Essays on Real Estate Investment and Asset Returns

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To my loving parents

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Abstract

This thesis, consisting of three interrelated essays, uncovers the property investment behaviour of commercial real estate market players and the return patterns of the asset class. The first essay is titled "Real Estate Investment and Asset Return Dynamics: Evidence from REITs." In this essay, I examine the relationship between aggregate REIT property investment and future public commercial real estate returns. Aggregate investment negatively predicts excess market returns over the subsequent year. The return predictive power survives controls for financial ratios, term-structure variables, investor sentiment measures, equity issuance, and operating accruals. In addition, aggregate REIT investment is weakly related to investor sentiment measures and fails to predict future firm earnings news indicators. Instead, aggregate investment is strongly tied to discount rate proxies and positively predicts macroeconomic growth indicators. And the investment's return predictability is not subsumed by the future materialization of firm cash-flow shocks and macroeconomic fundamentals. These results suggest that the predictive relation is mainly driven by time-variation in expected returns, rather than investor sentiment.

The second essay is titled "Real Estate Investment Plans and the Cross Section of Asset Returns: Evidence from REITs." In this essay, I examine the cross-sectional expected return implications of planned real estate investments. I forecast the future investment growth of REITs using Tobin's q, gross profitability, changes in return on assets, and prior stock returns. The forecasted future investment-to-asset changes generate a positive premium in the cross section of REIT returns. To capture the return variation, I construct a factor-mimicking portfolio based on a two-way monthly sort on size and the expected investment growth. Using the factor, an augmented REIT-based investment-based model not only holds up against comparisons with competing REIT-based and common stock-based factor models but also outperforms them in dissecting prominent REIT return patterns. I finally propose an alternative risk-based explanation for the premium. Firms with higher expected investment growth demonstrate higher future profitability, yet they also exhibit a greater degree of future operating and financial leverages and increased sensitivity of future cash flows to economic conditions, leading to higher discount rates.

The third essay is titled "Climate Change Exposure, Green Investment, and Financial Performance: The Case of Publicly Listed Real Estate." In this essay, I examine the real and financial implications of climate change exposure among publicly listed real estate firms. Exposure reflects earnings call participants' attention to a firm's climate-related opportunities, as well as regulatory and physical shocks. I find that firms with higher climate change exposure allocate more capital towards green building initiatives over the subsequent year. Additionally, tenants of high-exposure firms tend to achieve superior aggregate environmental scores in the future. The overall exposure effects are primarily attributable to firms with higher regulatory exposure. However, doing good may not mean doing well. High-exposure firms experience lower future operating and rental performance. The effect is primarily due to the reduced cash flows in firms with higher opportunity exposure. Furthermore, the opportunity exposure negatively predicts subsequent market valuations and stock returns, suggesting that investors may overlook the adverse signal of exposure for firms' future fundamentals, or may have non-financial preferences, accepting lower expected returns.

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Abbreviations

10-K	10K Form
AMEX	American Stock Exchange
AR(1)	First-Order Autoregressive Coefficient
BX3	Bond and Xue (2017) Three-Factor Model (REITs)
CA	Climate Action
CAPM	Capital Asset Pricing Model (REITs)
CAPM*	Capital Asset Pricing Model (Common Stocks)
Carhart4	Carhart (1997) Four-Factor Model (REITs)
Carhart4*	Carhart (1997) Four-Factor Model (Common Stocks)
CC	Climate Change
CFNAI	Chicago Federal National Activity Index
CO	Climate Opinion
COP	Conference of the Parties
CRSP	Center for Research in Security Prices
EPA	Environmental Protection Agency
EPS	Earnings Per Share
ESG	Environmental, Social, and Governance
FF3	Fama and French (1993) Three-Factor Model (REITs)
FF3*	Fama and French (1993) Three-Factor Model (Common Stocks)
FF5	Fama and French (2015) Five-Factor Model (REITs)
FF5*	Fama and French (2015) Five-Factor Model (Common Stocks)
FF6	Fama and French (2018) Six-Factor Model (REITs)
FF6*	Fama and French (2018) Six-Factor Model (Common Stocks)
FRED	St. Louis Federal Reserve Economic Database
FTSE	Financial Times Stock Exchange
GAAP	Generally Accepted Accounting Principles
GDP	Gross Domestic Product
GRESB	Global Real Estate Sustainability Benchmark
GRS	Gibbons, Ross, and Shanken (1989)
HMXZ$\boldsymbol{q^5}$	Hou, Mo, Xue, and Zhang (2021) q^5-factor model (REITs)
HMXZ$\boldsymbol{q^5*}$	Hou, Mo, Xue, and Zhang (2021) q^5-factor model (Common Stocks)

HXZq	Hou, Xue, and Zhang (2015) q-factor model (REITs)
HXZq*	Hou, Xue, and Zhang (2015) q-factor model (Common Stocks)
I/B/E/S	The Institutional Brokers' Estimate System
IP	Industrial Production
IPO	Initial Public Offering
LEED	Leadership in Energy and Environmental Design
LSEG	London Stock Exchange Group
MI	Market Intelligence
MTS	Manufacturing and Trade Industries Sales
MSCI	Morgan Stanley Capital International
NA	North America
NAREIT	National Association of Real Estate Investment Trusts
NASDAQ	National Association of Securities Dealers Automatic Quotation System
NBER	National Bureau of Economic Research
NCREIF	National Council of Real Estate Investment Fiduciaries
NPV	Net Present Value
NYSE	New York Stock Exchange
OLS	Ordinary Least Squares
REOC	Real Estate Operating Company
REIT	Real Estate Investment Trust
PCE	Personal Consumption Expenditures
SNL	Securities and Law
S&P	Standard and Poor's
SvLVZ	Sautner, van Lent, Vilkov, and Zhang (2023)
US	United States
USGBC	United States Green Building Council
WSJ	Wall Street Journal

Chapter 1 Introduction

The real estate market plays a pivotal role in the economy, being intricately linked to the financial markets and exerting substantial influence on the real economy. This thesis focuses on commercial real estate, the oldest asset class but not the most transparent or well-understood. Commercial real estate investment has undergone evolution over time. Once dominated by wealthy individuals, this asset class is now actively sought by diverse investors as a primary asset. For equity investors, this includes private equity, real estate operating companies, property real estate investment trusts, pension funds, and sovereign wealth funds. Each has its own risk profile and focus, such as income, fees, capital appreciation, and usage. This asset class has experienced a shift in capital financing from straightforward financing to complex financial instruments involving both equity and debt. Assets and portfolios are frequently restructured. This asset class has also transitioned from a local to a global asset and exhibited boom and bust cycles with broader implications for individuals, institutions, markets, and economies. In recent years, the emergence of climate change as a critical global issue has presented new risks and opportunities. To effectively manage this asset class, it is crucial to comprehend the investment behavior of market players and the return pattern of this asset class. This thesis aims to enhance this understanding by providing insights that are both academically valuable and practically relevant.

This thesis comprises three interrelated essays that concentrate on U.S. publicly traded commercial real estate equities. The initial two essays focus on equity real estate investment trusts (REITs), a type of entity that invests in real estate through properties and provides investors with a liquid stake in real estate. The first essay analyzes aggregate REIT property investment and examines its market return predictability. The second essay forecasts REIT future real estate investment growth and assesses its expected return implications in the cross section. The third essay incorporates real estate operating companies (REOCs) to reflect the broad impact of climate change on commercial real estate. A REOC is akin to a REIT but differs from a REIT in terms of dividend distributions and the composition of a company's assets. The last essay investigates both the real-economy and financial consequences of climate change exposure.

The first essay, titled "Real Estate Investment and Asset Return Dynamics: Evidence from REITs," explores whether aggregate corporate investment in income-generating properties serves as a predictor of future returns on commercial real estate. The global financial crisis of 2008–2009 marked a turning point for the commercial real estate market, particularly in the United States, where both private and public real estate have experienced remarkable price growth since then. Today, these assets trade well above their pre-crisis peak levels, raising critical questions about the factors that can predict future returns in this cyclical asset class. Understanding the potential factors is crucial for a diverse range of market participants, including high-net-worth individuals, institutional investors, and real estate firms.

The investment-based asset pricing model suggests the forecast of asset returns by investment-related variables (Cochrane, 1991). The model is derived from the producer's first-order conditions for optimal intertemporal investment demand, where optimal investment is linked to the cost of capital or expected returns. If we fix the investment process and make predictions about returns, it is an investment-based asset pricing model. The model might say "expected returns are high because investment is low". Also, expected returns can vary over time due to changes in the state of the economy (Fama, 1991). The model suggests that investment co-moves this time variation, serving as a proxy for changes in the investment opportunity set.

To empirically test this hypothesis and explore the underlying mechanisms, this study focuses on equity REITs, which primarily invest in institutional-quality properties. I employ a robust measure of REIT property investment, namely changes in operating assets, and construct an aggregate REIT investment series spanning from 1971 to 2018. The annual time horizon is crucial for mitigating the inherent lag in commercial real estate transactions and capturing the cyclical nature of the market. For return analysis, I utilize monthly return data on the FTSE NAREIT All Equity REITs Index from July 1972 to June 2020. The choice of NAREIT index, rather than private commercial property price indices, is driven by the relative efficiency of capital markets in reflecting information in REIT returns (Fisher et al., 2003; Yavas and Yildirim, 2011). Unlike private property indices, which suffer from significant market frictions, smoothing, serial correlation, and price adjustment lags (Ghysels et al., 2013; Ghent et al., 2019), REIT indices provide a more accurate and timely reflection of market conditions, making them ideal for predictability tests.

The findings of this study are both intriguing and significant. The analysis reveals that aggregate REIT investment negatively predicts future excess returns on the NAREIT index, with a one-standard-deviation increase in aggregate investment associated with a decrease of 7.1% in one-year-ahead excess returns. This predictive relationship remains robust even after controlling for several well-established return predictors, including the dividend-to-price ratio, book-to-market ratio, earnings-to-price ratio, short-term interest rate, term spread, default spread, equity share in total net issues, and aggregate accruals. Furthermore, investor sentiment indicators also predict future market returns, but they do not diminish the return predictability of aggregate investment.

The documented return predictability may arise from several economic sources. One potential explanation is market inefficiency, where information is not timely incorporated into prices by market participants (Fama, 1970), providing opportunities for informed investors to exploit serial dependencies. However, the minimal serial correlation found in NAREIT returns suggests that capital markets are relatively efficient in incorporating information. To further understand the economic forces driving the return predictive power, I investigate whether aggregate REIT investment captures time variation in expected returns (Campbell and Shiller, 1988a) and/or investor sentiment (Lee et al., 1991). I find that aggregate investment is weakly related to investor sentiment measures and fails to predict firm cash-flow shock indicators. Instead, it is strongly tied to discount rate proxies and positively predicts macroeconomic growth indicators. Furthermore, its return predictability is not subsumed by the future materialization of firm cash-flow shocks and macroeconomic fundamentals. These results suggest that the predictive relationship is mainly driven by time variation in expected returns rather than investor sentiment.

This study makes several important contributions to the existing literature. It first extends the literature on aggregate stock return predictability based on investment-related variables. Previous studies have predominantly focused on productive capital investment and aggregate stock market returns. This study provides new evidence from commercial real estate investment and its public market returns. In addition, previous studies have debated the economic force behind the investment's return predictability. This study provides new evidence strengthening the rational explanation of time-varying expected returns. Second, the first essay contributes to the literature on aggregate REIT return predictability, which has been addressed with different interests in previous studies. This study approaches the topic with new insight from the investment-based asset pricing models and suggests that aggregate REIT property investment is an alternative and possibly shaper measure of expected returns. Third, the first essay adds to the growing literature on REIT real investment decisions. Previous studies have documented the effects of biased managers or investors on REIT property investment at the firm level. This study shows contrasting evidence that at the aggregate level, investor sentiment is, in effect, a sideshow to REIT investment, conveying a signal of collective rationality.

The second essay, titled "Real Estate Investment Plans and the Cross-Section of Asset Returns: Evidence from REITs," shifts focus to planned real estate investment and its asset pricing implications in the cross section. Planned property acquisitions and/or constructions represent real estate firms' investment commitments. These real estate investment plans require significant time and resources to complete and, once initiated, are difficult and costly to reverse, making them inherently risky. Therefore, it is of great interest to examine their implications on cross-sectional expected returns.

Theoretically, the investment CAPM in a dynamic setting provides an equilibrium model, where expected returns vary cross-sectionally with current investment, expected profitability, and expected investment growth (Liu et al., 2009). Holding current investment and expected profitability constant, the model can make statements like "expected returns are high because a function of expected investment growth is high". Intuitively, according to the net present value rule of capital budgeting, high expected investment relative to current investment implies high discount rates, because the high discount rates are necessary to offset the high expected marginal benefits of current investment to generate low net present values of new projects and thereby maintain low current investment levels (Hou et al., 2021).

To empirically test the hypothesis, this study forecasts firms' future investment growth. Investment refers to investment-to-asset ratio and is measured as total asset growth rate (Fama and French, 2006; Hou et al., 2015). REITs provide a favourable setting for this forecasting exercise, as on average, 98.6% of their assets are real estate (Eichholtz and Yönder, 2015). This homogeneity in asset composition suggests that the total asset growth rate serves as an effective proxy for real estate investment. Given that investment-to-asset ratio is frequently negative, making the growth rate of investment-to-asset ratio ill-defined, I follow Hou et al. (2019 and 2021) and specifically forecast future investment-to-asset changes, using predictors such as the log of Tobin's q, gross profitability, changes in return on assets, and prior stock returns.

Consistent with the dynamic investment CAPM, the forecasted investment-to-asset changes are related to a significant positive premium in the cross-section of REIT returns. In firm-level predictive regressions, they positively predict excess returns over the subsequent month, even after controlling for a range of return predictors, including size, book-to-market ratio, prior 11-month returns, share turnover, standardized unexpected earnings, idiosyncratic volatility, investment-to-asset ratio, and return on assets. At the portfolio level, it earns a high-minus-low quintile premium that is not explained by a set of conventional and more recent factor models reconstructed for REITs, including the Fama and French (2018) six-factor model (FF6) and the Hou et al. (2015) q-factor model (HXZq). To capture the return variation, I construct a factor-mimicking portfolio. The resultant expected investment growth factor generates an average return of 0.34% per month, which not only surpasses the premium from its constituents but also remains robust across various empirical specifications.

With the factor, I construct a REIT-based Hou et al. (2021) q^5 model (HMXZq^5). The model is subsumed by neither the REIT-based FF6 model nor the common stock-based FF6* and HMXZq^5* models in spanning tests. Additionally, in stress-testing exercises, the model outperforms competing REIT-based factor models in explaining a set of testing portfolios formed on prominent REIT return predictors, including momentum, standardized unexpected earnings, idiosyncratic volatility, and share turnover. Given the importance of the factor in the model to dissecting REIT return patterns, I finally propose an alternative risk-based explanation for the factor premium, highlighting the role of operating and financial leverage. Firms with high expected investment growth show higher future profitability, but they also exhibit a greater degree of future operating and financial leverage and increased sensitivity of future cash flows to economic conditions, giving rise to high discount rates.

This study makes several contributions to the literature. It first extends the literature on investment plans and asset returns. Previous studies have focused on productive capital investment plans and stock returns at either the aggregate or cross-sectional level. This study provides new evidence from commercial real estate investment plans and the cross-section of REIT returns. Second, despite the dynamic investment CAPM, it remains an open question of why high expected investment growth commands high expected returns in the cross-section. This study proposes an alternative risk-based explanation that focuses on the risk amplification effect of operating and financial leverages heightened by expected investment growth. Third, this study contributes to the literature on real estate finance. The cross-section of REIT returns has long attracted various interests from real estate researchers. This study provides evidence of a new return pattern related to expected investment growth, which is not only a reincarnation of several existing return patterns but also an extension of them. Also, there is an ongoing debate on the integration or segmentation of REIT returns with or from stock markets. This study provides new evidence strengthening the segmentation argument.

The third essay, titled "Climate Change Exposure, Green Investment, and Financial Performance: The Case of Publicly Listed Real Estate," addresses one of the most pressing challenges facing the real estate industry today: climate change. As climate hazards and policies increase, firms within the industry face significant risks that could affect their financial performance. The presence of climate risk forces firms to adopt green practices to reduce their environmental impacts. The growing demand for sustainable and energy-efficient buildings presents new opportunities for firms to differentiate themselves in the market and attract environmentally conscious investors. This study therefore seeks to examine the extent to which firms' climate change exposure affects their green property investments and financial outcomes.

The models of "uncertainty about the path of climate change" (Giglio et al., 2021) and the ESG-efficient frontier framework (Pástor et al., 2021; Pedersen et al., 2021) are referred to as alternative theoretical foundations for pricing climate change in the cross-section. While the former concerns the covariance properties of asset payoffs with climate change as a systematic risk factor, the latter focuses on how investor beliefs and preferences regarding climate change—and ESG considerations more broadly—fit within the factor model paradigm. The former implies that climate change uncertainties make it difficult for investors to evaluate how individual stocks will be affected by climate change and thus should be associated with a risk premium. In the latter, investors with non-return preferences for sustainability or ESG may accept lower expected returns for stocks with higher climate change exposure, leading to zero or even a negative risk premium.

The empirical analysis draws on the firm-level climate change exposure measures proposed by Sautner et al. (2023a). The measures capture market participants' attention to firms' exposure to climate change by quantifying the portions of conversations during earnings calls that relate to climate change topics. The measures cover a broad range of climate-related issues, including physical shocks (e.g., extreme weather events), regulatory shocks (e.g., climate policies and regulations), and technological opportunities (e.g., green buildings). The initial analysis reveals that the climate change exposure measure varies across property types and increases over time. It is positively correlated with public climate change attention proxies, firms' S&P Global environmental scores, and the weather exposure measure proposed by Nagar and Schoenfeld (2022).

In terms of real economic impacts, firms with higher climate change exposure invest more in green buildings over the subsequent year. The overall exposure effect is primarily driven by firms with higher regulatory exposure. This finding suggests that firms tend to respond to regulatory pressures for sustainability by increasing their investment in environmentally certified buildings. This shift to sustainable buildings may not only help decarbonize the real estate sector but also support the low-carbon transition of other economic sectors by enabling building tenants or occupants to reduce their environmental footprints. I show that in aggregate, tenants of high-exposure firms achieve higher S&P Global environmental scores over the following year.

However, doing good may not mean doing well. Higher climate change exposure is associated with lower operating profitability and funds from operations over the subsequent years, particularly in firms with higher opportunity exposure. The negative association may be attributed to the high upfront costs and longer construction times associated with green building investments, which can strain firms' financial resources and reduce profitability in the short term. At the property level, high-exposure firms experience lower future rental net operating incomes and occupancy rates. The overall exposure effect stems from firms with higher opportunity and regulatory exposures, respectively. The results suggest that green retrofits may also erode rental incomes, while regulatory shocks can impact tenant occupancy decisions.

Regarding financial market outcomes, climate change exposure negatively predicts future market valuations and stock returns, particularly in firms with higher opportunity exposure. These findings are consistent with the notion that investors may either ignore the negative signal of climate change exposure for future firm cash flows or allocate capital to high-exposure stocks due to their preference for sustainability. In addition, the return predictability is persistent during the post-Copenhagen period, underscoring the long-term impact of climate change exposure. Finally, the return predictability extends to the portfolio level, generating a significantly negative high-minus-low quintile premium that is not explained by a set of conventional and more recent factor models.

This study makes several contributions to the literature. It first adds to the growing literature on climate change exposure and corporate green investment. Among others, Sautner et al. (2023a and 2023b) find that firms with high climate change exposure invest more in green jobs and green patents. This study provides new evidence on green buildings as well as transition enabling. Second, this study contributes to the literature on climate change exposure and asset prices. Saunter et al. document a positive premium related to climate change exposure, using option-implied expected returns and a sample of S&P 500 stocks. They align the positive premium with the model of "uncertainty about the path of climate change"(Giglio et al., 2021). This study finds contrasting evidence of a negative premium based on realized returns and a sample of SNL U.S. publicly traded real estate firms. The negative premium can be linked to the ESG-efficient frontier framework (Pedersen et al., 2021). Third, this study adds to the literature on climate change, sustainability, and real estate. A growing number of studies have examined the effects of green building certifications, environmental or broader ESG performance or disclosure, and physical climate hazards on the financial performance of publicly traded real estate firms. This study differs from previous studies by using the firm-level climate change exposure from Sautner et al. Compared with previous interest, this study provides a more comprehensive analysis, covering both climate risks and opportunities, and offers new insight from market participant perceptions of firms' climate change exposure. In addition, this study provides new evidence on green building investment and transition enabling as well as contrasting evidence on financial performance.

In general, this thesis makes several theoretical contributions. The theoretical predictions from the investment-based asset pricing models or the ESG-efficient frontier framework ultimately rest on how and whether capital market prices investment, expected investment growth, or climate change exposure. This thesis provides new evidence from commercial real estate through asset pricing tests of public real estate equity returns. Also, this thesis sheds light on the potential channels that investors are using to price those factors of interest in public commercial real estate markets through economic mechanism analyses. The findings would be of importance in the formation of hypotheses aimed at equilibrium model development.

This thesis also has practical implications. For instance, the first essay proposes that investors can assess the market's expected returns on public commercial real estate equity by analyzing the aggregate property investments of key market players. The second essay suggests that the augmented investment-based factor model can serve as an alternative benchmark to evaluate the risk-adjusted performance of REITs and dedicated REIT mutual funds. The third essay posits that the implementation of climate regulations and policies can facilitate the transition to sustainable practices within the real estate sector. It also underscores the significance of firm managers in strategically planning and allocating resources to green opportunities to mitigate the potential erosion of future profits.

In conclusion, this thesis examines the implications of investment-based asset pricing and the real and financial consequences of climate change exposure. It enhances comprehension of the investment behavior of commercial real estate market players and the return pattern of the asset class. The findings from this thesis emphasize the significance of informed investment strategies and the necessity for a comprehensive approach to managing risks in an increasingly intricate and uncertain market environment. This thesis serves as a foundation for future research and provides valuable tools for addressing the challenges and opportunities that lie ahead in the ever-evolving market.

The rest of this thesis is organized as follows. Chapter 2 presents the first essay, titled "Real Estate Investment and Asset Return Dynamics: Evidence from REITs." Chapter 3 presents the second essay, titled "Real Estate Investment Plans and the Cross-Section of Asset Returns: Evidence from REITs." Chapter 4 presents the third essay, titled "Climate Change Exposure, Green Investment, and Financial Performance: The Case of Publicly Listed Real Estate." Chapter 5 concludes.

Chapter 2 Real Estate Investment and Asset Return Dynamics: Evidence from REITs

Abstract

I examine the relationship between aggregate REIT property investment and future public commercial real estate returns. Aggregate investment negatively predicts excess market returns over the subsequent year. The return predictive power survives controls for financial ratios, term-structure variables, investor sentiment measures, equity issuance, and operating accruals. In addition, aggregate REIT investment is weakly related to investor sentiment measures and fails to predict future firm earnings news indicators. Instead, aggregate investment is strongly tied to discount rate proxies and positively predicts macroeconomic growth indicators. And the investment's return predictability is not subsumed by the future materialization of firm cash-flow shocks and macroeconomic fundamentals. These results suggest that the predictive relation is mainly driven by time-variation in expected returns, rather than investor sentiment.

2.1 Introduction

Commercial real estate, a cyclical asset class, has experienced nearly unprecedented price growth since the global financial crisis. Both U.S. private and public real estate have more than doubled in value since then and today are trading well above their pre-crisis peak levels.[1] This remarkable growth raises an important question: which factors can explain the future returns of this asset class? This question matters for a diverse range of market players, from traditional high-net-worth individuals to institutional investors, including private equity funds, real estate operating companies, property real estate investment trusts (REIT), pension funds, and sovereign wealth funds. This study presents novel evidence that aggregate corporate investment in commercial properties can predict future commercial real estate returns.

The investment-based asset pricing model suggests the forecast of asset returns by investment-related variables (Cochrane, 1991). The model is derived from the producer's first-order conditions for optimal intertemporal investment demand, where optimal investment is linked to the cost of capital or expected returns. If we fix the investment process and make predictions about returns, it is an investment-based asset pricing model. The model might say "expected returns are high because investment is low". Also, expected returns can vary over time due to changes in the state of the economy (Fama, 1991). The model suggests that investment co-moves this time variation, serving as a proxy for changes in the investment opportunity set.

To test the model prediction and explore the underlying economic mechanism, I focus on publicly traded commercial real estate companies, and in particular, equity Real Estate Investment Trusts (REITs), whose sole activity is the management of a real estate portfolio. REITs tend to purchase institutional-quality properties that are newer and larger than many other commercial properties purchased by private investors (Ghent et al., 2019). I employ the change in operating assets as a simple yet effective measure of REIT property investment, given that they hold nearly all their assets in commercial properties (Eichholtz and Yönder, 2015). My aggregate REIT investment series, constructed from bottom-up firm-level data, spans from 1972 to 2019. This annual horizon mitigates the "long lead time" nature of commercial real estate transactions. In this market, shifts do not instantly translate into

[1] See, e.g., the National Council of Real Estate Investment Fiduciaries (NCREIF) Property Index and the FTSE NAREIT U.S. All Equity REIT Index, respectively.

investment actions due to the asset class's inherent heterogeneity and lengthy valuation processes, causing a lag in investment expenditure in response to market conditions.[2]

For commercial real estate returns, I use monthly return data from the FTSE NAREIT All Equity REITs Index, covering the period from July 1973 to June 2020. This choice leverages the relative efficiency of capital markets in impounding information into REIT returns (Fisher et al., 2003; Yavas and Yildirim, 2011), as opposed to private commercial property price indices, such as the NCREIF Property Index. Private indices suffer from significant market frictions and exhibit substantial smoothing, serial correlation, and price adjustment lags, making them less suitable for predictability tests (Ghysels et al., 2013; Ghent et al., 2019). Additionally, it is well documented that unlevered REIT returns exceed NCREIF returns adjusted for property type, fees, leverage, appraisal smoothing, etc. (see, e.g., Pagliari Jr et al., 2005; Riddiough et al., 2005; Ling and Naranjo, 2015). Ang et al. (2018) further extend this evidence from raw to risk-adjusted returns, reinforcing the representativeness of REIT indices for the broader commercial real estate asset class (Van Nieuwerburgh, 2019).

I find that aggregate REIT investment negatively predicts future returns on the NAREIT Index. This predictive role is economically significant. A one-standard-deviation increase in aggregate investment is associated with a decrease of 7.1% in excess market returns over the subsequent year. The predictive relationship holds even after controlling for several well-established return predictors, including the dividend-to-price ratio, book-to-market ratio, earnings-to-price ratio, short-term interest rate, term spread, and default spread, as well as equity share in total net issues and aggregate accruals. Notably, while investor sentiment indicators also predict future NAREIT fluctuations, they do not diminish the significance of investment as a predictor. This result holds for several investor sentiment measures, including the University of Michigan Consumer Sentiment Index, Baker and Wurgler (2006) Stock Market Sentiment Index, and the constructed REIT market sentiment index.

The return predictability may arise from several economic sources. One potential explanation is market inefficiency, where information is not timely incorporated into prices by market

[2] Transaction closings are often reflective of values negotiated six months prior. The time estimate accounts for time to conduct contract negotiations, perform due diligence, and arrange financing. See, Understanding the Commercial Real Estate Investment Ecosystem: An Early Warning System Prototype, World Economic Forum, https://www3.weforum.org/docs/WEF_IU_Understanding_the_Commercial_Real_Estate_Investment_Ecosystem.pdf.

participants (Fama, 1970), providing opportunities for informed investors to exploit serial dependencies. I find minimal serial correlation in NAREIT returns, suggesting that capital markets are efficient in incorporating information into REIT returns. However, the reduced-form predictive regressions for NAREIT returns alone do not help further understand the economic forces driving the predictive relationship. Is the predictability driven by time variation in expected returns (Campbell and Shiller, 1988a), or by time-varying investor sentiment (Lee et al., 1991)?

To investigate these questions, I first examine whether aggregate REIT investment captures time variation in expected returns and/or investor sentiment.[3] I find that investment is significantly positively related to stock and REIT market sentiment indices when no other conditioning variables are included and when controlling for aggregate profits, market returns, and aggregate book-to-market ratio. However, the investment-sentiment relationship weakens sharply when adding state variables gauging the state of the economy: short-term interest rates, the term spread, and the default spread. This suggests that investment may capture unobservable fundamental components, rather than sentiment-related components, of the sentiment indices. Indeed, expected return proxies align strongly with investment.

If aggregate REIT investment reflects biased market expectations of future firm fundamentals, it should predict innovations in future firm cash flows. I test this implication by forecasting aggregate REIT earnings news. While investment significantly negatively predicts aggregate profits, it does not predict aggregate standardized unexpected earnings or aggregate errors in analyst forecasts of one-year-ahead or long-term earnings. In addition, higher investment is uncorrelated with more optimistic aggregate analyst forecasts of future earnings. To address potential concerns regarding the low statistical power of my tests, which may be due to the moderate persistence in aggregate analyst future earnings forecast errors, I forecast two alternative firm cash-flow shock series with much lower serial correlation: aggregate earnings announcement returns and the value premium. I find consistent results.

[3] Behavioral models of managerial decision-making deviate from standard models in two key ways. First, models of biased investors and analysts assume that rational managers with finite horizons either time non-rational investor beliefs or cater to non-standard investor demand (see, e.g., Stein, 1996; Baker and Wurgler, 2000 and 2002; Baker et al., 2003; Polk and Sapienza, 2008). Second, models of biased managers hypothesize that managers themselves exhibit biases, such as overconfidence (Malmendier and Tate, 2005 and 2008). In this study, I primarily test the implications of biased investor beliefs on corporate investment at the aggregate level.

