.491	0.499	0.503	0.506	0.506	0.509	0.5
	Materials	0.502	0.49	0.487	0.502	0.492	0.491	0.504	0.505	0.488	0.495	0.495	0.493
	Real Estate	0.489	0.488	0.518	0.533	0.501	0.502	0.494	0.502	0.491	0.515	0.516	0.49
	Utilities	0.52	0.512	0.477	0.449	0.474	0.507	0.521	0.469	0.497	0.453	0.427	0.518

NN5

Method		Equal-weighted Portfolio						Value-weighted Portfolio					
Portfolio	Sector	Value vs growth	Profitability	Investment	Intangibles	Trading frictions	Momentum	Value vs growth	Profitability	Investment	Intangibles	Trading frictions	Momentum
1	Communication Services	0.474	0.492	0.483	0.495	0.505	0.477	0.479	0.489	0.491	0.496	0.494	0.483
	Consumer Discretionary	0.517	0.49	0.498	0.516	0.505	0.475	0.501	0.507	0.496	0.509	0.517	0.493
	Consumer Staples	0.528	0.504	0.477	0.485	0.485	0.484	0.494	0.509	0.488	0.485	0.49	0.489
	Energy	0.499	0.485	0.47	0.5	0.499	0.463	0.495	0.497	0.484	0.504	0.497	0.474
	Financials	0.485	0.469	0.535	0.5	0.493	0.473	0.497	0.49	0.514	0.5	0.484	0.487
	Health Care	0.418	0.488	0.506	0.514	0.52	0.462	0.482	0.499	0.504	0.515	0.525	0.49
	Industrials	0.517	0.492	0.499	0.518	0.508	0.483	0.498	0.504	0.492	0.508	0.512	0.496
	Technology	0.457	0.504	0.505	0.519	0.516	0.472	0.494	0.505	0.502	0.521	0.52	0.491
	Materials	0.513	0.494	0.468	0.493	0.48	0.47	0.503	0.498	0.488	0.495	0.491	0.478
	Real Estate	0.469	0.472	0.507	0.54	0.52	0.46	0.49	0.504	0.496	0.516	0.523	0.493
	Utilities	0.563	0.473	0.482	0.423	0.458	0.486	0.533	0.464	0.486	0.451	0.406	0.463
10	Communication Services	0.488	0.498	0.484	0.495	0.505	0.523	0.486	0.486	0.485	0.495	0.493	0.51
	Consumer Discretionary	0.523	0.496	0.5	0.519	0.506	0.523	0.504	0.507	0.495	0.509	0.516	0.517
	Consumer Staples	0.527	0.506	0.484	0.492	0.49	0.53	0.492	0.508	0.492	0.491	0.502	0.519
	Energy	0.502	0.489	0.488	0.505	0.502	0.532	0.502	0.496	0.495	0.502	0.501	0.528
	Financials	0.493	0.476	0.541	0.509	0.497	0.525	0.499	0.499	0.512	0.505	0.496	0.519
	Health Care	0.431	0.494	0.506	0.513	0.524	0.512	0.486	0.494	0.508	0.509	0.523	0.517
	Industrials	0.519	0.497	0.504	0.521	0.51	0.531	0.498	0.504	0.495	0.509	0.515	0.523
	Technology	0.465	0.505	0.514	0.523	0.526	0.53	0.495	0.5	0.507	0.518	0.523	0.525
	Materials	0.512	0.495	0.482	0.506	0.488	0.521	0.503	0.494	0.495	0.501	0.5	0.516
	Real Estate	0.476	0.479	0.513	0.545	0.519	0.514	0.493	0.504	0.505	0.526	0.518	0.519
	Utilities	0.545	0.481	0.482	0.419	0.454	0.518	0.508	0.475	0.505	0.455	0.424	0.515

Method		Optimised - Low capital portfolio						Optimised - High capital portfolio					
Portfolio	Sector	Value vs growth	Profitability	Investment	Intangibles	Trading frictions	Momentum	Value vs growth	Profitability	Investment	Intangibles	Trading frictions	Momentum
1	Communication Services	0.475	0.512	0.46	0.467	0.506	0.497	0.495	0.511	0.486	0.517	0.512	0.502
	Consumer Discretionary	0.5	0.518	0.48	0.504	0.515	0.491	0.502	0.516	0.488	0.513	0.516	0.505
	Consumer Staples	0.499	0.522	0.47	0.483	0.495	0.497	0.501	0.521	0.479	0.505	0.508	0.507
	Energy	0.488	0.506	0.465	0.498	0.505	0.498	0.496	0.504	0.482	0.52	0.506	0.49
	Financials	0.491	0.505	0.49	0.495	0.499	0.498	0.501	0.51	0.5	0.514	0.499	0.509
	Health Care	0.48	0.5	0.491	0.491	0.514	0.489	0.489	0.494	0.502	0.518	0.517	0.491
	Industrials	0.495	0.508	0.48	0.494	0.506	0.492	0.494	0.51	0.484	0.517	0.516	0.504
	Technology	0.485	0.523	0.483	0.497	0.512	0.499	0.489	0.516	0.482	0.517	0.518	0.505
	Materials	0.491	0.524	0.451	0.487	0.506	0.493	0.497	0.511	0.476	0.514	0.514	0.499
	Real Estate	0.462	0.51	0.477	0.522	0.529	0.496	0.487	0.502	0.489	0.523	0.507	0.491
	Utilities	0.491	0.516	0.462	0.474	0.497	0.511	0.487	0.525	0.463	0.508	0.501	0.521
10	Communication Services	0.497	0.508	0.471	0.494	0.496	0.495	0.496	0.497	0.496	0.483	0.495	0.501
	Consumer Discretionary	0.509	0.497	0.499	0.513	0.503	0.494	0.517	0.501	0.517	0.479	0.501	0.497
	Consumer Staples	0.509	0.509	0.492	0.492	0.489	0.503	0.507	0.509	0.502	0.464	0.485	0.506
	Energy	0.502	0.494	0.484	0.491	0.483	0.492	0.511	0.484	0.496	0.49	0.482	0.491
	Financials	0.507	0.489	0.518	0.497	0.483	0.506	0.517	0.474	0.541	0.478	0.471	0.507
	Health Care	0.468	0.492	0.506	0.492	0.509	0.487	0.495	0.5	0.503	0.488	0.501	0.501
	Industrials	0.507	0.498	0.495	0.502	0.492	0.497	0.506	0.502	0.501	0.484	0.487	0.502
	Technology	0.485	0.495	0.508	0.51	0.512	0.492	0.502	0.495	0.506	0.503	0.498	0.496
	Materials	0.501	0.493	0.484	0.504	0.496	0.49	0.512	0.502	0.492	0.479	0.485	0.494
	Real Estate	0.491	0.449	0.552	0.523	0.48	0.491	0.488	0.479	0.517	0.513	0.497	0.504
	Utilities	0.527	0.513	0.481	0.445	0.474	0.503	0.526	0.469	0.511	0.451	0.428	0.528

Appendix 3Q: Means of predictive factors by functional category and sector, quarterly rebalancing

Appendix 3Q reports the mean value for the predictive factors when grouped by functional category (momentum, profitability, trading frictions, value vs. growth, intangibles and investment), as well as the eleven S&P sectors (communication services, consumer discretionary, consumer staples, energy, financials, health care, industrials, information technology, materials, real estate, utilities). The bottom portfolio is constructed by ranking stocks according to their machine learning predicted returns and form 10 portfolios and selling the lowest quintile portfolio. The top portfolio is constructed by ranking stocks according to their machine learning predicted returns and form 10 portfolios and buying the highest quintile portfolio. The long-short (HML) portfolio is constructed by ranking stocks according to their machine learning predicted returns and form 10 portfolios, buying the highest quantile portfolio and selling the lowest quintile portfolio. The factor realisations corresponding to the stocks chosen for the top and bottom portfolios are averaged cross-sectionally into the six functional categories and then averaged across the eleven S&P sectors to generate the results in the table. At each monthly period the factor input was rescaled to the [0,1] range and thus, the expected value for all factors is 0.5. For each portfolio, the heatmap illustrates the gradient of predictive factors The reported results the five neural network predictive models, NN1-NN5, respectively. The table is divided into four panels, A to D, which report the results for the equal-weighted, value-weighted, optimised portfolio trading a relatively small portfolio of 1 million USD and optimised portfolio trading a relatively large portfolio of 100 million USD, respectively. Investing horizon is three months and thus, rebalancing of the portfolio is performed quarterly based on predicted returns.

NN1

Method		Equal-weighted Portfolio						Value-weighted Portfolio					
Portfolio	Sector	Value vs growth	Profitability	Investment	Intangibles	Trading frictions	Momentum	Value vs growth	Profitability	Investment	Intangibles	Trading frictions	Momentum
1	Communication Services	0.472	0.486	0.471	0.487	0.505	0.464	0.478	0.49	0.485	0.495	0.495	0.474
	Consumer Discretionary	0.509	0.481	0.487	0.517	0.506	0.467	0.498	0.508	0.487	0.509	0.521	0.488
	Consumer Staples	0.514	0.491	0.469	0.495	0.491	0.482	0.492	0.51	0.481	0.492	0.504	0.491
	Energy	0.488	0.474	0.464	0.506	0.503	0.46	0.496	0.496	0.475	0.504	0.503	0.473
	Financials	0.481	0.46	0.527	0.499	0.494	0.471	0.496	0.485	0.511	0.5	0.487	0.483
	Health Care	0.412	0.483	0.504	0.516	0.523	0.459	0.481	0.497	0.505	0.516	0.527	0.486
	Industrials	0.505	0.481	0.49	0.522	0.511	0.475	0.494	0.507	0.484	0.512	0.522	0.496
	Technology	0.447	0.496	0.492	0.511	0.51	0.456	0.49	0.505	0.494	0.518	0.519	0.48
	Materials	0.493	0.48	0.466	0.507	0.488	0.474	0.498	0.497	0.481	0.502	0.504	0.486
	Real Estate	0.473	0.45	0.5	0.553	0.514	0.461	0.486	0.503	0.484	0.53	0.522	0.489
	Utilities	0.545	0.471	0.468	0.431	0.467	0.489	0.509	0.474	0.484	0.464	0.443	0.484
10	Communication Services	0.493	0.506	0.501	0.496	0.507	0.534	0.49	0.494	0.498	0.492	0.497	0.52
	Consumer Discretionary	0.535	0.509	0.512	0.515	0.509	0.542	0.507	0.51	0.503	0.509	0.515	0.531
	Consumer Staples	0.534	0.517	0.495	0.483	0.49	0.54	0.5	0.506	0.502	0.484	0.49	0.523
	Energy	0.507	0.505	0.488	0.489	0.499	0.557	0.502	0.492	0.499	0.496	0.485	0.545
	Financials	0.499	0.485	0.544	0.508	0.497	0.54	0.501	0.491	0.522	0.505	0.484	0.53
	Health Care	0.438	0.502	0.512	0.508	0.519	0.522	0.487	0.503	0.508	0.508	0.523	0.528
	Industrials	0.531	0.512	0.51	0.515	0.508	0.544	0.505	0.507	0.499	0.507	0.51	0.529
	Technology	0.471	0.516	0.523	0.52	0.526	0.544	0.496	0.509	0.509	0.519	0.525	0.537
	Materials	0.522	0.509	0.482	0.498	0.481	0.531	0.508	0.496	0.497	0.497	0.492	0.521
	Real Estate	0.481	0.482	0.511	0.546	0.521	0.525	0.489	0.513	0.503	0.528	0.524	0.525
	Utilities	0.563	0.486	0.496	0.427	0.46	0.537	0.519	0.475	0.5	0.454	0.414	0.521

Method		Optimised - Low capital portfolio						Optimised - High capital portfolio					
Portfolio	Sector	Value vs growth	Profitability	Investment	Intangibles	Trading frictions	Momentum	Value vs growth	Profitability	Investment	Intangibles	Trading frictions	Momentum
1	Communication Services	0.486	0.508	0.475	0.487	0.507	0.496	0.489	0.51	0.489	0.515	0.515	0.503
	Consumer Discretionary	0.496	0.516	0.483	0.502	0.522	0.496	0.5	0.517	0.491	0.514	0.521	0.503
	Consumer Staples	0.492	0.523	0.476	0.485	0.509	0.508	0.494	0.521	0.481	0.505	0.515	0.512
	Energy	0.492	0.5	0.469	0.496	0.501	0.489	0.491	0.506	0.478	0.517	0.511	0.502
	Financials	0.494	0.491	0.511	0.502	0.492	0.501	0.496	0.503	0.508	0.516	0.501	0.509
	Health Care	0.476	0.514	0.486	0.499	0.524	0.497	0.486	0.497	0.511	0.518	0.523	0.505
	Industrials	0.493	0.51	0.476	0.501	0.509	0.496	0.495	0.512	0.485	0.515	0.514	0.506
	Technology	0.486	0.515	0.486	0.514	0.527	0.498	0.493	0.514	0.493	0.521	0.526	0.502
	Materials	0.492	0.513	0.47	0.489	0.504	0.499	0.495	0.507	0.483	0.511	0.506	0.501
	Real Estate	0.489	0.488	0.503	0.531	0.522	0.49	0.485	0.505	0.499	0.535	0.516	0.511
	Utilities	0.514	0.505	0.475	0.468	0.483	0.515	0.513	0.5	0.479	0.48	0.473	0.513
10	Communication Services	0.478	0.495	0.477	0.474	0.487	0.492	0.495	0.502	0.494	0.489	0.506	0.502
	Consumer Discretionary	0.512	0.494	0.506	0.501	0.497	0.492	0.511	0.508	0.505	0.503	0.513	0.499
	Consumer Staples	0.498	0.506	0.493	0.483	0.481	0.497	0.51	0.513	0.497	0.483	0.497	0.506
	Energy	0.5	0.49	0.489	0.496	0.481	0.499	0.5	0.499	0.486	0.501	0.495	0.502
	Financials	0.502	0.48	0.523	0.496	0.476	0.5	0.505	0.485	0.526	0.499	0.48	0.507
	Health Care	0.482	0.492	0.505	0.492	0.502	0.491	0.493	0.502	0.504	0.5	0.513	0.504
	Industrials	0.506	0.494	0.499	0.497	0.485	0.492	0.509	0.5	0.5	0.498	0.497	0.498
	Technology	0.496	0.492	0.509	0.504	0.501	0.488	0.501	0.506	0.505	0.507	0.514	0.505
	Materials	0.5	0.499	0.482	0.494	0.487	0.49	0.509	0.507	0.486	0.499	0.502	0.495
	Real Estate	0.495	0.48	0.526	0.535	0.503	0.499	0.497	0.484	0.518	0.515	0.51	0.494
	Utilities	0.511	0.498	0.479	0.463	0.463	0.51	0.524	0.493	0.492	0.473	0.459	0.506

NN2

Method		Equal-weighted Portfolio						Value-weighted Portfolio					
Portfolio	Sector	Value vs growth	Profitability	Investment	Intangibles	Trading frictions	Momentum	Value vs growth	Profitability	Investment	Intangibles	Trading frictions	Momentum
1	Communication Services	0.486	0.49	0.484	0.508	0.507	0.464	0.486	0.487	0.491	0.505	0.498	0.471
	Consumer Discretionary	0.513	0.485	0.492	0.52	0.502	0.461	0.502	0.503	0.493	0.509	0.513	0.478
	Consumer Staples	0.515	0.491	0.472	0.5	0.489	0.479	0.495	0.505	0.484	0.493	0.496	0.485
	Energy	0.491	0.485	0.472	0.508	0.5	0.466	0.504	0.494	0.485	0.504	0.494	0.469
	Financials	0.481	0.452	0.533	0.509	0.485	0.462	0.498	0.48	0.517	0.506	0.48	0.478
	Health Care	0.412	0.483	0.508	0.522	0.525	0.455	0.483	0.492	0.507	0.52	0.525	0.479
	Industrials	0.507	0.482	0.495	0.535	0.511	0.472	0.497	0.504	0.489	0.518	0.517	0.489
	Technology	0.454	0.49	0.499	0.53	0.517	0.457	0.49	0.497	0.499	0.527	0.516	0.477
	Materials	0.496	0.482	0.467	0.506	0.487	0.463	0.503	0.489	0.487	0.499	0.491	0.468
	Real Estate	0.472	0.465	0.506	0.548	0.509	0.467	0.487	0.503	0.493	0.525	0.512	0.489
	Utilities	0.562	0.473	0.477	0.428	0.463	0.482	0.514	0.477	0.493	0.46	0.427	0.484
10	Communication Services	0.496	0.511	0.49	0.482	0.505	0.536	0.487	0.493	0.496	0.488	0.497	0.52
	Consumer Discretionary	0.535	0.507	0.509	0.509	0.51	0.548	0.505	0.51	0.503	0.505	0.519	0.534
	Consumer Staples	0.542	0.518	0.491	0.48	0.493	0.549	0.501	0.51	0.499	0.484	0.498	0.532
	Energy	0.509	0.503	0.483	0.482	0.502	0.561	0.507	0.497	0.497	0.493	0.495	0.549
	Financials	0.501	0.485	0.544	0.504	0.5	0.548	0.501	0.493	0.519	0.502	0.487	0.535
	Health Care	0.432	0.497	0.509	0.504	0.522	0.522	0.49	0.497	0.511	0.508	0.523	0.527
	Industrials	0.534	0.509	0.51	0.513	0.513	0.551	0.503	0.506	0.5	0.505	0.515	0.538
	Technology	0.471	0.514	0.525	0.517	0.529	0.548	0.497	0.506	0.511	0.518	0.526	0.538
	Materials	0.528	0.506	0.481	0.495	0.486	0.536	0.51	0.494	0.494	0.494	0.499	0.523
	Real Estate	0.491	0.48	0.519	0.539	0.512	0.524	0.495	0.505	0.505	0.527	0.523	0.52
	Utilities	0.564	0.48	0.485	0.42	0.464	0.537	0.529	0.471	0.503	0.45	0.419	0.518

Method		Optimised - Low capital portfolio						Optimised - High capital portfolio					
Portfolio	Sector	Value vs growth	Profitability	Investment	Intangibles	Trading frictions	Momentum	Value vs growth	Profitability	Investment	Intangibles	Trading frictions	Momentum
1	Communication Services	0.481	0.5	0.464	0.487	0.501	0.491	0.484	0.51	0.49	0.516	0.508	0.509
	Consumer Discretionary	0.495	0.516	0.48	0.505	0.52	0.502	0.491	0.516	0.492	0.514	0.518	0.505
	Consumer Staples	0.501	0.52	0.478	0.494	0.504	0.502	0.49	0.52	0.485	0.51	0.51	0.515
	Energy	0.49	0.512	0.463	0.505	0.508	0.496	0.491	0.503	0.487	0.513	0.505	0.503
	Financials	0.493	0.506	0.492	0.504	0.505	0.5	0.493	0.511	0.501	0.52	0.506	0.513
	Health Care	0.47	0.507	0.483	0.502	0.523	0.491	0.484	0.498	0.507	0.52	0.519	0.502
	Industrials	0.492	0.514	0.475	0.506	0.513	0.498	0.49	0.515	0.485	0.522	0.517	0.506
	Technology	0.484	0.514	0.483	0.513	0.523	0.499	0.489	0.512	0.492	0.516	0.514	0.501
	Materials	0.493	0.513	0.465	0.497	0.503	0.501	0.489	0.514	0.474	0.518	0.51	0.501
	Real Estate	0.487	0.506	0.508	0.529	0.5	0.508	0.476	0.495	0.5	0.515	0.494	0.495
	Utilities	0.496	0.511	0.464	0.481	0.497	0.512	0.504	0.518	0.474	0.504	0.507	0.515
10	Communication Services	0.491	0.503	0.477	0.485	0.49	0.498	0.498	0.494	0.499	0.485	0.496	0.497
	Consumer Discretionary	0.509	0.495	0.505	0.506	0.498	0.492	0.51	0.502	0.507	0.489	0.5	0.494
	Consumer Staples	0.51	0.502	0.499	0.487	0.484	0.499	0.505	0.51	0.491	0.475	0.485	0.498
	Energy	0.497	0.494	0.483	0.491	0.48	0.495	0.486	0.498	0.474	0.501	0.484	0.486
	Financials	0.504	0.488	0.518	0.494	0.483	0.503	0.507	0.49	0.515	0.494	0.483	0.502
	Health Care	0.479	0.492	0.504	0.488	0.505	0.491	0.496	0.495	0.501	0.497	0.508	0.496
	Industrials	0.507	0.493	0.499	0.497	0.483	0.494	0.506	0.498	0.498	0.491	0.493	0.496
	Technology	0.492	0.493	0.512	0.5	0.503	0.489	0.503	0.494	0.507	0.498	0.502	0.497
	Materials	0.501	0.495	0.482	0.489	0.481	0.489	0.503	0.506	0.478	0.492	0.492	0.491
	Real Estate	0.489	0.489	0.514	0.524	0.507	0.494	0.491	0.497	0.493	0.511	0.506	0.493
	Utilities	0.527	0.49	0.486	0.453	0.455	0.497	0.522	0.487	0.491	0.468	0.455	0.506