To shed further light on whether aggregate REIT investment reflects non-rational market beliefs about future broader macroeconomic fundamentals, I use it to forecast macroeconomic growth. I find that investment significantly predicts the real GDP growth rate; however, the predictive relationship is positive, not negative. This suggests that investment is more likely to capture expected future macroeconomic fundamentals rather than biased expectations. The results are further confirmed by predictive regressions using alternative economic growth indicators. Finally, I demonstrate that aggregate REIT investment's predictive power for NAREIT returns cannot be subsumed by the inclusion of measures of aggregate firm cash-flow shocks and macroeconomic fundamental realizations. This finding also suggests that the economic force behind the predictive relationship is primarily time variation in NAREIT expected returns.

This study makes several contributions to the existing literature. Firstly, it enhances the literature on aggregate stock return predictability based on investment-related variables. Prior studies have examined gross private domestic investment (Cochrane, 1991), net non-residential fixed capital stock change (Baker and Wurgler, 2000), investment plan (Lamont, 2000), new orders of durable goods (Jones and Tuzel, 2013), aggregate corporate asset investment (Arif and Lee, 2014; Wen, 2019; Guo and Qiu, 2021; Chue and Xu, 2022), and aggregate expected investment growth (Li et al., 2021a).[4] These investment quantities largely gauge nonfinancial corporate investment in capital as production inputs. I examine financial corporations—specifically REITs—investing in commercial real estate as portfolio holdings. I show that in addition to productive-capital investment, income-producing property investment also captures future asset return dynamics. In particular, I extend the evidence of investment's market return predictability to public commercial real estate.

Secondly, this study contributes to the literature on aggregate REIT return predictability. Liu and Mei (1992) are among the earliest studies that document the predictability. Some follow-up studies suggest that the predictability might be exploitable (see, e.g., Mei and Liu, 1994; Ling et al., 2000). Others have employed more complex forecasting models (see, e.g., Cabrera

[4] Notwithstanding the return predictability, the underlying economic forces remain unclear. Earlier works, such as Cochrane (1991), Lamont (2000), and Jones and Tuzel (2013), note that their findings could be due to time-varying expected returns. This interpretation is later echoed by Guo and Qiu (2021), Li et al. (2021a), and Chue and Xu (2022). In contrast, Arif and Lee (2014) and Wen (2019) show that their investment variables mainly—and at least partially—reflect investor sentiment, respectively. This study contributes to this debate by demonstrating that the predictability is generally consistent with an explanation based on rational risk premiums rather than mispricing.

et al., 2011; Chen et al., 2014) or examined performance continuations and reversals at different return horizons (see, e.g., Mei and Gao, 1995; Stevenson, 2002). While previous studies have addressed REIT market return predictability with different interests, this study approaches the topic with new insight from the investment-based asset pricing model that expected returns vary time serially with aggregate investment. The results suggest that aggregate REIT investment may serve as an alternative, and possibly sharper, measure of the expected returns of public commercial real estate.

Thirdly, this study contributes to the growing literature on REIT real economic decisions. The effects of biased investors and/or biased managers on corporate decisions have been the subject of numerous studies in finance literature.[5] For publicly traded real estate companies, Eichholtz and Yönder (2015) report REIT investment's response to managerial overconfidence. Kim and Wiley (2019) document the effect of non-rational investor beliefs on REIT property transactions. However, my results suggest that investor sentiment is, in effect, a sideshow to aggregate REIT investment, aligning with standard models of managerial decision-making.[6] The novel results may arise from the focus of REIT investment at the aggregate level, which reflects the common variation in individual REIT investment. While previous studies suggest that individual REIT investment decisions are susceptible to behavioural biases, this study indicates that aggregating REIT investment decisions convey a signal of collective rationality, reflecting broad economic states.

Fourthly, this study contributes to theoretical development of investment-based asset pricing models. Kogan and Papanikolaou (2012) review studies investigating how firms' systematic risk and investment and production decisions are jointly determined in equilibrium. Models incorporating investment provide insights into various empirical patterns, including the correlations between firms' economic characteristics and their risk premia. This study presents new evidence supporting the theoretical prediction of asset return forecasts by investment from public commercial real estate equity and aggregate REIT property investment. Additionally, Kogan and Papanikolaou suggest that the first-order optimality condition of the firm's optimal investment faces limitations as a basis for empirical testing. Primarily, it lacks causal content,

[5] See a recent review on behavioral corporate finance by Malmendier (2018).

[6] In these models, corporate managers behave rationally, and investor sentiment is considered irrelevant. This irrelevance arises either because market prices are efficient (Cochrane, 1991; Carlson et al., 2006; Lyandres et al., 2008) or because managers who optimize long-term firm value rationally ignore any short-term sentiment-induced mispricing (e.g., Stein, 1996, the long-horizon case).

as it links endogenous variables. Consequently, it cannot address the economic causes of time-varying differences in firms' expected returns and their observable characteristics. This thesis conducts a series of tests to distinguish between rational and sentiment interpretations for the investment's ability to predict future asset returns. The findings would be of significance in developing hypotheses for equilibrium models.

The rest of the chapter is organized as follows. Section 2.2 describes the data and methodology. Section 2.3 forecasts aggregate REIT market returns. Section 2.4 explains aggregate REIT investment. Section 2.5 forecasts aggregate REIT earnings news. Section 2.6 forecasts aggregate REIT earnings announcement returns and the value premium. Section 2.7 forecasts macroeconomic growth. Section 2.8 subsumes aggregate REIT market returns. Section 2.9 concludes.

2.2 Data and Methodology

The sample includes 442 U.S. publicly traded equity REITs identified by the National Association of Real Estate Investment Trusts (NAREIT). Glascock and Hughes (1995) provide a list of all REITs identified by NAREIT that appear in the CRSP data file from January 1972 to December 1991. In this list, 74 out of 151 REITs are classified as equity REITs. The NAREIT website offers monthly constituent data for the FTSE NAREIT U.S. Real Estate Index Series starting from December 1991. In this list, 436 out of 560 REITs are classified as equity REITs from December 1991 to December 2019. I merge these two lists to create a consolidated list of 460 equity REITs. I exclude 18 firms because they do not appear in the Compustat data file.

I measure annual aggregate REIT market returns, R_{t+1}, by compounding monthly excess total returns (returns minus risk-free rate) of FTSE NAREIT All Equity REITs Index from July of year t+1 to June of year t+2 for the period from July 1972 to June 2020.[7] This return cumulation period ensures that firms' accounting data are publicly available before future stock returns are realized (Fama and French, 1992). Additionally, I compute non-overlapping annual horizon returns. Overlapping returns can lead to severe serial correlation, distorting inference and producing falsely high t-statistics (Valkanov, 2003).

Utilizing annual financial statement data from Compustat, I construct an annual aggregate investment series, $Invest_t$, from 1971 to 2018. The aggregate investment series is the value-weighted average of annual firm-level investments, aggregated to the market level using fiscal-year-end market capitalizations as weights. Firm-level investment is measured as the annual growth rate in non-cash assets or operating assets.[8] Specifically, non-cash assets are computed as total assets (Compustat AT) minus cash and short-term investments (CHE). I require the

[7] The FTSE NAREIT All Equity REITs Index is a free-float adjusted, market capitalization-weighted index of U.S. equity REITs. Constituents of the index include all tax-qualified REITs with more than 50% of total assets in qualifying real estate assets other than mortgages secured by real property. The monthly return data on the index are available from the NAREIT website, starting from January 1972 onwards.

[8] Corporate investment is measured in various ways within the REIT literature. Utilizing the data item 'real estate investment' from the SNL Financial Real Estate database, Eichholtz and Yönder (2015) and Kim and Wiley (2019) measure REIT investment as the annual growth rate in this data item. Based on relevant accounting data from Compustat, Bond and Xue (2017) and Ling et al. (2019) measure REIT investment as the annual growth rate in non-cash assets and total assets, respectively. Bond and Xue (2017) note that growth in non-cash assets is a comprehensive measure of firms' investment in various operating assets, such as fixed assets and working capital. I obtain similar results using the annual growth rate in total assets.

availability of Compustat annual data items CHE and AT in both current and previous years to retain a firm-year observation in the sample.

Table 2.1 presents summary statistics for $Invest$ and R. The investment series has an average of 18.6% and a standard deviation of 16.9%, indicating that aggregate REIT property investment exhibits substantial fluctuations over the sample period. The investment series also demonstrates significant serial dependence, with an AR(1) coefficient of 0.648. The return series is similarly volatile, with a mean of 7.95% and a standard deviation of 17.3%. Additionally, the return series displays an extremely low first-order serial correlation of -0.002.

Following the extensive predictive literature in finance and real estate, I consider the following linear predictive regression model:

$$r_{t+1} = \alpha + \beta' \boldsymbol{X_t} + \varepsilon_{t+1} \text{ (2.1)},$$

where r_{t+1} represents the return (or price change) and $\boldsymbol{X_t}$ is a vector of variables observable at time t. Predictability in r_{t+1} might stem from market inefficiency if some available information is not incorporated into prices in a timely manner by market participants (Fama, 1970). For a market to be inefficient, investors should be able to exploit some of the serial dependence. However, I demonstrate low serial correlation in the return series, thereby rejecting the weak-form market efficiency.

Predictability might stem from time variation in expected returns (Campbell and Shiller, 1988a). To capture this, I select a set of conditioning variables to proxy for time variation in the state of the economy and thus in the prevailing investment opportunity set. These variables have been shown to effectively capture time variation in expected returns of the aggregate U.S. stock market, bond market, and real estate market. I discuss these variables below based on the predictive information included in $\boldsymbol{X_t}$. Details on the data sources and construction are provided in Appendix 2.1.

Valuation ratios have a long-standing tradition as predictors of equity market returns, including the dividend-to-price ratio (Fama and French, 1988; Lewellen, 2004; Lettau and Van Nieuwerburgh, 2008), the book-to-market ratio (Kothari and Shanken, 1997; Pontiff and Schall, 1998), and the earnings-to-price ratio (Campbell and Shiller, 1988a and b and 2005). The economic rationale for using valuation ratios to predict future returns is based on the reasonable assumption that the ratio components are cointegrated in logs (Engle and Granger, 1987). For example, if log dividends and log prices are cointegrated, then the log dividend-price ratio must be a mean-reverting process. If, at time *t*, the ratio is higher than its unconditional mean, this suggests that either expected dividend growth will be low, expected returns will be high, or a combination of the two (Campbell et al., 2009). To capture time variation in the expected returns of the aggregate REIT market, I construct three valuation ratios: the value-weighted averages of firm-specific REIT valuation ratios—aggregate dividend-to-price (D/P), aggregate book-to-market (B/M), and aggregate earnings-to-price (E/P).

Despite the appeal of using valuation ratios in predictive regressions, an obvious problem is that the predictive ratios might not capture all time variation in the conditioning information set, $\boldsymbol{X_t}$. Indeed, there is considerable evidence that term structure variables, other than past returns or valuation ratios, are associated with future stock market returns. These variables include the short-term interest rate (Fama and Schwert, 1977; Hodrick, 1992; Ang and Bekaert, 2007), the term spread (Fama and French, 1989; Campbell and Vuolteenaho, 2004; Campbell et al., 2010), and the default spread (Keim and Stambaugh, 1986; Fama and French, 1989). To alleviate potential omitted-variable bias in the predictive regressions, I include three interest rate variables: $Tbill$, the 3-month Treasury bill rate; $Term$, the difference between 10-year and 1-year Treasury constant maturity rate; and $Default$, the difference between Moody's Seasoned Baa and Aaa corporate bond yields.

Predictability in r_{t+1} might also arise from time variation in investor sentiment, broadly defined as demand unjustified by existing fundamentals. A natural prediction of the noise trader model is that returns should be lower following high-sentiment periods (Lee et al., 1991). There is ample evidence of the cross-sectional effect of sentiment on stock returns (see, e.g., Baker and Wurgler, 2006 and 2007; Baker et al., 2012; Ben-Rephael et al., 2012). The sentiment effect on REIT returns is also well documented (see, e.g., Clayton and MacKinnon, 2002; Ambrose et al., 2007; Lin et al., 2009; Ling et al., 2014; Das et al., 2015). I employ three measures of investor sentiment: SI^{Cons}, the University of Michigan Consumer Sentiment Index; $SI^{Stock\perp}$, the Baker and Wurgler (2006) composite stock-market-based sentiment index; and $SI^{REIT\perp}$, the constructed composite REIT-market-based sentiment index. The definition, data sources, and construction of the investor sentiment measures are provided in Appendix 2.2.

Prior research has examined various corporate decision variables, in addition to investment, for their predictive power over stock returns. For example, Baker and Wurgler (2000) demonstrate that when investor sentiment is high, firms increase the equity share in total new (equity plus debt) issues, which is subsequently followed by lower market returns. Hirshleifer et al. (2009) find that aggregate accruals positively predict aggregate returns and suggest that aggregate accruals might serve as a proxy for discount rates. Additionally, Ling et al. (2019) predict the stock returns of individual REITs using firm-level equity issuance and accruals variables. Consequently, this study includes two additional corporate decision variables to proxy for time variation in investor sentiment and/or expected returns. $Eshare$ represents the equity share in REIT total net equity and debt issues, while $Accrual$ denotes aggregate operating accruals, calculated as the value-weighted average of firm-level accruals.

As noted in the existing literature, statistical complications in linear predictive regressions may arise when the predictor $\boldsymbol{X}_t$ is persistent and its innovations are correlated with ε_{t+1}, inducing small-sample bias in the estimation of β (Stambaugh, 1999). Table 2.1 shows that the valuation ratios exhibit moderate to high serial correlation. The interest rate variables are also moderately to highly serially correlated, as are the three investor sentiment measures. Only the two corporate decision variables are nearly serially uncorrelated. To address the potential small-sample bias in OLS estimates, this study adjust the coefficient estimates using the Stambaugh (1999) correlation. The t-statistics are calculated with Newey and West (1987) standard errors, using three lags.

[Insert Table 2.1]

2.3 Forecasting Aggregate REIT Market Returns

Equation (2.2) presents the regression model of future aggregate REIT market returns on a constant and a set of conditioning variables:

$$R_{t+1} = \alpha + \beta_1 Invest_t + \beta_2 SI_t + \beta_3 Tbill_t + \beta_4 Term_t + \beta_5 Default_t + \beta_6 D/P_t + \beta_7 B/M_t + \beta_8 E/P_t + \beta_9 Eshare_t + \beta_{10} Accrual_t + \varepsilon_{t+1} \quad (2.2)$$

R_{t+1} is the compounded monthly excess total return (return minus risk-free rate) on the FTSE NAREIT All Equity REITs Index from July in year t+1 to June in year t+2. $Invest_t$ is aggregate investment as of the end of fiscal year t. SI_t represents one of three sentiment indices: SI_t^{Cons} is the average value of the monthly University of Michigan Consumer Sentiment Index over year t; SI_t^{Stock} is the average value of the monthly Baker and Wurgler (2006) composite stock market sentiment index over year t; and SI_t^{REIT} is the average value of the monthly constructed composite REIT market sentiment index over year t. $Tbill_t$ is the 3-month Treasury bill rate as of the beginning of July in year t+1. $Term_t$ is the difference between 10-year and 1-year Treasury constant maturity rates as of the beginning of July in year t+1. $Default_t$ is the difference between Moody's Seasoned Baa and Aaa corporate bond yields as of the beginning of July in year t+1. D/P_t represents the dividend yield on the FTSE NAREIT All Equity REITs Index as of the end of June in year t+1. B/M_t is aggregate book-to-market equity ratio as of the end of fiscal year t. E/P_t is aggregate earnings-to-price ratio as of the end of fiscal year t. $Eshare_t$ represents the equity share in REIT total net equity and debt issues over year t. $Accrual_t$ is aggregate operating accruals as of the end of fiscal year t. The horizon t is annual from 1971 to 2018.

Table 2.2 presents OLS slope estimates of Equation (2.2). Panels (1) through (13) present various specifications of annual predictive regression. In Panel (1), where aggregate investment is included as a standalone variable, it serves as a strong predictor of REIT market returns, with a negative coefficient of -0.343 that is statistically significant (t-statistic = -2.58). When I add interest rate variables as control variables in Panel (2), the coefficient for aggregate investment becomes less negative, changing to -0.204 with a t-statistic of -1.88. All estimates for the interest rate variables are positive; however, only the coefficient for the term spread is statistically significant.

Panel (3) presents the results of the predictive regression incorporating both valuation ratios and corporate decision variables as additional conditioning variables. The estimate for the investment variable decreases to -0.416, and the corresponding t-statistic decreases to -3.54. I observe a positive, albeit insignificant, relationship between dividend yields and future REIT returns. In contrast, the book-to-market ratio exhibits a significantly positive relationship with future REIT returns. It is surprising to observe a significantly negative relationship between the earnings-to-price ratio and future REIT returns.[9] Consistent with Baker and Wurgler (2000), I demonstrate that the equity share in total net issues significantly and negatively predicts REIT market returns. While aggregate operating accruals positively predict market returns, consistent with Hirshleifer et al. (2009), the relationship is not statistically significant in my REIT sample.

Panel (4), which includes interest rate variables, valuation ratios, and corporate decision variables as control variables, reconfirms that aggregate investment is a strong predictor of REIT market returns. All interest rate variables predict aggregate returns with a negative sign; however, only the short-term interest rate variable is statistically significant. Valuation ratios are all significant in predicting returns. In particular, the point estimate for the dividend-to-price ratio increases dramatically in magnitude, as does the corresponding t-statistic. The equity share in total net issues remains significant for aggregate REIT returns, while aggregate operating accruals remain insignificant.

In the remaining panels, I present results from the predictive regressions that include investor sentiment. In univariate settings, investor sentiment measures are not significant predictors of REIT market returns, with the notable exception of the constructed composite REIT market sentiment index. Panel (7), (10), and (13) present the most comprehensive specifications that include all conditioning variables. The investment variable remains a strong predictor of REIT returns, with point estimates in the range of -0.3 and t-statistics above -2. It is noteworthy that the estimates for both the University of Michigan Consumer Sentiment Index and the Baker and Wurgler composite stock market sentiment index become statistically significant. For the

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[9] The negative sign of the earnings-to-price ratio deviates from expectations when the variable is interpreted as an expected return proxy. Presumably, the ratio components are cointegrated in logarithms, implying that the logarithmic earnings-to-price ratio is a mean-reverting process. If, at any time t, the ratio exceeds its unconditional mean, either expected earnings growth will be subdued, expected returns will be elevated, or a combination of both will occur. The negative sign suggests that the variable primarily functions as a proxy for expected earnings growth rather than expected returns. Consequently, higher earnings-to-price ratios correspond to lower expected earnings growth and diminished future returns.

remaining state variables, their relationships with future REIT returns do not exhibit significant changes.

The in-sample significance of my predictive results appears to be somewhat greater than that documented in previous studies (see, e.g., Liu and Mei, 1992; Ghysels et al., 2013; Ghent et al., 2019). This difference may be partly attributable to my focus on longer return horizons, aligning with the argument in prior research that returns are more predictable at extended horizons. In Table 2.2, I emphasize that aggregate investment strongly predicts REIT market returns.

[Insert Table 2.2]

2.4 Explaining Aggregate REIT Investment

Despite the existence of predictability, the reduced-form version of predictive regressions does not help further understand the economic forces that are behind the predictive relationship. Is the forecastability due to time variation in the expected returns of aggregate REIT market, or is it driven by time-varying investor sentiment? These questions can be investigated by either directly explaining the predictive variable of interest or indirectly introducing additional response variables in predictive regressions (Arif and Lee, 2014). To trace the economic provenance of the predictability, I begin by explaining aggregate REIT investment.

Specifically, I examine whether aggregate REIT investment is contemporaneously related to investor sentiment or expected returns. If the predictability is driven by time-varying investor sentiment, the investment variable should be contemporaneously positively related to the sentiment measures. Corporate investment is related to investor sentiment either because corporate managers rationally exploit market mispricing (see, e.g., Baker and Wurgler, 2000 and 2002; Polk and Sapienza, 2008) or because they are themselves caught up in market euphoria (Arif and Lee, 2014). Conversely, if the predictive relationship is due to time variation in expected returns, one would expect a strong association between the investment variable and expected return proxies, since firms rationally align their investment policies with their costs of capital.

Table 2.3 presents the results from the OLS regressions of aggregate REIT investment on a constant and a set of conditioning variables suggested by prior literature.[10] Given that the investment variable is moderately to highly persistent (AR(1) coefficient of 0.648), I include a one-period lagged value. I employ three previously mentioned investor sentiment measures. Aggregate return on assets gauges aggregate REIT profitability, while REIT market returns capture the state of the market. The aggregate book-to-market ratio serve as a proxy for

[10] A range of economic state-related variables have been shown in the literature to be associated with aggregate investment quantity. For example, Barro (1990) and Morck et al. (1990) report that stock market returns forecast future aggregate investment. In addition to stock market returns, Morck et al. (1990) also document the association of aggregate corporate profits and new equity issues with subsequent aggregate investment. Blanchard et al. (1993) demonstrate that Tobin's q and aggregate profits positively predict future aggregate investment. More recently, Kothari et al. (2014) investigate the association of aggregate investment rate with current and past changes in corporate profits, stock prices, market volatility, nominal risk-free interest rate, the maturity premium, and the default risk premium.

investment Q. Additionally, I include three interest rate variables as proxies for expected returns: the short-term interest rate, the term spread, and the default spread.

The first three panels of Table 2.3 show that, in a univariate setting, aggregate investment is significantly positively associated with all sentiment measures except the University of Michigan Consumer Sentiment Index. The point estimate for the constructed composite REIT market sentiment index is comparable in magnitude to that for the Baker and Wurgler composite stock market sentiment index. Panels (4) through (6) present results for more comprehensive specifications that include all other conditioning variables except the expected return proxies. I observe that the estimates for both the stock and REIT market sentiment indexes are significant at the 5% confidence level for aggregate investment. As expected, aggregate investment is significantly positively related to aggregate profits. Additionally, the investment variable exhibits a significant positive relationship to REIT market returns.

The last three panels of Table 2.3 present the results from regressions that include the three interest rate variables. Surprisingly, the estimate for the REIT market sentiment index becomes insignificant. The estimate for the stock market sentiment index remains significant; however, its magnitude declines from 0.056 to 0.041, and it is now significant at the 10% level. In contrast, the estimates for the aggregate book-to-market ratio increase dramatically in absolute value and become significant at the 5% level across all specifications. The three expected return proxies exhibit a strong relationship with aggregate investment. Notably, while the investment variable negatively responds to the default spread, it positively responds to both the short-term interest rate and the term spread. The diminishing relationship between investment and sentiment suggests that the investment variable responds to some unobservable fundamental factors rather than the sentimental components of the stock and REIT market sentiment indexes.

Taken together, Table 2.3 provides strong evidence of the relationship between investment and expected returns, supporting the claim that the predictive relationship is due to time variation in expected returns. The weak evidence of the investment-sentiment relationship appears to conflict with the cross-sectional evidence documented in previous studies (see, e.g., Eichholtz and Yönder, 2015; Kim and Wiley, 2019). This discrepancy may be attributed to the focus on aggregate REIT investment, which captures the common variation across individual REIT investments. Previous studies suggest that individual REIT investment decisions may be influenced by biased investors and/or biased managers. In contrast, this study posits that aggregate REIT investment decisions tend to be aligned with the overall state of the economy.

[Insert Table 2.3]

2.5 Forecasting Aggregate REIT Earnings News

To further understand the economic forces behind the return predictability of aggregate investment, I next introduce additional response variables in predictive regressions. I first forecast aggregate REIT earnings news. If the predictability is driven by time-varying market sentiment, the investment variable should forecast aggregate firm earnings news measures, as it proxies for market-wide "optimism" or "pessimism" about future cash flows. Irrational beliefs about future profits will lead to greater shocks on future realized cash flows.

I utilize multiple measures of aggregate firm earnings shocks, which are based on firm earnings, analyst forecast of one-year-ahead earnings, and analyst forecast of long-term earnings growth. For firm earnings, I gauge earnings surprise as standardized unexpected earnings. For analyst earnings forecasts, earnings surprise is measured as corresponding forecast error, which equals the difference between analyst earnings forecast and actual realized earnings. Details on data sources and construction are provided in Appendix 2.1.

Table 2.4 presents the OLS slope estimates from the predictive regressions for aggregate REIT earnings news. I control for a one-period lagged term, given that all the earnings news variables except aggregate standardized unexpected earnings exhibit moderate serial dependence. The first two columns of Panel A show that when included as a standalone variable, aggregate investment yields an insignificant estimate for future aggregate return on assets. However, the estimate becomes significant when controlling for lagged aggregate profitability in column (2), albeit at the 10% significance level. This result suggests that aggregate investment may capture optimistic (pessimistic) expectations about future earnings, which are subsequently followed by lower (higher) earnings realization. Conversely, the last two columns demonstrate that the investment variable does not exhibit significant positive predictive relationship with aggregate standardized unexpected earnings, weakening the aforementioned suggestion.

Panel B presents the predictive results for aggregate analyst forecasts of one-year-ahead earnings and the corresponding aggregate earnings forecast error. Column (1) shows that, in a univariate setting, higher aggregate investment is significantly associated with higher aggregate analyst forecasts for one-year-ahead earnings. However, the estimate for the investment variable drops sharply and loses its statistical significance after including a lagged term in column (2). In the subsequent two columns, I observe that aggregate investment significantly positively predicts aggregate earnings forecast error in a univariate setting, but the predictive relationship diminishes once a lagged term is controlled for. These results suggest that aggregate investment is unlikely to reflect analysts' biased expectations of one-year-ahead earnings.

Panel C displays the results for aggregate analyst forecast of long-term earnings growth and the relevant aggregate long-term earnings forecast error. The results are very much in agreement with those in Panel B. I observe neither a significantly positive relation between aggregate investment and aggregate analyst long-term earnings growth forecast nor the predictability of the aggregate long-term earnings forecast errors by the investment variable. The result reaffirms the unlikelihood of aggregate investment to capture analysts' biased expectations of future earnings. Note that because data on analyst forecast of long-term earnings growth are available for a shorter period, the power of the tests for analyst long-term earnings growth forecast is lower than that of the tests for analyst one-year-ahead earnings forecast.

Table 2.4 shows little evidence of the predictability of aggregate REIT earnings news by aggregate investment, suggesting that aggregate investment tends to be unrelated to biased market expectations about future cash flows. However, it should be noted that the inability to reject the null hypothesis of no predictability might also be due to a lack of power in my tests, especially given the presence of noise in the earnings news series. Admittedly, even if predictability were present, it would be hard to detect in series that are highly serially correlated. I explore this issue further in the following section, as I have alternative response variables that proxy for aggregate REIT earnings shocks but are far less persistent.

[Insert Table 2.4]

2.6 Forecasting Aggregate REIT Earnings Announcement Returns and the Value Premium

In this section, I forecast aggregate REIT earnings announcement returns and the REIT value premium to mitigate the concern that the lack of predictability in aggregate REIT earnings news might be due to insufficient statistical power. The two response variables exhibit much lower serial correlation, with AR(1) coefficients of -0.162 and 0.026, respectively, making them suitable for forecasting exercises.

Panel A of Table 2.5 presents the OLS slope estimates from regressions of future aggregate REIT earnings announcement returns on a constant and a set of conditioning variables.[11] If aggregate investment reflects biased market expectations of future earnings, the investment variable should negatively predict aggregate earnings announcement returns. This is because if noise traders fail to forecast a decrease in future profits, they will be disappointed by the subsequently released lower earnings.

The first column of Panel A shows that, in a univariate setting, aggregate investment negatively but insignificantly forecasts aggregate earnings announcement returns. In the second column, I control for three interest rate variables. I find that the sign of the coefficient on investment changes from negative to positive, although it remains statistically insignificant. In the third column of the panel, I add three valuation ratios and two corporate decision variables. The results indicate that the estimate for the investment variable becomes smaller but highly statistically significant. Since the three discount rate proxies are not controlled for in this specification, aggregate investment may still simply proxy for expected returns rather than market sentiment. The last column of the panel presents results from a comprehensive regression, where the estimate of aggregate investment remains negative but insignificant. Interestingly, equity share in total net issues demonstrates strong positive predictive power. To the extent that the short-window returns around the report dates of quarterly earnings

[11] My forecasting exercises suggest that the relationship between aggregate investment and future aggregate earnings announcement returns tends to be long-term, extending beyond the immediately following year. Therefore, I report results for $Invest_{(t-1,t)}$, calculated as the arithmetic average of $Invest_{t-1}$ and $Invest_t$. Similarly, $EAR_{(t+1,t+2)}$ is computed as the arithmetic average of EAR_{t+1} and EAR_{t+2}. As with forecasting aggregate REIT market returns, the conditioning variables in forecasting aggregate earnings announcement returns include valuation ratios, interest rate variables, and corporate decision variables. I also apply the above specifications in forecasting the REIT value premium.

announcements largely reflect the "surprise" element of such information releases, the results suggest that aggregate investment may not capture investors' irrational expectations about future earnings.

Panel B of Table 2.5 presents the results of predictive regressions for REIT value premium. Prior research indicates that the price of growth stocks reflects irrational market expectations about future earnings growth (e.g., Lakonishok et al., 1994; Dechow and Sloan, 1997).[12] The noise trader model naturally predicts that stock returns should be lower following high-sentiment periods, and growth stocks in particular are expected to perform poorly in subsequent periods.[13] If aggregate investment reflects biased market expectations of future earnings growth, the investment variable should positively forecast the value premium.

The first column of Panel B shows that, in a univariate setting, higher aggregate investment is significantly associated with a higher future value premium. The coefficient for investment is similar in magnitude but become statistically significant in the next column after including discount rate proxies. In the third column, the aggregate investment estimate returns significant when I control for valuation ratios and corporate decision variables. Nevertheless, the last column exhibits that the estimate again becomes statistically insignificant in a specification that further includes interest rate variables. It is also noteworthy to observe strong predictability from short-term interest rates and dividend yields. To the extent that the increase in the value premium is driven by the particularly poor performance of REITs with low book-to-market ratios following excessive optimism about future earnings growth, the findings imply that aggregate investment is very likely not correlated with such biased expectations of future earnings growth.[14]

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[12] Lakonishok et al. (1994) find that value strategies generate higher returns because these strategies exploit the suboptimal behavior of typical investors who naively extrapolate past trends in earnings and sales growth. A subsequent study by Dechow and Sloan (1997) argues that stock prices appear to naively reflect analysts' biased expectations of future profit growth rather than investors' over-extrapolation of past earnings growth. They find that higher returns to value strategies are largely attributable to naive reliance on analysts' forecasts of future earnings growth.

[13] The cross-sectional effect of sentiment on returns—that sentiment has a stronger effect on smaller, hard-to-value, and difficult-to-arbitrage firms—is well documented in the literature (see, e.g., Lee et al., 1991; Baker and Wurgler, 2006 and 2007; Baker et al., 2012; Ben-Rephael et al., 2012).

[14] In addition to the value premium, the REIT literature has well documented a range of other factor premiums associated with price momentum (Chui et al., 2003a and b), earnings surprises (Price et al., 2012; Feng et al., 2014), share turnover (Clayton and MacKinnon, 2000; Cannon and Cole, 2011), and idiosyncratic volatility (Ooi et al., 2009; DeLisle et al., 2013). I find no predictability of these factor premiums by aggregate investment (results are available upon request).

The results in Table 2.5 provide only weak evidence of the predictability of aggregate REIT earnings announcement returns and the REIT value premium by aggregate investment. These findings are consistent with those in Table 2.4, which forecasts aggregate REIT earnings news. However, the inability to establish that aggregate investment proxies for biased expectations about future fundamentals may be due to a narrow focus on firm-specific fundamentals, given that the response variables in predictive regressions pertain solely to future firm cash flow innovations. If aggregate investment captures biased expectations about broader macroeconomic fundamentals, it is not necessary for it to demonstrate predictive power for series related to firm earnings shocks. I will further investigate the implications of a broader focus on fundamentals in the following section, where I employ alternative response variables that measure future macroeconomic fundamentals.

[Insert Table 2.5]

2.7 Forecasting Macroeconomic Growth

In this section, I conduct forecasting exercises on macroeconomic growth, considering that aggregate investment may also propagate biased expectations about future macroeconomic fundamentals in addition to firm-level cash flows. If this is the case, the investment variable should negatively predict economic growth variables. Conversely, if aggregate investment captures time variation in expected economic fundamentals, the predictive relationship should be positive.

I employ two measures of economic growth: the Chicago Federal National Activity Index (CFNAI) and the real GDP growth rate.[15] These two measures exhibit low serial correlation, with AR(1) coefficients of 0.098 and 0.094, respectively, which enhances the statistical power in predictive regressions. Table 2.6 presents the OLS slope estimates from regressions of the future economic growth measures on a constant and a set of conditioning variables suggested by Fama (1981), including a one-period lagged economic growth variable, aggregate REIT market returns, and industrial production growth.

Panel A presents the results of predictive regressions for CFNAI. When included as a standalone variable in column (1), aggregate investment significantly and positively predicts CFNAI, with a point estimate of 0.305 (t-statistic = 2.04). In the following column, I control for a lagged term. The estimate for the investment variable decreases slightly to 0.240 and loses its statistical significance (t-statistic = 1.35). However, the estimate increases sharply to 0.467 (t-statistic = 2.81) when I further control for aggregate REIT market returns and industrial production growth. The predictive result is also economically significant. A one-standard-deviation increase in aggregate investment is associated with an increase of 0.079 in CFNAI in the following year. For reference, the average annual CFNAI is -0.032, with a standard deviation of 0.472.

[15] The CFNAI corresponds to the index of economic activity developed by Stock and Watson (1999). This index is the first principal component of 85 macroeconomic indicators drawn from four broad categories of data: production and income; employment, unemployment, and hours; personal consumption and housing; and sales, orders, and inventories. The index has been proven to be highly accurate in identifying U.S. recessions and expansions. Positive values indicate above-average growth, while negative values indicate below-average growth.

Panel B reports the predictive regression results for the real GDP growth rate, which are consistent with those for CFNAI. Specifically, I observe a positive relationship between aggregate investment and future real GDP growth, with point estimates ranging from 0.036 to 0.048, all of which are significant at the 1% level. In economic terms, a one-standard-deviation increase in aggregate investment is associated with a 0.81% higher real GDP growth rate in the following year. For reference, the average annual real GDP growth rate is 2.50%, with a standard deviation of 2.76%.

The results in Table 2.6 provide strong evidence of the predictability of macroeconomic fundamentals by aggregate investment. The positive predictive relationship suggests that aggregate investment is more likely to reflect expected future macroeconomic fundamentals rather than biased expectations.

[Insert Table 2.6]

2.8 Subsuming Aggregate REIT Market Return Predictability

The results in the previous sections indicate that aggregate investment is strongly linked to discount rate proxies and appears unrelated to biased expectations of future firm cash flows and macroeconomic fundamentals. In this section, I make the last attempt in exploring the economic forces behind the aggregate REIT return predictability by aggregate investment. Specifically, I examine whether the return predictability would be subsumed, should future firm earnings news and macroeconomic growth materialize. If the predictability stems from time variation in expected returns, it should not be subsumed. Conversely, if the predictability is driven by time-varying market sentiment, it would be subsumed.

Table 2.7 presents the OLS slope estimates from regressions of future aggregate REIT market returns on a constant, aggregate REIT investment, future firm earnings news measures, and future macroeconomic growth indicators. The first column of Panel A reproduces the return predictability by the investment variable in a univariate setting, generating a point estimate of -0.343 (t-statistic = -2.58). From columns (2) to (8), I control for one of the following measures: aggregate return on assets, aggregate standardized unexpected earnings, aggregate errors in analyst forecasts of one-year-ahead earnings, aggregate errors in analyst forecasts of long-term earnings, aggregate earnings announcement returns, value premium, and CFNAI. I find that the estimates for the investment variable remain negative and statistically significant across all specifications, ranging from -0.387 (t-statistic = -2.86) to -0.322 (t-statistic = -2.66). The next six columns present results for a more comprehensive specification, which includes CFNAI and one of the future firm earnings news measures. The predictive power of aggregate investment increases slightly, with higher point estimates and t-statistics in absolute terms. Interestingly, CFNAI tends to dominate firm earnings news measures in explaining aggregate REIT market returns. The final column presents results for a kitchen sink regression. The estimate for the investment variable declines slightly to -0.296 but remains highly statistically significant (t-statistic = -4.77).

In Panel B, I find similar results by substituting CFNAI with the real GDP growth rate. Taken together, the results in Table 2.7 demonstrate that the return predictability by aggregate investment is not subsumed by the subsequent materialization of future firm earnings news and macroeconomic growth, indicating that time variation in expected returns is the primary economic force behind the predictive relationship.

[Insert Table 2.7]

2.9 Conclusion

Motivated by the investment-based asset pricing model, I investigate whether aggregate corporate investment in income-producing properties serves as a predictor of future market returns on commercial real estate. I find that aggregate REIT property investment negatively predicts public commercial real estate returns. The predictive relationship is robust even when accounting for other predictors, including valuation ratios, interest rate variables, investor sentiment measures, and other corporate decision variables.

Additional analyses suggest that time-varying market sentiment does not well explain the return predictability. Aggregate investment is only weakly related to investor sentiment and does not significantly predict aggregate firm earnings news. Instead, it is more likely that time variation in expected returns drives the predictability. Aggregate investment is strongly linked to interest rate variables and positively predicts macroeconomic growth. Additionally, the return predictability is not subsumed by the materialization of future firm cash-flow shocks or macroeconomic fundamentals. This study concludes that aggregate REIT property investment may serve as an alternative, and possibly sharper, measure of the expected returns of public commercial real estate, particularly the long-horizon component.

This study makes several important contributions to the existing literature. It first extends the literature on aggregate stock return predictability based on investment-related variables. Previous studies have predominantly focused on productive capital investment and aggregate stock market returns. This study provides new evidence from commercial real estate investment and its public market returns. In addition, previous studies have debated the economic force behind the investment's return predictability. This study provides new evidence strengthening the rational explanation of time-varying expected returns.

This study secondly contributes to the literature on aggregate REIT return predictability, which has been addressed with different interests in previous studies. This study approaches the topic with new insight from the investment-based asset pricing models and suggests that aggregate REIT property investment is an alternative and possibly shaper measure of expected returns. Third, this study adds to the growing literature on REIT real investment decisions. Previous studies have documented the effects of biased managers or investors on REIT property investment at the firm level. This study shows contrasting evidence that at the aggregate level, investor sentiment is, in effect, a sideshow to REIT investment, conveying a signal of collective rationality.

This study has practical implications for investors. The finding that aggregate REIT property investment closely tracks future market return dynamics can guide commercial real estate investors in their investment management. For instance, they can evaluate the expected returns on public commercial real estate equity by analysing the aggregate property investments of prominent commercial real estate market players, such as real estate investment trusts and real estate operating companies, and so on.

It is imperative to acknowledge the limitations of this study. One of the primary limitations of this study is the data constraints. The analysis heavily relies on the non-cash asset growth rate as a proxy for equity REIT property investment. While this proxy provides a practical measurement of real estate investment, its quality may vary across the sample period from 1972 to 2018. In the earlier years, the REIT industry underwent significant structural changes, such as the Revenue Reconciliation Act of 1993. These changes could introduce inconsistencies into the rules governing the composition of firms' assets.

Another limitation concerns the predictive regression models, which are based on linear assumptions. While these models are effective in capturing general trends and relationships between variables, statistical complications can arise when predictors persist and their innovations are correlated with residuals. This leads to small-sample bias in coefficient estimation. To address this potential bias, I apply the Stambaugh (1999) correction to adjust coefficient estimates. However, alternative estimation procedures could have been employed to ensure the robustness of the results.

Finally, the scope and generalizability of the findings are also concerns. While the study focuses on public commercial real estate equity, providing rich and relevant datasets, it limits the applicability of the results to other types of commercial real estate equity, such as private commercial real estate equity.

Tables

Table 2.1 Descriptive Statistics

Variable	Mean	Std Dev	Q1	Median	Q3	$AR(1)$	N
R	0.0795	0.1736	-0.0011	0.0675	0.1623	-0.0020	48
$Invest$	0.1863	0.1696	0.1047	0.1317	0.1945	0.6478	48
D/P	0.0646	0.0199	0.0420	0.0712	0.0782	0.8468	48
B/M	0.5711	0.1432	0.4392	0.5867	0.6696	0.6705	48
E/P	0.1033	0.0487	0.0612	0.0992	0.1325	0.7662	48
$Tbill$	0.0455	0.0345	0.0148	0.0496	0.0687	0.8450	48
$Term$	0.0117	0.0114	0.0049	0.0114	0.0199	0.4805	48
$Default$	0.0106	0.0037	0.0077	0.0094	0.0127	0.5566	48
SI^{Cons}	-0.0112	0.0848	-0.0668	-0.0048	0.0425	0.7465	48
SI^{Stock}	-0.0171	0.8720	-0.2276	0.0016	0.5604	0.7353	48
SI^{REIT}	0.0272	0.9260	-0.4591	0.0711	0.4864	0.4691	48
$Eshare$	0.4440	1.5955	0.3522	0.6290	0.9620	0.0590	48
$Accrual$	0.0038	0.0154	-0.0021	-0.0001	0.0057	-0.0864	48
ROA	0.0450	0.0225	0.0282	0.0397	0.0552	0.7949	48
SUE	0.1902	0.8416	-0.0905	0.2031	0.6617	-0.0457	48
$FROA$	0.0272	0.0066	0.0219	0.0271	0.0326	0.6237	44
$Error$	-0.0154	0.0315	-0.0179	-0.0064	-0.0019	0.3381	44
$FLTG$	0.0979	0.0253	0.0762	0.0935	0.1154	0.6029	39
$LTError$	0.0183	0.0218	0.0063	0.0143	0.0299	0.3728	37
EAR	0.0008	0.0134	-0.0029	0.0001	0.0039	-0.1616	48
HML	0.0112	0.1447	-0.0648	0.0008	0.0464	0.0259	48
$CFNAI$	-0.0322	0.4715	-0.1096	0.0317	0.2271	0.0976	48
$GDPGR$	0.0250	0.0276	0.0155	0.0295	0.0405	0.0941	48
$Indprod$	0.0179	0.0522	0.0001	0.0257	0.0504	-0.0165	48

This table presents descriptive statistics for the variables used in the study. R denotes aggregate REIT market returns, and $Invest$ refers to aggregate investment. D/P represents aggregate dividend-to-price ratio, B/M is aggregate book-to-market equity ratio, and E/P is aggregate earnings-to-price ratio. $Tbill$ refers to the short-term interest rate, $Term$ represents the term spread, and $Default$ is the default spread. SI^{Cons} is the University of Michigan Consumer Sentiment Index, SI^{Stock} is the Baker and Wurgler (2006) composite stock market sentiment index, and SI^{REIT} is the constructed composite REIT market sentiment index. $Eshare_t$ is the equity share in REIT total net equity and debt issues, while $Accrual$ denotes aggregate operating accruals. ROA refers to aggregate return on assets, and SUE is aggregate standardized unexpected earnings. $FROA$ represents aggregate analyst forecast of one-year-ahead ROA, and $Error$ is aggregate difference between analyst forecast of one-year-ahead ROA and actual realized ROA. $FLTG$ stands for aggregate analyst forecast of long-term earnings growth, and $LTError$ is aggregate difference between analyst forecast of long-term ROA and actual realized long-term ROA. EAR represents aggregate earnings announcement returns, and HML is the value premium. $CFNAI$ is the Chicago Federal National Activity Index, $GDPGR$ is the growth rate of real GDP, and $Indprod$ is the growth rate of industrial production. AR(1) presents the first-order autoregressive coefficient for the variables. N is the number of observations. See Appendix 2.1 and 2.2 for details on variable definitions, data sources, and construction.

Table 2.2 Forecasting Aggregate REIT Market Returns

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
$Invest_t$	-0.3429**	-0.2045*	-0.4164***	-0.4170**		-0.3480**	-0.3443**		-0.3326**	-0.3162**		-0.3136**	-0.3970**
	(-2.58)	(-1.88)	(-3.54)	(-2.36)		(-2.63)	(-2.46)		(-2.60)	(-2.14)		(-2.16)	(-2.21)
SI_t^{Cons}					-0.2899	0.0230	-0.5103*						
					(-1.33)	(0.10)	(-1.96)						
SI_t^{Stock}								-0.0246	-0.0075	-0.0687***			
								(-1.06)	(-0.36)	(-3.84)			
SI_t^{REIT}											-0.0353*	-0.0158	-0.0180
											(-1.84)	(-0.69)	(-1.00)
$Tbill_t$		0.6568		-2.2083**			-2.8557***			-1.7405			-2.1096*
		(0.85)		(-2.05)			(-3.10)			(-1.52)			(-1.89)
$Term_t$		7.1915***		-0.4386			-1.8622			1.2908			-0.3834
		(3.64)		(-0.17)			(-0.80)			(0.55)			(-0.15)
$Default_t$		2.2637		-1.2157			-3.6225			-0.3898			-2.6698
		(0.26)		(-0.14)			(-0.38)			(-0.05)			(-0.31)
D/P_t			1.1525	3.9041**			4.0471**			3.3448*			4.0406**
			(0.75)	(2.16)			(2.20)			(1.79)			(2.18)
B/M_t			1.2121***	1.2654**			1.5161**			1.5374***			1.2885**
			(3.32)	(2.45)			(2.71)			(3.17)			(2.44)
E/P_t			-3.1306***	-3.2266**			-3.6674**			-4.0923***			-3.4238**
			(-2.88)	(-2.15)			(-2.34)			(-2.89)			(-2.32)
$Eshare_t$			-0.0140**	-0.0093*			-0.0094*			-0.0024			-0.0102*
			(-2.36)	(-1.75)			(-1.79)			(-0.48)			(-1.91)
$Accrual_t$			1.6309	1.3739			1.2210			1.5714			1.4258
			(0.99)	(0.80)			(0.73)			(1.01)			(0.84)
Constant	0.1436***	-0.0218	-0.2856**	-0.3659**	0.0751***	0.1450***	-0.4212**	0.0785***	0.1414***	-0.4714***	0.0806***	0.1386***	-0.3604**
	(4.42)	(-0.26)	(-2.06)	(-2.39)	(3.49)	(4.19)	(-2.65)	(3.48)	(4.43)	(-3.03)	(3.84)	(4.14)	(-2.27)
N	48	48	48	48	48	48	48	48	48	48	48	48	48
Adj. R^2	9.26%	20.06%	30.19%	33.82%	-0.14%	7.25%	36.53%	-0.60%	7.38%	41.83%	1.44%	7.89%	32.92%

The table presents OLS slope estimates from regressions of future aggregate REIT market returns on a constant and a set of conditioning variables:

$$R_{t+1} = \alpha + \beta_1 Invest_t + \beta_2 SI_t + \beta_3 Tbill_t + \beta_4 Term_t + \beta_5 Default_t + \beta_6 D/P_t + \beta_7 B/M_t + \beta_8 E/P_t + \beta_9 Eshare_t + \beta_{10} Accrual_t + \varepsilon_{t+1}$$

R_{t+1} is the compounded monthly excess total return (return minus risk-free rate) on the FTSE NAREIT All Equity REITs Index from July in year t+1 to June in year t+2. $Invest_t$ is aggregate investment as of the end of fiscal year t. SI_t represents one of three sentiment indices: SI_t^{Cons} is the average value of the monthly University of Michigan Consumer Sentiment Index over year t; SI_t^{Stock} is the average value of the monthly Baker and Wurgler (2006) composite stock market sentiment index over year t; and SI_t^{REIT} is the average value of the monthly constructed composite REIT market sentiment index over year t. $Tbill_t$ is the 3-month Treasury bill rate as of the beginning of July in year t+1. $Term_t$ is the difference between 10-year and 1-year Treasury constant maturity rates as of the beginning of July in year t+1. $Default_t$ is the difference between Moody's Seasoned Baa and Aaa corporate bond yields as of the beginning of July in year t+1. D/P_t represents the dividend yield on the FTSE NAREIT All Equity REITs Index as of the end of June in year t+1. B/M_t is aggregate book-to-market equity ratio as of the end of fiscal year t. E/P_t is aggregate earnings-to-price ratio as of the end of fiscal year t. $Eshare_t$ represents the equity share in REIT total net equity and debt issues over year t. $Accrual_t$ is aggregate operating accruals as of the end of fiscal year t. The horizon t is annual from 1971 to 2018. *, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively. Newey and West (1987) HAC t-statistics based on three lags are reported in parenthesis below the estimates.

Table 2.3 Explaining Aggregate REIT Investment

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
SI_t^{Cons}	0.8627			0.4254			0.3640		
	(1.68)			(1.36)			(1.27)		
SI_t^{Stock}		0.0503*			0.0559**			0.0405*	
		(1.73)			(2.23)			(1.96)	
SI_t^{REIT}			0.0627**			0.0428**			0.0264
			(2.24)			(2.36)			(1.28)
ROA_t				1.4352*	1.8634**	1.0877**	0.1649	0.6793	-0.2375
				(1.99)	(2.51)	(2.20)	(0.23)	(1.03)	(-0.45)
R_t				0.2008**	0.2603**	0.1908**	0.2224**	0.2561**	0.2311**
				(2.32)	(2.64)	(2.04)	(2.37)	(2.53)	(2.09)
R_{t-1}				0.1980	0.1300	0.1834	0.1162	0.0676	0.1157
				(1.66)	(1.35)	(1.54)	(1.03)	(0.69)	(1.06)
$Invest_{t-1}$				0.6682***	0.7575***	0.7215***	0.6281***	0.6963***	0.6685***
				(4.89)	(4.87)	(4.69)	(5.11)	(4.92)	(4.97)
B/M_{t-1}				-0.1898	-0.3002**	-0.1456	-0.4984**	-0.4892**	-0.4123**
				(-1.47)	(-2.08)	(-1.43)	(-2.15)	(-2.28)	(-2.04)
$Tbill_{t-1}$							2.8988**	2.2341**	2.4327**
							(2.38)	(2.07)	(2.11)
$Term_{t-1}$							5.1304*	4.1238*	3.3339
							(1.77)	(1.73)	(1.26)
$Default_{t-1}$							-11.3470**	-11.5044**	-10.5937**
							(-2.69)	(-2.52)	(-2.19)
Constant	0.1959***	0.1871***	0.1846***	0.0788	0.1026*	0.0554	0.2495***	0.2502**	0.2401**
	(5.34)	(5.19)	(5.36)	(1.12)	(1.70)	(1.03)	(2.94)	(2.71)	(2.59)
N	48	48	48	47	47	47	47	47	47
Adj. R^2	16.86%	4.66%	9.82%	45.13%	48.58%	47.73%	48.78%	49.74%	48.44%

The table presents OLS slope estimates from regressions of aggregate investment on a constant and a set of conditioning variables:

$$Invest_t = \alpha + \beta_1 SI_t + \beta_2 ROA_t + \beta_3 R_t + \beta_4 R_{t-1} + \beta_5 Invest_{t-1} + \beta_6 B/M_{t-1} + \beta_7 Tbill_{t-1} + \beta_8 Term_{t-1} + \beta_9 Default_{t-1} + \varepsilon_t$$

$Invest_t$ is aggregate investment as of the end of fiscal year t. SI_t represents one of three sentiment indices: SI_t^{Cons} is the average value of the monthly University of Michigan Consumer Sentiment Index over year t; SI_t^{Stock} is the average value of the monthly Baker and Wurgler (2006) composite stock market sentiment index over year t; and SI_t^{REIT} is the average value of the monthly constructed composite REIT market sentiment index over year t. ROA_t is aggregate return on assets as of the end of fiscal year t. R_t is the compounded monthly excess total return (return minus the risk free rate) on the FTSE NAREIT All Equity REITs Index from July of year t to June of year t+1. B/M_{t-1} is aggregate book-to-market equity ratio as of the end of fiscal year t-1. $Tbill_{t-1}$ is the 3-month Treasury bill rate as of the beginning of July in year t. $Term_{t-1}$ is the difference between 10-year and 1-year Treasury constant maturity rates as of the beginning of July in year t. $Default_{t-1}$ is the difference between Moody's Seasoned Baa and Aaa corporate bond yields as of the beginning of July in year t. *, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively. Newey and West (1987) HAC t-statistics based on three lags are reported in parenthesis below the estimates.

Table 2.4 Forecasting Aggregate REIT Earnings News

The dependent variable is $Variable_{t+1}$

	Panel A				Panel B				Panel C			
	ROA_{t+1}		SUE_{t+1}		$FROA_{t+1}$		$Error_{t+1}$		$FLTG_{t+1}$		$LTError_{t+1}$	
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
$Invest_t$	-0.0172	-0.0118*	0.3776	0.3494	0.0111***	0.0052	0.0276*	0.0200	0.0030	0.0072	0.0250	0.0229
	(-1.09)	(-1.96)	(1.25)	(1.18)	(2.88)	(1.24)	(1.81)	(1.54)	(0.22)	(0.84)	(1.25)	(1.05)
$Variable_t$		0.7954***		0.0487		0.5911***		0.3318*		0.6176***		0.3455**
		(8.99)		(0.38)		(3.42)		(1.99)		(6.05)		(2.20)
Constant	0.0482***	0.0112**	0.0755	0.0744	0.0250***	0.0101**	-0.0206**	-0.0133	0.0973***	0.0350***	0.0131**	0.0061
	(5.73)	(2.18)	(0.63)	(0.63)	(11.93)	(2.38)	(-2.26)	(-1.61)	(11.62)	(3.29)	(2.37)	(0.95)
N	48	48	48	48	44	43	44	43	39	38	37	36
Adj. R2	-0.46%	63.13%	-1.26%	-3.26%	6.70%	38.48%	0.05%	8.73%	-2.65%	38.81%	1.87%	15.14%

The table presents OLS slope estimates from predictive regressions for aggregate REIT earnings news.

$$Variable_{t+1} = \alpha + \beta_1 Invest_t + \beta_2 Variable_t + \varepsilon_{t+1}$$

I use multiple measures of aggregate firm earnings news. In Panel A, ROA_{t+1} is aggregate return on assets as of the end of fiscal year t+1, and SUE_{t+1} is aggregate standardized unexpected earnings as of the end of last quarter of fiscal year t+1. In Panel B, $FROA_{t+1}$ is aggregate forecast of fiscal year t+1 ROA, computed using analyst forecasts of one-year-ahead EPS available as of the end of fiscal year t, and $Error_{t+1}$ is aggregate difference between the forecast of fiscal year t+1 ROA and the actual realized ROA in fiscal year t+1. In Panel C, $FLTG_{t+1}$ is aggregate forecast of long-term earnings growth, computed using analyst forecasts of long-term EPS growth available as of the end of fiscal year t, and $LTError_{t+1}$ is aggregate difference between the forecast of long-term ROA and the actual realized long-term ROA. $Invest_t$ is aggregate investment as of the end of fiscal year t. Aggregate return on assets and aggregate standardized unexpected earnings cover the period 1972–2019. Aggregate analyst forecasts of one-year-ahead earnings and the corresponding aggregate earnings forecast error cover the period 1976–2019. Aggregate analyst forecasts of long-term earnings growth and the corresponding aggregate long-term earnings forecast error cover the period 1981–2019. *, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively. Newey and West (1987) HAC t-statistics based on three lags are reported in parenthesis below the estimates.

Table 2.5 Forecasting Aggregate REIT Earnings Announcement Returns and the Value Premium

	Panel A: Forecasting $EAR_{(t+1,t+2)}$				Panel B: Forecasting $HML_{(t+1,t+2)}$			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
$Invest_{(t-1,t)}$	-0.0044	0.0021	-0.0116^{***}	-0.0015	0.1279^{**}	0.1269	0.1349^{*}	0.1010
	(-1.07)	(0.34)	(-3.30)	(-0.16)	(2.08)	(1.45)	(1.87)	(1.42)
$Tbill_t$		0.1314^{***}		0.1555^{*}		-0.3438		-2.0775^{**}
		(3.81)		(1.81)		(-0.59)		(-2.29)
$Term_t$		0.3610^{**}		0.3262		-0.9696		-2.3647
		(2.20)		(1.43)		(-0.49)		(-0.91)
$Default_t$		0.1624		0.1228		1.6112		2.9838
		(0.57)		(0.43)		(0.34)		(0.63)
D/P_t			0.0453	-0.1161			2.3644^{*}	4.3849^{***}
			(0.44)	(-0.75)			(1.96)	(5.24)
B/M_t			0.0466^{**}	0.0204			-0.2722	-0.1428
			(2.66)	(0.78)			(-1.41)	(-0.46)
E/P_t			-0.1048^{***}	-0.0396			0.0351	-0.2117
			(-3.10)	(-0.57)			(0.09)	(-0.33)
$Eshare_t$			0.0011^{***}	0.0009^{***}			-0.0049	-0.0006
			(4.24)	(4.10)			(-1.54)	(-0.19)
$Accrual_t$			0.0451	0.0231			0.6287	0.5799
			(1.00)	(0.51)			(1.01)	(0.73)
Constant	0.0014	-0.0121^{**}	-0.0167^{**}	-0.0121	-0.0075	0.0034	-0.0119	-0.0939
	(0.73)	(-2.17)	(-2.69)	(-1.32)	(-0.28)	(0.05)	(-0.20)	(-1.32)
N	47	47	47	47	47	47	47	47
Adj. R^2	-1.58%	13.63%	9.29%	10.69%	1.70%	-4.57%	7.82%	11.62%

The table presents OLS slope estimates from regressions of future aggregate REIT earnings announcement returns or the value premium on a constant and a set of conditioning variables:

$$DepVar_{(t+1,t+2)} = \alpha + \beta_1 Invest_{(t-1,t)} + \beta_2 Tbill_t + \beta_3 Term_t + \beta_4 Default_t + \beta_5 D/P_t + \beta_6 B/M_t + \beta_7 E/P_t + \beta_8 Eshare_t + \beta_9 Accrual_t + \varepsilon_{(t+1,t+2)}$$

In Panel A, the dependent variable is $EAR_{(t+1,t+2)}$, which is the arithmetic average of EAR_{t+1} and EAR_{t+2}, where EAR_{t+1} denotes aggregate earnings announcement returns over the period from July in year t+1 to June in year t+2. In Panel B, the dependent variable is $HML_{(t+1,t+2)}$, which is the arithmetic average of HML_{t+2} and HML_{t+1}, where HML_{t+1} denotes the compounded monthly returns to a REIT-based value-weighted HML (high book-to-market minus low book-to-market) portfolio over the period from July in year t+1 to June in year t+2. $Invest_{(t-1,t)}$ is the arithmetic average of $Invest_{t-1}$ and $Invest_t$, where $Invest_{t-1}$ denotes aggregate investment as of the end of fiscal year t-1. $Tbill_t$ is the 3-month Treasury bill rate as of the beginning of July in year t+1. $Term_t$ is the difference between 10-year and 1-year Treasury constant maturity rates as of the beginning of July in year t+1. $Default_t$ is the difference between Moody's Seasoned Baa and Aaa corporate bond yields as of the beginning of July in year t+1. D/P_t is the dividend yield on the FTSE NAREIT All Equity REITs Index as of the end of June in year t+1. B/M_t is aggregate book-to-market equity ratio as of the end of fiscal year t. E/P_t is aggregate earnings-to-price ratio as of the end of fiscal year t. $Eshare_t$ represents the equity share in REIT total net equity and debt issues over year t. $Accrual_t$ is aggregate operating accruals as of the end of fiscal year t. *, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively. Newey and West (1987) HAC t-statistics based on three lags are reported in parenthesis below the estimates.