NN3

Method		Equal-weighted Portfolio						Value-weighted Portfolio					
Portfolio	Sector	Value vs growth	Profitability	Investment	Intangibles	Trading frictions	Momentum	Value vs growth	Profitability	Investment	Intangibles	Trading frictions	Momentum
1	Communication Services	0.472	0.491	0.475	0.483	0.504	0.473	0.476	0.489	0.488	0.489	0.491	0.476
	Consumer Discretionary	0.509	0.489	0.488	0.508	0.503	0.473	0.498	0.509	0.49	0.504	0.516	0.493
	Consumer Staples	0.522	0.501	0.47	0.484	0.483	0.489	0.49	0.512	0.484	0.485	0.493	0.494
	Energy	0.491	0.487	0.462	0.492	0.499	0.461	0.499	0.497	0.48	0.496	0.493	0.47
	Financials	0.484	0.458	0.53	0.497	0.488	0.471	0.498	0.489	0.512	0.498	0.486	0.488
	Health Care	0.415	0.486	0.503	0.512	0.52	0.465	0.481	0.499	0.502	0.514	0.523	0.49
	Industrials	0.513	0.491	0.487	0.512	0.506	0.481	0.497	0.506	0.485	0.504	0.511	0.495
	Technology	0.459	0.508	0.494	0.507	0.506	0.473	0.495	0.508	0.498	0.512	0.513	0.491
	Materials	0.508	0.497	0.459	0.491	0.478	0.473	0.502	0.5	0.484	0.493	0.492	0.481
	Real Estate	0.476	0.47	0.507	0.531	0.521	0.464	0.497	0.502	0.496	0.511	0.522	0.485
	Utilities	0.55	0.467	0.465	0.418	0.461	0.484	0.519	0.466	0.484	0.449	0.421	0.468
10	Communication Services	0.495	0.498	0.495	0.51	0.511	0.532	0.494	0.489	0.488	0.503	0.497	0.524
	Consumer Discretionary	0.533	0.499	0.515	0.526	0.511	0.536	0.509	0.503	0.506	0.512	0.516	0.525
	Consumer Staples	0.541	0.508	0.502	0.508	0.497	0.536	0.507	0.503	0.502	0.498	0.501	0.522
	Energy	0.503	0.492	0.491	0.505	0.507	0.548	0.506	0.489	0.5	0.503	0.496	0.536
	Financials	0.497	0.482	0.542	0.514	0.501	0.535	0.501	0.495	0.514	0.507	0.494	0.524
	Health Care	0.436	0.495	0.517	0.518	0.529	0.52	0.492	0.49	0.515	0.513	0.528	0.522
	Industrials	0.527	0.502	0.514	0.525	0.514	0.541	0.505	0.5	0.504	0.51	0.513	0.529
	Technology	0.469	0.504	0.528	0.535	0.535	0.538	0.497	0.5	0.513	0.526	0.53	0.531
	Materials	0.518	0.497	0.492	0.515	0.492	0.526	0.506	0.492	0.498	0.502	0.501	0.511
	Real Estate	0.481	0.485	0.516	0.543	0.516	0.511	0.497	0.501	0.517	0.524	0.511	0.504
	Utilities	0.544	0.482	0.483	0.435	0.459	0.529	0.52	0.468	0.504	0.458	0.425	0.524

Method		Optimised - Low capital portfolio						Optimised - High capital portfolio					
Portfolio	Sector	Value vs growth	Profitability	Investment	Intangibles	Trading frictions	Momentum	Value vs growth	Profitability	Investment	Intangibles	Trading frictions	Momentum
1	Communication Services	0.48	0.504	0.467	0.492	0.494	0.485	0.489	0.508	0.486	0.517	0.513	0.499
	Consumer Discretionary	0.495	0.517	0.481	0.503	0.518	0.495	0.496	0.512	0.492	0.516	0.518	0.5
	Consumer Staples	0.488	0.522	0.465	0.483	0.497	0.498	0.495	0.522	0.481	0.498	0.508	0.507
	Energy	0.483	0.511	0.454	0.505	0.504	0.489	0.488	0.51	0.471	0.514	0.509	0.498
	Financials	0.491	0.496	0.503	0.504	0.491	0.495	0.498	0.501	0.506	0.509	0.496	0.506
	Health Care	0.476	0.503	0.492	0.503	0.518	0.487	0.486	0.499	0.504	0.515	0.518	0.496
	Industrials	0.493	0.513	0.474	0.498	0.506	0.495	0.495	0.517	0.481	0.517	0.513	0.502
	Technology	0.484	0.51	0.489	0.509	0.515	0.49	0.489	0.515	0.491	0.523	0.521	0.496
	Materials	0.492	0.518	0.465	0.497	0.504	0.491	0.495	0.506	0.482	0.511	0.506	0.494
	Real Estate	0.486	0.508	0.492	0.509	0.511	0.494	0.486	0.489	0.504	0.524	0.502	0.49
	Utilities	0.498	0.5	0.468	0.463	0.476	0.503	0.503	0.509	0.469	0.486	0.483	0.514
10	Communication Services	0.495	0.498	0.479	0.48	0.484	0.487	0.497	0.496	0.495	0.488	0.502	0.493
	Consumer Discretionary	0.511	0.497	0.501	0.507	0.502	0.494	0.514	0.506	0.507	0.49	0.506	0.5
	Consumer Staples	0.507	0.503	0.494	0.49	0.484	0.503	0.507	0.515	0.491	0.483	0.499	0.51
	Energy	0.493	0.491	0.485	0.497	0.481	0.5	0.495	0.496	0.48	0.493	0.486	0.497
	Financials	0.505	0.488	0.518	0.491	0.481	0.503	0.509	0.484	0.523	0.493	0.477	0.511
	Health Care	0.476	0.487	0.509	0.49	0.507	0.489	0.492	0.496	0.507	0.499	0.508	0.499
	Industrials	0.504	0.498	0.497	0.498	0.489	0.497	0.507	0.499	0.498	0.492	0.496	0.5
	Technology	0.49	0.488	0.515	0.509	0.508	0.491	0.498	0.5	0.505	0.511	0.509	0.492
	Materials	0.497	0.499	0.481	0.492	0.495	0.493	0.509	0.505	0.486	0.489	0.494	0.498
	Real Estate	0.513	0.491	0.51	0.521	0.492	0.482	0.495	0.504	0.5	0.516	0.512	0.502
	Utilities	0.523	0.498	0.483	0.442	0.455	0.501	0.521	0.481	0.495	0.459	0.445	0.517

NN4

Method		Equal-weighted Portfolio						Value-weighted Portfolio					
Portfolio	Sector	Value vs growth	Profitability	Investment	Intangibles	Trading frictions	Momentum	Value vs growth	Profitability	Investment	Intangibles	Trading frictions	Momentum
1	Communication Services	0.468	0.49	0.476	0.485	0.503	0.474	0.477	0.487	0.489	0.489	0.491	0.477
	Consumer Discretionary	0.51	0.488	0.488	0.509	0.505	0.47	0.499	0.508	0.491	0.505	0.516	0.488
	Consumer Staples	0.52	0.501	0.469	0.487	0.485	0.482	0.492	0.51	0.486	0.486	0.496	0.491
	Energy	0.491	0.485	0.463	0.497	0.5	0.46	0.499	0.496	0.479	0.499	0.497	0.47
	Financials	0.482	0.456	0.532	0.498	0.488	0.468	0.498	0.487	0.514	0.498	0.486	0.486
	Health Care	0.415	0.487	0.501	0.511	0.519	0.463	0.482	0.499	0.503	0.513	0.524	0.488
	Industrials	0.515	0.492	0.489	0.514	0.508	0.48	0.498	0.505	0.487	0.505	0.512	0.493
	Technology	0.459	0.509	0.493	0.507	0.507	0.469	0.493	0.51	0.497	0.511	0.516	0.489
	Materials	0.509	0.496	0.46	0.492	0.479	0.471	0.504	0.499	0.483	0.492	0.492	0.478
	Real Estate	0.476	0.462	0.516	0.548	0.518	0.466	0.49	0.505	0.495	0.519	0.522	0.49
	Utilities	0.548	0.468	0.469	0.424	0.463	0.487	0.525	0.462	0.482	0.451	0.421	0.465
10	Communication Services	0.492	0.497	0.493	0.507	0.507	0.533	0.494	0.488	0.487	0.502	0.493	0.522
	Consumer Discretionary	0.533	0.499	0.513	0.524	0.508	0.535	0.508	0.504	0.503	0.511	0.514	0.526
	Consumer Staples	0.542	0.507	0.5	0.502	0.492	0.538	0.505	0.504	0.5	0.494	0.498	0.524
	Energy	0.507	0.495	0.488	0.499	0.505	0.552	0.506	0.49	0.498	0.499	0.495	0.54
	Financials	0.498	0.481	0.542	0.513	0.5	0.536	0.5	0.496	0.512	0.507	0.493	0.524
	Health Care	0.435	0.494	0.517	0.518	0.528	0.522	0.49	0.489	0.514	0.512	0.527	0.525
	Industrials	0.527	0.501	0.513	0.523	0.511	0.542	0.503	0.5	0.501	0.51	0.51	0.53
	Technology	0.469	0.504	0.527	0.534	0.533	0.541	0.496	0.5	0.511	0.526	0.528	0.533
	Materials	0.521	0.501	0.49	0.51	0.488	0.528	0.507	0.492	0.5	0.502	0.496	0.516
	Real Estate	0.48	0.486	0.515	0.541	0.516	0.519	0.498	0.5	0.517	0.524	0.512	0.508
	Utilities	0.552	0.483	0.484	0.427	0.458	0.527	0.517	0.474	0.507	0.456	0.418	0.522

Method		Optimised - Low capital portfolio						Optimised - High capital portfolio					
Portfolio	Sector	Value vs growth	Profitability	Investment	Intangibles	Trading frictions	Momentum	Value vs growth	Profitability	Investment	Intangibles	Trading frictions	Momentum
1	Communication Services	0.478	0.505	0.471	0.486	0.501	0.489	0.487	0.505	0.484	0.51	0.505	0.498
	Consumer Discretionary	0.496	0.517	0.483	0.502	0.514	0.495	0.495	0.512	0.49	0.509	0.511	0.498
	Consumer Staples	0.489	0.526	0.47	0.491	0.515	0.505	0.494	0.517	0.477	0.504	0.502	0.501
	Energy	0.482	0.512	0.455	0.507	0.508	0.489	0.493	0.503	0.471	0.512	0.507	0.49
	Financials	0.489	0.498	0.502	0.504	0.495	0.496	0.493	0.501	0.5	0.512	0.496	0.499
	Health Care	0.472	0.508	0.485	0.501	0.518	0.489	0.493	0.493	0.508	0.512	0.515	0.49
	Industrials	0.492	0.516	0.475	0.503	0.511	0.496	0.49	0.512	0.481	0.512	0.508	0.502
	Technology	0.484	0.515	0.484	0.511	0.519	0.493	0.492	0.512	0.49	0.52	0.52	0.5
	Materials	0.489	0.511	0.468	0.491	0.5	0.483	0.491	0.504	0.477	0.51	0.502	0.49
	Real Estate	0.476	0.51	0.479	0.523	0.53	0.5	0.473	0.496	0.482	0.512	0.499	0.483
	Utilities	0.492	0.506	0.468	0.464	0.479	0.511	0.508	0.498	0.48	0.476	0.466	0.509
10	Communication Services	0.493	0.496	0.48	0.48	0.482	0.491	0.494	0.501	0.492	0.484	0.499	0.502
	Consumer Discretionary	0.51	0.495	0.503	0.506	0.5	0.492	0.508	0.503	0.509	0.492	0.506	0.498
	Consumer Staples	0.512	0.497	0.497	0.489	0.48	0.501	0.504	0.513	0.498	0.478	0.493	0.509
	Energy	0.493	0.49	0.487	0.493	0.48	0.5	0.495	0.497	0.483	0.502	0.488	0.498
	Financials	0.503	0.488	0.517	0.494	0.482	0.503	0.512	0.482	0.53	0.489	0.48	0.507
	Health Care	0.477	0.486	0.51	0.491	0.508	0.488	0.492	0.497	0.506	0.496	0.507	0.497
	Industrials	0.504	0.498	0.495	0.498	0.487	0.495	0.501	0.504	0.494	0.496	0.497	0.501
	Technology	0.492	0.487	0.517	0.512	0.509	0.489	0.503	0.501	0.504	0.511	0.507	0.498
	Materials	0.498	0.495	0.482	0.494	0.494	0.495	0.509	0.501	0.488	0.492	0.494	0.494
	Real Estate	0.513	0.494	0.521	0.521	0.486	0.488	0.487	0.504	0.493	0.508	0.5	0.492
	Utilities	0.527	0.499	0.484	0.438	0.453	0.498	0.523	0.494	0.5	0.468	0.461	0.516

NN5

Method		Equal-weighted Portfolio						Value-weighted Portfolio					
Portfolio	Sector	Value vs growth	Profitability	Investment	Intangibles	Trading frictions	Momentum	Value vs growth	Profitability	Investment	Intangibles	Trading frictions	Momentum
1	Communication Services	0.475	0.493	0.482	0.49	0.503	0.48	0.476	0.49	0.488	0.495	0.494	0.484
	Consumer Discretionary	0.516	0.49	0.496	0.514	0.504	0.476	0.499	0.511	0.493	0.509	0.519	0.498
	Consumer Staples	0.523	0.503	0.475	0.485	0.484	0.488	0.492	0.51	0.488	0.485	0.49	0.491
	Energy	0.496	0.485	0.468	0.498	0.498	0.468	0.493	0.5	0.48	0.504	0.5	0.48
	Financials	0.483	0.468	0.533	0.498	0.492	0.478	0.495	0.494	0.512	0.499	0.488	0.493
	Health Care	0.417	0.489	0.506	0.513	0.519	0.466	0.48	0.503	0.501	0.516	0.526	0.494
	Industrials	0.515	0.492	0.498	0.517	0.508	0.484	0.497	0.505	0.49	0.508	0.513	0.498
	Technology	0.455	0.504	0.503	0.519	0.515	0.474	0.493	0.509	0.5	0.52	0.522	0.495
	Materials	0.512	0.495	0.465	0.492	0.48	0.471	0.502	0.5	0.486	0.494	0.492	0.48
	Real Estate	0.468	0.47	0.51	0.541	0.523	0.464	0.491	0.504	0.499	0.515	0.522	0.489
	Utilities	0.564	0.472	0.479	0.42	0.455	0.478	0.531	0.466	0.485	0.45	0.408	0.455
10	Communication Services	0.491	0.498	0.484	0.496	0.505	0.522	0.486	0.487	0.481	0.493	0.492	0.511
	Consumer Discretionary	0.525	0.496	0.5	0.517	0.506	0.521	0.504	0.508	0.494	0.508	0.517	0.516
	Consumer Staples	0.53	0.508	0.486	0.488	0.49	0.531	0.494	0.509	0.492	0.488	0.501	0.52
	Energy	0.505	0.491	0.491	0.502	0.503	0.535	0.503	0.498	0.494	0.499	0.502	0.529
	Financials	0.492	0.476	0.541	0.507	0.495	0.525	0.499	0.498	0.512	0.504	0.495	0.518
	Health Care	0.433	0.496	0.507	0.51	0.525	0.512	0.487	0.494	0.508	0.506	0.524	0.518
	Industrials	0.52	0.498	0.504	0.518	0.51	0.53	0.499	0.504	0.495	0.508	0.514	0.523
	Technology	0.466	0.504	0.516	0.524	0.527	0.532	0.495	0.5	0.507	0.519	0.524	0.527
	Materials	0.512	0.496	0.483	0.502	0.487	0.519	0.503	0.496	0.493	0.5	0.502	0.513
	Real Estate	0.479	0.482	0.515	0.543	0.518	0.506	0.495	0.507	0.507	0.526	0.519	0.509
	Utilities	0.544	0.481	0.484	0.416	0.455	0.516	0.507	0.475	0.507	0.452	0.419	0.508

Method		Optimised - Low capital portfolio						Optimised - High capital portfolio					
Portfolio	Sector	Value vs growth	Profitability	Investment	Intangibles	Trading frictions	Momentum	Value vs growth	Profitability	Investment	Intangibles	Trading frictions	Momentum
1	Communication Services	0.473	0.518	0.461	0.486	0.509	0.502	0.492	0.51	0.485	0.52	0.514	0.506
	Consumer Discretionary	0.496	0.52	0.485	0.501	0.521	0.493	0.501	0.519	0.486	0.522	0.521	0.506
	Consumer Staples	0.484	0.525	0.47	0.485	0.498	0.5	0.498	0.522	0.482	0.515	0.51	0.513
	Energy	0.491	0.498	0.454	0.494	0.484	0.469	0.489	0.508	0.475	0.532	0.513	0.497
	Financials	0.49	0.495	0.501	0.494	0.486	0.494	0.493	0.51	0.496	0.523	0.503	0.509
	Health Care	0.474	0.502	0.492	0.501	0.519	0.483	0.484	0.497	0.503	0.527	0.522	0.502
	Industrials	0.489	0.514	0.469	0.494	0.503	0.494	0.493	0.517	0.477	0.528	0.521	0.504
	Technology	0.485	0.511	0.486	0.518	0.519	0.492	0.487	0.517	0.482	0.528	0.522	0.504
	Materials	0.49	0.513	0.46	0.485	0.494	0.485	0.494	0.516	0.471	0.524	0.518	0.499
	Real Estate	0.473	0.5	0.483	0.524	0.52	0.496	0.483	0.508	0.481	0.53	0.513	0.501
	Utilities	0.494	0.511	0.462	0.466	0.487	0.511	0.508	0.51	0.482	0.499	0.497	0.521
10	Communication Services	0.492	0.496	0.477	0.479	0.485	0.49	0.499	0.499	0.5	0.489	0.506	0.502
	Consumer Discretionary	0.507	0.495	0.499	0.509	0.502	0.492	0.512	0.506	0.512	0.489	0.506	0.499
	Consumer Staples	0.509	0.5	0.495	0.486	0.48	0.502	0.51	0.505	0.504	0.467	0.484	0.502
	Energy	0.496	0.5	0.477	0.502	0.49	0.504	0.498	0.494	0.485	0.497	0.486	0.494
	Financials	0.504	0.485	0.521	0.493	0.479	0.501	0.513	0.485	0.528	0.487	0.479	0.506
	Health Care	0.471	0.495	0.501	0.494	0.51	0.488	0.493	0.495	0.512	0.491	0.505	0.5
	Industrials	0.504	0.496	0.496	0.501	0.49	0.495	0.509	0.499	0.501	0.489	0.493	0.497
	Technology	0.488	0.487	0.514	0.514	0.511	0.489	0.506	0.497	0.512	0.497	0.504	0.5
	Materials	0.498	0.496	0.481	0.492	0.491	0.493	0.514	0.496	0.495	0.486	0.49	0.491
	Real Estate	0.487	0.476	0.517	0.534	0.508	0.496	0.496	0.492	0.52	0.504	0.51	0.493
	Utilities	0.529	0.502	0.483	0.438	0.457	0.499	0.531	0.467	0.509	0.442	0.427	0.508

Mean across all models

Method		Panel A: Equal-weighted Portfolio						Panel B: Value-weighted Portfolio					
Portfolio	Sector	Value vs growth	Profitability	Investment	Intangibles	Trading frictions	Momentum	Value vs growth	Profitability	Investment	Intangibles	Trading frictions	Momentum
1	Communication Services	0.475	0.490	0.478	0.491	0.504	0.471	0.479	0.489	0.488	0.495	0.494	0.476
	Consumer Discretionary	0.511	0.487	0.490	0.514	0.504	0.469	0.499	0.508	0.491	0.507	0.517	0.489
	Consumer Staples	0.519	0.497	0.471	0.490	0.486	0.484	0.492	0.509	0.485	0.488	0.496	0.490
	Energy	0.491	0.483	0.466	0.500	0.500	0.463	0.498	0.497	0.480	0.501	0.497	0.472
	Financials	0.482	0.459	0.531	0.500	0.489	0.470	0.497	0.487	0.513	0.500	0.485	0.486
	Health Care	0.414	0.486	0.504	0.515	0.521	0.462	0.481	0.498	0.504	0.516	0.525	0.487
	Industrials	0.511	0.488	0.492	0.520	0.509	0.478	0.497	0.505	0.487	0.509	0.515	0.494
	Technology	0.455	0.501	0.496	0.515	0.511	0.466	0.492	0.506	0.498	0.518	0.517	0.486
	Materials	0.504	0.490	0.463	0.498	0.482	0.470	0.502	0.497	0.484	0.496	0.494	0.479
	Real Estate	0.473	0.463	0.508	0.544	0.517	0.464	0.490	0.503	0.493	0.520	0.520	0.488
	Utilities	0.554	0.470	0.472	0.424	0.462	0.484	0.520	0.469	0.486	0.455	0.424	0.471
10	Communication Services	0.493	0.502	0.493	0.498	0.507	0.531	0.490	0.490	0.490	0.496	0.495	0.519
	Consumer Discretionary	0.532	0.502	0.510	0.518	0.509	0.536	0.507	0.507	0.502	0.509	0.516	0.526
	Consumer Staples	0.538	0.512	0.495	0.492	0.492	0.539	0.501	0.506	0.499	0.490	0.498	0.524
	Energy	0.506	0.497	0.488	0.495	0.503	0.551	0.505	0.493	0.498	0.498	0.495	0.540
	Financials	0.497	0.482	0.543	0.509	0.499	0.537	0.500	0.495	0.516	0.505	0.491	0.526
	Health Care	0.435	0.497	0.512	0.512	0.525	0.520	0.489	0.495	0.511	0.509	0.525	0.524
	Industrials	0.528	0.504	0.510	0.519	0.511	0.542	0.503	0.503	0.500	0.508	0.512	0.530
	Technology	0.469	0.508	0.524	0.526	0.530	0.541	0.496	0.503	0.510	0.522	0.527	0.533
	Materials	0.520	0.502	0.486	0.504	0.487	0.528	0.507	0.494	0.496	0.499	0.498	0.517
	Real Estate	0.482	0.483	0.515	0.542	0.517	0.517	0.495	0.505	0.510	0.526	0.518	0.513
	Utilities	0.553	0.482	0.486	0.425	0.459	0.529	0.518	0.473	0.504	0.454	0.419	0.519
HML	Communication Services	0.019	0.012	0.015	0.008	0.003	0.060	0.012	0.002	0.002	0.001	0.001	0.043
	Consumer Discretionary	0.021	0.015	0.020	0.005	0.005	0.067	0.007	-0.001	0.011	0.002	-0.001	0.037
	Consumer Staples	0.019	0.014	0.024	0.002	0.006	0.055	0.009	-0.003	0.014	0.001	0.002	0.034
	Energy	0.015	0.014	0.022	-0.005	0.003	0.088	0.007	-0.003	0.018	-0.003	-0.003	0.067
	Financials	0.015	0.023	0.012	0.009	0.009	0.067	0.003	0.008	0.003	0.005	0.005	0.041
	Health Care	0.021	0.011	0.008	-0.003	0.003	0.058	0.008	-0.003	0.008	-0.006	0.000	0.037
	Industrials	0.017	0.017	0.018	-0.001	0.002	0.063	0.006	-0.002	0.013	-0.001	-0.003	0.036
	Technology	0.014	0.007	0.028	0.011	0.019	0.075	0.004	-0.003	0.013	0.004	0.009	0.047
	Materials	0.017	0.012	0.022	0.006	0.004	0.058	0.005	-0.003	0.012	0.003	0.004	0.038
	Real Estate	0.009	0.020	0.007	-0.002	0.000	0.053	0.005	0.002	0.016	0.006	-0.002	0.025
	Utilities	0.000	0.012	0.015	0.001	-0.003	0.045	-0.001	0.004	0.019	-0.001	-0.005	0.047

Method		Panel C: Optimised Small Portfolio						Panel D: Optimised Large Portfolio					
Portfolio	Sector	Value vs growth	Profitability	Investment	Intangibles	Trading frictions	Momentum	Value vs growth	Profitability	Investment	Intangibles	Trading frictions	Momentum
1	Communication Services	0.480	0.507	0.468	0.488	0.502	0.493	0.488	0.509	0.487	0.516	0.511	0.503
	Consumer Discretionary	0.496	0.517	0.482	0.503	0.519	0.496	0.497	0.515	0.490	0.515	0.518	0.502
	Consumer Staples	0.491	0.523	0.472	0.488	0.505	0.503	0.494	0.520	0.481	0.506	0.509	0.510
	Energy	0.488	0.507	0.459	0.501	0.501	0.486	0.490	0.506	0.476	0.518	0.509	0.498
	Financials	0.491	0.497	0.502	0.502	0.494	0.497	0.495	0.505	0.502	0.516	0.500	0.507
	Health Care	0.474	0.507	0.488	0.501	0.520	0.489	0.487	0.497	0.507	0.518	0.519	0.499
	Industrials	0.492	0.513	0.474	0.500	0.508	0.496	0.493	0.515	0.482	0.519	0.515	0.504
	Technology	0.485	0.513	0.486	0.513	0.521	0.494	0.490	0.514	0.490	0.522	0.521	0.501
	Materials	0.491	0.514	0.466	0.492	0.501	0.492	0.493	0.509	0.477	0.515	0.508	0.497
	Real Estate	0.482	0.502	0.493	0.523	0.517	0.498	0.481	0.499	0.493	0.523	0.505	0.496
10	Utilities	0.499	0.507	0.467	0.468	0.484	0.510	0.507	0.507	0.477	0.489	0.485	0.514
	Communication Services	0.490	0.498	0.478	0.480	0.486	0.492	0.497	0.498	0.496	0.487	0.502	0.499
	Consumer Discretionary	0.510	0.495	0.503	0.506	0.500	0.492	0.511	0.505	0.508	0.493	0.506	0.498
	Consumer Staples	0.507	0.502	0.496	0.487	0.482	0.500	0.507	0.511	0.496	0.477	0.492	0.505
	Energy	0.496	0.493	0.484	0.496	0.482	0.500	0.495	0.497	0.482	0.499	0.488	0.495
	Financials	0.504	0.486	0.519	0.494	0.480	0.502	0.509	0.485	0.524	0.492	0.480	0.507
	Health Care	0.477	0.490	0.506	0.491	0.506	0.489	0.493	0.497	0.506	0.497	0.508	0.499
	Industrials	0.505	0.496	0.497	0.498	0.487	0.495	0.506	0.500	0.498	0.493	0.495	0.498
	Technology	0.492	0.489	0.513	0.508	0.506	0.489	0.502	0.500	0.507	0.505	0.507	0.498
	Materials	0.499	0.497	0.482	0.492	0.490	0.492	0.509	0.503	0.487	0.492	0.494	0.494
HML	Real Estate	0.499	0.486	0.518	0.527	0.499	0.492	0.493	0.496	0.505	0.511	0.508	0.495
	Utilities	0.523	0.497	0.483	0.447	0.457	0.501	0.524	0.484	0.497	0.462	0.449	0.511
	Communication Services	0.010	-0.009	0.010	-0.008	-0.017	-0.001	0.008	-0.010	0.009	-0.029	-0.009	-0.004
	Consumer Discretionary	0.014	-0.022	0.020	0.003	-0.019	-0.004	0.014	-0.010	0.018	-0.022	-0.012	-0.004
	Consumer Staples	0.016	-0.022	0.024	-0.001	-0.023	-0.002	0.013	-0.009	0.015	-0.029	-0.017	-0.005
	Energy	0.008	-0.014	0.025	-0.006	-0.019	0.013	0.004	-0.009	0.005	-0.019	-0.021	-0.003
	Financials	0.012	-0.011	0.018	-0.008	-0.014	0.005	0.015	-0.020	0.022	-0.024	-0.021	-0.001
	Health Care	0.003	-0.016	0.018	-0.010	-0.014	0.000	0.007	0.000	-0.001	-0.022	-0.011	0.000
	Industrials	0.013	-0.018	0.023	-0.002	-0.022	-0.001	0.014	-0.015	0.016	-0.026	-0.019	-0.006
	Technology	0.007	-0.024	0.028	-0.005	-0.014	-0.005	0.012	-0.014	0.017	-0.017	-0.013	-0.002
	Materials	0.008	-0.017	0.016	0.000	-0.011	0.000	0.016	-0.006	0.009	-0.023	-0.014	-0.003
	Real Estate	0.017	-0.016	0.025	0.004	-0.017	-0.006	0.013	-0.002	0.012	-0.012	0.003	-0.001
	Utilities	0.025	-0.009	0.016	-0.022	-0.028	-0.009	0.017	-0.023	0.021	-0.027	-0.036	-0.004

Appendix 3R: Means of predictive factors by functional category and sector, annual rebalancing

Appendix 3R reports the mean value for the predictive factors when grouped by functional category (momentum, profitability, trading frictions, value vs. growth, intangibles and investment), as well as the eleven S&P sectors (communication services, consumer discretionary, consumer staples, energy, financials, health care, industrials, information technology, materials, real estate, utilities). The bottom portfolio is constructed by ranking stocks according to their machine learning predicted returns and form 10 portfolios and selling the lowest quintile portfolio. The top portfolio is constructed by ranking stocks according to their machine learning predicted returns and form 10 portfolios and buying the highest quintile portfolio. The long-short (HML) portfolio is constructed by ranking stocks according to their machine learning predicted returns and form 10 portfolios, buying the highest quantile portfolio and selling the lowest quintile portfolio. The factor realisations corresponding to the stocks chosen for the top and bottom portfolios are averaged cross-sectionally into the six functional categories and then averaged across the eleven S&P sectors to generate the results in the table. At each monthly period the factor input was rescaled to the [0,1] range and thus, the expected value for all factors is 0.5. For each portfolio, the heatmap illustrates the gradient of predictive factors The reported results the five neural network predictive models, NN1-NN5, respectively. The table is divided into four panels, A to D, which report the results for the equal-weighted, value-weighted, optimised portfolio trading a relatively small portfolio of 1 million USD and optimised portfolio trading a relatively large portfolio of 100 million USD, respectively. Investing horizon is twelve months and thus, rebalancing of the portfolio is performed annual based on predicted returns.

NN1

Method		Equal-weighted Portfolio						Value-weighted Portfolio					
Portfolio	Sector	Value vs growth	Profitability	Investment	Intangibles	Trading frictions	Momentum	Value vs growth	Profitability	Investment	Intangibles	Trading frictions	Momentum
1	Communication Services	0.467	0.491	0.469	0.477	0.506	0.474	0.474	0.483	0.494	0.489	0.487	0.476
	Consumer Discretionary	0.51	0.49	0.487	0.509	0.505	0.477	0.499	0.503	0.49	0.505	0.516	0.489
	Consumer Staples	0.514	0.5	0.466	0.491	0.489	0.487	0.49	0.507	0.484	0.489	0.503	0.491
	Energy	0.489	0.483	0.462	0.494	0.503	0.464	0.503	0.495	0.477	0.492	0.495	0.466
	Financials	0.481	0.467	0.529	0.498	0.494	0.48	0.496	0.488	0.512	0.499	0.488	0.485
	Health Care	0.409	0.486	0.507	0.512	0.523	0.464	0.482	0.496	0.508	0.516	0.528	0.488
	Industrials	0.503	0.488	0.485	0.514	0.509	0.48	0.491	0.506	0.485	0.508	0.522	0.494
	Technology	0.445	0.506	0.491	0.499	0.507	0.465	0.489	0.504	0.498	0.513	0.516	0.485
	Materials	0.502	0.487	0.467	0.503	0.485	0.476	0.499	0.494	0.483	0.498	0.501	0.481
	Real Estate	0.47	0.458	0.483	0.549	0.511	0.449	0.49	0.503	0.482	0.531	0.526	0.474
10	Utilities	0.543	0.469	0.465	0.434	0.467	0.495	0.509	0.473	0.489	0.463	0.448	0.49
	Communication Services	0.493	0.498	0.499	0.496	0.505	0.514	0.485	0.495	0.502	0.493	0.497	0.507
	Consumer Discretionary	0.535	0.505	0.507	0.513	0.507	0.528	0.506	0.506	0.499	0.509	0.514	0.522
	Consumer Staples	0.536	0.516	0.494	0.483	0.487	0.528	0.498	0.505	0.499	0.484	0.486	0.52
	Energy	0.512	0.499	0.485	0.494	0.496	0.541	0.503	0.492	0.492	0.497	0.478	0.535
	Financials	0.495	0.481	0.543	0.508	0.498	0.533	0.5	0.492	0.52	0.507	0.484	0.529
	Health Care	0.442	0.5	0.509	0.51	0.516	0.506	0.484	0.502	0.504	0.512	0.519	0.519
	Industrials	0.53	0.515	0.508	0.512	0.505	0.53	0.503	0.509	0.497	0.508	0.509	0.519
	Technology	0.473	0.511	0.519	0.519	0.522	0.528	0.495	0.508	0.506	0.519	0.524	0.53
	Materials	0.523	0.51	0.481	0.501	0.478	0.519	0.504	0.498	0.493	0.5	0.491	0.511
	Real Estate	0.476	0.481	0.504	0.544	0.521	0.512	0.486	0.512	0.498	0.529	0.526	0.521
	Utilities	0.559	0.484	0.495	0.428	0.461	0.522	0.512	0.474	0.499	0.457	0.415	0.507

Method		Optimised - Low capital portfolio						Optimised - High capital portfolio					
Portfolio	Sector	Value vs growth	Profitability	Investment	Intangibles	Trading frictions	Momentum	Value vs growth	Profitability	Investment	Intangibles	Trading frictions	Momentum
1	Communication Services	0.48	0.511	0.479	0.492	0.514	0.501	0.478	0.513	0.479	0.512	0.514	0.497
	Consumer Discretionary	0.499	0.516	0.486	0.509	0.523	0.5	0.501	0.516	0.488	0.515	0.521	0.5
	Consumer Staples	0.499	0.518	0.48	0.49	0.506	0.507	0.494	0.524	0.477	0.498	0.507	0.509
	Energy	0.493	0.507	0.467	0.503	0.508	0.498	0.493	0.518	0.468	0.519	0.517	0.499
	Financials	0.495	0.495	0.509	0.505	0.497	0.507	0.491	0.505	0.503	0.515	0.503	0.511
	Health Care	0.481	0.511	0.492	0.506	0.524	0.5	0.482	0.509	0.495	0.513	0.525	0.503
	Industrials	0.497	0.511	0.481	0.503	0.508	0.499	0.495	0.519	0.479	0.516	0.517	0.505
	Technology	0.486	0.519	0.486	0.517	0.528	0.502	0.489	0.518	0.491	0.522	0.525	0.5
	Materials	0.493	0.511	0.471	0.5	0.508	0.496	0.495	0.512	0.471	0.509	0.508	0.493
	Real Estate	0.487	0.503	0.492	0.536	0.521	0.499	0.486	0.504	0.506	0.535	0.516	0.505
	Utilities	0.51	0.499	0.475	0.465	0.468	0.512	0.503	0.509	0.475	0.489	0.494	0.516
10	Communication Services	0.493	0.495	0.492	0.475	0.488	0.494	0.499	0.497	0.504	0.486	0.503	0.502
	Consumer Discretionary	0.515	0.498	0.508	0.501	0.499	0.496	0.517	0.502	0.513	0.497	0.506	0.501
	Consumer Staples	0.505	0.507	0.496	0.479	0.482	0.503	0.507	0.51	0.501	0.478	0.489	0.51
	Energy	0.501	0.492	0.491	0.497	0.481	0.502	0.505	0.494	0.492	0.499	0.487	0.503
	Financials	0.502	0.481	0.526	0.497	0.473	0.504	0.506	0.486	0.529	0.5	0.481	0.507
	Health Care	0.489	0.493	0.508	0.494	0.509	0.497	0.501	0.492	0.515	0.501	0.51	0.502
	Industrials	0.51	0.494	0.503	0.496	0.488	0.494	0.511	0.498	0.503	0.495	0.495	0.501
	Technology	0.5	0.496	0.511	0.508	0.509	0.494	0.506	0.499	0.509	0.506	0.51	0.502
	Materials	0.508	0.499	0.487	0.49	0.484	0.494	0.508	0.504	0.491	0.496	0.496	0.499
	Real Estate	0.491	0.488	0.515	0.519	0.509	0.492	0.506	0.473	0.532	0.523	0.501	0.489
	Utilities	0.517	0.489	0.487	0.457	0.447	0.506	0.514	0.489	0.492	0.47	0.454	0.51