Table 2.6 Forecasting Macroeconomic Growth

	Panel A: Forecasting $CFNAI_{t+1}$			Panel B: Forecasting $GDPGR_{t+1}$		
	(1)	(2)	(3)	(1)	(2)	(3)
$Invest_t$	0.3054**	0.2395	0.4673***	0.0400***	0.0361***	0.0479***
	(2.04)	(1.35)	(2.81)	(3.20)	(2.82)	(3.64)
$Variable_t$		0.1413	-0.0065		0.1329	0.2722
		(1.32)	(-0.02)		(1.40)	(1.01)
R_t			0.9286**			0.0448**
			(2.66)			(2.44)
$Indprod_t$			-0.3253			-0.1560
			(-0.09)			(-0.92)
Constant	-0.0893	-0.0773	-0.2075**	0.0175***	0.0145**	0.0072
	(-1.15)	(-1.07)	(-2.06)	(3.13)	(2.47)	(1.31)
N	48	48	47	48	48	47
Adj. R^2	-0.94%	-1.31%	4.28%	3.97%	2.95%	6.07%

The table presents OLS slope estimates from regressions of future macroeconomic growth on a constant and a set of conditioning variables:

$$Variable_{t+1} = \alpha + \beta_1 Invest_t + \beta_2 Variable_t + \beta_3 R_t + \beta_4 Indprod_t + \varepsilon_{t+1}$$

I employ two measures of macroeconomic growth. In Panel A, $CFNAI_{t+1}$ is the average value of the monthly Chicago Federal National Activity Index (CFNAI) from July in year t+1 to June in year t+2. In Panel B, $GDPGR_{t+1}$ is the growth rate in real GDP over the period from July in year t+1 to June in year t+2. $Invest_t$ is aggregate investment as of the end of fiscal year t. R_t is the compounded monthly excess total returns (returns minus the risk-free rate) on the FTSE NAREIT All Equity REITs Index over the period from July of year t to June of year t+1. $Indprod_t$ is the growth rate in industrial production over the period from July in year t to June in year t+1. *, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively. Newey and West (1987) HAC t-statistics based on three lags are reported in parenthesis below the estimates.

Table 2.7 Subsuming Aggregate REIT Market Return Predictability

	Panel A: using $CFNAI_{t+1}$ as the future macroeconomic growth measure														
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
$Invest_t$	-0.3429**	-0.3737***	-0.3234***	-0.3407**	-0.3298***	-0.3223**	-0.3439***	-0.3872***	-0.4303***	-0.3717***	-0.4191***	-0.3960***	-0.3752***	-0.3913***	-0.2962***
	(-2.58)	(-2.99)	(-2.79)	(-2.64)	(-3.80)	(-2.66)	(-2.77)	(-2.86)	(-3.46)	(-2.83)	(-3.23)	(-3.80)	(-2.88)	(-3.16)	(-4.77)
ROA_{t+1}		-1.7961*							-2.2508**						-7.9050***
		(-1.74)							(-2.57)						(-7.22)
SUE_{t+1}			0.0462*							0.0277					0.0357**
			(2.01)							(1.25)					(2.21)
$Error_{t+1}$				-0.9501**							-0.1569				-1.7147***
				(-2.40)							(-0.28)				(-6.56)
$LTError_{t+1}$					-2.4631*							-1.6620			0.8736
					(-1.90)							(-1.60)			(0.87)
EAR_{t+1}						3.4864							1.1488		12.3427***
						(0.95)							(0.30)		(7.56)
HML_{t+1}							0.2360							0.2884	0.3690***
							(1.46)							(1.36)	(2.83)
$CFNAI_{t+1}$								0.1451**	0.1596**	0.1328*	0.1958***	0.1959**	0.1281*	0.1544**	0.1383***
								(2.13)	(2.14)	(1.89)	(2.77)	(2.17)	(1.96)	(2.41)	(4.28)
Constant	0.1436***	0.2302***	0.1312***	0.1418***	0.2018***	0.1371***	0.1412***	0.1566***	0.2664***	0.1480***	0.1769***	0.2082***	0.1529***	0.1544***	0.3975***
	(4.42)	(4.11)	(3.95)	(4.14)	(5.29)	(4.43)	(4.61)	(4.36)	(5.41)	(3.71)	(4.48)	(5.05)	(4.78)	(4.55)	(10.89)
N	48	48	48	44	37	48	48	48	48	48	44	37	48	48	37
Adj. R^2	9.26%	12.79%	12.44%	12.95%	19.45%	14.76%	11.28%	23.27%	30.28%	23.33%	33.92%	35.98%	22.14%	27.63%	78.11%

The table presents OLS slope estimates from regressions of future aggregate REIT market returns on a constant, aggregate REIT investment, future firm earnings news measures, and future macroeconomic growth measures:

$$R_{t+1} = \alpha + \beta_1 Invest_t + \beta_2 CFNAI_{t+1} + \beta_3 ROA_{t+1} + \beta_4 SUE_{t+1} + \beta_5 Error_{t+1} + \beta_6 LTError_{t+1} + \beta_7 EAR_{t+1} + \beta_8 HML_{t+1} + \varepsilon_{t+1}$$

R_{t+1} represents the compounded monthly excess total returns (returns minus risk-free rate) on the FTSE NAREIT All Equity REITs Index over the period from July in year t+1 to June in year t+2. $Invest_t$ is aggregate investment as of the end of fiscal year t. $CFNAI_{t+1}$ is the average value of the monthly CFNAI over the period from July in year t+1 to June in year t+2. ROA_{t+1} is aggregate return on assets as of the end of fiscal year t+1. SUE_{t+1} is aggregate standardized unexpected earnings as of the end of the last quarter of fiscal year t+1. $Error_{t+1}$ represents aggregate difference between analyst forecasts of fiscal year t+1 earnings and actual realized ROA for fiscal year t+1. $LTError_{t+1}$ represents aggregate difference between analyst forecasts of long-term earnings and actual realized long-term ROA. EAR_{t+1} is aggregate earnings announcement returns over the period from July in year t+1 to June in year t+2. HML_{t+1} denotes the compounded monthly returns to a REIT-based value-weighted HML portfolio over the period from July in year t+1 to June in year t+2. *, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively. Newey and West (1987) HAC t-statistics based on three lags are reported in parenthesis below the estimates.

Table 2.7 Continued

	Panel B: using $GDPGR_{t+1}$ as the future macroeconomic growth measure														
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
$Invest_t$	-0.3429**	-0.3737***	-0.3234***	-0.3407**	-0.3298***	-0.3223**	-0.3439***	-0.4469***	-0.4837***	-0.4258***	-0.4692***	-0.4508***	-0.4222***	-0.4456***	-0.3320***
	(-2.58)	(-2.99)	(-2.79)	(-2.64)	(-3.80)	(-2.66)	(-2.77)	(-2.98)	(-3.44)	(-3.05)	(-3.07)	(-3.44)	(-3.04)	(-3.14)	(-4.49)
ROA_{t+1}		-1.7961*							-1.9553**						-7.8454***
		(-1.74)							(-2.47)						(-6.84)
SUE_{t+1}			0.0462*							0.0341					0.0361**
			(2.01)							(1.55)					(2.16)
$Error_{t+1}$				-0.9501**							-0.2204				-1.6245***
				(-2.40)							(-0.50)				(-5.92)
$LTError_{t+1}$					-2.4631*							-1.7532			0.7929
					(-1.90)							(-1.64)			(0.75)
EAR_{t+1}						3.4864							1.9443		12.4947***
						(0.95)							(0.57)		(7.05)
HML_{t+1}							0.2360							0.2129	0.3844***
							(1.46)							(1.16)	(2.94)
$GDPGR_{t+1}$								2.6001**	2.6807**	2.4342**	2.8302**	3.7903*	2.2714**	2.5437**	2.5269**
								(2.56)	(2.49)	(2.60)	(2.19)	(1.70)	(2.52)	(2.41)	(2.52)
Constant	0.1436***	0.2302***	0.1312***	0.1418***	0.2018***	0.1371***	0.1412***	0.0980***	0.1908***	0.0918***	0.1070***	0.1104**	0.1001***	0.0968***	0.3309***
	(4.42)	(4.11)	(3.95)	(4.14)	(5.29)	(4.43)	(4.61)	(3.59)	(4.06)	(3.31)	(3.77)	(2.12)	(3.50)	(3.29)	(8.25)
N	48	48	48	44	37	48	48	48	48	48	44	37	48	48	37
Adj. R^2	9.26%	12.79%	12.44%	12.95%	19.45%	14.76%	11.28%	24.03%	29.02%	25.13%	27.92%	33.18%	24.42%	25.66	75.44%

The table presents OLS slope estimates from regressions of future aggregate REIT market returns on a constant, aggregate REIT investment, future firm earnings news measures, and future macroeconomic growth measures:

$$R_{t+1} = \alpha + \beta_1 Invest_t + \beta_2 GDPGR_{t+1} + \beta_3 ROA_{t+1} + \beta_4 SUE_{t+1} + \beta_5 Error_{t+1} + \beta_6 LTError_{t+1} + \beta_7 EAR_{t+1} + \beta_8 HML_{t+1} + \varepsilon_{t+1}$$

R_{t+1} represents the compounded monthly excess total returns (returns minus risk-free rate) on the FTSE NAREIT All Equity REITs Index over the period from July in year t+1 to June in year t+2. $Invest_t$ is aggregate investment as of the end of fiscal year t. $GDPGR_{t+1}$ is the growth rate in real GDP over the period from July in year t+1 to June in year t+2. ROA_{t+1} is aggregate return on assets as of the end of fiscal year t+1. SUE_{t+1} is aggregate standardized unexpected earnings as of the end of the last quarter of fiscal year t+1. $Error_{t+1}$ represents aggregate difference between analyst forecasts of fiscal year t+1 earnings and actual realized ROA for fiscal year t+1. $LTError_{t+1}$ represents the aggregate difference between analyst forecasts of long-term earnings and actual realized long-term ROA. EAR_{t+1} is aggregate earnings announcement returns over the period from July in year t+1 to June in year t+2. HML_{t+1} denotes the compounded monthly returns to a REIT-based value-weighted HML portfolio over the period from July in year t+1 to June in year t+2. *, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively. Newey and West (1987) HAC t-statistics based on three lags are reported in parenthesis below the estimates.

Appendices

Appendix 2.1 Variable Definitions, Data Sources, and Construction

$Invest_t$ represents aggregate investment as of the end of fiscal year t. This variable is calculated as the value-weighted average of annual firm-level investment, aggregated to market level using fiscal-year-end market capitalizations as weights. Firm-level investment is measured by the annual growth rate in non-cash assets or operating assets. Specifically, non-cash assets are computed as total assets (Compustat data item AT) minus cash and short-term investments (CHE).

R_{t+1} represents annual aggregate REIT market returns. This variable is constructed by compounding monthly excess returns of the FTSE NAREIT All Equity REITs Index (including dividends) over the risk-free rate from July in year t+1 to June in year t+2 for the period from July 1972 to June 2020. This return accumulation period ensures that firm's accounting data are fully available before future stock returns are realized (Fama and French, 1992). The index's return data are sourced from NAREIT.

D/P_t represents the dividend yield for the FTSE NAREIT All Equity REITs Index as of the end of June in year t+1. The index dividend yield data are sourced from NAREIT.

B/M_t represents aggregate book-to-market equity ratio as of the end of fiscal year t. This variable is calculated as the value-weighted average of annual firm-level book-to-market equity ratio, aggregated to market level using fiscal-year-end market capitalizations as weights. Firm-level book-to-market equity ratio is measured as book equity divided by market equity at fiscal year-end. Book equity is defined as stockholder's equity (Compustat SEQ), plus balance sheet deferred tax and investment tax credit (TXDITC, if available), minus the book value of preferred stock (liquidating value PSTKL if available, or else redemption value PSTKRV if available, or else carrying value PSTK). Market equity is calculated as price close (PRCC_F) multiplied by common shares outstanding (CSHO).

E/P_t represents aggregate earnings-to-price ratio as of the end of fiscal year t. This variable is calculated as the value-weighted average of annual firm-level earnings-to-price ratio, aggregated to market level using fiscal-year-end market capitalizations as weights. Firm-level earnings-to-price ratio is computed as operating income after depreciation (Compustat OIADP) scaled by market capitalization at fiscal year-end.

$Tbill_t$ represents short-term interest rate, measured as the 3-month Treasury bill rate as of the beginning of July in year t+1. $Term_t$ represents term spread, measured as the difference between the 10-year and 1-year Treasury constant maturity rates as of the beginning of July in year t+1. $Default_t$ represents default spread, measured as the difference between Moody's Seasoned Baa and Aaa corporate bond yields as of the beginning of July in year t+1. All these data are sourced from the St. Louis Federal Reserve Economic Database (FRED).

$Eshare_t$ represents the equity share in REIT total net equity and debt issues over year t. Data on annual REIT net equity issues and net debt issues are obtained from the Federal Financial Accounts.

$Accrual_t$ represents aggregate operating accruals as of the end of fiscal year t. This variable is calculated as the value-weighted average of annual firm-level operating accruals, aggregated to market level using fiscal-year-end market capitalizations as weights. Firm-level operating accruals are computed as the change in noncash current assets (Compustat RECT plus INVT plus ACO) minus the change in current liabilities (Compustat AP plus LCO), scaled by the average of total assets (Compustat AT).

ROA_t represents aggregate return on assets as of the end of fiscal year t.[16] This variable is calculated as the value-weighted average of annual firm-level return on assets, aggregated to

[16] Empirically, REIT performance is measured in various ways. Net income, based on Generally Accepted Accounting Principles (GAAP), is a conventional measure of firm performance. Funds from Operations (FFOs), a voluntarily disclosed, accounting-based performance measure, have long been advocated as the standard in REIT industry. According to the revised NAREIT definition for 2000, FFOs are equal to a REIT's net income, excluding gains or losses from property sales, and adding back real estate depreciation. Fields et al. (1998) evaluate the usefulness of FFOs compared to net income in REIT industry and suggest that the superiority of one measure over the other is highly contextual. Vincent (1999) examines both the incremental and relative information content of FFOs in relation to net income and other GAAP earnings items, indicating that both FFOs and net income provide incremental information, but net income has greater relative information content. I nominate net income as the

market level using fiscal-year-end market capitalizations as weights. Firm-level return on assets is computed as net income (Compustat IB) scaled by the average of total assets (Compustat AT).

SUE_t represents aggregate standardized unexpected earnings as of the end of the last quarter of fiscal year t. This variable is calculated as the value-weighted average of firm-level standardized unexpected earnings, aggregated to market level using fiscal-year-end market capitalizations as weights. Firm-level standardized unexpected earnings are computed as the change in quarterly earnings per share (Compustat quarterly item EPSPXQ) from its value four quarters ago, scaled by the standard deviation of this change over the past eight quarters. The earnings surprise is considered known on the report dates of quarterly earnings announcements (Compustat RDQ).

$FROA_{t+1}$ represents aggregate forecast of fiscal year t+1 ROA, computed using analyst forecasts of one-year-ahead EPS available as of the end of fiscal year t. For each firm, the median forecast of one-year-ahead ROA is calculated as the median forecast of one-year-ahead EPS multiplied by the number of shares outstanding, scaled by total assets as of the end of fiscal year t. Firm-level forecasts of one-year-ahead ROA are then aggregated to market level using market capitalizations as of the end of fiscal year t as weights. This variable covers the period from 1976 to 2019. Data on analyst forecasts are obtained from the I/B/E/S Database.

$Error_{t+1}$ represents aggregate difference between the forecasted ROA for fiscal year t+1 and the actual realized ROA in fiscal year t+1.

$FLTG_{t+1}$ represents aggregate forecast of long-term earnings growth, computed using analyst forecasts of long-term EPS growth available as of the end of fiscal year t. For each firm, the median forecast of long-term EPS growth is obtained from the I/B/E/S database and aggregated to the market level using market capitalizations as of the end of fiscal year t as weights. This variable covers the period from 1981 to 2019.

REIT performance measure, primarily because I use multiple measures of firm cash-flow news based on GAAP net income (EPS); using FFOs would not be consistent with these measures. In addition to FFOs, I found similar results using return on equity (ROE), computed as net income scaled by the average of book equity.

$LTError_{t+1}$ represents aggregate difference between the forecasted long-term ROA and the actual realized long-term ROA. For each firm, the forecast of long-term ROA is computed by applying the median forecast of long-term earnings growth as the interest rate over a four-year time horizon to the actual realized ROA in fiscal year t-1. The actual realized long-term ROA is calculated as the arithmetic average of the actual realized ROA in fiscal years t+2 and t+3.

EAR_t represents aggregate earnings announcement returns over the period from July in year t to June in year t+1. For each firm, earnings announcement return is calculated as the arithmetic average of cumulative stock returns (CRSP daily item RET) over the trading days [−1,+1] surrounding each of the firm's report dates of quarterly earnings announcements (Compustat quarterly item RDQ) that take place over the period from July in year t to June in year t+1. Firm-level earnings announcement returns are then aggregated to market level using market capitalizations as of the end of fiscal year t as weights. The data cover the period from July 1972 to June 2020.

HML_t represents the compounded monthly returns on a REIT-based value-weighted HML (High book-to-market Minus Low book-to-market) portfolio over the period from July in year t to June in year t+1. The construction of the portfolio largely follows the standard Fama and French (1993) approach. Specifically, at the beginning of each month, all equity REITs are sorted into two portfolios based on their market equity (size). Independently, all equity REITs are also sorted into three portfolios based on their book-to-market equity ratio (B/M). The two-way sort on size and B/M produces six portfolios, which are value-weighted and rebalanced monthly. The monthly return on the HML portfolio is defined as the return spread between the simple average of the small-value and big-value portfolios and the simple average of the small-growth and big-growth portfolios.

$CFNAI_t$ represents the average value of the monthly CFNAI (Chicago Federal National Activity Index) over the period from July in year t to June in year t+1. Data on the monthly CFNAI are obtained from the Federal Reserve Bank of Chicago's website.

$GDPGR_t$ represents the growth rate of real GDP over the period from July in year t to June in year t+1.

$Indprod_t$ represents the growth rate of industrial production over the period from July in year t to June in year t+1. Data on real GDP and industrial production are available from the St. Louis Federal Reserve Economic Database.

Appendix 2.2 Investor Sentiment Measures: Definitions, Data Sources, and Construction

University of Michigan Consumer Sentiment Index

I first consider including an investor sentiment proxy that spans across asset classes. The University of Michigan Consumer Sentiment Index is a widely used proxy for investor sentiment based on consumer confidence. This index is derived from telephone surveys conducted with adults living in U.S. households. An alternative well-known consumer confidence-based measure of investor sentiment is the Conference Board Consumer Confidence Index, which is based on mail surveys conducted with a random sample of U.S. households. While the Conference Board's Index places more emphasis on macroeconomic conditions, the University of Michigan Index focuses more on financial conditions, particularly the respondents' own financial situations. Qiu and Welch (2004) suggest that, compared to the Conference Board's Index, the University of Michigan's Index is more suitable as a proxy for financial market sentiment.

SI_t^{Cons} represents the average value of the monthly University of Michigan Consumer Sentiment Index over year t. The monthly index is scaled by 100 and orthogonalized with respect to a set of six macroeconomic indicators following the methodology of Baker and Wurgler (2006). Specifically, the monthly index is calculated as the residual from a regression of the monthly index value on the growth rate in industrial production, durable, nondurable, and services consumption, and employment, and the NBER recession indicator. Data on the monthly index are obtained from the St. Louis Federal Reserve Economic Database, while data on the six macroeconomic indicators are available on Jeffrey Wurgler's website (https://pages.stern.nyu.edu/~jwurgler/).

Baker and Wurgler Composite Stock Market Sentiment Index

Given that listed REITs' shares, like other public companies' shares, are publicly traded on major stock exchanges, I next include a sentiment measure covering the general stock market. A substantial body of research has proposed various sentiment indexes, including the more recent Financial and Economic Attitudes Revealed by Search (FEARS) investor sentiment index by Da et al. (2015), the aligned investor sentiment index by Huang et al. (2015), and the manager sentiment index by Jiang et al. (2019). Zhou (2018) provides a comprehensive literature review on measuring investor sentiment. Despite the emergence of these modified and novel sentiment indexes, the Baker and Wurgler (2006) investor sentiment index continues to be regarded as an important benchmark in many of these studies.

SI_t^{Stock} is the average value of the monthly Baker and Wurgler (2006) composite stock market sentiment index over year t. I use the updated orthogonalized version of the sentiment index, which is based on the first principal component of five standardized sentiment proxies, each of which has first been orthogonalized with respect to a set of six macroeconomic indicators. Unlike the original orthogonalized version of the sentiment index in Baker and Wurgler (2006), the updated index on Jeffrey Wurgler's website excludes NYSE turnover as one of the six sentiment proxies. He suggests that turnover no longer carries the same meaning due to the rise of institutional high-frequency trading and the migration of trading to various venues. The sentiment index now maintained on his website and going forward is based on five proxies. These five proxies are the value-weighted dividend premium, first-day returns on IPOs, IPO volume, the closed-end fund discount, and the equity share in total new issues. I obtain data on the monthly index from Jeffrey Wurgler's website.

The Constructed Composite REIT Market Sentiment Index

I finally construct a composite sentiment index for the REIT market, recognizing the potential differences in investor sentiment between the general stock market and the public commercial real estate market. Following Baker and Wurgler (2006) framework, Ling et al. (2014) apply principal component analysis to build a sentiment index for the broader commercial real estate market. Specifically, their index is based on the common variation in eight underlying proxies of investor sentiment in the market.[17] They find that during their sample period (1992:Q2–2009:Q4), the correlation between Baker and Wurgler (2006) stock market sentiment index and their commercial real estate market sentiment index is effectively zero. Moreover, the estimates from VAR models support their unconditional analysis, indicating that the two sentiment

[17] The eight underlying sentiment proxies are: (1) the average REIT stock price premium to NAV; (2) the percentage of properties sold each quarter from the NCREIF Property Index; (3) the share turnover of equity REITs; (4) the number of REIT IPOs; (5) the average first-day returns on REIT IPOs; (6) the share of net REIT equity issues relative to total net REIT equity and debt issues; (7) net mortgage flows as a percentage of GDP; and (8) net capital flows to dedicated REIT mutual funds.

indexes are distinct and do not influence each other. These findings suggest that investors tend to perceive the general stock market and the commercial real estate market as different asset classes. While Ling et al.'s sentiment index covers both private and public commercial real estate markets, the sentiment index constructed in this study focus on the REIT market, given the scope of the study.

SI_t^{REIT} is the average value of the quarterly constructed composite REIT market sentiment index over year t. Specifically, the quarterly index is derived as the first principal component of four standardized sentiment proxies, each of which has first been orthogonalized with respect to a set of six macroeconomic indicators. The four sentiment proxies are the number of REIT IPOs, first day returns on REIT IPOs, net capital inflows from investors into REITs, and the equity share in REIT total net equity and debt issues. Unlike the updated version of the Baker and Wurgler (2006) stock market sentiment index, I exclude the value-weighted dividend premium as one of the sentiment proxies in the constructed REIT market sentiment index. This exclusion is due to the legal requirement that REITs must distribute at least 90% of their taxable income as dividends to maintain their REIT status, which eliminates the existence of a premium between dividend-paying and non-dividend-paying REITs.

I also substitute the closed-end fund discount with net capital inflows from investors into REITs in constructing the REIT market sentiment index. Although Green Street Advisors reports monthly discount (premium) to net asset value data for aggregate REIT market, the data only extends back to February 1990, which is too short to cover the sample period of this study. The inclusion of net capital inflows from investors into REITs is inspired by Dichev (2007) and Ling et al. (2014). While Ling et al. (2014) include net capital inflows into dedicated REIT mutual funds in their commercial real estate market sentiment index, Dichev (2007) suggests using net capital inflows into listed firms as a sentiment measure. It may be more appropriate to use net capital inflows from investors into REITs rather than dedicated REIT mutual funds to measure REIT market sentiment, as the former directly reflects investors' demand for REIT shares.

$NIPO_m$ is the monthly number of REIT IPOs. The index uses the sum of $NIPO$ over the prior 12 months to smooth noise. $RIPO_m$ is the monthly average of first day returns on REIT IPOs. The index uses the $NIPO$-weighted average of monthly $RIPOs$ over the prior 12 months to smooth noise, and then use the m-12 value of the result. Following Glascock and Hughes (1995), I obtain data on the beginning of stock data (CRSP data item BEGDAT) and daily stock returns (CRSP daily data item RET) from the CRSP Database using a list of REITs identified by NAREIT. The list includes 608 publicly traded REITs identified by NAREIT from January 1972 to December 2019. However, this list does not represent the entire universe of publicly traded REITs. It includes publicly traded REITs that are or were once qualified by NAREIT and that appear in the CRSP data file. The list covers all types of publicly traded REITs: equity, mortgage, and hybrid.

$InFlow_m$ is the monthly aggregate net capital inflows from investors into REITs. The index uses the average value of $InFlow$ over the prior 12 months to smooth noise. The variable is calculated as the value-weighted average of monthly firm-level net capital inflows, aggregated to market level using end-of-month market capitalizations as weights. Firm-level net capital inflow is defined following the formula: $InFlow_{i,m} = -1^{*}(MV_{i,m-1}^{*}\left(1 + r_{i,m}\right) - MV_{i,m})$, where $MV_{i,m}$ is the market capitalization of firm i at the end of month m, and $r_{i,m}$ is the stock return of firm i in month m (including dividends). Data on monthly stock returns (CRSP monthly data item RET), price (PRC), and number of shares outstanding (SHROUT) are available from CRSP.

$Eshare_q$ is the share of REIT net equity issues in total equity and debt issues over quarter q. To smooth noise, the index uses the total amount of net equity issues over the prior 4 quarters divided by the total amount of net equity and debt issues over the prior 4 quarters. Data on quarterly REIT net equity and debt issues are sourced from the Federal Financial Account.

Chapter 3 Real Estate Investment Plans and the Cross-Section of Asset Returns: Evidence from REITs

Abstract

I examine the cross-sectional expected return implications of planned real estate investments. I forecast the future investment growth of REITs using Tobin's q, gross profitability, changes in return on assets, and prior stock returns. The forecasted future investment-to-asset changes generate a positive premium in the cross section of REIT returns. To capture the return variation, I construct a factor-mimicking portfolio based on a two-way monthly sort on size and the expected investment growth. Using the factor, an augmented REIT-based investment-based model not only holds up against comparisons with competing REIT-based and common stock-based factor models but also outperforms them in dissecting prominent REIT return patterns. I finally propose an alternative risk-based explanation for the premium. Firms with higher expected investment growth demonstrate higher future profitability, yet they also exhibit a greater degree of future operating and financial leverages and increased sensitivity of future cash flows to economic conditions, leading to higher discount rates.

3.1 Introduction

Planned acquisitions and development pipelines in the real estate industry typically represent firms' commitments to property investments. Both types of real estate investment plans require significant time to complete. While a straightforward acquisition generally takes several months—encompassing pre-acquisition activities, property identification, due diligence, contract negotiation, and closing—the development process is usually more complex. It involves multiple lengthy phases, including pre-development, design and planning, pre-construction, and construction. Moreover, undoing planned acquisitions or developments is costly. Once underway, these plans are resource-intensive, demanding ongoing investment to maintain momentum, and reversing course midway can result in significant additional expenses. The inherent time-to-build (or acquire) and costly-to-reverse nature make real estate investment plans particularly risky. This study examines the expected return implications of planned real estate investment in the cross-section.

Why should high expected investment growth command high expected returns? Theoretically, the investment CAPM in a dynamic setting provides an equilibrium model, where expected returns vary cross-sectionally with current investment, expected profitability, and expected investment growth (Liu et al., 2009). Holding current investment and expected profitability constant, the model can make statements like "expected returns are high because a function of expected investment growth is high". Intuitively, according to the net present value rule of capital budgeting, high expected investment relative to current investment implies high discount rates, because the high discount rates are necessary to offset the high expected marginal benefits of current investment to generate low net present values of new projects and thereby maintain low current investment levels (Hou et al., 2021).

Bond and Xue (2017) are the first to apply the investment-based asset pricing to real estate finance research. They implement the static version of the investment CAPM (Hou et al., 2015), which posits that current investment and expected profitability are two "determinants" of cross-sectional expected returns. Based on Fama and French (1993) portfolio approach, they follow Hou et al. (2015) and find a negative investment premium and a positive profitability premium in the cross section of REIT returns. In contrast, I explore the unique insight from the dynamic investment CAPM, where expected investment growth serves as an additional "determinant" of the expected returns. One could expect that expected investment growth captures a new dimension of variation in the cross-section of expected REIT returns.[18]

Given data constraints on planned property acquisitions and construction, I forecast firms' future investment growth. Investment refers to investment-to-asset ratio and is measured as total asset growth rate (Fama and French, 2006; Hou et al., 2015). REITs provide a favorable setting for the forecasting exercises. Eichholtz and Yönder (2015) demonstrate that, on average, 98.6% of REIT assets are invested in real estate. Such homogeneity in asset composition makes total asset growth rate an effective proxy for real estate investment. Given that the investment-to-asset ratio can be both positive and negative, I follow Hou et al. (2021) and specifically forecast firms' future investment-to-asset changes. The forecasting framework employs the monthly Fama and MacBeth (1973) cross-sectional predictive regressions, using the log of Tobin's q, gross profitability, changes in return on assets, and prior stock returns as predictors. In the benchmark specification, all regressors predict highly significant and positive slopes for one-year-ahead investment-to-asset changes. The out-of-sample Pearson and Rank correlations between the forecasted and realized changes are both statistically significant. The forecasted changes also closely track the subsequent realized changes at the portfolio level.