NN2

Method		Equal-weighted Portfolio						Value-weighted Portfolio					
Portfolio	Sector	Value vs growth	Profitability	Investment	Intangibles	Trading frictions	Momentum	Value vs growth	Profitability	Investment	Intangibles	Trading frictions	Momentum
1	Communication Services	0.482	0.496	0.48	0.498	0.507	0.465	0.489	0.49	0.493	0.5	0.497	0.474
	Consumer Discretionary	0.514	0.493	0.493	0.511	0.502	0.474	0.5	0.508	0.492	0.507	0.515	0.489
	Consumer Staples	0.52	0.498	0.474	0.496	0.486	0.495	0.495	0.506	0.487	0.491	0.493	0.496
	Energy	0.492	0.491	0.471	0.5	0.501	0.47	0.506	0.5	0.483	0.492	0.492	0.472
	Financials	0.481	0.459	0.536	0.505	0.484	0.475	0.497	0.482	0.522	0.502	0.479	0.485
	Health Care	0.408	0.486	0.505	0.515	0.524	0.456	0.483	0.498	0.504	0.52	0.53	0.486
	Industrials	0.506	0.489	0.496	0.529	0.508	0.481	0.494	0.505	0.49	0.516	0.515	0.493
	Technology	0.451	0.496	0.499	0.523	0.514	0.463	0.491	0.504	0.501	0.525	0.518	0.487
	Materials	0.502	0.489	0.468	0.5	0.487	0.476	0.503	0.492	0.487	0.497	0.492	0.478
10	Real Estate	0.477	0.471	0.505	0.539	0.508	0.474	0.483	0.508	0.491	0.522	0.517	0.492
	Utilities	0.56	0.477	0.483	0.431	0.463	0.48	0.511	0.474	0.496	0.466	0.431	0.491
	Communication Services	0.492	0.51	0.49	0.48	0.502	0.523	0.485	0.491	0.499	0.485	0.492	0.509
	Consumer Discretionary	0.539	0.507	0.507	0.506	0.509	0.525	0.502	0.509	0.501	0.503	0.519	0.52
	Consumer Staples	0.545	0.517	0.489	0.477	0.487	0.536	0.499	0.51	0.496	0.482	0.491	0.522
	Energy	0.514	0.5	0.483	0.487	0.502	0.537	0.51	0.498	0.502	0.494	0.499	0.54
	Financials	0.501	0.481	0.541	0.507	0.502	0.534	0.5	0.492	0.516	0.507	0.491	0.52
	Health Care	0.436	0.496	0.508	0.502	0.519	0.522	0.498	0.498	0.511	0.5	0.525	0.534
	Industrials	0.536	0.509	0.508	0.514	0.512	0.537	0.501	0.506	0.496	0.506	0.517	0.523
	Technology	0.473	0.51	0.524	0.52	0.529	0.529	0.494	0.506	0.508	0.52	0.529	0.525
	Materials	0.526	0.506	0.475	0.49	0.481	0.523	0.507	0.493	0.491	0.489	0.493	0.51
	Real Estate	0.474	0.465	0.515	0.547	0.511	0.488	0.482	0.506	0.489	0.529	0.529	0.505
	Utilities	0.567	0.475	0.486	0.42	0.465	0.519	0.524	0.475	0.506	0.45	0.416	0.496

Method		Optimised - Low capital portfolio						Optimised - High capital portfolio					
Portfolio	Sector	Value vs growth	Profitability	Investment	Intangibles	Trading frictions	Momentum	Value vs growth	Profitability	Investment	Intangibles	Trading frictions	Momentum
1	Communication Services	0.483	0.51	0.475	0.498	0.512	0.507	0.483	0.518	0.468	0.514	0.52	0.506
	Consumer Discretionary	0.501	0.518	0.484	0.513	0.521	0.504	0.497	0.522	0.484	0.516	0.527	0.502
	Consumer Staples	0.497	0.524	0.471	0.497	0.516	0.508	0.495	0.526	0.471	0.501	0.518	0.511
	Energy	0.492	0.509	0.468	0.509	0.51	0.496	0.493	0.514	0.466	0.518	0.515	0.5
	Financials	0.494	0.506	0.499	0.511	0.507	0.509	0.491	0.509	0.495	0.518	0.507	0.51
	Health Care	0.477	0.511	0.488	0.51	0.527	0.498	0.48	0.512	0.491	0.516	0.525	0.5
	Industrials	0.494	0.519	0.478	0.51	0.518	0.505	0.49	0.523	0.473	0.518	0.522	0.506
	Technology	0.485	0.521	0.483	0.522	0.536	0.502	0.486	0.522	0.481	0.525	0.529	0.498
	Materials	0.493	0.521	0.469	0.505	0.514	0.507	0.495	0.516	0.472	0.515	0.514	0.495
	Real Estate	0.479	0.509	0.486	0.531	0.53	0.503	0.475	0.503	0.496	0.531	0.518	0.502
	Utilities	0.513	0.509	0.474	0.473	0.484	0.52	0.502	0.508	0.469	0.481	0.484	0.514
10	Communication Services	0.492	0.498	0.49	0.487	0.494	0.499	0.492	0.5	0.495	0.488	0.501	0.502
	Consumer Discretionary	0.51	0.498	0.51	0.501	0.498	0.495	0.509	0.509	0.501	0.506	0.513	0.502
	Consumer Staples	0.504	0.507	0.498	0.483	0.481	0.501	0.506	0.507	0.502	0.486	0.486	0.505
	Energy	0.502	0.491	0.489	0.489	0.481	0.5	0.5	0.498	0.489	0.494	0.487	0.506
	Financials	0.505	0.481	0.525	0.498	0.475	0.498	0.506	0.488	0.524	0.502	0.484	0.508
	Health Care	0.494	0.485	0.515	0.489	0.505	0.491	0.499	0.493	0.515	0.502	0.517	0.5
	Industrials	0.508	0.493	0.506	0.495	0.485	0.494	0.507	0.5	0.502	0.5	0.499	0.502
	Technology	0.498	0.492	0.516	0.504	0.507	0.494	0.501	0.502	0.512	0.51	0.516	0.506
	Materials	0.506	0.498	0.487	0.494	0.49	0.493	0.509	0.5	0.489	0.492	0.49	0.493
	Real Estate	0.493	0.479	0.523	0.537	0.497	0.5	0.506	0.489	0.513	0.53	0.513	0.503
	Utilities	0.521	0.491	0.489	0.457	0.453	0.505	0.529	0.481	0.496	0.458	0.43	0.497

NN3

Method		Equal-weighted Portfolio						Value-weighted Portfolio					
Portfolio	Sector	Value vs growth	Profitability	Investment	Intangibles	Trading frictions	Momentum	Value vs growth	Profitability	Investment	Intangibles	Trading frictions	Momentum
1	Communication Services	0.479	0.495	0.476	0.486	0.504	0.47	0.481	0.491	0.491	0.491	0.487	0.479
	Consumer Discretionary	0.512	0.497	0.49	0.505	0.503	0.485	0.505	0.507	0.493	0.503	0.509	0.491
	Consumer Staples	0.529	0.507	0.473	0.488	0.484	0.503	0.501	0.514	0.488	0.486	0.502	0.504
	Energy	0.493	0.501	0.462	0.486	0.497	0.473	0.509	0.502	0.478	0.486	0.487	0.473
	Financials	0.487	0.464	0.532	0.499	0.486	0.485	0.498	0.494	0.511	0.5	0.49	0.497
	Health Care	0.419	0.491	0.502	0.507	0.516	0.47	0.485	0.499	0.5	0.513	0.524	0.493
	Industrials	0.516	0.503	0.491	0.508	0.505	0.489	0.502	0.513	0.493	0.504	0.519	0.498
	Technology	0.466	0.516	0.497	0.501	0.504	0.477	0.496	0.514	0.498	0.509	0.513	0.492
	Materials	0.513	0.502	0.465	0.494	0.474	0.482	0.505	0.499	0.491	0.492	0.487	0.483
10	Real Estate	0.478	0.485	0.494	0.511	0.514	0.447	0.497	0.502	0.503	0.506	0.516	0.471
	Utilities	0.566	0.473	0.47	0.418	0.459	0.5	0.522	0.467	0.491	0.445	0.417	0.487
	Communication Services	0.489	0.491	0.49	0.508	0.507	0.513	0.491	0.481	0.468	0.501	0.489	0.523
	Consumer Discretionary	0.533	0.496	0.511	0.523	0.509	0.521	0.508	0.501	0.505	0.511	0.516	0.517
	Consumer Staples	0.544	0.507	0.499	0.506	0.493	0.52	0.507	0.504	0.502	0.496	0.499	0.509
	Energy	0.501	0.486	0.486	0.508	0.508	0.537	0.503	0.485	0.491	0.507	0.501	0.531
	Financials	0.493	0.48	0.543	0.513	0.501	0.524	0.492	0.49	0.511	0.507	0.494	0.509
	Health Care	0.437	0.495	0.513	0.517	0.529	0.514	0.497	0.491	0.518	0.503	0.529	0.534
	Industrials	0.527	0.498	0.511	0.525	0.512	0.531	0.503	0.499	0.502	0.51	0.513	0.522
	Technology	0.47	0.499	0.525	0.538	0.533	0.519	0.494	0.498	0.513	0.528	0.53	0.521
	Materials	0.519	0.502	0.49	0.518	0.492	0.51	0.507	0.491	0.498	0.507	0.502	0.502
	Real Estate	0.466	0.477	0.509	0.545	0.517	0.496	0.492	0.504	0.512	0.523	0.513	0.492
	Utilities	0.556	0.477	0.492	0.434	0.462	0.515	0.516	0.467	0.517	0.458	0.416	0.512

Method		Optimised - Low capital portfolio						Optimised - High capital portfolio					
Portfolio	Sector	Value vs growth	Profitability	Investment	Intangibles	Trading frictions	Momentum	Value vs growth	Profitability	Investment	Intangibles	Trading frictions	Momentum
1	Communication Services	0.475	0.521	0.466	0.498	0.516	0.498	0.479	0.514	0.479	0.504	0.513	0.5
	Consumer Discretionary	0.499	0.518	0.484	0.506	0.522	0.5	0.499	0.522	0.487	0.517	0.526	0.507
	Consumer Staples	0.491	0.525	0.474	0.484	0.503	0.508	0.496	0.533	0.478	0.504	0.52	0.521
	Energy	0.486	0.51	0.464	0.506	0.506	0.493	0.489	0.518	0.467	0.522	0.515	0.505
	Financials	0.49	0.498	0.507	0.505	0.493	0.503	0.496	0.506	0.505	0.513	0.507	0.512
	Health Care	0.479	0.511	0.488	0.505	0.522	0.497	0.483	0.51	0.498	0.516	0.525	0.503
	Industrials	0.493	0.515	0.479	0.505	0.509	0.499	0.497	0.523	0.481	0.518	0.521	0.509
	Technology	0.485	0.518	0.485	0.515	0.525	0.499	0.488	0.523	0.488	0.527	0.527	0.5
	Materials	0.493	0.513	0.468	0.496	0.502	0.496	0.496	0.524	0.474	0.511	0.519	0.505
	Real Estate	0.477	0.496	0.509	0.515	0.493	0.49	0.491	0.51	0.497	0.533	0.522	0.488
	Utilities	0.504	0.51	0.47	0.473	0.482	0.519	0.511	0.509	0.48	0.479	0.484	0.521
10	Communication Services	0.496	0.498	0.484	0.496	0.495	0.496	0.5	0.506	0.495	0.495	0.507	0.505
	Consumer Discretionary	0.514	0.494	0.506	0.499	0.495	0.491	0.513	0.505	0.507	0.509	0.51	0.501
	Consumer Staples	0.507	0.504	0.496	0.485	0.485	0.499	0.507	0.513	0.497	0.488	0.497	0.51
	Energy	0.498	0.488	0.488	0.496	0.482	0.5	0.503	0.495	0.498	0.505	0.495	0.509
	Financials	0.501	0.489	0.516	0.498	0.485	0.505	0.507	0.494	0.521	0.501	0.495	0.515
	Health Care	0.486	0.485	0.515	0.492	0.507	0.494	0.494	0.497	0.513	0.503	0.512	0.502
	Industrials	0.508	0.494	0.501	0.497	0.49	0.495	0.511	0.501	0.504	0.505	0.503	0.504
	Technology	0.495	0.492	0.515	0.508	0.506	0.492	0.502	0.501	0.514	0.517	0.518	0.502
	Materials	0.502	0.496	0.491	0.493	0.487	0.489	0.511	0.503	0.49	0.496	0.495	0.499
	Real Estate	0.498	0.478	0.529	0.522	0.497	0.497	0.504	0.502	0.512	0.521	0.526	0.506
	Utilities	0.519	0.501	0.487	0.457	0.466	0.511	0.528	0.484	0.504	0.452	0.441	0.506

NN4

Method		Equal-weighted Portfolio						Value-weighted Portfolio					
Portfolio	Sector	Value vs growth	Profitability	Investment	Intangibles	Trading frictions	Momentum	Value vs growth	Profitability	Investment	Intangibles	Trading frictions	Momentum
1	Communication Services	0.474	0.492	0.477	0.489	0.503	0.473	0.478	0.489	0.491	0.49	0.485	0.48
	Consumer Discretionary	0.516	0.496	0.491	0.505	0.505	0.482	0.502	0.509	0.494	0.504	0.514	0.493
	Consumer Staples	0.524	0.507	0.473	0.486	0.485	0.501	0.495	0.513	0.488	0.485	0.494	0.502
	Energy	0.494	0.503	0.464	0.487	0.498	0.473	0.504	0.503	0.478	0.485	0.491	0.476
	Financials	0.487	0.463	0.534	0.502	0.485	0.485	0.498	0.495	0.514	0.502	0.488	0.497
	Health Care	0.418	0.493	0.501	0.506	0.517	0.47	0.486	0.499	0.505	0.513	0.522	0.492
	Industrials	0.52	0.498	0.488	0.51	0.504	0.489	0.5	0.507	0.487	0.504	0.508	0.497
	Technology	0.465	0.515	0.497	0.503	0.502	0.476	0.495	0.513	0.499	0.509	0.511	0.49
	Materials	0.516	0.503	0.463	0.494	0.475	0.479	0.505	0.503	0.487	0.492	0.488	0.481
	Real Estate	0.475	0.469	0.512	0.542	0.504	0.456	0.486	0.508	0.493	0.522	0.516	0.477
	Utilities	0.557	0.475	0.476	0.424	0.463	0.494	0.524	0.466	0.495	0.447	0.42	0.478
10	Communication Services	0.489	0.488	0.489	0.51	0.505	0.513	0.492	0.481	0.47	0.503	0.488	0.516
	Consumer Discretionary	0.533	0.492	0.509	0.525	0.508	0.519	0.507	0.5	0.5	0.513	0.515	0.516
	Consumer Staples	0.543	0.5	0.498	0.506	0.491	0.521	0.505	0.503	0.5	0.495	0.501	0.513
	Energy	0.504	0.489	0.484	0.503	0.508	0.539	0.503	0.486	0.491	0.504	0.501	0.533
	Financials	0.495	0.478	0.544	0.515	0.501	0.524	0.492	0.491	0.511	0.508	0.495	0.51
	Health Care	0.439	0.492	0.517	0.52	0.528	0.514	0.494	0.491	0.513	0.505	0.528	0.534
	Industrials	0.527	0.497	0.512	0.526	0.51	0.529	0.501	0.499	0.499	0.512	0.511	0.519
	Technology	0.469	0.496	0.523	0.537	0.532	0.52	0.493	0.496	0.51	0.528	0.529	0.522
	Materials	0.521	0.503	0.49	0.516	0.487	0.516	0.505	0.492	0.497	0.506	0.497	0.504
	Real Estate	0.463	0.476	0.504	0.537	0.518	0.496	0.497	0.495	0.517	0.52	0.513	0.496
	Utilities	0.558	0.477	0.49	0.426	0.459	0.518	0.513	0.47	0.519	0.455	0.408	0.512

Method		Optimised - Low capital portfolio						Optimised - High capital portfolio					
Portfolio	Sector	Value vs growth	Profitability	Investment	Intangibles	Trading frictions	Momentum	Value vs growth	Profitability	Investment	Intangibles	Trading frictions	Momentum
1	Communication Services	0.469	0.519	0.462	0.488	0.511	0.498	0.482	0.52	0.473	0.514	0.521	0.503
	Consumer Discretionary	0.496	0.521	0.481	0.508	0.524	0.501	0.503	0.518	0.491	0.513	0.524	0.501
	Consumer Staples	0.489	0.523	0.473	0.489	0.505	0.509	0.496	0.525	0.48	0.496	0.509	0.511
	Energy	0.486	0.508	0.466	0.505	0.507	0.492	0.493	0.508	0.468	0.514	0.507	0.498
	Financials	0.492	0.496	0.508	0.506	0.492	0.502	0.498	0.503	0.504	0.509	0.499	0.508
	Health Care	0.476	0.511	0.489	0.51	0.53	0.497	0.484	0.504	0.497	0.514	0.52	0.498
	Industrials	0.493	0.519	0.477	0.508	0.513	0.502	0.499	0.517	0.481	0.514	0.518	0.501
	Technology	0.486	0.518	0.485	0.511	0.518	0.497	0.494	0.52	0.489	0.522	0.527	0.505
	Materials	0.492	0.521	0.469	0.5	0.511	0.499	0.496	0.519	0.472	0.507	0.516	0.499
	Real Estate	0.48	0.505	0.498	0.528	0.519	0.506	0.475	0.521	0.479	0.529	0.532	0.493
	Utilities	0.502	0.513	0.47	0.475	0.486	0.518	0.514	0.498	0.477	0.461	0.462	0.515
10	Communication Services	0.497	0.499	0.484	0.495	0.498	0.498	0.493	0.505	0.488	0.493	0.503	0.503
	Consumer Discretionary	0.514	0.495	0.505	0.502	0.498	0.492	0.512	0.507	0.504	0.508	0.512	0.502
	Consumer Staples	0.508	0.503	0.498	0.482	0.485	0.5	0.508	0.512	0.497	0.489	0.496	0.507
	Energy	0.499	0.489	0.491	0.495	0.482	0.499	0.501	0.498	0.489	0.495	0.49	0.506
	Financials	0.501	0.488	0.518	0.499	0.484	0.506	0.506	0.488	0.527	0.498	0.487	0.516
	Health Care	0.485	0.491	0.511	0.492	0.506	0.496	0.491	0.499	0.512	0.505	0.517	0.501
	Industrials	0.508	0.494	0.501	0.498	0.49	0.494	0.509	0.503	0.5	0.505	0.504	0.503
	Technology	0.498	0.489	0.517	0.509	0.509	0.492	0.499	0.504	0.51	0.519	0.52	0.503
	Materials	0.502	0.495	0.488	0.492	0.488	0.489	0.51	0.505	0.486	0.499	0.499	0.495
	Real Estate	0.506	0.466	0.545	0.506	0.484	0.49	0.5	0.491	0.517	0.533	0.519	0.506
	Utilities	0.524	0.5	0.487	0.456	0.461	0.509	0.525	0.489	0.499	0.456	0.443	0.509

NN5

Method		Equal-weighted Portfolio						Value-weighted Portfolio					
Portfolio	Sector	Value vs growth	Profitability	Investment	Intangibles	Trading frictions	Momentum	Value vs growth	Profitability	Investment	Intangibles	Trading frictions	Momentum
1	Communication Services	0.479	0.502	0.483	0.479	0.503	0.475	0.479	0.487	0.494	0.484	0.484	0.475
	Consumer Discretionary	0.518	0.498	0.493	0.507	0.504	0.489	0.501	0.514	0.49	0.507	0.52	0.504
	Consumer Staples	0.53	0.512	0.475	0.48	0.481	0.504	0.493	0.512	0.487	0.481	0.483	0.498
	Energy	0.498	0.495	0.467	0.486	0.497	0.477	0.503	0.501	0.483	0.501	0.495	0.485
	Financials	0.488	0.474	0.532	0.499	0.492	0.496	0.495	0.503	0.509	0.503	0.496	0.505
	Health Care	0.424	0.495	0.504	0.506	0.515	0.474	0.483	0.505	0.499	0.513	0.524	0.498
	Industrials	0.513	0.5	0.494	0.509	0.505	0.491	0.497	0.515	0.49	0.506	0.516	0.499
	Technology	0.46	0.513	0.502	0.508	0.51	0.486	0.496	0.512	0.504	0.514	0.514	0.496
	Materials	0.519	0.504	0.467	0.486	0.474	0.478	0.503	0.501	0.487	0.491	0.491	0.482
	Real Estate	0.477	0.482	0.496	0.523	0.513	0.451	0.495	0.503	0.499	0.517	0.514	0.473
	Utilities	0.568	0.469	0.476	0.416	0.454	0.482	0.527	0.469	0.491	0.447	0.413	0.477
10	Communication Services	0.487	0.491	0.48	0.496	0.503	0.5	0.483	0.481	0.466	0.494	0.49	0.508
	Consumer Discretionary	0.527	0.498	0.499	0.516	0.505	0.509	0.505	0.511	0.496	0.51	0.515	0.511
	Consumer Staples	0.528	0.505	0.485	0.494	0.489	0.521	0.491	0.51	0.49	0.49	0.502	0.513
	Energy	0.504	0.491	0.492	0.502	0.504	0.528	0.504	0.501	0.495	0.499	0.506	0.525
	Financials	0.489	0.476	0.543	0.509	0.496	0.52	0.498	0.5	0.507	0.505	0.5	0.517
	Health Care	0.434	0.495	0.505	0.512	0.524	0.507	0.494	0.493	0.509	0.5	0.526	0.53
	Industrials	0.523	0.497	0.504	0.521	0.508	0.521	0.5	0.505	0.494	0.511	0.515	0.518
	Technology	0.465	0.501	0.515	0.527	0.526	0.515	0.494	0.498	0.508	0.522	0.524	0.516
	Materials	0.513	0.5	0.483	0.504	0.486	0.508	0.501	0.497	0.491	0.501	0.502	0.505
	Real Estate	0.464	0.473	0.497	0.54	0.515	0.484	0.498	0.511	0.499	0.52	0.522	0.501
	Utilities	0.553	0.476	0.488	0.415	0.456	0.514	0.504	0.47	0.519	0.451	0.409	0.497

Method		Optimised - Low capital portfolio						Optimised - High capital portfolio					
Portfolio	Sector	Value vs growth	Profitability	Investment	Intangibles	Trading frictions	Momentum	Value vs growth	Profitability	Investment	Intangibles	Trading frictions	Momentum
1	Communication Services	0.482	0.512	0.472	0.502	0.512	0.503	0.486	0.519	0.472	0.516	0.518	0.505
	Consumer Discretionary	0.5	0.52	0.483	0.514	0.524	0.506	0.501	0.522	0.486	0.515	0.525	0.505
	Consumer Staples	0.494	0.525	0.472	0.498	0.516	0.509	0.495	0.525	0.48	0.494	0.509	0.51
	Energy	0.492	0.512	0.466	0.505	0.511	0.497	0.487	0.517	0.465	0.515	0.511	0.502
	Financials	0.494	0.507	0.496	0.512	0.51	0.509	0.496	0.509	0.496	0.514	0.51	0.514
	Health Care	0.479	0.512	0.488	0.509	0.528	0.498	0.485	0.51	0.496	0.518	0.525	0.5
	Industrials	0.492	0.519	0.476	0.51	0.519	0.506	0.496	0.52	0.481	0.519	0.523	0.511
	Technology	0.486	0.52	0.483	0.52	0.534	0.504	0.492	0.519	0.491	0.526	0.523	0.502
	Materials	0.493	0.521	0.468	0.508	0.518	0.507	0.495	0.522	0.472	0.509	0.517	0.503
	Real Estate	0.484	0.507	0.492	0.536	0.522	0.506	0.487	0.509	0.501	0.542	0.514	0.498
	Utilities	0.504	0.511	0.473	0.481	0.493	0.519	0.509	0.515	0.482	0.483	0.493	0.528
10	Communication Services	0.493	0.5	0.489	0.489	0.497	0.5	0.495	0.503	0.491	0.492	0.502	0.5
	Consumer Discretionary	0.51	0.498	0.51	0.501	0.497	0.494	0.512	0.504	0.507	0.504	0.508	0.498
	Consumer Staples	0.503	0.506	0.498	0.483	0.482	0.501	0.507	0.51	0.498	0.486	0.492	0.506
	Energy	0.501	0.49	0.491	0.49	0.479	0.5	0.502	0.5	0.487	0.498	0.493	0.506
	Financials	0.504	0.482	0.525	0.499	0.476	0.499	0.506	0.493	0.523	0.504	0.494	0.516
	Health Care	0.494	0.486	0.514	0.49	0.505	0.491	0.493	0.497	0.512	0.502	0.513	0.502
	Industrials	0.507	0.492	0.506	0.495	0.484	0.495	0.508	0.503	0.5	0.504	0.504	0.503
	Technology	0.498	0.492	0.517	0.504	0.507	0.493	0.501	0.5	0.512	0.515	0.513	0.5
	Materials	0.505	0.498	0.487	0.491	0.487	0.492	0.51	0.502	0.489	0.497	0.497	0.496
	Real Estate	0.489	0.493	0.51	0.536	0.505	0.501	0.503	0.489	0.521	0.522	0.513	0.503
	Utilities	0.521	0.49	0.489	0.457	0.453	0.505	0.528	0.483	0.502	0.453	0.439	0.505

Mean across all models

Method		Panel A: Equal-weighted Portfolio						Panel B: Value-weighted Portfolio					
Portfolio	Sector	Value vs growth	Profitability	Investment	Intangibles	Trading frictions	Momentum	Value vs growth	Profitability	Investment	Intangibles	Trading frictions	Momentum
1	Communication Services	0.476	0.495	0.477	0.486	0.505	0.471	0.480	0.488	0.493	0.491	0.488	0.477
	Consumer Discretionary	0.514	0.495	0.491	0.507	0.504	0.481	0.501	0.508	0.492	0.505	0.515	0.493
	Consumer Staples	0.523	0.505	0.472	0.488	0.485	0.498	0.495	0.510	0.487	0.486	0.495	0.498
	Energy	0.493	0.495	0.465	0.491	0.499	0.471	0.505	0.500	0.480	0.491	0.492	0.474
	Financials	0.485	0.465	0.533	0.501	0.488	0.484	0.497	0.492	0.514	0.501	0.488	0.494
	Health Care	0.416	0.490	0.504	0.509	0.519	0.467	0.484	0.499	0.503	0.515	0.526	0.491
	Industrials	0.512	0.496	0.491	0.514	0.506	0.486	0.497	0.509	0.489	0.508	0.516	0.496
	Technology	0.457	0.509	0.497	0.507	0.507	0.473	0.493	0.509	0.500	0.514	0.514	0.490
	Materials	0.510	0.497	0.466	0.495	0.479	0.478	0.503	0.498	0.487	0.494	0.492	0.481
	Real Estate	0.475	0.473	0.498	0.533	0.510	0.455	0.490	0.505	0.494	0.520	0.518	0.477
	Utilities	0.559	0.473	0.474	0.425	0.461	0.490	0.519	0.470	0.492	0.454	0.426	0.485
10	Communication Services	0.490	0.496	0.490	0.498	0.504	0.513	0.487	0.486	0.481	0.495	0.491	0.513
	Consumer Discretionary	0.533	0.500	0.507	0.517	0.508	0.520	0.506	0.505	0.500	0.509	0.516	0.517
	Consumer Staples	0.539	0.509	0.493	0.493	0.489	0.525	0.500	0.506	0.497	0.489	0.496	0.515
	Energy	0.507	0.493	0.486	0.499	0.504	0.536	0.505	0.492	0.494	0.500	0.497	0.533
	Financials	0.495	0.479	0.543	0.510	0.500	0.527	0.496	0.493	0.513	0.507	0.493	0.517
	Health Care	0.438	0.496	0.510	0.512	0.523	0.513	0.493	0.495	0.511	0.504	0.525	0.530
	Industrials	0.529	0.503	0.509	0.520	0.509	0.530	0.502	0.504	0.498	0.509	0.513	0.520
	Technology	0.470	0.503	0.521	0.528	0.528	0.522	0.494	0.501	0.509	0.523	0.527	0.523
	Materials	0.520	0.504	0.484	0.506	0.485	0.515	0.505	0.494	0.494	0.501	0.497	0.506
	Real Estate	0.469	0.474	0.506	0.543	0.516	0.495	0.491	0.506	0.503	0.524	0.521	0.503
	Utilities	0.559	0.478	0.490	0.425	0.461	0.518	0.514	0.471	0.512	0.454	0.413	0.505
HML	Communication Services	0.014	0.000	0.013	0.012	0.000	0.041	0.007	-0.002	-0.012	0.004	0.003	0.036
	Consumer Discretionary	0.019	0.005	0.016	0.009	0.004	0.039	0.004	-0.003	0.008	0.004	0.001	0.024
	Consumer Staples	0.016	0.004	0.021	0.005	0.004	0.027	0.005	-0.004	0.011	0.003	0.001	0.017
	Energy	0.014	-0.002	0.021	0.008	0.004	0.065	0.000	-0.008	0.014	0.009	0.005	0.058
	Financials	0.010	0.014	0.010	0.010	0.011	0.043	0.000	0.001	-0.001	0.006	0.005	0.023
	Health Care	0.022	0.005	0.007	0.003	0.004	0.046	0.010	-0.004	0.008	-0.011	0.000	0.039
	Industrials	0.017	0.008	0.018	0.006	0.003	0.044	0.005	-0.006	0.009	0.002	-0.003	0.024
	Technology	0.013	-0.006	0.024	0.021	0.021	0.049	0.001	-0.008	0.009	0.009	0.013	0.033
	Materials	0.010	0.007	0.018	0.010	0.006	0.037	0.002	-0.004	0.007	0.007	0.005	0.025
	Real Estate	-0.007	0.001	0.008	0.010	0.006	0.040	0.001	0.001	0.009	0.005	0.003	0.026
	Utilities	0.000	0.005	0.016	0.000	-0.001	0.027	-0.005	0.001	0.020	0.001	-0.013	0.020

Method		Panel C: Optimised Small Portfolio						Panel D: Optimised Large Portfolio					
Portfolio	Sector	Value vs growth	Profitability	Investment	Intangibles	Trading frictions	Momentum	Value vs growth	Profitability	Investment	Intangibles	Trading frictions	Momentum
1	Communication Services	0.478	0.515	0.471	0.496	0.513	0.501	0.482	0.517	0.474	0.512	0.517	0.502
	Consumer Discretionary	0.499	0.519	0.484	0.510	0.523	0.502	0.500	0.520	0.487	0.515	0.525	0.503
	Consumer Staples	0.494	0.523	0.474	0.492	0.509	0.508	0.495	0.527	0.477	0.499	0.513	0.512
	Energy	0.490	0.509	0.466	0.506	0.508	0.495	0.491	0.515	0.467	0.518	0.513	0.501
	Financials	0.493	0.500	0.504	0.508	0.500	0.506	0.494	0.506	0.501	0.514	0.505	0.511
	Health Care	0.478	0.511	0.489	0.508	0.526	0.498	0.483	0.509	0.495	0.515	0.524	0.501
	Industrials	0.494	0.517	0.478	0.507	0.513	0.502	0.495	0.520	0.479	0.517	0.520	0.506
	Technology	0.486	0.519	0.484	0.517	0.528	0.501	0.490	0.520	0.488	0.524	0.526	0.501
	Materials	0.493	0.517	0.469	0.502	0.511	0.501	0.495	0.519	0.472	0.510	0.515	0.499
	Real Estate	0.481	0.504	0.495	0.529	0.517	0.501	0.483	0.509	0.496	0.534	0.520	0.497
	Utilities	0.507	0.508	0.472	0.473	0.483	0.518	0.508	0.508	0.477	0.479	0.483	0.519
10	Communication Services	0.494	0.498	0.488	0.488	0.494	0.497	0.496	0.502	0.495	0.491	0.503	0.502
	Consumer Discretionary	0.513	0.497	0.508	0.501	0.497	0.494	0.513	0.505	0.506	0.505	0.510	0.501
	Consumer Staples	0.505	0.505	0.497	0.482	0.483	0.501	0.507	0.510	0.499	0.485	0.492	0.508
	Energy	0.500	0.490	0.490	0.493	0.481	0.500	0.502	0.497	0.491	0.498	0.490	0.506
	Financials	0.503	0.484	0.522	0.498	0.479	0.502	0.506	0.490	0.525	0.501	0.488	0.512
	Health Care	0.490	0.488	0.513	0.491	0.506	0.494	0.496	0.496	0.513	0.503	0.514	0.501
	Industrials	0.508	0.493	0.503	0.496	0.487	0.494	0.509	0.501	0.502	0.502	0.501	0.503
	Technology	0.498	0.492	0.515	0.507	0.508	0.493	0.502	0.501	0.511	0.513	0.515	0.503
	Materials	0.505	0.497	0.488	0.492	0.487	0.491	0.510	0.503	0.489	0.496	0.495	0.496
	Real Estate	0.495	0.481	0.524	0.524	0.498	0.496	0.504	0.489	0.519	0.526	0.514	0.501
	Utilities	0.520	0.494	0.488	0.457	0.456	0.507	0.525	0.485	0.499	0.458	0.441	0.505
HML	Communication Services	0.016	-0.017	0.017	-0.007	-0.019	-0.004	0.014	-0.015	0.020	-0.021	-0.014	0.000
	Consumer Discretionary	0.014	-0.022	0.024	-0.009	-0.025	-0.009	0.012	-0.015	0.019	-0.010	-0.015	-0.002
	Consumer Staples	0.011	-0.018	0.023	-0.009	-0.026	-0.007	0.012	-0.016	0.022	-0.013	-0.021	-0.005
	Energy	0.010	-0.019	0.024	-0.012	-0.027	0.005	0.011	-0.018	0.024	-0.019	-0.023	0.005
	Financials	0.010	-0.016	0.018	-0.010	-0.021	-0.004	0.012	-0.017	0.024	-0.013	-0.017	0.001
	Health Care	0.011	-0.023	0.024	-0.017	-0.020	-0.004	0.013	-0.013	0.018	-0.013	-0.010	0.001
	Industrials	0.014	-0.023	0.025	-0.011	-0.026	-0.008	0.014	-0.019	0.023	-0.015	-0.019	-0.004
	Technology	0.012	-0.027	0.031	-0.010	-0.021	-0.008	0.012	-0.019	0.023	-0.011	-0.011	0.002
	Materials	0.012	-0.020	0.019	-0.010	-0.023	-0.010	0.014	-0.016	0.017	-0.014	-0.019	-0.003
	Real Estate	0.014	-0.023	0.029	-0.005	-0.019	-0.005	0.021	-0.021	0.023	-0.008	-0.006	0.004
	Utilities	0.014	-0.014	0.015	-0.017	-0.027	-0.010	0.017	-0.023	0.022	-0.021	-0.042	-0.013

Appendix 3S: Mean machine learning predicted excess returns and out-of-sample R² for double-sorted portfolios on predictive factors

Appendix 3S reports the average monthly portfolio predicted excess returns and out-of-sample R² for 5x5 bivariate sorted portfolio on certain major factors. At the end of each month all stocks are independently sorted from lowest to highest for the two factors and each is divided in five deciles. Subsequently, stocks are allocated in the 25 portfolios which are created according to their rank in the deciles for the two factors. For each portfolio the machine learning predicted excess returns are calculated at each monthly period and these monthly returns are averaged across time to yield the results in the table. Both mean predicted excess returns and out-of-sample R² are presented in percentage basis. The reported results are for the average across the five neural network predictive models (NN1-NN5). The table is divided into four panels, A to D, which report the results for the equal-weighted, value-weighted, optimised portfolio trading a relatively small portfolio of 1 million USD and optimised portfolio trading a relatively large portfolio of 100 million USD, respectively. Investing horizon is one month and thus, rebalancing of the portfolio is performed monthly based on predicted returns.

Size (vertical) X book-to-market (horizontal)

		Mean predicted returns (%)					R ² Out-of-sample (%)				
Portfolio		1	2	3	4	5	1	2	3	4	5
Equally weighted	1	0.69	0.70	0.72	0.70	0.72	-0.01	0.10	0.08	0.30	0.45
	2	0.66	0.67	0.69	0.70	0.71	-0.08	0.02	0.18	0.37	0.38
	3	0.64	0.67	0.69	0.70	0.68	-0.07	0.11	0.32	0.44	0.34
	4	0.67	0.67	0.69	0.68	0.65	-0.02	0.21	0.35	0.41	0.21
	5	0.67	0.68	0.67	0.65	0.63	0.08	0.06	0.14	0.22	0.17
Value weighted	1	0.34	0.34	0.35	0.35	0.36	-0.01	0.10	0.08	0.30	0.45
	2	0.33	0.33	0.35	0.35	0.35	-0.08	0.02	0.18	0.37	0.38
	3	0.32	0.33	0.34	0.35	0.34	-0.07	0.11	0.32	0.44	0.34
	4	0.33	0.34	0.35	0.34	0.32	-0.02	0.21	0.35	0.41	0.21
	5	0.33	0.34	0.33	0.31	0.30	0.08	0.06	0.14	0.22	0.17
Optimised Small	1	0.02	0.02	0.02	0.04	0.08	1.11	1.11	1.42	1.72	1.77
	2	0.03	0.02	0.02	0.03	0.04	1.00	1.86	1.37	1.35	2.71
	3	0.02	0.02	0.02	0.02	0.02	0.85	1.74	0.83	1.57	1.77
	4	0.02	0.02	0.02	0.02	0.02	0.72	0.17	0.67	1.48	1.20
	5	0.02	0.02	0.01	0.01	0.01	-0.42	-0.01	0.10	0.75	-0.04
Optimised Large	1	-0.05	-0.10	-0.04	-0.10	-0.11	0.93	1.42	0.40	1.06	1.59
	2	-0.10	0.02	-0.09	-0.13	-0.10	0.88	-1.31	-0.88	-0.63	0.06
	3	-0.08	-0.10	-0.06	-0.07	-0.04	-0.38	-1.37	-1.58	-0.57	0.08
	4	-0.12	-0.12	-0.11	-0.08	-0.06	-0.66	-1.89	-0.30	-0.27	-0.05
	5	-0.12	-0.07	-0.06	-0.05	0.01	-2.96	-3.72	-1.43	-1.18	-0.02

Size (vertical) X momentum 1 month (horizontal)

		Mean predicted returns (%)					R ² Out-of-sample (%)				
Portfolio		1	2	3	4	5	1	2	3	4	5
Equally weighted	1	0.95	0.77	0.68	0.60	0.28	0.36	0.07	0.07	0.22	0.17
	2	0.93	0.77	0.69	0.61	0.34	0.15	0.16	0.20	0.27	0.17
	3	0.92	0.77	0.69	0.60	0.37	0.15	0.20	0.36	0.30	0.16
	4	0.91	0.77	0.69	0.61	0.40	0.08	0.34	0.42	0.21	0.15
	5	0.88	0.76	0.68	0.60	0.43	-0.16	0.24	0.44	0.32	-0.11
Value weighted	1	0.47	0.39	0.35	0.30	0.15	0.36	0.07	0.07	0.22	0.17
	2	0.46	0.39	0.35	0.30	0.17	0.15	0.16	0.20	0.27	0.17
	3	0.46	0.38	0.34	0.30	0.19	0.15	0.20	0.36	0.30	0.16
	4	0.45	0.38	0.34	0.30	0.20	0.08	0.34	0.42	0.21	0.15
	5	0.43	0.37	0.34	0.30	0.22	-0.16	0.24	0.44	0.32	-0.11
Optimised Small	1	0.05	0.03	0.02	0.03	0.04	0.99	2.20	1.18	1.57	1.92
	2	0.04	0.03	0.02	0.02	0.03	1.67	1.53	1.32	1.50	1.23
	3	0.02	0.02	0.02	0.02	0.03	1.15	1.01	0.98	1.20	1.46
	4	0.01	0.02	0.02	0.02	0.02	1.23	0.55	0.30	0.31	0.93
	5	0.00	0.02	0.01	0.02	0.02	-0.09	0.50	-0.72	-0.72	0.13
Optimised Large	1	-0.11	-0.09	-0.07	-0.06	-0.03	0.82	1.41	1.33	1.71	1.45
	2	-0.06	-0.06	-0.05	-0.11	-0.10	0.53	-0.61	-0.50	-0.50	0.71
	3	-0.06	-0.06	-0.07	-0.04	-0.10	-0.04	-0.45	-1.33	-1.04	0.48
	4	-0.06	-0.03	-0.17	-0.09	-0.10	-0.25	-1.06	-0.35	-1.01	-0.32
	5	-0.01	-0.11	-0.03	-0.05	-0.07	-0.79	-1.70	-3.16	-2.97	-3.32