I begin by demonstrating that the expected investment-to-asset changes generate a significantly positive premium in the cross section of REIT returns. At the firm level, the variable is a significant characteristic in monthly Fama and MacBeth (1973) cross-sectional regressions of future one-month-ahead excess returns, with controls of size, book-to-market ratio, prior 11-month returns, share turnover, standardized unexpected earnings, idiosyncratic volatility, investment-to-asset ratio, and return on assets. At the portfolio level, the high-minus-low quintile sorted on expected one-year-ahead investment-to-asset changes earns an average return of 0.51% per month (t = 2.11). This high-minus-low premium cannot be explained by

[18] The cross section of REIT returns has long attracted interest from real estate researchers. Chui et al. (2003a) demonstrate that while momentum, size, turnover, and analyst coverage are strong predictors of REIT returns in the pre-1990 period, momentum and turnover emerge as the dominant and secondary predictors, respectively, in the post-1990 period. The momentum effect is later confirmed by Hung and Glascock (2008 and 2010). Goebel et al. (2013) further add that, after controlling for momentum, book-to-market ratio, institutional ownership, and illiquidity are highly related to REIT returns, whereas size and analyst coverage are not. Price et al. (2012) identify a significant post-earnings announcement drift, while Feng et al. (2014) observe that the earnings surprise effect supersedes the price momentum effect. DeLisle et al. (2013) report that trading frictions, such as idiosyncratic volatility, are priced in the cross section of REIT returns. Drawing on insights from investment-based asset pricing, Bond and Xue (2017) document an investment premium and a profitability premium. The return predictive power of investment and profitability further supported by Ling et al. (2019) and Glascock and Lu-Andrews (2014), respectively. This study aligns with and contributes to this line of research.

various asset pricing factor models constructed for REITs, including the CAPM, the Fama and French (1993) three-factor model (FF3), the Carhart (1997) four-factor model (Carhart4), the Fama and French (2015) five-factor model (FF5), the Fama and French (2018) six-factor model (FF6), the Hou et al. (2015) q-factor model (HXZq), and the Bond and Xue (2017) investment-based three-factor model (BX3).

To capture the return variation, I construct a factor-mimicking portfolio by interacting the expected one-year-ahead investment-to-asset changes with size in an independent two-way (2 × 3) monthly sort. The expected investment growth factor earns an average return of 0.34% per month (t = 2.01). The factor premium cannot be explained by any of the reconstructed REIT-based factor models, leaving the bulk of the average returns unexplained. In addition, the factor premium surpasses the premium generated from the individual predictors used to forecast future investment-to-asset changes, highlighting the unique role of the expected investment growth in driving the premium. The robustness of the factor premium is confirmed across various empirical specifications.

With the expected investment growth factor, I construct an augmented REIT-based investment-based factor model, the q^5 model (HMXZq^5), as suggested by Hou et al. (2021). The model provides superior information about the cross-section of expected REIT returns. Conceptually, the HMXZq^5 differs from standard factor models by being based on the dynamic investment CAPM, while the FF5 is grounded in valuation theory and the FF6 adds a momentum factor that is ad hoc and statistically motivated.[19, 20] Despite these differences, the HMXZq^5 and FF6 are closely related empirically. I compare them using spanning regressions and find that the HMXZq^5 largely subsumes the FF6, while the FF6 does not subsume the HMXZq^5. As a complement to the spanning tests, I stress-test the two models using testing quintiles based on four prominent REIT return predictors (momentum, standardized unexpected earnings,

[19] Hou et al. (2019) critique the FF5 by arguing that it cannot be fully justified by valuation theory. Instead, they propose a reformulation of valuation theory based on one-period-ahead expected return, leading to a different implication: a positive relationship between expected investment and expected returns. This revised implication aligns more closely with the predictions of the dynamic investment CAPM.
[20] "We include momentum factors (somewhat reluctantly) now to satisfy insistent popular demand. We worry, however, that opening the game to factors that seem empirically robust but lack theoretical motivation has a destructive downside: the end of discipline that produces parsimonious models and the beginning of a dark age of data dredging that produces a long list of factors with little hope of sifting through them in a statistically reliable way" (Fama and French, 2018, p.237)

idiosyncratic volatility, and share turnover) compiled by Bond and Xue (2017). The HMXZq^5 outperforms the FF6 in explaining the high-minus-low quintiles.

The ongoing debate regarding the integration of REIT returns with common stock returns prompts the consideration of selecting between REIT-based and common stock-based factor models. Consequently, I conduct additional spanning tests to compare the REIT-based HMXZ q^5 against common stock-based factor models, including the HMXZ q^5*.[21] The HMXZq^5* explains all factors present in the HMXZq^5 except for the size and expected investment growth factors. Notably, the common stock-based expected investment growth factor loading exhibits a small and insignificant value, suggesting distinct factor pricing information between common stocks and REITs. GRS tests further corroborate the HMXZq^5's non-subsumption by the HMXZq^5*, implying divergent cross-sectional investment-based expected returns between REITs and common stocks.

Given the critical role of the expected investment growth factor in the HMXZq^5, I finally examine the economic driving forces behind the factor premium. Liu et al. (2009) model does not address the underlying mechanism driving the positive relationship between expected investment growth and expected returns. According to the standard theory of investment, Hou et al. (2021) suggest that if expected investment growth is high, high discount rates are required to offset the high anticipated benefits of current investment, thereby maintaining low current investment levels. Li et al. (2021a and 2021b) provide a risk-based explanation, arguing that investment plan frictions create an embedded leverage effect, which amplifies firms' future cash flow risk, leading to a higher risk premium. This interpretation assumes that expected investment is predetermined, irreversible, and not influenced by future business conditions.

I propose an alternative risk-based explanation that emphasizes the role of operating and financial leverage. This emphasis is particularly pertinent because REITs are highly leveraged

[21] The spanning analysis between the REIT-based and common stock-based factor models contributes significantly to the ongoing debate about the integration (segmentation) of REIT returns with (from) stock returns. For example, Li and Wang (1995) find no evidence that REIT returns are more predictable than the returns of other stocks. Glascock et al. (2000) observe that REITs begin to behave more like stocks following the structural changes of the early 1990s. Clayton and MacKinnon (2001 and 2003) demonstrate that REITs exhibit a strong sensitivity to small-cap returns during the 1990s. Fei et al. (2010) report that correlations between REIT returns and stock returns show little asymmetry. Asteriou and Begiazi (2013) add that while the stock market has a significant general impact on REIT returns, it has little influence on the day-of-the-week effect. Li (2016) further shows that expected REIT returns compensate for general stock market risk rather than for the volatility specific to individual REITs.

relative to industrial firms (Giacomini et al., 2017) and the realization of planned property acquisitions and/or developments will likely increase a REIT's fixed and financial costs.[22] Given this premise, a positive idiosyncratic productivity shock can generate two conflicting effects on firms' expected investment growth.[23] On the one hand, the enhanced productivity leads to a positive cash flow effect, encouraging firms to expect greater future investment growth. On the other hand, the higher expected investment growth elevates firms' future operating and financial leverages, thereby rising future cash flow risk. The cash flow effect generally prevails over the discount rate effect. As a result, firms experiencing a positive cash flow shock will optimally expect higher future investment growth, even in the presence of potentially higher discount rates.

I find empirical evidence supporting both competing effects. The quintile with high expected one-year-ahead investment-to-asset changes exhibits higher one-year-ahead sales growth and gross profit growth on average compared to the low quintile. Additionally, the high quintile demonstrates a higher degree of operating leverage and financial leverage over the subsequent year. More importantly, the expected investment-to-asset changes and future GDP growth are positively related to future net income growth, and their interaction term shows a significantly positive coefficient, indicating that the concurrent response of net income growth to GDP growth increases with expected investment-to-asset changes.

This study contributes to the real estate finance literature in several ways. First, it enhances the understanding of the cross-section of REIT returns by documenting a new return pattern associated with firms' real estate investment plans. I capture this return variation by constructing a factor-mimicking portfolio based on expected investment growth. Second, it adds to the debate on the integration (segmentation) of REIT returns with (from) common stock returns. I find that, with this factor, the REIT-based HMXZq^5 holds its own against competing common stock-based factor models in spanning tests. Third, it contributes to the literature on

[22] The realization of planned property acquisitions and/or developments is likely to augment a REIT's fixed costs across various domains, including property management, maintenance, insurance, administrative expenses, and depreciation. Furthermore, it is probable to elevate a REIT's financial costs due to increased interest expenses, costs associated with issuing new debt or equity, and potentially higher hedging and refinancing costs.
[23] Vuolteenaho (2002) finds that cash flow shocks play a crucial role at the firm level. Therefore, my conceptual argument abstracts from time-varying volatilities in aggregate productivity, such as exogenous shocks to discount rates, and instead focuses on the economic mechanism within the cross section.

the effect of leverage on REIT returns. [24] I demonstrate that expected investment growth positively predicts future operating and financial leverage, suggesting that it is a leading indicator of firms' future leverage. Fourth, it has practical implications. I find the REIT-based HMXZ q^5 outperforms its competing REIT-based factor models in spanning tests and in explaining prominent patterns of REIT returns in the cross-section. These results support the model's utility for future REIT asset pricing research and applications. For example, it can serve as an alternative benchmark for evaluating risk-adjusted REIT returns or the performance of dedicated REIT mutual funds.

This study also contributes to the literature on investment plans and asset returns. Lamont (2000) employs data on investment plans from a survey of capital expenditure plans conducted by the U.S. Commerce Department. Jones and Tuzel (2013) introduce the ratio of new orders to shipments of durable goods as an indicator of investment plans. Li et al. (2021a) propose a bottom-up measure of aggregate investment plans. It is well-documented that these aggregate measures negatively predict stock market returns, indicating that time-varying discount rates affect planned investment. In contrast, Hou et al. (2021) and Li et al. (2021b) forecast firms' future investment growth, demonstrating that the forecasts positively predict stock returns. The opposite sign observed at the firm level may be because idiosyncratic cash-flow shocks play a more crucial role than exogenous shocks to discount rates at the firm level (Vuolteenaho, 2002). This study complements previous studies by focusing on real estate investment plans, which are inherently risky due to the significant time to build and the high costs of reversal, and their expected return implications on public commercial real estate.

Finally, this study sheds light on the economic mechanism underlying the relationship between expected returns and expected investment growth. The dynamic investment CAPM lacks causal content because it links endogenous variables. Consequently, it cannot explain the economic causes of the relationship between expected returns and their "determinants" (Kogan and Papanikolaou, 2012). Hou et al. (2021) offer an intuition based on the net present value

[24] Several studies have examined the effect of financial leverage on REIT returns. For example, Allen et al. (2000) find a significant positive relationship between financial leverage and the sensitivity of U.S. REIT returns to general stock market returns. Chaudhry et al. (2004) show that REIT idiosyncratic risk is affected by financial leverage. Giacomini et al. (2015) document that levered public market real estate returns are significantly higher and more volatile than unlevered returns. Giacomini et al. (2017) add that REITs are highly levered relative to industrial firms; REITs with high leverage relative to their target levels perform better on a risk-adjusted basis than underlevered REITs. This study contributes to the literature by suggesting that expected investment growth is a leading indicator of firms' future degree of leverage.

rule of capital budgeting but call for further investigations into the economic driving forces behind the expected investment growth premium. Li et al. (2021a and 2021b) offer a risk-based explanation that highlights the role of investment plan frictions. This study emphasizes the role of operating and financial leverages, particularly since REITs are more leveraged than industrial firms (Giacomini et al., 2017). When a REIT plans to acquire or develop more properties, the resulting expansion in its property portfolio will likely lead to higher fixed and financial costs, thereby increasing cash flow risks. Although operating and financial leverages have been used to explain other asset pricing phenomena, such as the value premium (e.g., Carlson et al., 2004; Novy-Marx, 2011; Choi, 2013), this study applies these concepts to interpret the expected investment growth premium.

The rest of the chapter is organized as follows. Section 3.2 describes the data and methodology. Section 3.3 presents the expected investment growth premium. Section 3.4 details the spanning tests. Section 3.5 presents the stress-testing of factor models. Section 3.6 discusses the economic mechanism. Section 3.7 concludes.

3.2 Data and Methodology

3.2.1 Cross-Sectional Forecasts of Future Investment Growth

In this subsection, I form cross-sectional forecasts of future investment growth. Data on monthly returns are obtained from the Center for Research in Security Prices (CRSP). Accounting information is sourced from the Compustat Annual and Quarterly Fundamental Files. The sample includes 438 U.S. publicly traded equity REITs identified by the National Association of Real Estate Investment Trusts (NAREIT). Firms with negative book equity are excluded from analysis. The sample period spans from July 1994 to December 2021.[25]

In Fama and French (2006 and 2015) and Hou et al. (2015), investment refers to investment-to-asset ratio, which is measured as total asset growth rate, as defined by Cooper et al. (2008). Total asset growth rate is the most comprehensive measure of investment-to-asset ratio, where asset is interpreted as all productive assets, and investment is the changes in total assets (Zhang, 2017). REITs provide a favourable setting for the forecasting exercises. Eichholtz and Yönder (2015) show that REITs have, on average, 98.6% of their assets in real estate. This homogeneity in asset composition suggests that the total asset growth rate serves as an effective proxy for real estate investment. Bond and Xue (2017) measure REIT investment as non-cash asset growth rate, I find similar results using the growth rate of operating assets. Given that firm's investment-to-asset ratio is frequently negative, making the growth rate of investment-to-asset ratio ill-defined, I follow Hou et al. (2019 and 2021) and specifically forecast future investment-to-asset changes.[26]

The forecasting framework employs monthly Fama and MacBeth (1973) cross-sectional predictive regressions. The predictors are based on prior literature on corporate investment. For example, Fazzari et al. (1988) show that Tobin's q is a strong predictor of future investment

[25] NAREIT website offers monthly constituent data for the FTSE NAREIT U.S. Real Estate Index Series starting from December 1991. I examine the post 1993 period, as the structure of the REIT market changed substantially after 1993. The 1990s witnessed significant transformations within the United States REIT industry. Structural changes, particularly those enacted after the 1993 Revenue Reconciliation Act, catalyzed substantial inflows of capital into the system by enabling institutional investors to participate in REITs. Consequently, the industry experienced remarkable asset growth, with numerous initial public offerings and substantial increases in market capitalization. The six-month lag after December 1993 is to ensure that firms' accounting data for fiscal year 1993 are publicly available as of the beginning of July 1994.

[26] Alternatively, Li et al. (2021a and 2021b) forecast future gross capital investment growth using capital investment data from Compustat annual item CAPX. However, REITs commonly have missing values for the CAPX item in Compustat.

rates, consistent with the q-theory argument that a firm should invest if its average q exceeds one (Tobin, 1969). Fazzari et al. (1988) also find that cash flow produces a significant slope when included in the future investment-q regression. They note that while the cash-flow effect on investment may indicate measurement errors in Tobin's q, an alternative explanation is that cash flow reflects current and presumably future profitability and facilitates investment if a firm is financially constrained. Liu et al. (2009) add that recent earnings shocks contain useful information about future investment growth in the short term. Barro (1990) and Morck et al. (1990) document that past returns strongly forecast investment growth. The positive relationship between stock returns and future investment growth can be interpreted through neoclassical models (e.g., Lamont, 2000) or (mis)valuation (Baker et al., 2003; Polk and Sapienza, 2008). I remain agnostic about the exact interpretation and take the empirical findings as given to form cross-sectional forecasts of future investment growth.

I begin by estimating monthly Fama-MacBeth cross-sectional predictive regressions of τ-year-ahead investment-to-asset changes, $d^{\tau}I/A$, where τ = 1 and 2, on the natural log of Tobin's q, $\log(q)$, gross profitability, Gp, changes in return on assets, $dRoa$, and prior 11-month returns, Ret^{11}, covering the period from July 1995 to December 2021.

$$d^{\tau}I/A_{it+12\tau} = \beta_{0,t+12\tau} + \beta_{1,t+12\tau}log(q)_{it} + \beta_{2,t+12\tau}Gp_{it} + \beta_{3,t+12\tau}dRoa_{it} + \beta_{4,t+12\tau}Ret_{it}^{11} + \varepsilon_{it+12\tau} \quad (3.1).$$

At the beginning of each month t, I measure current investment-to-asset ratio as total assets (Compustat annual item AT) from the most recent fiscal year-end at least four months ago minus the total assets from one year prior, scaled by the average total assets. The τ-year-ahead investment-to-asset changes, $d^{\tau}I/A$, are the investment-to-asset ratio from the τth fiscal year after the most recent fiscal year minus the current investment-to-asset ratio. Tobin's q is calculated as the sum of market equity (items PRCC_F multiplied by CSHO), long-term debt (item DLTT), and short-term debt (item DLC), scaled by book assets, all from the most recent fiscal year-end at least four months ago. Gross profitability, Gp, is calculated as total revenue (item REVT) minus cost of goods sold (item COGS), scaled by book assets, all from the most recent fiscal year-end at least four months ago.[27]

[27] I start with gross profits as the profitability measure, as Novy-Marx (2013, p.2) argues that "Gross profits is the cleanest accounting measure of true economic profitability. The farther down the income statement one goes, the more polluted profitability measures become, and the less related they are to true economic profitability."

Changes in return on assets, $dRoa$, are defined as Roa minus the four-quarter-lagged Roa. Roa is income before extraordinary items (Compustat quarterly item IBQ) scaled by the one-quarter-lagged book assets (item ATQ). [28] I compute $dRoa$ using earnings from the most recent announcement date (item RDQ) and, if not available, from the most recent fiscal quarter-end at least four months ago. Prior 11-month returns, Ret^{11}, are the cumulative returns (CRSP monthly item RET) from month t-12 to month t-2; month t-1 returns are skipped to eliminate the bid-ask bounce effect. I winsorize all variables at the 1st and 99th percentiles of their distributions. Missing $dRoa$ values are set to zero in the cross-sectional forecasting regressions. I report the time-series average slopes, the t-values adjusted for heteroscedasticity and autocorrelations, and goodness-of-fit coefficients.

I next form out-of-sample forecasts of τ-year-ahead investment-to-asset changes, $E_{it}[d^{\tau}I/A]$, in which τ = 1 and 2.

$$E_{it}[d^{\tau}I/A] = \bar{\beta}_{0,t-1:t-120(30)} + \bar{\beta}_{1,t-1:t-120(30)}log(q)_{it} + \bar{\beta}_{2,t-1:t-120(30)}Gp_{it} + \bar{\beta}_{3,t-1:t-120(30)}dRoa_{it} + \bar{\beta}_{4,t-1:t-120(30)}Ret^{11}_{it} \quad (3.2).$$

At the beginning of each month t, I combine the most recent winsorized predictors with the average slopes estimated from the prior 120-month rolling window (minimum 30 months). The most recent predictors— $\log(q)$ and Gp —are from the most recent fiscal year-end at least four months ago as of the beginning of month t. $dRoa$ is computed using the latest announced quarterly earnings and, if not available, from the most recent fiscal quarter-end at least four months ago as of the beginning of month t. Ret^{11} represents the prior 11-month cumulative returns as of the beginning of month t (skipping month t-1). To avoid look-ahead bias, the average slopes are estimated from the rolling window spanning months t-1 to t-120 (minimum

Glascock and Lu-Andrews (2014) echo the use of gross profits in their study of the profitability premium in REITs. They argue that the two main measures—earnings (net income excluding extraordinary items) and funds from operations (FFOs)—may be manipulated in firms' financial reports. In a subsequent study, Bond and Xue (2017) also find a profitability premium in REITs using earnings before extraordinary items (Compustat item IB). I find similar results using operating profits (item REVT – COGS – XSGA) and net income (loss) (item NI).

[28] To ensure consistency between the deflator applied to the earnings measure and that used for the dependent variable in the predictive regressions, I deflate earnings by book assets. As suggested by Ball et al. (2015), a mismatch in deflators may exaggerate the explanatory power of the earnings variable. Compared to consistently deflating both dependent and independent variables by book assets, deflating earnings by book equity results in an explanatory variable that is the product of earnings deflated by book assets and the ratio of book assets to book equity. In the context of REITs, Bond and Xue (2017) scale earnings by book equity, while Ling et al. (2019) deflate earnings by book assets. I obtain similar results using earnings deflated by book equity.

30 months). In the latest regression, $d^{\tau}I/A$ is from the most recent fiscal year-end at least four months ago as of the beginning of month t-1, and the regressors are further lagged by 12τ months. The resulting $E_{it}[d^{\tau}I/A]$ starts from January 1998. I report the time-series averages of cross-sectional Pearson and Rank correlations between $E_{it}[d^{\tau}I/A]$ calculated at the beginning of month t and the subsequently realized τ-year-ahead investment-to-asset changes. The p-values test whether a given correlation is zero.

Table 3.1 reports the results of the cross-sectional forecasts of future investment growth. At 1-year horizon (τ = 1), Tobin's q alone is a strong predictor, with a slope of 0.10 (t = 6.60) and an in-sample R^2 of 2.4%. The out-of-sample Pearson and Rank correlations are both around 0.10. Gross profitability slightly outperforms Tobin's q, yielding a slope of 1.06 (t = 8.67) and a R^2 of 3.8%. Changes in return on assets have a slope of 0.96 (t = 2.77), but it does not perform as well as Tobin's q, with a R^2 of 1.7%. Both the Pearson and Rank correlations drop to about 0.05. Prior 11-month returns are comparable to Tobin's q, with a similar slope and R^2. At 2-year horizon (τ = 2), Tobin's q alone experiences a decline in its ability to predict future investment-to-asset changes, while the other predictors increase their predictive powers.

In multivariate regressions that include all predictors, all slopes except for the slope of change in return on assets are smaller than those from univariate regressions. At 1-year horizon (τ = 1), the Tobin's q's slope decreases to 0.04; the gross profitability's slope declines to 0.71; and the prior 11-month returns' slope falls to 0.12. Nevertheless, all slopes remain highly statistically significant, with t-values ranging from 3.19 to 6.81. With multiple predictors, the in-sample R^2 increases to 8.4%. The out-of-sample Pearson and Rank correlations are 0.14 and 0.16, respectively, both of which are highly significant. At 2-year horizon (τ = 2), the Tobin's q's slope plunges to 0.007 and becomes statistically insignificant (t = 0.46), while the other predictors increase their predictive powers. The in-sample R^2 rises to 9.5%, and the Pearson and Rank correlations are 0.12 and 0.14, respectively.

[Insert Table 3.1]

To further validate the forecasts, I form quintiles based on the forecasted τ-year-ahead investment-to-asset changes, $E_{it}[d^{\tau}I/A]$, where τ = 1 and 2. At the beginning of each month t, I sort all firms into quintiles based on the ranked values of $E_{it}[d^{\tau}I/A]$. The quintiles are value-weighted using the end-of-prior-month market equity as weights and rebalanced at the beginning of month t+1.

Table 3.2 reports the time-series averages of quintile expected τ-year-ahead investment-to-asset changes and subsequent realized changes, as well as their heteroskedasticity-and-autocorrelation-adjusted t-statistics beneath the corresponding estimates. At portfolio level, the expected changes closely track the subsequent realized changes. At 1-year horizon (τ = 1), the average expected changes rise from -10.15% (t = -20.09) to 5.13% (t = 19.69) from the low to high quintile, while the average subsequent realized changes range from -9.10% (t = -5.72) to 3.06% (t = 3.04). The 2-year horizon (τ = 2) shows a similar pattern. Moving from the low to high quintile, the average expected changes increase from -12.54% (t = -16.66) to 5.60% (t = 9.37), and the average subsequent realized changes range from -9.46% (t = -4.72) to 1.67% (t = 1.51). The time-series averages of cross-sectional correlations between the quintile expected changes and subsequent realized changes are 0.43 and 0.41 for the 1-year and 2-year horizons, respectively (untabulated). Both are highly significant. Therefore, my forecast of future investment-to-asset changes is close to an unbiased estimator at portfolio level.

[Insert Table 3.2]

3.3 The Expected Investment Growth Premium

3.3.1 Cross-Sectional Return Predictive Regressions

Based on the forecasted future investment-to-asset changes, I examine the expected return implications of expected investment growth. This involves several steps. In this subsection, I perform monthly Fama and MacBeth (1973) cross-sectional return predictive regressions.

The return predictors are based on prior findings regarding patterns in the cross-section of REIT returns. Chui et al. (2003a) show that while momentum, size, turnover, and analyst coverage predict REIT returns well in the pre-1990 period, momentum and turnover become the dominant and secondary predictors, respectively, in the post-1990 period. The momentum effect is later confirmed by Hung and Glascock (2008 and 2010). Goebel et al. (2013) add that, after controlling for momentum, the book-to-market ratio, institutional ownership, and illiquidity are highly related to REIT returns, while size and analyst coverage are not. Price et al. (2012) find a significant post-earnings announcement drift. Feng et al. (2014) note that the earnings surprise effect dominates the momentum effect. DeLisle et al. (2013) report that trading frictions, such as idiosyncratic volatility, are priced in the cross section of REIT returns. Based on the insights from investment-based asset pricing, Bond and Xue (2017) document an investment premium and a profitability premium. The return predictive power of investment and profitability is also reported by Ling et al. (2019) and Glascock and Lu-Andrews (2014), respectively.

I estimate the following monthly Fama-MacBeth cross-sectional regressions of one-month-ahead excess returns on the expected τ-year-ahead investment-to-asset changes and a set of return predictors,

$$Ret_{it+1} = \beta_{0,t+1} + \beta_{1,t+1}E_{it}[d^{\tau}I/A] + \beta_{2,t+1}Me_{it} + \beta_{3,t+1}B/M_{it} + \beta_{4,t+1}Ret_{it}^{11} + \beta_{5,t+1}Tur_{it} + \beta_{6,t+1}Sue_{it} + \beta_{7,t+1}Ivff_{it} + \beta_{8,t+1}I/A_{it} + \beta_{9,t+1}Roa_{it} + \varepsilon_{it+1} \quad (3.3).$$[29]

[29] I implement the Fama and MacBeth (1973) two step procedure. In the first step, for each single time period from January 1998 to December 2021, I perform a cross-sectional regression. Then, in the second step, I obtain the final coefficient estimates as the average of the first step coefficient estimates. I use the lag number of five to generate the heteroscedasticity and autocorrelation-consistent Newey-West standard error estimates.

Ret_{it+1} is excess returns at the end of month t (or the beginning of month t+1), calculated as returns (CRSP monthly item RET) minus one-month Treasury bill rate. $E_{it}[d^{\tau}I/A]$ represents the expected τ-year-ahead investment-to-asset changes calculated at the beginning of month t (τ = 1 and τ = 2). At the beginning of month t. I measure size or market equity, Me, as price per share (item PRC) multiplied by the number of shares outstanding (item SHROUT), both from the end of month t-1. Book-to-market equity, B/M, is calculated as book equity scaled by market equity, both from the most recent fiscal year-end at least four months ago.[30] Prior 11-month returns, Ret^{11}, are the cumulative returns (CRSP monthly item RET) from month t-12 to month t-2, with month t-1 returns skipped to eliminate the bid-ask bounce effect. Share turnover, Tur, is the average daily share turnover over the prior six months from month t-6 to t-1, requiring a minimum of 50 days. Daily turnover is the number of shares traded (CRSP daily item VOL) on a given day divided by the number of shares outstanding (item SHROUT) on that day.[31]

Standardized unexpected earnings, Sue, are calculated as the change in split-adjusted quarterly earnings per share (Compustat quarterly item EPSPXQ divided by item AJEXQ) from its value four quarters ago, divided by the standard deviation of this changes in quarterly earnings over the prior eight quarters (minimum six quarters). I compute Sue using earnings from the most recent announcement date (item RDQ), and, if unavailable, from the most recent fiscal quarter-end at least four months ago.[32] Idiosyncratic volatility, $Ivff$, is the residual volatility obtained from regressing a stock's excess returns on the REIT-based Fama and French (1993) three factors. At the beginning of month t, I use $Ivff$ estimated with daily returns (CRSP daily item RET) from month t-1, requiring a minimum of 15 daily returns.

[30] Book equity is calculated as stockholders' book equity plus balance sheet deferred taxes and investment tax credit (Compustat annual item TXDITC), if available, minus the book value of preferred stocks. Stockholders' equity is obtained from Compustat (item SEQ), if available. Otherwise, I use the book value of common equity (item CEQ) plus the par value of preferred stock (item PSTK), or the book value of assets (item AT) minus total liabilities (item LT). Depending on availability, I use the redemption value (item PSTKRV), liquidating value (item PSTKL), or par value (item PSTK) for the book value of preferred stock.

[31] I adjust the NASDAQ trading volume to account for the institutional differences between NASDAQ and NYSE-Amex volumes, following the method outlined by Gao and Ritter (2010). Specifically, prior to February 1, 2001, I divide NASDAQ volume by 2. From February 1, 2001, to December 31, 2001, I divide NASDAQ volume by 1.8. For the years 2002 and 2003, I divide NASDAQ volume by 1.6. From 2004 onward, I use a divisor of 1.

[32] I require that the end of the fiscal quarter corresponding to the most recent Sue falls within six months prior to the beginning of month t. This ensures that stale earnings information is excluded. Additionally, to avoid potentially erroneous records, I require that the earnings announcement date occurs after the corresponding fiscal quarter end.

Investment-to-asset ratio, I/A, is calculated as total assets (Compustat annual item AT) from the most recent fiscal year-end at least four months ago minus total assets from one year prior, scaled by the average total assets. Return on assets, Roa, is defined as income before extraordinary items (Compustat quarterly item IBQ) scaled by the one-quarter-lagged book assets (item ATQ). I compute Roa using earnings from the most recent announcement date (item RDQ) and, if unavailable, from the most recent fiscal quarter-end at least four months ago. When performing the monthly cross-sectional regressions, I winsorize the regressors at the 1st and 99th percentiles to mitigate the impact of outliers. Additionally, since different variables have different units, I standardize each winsorized regressor by subtracting its cross-sectional mean and dividing by its cross-sectional standard deviation. I report the time-series average slopes, the t-values adjusted for heteroscedasticity and autocorrelations (in parentheses), and goodness-of-fit coefficients.