Size (vertical) X momentum 12 months (horizontal)

		Mean predicted returns (%)					R ² Out-of-sample (%)				
Portfolio		1	2	3	4	5	1	2	3	4	5
Equally weighted	1	0.57	0.68	0.72	0.78	0.94	0.11	0.26	0.29	0.62	0.48
	2	0.50	0.63	0.68	0.74	0.88	-0.07	0.07	0.13	0.60	0.61
	3	0.46	0.60	0.65	0.71	0.85	-0.03	0.08	0.26	0.55	0.37
	4	0.46	0.57	0.64	0.70	0.82	0.01	0.12	0.29	0.30	0.34
	5	0.44	0.56	0.63	0.69	0.79	-0.11	0.10	0.07	0.23	0.27
Value weighted	1	0.27	0.33	0.35	0.38	0.46	0.11	0.26	0.29	0.62	0.48
	2	0.24	0.31	0.34	0.37	0.44	-0.07	0.07	0.13	0.60	0.61
	3	0.23	0.30	0.33	0.36	0.42	-0.03	0.08	0.26	0.55	0.37
	4	0.23	0.29	0.32	0.35	0.41	0.01	0.12	0.29	0.30	0.34
	5	0.22	0.28	0.31	0.35	0.39	-0.11	0.10	0.07	0.23	0.27
Optimised Small	1	0.05	0.03	0.03	0.02	0.04	1.03	2.21	2.61	1.70	1.98
	2	0.03	0.02	0.02	0.02	0.05	1.14	1.74	0.87	1.49	2.39
	3	0.00	0.01	0.02	0.02	0.04	1.01	0.66	0.51	1.68	1.83
	4	0.01	0.01	0.02	0.02	0.04	1.08	0.52	0.39	0.44	0.98
	5	0.00	0.00	0.02	0.02	0.02	0.54	0.03	-0.81	-1.47	0.63
Optimised Large	1	-0.14	-0.08	-0.02	-0.07	-0.05	0.64	1.62	1.90	2.21	2.92
	2	-0.08	-0.06	-0.06	-0.08	-0.09	-0.35	-0.72	-0.49	0.56	1.20
	3	-0.05	-0.12	0.01	-0.11	-0.04	-1.24	-0.96	-1.65	0.38	1.05
	4	-0.03	-0.05	-0.15	-0.10	-0.11	-0.50	-1.84	-1.64	-1.63	1.33
	5	-0.03	-0.03	-0.04	-0.10	-0.08	-1.71	-2.64	-4.20	-3.34	-0.25

Size (vertical) X CAPM beta (horizontal)

		Mean predicted returns (%)					R ² Out-of-sample (%)				
Portfolio		1	2	3	4	5	1	2	3	4	5
Equally weighted	1	0.68	0.70	0.66	0.65	0.62	0.25	0.41	0.24	0.35	0.22
	2	0.68	0.68	0.65	0.64	0.59	0.28	0.26	0.22	0.24	0.16
	3	0.68	0.66	0.64	0.64	0.59	0.41	0.45	0.27	0.22	0.11
	4	0.66	0.66	0.64	0.64	0.59	0.40	0.46	0.35	0.24	0.11
	5	0.67	0.64	0.62	0.61	0.58	0.15	0.40	0.12	0.22	0.07
Value weighted	1	0.34	0.35	0.33	0.32	0.31	0.25	0.41	0.24	0.35	0.22
	2	0.34	0.34	0.33	0.32	0.30	0.28	0.26	0.22	0.24	0.16
	3	0.34	0.33	0.32	0.32	0.30	0.41	0.45	0.27	0.22	0.11
	4	0.33	0.33	0.32	0.32	0.30	0.40	0.46	0.35	0.24	0.11
	5	0.33	0.32	0.30	0.30	0.28	0.15	0.40	0.12	0.22	0.07
Optimised Small	1	0.05	0.04	0.03	0.03	0.02	1.26	1.68	2.23	1.39	1.06
	2	0.04	0.03	0.02	0.02	0.02	0.73	1.67	1.66	1.96	1.38
	3	0.02	0.02	0.02	0.02	0.03	0.80	0.45	0.74	1.25	1.76
	4	0.01	0.01	0.02	0.02	0.03	0.16	0.67	1.09	0.48	1.13
	5	0.01	0.01	0.01	0.02	0.02	-0.25	-1.15	-0.89	-0.01	1.16
Optimised Large	1	-0.11	-0.04	-0.07	-0.09	-0.08	1.04	2.14	1.99	1.53	1.14
	2	-0.11	-0.07	-0.06	-0.07	-0.08	0.70	-0.39	-0.12	1.21	0.85
	3	-0.04	-0.08	-0.09	-0.03	-0.10	1.10	0.17	0.01	-0.08	0.31
	4	-0.10	-0.09	-0.07	-0.05	-0.16	0.16	0.33	-0.20	-0.35	1.19
	5	-0.05	-0.10	-0.05	-0.06	-0.02	-0.43	-0.55	-3.74	-2.78	-0.29

Size (vertical) X operating profitability (horizontal)

		Mean predicted returns (%)					R ² Out-of-sample (%)				
Portfolio		1	2	3	4	5	1	2	3	4	5
Equally weighted	1	0.70	0.68	0.70	0.70	0.71	0.19	0.17	0.41	0.39	0.34
	2	0.67	0.67	0.70	0.68	0.68	0.12	0.14	0.28	0.36	0.23
	3	0.63	0.65	0.69	0.68	0.67	0.00	0.21	0.33	0.44	0.34
	4	0.61	0.65	0.68	0.68	0.67	0.13	0.24	0.10	0.37	0.23
	5	0.57	0.63	0.66	0.67	0.67	0.08	0.23	-0.08	0.09	0.22
Value weighted	1	0.35	0.34	0.35	0.35	0.35	0.19	0.17	0.41	0.39	0.34
	2	0.33	0.33	0.35	0.34	0.34	0.12	0.14	0.28	0.36	0.23
	3	0.32	0.32	0.35	0.34	0.34	0.00	0.21	0.33	0.44	0.34
	4	0.30	0.32	0.34	0.34	0.33	0.13	0.24	0.10	0.37	0.23
	5	0.28	0.30	0.32	0.33	0.33	0.08	0.23	-0.08	0.09	0.22
Optimised Small	1	0.07	0.05	0.02	0.02	0.02	1.10	1.57	2.41	1.48	1.26
	2	0.05	0.03	0.02	0.02	0.02	2.30	0.96	0.70	0.82	0.82
	3	0.02	0.02	0.02	0.02	0.02	1.57	1.24	-0.06	0.52	0.94
	4	0.01	0.01	0.02	0.02	0.02	1.33	1.40	-1.42	-0.15	0.63
	5	0.00	0.01	0.00	0.02	0.04	1.02	0.58	-0.84	-1.01	-0.50
Optimised Large	1	-0.19	-0.08	-0.04	-0.05	-0.01	1.18	1.07	0.52	0.87	0.96
	2	-0.03	-0.14	-0.11	-0.08	-0.02	1.04	0.03	-1.21	-1.36	-0.85
	3	-0.04	-0.12	-0.07	-0.04	-0.06	0.11	-0.11	-1.79	-1.79	-0.28
	4	-0.01	-0.08	-0.18	-0.06	-0.11	1.38	-0.12	-1.23	-2.16	-0.93
	5	-0.03	-0.01	-0.09	-0.05	-0.10	-0.59	-0.92	-2.72	-2.30	-3.19

Book-to-market (vertical) X momentum 1 month (horizontal)

		Mean predicted returns (%)					R ² Out-of-sample (%)				
Portfolio		1	2	3	4	5	1	2	3	4	5
Equally weighted	1	0.93	0.77	0.69	0.61	0.32	-0.11	-0.17	0.02	0.16	0.07
	2	0.94	0.77	0.69	0.61	0.38	0.22	0.01	0.10	0.13	0.01
	3	0.95	0.79	0.70	0.62	0.40	0.29	0.23	0.23	0.22	0.05
	4	0.95	0.79	0.70	0.62	0.39	0.39	0.48	0.50	0.34	0.13
	5	0.96	0.80	0.71	0.62	0.35	0.41	0.34	0.42	0.35	0.35
Value weighted	1	0.44	0.37	0.34	0.30	0.21	-0.11	-0.17	0.02	0.16	0.07
	2	0.45	0.39	0.35	0.31	0.23	0.22	0.01	0.10	0.13	0.01
	3	0.44	0.38	0.34	0.30	0.22	0.29	0.23	0.23	0.22	0.05
	4	0.44	0.37	0.34	0.29	0.21	0.39	0.48	0.50	0.34	0.13
	5	0.44	0.37	0.32	0.29	0.19	0.41	0.34	0.42	0.35	0.35
Optimised Small	1	0.03	0.02	0.02	0.02	0.04	0.93	1.13	0.27	1.23	0.84
	2	0.02	0.02	0.02	0.02	0.03	1.02	1.54	0.95	0.91	1.66
	3	0.02	0.02	0.02	0.02	0.02	1.26	1.25	0.10	0.43	2.00
	4	0.02	0.03	0.02	0.02	0.02	1.52	1.93	1.19	1.15	1.92
	5	0.03	0.04	0.03	0.02	0.03	1.39	1.90	2.20	2.15	2.54
Optimised Large	1	-0.08	-0.09	-0.05	-0.12	-0.12	0.66	-0.10	-0.69	-0.25	0.33
	2	-0.06	-0.11	-0.09	-0.02	-0.09	-0.12	-0.42	-0.79	-1.54	-1.13
	3	-0.07	-0.04	-0.09	-0.11	-0.05	0.42	-2.05	-0.70	-0.52	-0.50
	4	-0.02	-0.05	-0.13	-0.13	-0.09	-0.36	0.65	0.46	-1.06	0.69
	5	-0.09	-0.08	-0.06	0.02	-0.08	1.05	0.43	-0.22	0.23	2.27

Book-to-market (vertical) X momentum 12 months (horizontal)

		Mean predicted returns (%)					R ² Out-of-sample (%)				
Portfolio		1	2	3	4	5	1	2	3	4	5
Equally weighted	1	0.51	0.62	0.68	0.73	0.85	-0.10	-0.02	-0.08	0.00	0.12
	2	0.51	0.61	0.67	0.74	0.85	0.07	0.05	0.00	0.22	0.19
	3	0.53	0.62	0.68	0.74	0.87	-0.06	0.14	0.22	0.55	0.45
	4	0.52	0.63	0.67	0.73	0.87	0.12	0.24	0.36	0.78	0.61
	5	0.53	0.65	0.67	0.73	0.89	0.10	0.22	0.27	0.70	0.87
Value weighted	1	0.23	0.29	0.32	0.35	0.38	-0.10	-0.02	-0.08	0.00	0.12
	2	0.23	0.29	0.32	0.36	0.41	0.07	0.05	0.00	0.22	0.19
	3	0.23	0.28	0.31	0.36	0.41	-0.06	0.14	0.22	0.55	0.45
	4	0.22	0.27	0.30	0.34	0.40	0.12	0.24	0.36	0.78	0.61
	5	0.22	0.27	0.30	0.33	0.40	0.10	0.22	0.27	0.70	0.87
Optimised Small	1	0.03	0.02	0.02	0.02	0.04	0.82	1.26	-0.03	0.74	1.40
	2	0.02	0.01	0.02	0.03	0.03	1.04	1.17	1.58	0.48	1.68
	3	0.01	0.02	0.02	0.02	0.03	1.36	1.35	0.82	0.59	1.10
	4	0.02	0.02	0.02	0.02	0.04	1.54	1.42	0.68	1.79	2.23
	5	0.02	0.02	0.04	0.03	0.06	1.25	2.45	2.17	2.34	2.79
Optimised Large	1	-0.12	-0.05	-0.08	-0.13	-0.09	0.37	-0.22	-1.17	0.57	1.14
	2	-0.04	-0.08	-0.04	-0.10	-0.09	-0.31	-1.21	-1.31	-1.89	0.03
	3	-0.05	-0.10	-0.07	-0.05	-0.08	-0.03	-0.63	-1.30	-0.78	-0.52
	4	-0.04	-0.12	-0.05	-0.14	-0.06	0.23	-0.62	-0.95	-1.00	1.71
	5	-0.10	-0.02	-0.04	-0.07	-0.06	0.56	0.35	-0.21	1.95	3.13

Book-to-market (vertical) X CAPM beta (horizontal)

		Mean predicted returns (%)					R ² Out-of-sample (%)				
Portfolio		1	2	3	4	5	1	2	3	4	5
Equally weighted	1	0.72	0.69	0.66	0.63	0.60	-0.07	0.16	-0.10	0.04	0.02
	2	0.69	0.66	0.66	0.65	0.61	0.14	0.21	0.18	0.24	0.12
	3	0.68	0.67	0.68	0.67	0.62	0.20	0.45	0.24	0.32	0.15
	4	0.67	0.68	0.66	0.65	0.63	0.57	0.54	0.31	0.39	0.28
	5	0.71	0.69	0.64	0.66	0.62	0.40	0.50	0.33	0.37	0.24
Value weighted	1	0.32	0.33	0.31	0.30	0.30	-0.07	0.16	-0.10	0.04	0.02
	2	0.35	0.32	0.32	0.31	0.29	0.14	0.21	0.18	0.24	0.12
	3	0.34	0.32	0.32	0.31	0.29	0.20	0.45	0.24	0.32	0.15
	4	0.31	0.32	0.29	0.30	0.29	0.57	0.54	0.31	0.39	0.28
	5	0.32	0.31	0.29	0.29	0.29	0.40	0.50	0.33	0.37	0.24
Optimised Small	1	0.02	0.03	0.02	0.02	0.04	0.66	0.75	1.38	0.99	0.98
	2	0.02	0.02	0.02	0.02	0.03	0.92	1.34	1.53	1.07	1.56
	3	0.02	0.02	0.02	0.02	0.02	1.07	1.00	1.33	1.37	1.24
	4	0.03	0.03	0.02	0.02	0.02	1.46	1.95	0.97	1.50	2.14
	5	0.05	0.03	0.03	0.03	0.02	1.53	2.29	2.24	1.97	1.78
Optimised Large	1	-0.05	-0.11	-0.07	-0.15	-0.11	0.42	0.88	0.86	1.56	0.95
	2	-0.05	-0.06	-0.11	-0.04	-0.11	-0.32	0.38	-0.13	0.32	0.43
	3	-0.09	-0.10	-0.04	-0.06	-0.07	0.62	1.84	-0.31	-0.75	0.44
	4	-0.16	-0.12	-0.09	-0.01	-0.06	0.71	-0.72	-1.22	0.21	1.48
	5	-0.08	-0.01	-0.06	-0.06	-0.09	1.45	0.76	0.99	1.58	0.94

Book-to-market (vertical) X operating profitability (horizontal)

		Mean predicted returns (%)					R ² Out-of-sample (%)				
Portfolio		1	2	3	4	5	1	2	3	4	5
Equally weighted	1	0.63	0.68	0.67	0.67	0.69	-0.08	0.02	-0.24	-0.03	0.11
	2	0.65	0.66	0.68	0.69	0.68	0.06	0.03	-0.02	0.22	0.25
	3	0.70	0.67	0.70	0.69	0.68	0.12	0.13	0.16	0.39	0.40
	4	0.70	0.68	0.70	0.68	0.70	0.20	0.39	0.51	0.58	0.35
	5	0.72	0.65	0.71	0.72	0.74	0.35	0.32	0.46	0.52	0.59
Value weighted	1	0.28	0.34	0.31	0.32	0.33	-0.08	0.02	-0.24	-0.03	0.11
	2	0.28	0.31	0.33	0.34	0.34	0.06	0.03	-0.02	0.22	0.25
	3	0.33	0.32	0.33	0.33	0.33	0.12	0.13	0.16	0.39	0.40
	4	0.31	0.30	0.33	0.32	0.33	0.20	0.39	0.51	0.58	0.35
	5	0.32	0.29	0.32	0.34	0.35	0.35	0.32	0.46	0.52	0.59
Optimised Small	1	0.04	0.02	0.01	0.01	0.04	1.09	0.91	-1.61	0.22	0.28
	2	0.02	0.01	0.01	0.03	0.04	1.31	1.71	0.68	0.56	0.82
	3	0.02	0.02	0.02	0.03	0.02	1.57	1.58	0.33	0.04	1.02
	4	0.03	0.03	0.03	0.02	0.01	2.12	1.37	0.66	1.01	2.18
	5	0.06	0.05	0.03	0.02	0.01	2.05	1.77	1.43	1.45	1.26
Optimised Large	1	-0.13	-0.10	-0.07	0.00	-0.17	0.77	0.85	-1.51	-2.41	-1.19
	2	-0.03	-0.10	-0.07	-0.10	-0.07	0.49	0.82	-2.25	-2.29	-2.11
	3	-0.04	-0.04	-0.20	-0.03	-0.04	1.49	-0.91	-1.97	-2.31	0.04
	4	-0.04	-0.10	-0.14	-0.11	-0.04	1.37	0.26	-1.56	-1.29	-0.64
	5	-0.07	-0.13	-0.03	-0.06	0.00	1.87	0.44	-0.25	0.44	0.41

Momentum 1 month (vertical) X momentum 12 months (horizontal)

		Mean predicted returns (%)					R ² Out-of-sample (%)				
Portfolio		1	2	3	4	5	1	2	3	4	5
Equally weighted	1	0.80	0.87	0.91	0.97	1.13	0.08	0.27	0.23	0.49	0.39
	2	0.60	0.70	0.75	0.81	0.94	-0.12	0.13	0.15	0.62	0.43
	3	0.52	0.62	0.67	0.73	0.85	-0.03	0.12	0.39	0.65	0.41
	4	0.43	0.54	0.59	0.65	0.77	0.01	0.12	0.32	0.36	0.58
	5	0.13	0.33	0.38	0.46	0.56	0.10	-0.02	0.06	0.20	0.34
Value weighted	1	0.35	0.39	0.42	0.45	0.52	0.08	0.27	0.23	0.49	0.39
	2	0.28	0.32	0.36	0.39	0.44	-0.12	0.13	0.15	0.62	0.43
	3	0.24	0.29	0.32	0.35	0.40	-0.03	0.12	0.39	0.65	0.41
	4	0.20	0.25	0.28	0.32	0.36	0.01	0.12	0.32	0.36	0.58
	5	0.10	0.17	0.21	0.24	0.28	0.10	-0.02	0.06	0.20	0.34
Optimised Small	1	0.03	0.01	0.01	0.01	0.05	0.81	1.14	1.92	1.63	2.05
	2	0.01	0.02	0.02	0.03	0.03	1.41	1.47	1.35	1.73	1.66
	3	0.01	0.02	0.02	0.02	0.03	1.03	1.37	-0.18	0.69	1.16
	4	0.01	0.02	0.03	0.02	0.03	1.86	1.66	-0.33	0.23	1.08
	5	0.02	0.02	0.02	0.03	0.05	1.18	1.81	1.14	1.66	1.85
Optimised Large	1	-0.07	-0.07	-0.05	-0.05	-0.06	0.09	0.36	0.54	1.36	2.88
	2	-0.07	-0.09	-0.03	-0.07	-0.08	0.36	-0.71	-0.49	-0.44	0.67
	3	-0.04	-0.10	-0.06	-0.15	-0.06	0.41	-1.08	-1.81	0.14	1.02
	4	-0.10	-0.04	-0.07	-0.05	-0.08	1.28	-0.44	-2.16	-1.56	0.64
	5	-0.06	-0.05	-0.07	-0.14	-0.08	0.54	0.72	-0.70	0.95	1.56