Table 3.3.1 shows that the expected one-year-ahead investment-to-asset changes ($E_{it}[d^1 I/A]$) strongly predict the excess returns over the subsequent one month. On its own, it yields a slope of 0.11% (t = 2.16) with an in-sample R^2 of 3.7%. In the benchmark specification with all predictors, a one-standard-deviation increase in the expected changes is related to a 0.19% (t = 2.29) increase in one-month-ahead excess returns on average. Unlike Chui et al. (2003a) and Hung and Glascock (2008 and 2010), I find that the momentum is not a significant return predictor across all specifications. The momentum effect may be subsumed by the expected investment growth effect, as prior stock returns are one of the predictors of the expected investment-to-asset changes. In line with Goebel et al. (2013), the book-to-market equity remains highly significant even after controlling for momentum, while size and share turnover are not.

Additionally, both the standardized unexpected earnings and the idiosyncratic volatility are strong predictors of returns. In the benchmark specification, they have slopes of approximately 0.12% in absolute magnitude. While the positive earnings surprise effect aligns with Price et al. (2012), the negative idiosyncratic volatility effect is consistent with DeLisle et al. (2013). As suggested by Feng et al. (2014), the earnings drift effect may also dominate the momentum effect. Unlike Bond and Xue (2017), I find that the investment-to-asset ratio and the return on assets are not significant characteristics in the cross-sectional return predictive regressions. These characteristics may be subsumed by the expected investment-to-asset changes, as they are related to the average slopes and the changes in return on assets used to forecaste future investment growth, respectively.

Table 3.3.2 shows that using the expected two-year-ahead investment-to-asset changes ($E_{it}[d^2I/A]$) strengthens the predictability for the one-month-ahead excess returns. The slopes increase to approximately 0.13% (t = 2.84) and 0.21% (t = 3.08) in the univariate and the benchmark specifications, respectively. The book-to-market equity and the standardized unexpected earnings remain highly significant in the predictive regressions, although their slopes in absolute value experience a slight decline. There is no significant changes in the return predictive power of the idiosyncratic volatility. The remaining predictors continue to be insignificant.

[Insert Table 3.3.1]

[Insert Table 3.3.2]

3.3.2 Quintiles

In this subsection, I investigate whether the expected investment growth premium documented at firm level extends to portfolio level. At the beginning of each month t, I sort all firms into quintiles based on the ranked values of τ-year-ahead investment-to-asset changes, $E_{it}[d^{\tau}I/A]$, in which τ = 1 and τ = 2. I then compute value-weighted quintile excess returns for the current month t, using the end-of-prior-month market equity as weights. The quintiles are rebalanced at the beginning of month t+1.

Panel A in Table 3.4 shows the time-series average of quintile excess returns. The high-minus-low quintile, sorted on expected one-year-ahead investment-to-asset changes, earns an average return of 0.51% (t = 2.11) per month during the period from January 1998 to December 2021. At two-year horizon (τ = 2), the high-minus-low quintile has an average return of 0.39% (t = 1.99). The high-minus-low premium is consistent with the firm-level evidence that expected investment-to-asset changes positively predict future excess returns.[33]

I further evaluate whether the high-minus-low premium is captured by asset pricing factor models. I draw on both conventional and more recent models: the Capital Asset Pricing Model (CAPM), the Fama and French (1993) three-factor model (FF3), the Carhart (1997) four-factor model (Carhart4), the Fama and French (2015) five-factor model (FF5), the Fama and French (2018) six-factor model (FF6), the Hou et al. (2015) q-factor model (HXZq), and the Bond and Xue (2017) investment-based three-factor model (BX3). Like Bond and Xue (2017), I construct these factor models for REITs. Appendix 3.1 details the construction.

In Panels B to H in Table 3.4, I perform time-series factor model regressions for each quintile. Appendix 3.1 details the regression specification. I report the CAPM alpha, α_{CAPM}, the FF3 alpha, α_{FF3}, the Carhart4 alpha, $\alpha_{Carhart4}$, the FF5 alpha, α_{FF5}, the FF6 alpha, α_{FF6}, the HXZq alpha, α_{HXZq}, and the BX3 alpha, α_{BX3}, as well as their heteroskedasticity-and-autocorrelation-adjusted t-statistics. Additionally, I report the mean absolute alpha for each set of quintiles and

[33] Per Fama (1976), the slope of the expected investment-to-asset changes in the cross-sectional return predictive regressions represents the return to a zero-investment long-short portfolio. However, Hou et al. (2020, p.2026) argue that "the long and short legs of the slope portfolio do not have total weights that sum to one. As such, the magnitude of the slopes is not directly comparable to the magnitude of the average returns of the high-minus-low (quintile)"

the p-value from the Gibbons et al. (1989, GRS) test on the null hypothesis that the alphas across the quintiles are jointly zero.

At one-year horizon ($\tau = 1$), the CAPM yields an alpha of 0.96% (t = 3.65) for the high-minus-low quintile. The mean absolute alpha from the low to high quintile is 0.22%, and the GRS test rejects the CAPM (p = 0.01). The high-minus-low alpha increases to 1.15% (t = 3.88) in the FF3. The mean absolute alpha also increases, reaching 0.28%. Per the GRS test, the alphas from the low to high quintile are not jointly zero (p = 0.00). With the addition of momentum factor, the Carhart4 generates a lower high-minus-low alpha of 0.84% (t = 2.74), but the model is still rejected by the GRS test (p = 0.00), with a mean absolute alpha of 0.22%. With the investment and operating profitability factors, the FF5 outperforms the Carhart4, with the high-minus-low alpha decreasing to 0.77% (t = 4.03). Despite a decline in the mean absolute alpha to 0.19%, the FF5 fails to survive the GRS test (p = 0.02).

The FF6 further reduces the high-minus-low alpha to 0.63% (t = 2.67), but the magnitude remains above the high-minus-low premium. The mean absolute alpha remains significant in magnitude at 0.18%, and the GRS test rejects the FF6 (p = 0.04). The HXZq is comparable to the CAPM, producing a high-minus-low alpha of 0.98% (t = 3.43). The mean absolute alpha is 0.24%, and the model is rejected in the GRS test (p = 0.00). The BX3 improves on the HXZq, with the high-minus-low alpha shrinking to 0.86% (t = 3.22). Across the quintiles, the mean absolute alpha is 0.22%. With a p-value of 0.01, the GRS test rejects the model.

The results for the one-year horizon broadly extend to the two-year horizon. None of the factor models capture the high-minus-low premium, producing high-minus-low alphas ranging from 0.65% (t = 2.51) to 1.09% (t = 4.64). All factor models except for FF5 and FF6 are rejected by the GRS tests, with mean absolute alphas ranging from 0.16% to 0.29%. [34]

[Insert Table 3.4]

[34] The results on the asset pricing factor model alphas are based on the constructed REIT-based factors. When the corresponding common stock-based factors, obtained from the Kenneth R. French website and Global-q.org, are used in the time-series factor model regressions, our conclusion is further reinforced: the high-minus-low premium remains uncaptured by both conventional and more recent factor models, and these models perform poorly in explaining the excess returns across quintiles.

3.3.3 A REIT Factor

Given that the high-minus-low premium is largely unexplained by a set of REIT-based factor models, in this subsection I construct a factor-mimicking portfolio to capture the cross-sectional REIT return variation related to expected investment growth.

The expected investment growth factor, R_{Eg}, is constructed using an independent two-way (2 x 3) monthly sort based on size and $E_{it}[d^1I/A]$. At the beginning of each month t, I split REITs into two groups, small and large, using the end-of-prior-month median market equity. Independently, I divide all REITs into three groups—low, median, and high—based on the lowest 30%, middle 40%, and highest 30% of the ranked $E_{it}[d^1I/A]$ values. The intersection of the two size groups and the three $E_{it}[d^1I/A]$ groups forms six benchmark portfolios. I calculate value-weighted portfolio returns for the current month t and rebalance the portfolios at the beginning of month t+1. The expected investment growth factor is the difference (high-minus-low) each month between the simple average returns of the two high $E_{it}[d^1I/A]$ portfolios and the simple average returns of the two low $E_{it}[d^1I/A]$ portfolios.

I conduct time-series factor model regressions of the expected investment growth factor, including the CAPM, FF3, Carhart4, FF5, FF6, HXZq, and BX3. In Table 3.5.1, Panel A presents the time-series average of the expected investment growth factor, R_{Eg}, alongside the model alphas, factor loadings, and R^2 values from the regressions. The t-values, adjusted for heteroscedasticity and autocorrelation, are reported in parentheses. Panel B provides the correlations of the expected investment growth factor with model factors.

The expected investment growth factor earns an average of 0.34% per month (t = 2.01) during the period from January 1998 to December 2021. The CAPM alpha is substantial at 0.70% (t = 4.27), with a significantly negative market factor loading of -0.45 (t = -4.61). When the size and value factors are added, the FF3 model's R^2 jumps from 32% to 60%. However, similar to the market factor, both the size and value factors have significantly negative slopes, -0.73 (t = -6.29) and -0.41 (t = -3.89), respectively, which further increases the alpha to 0.85% (t = 3.83). Introducing the momentum factor to the FF3 reduces the alpha to 0.51% (t = 2.78), driven by a significantly positive loading on the momentum factor of 0.42 (t = 9.60). The FF5 model improves upon the FF3 in explaining the expected investment growth factor, with the alpha decreasing to 0.54% (t = 3.90), primarily due to a significantly positive loading on the operating profitability factor, 0.47 (t = 4.95).

With both the momentum and operating profitability factors included, the FF6 further reduces the alpha to 0.36% (t = 2.75), but the alpha still exceeds the expected investment growth factor premium. The return on asset factor in the HXZq and the alternative return on asset factor in the BX3 both generate significantly positive slopes of 0.30 (t = 3.66) and 0.38 (t = 2.74), respectively. Compared to the CAPM, both investment-based factor models produce slightly smaller alphas, 0.67 (t = 3.70) and 0.61 (t = 4.08), respectively. Overall, none of the factor models fully subsume the expected investment growth factor, leaving a significant portion of average returns unexplained. This finding suggests that the expected investment growth factor captures a new dimension of variation in the cross-section of REIT returns.

3.3.4 Sources

Given that the expected investment growth factor is closely correlated with some of the model factors as shown in Panel B of Table 3.5.1, I next attempt to identify the sources behind the expected investment growth factor premium. I adopt the HXZq factor model regression framework because, unlike the FF6 model, the HXZq does not include factors for momentum and operating profitability, which are directly related to the expected investment-to-assets change predictors, specifically prior 11-month returns and gross profitability.[35] Specifically, I perform time-series regressions of the expected investment growth factor, R_{Eg}, on the HXZq model factors, as well as the augmented factors on Tobin's q, $R_{\log(q)}$, gross profitability, R_{Gp}, changes in return on assets, R_{dRoa}, and prior 11-month returns, $R_{Ret^{11}}$. Analogous to the expected investment growth factor, the factors for $\log(q)$, Gp, $dRoa$, and Ret^{11} are formed by interacting each of them separately with size in 2 x 3 monthly sorts.

Panel A of Table 3.5.2 presents the regression results. For reference, the HXZq model alone generates an alpha of 0.67% (t = 3.70). Both $\log(q)$ and $dRoa$ play a limited role in contributing to the expected investment growth factor premium. Adding $R_{\log(q)}$ to the model reduces the alpha to 0.62% (t = 3.90), despite the factor has a significantly positive slope of 0.35 (t = 3.79). Similarly, including R_{dRoa} slightly lowers the alpha to 0.61% (t = 2.95). In contrast, Gp and Ret^{11} are more significant contributors to the expected investment growth factor premium. The addition of R_{Gp} moderately reduces the alpha to 0.51% (t = 3.80), with a factor loading of 0.52 (t = 3.88). Augmenting the model with $R_{Ret^{11}}$ results in a similar reduction in the alpha, 0.50% (t = 2.86), with a factor loading of 0.35 (t = 6.01).

While adding $R_{\log(q)}$ and R_{dRoa} together reduces the alpha only to 0.55% (t = 3.20), including both R_{Gp} and $R_{Ret^{11}}$ sharply reduces the alpha to 0.31% (t = 2.57). Augmenting the model with all factors together still yields an alpha of 0.26% (t = 2.16), slightly below the expected investment growth premium. These results suggest that while the expected investment growth

[35] Using the BX3 factor model regression framework produces similar results. However, I argue that the HXZq regression framework is more appropriate for identifying the sources behind the expected investment growth factor premium. The augmented factors for Tobin's q, gross profitability, change in return on assets, and prior 11-month returns are constructed using an independent two-way (2 x 3) monthly sort on size and each variable. This factor construction is consistent with the methodology used in the HXZq model but not in the BX3 model. Additionally, employing size in the two-way sort helps to orthogonalize the size factor from the augmented factors, whereas the BX3 model does not include a size factor.

factor premium is a reincarnation of those cross-sectional return patterns related to valuation ratios, profitability, and momentum, it extends far beyond them, emphasizing the significant role of the forecasted investment-to-asset changes in generating the factor premium.

[Insert Table 3.5.1]

[Insert Table 3.5.2]

3.3.5 Robustness Tests

Unlike current investment, expected investment growth cannot be directly observed. Indeed, the cross-sectional forecasts of future investment growth depend on empirical specifications. In this subsection, I explore several alternative formulations for the expected investment growth factor.

The expected investment growth factor remains robust when I combine mechanically the log of Tobin's q, gross profitability, changes in return on assets, and prior 11-month returns. For each portfolio formation month, I create a composite score that aggregates the four predictors by equally weighting a firm's percentage rankings across these variables, each realigned to yield a positive slope in forecasting returns. R_{Eg}^{C} is an alternative expected investment growth factor derived from an independent two-way (2 x 3) monthly sort on size and the composite score. As shown in Table 3.6, the alternative factor earns an average return of 0.49% per month (t = 2.65). The HXZq model yields an alpha of 0.65% (t = 3.98). The alternative factor is highly correlated with the benchmark expected investment growth factor, R_{Eg}, with a correlation coefficient of 0.87 (p = 0.00). The HXZq model augmented with R_{Eg} subsumes R_{Eg}^{C}, resulting in an alpha of 0.20% (t = 1.78). Similarly, the HXZq model augmented with R_{Eg}^{C} also subsumes R_{Eg}, yielding an alpha of 0.19% (t = 1.43).

The expected investment growth factor remains robust when using alternative dependent variables in the cross-sectional forecasts of future investment growth. Given that firm-level investment-to-assets ratio (I/A, net total asset growth) is not always positive, I forecast future investment-to-asset changes, d^{τ}I/A, in which τ = 1 and τ = 2. Alternatively, I forecast τ-year-ahead changes in the natural logarithm of gross total asset growth, $d^{\tau}\log(1+I/A)$, and τ-year-ahead changes in net non-cash asset growth, $d^{\tau}I/A_{NCA}$. R_{Eg}^{L} and R_{Eg}^{NCA} are alternative expected investment growth factors formed by interacting $E[d^{1}\log(1+I/A)]$ and $E\left[d^{1}\,I/A_{NCA}\right]$ separately with size in 2 x 3 monthly sorts. As shown in Table 3.7.2, R_{Eg}^{L} and R_{Eg}^{NCA} earn an average return of 0.37% (t = 2.09) and 0.39% (t = 1.88), respectively, with HXZq model alphas of 0.70% (t = 3.82) and 0.71% (t = 3.01). Their correlations with the benchmark expected investment growth factor are 0.99 and 0.96, respectively. Both correlations are highly statistically significant.

The expected investment growth factor remains robust when using alternative predictors in the cross-sectional forecasts of future investment growth. I begin by substituting gross profitability with operating profitability. Using operating profitability does not affect the results. Panel A of Table 3.8.1 shows that its slope, 1.130 (t = 6.53), is highly significantly positive in forecasting one-year-ahead investment-to-asset changes. The resulting expected investment growth factor, R_{Eg}^{Opp}, has an average return of 0.38% (t = 2.02), with a HXZq alpha of 0.68% (t = 3.40) and a correlation of 0.97 with R_{Eg}. Replacing the changes in return on assets with the changes in return on equity generates a slope of 0.167 (t = 1.77) in the predictive regression. The corresponding factor, R_{Eg}^{dRoe}, earns an average return of 0.36% (t = 2.05), with a HXZq alpha of 0.70% (t = 3.61). The correlation between R_{Eg}^{dRoe} and R_{Eg} is 0.99. If prior 11-month returns are substituted with abnormal returns, the slope remains positive at 0.097 (t = 6.51). The resulting factor, $R_{Eg}^{Aret^{11}}$, earns an average return of 0.32% (t = 1.75), with a HXZq alpha of 0.66% (t = 3.47). Its correlation with R_{Eg} is 0.95.

The expected investment growth factor remains robust when augmenting with additional predictors in the cross-sectional forecasts of future investment growth. Barro (1990) forecasts aggregate investment growth using a range of predictors, including the logarithm of Tobin's q growth, the first difference of the ratio of after-tax corporate profits to sales, gross national product growth, prior one-year stock market returns, and lagged aggregate investment growth. Since my benchmark specification already includes the logarithm of Tobin's q and prior 11-month returns, I have only incorporated non-conflicting variables from Barro's model to avoid multicollinearity. Specifically, I substitute the growth of gross national product with sales growth, which is more suitable for forecasting firm-level investment growth. Additionally, I include two variables representing current and past investment growth: the current and the one-year-lagged investment-to-asset changes.

Augmenting the first difference of the ratio of after-tax corporate profits to sales, $dNis$, produces similar results. As shown in Panel A of Table 3.9.1, its slope in the predictive regression of one-year-ahead investment-to-asset changes is significantly positive, 0.048 (t =

2.79). Table 3.9.2 further shows that the corresponding expected investment growth factor, R_{Eg}^{dNis}, earns a premium of 0.44% (t = 2.35), with a HXZq alpha of 0.79% (t = 3.77). Its correlation with R_{Eg} is 0.97. In contrast to $dNis$, the annual growth rate of sales, $gSale$, yields a negative slope of -0.154 (t = -10.41) in the predictive regression. The factor premium decreases to 0.20% (t = 1.91), with a HXZq alpha of 0.51% (t = 3.91). R_{Eg}^{gSale} has a correlation of 0.93 with R_{Eg}. Adding the current investment-to-asset changes, $lag0d^1\,I/A$, generates a much negative slope of -0.394 (t = -22.19). The factor premium sinks to 0.13% (t = 1.20), with a HXZq alpha of 0.23% (t = 2.13). The correlation between $R_{Eg}^{lag0d^1I/A}$ and R_{Eg} is only 0.73.

The large negative slope of the current investment-to-asset changes may be driven by a mechanical relationship in the predictive regression, as the current investment-to-asset ratio now appears on both sides of the regression.[36] Indeed, the R^2 surges to 0.261 from 0.084 in the benchmark specification. Such a high R^2 is somewhat suspicious in the context of predictive regressions. Moreover, when I add the one-year-lagged investment-to-asset changes, $lag1d^1\,I/A$, the slope remains negative but sharply increase to -0.020 (t = -2.08), and the R^2 plunges to 0.091. The factor premium rises to 0.25% (t = 2.01), with a HXZq alpha of 0.65% (t = 3.16). The correlation between $R_{Eg}^{lag1d^1I/A}$ and R_{Eg} increases to 0.95. I emphasize the robustness of these results, given that it is a convention in empirical finance to impose a time lag between a dependent variable and its lagged value in a predictive regression to avoid any mechanical relationships.[37]

[Insert table 3.6]

[Insert table 3.7.1]

[Insert table 3.7.2]

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[36] The large negative slope of sales growth may also be driven by the same mechanical relationship present in the predictive regression. Indeed, a R^2 of 0.185 in the predictive regression is suspiciously high, suggesting potential multicollinearity or model specification issues. In untabulated results, I observe a highly significant positive contemporaneous relationship between sales growth and investment-to-asset changes. This indicates that sales growth may be capturing similar information as investment growth, effectively serving as a reincarnation of investment growth.

[37] For example, when measuring momentum, it is standard practice to impose a one-month lag between prior and subsequent returns to avoid the bid-ask bounce effect caused by market microstructure frictions.

[Insert table 3.8.1]

[Insert table 3.8.2]

[Insert table 3.9.1]

[Insert table 3.9.2]

3.4 An Augmented Investment-Based Factor Model

3.4.1 A REIT-Based HMXZq^5 model

Hou et al. (2015) base their q-factor model on the static investment CAPM. Following their framework, Bond and Xue (2017) construct an investment factor and a return on equity factor to form an investment-based three-factor model for REITs. Building on the dynamic investment CAPM, Hou et al. (2021) expand the q-factor model by incorporating an expected investment growth factor, resulting in a q^5 model (HMXZq^5). In line with this approach, I apply the constructed expected investment growth factor to formulate a REIT-based HMXZq^5 model.[38] Given the presence of the expected investment growth factor, the augmented investment-based factor model is expected to provide superior information regarding the variation in the cross section of expected REIT returns.

In the model, the expected excess return of a REIT is described by its loadings on the expected premium of five factors: the market factor, R_{Mkt}, the size factor, R_{Me}, the investment factor, $R_{I/A}$, the return on assets factor, R_{Roa}, and the expected investment growth factor, R_{Eg},

$$E\left[R_i - R_f\right] = \beta^i_{Mkt}E[R_{Mkt}] + \beta^i_{Me}E[R_{Me}] + \beta^i_{I/A}E\left[R_{I/A}\right] + \beta^i_{Roa}E[R_{Roa}] + \beta^i_{Eg}E\left[R_{Eg}\right]$$

(3.4),

in which $E[R_{Mkt}]$, $E[R_{Me}]$, $E\left[R_{I/A}\right]$, $E[R_{Roa}]$, and $E\left[R_{Eg}\right]$ are the expected premium on the market, size, investment, return on assets, and expected investment growth factors, respectively, and β^i_{Mkt}, β^i_{Me}, $\beta^i_{I/A}$, β^i_{Roa}, and β^i_{Eg} the corresponding factor loadings. Appendix 3.1 details the factor construction and the factor model regression specification.

In Table 3.10, I perform time-series HMXZq^5 factor-model regressions for each expected investment growth quintile. At 1-year horizon, the model generates an alpha of 0.21% (t = 1.74)

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[38] Alternatively, I augment the Bond and Xue (2017) investment-based three-factor model with the expected investment growth factor, R_{Eg}, to create an investment-based four-factor model for REITs (BX4). While this alternative model produces similar results, I argue that it is more appropriate to add R_{Eg} to HXZq rather than to BX3. This preference stems from the fact that R_{Eg} is derived from a two-way (2 x 3) monthly sort on size and expected one-year-ahead investment-to-asset changes, aligning with the construction of $R_{I/A}$ and R_{Roa} in HXZq. In contrast, BX3 employs alternative versions of $R_{I/A\_}$ and $R_{Roa\_}$, which are based on a two-way (3 x 3) sort on investment and return on assets and do not include a size factor.

for the high-minus-low quintile. For reference, the high-minus-low alpha is 0.98% (t = 3.43) in the HXZq. The reduction in alpha is attributed to the large loading of the expected investment growth factor, 1.16 (t = 21.39). The mean absolute alpha from the low to high quintile is just 0.10%, and the GRS test fails to reject the HMXZq^5 (p = 0.18). At 2-year horizon, the high-minus-low alpha is 0.23% (t = 2.10), a sharp decrease from 1.00% (t = 3.75) in the HXZq. The expected investment growth factor loading remains at 1.16 (t = 17.76). The mean absolute alpha across the quintiles stays at 0.10%. According to the GRS test (p = 0.43), the alphas across the quintiles are jointly zero. These results demonstrate that although the expected investment growth factor is formed based on expected one-year-ahead investment-to-asset changes, it exhibits strong explanatory power for the cross-sectional return patterns associated with expected two-year-ahead investment-to-asset changes.

[Insert Table 3.10]

3.4.2 Spanning Tests

The dynamic investment CAPM underpins the HMXZq^5 as a factor pricing model in the cross-section of expected REIT returns. However, despite the differences in theoretical foundation between the HMXZq^5 and the FF6, they are closely related in empirical terms. Additionally, the ongoing debate regarding the integration (segmentation) of REIT returns with (from) common stock returns questions the choice between REIT-based versus common stock-based factor models. To address these concerns, in this subsection, I compare factor models on economic grounds using spanning tests, which have been employed by Fama and French (2015 and 2018), Barillas and Shanken (2017 and 2018), and Hou et al. (2019). Barillas and Shanken (2017 and 2018) posit that for models with traded factors, the crucial aspect for model comparison is the degree to which the alphas of the factors excluded from a nested model are jointly zero when regressed on the nested model factors.

In Subsubsection 3.4.2.1, I detail the spanning tests of the HMXZq^5 against the FF6. I examine whether the HMXZq^5 is subsumed by the FF6, and vice versa. In the following subsubsection 3.4.2.2 and 3.4.2.3, I compare the REIT-based factor models, HMXZq^5 and FF6, with four common stock-based factor models: the Fama and French (2015) five-factor model (FF5*), Fama and French (2018) six-factor model (FF6*), Hou et al. (2015) q-factor model (HXZq*), and Hou et al. (2021) q^5 model (HMXZq^5*). My primary focus is to determine whether the HMXZq^5 and FF6 are subsumed by the FF5*, FF6*, HXZq* and HMXZq^5*.

3.4.2.1 HMXZq^5 versus FF6

In Panel A of Table 3.11, I regress the size and return on asset factors, R_{Me} and R_{Roa}, from the HXZq model, and the expected investment growth factor, R_{Eg}, from the HMXZq^5 model, on the FF5 and FF6 models. The size factor earns an average return of 0.19% (t = 1.58). Both the FF5 and the FF6 account for the R_{Me} premium, with alphas of -0.04% (t = -2.83) and -0.01% (t = -0.34), respectively, due to the presence of SMB5 and SMB6. In an untabulated result, the investment factor, $R_{I/A}$, in the HXZq model earns an average return of 0.10% (t = 0.68). Given that both $R_{I/A}$ and R_{CMA} are constructed from sorts on size and I/A, the $R_{I/A}$ premium is fully subsumed by the FF5 and FF6 models.

The return on asset factor earns an average return of 0.21% (t = 0.99). Due to the presence of the operating profitability factor, R_{RMW}, the FF5 model explains the R_{Roa} premium, with an alpha of 0.01% (t = 0.07). The FF6 model yields similar results. Although R_{Roa} is constructed from sorts on the latest known quarterly earnings, whereas R_{RMW} is based on sorts from the staler operating profitability from the most recent fiscal year end, R_{Roa} is not more powerful than R_{RMW}. The expected investment growth factor, R_{Eg}, earns an average return of 0.34% (t = 2.01). The FF5 model does not reduce the R_{Eg} premium, with an alpha of 0.54% (t = 3.90). The FF6 model shrinks the alpha to 0.36%, aided by the R_{UMD} loading of 0.34 (t = 5.59), but the alpha remains highly significant (t = 2.75).

In Panel B of Table 3.11, I regress the size, value, operating profitability, and momentum factors (R_{SMB} , R_{HML} , R_{RMW} , and R_{UMD}) from the FF6 model on the HXZq and HMXZq^5 models. The R_{SMB6} factor earns an average return of 0.19% (t = 1.65), with alphas of 0.04% (t = 2.62) from the HXZq model and 0.02% (t = 0.93) from the HMXZq^5 model. The size factor, R_{Me}, provides substantial explanatory power, yielding regression R^2 values of 0.98. The R_{HML} factor has an average return of 0.08% (t = 0.54), and its alphas for the HXZq and HMXZq^5 models are 0.06% (t = 0.41) and 0.15% (t = 0.91), respectively. The investment factor, $R_{I/A}$, primarily contributes to the explanatory power, with factor loadings of 0.51 (t = 3.74) for the HXZq model and 0.51 (t = 3.50) for the HMXZq^5 model.

The R_{RMW} factor has an average return of 0.30% (t = 1.64). It remains significant after controlling for the HXZq factors, with an alpha of 0.37% (t = 1.83). The R_{Roa} loading is statistically significant (t = 6.20) with a magnitude of 0.53. The HMXZq^5 model further reduces the alpha of R_{RMW} to 0.17% (t = 0.90), aided by both the return on asset and expected investment growth factors. The momentum factor, R_{UMD}, earns an average return of 0.22% (t = 1.01). The HXZq model yields an alpha of 0.48% (t = 3.07), despite a substantial R_{Roa} loading of 0.53 (t = 3.87). In contrast, the HMXZq^5 model shrinks the momentum factor alpha to 0.05% (t = 0.35). The explanatory power is largely provided by the expected investment growth factor, which has a large and highly significant factor loading of 0.65 (t = 7.37).

In Panel C of Table 3.11, I perform the GRS test on the null hypothesis that the alphas of the key HMXZq^5 factors in the FF5 and FF6 factor-model regressions are jointly zero. Specifically, for the null hypothesis that the alphas of the return on asset and expected investment growth factors are jointly zero, the GRS statistic is 5.59 (p-value = 0.00) for the FF5 model and 3.31 (p-value = 0.04) for the FF6 model. Therefore, neither the FF5 nor the FF6 can fully explain the HMXZq^5 factors.

Additionally, I conduct the GRS test on the null hypothesis that the alphas of the key FF6 factors in the HXZq and HMXZq^5 factor-model regressions are jointly zero. For the null hypothesis that the alphas of the value, operating profitability, and momentum factors are jointly zero, the GRS statistic is 3.87 (p-value = 0.01) for the HXZq model and 0.97 (p-value = 0.41) for the HMXZq^5model. Thus, although the FF6 factors survive in the HXZq model, they are subsumed by the HMXZq^5 model. These results suggest that the HMXZq^5 model contains valuable additional information about expected REIT return variation in the cross section that is not captured by the FF6 model.

[Insert Table 3.11]

3.4.2.2 HMXZq^5 versus FF5*, FF6*, HXZq*, and HMXZq^5*

In Panel A of Table 3.12, I regress the HMXZq^5 factors on the FF5* and FF6* models. The REIT-based market factor, R_{Mkt}, from the HMXZq^5 model earns an average return of 0.81% (t = 2.63). Both the FF5* and FF6* models explain this market factor premium, with alphas of 0.09% (t = 0.43) and 0.12% (t = 0.58), respectively. The explanatory power largely stems from the common stock-based market factor, R_{MKT^*}, which has factor loadings of 0.79 (t = 6.13) and 0.75 (t = 6.59) for the FF5* and FF6* models, respectively. Similarly, both models account for the REIT-based size factor, R_{Me}, with alphas of 0.08% (t = 0.70) for the FF5* and 0.16% (t = 1.35) for the FF6*, primarily due to the presence of the common stock-based size factors, R_{SMB5^*} and R_{SMB6^*}.