Momentum 1 month (vertical) X CAPM beta (horizontal)

		Mean predicted returns (%)					R ² Out-of-sample (%)				
Portfolio		1	2	3	4	5	1	2	3	4	5
Equally weighted	1	0.94	0.92	0.94	0.93	0.92	0.16	0.15	0.39	0.50	0.24
	2	0.76	0.76	0.79	0.78	0.78	-0.03	0.07	0.33	0.59	0.29
	3	0.68	0.67	0.70	0.70	0.69	0.06	0.24	0.41	0.43	0.41
	4	0.59	0.59	0.62	0.61	0.61	0.19	0.29	0.17	0.20	0.42
	5	0.29	0.32	0.41	0.41	0.41	0.20	0.24	-0.07	-0.07	0.05
Value weighted	1	0.42	0.44	0.44	0.43	0.44	0.16	0.15	0.39	0.50	0.24
	2	0.35	0.36	0.37	0.37	0.38	-0.03	0.07	0.33	0.59	0.29
	3	0.31	0.32	0.33	0.34	0.35	0.06	0.24	0.41	0.43	0.41
	4	0.27	0.28	0.30	0.30	0.30	0.19	0.29	0.17	0.20	0.42
	5	0.16	0.19	0.21	0.22	0.22	0.20	0.24	-0.07	-0.07	0.05
Optimised Small	1	0.05	0.03	0.01	0.02	0.02	0.99	1.44	0.76	1.14	0.95
	2	0.02	0.02	0.02	0.03	0.02	1.89	1.59	0.84	0.87	0.76
	3	0.02	0.02	0.02	0.02	0.02	1.16	1.24	0.14	-0.06	0.81
	4	0.02	0.02	0.02	0.02	0.02	1.90	1.19	-0.25	-0.71	0.27
	5	0.05	0.03	0.02	0.02	0.03	1.91	1.01	0.96	1.05	0.83
Optimised Large	1	-0.08	-0.05	-0.12	-0.01	-0.05	0.80	1.06	-0.70	-0.46	-0.14
	2	-0.06	-0.09	-0.07	-0.06	-0.07	1.07	0.50	-1.90	-1.27	-0.89
	3	-0.02	-0.13	-0.14	-0.09	-0.01	1.13	-1.21	-1.08	-2.10	-0.67
	4	-0.07	-0.08	-0.06	-0.07	-0.07	1.36	-0.85	-1.79	-1.79	-1.16
	5	-0.07	-0.09	-0.08	-0.06	-0.11	1.61	0.77	-0.68	-1.19	-1.57

Momentum 1 month (vertical) X operating profitability (horizontal)

		Mean predicted returns (%)					R ² Out-of-sample (%)				
Portfolio		1	2	3	4	5	1	2	3	4	5
Equally weighted	1	0.69	0.70	0.72	0.70	0.72	-0.01	0.10	0.08	0.30	0.45
	2	0.66	0.67	0.69	0.70	0.71	-0.08	0.02	0.18	0.37	0.38
	3	0.64	0.67	0.69	0.70	0.68	-0.07	0.11	0.32	0.44	0.34
	4	0.67	0.67	0.69	0.68	0.65	-0.02	0.21	0.35	0.41	0.21
	5	0.67	0.68	0.67	0.65	0.63	0.08	0.06	0.14	0.22	0.17
Value weighted	1	0.34	0.34	0.35	0.35	0.36	-0.01	0.10	0.08	0.30	0.45
	2	0.33	0.33	0.35	0.35	0.35	-0.08	0.02	0.18	0.37	0.38
	3	0.32	0.33	0.34	0.35	0.34	-0.07	0.11	0.32	0.44	0.34
	4	0.33	0.34	0.35	0.34	0.32	-0.02	0.21	0.35	0.41	0.21
	5	0.33	0.34	0.33	0.31	0.30	0.08	0.06	0.14	0.22	0.17
Optimised Small	1	0.02	0.02	0.02	0.04	0.08	1.11	1.11	1.42	1.72	1.77
	2	0.03	0.02	0.02	0.03	0.04	1.00	1.86	1.37	1.35	2.71
	3	0.02	0.02	0.02	0.02	0.02	0.85	1.74	0.83	1.57	1.77
	4	0.02	0.02	0.02	0.02	0.02	0.72	0.17	0.67	1.48	1.20
	5	0.02	0.02	0.01	0.01	0.01	-0.42	-0.01	0.10	0.75	-0.04
Optimised Large	1	-0.05	-0.10	-0.04	-0.10	-0.11	0.93	1.42	0.40	1.06	1.59
	2	-0.10	0.02	-0.09	-0.13	-0.10	0.88	-1.31	-0.88	-0.63	0.06
	3	-0.08	-0.10	-0.06	-0.07	-0.04	-0.38	-1.37	-1.58	-0.57	0.08
	4	-0.12	-0.12	-0.11	-0.08	-0.06	-0.66	-1.89	-0.30	-0.27	-0.05
	5	-0.12	-0.07	-0.06	-0.05	0.01	-2.96	-3.72	-1.43	-1.18	-0.02

Momentum 12 months (vertical) X CAPM beta (horizontal)

		Mean predicted returns (%)					R ² Out-of-sample (%)				
Portfolio		1	2	3	4	5	1	2	3	4	5
Equally weighted	1	0.53	0.53	0.50	0.47	0.44	0.09	0.09	0.10	0.13	0.08
	2	0.61	0.59	0.59	0.58	0.56	-0.04	0.28	0.26	0.24	0.11
	3	0.65	0.64	0.63	0.64	0.62	0.21	0.48	0.24	0.21	0.09
	4	0.71	0.70	0.68	0.69	0.67	0.79	0.76	0.35	0.30	0.28
	5	0.85	0.83	0.82	0.82	0.80	0.58	0.60	0.41	0.54	0.29
Value weighted	1	0.24	0.23	0.22	0.21	0.20	0.09	0.09	0.10	0.13	0.08
	2	0.29	0.27	0.26	0.26	0.25	-0.04	0.28	0.26	0.24	0.11
	3	0.31	0.30	0.29	0.29	0.27	0.21	0.48	0.24	0.21	0.09
	4	0.34	0.33	0.33	0.32	0.31	0.79	0.76	0.35	0.30	0.28
	5	0.38	0.38	0.37	0.38	0.37	0.58	0.60	0.41	0.54	0.29
Optimised Small	1	0.02	0.02	0.01	0.01	0.02	1.17	1.55	1.80	0.95	0.87
	2	0.02	0.02	0.02	0.01	0.01	1.71	1.34	1.62	1.46	1.47
	3	0.03	0.03	0.02	0.02	0.01	0.30	0.87	1.04	1.33	1.70
	4	0.03	0.02	0.02	0.02	0.03	1.08	0.81	0.58	1.29	2.11
	5	0.03	0.03	0.03	0.05	0.05	1.01	1.78	1.66	2.20	2.17
Optimised Large	1	-0.03	-0.05	-0.03	-0.12	-0.12	0.79	1.31	0.23	0.54	0.42
	2	-0.09	-0.07	-0.10	-0.06	-0.04	0.99	0.81	-0.12	-0.25	0.59
	3	-0.04	-0.09	-0.08	-0.01	-0.06	0.24	-0.54	-1.23	0.33	0.75
	4	-0.15	-0.06	-0.09	-0.06	-0.11	-0.07	0.04	0.63	0.86	2.49
	5	-0.09	-0.11	-0.05	-0.05	-0.09	2.19	1.56	1.57	2.26	2.59

Momentum 12 months (vertical) X operating profitability (horizontal)

		Mean predicted returns (%)					R ² Out-of-sample (%)				
Portfolio		1	2	3	4	5	1	2	3	4	5
Equally weighted	1	0.51	0.52	0.50	0.50	0.50	0.04	0.04	0.02	0.07	-0.04
	2	0.64	0.62	0.62	0.60	0.60	0.08	0.11	0.16	0.17	0.20
	3	0.69	0.65	0.67	0.66	0.66	0.17	0.19	0.18	0.40	0.34
	4	0.74	0.71	0.74	0.72	0.71	0.32	0.38	0.48	0.65	0.56
	5	0.86	0.84	0.85	0.85	0.84	0.30	0.46	0.54	0.53	0.46
Value weighted	1	0.20	0.23	0.22	0.23	0.23	0.04	0.04	0.02	0.07	-0.04
	2	0.26	0.27	0.27	0.27	0.28	0.08	0.11	0.16	0.17	0.20
	3	0.29	0.30	0.31	0.31	0.32	0.17	0.19	0.18	0.40	0.34
	4	0.31	0.33	0.34	0.35	0.35	0.32	0.38	0.48	0.65	0.56
	5	0.36	0.39	0.39	0.40	0.39	0.30	0.46	0.54	0.53	0.46
Optimised Small	1	0.04	0.02	0.01	0.01	0.01	1.12	0.89	1.00	0.97	0.89
	2	0.02	0.02	0.01	0.01	0.01	1.65	1.70	0.92	0.30	1.05
	3	0.02	0.02	0.02	0.02	0.02	2.07	0.96	0.28	-0.27	0.35
	4	0.02	0.03	0.02	0.02	0.03	1.55	2.25	-0.16	0.08	-0.58
	5	0.06	0.04	0.03	0.04	0.04	2.01	1.81	0.27	1.41	1.29
Optimised Large	1	-0.10	-0.12	-0.06	-0.01	-0.05	0.59	0.27	-0.85	-0.40	-0.59
	2	-0.08	-0.04	-0.11	-0.04	-0.08	0.65	-0.04	-1.26	-1.44	-1.11
	3	-0.04	-0.05	-0.11	-0.04	-0.04	1.58	0.00	-2.10	-3.14	-2.91
	4	-0.03	-0.17	-0.10	-0.09	-0.08	1.70	0.56	-1.35	-2.52	-1.14
	5	-0.05	-0.06	-0.10	-0.10	-0.05	2.50	1.74	-0.82	-0.19	0.29

Appendix 4A: List of factors

Factor	Firm characteristic	Definition
absacc	Absolute accruals	Absolute value of acc.
acc	Working capital accruals	Annual income before extraordinary items (ib) minus operating cash flows (oancf) divided by average total assets (at); if oancf is missing then set to change in act - change in che - change in lct + change in dlc + change in txp-dp.
aeavol	Abnormal earnings announcement volume	Average daily trading volume (vol) for 3 days around earnings announcement minus average daily volume for 1-month ending 2 weeks before earnings announcement divided by 1-month average daily volume. Earnings announcement day from Compustat quarterly (rdq).
agr	Asset growth	Annual percent change in total assets (at).
baspread	Bid-ask spread	Monthly average of daily bid-ask spread divided by average of daily spread
beta	Beta	Estimated market beta from weekly returns and equal weighted market returns for 3 years ending month t-1 with at least 52 weeks of returns.
bm	Book-to-market	Book value of equity (ceq) divided by end of fiscal-year-end market capitalisation.
bm_ia	Industry-adjusted book to market	Industry adjusted book-to-market ratio.
cash	Cash holdings	Cash and cash equivalents divided by average total assets
cashdebt	Cash flow to debt	Earnings before depreciation and extraordinary items (ib+dp) divided by avg. total liabilities (lt).
cashpr	Cash productivity	Fiscal year end market capitalisation plus long term debt (dltt) minus total assets (at) divided by cash and equivalents (che).
cfp	Cash flow to price ratio	Operating cash flows divided by fiscal-year-end market capitalisation
cfp_ia	Industry-adjusted cash flow to price ratio	Industry adjusted cfp.
chatoia	Industry-adjusted change in asset turnover	2-digit SIC - fiscal-year mean adjusted change in sales (sale) divided by average total assets (at).
chcsho	Change in shares outstanding	Annual percent change in shares outstanding (csho).

chempia	Industry-adjusted change in employees	Industry-adjusted change in number of employees.
chin	Change in inventory	Change in inventory (inv) scaled by average total assets (at).
chmom	Change in 6-month momentum	Cumulative returns from months t-6 to t-1 minus months t-12 to t-7.
chpmia	Industry-adjusted change in profit margin	2-digit SIC - fiscal-year mean adjusted change in income before extraordinary items (ib) divided by sales (sale).
chtx	Change in tax expense	Percent change in total taxes (txtq) from quarter t-4 to t.
cinvest	Corporate investment	Change over one quarter in net PP&E (ppentq) divided by sales (saleq) - average of this variable for prior 3 quarters; if saleq = 0, then scale by 0.01.
currat	Current ratio	Current assets / current liabilities.
depr	Depreciation / PP&E	Depreciation divided by PP&E.
dy	Dividend to price	Total dividends (dvt) divided by market capitalisation at fiscal year-end.
ear	Earnings announcement return	Sum of daily returns in three days around earnings announcement. Earnings announcement from Compustat quarterly file (rdq).
egr	Growth in common shareholder equity	Annual percent change in book value of equity (ceq).
ep	Earnings to price	Annual income before extraordinary items (ib) divided by end of fiscal year market cap.
gma	Gross profitability	Revenues (revt) minus cost of goods sold (cogs) divided by lagged total assets (at).
grcapx	Growth in capital expenditures	Percent change in capital expenditures from year t-2 to year t.
grltnoa	Growth in long term net operating assets	Growth in long term net operating assets.
herf	Industry sales concentration	2-digit SIC - fiscal-year sales concentration (sum of squared percent of sales in industry for each company).
hire	Employee growth rate	Percent change in number of employees (emp).

idiovol	Idiosyncratic return volatility	Standard deviation of residuals of weekly returns on weekly equal weighted market returns for 3 years prior to month end.
ill	Illiquidity	Average of daily (absolute return / dollar volume).
indmom	Industry momentum	Equal weighted average industry 12-month returns.
invest	Capital expenditures and inventory	Annual change in gross property, plant, and equipment (ppeg _t) + annual change in inventories (inv _t) all scaled by lagged total assets (at).
lev	Leverage	Total liabilities (lt) divided by fiscal year end market capitalisation.
mom12m	12-month momentum	11-month cumulative returns ending one month before month end.
mom1m	1-month momentum	1-month cumulative return.
mom36m	36-month momentum	Cumulative returns from months t-36 to t-13.
ms	Financial statement score	Sum of 8 indicator variables for fundamental performance.
mve_ia	Industry-adjusted size	2-digit SIC industry-adjusted fiscal year-end market capitalisation
mvel1	Size	Natural log of market capitalisation at end of month t-1.
nincr	Number of earnings increases	Number of consecutive quarters (up to eight quarters) with an increase in earnings (ibq) over same quarter in the prior year.
operprof	Operating profitability	Revenue minus cost of goods sold - SG&A expense - interest expense divided by lagged common shareholders' equity.
orgcap	Organizational capital	Capitalized SG&A expenses.
pchcapx_ia	Industry adjusted % change in capital expenditures	2-digit SIC - fiscal-year mean adjusted percent change in capital expenditures (capx).
pchcurrat	% change in current ratio	Percent change in currat
pchdepr	% change in depreciation	Percent change in depr.
pchg_{gm}_pchsale	% change in gross margin - % change in sales	Percent change in gross margin (sale-cogs) minus percent change in sales (sale).
pchsale_pchinvt	% change in sales - % change in inventory	Annual percent change in sales (sale) minus annual percent change in inventory (inv _t).
pchsale_pchrect	% change in sales - % change in A/R	Annual percent change in sales (sale) minus annual percent change in receivables (rect).

pchsale_pchxsga	% change in sales - % change in SG&A	Annual percent change in sales (sale) minus annual percent change in SG&A (xsga).
pchsaleinv	% change sales-to-inventory	Percent change in saleinv.
pctacc	Percent accruals	Same as acc except that the numerator is divided by the absolute value of ib; if ib = 0 then ib set to 0.01 for denominator
ps	Financial statements score	Sum of 9 indicator variables to form fundamental health score.
rd_mve	R&D to market capitalisation	R&D expense divided by end-of-fiscal-year market capitalisation
rd_sale	R&D to sales	R&D expense divided by sales (xrd/sale).
realestate	Real estate holdings	Buildings and capitalized leases divided by gross PP&E.
retvol	Return volatility	Standard deviation of daily returns from month t-1.
roaq	Return on assets	Income before extraordinary items (ibq) divided by one quarter lagged total assets (atq).
roavol	Earnings volatility	Standard deviation for 16 quarters of income before extraordinary items (ibq) divided by average total assets (atq).
roeq	Return on equity	Earnings before extraordinary items divided by lagged common shareholders' equity.
roic	Return on invested capital	Annual earnings before interest and taxes (ebit) minus non-operating income (nopi) divided by non-cash enterprise value (ceq+lt-che).
rsup	Revenue surprise	Sales from quarter t minus sales from quarter t-4 (saleq) divided by fiscal-quarter-end market capitalisation (cshoq * prccq).
salecash	Sales to cash	Annual sales divided by cash and cash equivalents.
saleinv	Sales to inventory	Annual sales divided by total inventory.
salerec	Sales to receivables	Annual sales divided by accounts receivable.
secured	Secured debt	Total liability scaled secured debt.
sgr	Sales growth	Annual percent change in sales (sale).
sp	Sales to price	Annual revenue (sale) divided by fiscal-year-end market capitalisation
std_dolvol	Volatility of liquidity (dollar trading volume)	Monthly standard deviation of daily dollar trading volume

std_turn	Volatility of liquidity (share turnover)	Monthly standard deviation of daily share turnover.
stdcf	Cash flow volatility	Standard deviation for 16 quarters of cash flows divided by sales (saleq); if saleq = 0, then scale by 0.01. Cash flows defined as ibq minus quarterly accruals.
tang	Debt capacity/firm tangibility	Cash holdings + 0.715 × receivables + 0.547 × inventory + 0.535 × PPE/ total assets
tb	Tax income to book income	Tax income, calculated from current tax expense divided by maximum federal tax rate, divided by income before extraordinary items
turn	Share turnover	Average monthly trading volume for most recent 3 months scaled by number of shares outstanding in current month
zerotrade	Zero trading days	Turnover weighted number of zero trading days for most recent 1 month.

Table A4.1 - List of the factors used in the dataset

This table was created from the Appendix in Green et al. (2017) and lists the 78 factors used in this chapter.

Appendix 4B: $\widehat{W}$ matrix
The $\widehat{W}$ matrix

Given that the formulation derived by Raponi et. al. (2020) computes the asymptotically valid variance with respect to the length of the time dimension, one wonders why not just set that framework as *modus operandi*, but rather be concerned with an empirical investigation about the level at which the effects of a short time window seize to be significant. The answer is that the formulation, although accurate, is not computationally efficient for use with the real data spanning the large cross section of expected returns. Specifically, the challenge lies in the computation of the $\widehat{W}$ matrix of equation 4.17, given that this requires intermediate steps of dimensions $T^2 \times T^2$. When individual stocks are considered, such matrices are not computationally feasible¹⁷.