The FF5* model yields an alpha of -0.05% (t = -0.32) for the REIT-based investment factor, $R_{I/A}$. The common stock-based investment factor, R_{CMA^*}, does not contribute significantly, exhibiting a factor loading of virtually zero (t = 0.05). Similarly, the FF6* model produces a negligible alpha of -0.06% (t = -0.35) for $R_{I/A}$, with an insignificant R_{CMA^*} loading. While the FF5* and FF6* models explain the REIT-based market, size, and investment factors, they do not fully account for the return on asset factor, R_{Roa}. The alphas for R_{Roa} are 0.41% (t = 2.63) for the FF5* and 0.33% (t = 1.82) for the FF6*. The common stock-based operating profitability factor, R_{RMW^*}, yields small and insignificant loadings of 0.19 (t = 1.57) for the FF5* and 0.14 (t = 1.18) for the FF6*, respectively. Additionally, the REIT-based expected investment growth factor, R_{Eg}, persists in both models, with alphas of 0.59% (t = 3.08) for the FF5* and 0.48% (t = 2.02) for the FF6*.

In Panel B, I use the HXZq* and HMXZq^5* models to explain the HMXZq^5 factors. For the R_{Mkt} factor, the HXZq* alpha is only 0.08% (t = 0.29), and the HMXZq^5* alpha is virtually zero (t = -0.01), supported by a large R_{Mkt^*} loading of 0.80 (t = 5.39) and 0.82 (t = 4.96), respectively. The R_{Me} factor survives the HXZq* but not the HMXZq^5*, with an alpha of 0.19% (t = 1.42) and 0.24% (t = 2.00), respectively. The R_{Me^*} factor has limited explanatory power, with a loading of around 0.24 (t = 2.64) and 0.23 (t = 2.52), respectively. The HXZq* and HMXZq^5* alphas for the $R_{I/A}$ factor are -0.05% (t = -0.30) and 0.09% (t = 0.64), respectively, with most of the explanatory power coming from the R_{I/A^*} factor, which has a loading of 0.36 (t = 4.22) and 0.34 (t = 4.91), respectively.

The HXZq* explains the R_{Roa} factor, with an alpha of 0.23% (t = 1.20), aided by a R_{Roe^*} loading of 0.52 (t = 3.76). The HMXZq^5* further reduces the alpha to 0.13% (t = 0.81), and the R_{Roe^*} factor yields a smaller factor loading of 0.46 (t = 2.88) due to the presence of the R_{Eg^*} factor. The R_{Eg} factor survives the regressions on the HXZq* factors, with an alpha of 0.51% (t = 2.66). Although the R_{Roe^*} factor loading is significant (t = 1.85), its magnitude is only 0.36. The HMXZq^5* reduces the alpha further to 0.36% (t = 1.73), but the magnitude remains above the R_{Eg} factor premium. The R_{Eg^*} factor provides a rather limited amount of explanatory power, with a factor loading of 0.26 (t = 1.64). This result indicates that the factor pricing information in expected investment growth differs between common stocks and REITs.

In Panel C of Table 3.12, I perform the GRS tests on the null hypothesis that the alphas of the HMXZq^5 factors are jointly zero across the FF5*, FF6*, HXZq* and HMXZq^5* models. Specifically, for the null hypothesis that the REIT-based market, size, investment, return on assets, and expected investment growth factors are jointly zero, the GRS statistic is 2.89 (p-value = 0.02) for the FF5* model, 2.72 (p-value = 0.02) for the FF6* model, 3.21 (p-value = 0.01) for the HXZq* model, and 2.12 (p-value = 0.06) for the HMXZq^5* model. Therefore, the HMXZq^5 model is not subsumed by the FF5*, FF6*, HXZq*, and HMXZq^5* models. This result further implies a difference in the cross-sectional expected returns captured by HMXZq^5 between REITs and common stocks.

[Insert Table 3.12]

3.4.2.3 FF6 versus FF5*, FF6*, HXZq*, and HMXZq^{5}*

In Panel A of Table 3.13, I regress the FF6 factors on the FF5* and FF6* models. Both common stock-based factor models explain the REIT-based size factor, R_{SMB6}, in the FF6, with an alpha of 0.10% (t = 0.93) for the FF5* and 0.16% (t = 1.49) for the FF6*, respectively. The common stock-based size factors, R_{SMB5^*} and R_{SMB6^*}, are the main sources of explanatory power for the R_{SMB6}, exhibiting a factor loading of 0.37 (t = 5.20) and 0.41 (t = 6.37), respectively. The REIT-based value factor, R_{HML}, does not survive the regression on the FF5* and FF6*, with resulting alphas both close to zero. The common stock-based value factor, R_{HML^*}, provides the explanatory power, albeit with small factor loadings slightly above 0.20 (t-values above 2.50).

The REIT-based investment factor, R_{CMA}, is also explained by the two models; however, the common stock-based investment factor, R_{CMA^*}, has nearly zero factor loadings. In contrast, the FF5* and FF6* cannot fully explain the REIT-based operating profitability factor, R_{RMW}, yielding an alpha of 0.41% (t = 2.20) and 0.38% (t = 2.00), respectively. The common stock-based operating profitability factor, R_{RMW^*}, has limited power to explain the R_{RMW}, with a factor loading of 0.25 (t = 3.67) for the FF5* and 0.23 (t = 2.61) for the FF6*, respectively. For the REIT-based momentum factor, R_{UMD}, the FF5* model yields an alpha of 0.53% (t = 2.62). With the inclusion of the common stock-based momentum factor, R_{UMD^*}, the FF6* reduces the alpha to 0.28% (t = 1.16). The factor loading of the R_{UMD^*} is 0.63 (t = 3.39).

In Panel B of Table 3.13, I regress the FF6 factors on the HXZq* and HMXZq5* models. While the HXZq* yields an alpha of 0.20% (t = 1.55) for the REIT-based size factor, R_{SMB6}, the HMXZq^{5}* model raises the alpha to 0.25% (t = 2.06). The common stock-based size factors, R_{Me^*}, make a slight contribution to the models' explanatory power for the R_{SMB6}, with a factor loading of 0.23 (t = 2.92) for the HXZq* and 0.22 (t = 2.77) for the HMXZq^{5}*, respectively. Both models explain the REIT-based value factor, R_{HML}, with a alpha of 0.06% (t = 0.39) for the HXZq* and 0.16% (t = 0.95) for the HMXZq^{5}*. The R_{I/A^*} factor is the main source of explanatory power, with a factor loading of 0.23 (t = 2.65) for the HXZq* and 0.22 (t = 2.37) for the HMXZq^{5}*, respectively.

The REIT-based investment factor, R_{CMA}, is also explained by the two models. The common stock-based investment factor, R_{I/A^*} has factor loadings of around 0.35 (t above 4.22).

Conversely, both models fail to explain the REIT-based operating profitability factor, R_{RMW}, yielding an alpha of 0.46% (t = 2.25) for the HXZq* and 0.37% (t = 1.79) for the HMXZq^{5}*. The common stock-based return on equity factor, R_{Roe^*}, has limited explanatory power, with a factor loading of 0.23 (t = 2.25) for HXZq* and 0.18 (t = 1.37) for the HMXZq^{5}*. For the REIT-based momentum factor, R_{UMD}, both models successfully subsume it, with an alpha of 0.24% (t = 1.01) for the HXZq* and 0.15% (t = 0.73) for the HMXZq^{5}*. This is aided by a large R_{Roe^*} factor loading of 0.80 (t = 2.52) for the HXZq* and 0.74 (t = 1.91) for the HMXZq^{5}*. The R_{Eg^*} does not significantly contribute to explaining the R_{UMD}, exhibiting an insignificant factor loading of 0.16 (t = 0.53).

In Panel C of Table 3.13, I perform the GRS tests on the null hypothesis that the alphas of the FF6 factors are jointly zero across the FF5*, FF6*, HXZq* and HMXZq^{5}* models. Specifically, for the null hypothesis that the REIT-based market, size, value, investment, operating profitability, and momentum factors are jointly zero, the GRS statistic is 1.90 (p-value = 0.08) for the FF5* model, 1.76 (p-value = 0.11) for the FF6* model, 2.26 (p-value = 0.04) for the HXZq* model, and 1.60 (p-value = 0.15) for the HMXZq^{5}* model. Therefore, the FF6 model is not subsumed by the FF5* and HXZq* models but is subsumed by the FF6* and HMXZq^{5}* models. This result suggests that there is no significant difference in the cross-sectional expected returns captured by FF6 between REITs and common stocks.

[Insert Table 3.13]

3.4.2.4 Correlation Matrix

To shed further light on the relationship between model factors, Table 3.14 presents their correlation matrix. The REIT-based market factor, R_{Mkt}, is moderately correlated with the common stock-based market factors in the HMXZq^5* and FF6*, R_{Mkt^*} and R_{MKT^*}, with a correlation of 0.60. The REIT-based size factors in the HMXZq^5 and FF6 models, R_{Me} and R_{SMB6}, are nearly identical, exhibiting a correlation of 0.99. Additionally, the R_{Me} factor has a moderate negative correlation of -0.60 with the momentum factor, R_{UMD}, in the FF6. The correlation between R_{Me} and R_{Me^*} is 0.40, while the correlation between R_{SMB6} and R_{SMB6^*} is 0.43.

The REIT-based investment factors in the HMXZq^5 and FF6, $R_{I/A}$ and R_{CMA}, are essentially identical. The $R_{I/A}$ factor is moderately correlated with the value factor, R_{HML}, in the FF6, with a correlation of 0.51. Furthermore, the $R_{I/A}$ exhibits a low correlation of 0.23 and 0.15 with the common stock-based investment factors in the HMXZq^5* and FF6*, R_{I/A^*} and R_{CMA^*}, respectively. The REIT-based return on asset factor, R_{Roa}, is moderately correlated with the operating profitability factor and the momentum factor in the FF6, with a correlation of 0.69 and 0.56, respectively. Additionally, the R_{Roa} has a correlation of 0.57 and 0.38 with the common stock-based return on equity factor and the operating profitability factor in the HMXZq^5* and FF6*, respectively.

The REIT-based expected investment growth factor, R_{Eg}, in the HMXZq^5 has a moderate correlation of 0.68 with the operating profitability factor and a high correlation of 0.77 with the momentum factor in the FF6. Conversely, it has a low correlation of 0.38 with the common stock-based expected investment growth factor, R_{Eg^*}, in the HMXZq^5*. Its correlation with the common stock-based operating profitability factor, R_{RMW^*}, in the FF6* is 0.07, which is not statistically different from zero, but it shows a moderate correlation of 0.43 with the momentum factor, R_{UMD^*}.

[Insert Table 3.14]

3.4.3 Stress-Testing Factor Models

In this subsection, I stress-test factor models using a set of testing quintiles. This analysis complements the spanning tests conducted earlier by providing an alternative method for comparing factor models (Hou et al., 2015; Fama and French, 2016; Hou et al., 2021). I construct testing portfolios based on four prominent REIT return predictors compiled by Bond and Xue (2017): momentum, standardized unexpected earnings, idiosyncratic volatility, and share turnover. Subsequently, I conduct an empirical horse race involving eight REIT-based factor models: the CAPM, FF3, Carhart4, FF5, FF6, HXZq, BX3, and HMXZq^5.[39] Presumably the HMXZq^5 provides superior information regarding the cross-sectional expected REIT returns, the model would outperform the other in explaining the testing quintiles.

3.4.3.1 Price Momentum

Table 3.15 shows that the high-minus-low momentum quintile earns an average return of 0.54% (t = 1.80). The CAPM fails to explain this quintile, exhibiting an alpha of 0.78% (t = 2.72). Out of the five quintiles, three have significant alphas. The mean absolute alpha across the quintiles is 0.22%. With a p-value of 0.06, the GRS test rejects the CAPM. The FF3 yields an even higher alpha of 0.88% (t = 2.97) for the high-minus-low quintile. Except for quintiles 2 and 3, the remaining quintiles have significant alphas. The mean absolute alpha increases to 0.26%, and the GRS test rejects the FF3 (p-value = 0.02). The Carhart4 reduces the high-minus-low alpha to 0.31% (t = 0.92), aided by a large momentum factor loading of 0.75 (t = 2.75). Although quintiles 2 and 4 still have significant alphas, the mean absolute alpha reduces to 0.16%, and the GRS test does not reject the Carhart4 (p-value = 0.12).

Adding the investment and operating profitability factors to the FF3 does not significantly improve the model's explanatory power for the high-minus-low quintile, which has an alpha of 0.73% (t = 2.98). Across the quintiles, three have significant alphas. Nevertheless, the FF5 reduces the mean absolute alpha to 0.19% and survives the GRS test (p-value = 0.13). As

[39] In untabulated results, I also conduct an empirical horse race using seven common stock-based factor models: the CAPM*, FF3*, Carhart4*, FF5*, FF6*, HXZq*, and HMXZq^5*. Compared to REIT-based factor models, the corresponding common stock-based factor models are less effective in explaining the quintiles sorted on momentum, standardized unexpected earnings, idiosyncratic volatility, and share turnover. These results are consistent with the findings from the spanning tests that compared to REIT-based factor models, the common stock-based factor models provide far less explanatory power for REIT-based factors from non-nested models.

expected, adding the momentum factor to the FF5 further reduces the high-minus-low alpha to 0.33% (t = 0.92), with only the alpha for quintile 2 remaining significant. The FF6 shrinks the mean absolute alpha to only 0.14%, and the model is not rejected by the GRS test (p-value = 0.27).

Like the FF5, the HXZq exhibits similar explanatory power for the high-minus-low quintile, yielding an alpha of 0.70% (t = 2.51), with two of the five quintiles having significant alphas. However, unlike the FF5, the HXZq produces a higher mean absolute alpha of 0.22%, and the model is rejected by the GRS test (p-value = 0.03). Utilizing the alternative investment and return on asset factors, the BX3 reduces the high-minus-low alpha to 0.63% (t = 2.13), with significant alphas in quintile 4 and 5. The mean absolute alpha decreases to 0.20%, but the model does not survive the GRS test (p-value = 0.08).

The HMXZq^5 outperforms the FF6 in explaining the momentum quintile, with a high-minus-low alpha of only 0.05% (t = 0.22). The expected investment growth factor primarily drives the explanatory power, exhibiting a loading of 0.97 (t = 6.02), which is slightly higher than the momentum factor loadings in the Carhart4 and the FF6. Across quintiles 1 to 5, none have significant alphas, and the expected investment growth factor loading increases monotonically from -0.53 (t = -2.91) to 0.44 (t = 6.68). The mean absolute alpha across the quintiles is merely 0.08%, and the GRS test does not reject the model (p-value = 0.69). Moving from quintile 1 to 5, the average expected one-year-ahead investment-to-asset changes increase from -4.68% (t = -5.80) to 1.45% (t = 2.08), and the expected two-year-ahead changes increase from -6.59% (t = -5.37) to 1.19% (t = 1.03). Intuitively, momentum winners have higher future investment growth expectations and load more heavily on the expected investment growth factor than momentum losers.

[Insert Table 3.15]

3.4.3.2 Standardized Unexpected Earnings

Table 3.16 shows that the high-minus-low quintile formed on standardized expected earnings earns a premium of 0.30% (t = 3.24). The high-minus-low premium is not captured by the CAPM, resulting in an alpha of 0.44% (t = 3.50). Quintiles 1, 4, and 5 also yield significant an alpha. The mean absolute alpha across the quintiles is 0.17%, and the CAPM does not pass the GRS test (p-value = 0.05). In the FF3, the high-minus-low alpha rises to 0.53% (t = 3.97), and the alphas for quintiles 1, 4, and 5 remain significant. The mean absolute alpha increases slightly to 0.18%, and the GRS test rejects the FF3 (p-value = 0.01). The Carhart4 reduces the high-minus-low alpha to 0.27% (t = 1.98). Although the alphas for quintiles 4 and 5 remain significant, the alpha for quintile 1 becomes insignificant. The mean absolute alpha falls to 0.12%, and with a p-value of 0.11, the GRS test does not reject the Carhart4.

Compared to the Carhart4, the FF5 performs slightly worse. The high-minus-low alpha increases to 0.35% (t = 2.99), and the alpha for quintile 1 becomes significant again. The mean absolute alpha grows to 0.14%, and the GRS test does not reject the FF5 (p-value = 0.09). With both the operating profitability and momentum factors, the FF6 reduces the high-minus-low alpha to 0.21%, but it remains statistically significant (t = 1.71). The alphas for quintiles 4 and 5 remain statistically significant. The mean absolute alpha is 0.10%, and the model survives the GRS test (p-value = 0.22).

The HXZq produces a high-minus-low alpha of 0.35% (t = 2.34), which is close to that in the FF5. Compared to the operating profitability factor in the FF5, the return on asset factor in the HXZq yields a higher loading of 0.34 (t = 3.79) in explaining the high-minus-low quintile. Unlike the FF5, the HXZq yields an insignificant alpha for quintile 1. The mean absolute alpha is 0.14%, and the model does not pass the GRS test (p-value = 0.04). Using the alternative investment and return on asset factors, the BX3 does not show much improvement in explaining the high-minus-low quintile, with an alpha of 0.37% (t = 2.53), and it yields a significant alpha for quintile 1. Despite the mean absolute alpha rising to 0.15%, the model is not rejected by the GRS test (p-value = 0.11).

The HMXZq^5 successfully explains the high-minus-low quintile, producing an alpha of 0.25%, which is statistically insignificant (t = 1.60). Across the quintiles, two have significant alphas. The mean absolute alpha is 0.12%, and the GRS test cannot reject the model (p-value = 0.28).

Moving from quintiles 1 to 5, the expected investment growth factor loading grows from 0.03 (t = 0.39) to 0.17 (t = 3.35). Accordingly, the average expected future investment-to-asset changes increase from -2.64% (t = -3.62) to -0.91% (t = -1.30) at 1-year horizon and from -5.10% (t = -4.13) to -0.98% (t = -0.88) at 2-year horizon. Intuitively, compared with earnings momentum losers, earnings momentum winners expect higher future investment growth and load more heavily on the expected investment growth factor.

[Insert Table 3.16]

3.4.3.3 Idiosyncratic Volatility

Table 3.17 presents the properties of idiosyncratic volatility quintiles. The high-minus-low quintile earns an average return of -0.34%, but this negative premium is statistically insignificant (t = -0.89). The CAPM yields a high-minus-low alpha of -0.68% (t = -1.93) and significant alphas in quintile 1 and 3. The mean absolute alpha across the quintiles is 0.22%, and the CAPM is rejected by the GRS test (p-value = 0.03). In the FF3, the high-minus-low alpha decreases further to -0.88% (t = -2.35). Across the quintiles, all except quintile 4 generate significant alphas. The mean absolute alpha increases to 0.28%, and the GRS test strongly rejects the FF3 (p-value = 0.00). The Carhart4 explains the high-minus-low quintile, producing an alpha of -0.25% (t = -0.83). The momentum factor provides the primary explanatory power, with a substantial loading of -0.78 (t = -5.48). Across the quintiles, only quintile 1 and quintile 3 have a significant alpha. The mean absolute alpha reduces to 0.11%, but the model does not survive the GRS test (p-value = 0.05).

The FF5 further increases the high-minus-low alpha to -0.16% (t = -0.59). The operating profitability factor is the main source of explanatory power, with a loading of -1.15 (t = -5.67). The alphas for quintiles 1 and 3 remain significant in the FF5. The mean absolute alpha rises slightly to 0.13%, and the GRS test rejects the model (p-value = 0.08). In the FF6, the high-minus-low alpha turns positive at 0.17% (t = 0.63), aided by the negative loadings of the operating profitability factor (-0.92, t = -5.81) and the momentum factor (-0.60, t = -6.31). Despite the alphas for quintile 1 and 3 remaining statistically significant and the mean absolute alpha increasing slightly to 0.15%, the FF6 passes the GRS test (p-value = 0.11).

The HXZq is comparable to the Carhart4, yielding a high-minus-low alpha of -0.31% (t = -1.40). The explanatory power of the HXZq largely stems from the return on asset factor, with a loading of -1.18 (t = -5.51). The alphas for quintiles 1 and 3 are significant in the HXZq. The mean absolute alpha is 0.13%, and the GRS test rejects the model (p-value = 0.00). In the BX3, the high-minus-low alpha drops to -0.37% (t = -1.47). The alternative return on asset factor has a loading of -1.02 (t = -5.29), which is higher than the return on asset factor loading in the HXZq. The alphas for quintiles 1 and 3 remain statistically significant in the BX3. The mean absolute alpha rises to 0.15%, and the model is rejected by the GRS test (p-value = 0.02).

Augmenting the HXZq with the expected investment growth factor increases the high-minus-low alpha to -0.22% (t = -1.00). The augmented factor has a loading of -0.13 (t = -1.34), while the return on asset factor loading is -1.14 (t = -5.17). The alphas for quintiles 1 and 3 remain significant in the HMXZq^5. The mean absolute alpha drops to 0.11%, and the GRS test does not reject the model (p -value = 0.23). From quintile 1 to 5, the expected investment growth factor loading declines from 0.20 (t = 5.26) to 0.07 (t = 0.66). Accordingly, the average expected future investment-to-asset changes decline from -1.33% (t = -1.70) to -1.90% (t = -2.26) at 1-year horizon and from -2.61% (t = -2.85) to -2.74% (t = -1.85) at 2-year horizon. Intuitively, firms with low idiosyncratic volatility expect higher future investment growth and load more heavily on the expected investment growth factor than firms with high idiosyncratic volatility.

[Insert Table 3.17]

3.4.3.4 Share Turnover

Table 3.18 shows the properties of share turnover quintiles. The high-minus-low quintile has an average return of -0.61% (t = -2.13). The CAPM cannot explain this negative premium, leaving an alpha of -0.81% (t = -2.89). Across the quintiles, two have significant alphas. The mean absolute alpha is 0.26% in the CAPM, and the model is rejected by the GRS test (p-value = 0.00). In the FF3, the high-minus-low alpha decreases further to -0.84% (t = -3.11). The alphas for quintiles 1 and 3 remain statistically significant. The mean absolute alpha is 0.27% in the FF3, and the GRS test rejects the model (p-value = 0.00). Adding the momentum factor to the FF3 increases the high-minus-low alpha to -0.68% (t = -1.95). The Carhart4 produces significant alphas for quintile 1, 3, and 4. The mean absolute alpha across the quintiles reduces to 0.24%, but the model is rejected by the GRS test (p-value = 0.00).

Adding the investment and profitability factors to the FF3 increases the high-minus-low alpha to -0.66% (t = -2.95). The alphas for quintiles 1 and 3 remain statistically significant in the FF5. The mean absolute alpha falls to 0.21%, but the model still does not pass the GRS test (p-value = 0.00). The FF6 further rises the high-minus-low alpha to -0.57% (t = -1.89). The alpha for quintile 4 becomes statistically significant in the FF6. The mean absolute alpha across the quintiles further falls to 0.19%, but the GRS test rejects the FF6 (p-value = 0.00).

The HXZq yields an alpha of -0.64% (t = -2.24) for the high-minus-low quintile. The return on asset factor is the primary contributor to the model's explanatory power, with a loading of -0.49 (t = -3.06), which is much lower than the loading of the operating profitability factor in the FF5, -0.29 (t = -1.95). Across the quintiles, three have significant alphas in the HXZq. The mean absolute alpha is 0.24%, and the GRS test rejects the model (p-value = 0.00). Using the alternative investment and return on asset factors, the BX3 yields a high-minus-low alpha of -0.67% (t = -2.32). The alternative return on asset factor generates a loading of -0.54 (t = -2.99) in the BX3, delivering the model's explanatory power. The alphas for quintiles 1, 3, and 4 remain statistically significant. The mean absolute alpha is 0.23%, and the BX3 fails to survive the GRS test (p-value = 0.00).

The HMXZq^5 explains the high-minus-low quintile, generating an insignificant alpha of -0.41% (t = -1.59). The model's explanatory power is largely due to the return on asset and expected investment growth factors, with a loading of -0.39 (t = -2.67) and -0.35 (t = -2.90), respectively.

While the alphas for quintiles 1 and 4 are statistically significant, the alpha for quintile 3 is insignificant. The mean absolute alpha across the quintiles shrinks sharply to 0.15%, but the model is still rejected by the GRS test (p-value = 0.01). Moving from quintile 1 to quintile 5, the expected investment growth factor loading declines monotonically from 0.32 (t = 6.74) to -0.04 (t = -0.29). Correspondingly, the average expected future investment-to-asset changes decline from -0.79% (t = -0.76) to -2.12% (t = -3.21) at 1-year horizon and from -2.36% (t = -1.95) to -2.85% (t = -2.16) at 2-year horizon. Intuitively, firms with lower share turnover expect higher future investment growth and load more heavily on the expected investment growth factor than firms with higher share turnover.

[Insert Table 3.18]

3.4.3.5 Overall Performance

In the spanning tests, the HMXZq^5 subsumes the FF6, but not vice versa. Consistent with these tests, the HMXZq^5 outperforms the FF6 in explaining the testing quintiles formed on the four prominent REIT return predictors: momentum, standardized unexpected earnings, idiosyncratic volatility, and share turnover. The HMXZq^5 successfully captures the high-minus-low quintiles for each predictor, producing statistically insignificant alphas, with an average high-minus-low alpha of 0.23%. In contrast, the FF6 explains the high-minus-low quintiles for momentum and idiosyncratic volatility but fails to capture those for standardized unexpected earnings and share turnover, resulting in a higher average high-minus-low alpha of 0.32%. Furthermore, compared to the FF6, the HMXZq^5 yields lower mean absolute alphas for the quintiles formed on momentum, idiosyncratic volatility, and share turnover, averaging 0.11% for the HMXZq^5 versus 0.14% for the FF6. The GRS test does not reject the HMXZq^5 when explaining the quintiles formed on momentum, standardized unexpected earnings, and idiosyncratic volatility. Overall, these results reaffirm that the HMXZq^5 contains superior information regarding the cross-sectional variation in expected REIT returns.

3.5 Economic Mechanism

3.5.1 An Alternative Risk-Based Explanation

The superior performance of the REIT-based HMXZq^5 in the spanning tests and stress-testing exercises is largely attributable to the presence of the expected investment growth factor. Given the important role of this factor, this subsection investigates the economic drivers behind the expected investment growth premium.

The Liu et al. (2009)model does not address the underlying mechanisms that drive the positive relationship between expected investment-to-asset growth and expected returns. According to the net present value rule of capital budgeting, Hou et al. (2021) suggest that if expected investment in the next period exceeds current investment, high discount rates are necessary to offset the expected high benefits of current investment, resulting in a low present value of new projects and thereby keeping current investment levels low. Li et al. (2021a and 2021b) provide a risk-based explanation, proposing that investment plan frictions induce an embedded leverage effect that amplifies firms' future cash flow risk, leading to a higher risk premium.[40]

I propose an alternative risk-based explanation that emphasizes the roles of operating and financial leverages. Operating and financial leverage effects generally refer to the risk amplification caused by fixed operating expenses and financial costs, respectively. Firms with a higher degree of operating and financial leverages face greater business risk. REITs are highly leveraged relative to industrial firms (Giacomini et al., 2017). Acquiring and/or developing more properties in the future is likely to increase the fixed costs for a REIT across various areas, including property management, maintenance, insurance, administrative expenses, and depreciation. Additionally, such acquisitions and/or development activities are also likely to increase a REIT's financial costs, including additional interest expenses, issuance costs for new debt or equity, increased principal repayments, and potential higher hedging and refinancing costs.

[40] Li et al. (2021a and 2021b) develop a two-period model with investment plan frictions, in which firms are endowed with an existing project and an investment option. A key assumption is that the investment plan is predetermined, irreversible, and not realized until the next period. Industrial firms rarely cancel their investment plans once they are initiated (Doms and Dunne, 1998; Ramey and Shapiro, 2001). As a result, expected investment is not exposed to the economic conditions in the next period, creating an embedded leverage effect that amplifies firms' future cash flow risk. The model predicts that firms with a high degree of investment plan frictions have higher risk premiums. However, this prediction may not apply to REITs, given the homogeneity of investment within the industry.

Given that cash flow shocks play a crucial role at firm level (Vuolteenaho, 2002), my conceptual argument abstracts from time-series variation in aggregate productivity, such as exogenous shocks to discount rates, and focuses on the economic mechanism in the cross-section. A positive shock to idiosyncratic productivity can create two competing effects on REITs' future investment growth expectations. On the one hand, higher productivity generates a positive cash flow effect, leading firms to expect higher future investment growth. On the other hand, higher expected future investment growth increases firms' future operating and financial leverages, resulting in higher future cash flow risk. The cash flow effect tend to dominate the discount rate effect, leading firms with a positive shock to cash flow to optimally expect higher future investment growth despite of the potentially higher cost of capital. I examine these two competing effects in the following subsections.

3.5.2 Future Profitability

Table 3.19 presents the time-series averages of future profitability across expected investment growth quintiles. I use two measures of profitability: sales growth and gross profit growth. The quintile with high expected one-year-ahead investment-to-asset changes exhibits an average one-year-ahead sales growth of 2.22% (t = 8.36), while the quintile with low expected one-year-ahead investment-to-asset changes shows an average one-year-ahead sales growth of 1.08% (t = 3.97). At two-year horizon, the average future sales growth increases from 1.83% (t = 5.20) in the low quintile to 4.92% (t = 7.51) in the high quintile.