To overcome the dimensionality challenge, this study employs two tools. First, a computational algorithm for $\widehat{W}$ was developed by analysing the apparent symmetries in the mathematical formulation and thereby, adapting Raponi's et. al. (2020) framework to a form applicable to the real cross-section of returns. Second, the algorithm was run via parallel processes on a High-Performance Computer provided by Supercomputing Wales. This appendix contains the detailed proof and development of the algorithm. This starts by computing $\widehat{W} = \widehat{Z}' \widehat{U}_\varepsilon \widehat{Z}$ as the sum of two elements; $\widehat{U}_{\varepsilon_d}$ which contains only the diagonal elements of $\widehat{U}_\varepsilon$ and $\widehat{U}_{\varepsilon_n}$ which considers only the non-diagonal elements, such that

$$\widehat{W} = \widehat{Z}' \widehat{U}_{\varepsilon_d} \widehat{Z} + \widehat{Z}' \widehat{U}_{\varepsilon_n} \widehat{Z} \quad (\text{A4.1})$$

The calculation of $\widehat{Z}' \widehat{U}_{\varepsilon_d} \widehat{Z}$ takes advantage of the fact that each diagonal submatrix $\widehat{U}_{i=j}$, of $\widehat{U}_\varepsilon \in \{\widehat{U}_{11} = \widehat{U}_{22} \dots = \widehat{U}_{TT}\}$, is a matrix of dimensions $T \times T$ with σ_4 in all diagonal positions except from the bottom corner which equals $2\sigma_4 + k_4$, as indicated by equation 4.17. The subscripts i

¹⁷ For example, when $T = 5$ years the data in cross-section of returns require RAM in excess of 300 GB.

and j denote the row and column position, respectively, and $k_4 = 0$ as per Raponi et al. (2020). This symmetric structure can limit the number of computations given that $\widehat{\mathbf{Z}}$ can be split in T parts of dimensions $T \times K$. Let these be $\mathbf{z}_{i,t}$ where $i = 1:T$. Therefore,

$$\widehat{\mathbf{Z}}' \widehat{\mathbf{U}}_{\varepsilon_d} \widehat{\mathbf{Z}} = \left[\sum_{i=1}^{T-1} \mathbf{z}_{i,t}' \sigma_4 \mathbf{z}_{i,t} \right] + 2(\mathbf{z}_{t,t}' \sigma_4 \mathbf{z}_{t,t}) \quad (\text{A4.2})$$

The calculation of $\widehat{\mathbf{Z}}' \widehat{\mathbf{U}}_{\varepsilon_n} \widehat{\mathbf{Z}}$ bases on the consideration that each non-diagonal submatrix of $\widehat{\mathbf{U}}_{\varepsilon}$ contains all zero elements except from the position t, s which contains the element σ_4 . The analysis in Appendix 4B, reveals that the non-zero elements of the non-diagonal submatrices are distributed at predictable positions and thus, an algorithm can be derived by extracting the pattern. Specifically, assuming $\widehat{\mathbf{Z}}'$ is split in T parts, $\mathbf{z}_{i,t}$, as before, the elements which contribute to $\widehat{\mathbf{Z}}' \widehat{\mathbf{U}}_{\varepsilon_n} \widehat{\mathbf{Z}}$ are found in the i^{th} positions. For example, $\mathbf{z}_{1,t}$ is the first $T \times K$ portion of $\widehat{\mathbf{Z}}$ and the first element of $\mathbf{z}_{1,t}$ is the only one contributing to $\widehat{\mathbf{Z}}' \widehat{\mathbf{U}}_{\varepsilon_n} \widehat{\mathbf{Z}}$. Let the contributing elements $z_{ii} \in \{\mathbf{z}_{11}, \mathbf{z}_{22}, \dots, \mathbf{z}_{TT}\}$, then

$$\widehat{\mathbf{Z}}' \widehat{\mathbf{U}}_{\varepsilon_n} \widehat{\mathbf{Z}} = 2\sigma_4 \sum_{1 < j < k < T} z_j z_k \quad (\text{A4.3})$$

where j and k loop over z_{ii} i.e., from $1 : T$. Tables A4.2 and A4.3 below illustrate how the algorithm for calculating $\widehat{\mathbf{W}}$ was implemented computationally.

The algorithm

$\widehat{\mathbf{W}} = \widehat{\mathbf{Z}}' \widehat{\mathbf{U}}_{\varepsilon} \widehat{\mathbf{Z}} \in K \times K$ where $\widehat{\mathbf{U}}_{\varepsilon} \in T^2 \times T^2$ has notable symmetries which may be exploited as discussed below. To begin with, consider that the matrix $\widehat{\mathbf{W}}$ can be computed as the sum of two elements. One considering only the diagonal elements of $\widehat{\mathbf{U}}_{\varepsilon}$ and one considering only the non-diagonal elements. Let these be $\widehat{\mathbf{U}}_{\varepsilon_d}$ and $\widehat{\mathbf{U}}_{\varepsilon_n}$, respectively. Therefore

$$\widehat{\mathbf{W}} = \widehat{\mathbf{Z}}' \widehat{\mathbf{U}}_{\varepsilon_d} \widehat{\mathbf{Z}} + \widehat{\mathbf{Z}}' \widehat{\mathbf{U}}_{\varepsilon_n} \widehat{\mathbf{Z}} \quad (A1)$$

$$\widehat{\mathbf{U}}_{\varepsilon} = \begin{bmatrix} U_{11} & \cdots & U_{1t} & \cdots & U_{1T} \\ \vdots & \ddots & \vdots & \vdots & \vdots \\ U_{t1} & \cdots & U_{tt} & \cdots & U_{tT} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ U_{T1} & \cdots & U_{Tt} & \cdots & U_{TT} \end{bmatrix}$$

Start with the calculation of $\widehat{\mathbf{Z}}' \widehat{\mathbf{U}}_{\varepsilon_d} \widehat{\mathbf{Z}}$. The diagonal elements, $\widehat{\mathbf{U}}_{i=j}$, of $\widehat{\mathbf{U}}_{\varepsilon} = \{\widehat{\mathbf{U}}_{11} = \widehat{\mathbf{U}}_{22} \dots = \widehat{\mathbf{U}}_{TT}\}$, where each is a submatrix of dimensions $T \times T$ with σ_4 in all diagonal positions except from the bottom corner which equals $2\sigma_4 + k_4$. The subscripts i and j denote the row and column position, respectively. Moreover, $k_4 = 0$ as per Raponi's et al. (2020). Given this symmetry, $\widehat{\mathbf{Z}}' \widehat{\mathbf{U}}_{\varepsilon_d} \widehat{\mathbf{Z}}$ can be computed separating the matrix $\widehat{\mathbf{Z}}$ in T elements, each of dimensions $T \times K$ and computing the sum of the sequence

$$= \sum_{i=1}^T \widehat{\mathbf{Z}}_i' \mathbf{u} \widehat{\mathbf{Z}}_i$$

$$\text{where } \mathbf{u} = \begin{pmatrix} \sigma_4 & 0 & \cdots & 0 \\ 0 & \sigma_4 & & \vdots \\ \vdots & & \ddots & 0 \\ 0 & \cdots & 0 & 2\sigma_4 \end{pmatrix}$$

The symmetric structure of $\mathbf{u}$ can be further used to limit the number of computations in the algorithm, such as

$$= \left[\sum_{j=1}^{T-1} \mathbf{z}_{i,t} \sigma_4 \mathbf{z}_{i,t} \right] + 2(\mathbf{z}_{t,t} \sigma_4 \mathbf{z}_{t,t})$$

This essentially multiplies all row elements of each $\hat{\mathbf{Z}}_t$ by σ_4 except from the last one which is multiplied by $2\sigma_4$.

Compute $\hat{\mathbf{W}}$ due to the diagonal elements
$\mathbf{w} \leftarrow \begin{pmatrix} 0 & \cdots & 0_K \\ \vdots & \ddots & \vdots \\ 0_K & \cdots & 0_{K,K} \end{pmatrix}$
for $i = 1 : T$ $\mathbf{zt} \leftarrow \mathbf{z}[i * T : (i + 1) * T]$
for $s = 1 : T$ if $s \neq T$ $\mathbf{w} \leftarrow \mathbf{w} + \mathbf{zt}[s] * \sigma_4 * \mathbf{zt}[s]$ else if $s = T$ $\mathbf{w} \leftarrow \mathbf{w} + \mathbf{zt}[s] * 2 * \sigma_4 * \mathbf{zt}[s]$

Table A4.2 - $\hat{\mathbf{W}}$ due to the diagonal elements

Then move to the calculation of the portion of $\hat{\mathbf{W}}$ due to the non-diagonal elements of $\hat{\mathbf{U}}_\varepsilon$, $\hat{\mathbf{Z}}' \hat{\mathbf{U}}_{\varepsilon_n} \hat{\mathbf{Z}}$. As Raponi et al. (2020) indicate each non-diagonal submatrix is zero everywhere except from the position t, s which contains the element σ_4 . This can be illustrated better by

$$\hat{\mathbf{U}}_\varepsilon = \begin{bmatrix} \hat{\mathbf{U}}_{t=1} & \hat{\mathbf{U}}_{t=2} & \cdots & \hat{\mathbf{U}}_{t=T} \\ s=1 & s=1 & & s=1 \\ \hline \hat{\mathbf{U}}_{t=1} & \ddots & \cdots & \vdots \\ s=2 & & & \\ \hline \vdots & \cdots & \ddots & \vdots \\ \hline \hat{\mathbf{U}}_{t=1} & \cdots & \cdots & \hat{\mathbf{U}}_{t=T} \\ s=T & & & s=T \end{bmatrix}$$

It becomes apparent that the non-diagonal elements are not equal, however analysing this matrix shows that the non-zero elements occur in predictable positions. Momentarily assume that that $T = 2$. In this case $\hat{\mathbf{U}}_\varepsilon$ is

$$\widehat{U}_\varepsilon = \left[\begin{array}{cc|cc} \sigma_4 & 0 & 0 & \sigma_4 \\ 0 & 2\sigma_4 & 0 & 0 \\ \hline 0 & 0 & \sigma_4 & 0 \\ \sigma_4 & 0 & 0 & 2\sigma_4 \end{array} \right]$$

$$\text{Let } \widehat{Z}' = [Z_{11} \quad Z_{12} \quad Z_{21} \quad Z_{22}]$$

$$\therefore \widehat{Z}' \widehat{U}_{\varepsilon_n} = [Z_{22} \quad 0 \quad 0 \quad Z_{11}] \sigma_4$$

$$\therefore \widehat{Z}' \widehat{U}_{\varepsilon_n} \widehat{Z} = (Z_{22}Z_{11} + 0 + 0 + Z_{11}Z_{22})\sigma_4$$

$$= 2\sigma_4 Z_{11}Z_{22}' \quad \in K \times K$$

$$\text{Given that } Z_{11}Z_{22}' = Z_{22}Z_{11}'$$

In the case $T = 3$:

$$\widehat{U}_\varepsilon = \left[\begin{array}{ccc|ccc|ccc} \sigma_4 & 0 & 0 & 0 & \sigma_4 & 0 & 0 & 0 & \sigma_4 \\ 0 & \sigma_4 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 2\sigma_4 & 0 & 0 & 0 & 0 & 0 & 0 \\ \hline 0 & 0 & 0 & \sigma_4 & 0 & 0 & 0 & 0 & 0 \\ \sigma_4 & 0 & 0 & 0 & \sigma_4 & 0 & 0 & 0 & \sigma_4 \\ 0 & 0 & 0 & 0 & 0 & 2\sigma_4 & 0 & 0 & 0 \\ \hline 0 & 0 & 0 & 0 & 0 & 0 & \sigma_4 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & \sigma_4 & 0 \\ \sigma_4 & 0 & 0 & 0 & \sigma_4 & 0 & 0 & 0 & 2\sigma_4 \end{array} \right]$$

$$\text{Let } \widehat{Z}' = [Z_{11} \quad Z_{12} \quad Z_{13} \quad Z_{21} \quad Z_{22} \quad Z_{23} \quad Z_{31} \quad Z_{32} \quad Z_{33}]$$

$$\therefore \widehat{Z}' \widehat{U}_{\varepsilon_n} = [(Z_{22} + Z_{33}) \quad 0 \quad 0 \quad 0 \quad (Z_{11} + Z_{33}) \quad 0 \quad 0 \quad 0 \quad (Z_{11} + Z_{22})] \sigma_4$$

$$\therefore \widehat{Z}' \widehat{U}_{\varepsilon_n} \widehat{Z} = Z_{11}(Z_{22} + Z_{33})\sigma_4 + Z_{22}(Z_{11} + Z_{33})\sigma_4 + Z_{33}(Z_{11} + Z_{22})\sigma_4$$

$$= 2\sigma_4 [Z_{11}Z_{22}' + Z_{22}Z_{33}' + Z_{11}Z_{33}'] \quad \in K \times K$$

In the case $T = 4$:

$$\begin{aligned}
& \therefore \hat{\mathbf{Z}}' \hat{\mathbf{U}}_{\varepsilon_n} \hat{\mathbf{Z}} \\
& = \mathbf{Z}_{11}(\mathbf{Z}_{22} + \mathbf{Z}_{33} + \mathbf{Z}_{44})\sigma_4 + \mathbf{Z}_{22}(\mathbf{Z}_{11} + \mathbf{Z}_{33} + \mathbf{Z}_{44})\sigma_4 \\
& \quad + \mathbf{Z}_{33}(\mathbf{Z}_{11} + \mathbf{Z}_{22} + \mathbf{Z}_{44})\sigma_4 + \mathbf{Z}_{44}(\mathbf{Z}_{11} + \mathbf{Z}_{22} + \mathbf{Z}_{33})\sigma_4 \\
& = 2\sigma_4 [\mathbf{Z}_{11}\mathbf{Z}_{22}' + \mathbf{Z}_{11}\mathbf{Z}_{33}' + \mathbf{Z}_{11}\mathbf{Z}_{44}' + \mathbf{Z}_{22}\mathbf{Z}_{33}' + \mathbf{Z}_{22}\mathbf{Z}_{44}' + \mathbf{Z}_{33}\mathbf{Z}_{44}']
\end{aligned}$$

As it is observed the non-zero elements of the non-diagonal submatrices are distributed at predictable positions and thus, an algorithm can be derived by extracting the pattern. Specifically, if the $\hat{\mathbf{Z}}$ matrix is split in T parts of dimensions $T \times K$, the elements which contribute to $\hat{\mathbf{Z}}' \hat{\mathbf{U}}_{\varepsilon_n} \hat{\mathbf{Z}}$ are found in the i^{th} position, where $i = 1:T$. Finally, the sum of products of all $\binom{T}{2}$ combinations multiplied by $2\sigma_4$ yields the portion of $\hat{\mathbf{W}}$ due to the non-diagonal elements. Specifically, let $z_{ii} \in \{\mathbf{Z}_{11}, \mathbf{Z}_{22}, \dots, \mathbf{Z}_{TT}\}$, then

$$\hat{\mathbf{Z}}' \hat{\mathbf{U}}_{\varepsilon_n} \hat{\mathbf{Z}} = 2\sigma_4 \sum_{1 < j < k < T} z_j z_k$$

where j and k loop over z_{ii} i.e. from $1 : T$.

Compute $\hat{\mathbf{W}}$ portion due to the non-diagonal elements

```

 $z_{ii} = [ \ ]$ 
for  $i = 1 : T$ 
     $zt \leftarrow z[i * T : (i + 1) * T]$ 
     $z_{ii} \leftarrow zt[i]$ 

    for  $j = 1 : T$ 
        for  $k = 1 : T$ 
            if  $k > j$ 
                 $w \leftarrow w + z_{ii}[j] * z_{ii}[k] * 2 * \sigma_4$ 

```

Table A4.3 - $\hat{\mathbf{W}}$ due to the non-diagonal elements

This algorithm has substantial computing advantages as it limits the memory requirements of the matrix $\hat{\mathbf{U}}_{\varepsilon}$ from the $T^2 \times T^2$ dimension to a single scalar, specifically, σ_4 . Additionally, the computing requirements are severely reduced, from $(T^2)^3$ iterations to $T^2 + T + \binom{T}{2}$ iterations.

Appendix 4C: Distribution of t -values

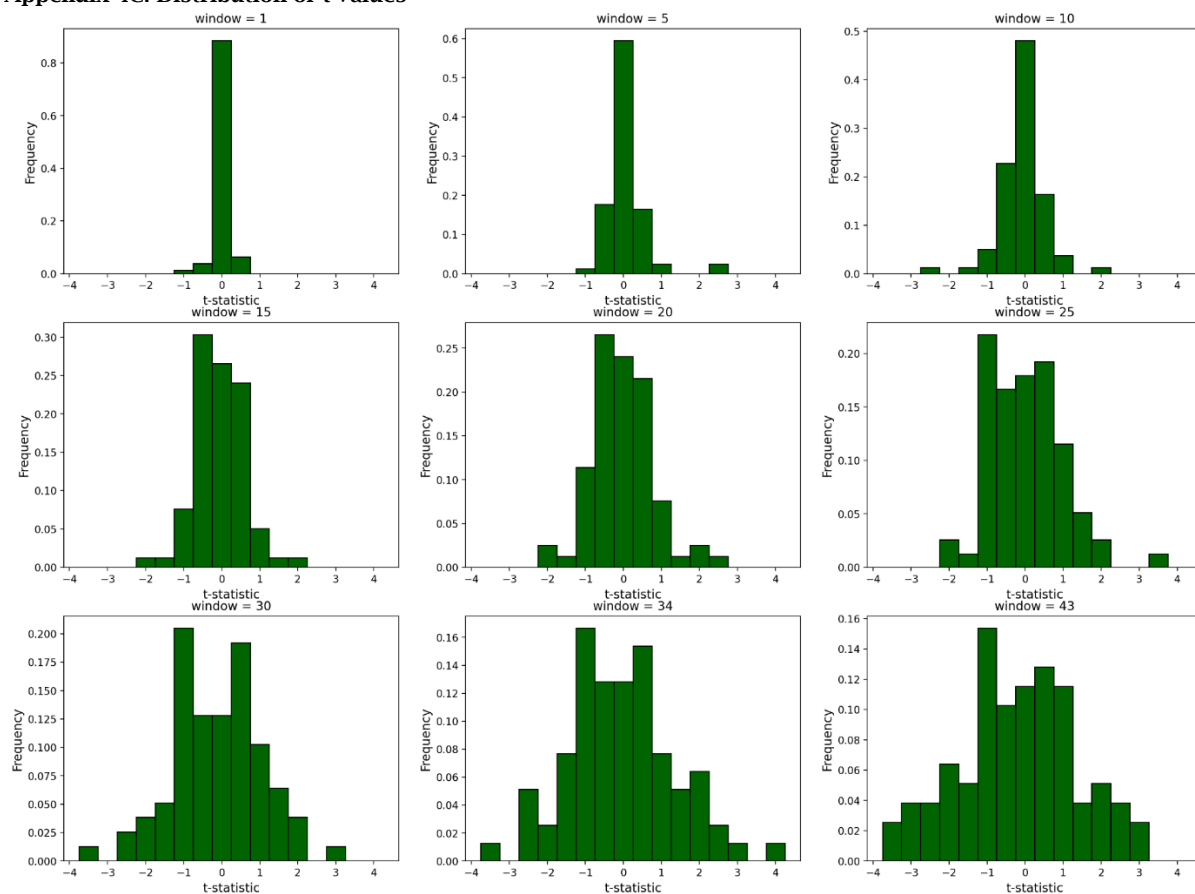


Figure A4.4 - Distribution of t -values

This figure shows examples of how the t -values of the collection of 78 factors are distributed at different levels of T .