Using gross profit growth as a profitability proxy yields similar results. The average one-year-ahead gross profit growth rises from 0.31% (t = 2.00) in the low quintile to 1.01% (t = 9.08) in the high quintile. At two-year horizon, the average future gross profit growth increases from 0.53% (t = 2.99) in the low quintile to 2.09% (t = 8.49) in the high quintile. These findings are consistent with the cash flow effect, where positive innovations in cash flow lead firms to expect higher future investment growth.

[Insert Table 3.19]

3.5.3 Future Leverage

Table 3.20 presents the future leverage across the expected investment growth quintiles. In Panel A, for each quintile, I run panel firm-month OLS regressions of the annual growth rate of operating income on the contemporaneous annual growth rate of sales. The degree of operating leverage is measured by the elasticity of operating income to sales. Compared to the low quintile, the high quintile exhibits a higher current degree of operating leverage, 1.47 (t = 5.78) versus 1.23 (t = 4.64). Additionally, the high quintile experiences a greater degree of operating leverage over the subsequent first year, 1.57 (t = 5.89) versus 1.19 (t = 5.81). However, moving from the low to high quintile, the degree of operating leverage in the subsequent second year decreases from 1.39 (t = 5.33) to 0.92 (t = 3.73).

In Panel B, for each quintile, I run panel firm-month OLS regressions of the annual growth rate of net income on the contemporaneous annual growth rate of operating income for each quintile. The degree of financial leverage is measured by the elasticity of net income to operating income. The current degree of financial leverage increases monotonically from 0.55 (t = 2.93) in the low quintile to 1.02 (t = 3.57) in the high quintile. More importantly, the high quintile exhibits a degree of financial leverage of 1.05 (t = 2.90) in the subsequent first year, significantly higher than that of 0.58 (t = 3.53) in the low quintile. This pattern persists in the subsequent second year. From the low to high quintile, the degree of financial leverage grows from 0.69 (t = 3.81) to 1.07 (t = 2.61). These findings suggest that firms that expect high future investment growth tend to have higher future leverage, particularly financial leverage.

[Insert Table 3.20]

3.5.4 Future Cash-Flow Risk

Table 3.21 presents the future cash flow risk among firms with different expected investment growth. I perform panel firm-month OLS regressions of future τ-year-ahead net income growth, where $\tau = 1$ and 2, on the expected one-year-ahead investment-to-asset changes, future one-year-ahead economic growth, and their interaction term. I employ four proxies for economic growth: gross domestic product growth (GDPG), personal consumption expenditure growth (PCEG), industrial production growth (IPG), and manufacturing and trade sales growth (MTSG).

Panel A reports the results for GDPG. I find that expected one-year-ahead investment-to-asset changes are significantly positively related to subsequent one- and two-year-ahead net income growth, with a coefficient of 0.051 (t = 4.37) and 0.077 (t = 4.22), respectively. This finding is consistent with the cash flow effect. Additionally, one-year-ahead GDP growth positively affects one-year-ahead net income growth, with a coefficient of 0.049 (t = 2.09) and has a much stronger impact on two-year-ahead net income growth. The interaction term loads a significantly positive coefficient of 0.865 (t = 2.18) in explaining one-year-ahead net income growth, even though the coefficient turns negative but insignificant at -0.769 (t = -1.36) in explaining two-year-ahead net income growth. The positive interaction term suggests that the response of net income growth to GDP growth increases with expected one-year-ahead investment-to-asset changes.

Using PCEG produces similar results. The interaction between expected one-year-ahead investment-to-asset changes and PCEG yields a coefficient of 0.707 (t = 2.12) when regressing the one-year-ahead net income growth. However, PCEG alone has an insignificantly negative coefficient of -0.002 (t = -0.15). In contrast, IPG and MTSG alone yield a significant positive coefficient of 0.035 (t = 2.19) and 0.036 (t = 1.90), respectively, but their interaction terms with the expected investment-to-asset changes are both insignificantly positive, with a coefficient of 0.279 (t = 1.19) and 0.353 (t = 1.32).

I emphasize the results of using GDPG in the regressions, as it is a more comprehensive measure of economic activity compared to other indicators. The results are consistent with the discount rate effect, suggesting that firms with high future investment growth expectations have higher future cash flow risk.

[Insert Table 3.21]

3.6 Conclusion

In this study, I examine the asset pricing implications of real estate investment plans among equity REITs. According to the dynamic investment CAPM, firms with high expected investment growth should have higher expected returns than firms with low expected investment growth. Due to data constraints on planned real estate investment, I form cross-sectional forecasts of future investment growth using Tobin's q, gross profitability, changes in return on assets, and prior stock returns.

I find that the forecasted future investment-to-asset changes positively predict excess returns over the subsequent month in Fama-MacBeth cross-sectional predictive regressions. The return predictability also extends to portfolio level, generating a significant high-minus-low premium not explained by a set of REIT-based factor models. To capture the return variation related to expected investment growth, I construct a factor-mimicking portfolio. The resultant factor premium exceeds those of the expected investment growth constituents and remains robust across alternative empirical specifications.

I subsequently apply the expected investment growth factor to build a REIT-based HMXZq^5 model. Given the presence of the augmented factor, the model is not subsumed by competing REIT-based and common stock-based factor models in spanning tests. Additionally, in stress-testing exercises, the model outperforms its competing REIT-based factor models in explaining the testing quintiles formed on four prominent REIT return predictors.

I finally propose an alternative risk-based explanation for the expected investment growth premium, emphasizing the roles of operating and financial leverages. I demonstrate that firms with high expected investment growth have higher future profitability; however, they also exhibit higher future degrees of operating and financial leverages and have future cash flows that are more sensitive to economic conditions, leading to higher discount rates.

This study makes several contributions to the literature. It first extends the literature on investment plans and asset returns. Previous studies have focused on productive capital investment plans and stock returns at either the aggregate or cross-sectional level. This study provides new evidence from commercial real estate investment plans and the cross-section of

REIT returns. Second, despite the dynamic investment CAPM, it remains an open question of why high expected investment growth commands high expected returns in the cross-section. This study proposes an alternative risk-based explanation that focuses on the risk amplification effect of operating and financial leverages heightened by expected investment growth.

This study thirdly contributes to the literature on real estate finance. The cross-section of REIT returns has long attracted various interests from real estate researchers. This study provides evidence of a new return pattern related to expected investment growth, which is not only a reincarnation of several existing return patterns but also an extension of them. Also, there is an ongoing debate on the integration or segmentation of REIT returns with or from stock markets. This study provides new evidence strengthening the segmentation argument.

This study also has practical implications for investors. The finding that the augmented investment-based factor model offers superior information on the cross-section of expected REIT returns implies that, beyond conventional factor models, the factor model can serve as an alternative benchmark for REIT asset pricing. For instance, the model can be utilized to assess REIT risk-adjusted performance and the performance of dedicated REIT mutual funds.

It is crucial to recognize the limitations of this study. One of the primary limitations is the data constraints. The measure of real estate investment plans is based on cross-sectional forecasts of future investment growth. While this approach offers a novel method for capturing REIT planned real estate investment, it is inherently dependent on the chosen predictors and forecasting methods. Furthermore, REITs may have broader investment plans beyond planned acquisition and development, including planned expansion and renovation. However, the future realization of planned expansion or renovation is usually treated as expenses rather than capitalized as assets in financial statements. Consequently, forecasting investment-to-asset changes may underestimate firms' actual planned investment.

Additionally, the REIT-based asset pricing factors are subject to the reconstruction process. I reconstruct a set of standard factors and the q and q^5 factors specifically for REITs. The factor reconstruction is driven by the ongoing debate on whether to integrate or segment REIT returns with or from common stock returns. While the reconstruction largely follows the original procedure, it requires adjustments in variable measurements and sorting methods to create factors suitable for a REIT context. For example, when constructing the q factors, I use an independent two-way sort instead of the original three-way sort due to the smaller REIT sample size to ensure reasonable portfolio diversification.

Finally, the scope and generalizability of the findings are also a concern. REITs are subject to specific regulatory requirements, market dynamics, and investor behaviors that are less representative of the broader commercial real estate. Consequently, the conclusions drawn from this thesis may not be fully applicable to other segments of commercial real estate.

Tables

Table 3.1 Monthly Cross-Sectional Forecasts of Future Investment Growth

	d^1I/A					d^2I/A				
	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
$log(q)$	0.100				0.042	0.087				0.007
	(6.60)				(3.32)	(5.19)				(0.46)
Gp		1.060			0.714		1.137			0.873
		(8.67)			(6.14)		(7.88)			(5.63)
$dRoa$			0.956		1.041			1.543		1.741
			(2.77)		(3.19)			(3.99)		(4.46)
Ret^{11}				0.144	0.116				0.168	0.146
				(8.69)	(6.81)				(8.74)	(8.29)
R^2	0.024	0.038	0.017	0.025	0.084	0.022	0.042	0.018	0.029	0.095
Pearson	0.103	0.102	0.045	0.081	0.136	0.065	0.091	0.046	0.109	0.124
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
Rank	0.104	0.129	0.052	0.102	0.163	0.063	0.095	0.072	0.134	0.135
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]

I begin by estimating monthly Fama-MacBeth cross-sectional predictive regressions of τ-year-ahead investment-to-asset changes, $d^{\tau}I/A$, where τ=1 and 2, on the natural log of Tobin's q (log(q)), gross profitability (Gp), changes in return on assets ($dRoa$), and prior 11-month returns (Ret^{11}), covering the period from July 1995 to December 2021.

$$d^{\tau}I/A_{it+12} = \beta_{0,t+12} + \beta_{1,t+12}log(q)_{it} + \beta_{2,t+12}Gp_{it} + \beta_{3,t+12}dRoa_{it} + \beta_{4,t+12}Ret_{it}^{11} + \varepsilon_{it+12}$$

At the beginning of each month t, I measure current investment-to-asset ratio as total assets (Compustat annual item AT) from the most recent fiscal year-end at least four months ago minus the total assets from one year prior, scaled by the average total assets. The τ-year-ahead investment-to-asset changes, $d^{\tau}I/A$, are calculated as the investment-to-asset ratio from the τth fiscal years after the most recent fiscal year minus the current investment-to-asset ratio. Tobin's q is defined as market equity (item PRCC_F multiplied by CSHO) plus long-term debt (item DLTT) and short-term debt (item DLC), scaled by book assets, all from the most recent fiscal year-end at least four months ago. Gross profitability (Gp) is total revenue (item REVT) minus cost of goods sold (item COGS), scaled by book assets, all from the most recent fiscal year-end at least four months ago. Changes in return on assets ($dRoa$) are calculated as Roa minus the four-quarter-lagged Roa. Roa is income before extraordinary items (Compustat quarterly item IBQ) scaled by the one-quarter-lagged book assets (item ATQ). I compute $dRoa$ using earnings from the most recent announcement date (item RDQ) and, if unavailable, from the most recent fiscal quarter-end at least four months ago. Prior 11-month returns (Ret^{11}) are the cumulative returns (CRSP monthly item RET) from month t−12 to month t−2; month t−1 returns are skipped to eliminate the bid-ask bounce effect. I winsorize all variables at the 1st and 99th percentiles of their distributions. Missing $dRoa$ values are set to zero in the cross-sectional forecasting regressions. I report the time-series average slopes, the t-values adjusted for heteroscedasticity and autocorrelations (in parentheses), and goodness-of-fit coefficients (R^2).

I next form out-of-sample forecasts of τ-year-ahead investment-to-assets changes, $E_{it}[d^{\tau}I/A]$, where τ=1 and 2.

$$E_{it}[d^{\tau}I/A] = \bar{\beta}_{0,t-1:t-120(30)} + \bar{\beta}_{1,t-1:t-120(30)}log(q)_{it} + \bar{\beta}_{2,t-1:t-120(30)}Gp_{it} + \bar{\beta}_{3,t-1:t-120(30)}dRoa_{it} + \bar{\beta}_{4,t-1:t-120(30)}Ret_{it}^{11}$$

At the beginning of each month t, I combine the most recent winsorized predictors with the average slopes estimated from the prior 120-month rolling window (minimum 30 months). The most recent predictors, log(q) and Gp, are from the most recent fiscal year-end at least four months ago as of the beginning of month t. $dRoa$ is computed using the latest announced quarterly earnings and, if not available, from the most recent fiscal quarter-end at least four months ago as of the beginning of month t. Ret^{11} represents the prior 11-month cumulative returns as of the beginning of month t (skipping month t−1). To avoid look-ahead bias, the average slopes are estimated from the rolling window spanning months t−1 to t−120 (minimum 30 months). In the latest regression, $d^{\tau}I/A$ is from the most recent fiscal year-end at least four months ago as of the beginning of month t−1, and the regressors are further lagged by 12τ months. The resulting $E_{it}[d^{\tau}I/A]$ starts from January 1998. I report the time-series averages of cross-sectional Pearson and Rank correlations between $E_{it}[d^{\tau}I/A]$ calculated at the beginning of month t and the subsequently realized τ-year-ahead investment-to-asset changes. The p-values testing whether a given correlation is zero are presented in brackets.

Table 3.2 Time-Series Average of Quintile Expected Investment Growth and Subsequent Realized Investment Growth

τ		Low	2	3	4	High	H-L
Panel A: Average expected τ-year-ahead investment-to-asset changes, $E[d^{\tau}I/A]$							
1	$E[d^{\tau}I/A]$	-10.15	-6.47	-4.22	-1.84	5.13	15.28
	t	-20.09	-14.38	-10.45	-5.07	19.69	33.27
2	$E[d^{\tau}I/A]$	-12.54	-8.09	-5.46	-2.74	5.60	18.14
	t	-16.66	-11.85	-8.69	-4.77	9.37	27.06
Panel B: Average subsequent realized τ-year-ahead investment-to-asset changes, $d^{\tau}I/A$							
1	$d^{\tau}I/A$	-9.10	-5.44	-3.32	0.67	3.06	12.16
	t	-5.72	-5.26	-3.14	0.77	3.04	5.93
2	$d^{\tau}I/A$	-9.46	-6.46	-3.13	-2.24	1.67	11.13
	t	-4.72	-4.68	-2.48	-1.79	1.51	5.44

I form quintiles based on the forecasted τ-year-ahead investment-to-asset changes, $E_{it}[d^{\tau}I/A]$, where $\tau = 1$ and 2. At the beginning of each month t, I sort all firms into quintiles based on the ranked values of $E_{it}[d^{\tau}I/A]$. The quintiles are value-weighted using the end-of-prior-month market equity as weights and rebalanced at the beginning of month t+1. I report the time-series averages of quintile expected τ-year-ahead investment-to-asset changes and subsequent realized changes, as well as their heteroskedasticity-and-autocorrelation-adjusted t-statistics (beneath the corresponding estimates).

Table 3.3.1 Monthly Fama-MacBeth Cross-Sectional Return Predictive Regressions on Expected One-Year-Ahead Investment Growth

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$E[d^1I/A]$	0.108	0.171	0.187	0.181	0.176	0.205	0.171	0.164	0.191
	(2.16)	(3.44)	(2.60)	(2.58)	(2.42)	(2.85)	(2.16)	(2.39)	(2.29)
Me		0.009	-0.013	-0.024	-0.021	-0.022	-0.017	-0.014	-0.042
		(0.22)	(-0.32)	(-0.59)	(-0.50)	(-0.51)	(-0.40)	(-0.33)	(-0.93)
B/M		0.197	0.174	0.188	0.168	0.239	0.168	0.180	0.242
		(3.01)	(2.64)	(2.90)	(2.53)	(3.18)	(2.44)	(2.70)	(3.26)
Ret^{11}			-0.006	0.008	-0.018	-0.036	0.000	0.014	-0.027
			(-0.09)	(0.13)	(-0.29)	(-0.57)	(0.01)	(0.24)	(-0.43)
Tur				0.045					0.059
				(0.63)					(0.88)
Sue					0.130				0.128
					(3.83)				(3.73)
$Ivff$						-0.150			-0.123
						(-2.77)			(-2.63)
I/A							0.009		0.021
							(0.18)		(0.45)
Roa								0.060	0.011
								(1.28)	(0.27)
R^2	0.037	0.091	0.122	0.147	0.130	0.151	0.133	0.141	0.209

I estimate the following monthly Fama-MacBeth cross-sectional regressions of one-month-ahead excess returns on the expected one-year-ahead investment-to-asset changes and a set of return predictors, covering the period from January 1998 to December 2021.

$$Ret_{it+1} = \beta_{0,t+1} + \beta_{1,t+1}E_{it}[d^1I/A] + \beta_{2,t+1}Me_{it} + \beta_{3,t+1}B/M_{it} + \beta_{4,t+1}Ret_{it}^{11} + \beta_{5,t+1}Tur_{it} + \beta_{6,t+1}Sue_{it} + \beta_{7,t+1}Ivff_{it} + \beta_{8,t+1}I/A_{it} + \beta_{9,t+1}Roa_{it} + \varepsilon_{it+1}$$

Ret_{it+1} is the excess returns at the end of month t (or the beginning of month t+1), calculated as returns (CRSP monthly item RET) minus one-month Treasury bill rate. $E_{it}[d^1I/A]$ represents the expected one-year-ahead investment-to-asset changes calculated at the beginning of month t. At the beginning of month t, I measure size or market equity (Me) as the price per share (item PRC) multiplied by the number of shares outstanding (item SHROUT), both from the end of month t−1. Book-to-market equity (B/M) is calculated as book equity scaled by market equity, both from the most recent fiscal year-end at least four months ago. Book equity is calculated as stockholders' book equity plus balance sheet deferred taxes and investment tax credit (Compustat annual item TXDITC), if available, minus the book value of preferred stocks. Stockholders' equity is obtained from Compustat (item SEQ) if available. Otherwise, I use the book value of common equity (item CEQ) plus the par value of preferred stock (item PSTK), or the book value of assets (item AT) minus total liabilities (item LT). Depending on availability, I use redemption value (item PSTKRV), liquidating value (item PSTKL), or par value (item PSTK) for the book value of preferred stock. Prior 11-month returns (Ret^{11}) are the cumulative returns (CRSP monthly item RET) from month t−12 to month t−2, with month t−1 returns skipped to eliminate the bid-ask bounce effect. Share turnover (Tur) is the average daily share turnover over the prior six months from month t−6 to month t−1, requiring a minimum of 50 days. Daily turnover is the number of shares traded (CRSP daily item VOL) on a given day divided by the number of shares outstanding (item SHROUT) on that day. Standardized unexpected earnings (Sue) are calculated as the change in split-adjusted quarterly earnings per share (Compustat quarterly item EPSPXQ divided by item AJEXQ) from its value four quarters ago, divided by the standard deviation of this changes in quarterly earnings over the prior eight quarters (minimum six quarters). I compute Sue using earnings from the most recent announcement date (item RDQ), and, if unavailable, from the most recent fiscal quarter-end at least four months prior. Idiosyncratic volatility ($Ivff$) is the residual volatility obtained from regressing a stock's excess returns on the REIT-based Fama-French (1993) three factors. At the beginning of month t, I use $Ivff$ estimated with daily returns (CRSP daily item RET) from month t−1, requiring a minimum of 15 daily returns. Investment-to-asset ratio (I/A) is calculated as total assets (Compustat annual item AT) from the most recent fiscal year-end at least four months ago minus total assets from one year prior, scaled by the average total assets. Return on assets (Roa) is defined as income before extraordinary items (Compustat quarterly item IBQ) scaled by the one-quarter-lagged book assets (item ATQ). I compute Roa using earnings from the most recent announcement date (item RDQ), and if unavailable, from the most recent fiscal quarter-end at least four months ago. I winsorize the regressors at the 1st and 99th percentiles to mitigate the impact of outliers. Additionally, I standardize each winsorized regressor by subtracting its cross-sectional mean and dividing by its cross-sectional standard deviation. I report the time-series average slopes, the t-values adjusted for heteroskedasticity and autocorrelations (in parentheses), and goodness-of-fit coefficients (R^2).

Table 3.3.2 Monthly Fama-MacBeth Cross-Sectional Return Predictive Regressions on Expected Two-Year-Ahead Investment Growth

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$E[d^2I/A]$	0.131	0.167	0.215	0.211	0.185	0.240	0.209	0.200	0.208
	(2.84)	(4.12)	(3.56)	(3.69)	(2.81)	(4.09)	(3.34)	(3.70)	(3.08)
Me		0.016	-0.007	-0.014	-0.010	-0.016	-0.015	-0.011	-0.035
		(0.40)	(-0.16)	(-0.34)	(-0.23)	(-0.37)	(-0.34)	(-0.26)	(-0.81)
B/M		0.168	0.147	0.164	0.136	0.208	0.141	0.163	0.209
		(2.67)	(2.29)	(2.58)	(2.07)	(2.84)	(2.12)	(2.46)	(2.83)
Ret^{11}			-0.037	-0.036	-0.038	-0.065	-0.030	-0.029	-0.068
			(-0.54)	(-0.55)	(-0.55)	(-1.02)	(-0.45)	(-0.44)	(-1.06)
Tur				0.049					0.060
				(0.71)					(0.96)
Sue					0.111				0.108
					(2.70)				(2.53)
$Ivff$						-0.142			-0.127
						(-2.34)			(-2.41)
I/A							0.026		0.022
							(0.55)		(0.49)
Roa								0.067	0.031
								(1.25)	(0.69)
R^2	0.039	0.092	0.124	0.149	0.135	0.156	0.136	0.142	0.215

I estimate the following monthly Fama-MacBeth cross-sectional regressions of one-month-ahead excess returns on the expected two-year-ahead investment-to-asset changes and a set of return predictors, covering the period from January 1999 to December 2021.

$$Ret_{it+1} = \beta_{0,t+1} + \beta_{1,t+1}E_{it}[d^2I/A] + \beta_{2,t+1}Me_{it} + \beta_{3,t+1}B/M_{it} + \beta_{4,t+1}Ret_{it}^{11} + \beta_{5,t+1}Tur_{it} + \beta_{6,t+1}Sue_{it} + \beta_{7,t+1}Ivff_{it} + \beta_{8,t+1}I/A_{it} + \beta_{9,t+1}Roa_{it} + \varepsilon_{it+1}$$

Ret_{it+1} is the excess returns at the end of month t (or the beginning of month t+1), calculated as returns (CRSP monthly item RET) minus one-month Treasury bill rate. $E_{it}[d^1I/A]$ represents the expected one-year-ahead investment-to-asset changes calculated at the beginning of month t. At the beginning of month t, I measure size or market equity (Me) as the price per share (item PRC) multiplied by the number of shares outstanding (item SHROUT), both from the end of month t−1. Book-to-market equity (B/M) is calculated as book equity scaled by market equity, both from the most recent fiscal year-end at least four months ago. Book equity is calculated as stockholders' book equity plus balance sheet deferred taxes and investment tax credit (Compustat annual item TXDITC), if available, minus the book value of preferred stocks. Stockholders' equity is obtained from Compustat (item SEQ) if available. Otherwise, I use the book value of common equity (item CEQ) plus the par value of preferred stock (item PSTK), or the book value of assets (item AT) minus total liabilities (item LT). Depending on availability, I use redemption value (item PSTKRV), liquidating value (item PSTKL), or par value (item PSTK) for the book value of preferred stock. Prior 11-month returns (Ret^{11}) are the cumulative returns (CRSP monthly item RET) from month t−12 to month t−2, with month t−1 returns skipped to eliminate the bid-ask bounce effect. Share turnover (Tur) is the average daily share turnover over the prior six months from month t−6 to month t−1, requiring a minimum of 50 days. Daily turnover is the number of shares traded (CRSP daily item VOL) on a given day divided by the number of shares outstanding (item SHROUT) on that day. Standardized unexpected earnings (Sue) are calculated as the change in split-adjusted quarterly earnings per share (Compustat quarterly item EPSPXQ divided by item AJEXQ) from its value four quarters ago, divided by the standard deviation of this changes in quarterly earnings over the prior eight quarters (minimum six quarters). I compute Sue using earnings from the most recent announcement date (item RDQ), and, if unavailable, from the most recent fiscal quarter-end at least four months prior. Idiosyncratic volatility ($Ivff$) is the residual volatility obtained from regressing a stock's excess returns on the REIT-based Fama-French (1993) three factors. At the beginning of month t, I use $Ivff$ estimated with daily returns (CRSP daily item RET) from month t−1, requiring a minimum of 15 daily returns. Investment-to-asset ratio (I/A) is calculated as total assets (Compustat annual item AT) from the most recent fiscal year-end at least four months ago minus total assets from one year prior, scaled by the average total assets. Return on assets (Roa) is defined as income before extraordinary items (Compustat quarterly item IBQ) scaled by the one-quarter-lagged book assets (item ATQ). I compute Roa using earnings from the most recent announcement date (item RDQ), and if unavailable, from the most recent fiscal quarter-end at least four months ago. I winsorize the regressors at the 1st and 99th percentiles to mitigate the impact of outliers. Additionally, I standardize each winsorized regressor by subtracting its cross-sectional mean and dividing by its cross-sectional standard deviation. I report the time-series average slopes, the t-values adjusted for heteroskedasticity and autocorrelations (in parentheses), and goodness-of-fit coefficients (R^2).

Table 3.4 Time-Series Average of Quintile Excess Returns and Asset Pricing Factor Model Alphas

τ		Low	2	3	4	High	H-L	$\overline{\lvert\alpha\rvert}$
				Panel A: Average excess returns, $\bar{R}$				
1	$\bar{R}$	0.50	0.92	0.76	0.87	1.01	0.51	
	t	0.96	2.23	2.10	2.49	3.70	2.11	
2	$\bar{R}$	0.63	0.99	0.90	0.94	1.02	0.39	
	t	1.23	2.30	2.55	2.73	3.70	1.99	
				Panel B: The CAPM alpha, α_{CAPM}				
1	α_{CAPM}	-0.49	0.00	-0.05	0.10	0.47	0.96	0.22
	t	-2.24	0.01	-0.61	0.84	4.04	3.65	[0.01]
2	α_{CAPM}	-0.53	-0.07	-0.03	0.12	0.43	0.95	0.24
	t	-2.58	-0.81	-0.26	0.93	3.82	4.17	[0.05]
				Panel C: The Fama-French three-factor model alpha, α_{FF3}				
1	α_{FF3}	-0.62	-0.07	-0.06	0.09	0.54	1.15	0.28
	t	-2.55	-0.57	-0.71	0.72	4.55	3.88	[0.00]
2	α_{FF3}	-0.59	-0.15	-0.06	0.13	0.51	1.09	0.29
	t	-2.72	-1.59	-0.49	0.92	4.73	4.64	[0.00]
				Panel D: The Carhart four-factor model alpha, $\alpha_{Carhart4}$				
1	$\alpha_{Carhart4}$	-0.35	0.10	-0.08	0.08	0.50	0.84	0.22
	t	-1.43	0.82	-0.71	0.65	4.08	2.74	[0.00]
2	$\alpha_{Carhart4}$	-0.36	0.08	-0.00	0.01	0.47	0.84	0.19
	t	-1.37	0.92	-0.04	0.11	4.30	2.86	[0.03]
				Panel E: The Fama-French five-factor model alpha, α_{FF5}				
1	α_{FF5}	-0.42	0.01	-0.12	0.07	0.34	0.77	0.19
		-2.44	0.08	-1.27	0.65	3.60	4.03	[0.02]
2	α_{FF5}	-0.46	-0.05	-0.08	0.06	0.31	0.77	0.19
		-2.30	-0.63	-1.06	0.51	2.65	3.75	[0.10]
				Panel F: The Fama-French six-factor model alpha, α_{FF6}				
1	α_{FF6}	-0.26	0.11	-0.12	0.06	0.36	0.63	0.18
		-1.33	1.00	-1.06	0.55	3.82	2.67	[0.04]
2	α_{FF6}	-0.32	0.09	-0.04	-0.02	0.34	0.65	0.16
		-1.25	1.11	-0.45	-0.15	3.02	2.51	[0.14]
				Panel G: The Hou-Xue-Zhang q-factor model alpha, α_{HXZq}				
1	α_{HXZq}	-0.44	0.04	-0.09	0.11	0.54	0.98	0.24
		-2.07	0.33	-1.08	0.89	4.38	3.43	[0.00]
2	α_{HXZq}	-0.47	-0.01	-0.04	0.12	0.54	1.00	0.24
		-2.06	-0.17	-0.42	0.99	4.82	3.75	[0.01]
				Panel H: The Bond-Xue investment-based three-factor model alpha, α_{BX3}				
1	α_{BX3}	-0.40	0.07	-0.09	0.09	0.47	0.86	0.22
	t	-1.80	0.54	-0.94	0.74	4.03	3.22	[0.01]
2	α_{BX3}	-0.42	-0.01	-0.05	0.11	0.44	0.86	0.21
	t	-1.95	-0.06	-0.46	0.91	4.31	3.53	[0.07]

At the beginning of each month t, I sort all firms into quintiles based on the ranked values of expected τ-year-ahead investment-to-asset changes, $E_{it}[d^{\tau}I/A]$, where τ = 1 and 2. I then compute value-weighted quintile excess returns for the current month t, using the end-of-prior-month market equity as weights. The quintiles are rebalanced at the beginning of month t+1. I construct a set of asset pricing factor models for REITs, including the Capital Asset Pricing Model (CAPM), Fama-French three-factor model (FF3), Carhart four-factor model (Carhart4), Fama-French five-factor model (FF5), Fama-French six-factor model (FF6), Hou-Xue-Zhang q-factor model (HXZq), and Bond-Xue investment-based three-factor model (BX3). Appendix 3.1 details the construction. For each quintile, I perform time-series factor model regressions. Appendix 3.1 details the regression specifications. I report the time-series averages of quintile excess returns ($\bar{R}$), alongside the CAPM alpha (α_{CAPM}), the FF3 alpha (α_{FF3}), the Carhart4 alpha ($\alpha_{Carhart4}$), the FF5 alpha (α_{FF5}), the FF6 alpha (α_{FF6}), the HXZq alpha (α_{HXZq}), and the BX3 alpha (α_{BX3}). Additionally, I provide their heteroskedasticity-and-autocorrelation-adjusted t-statistics beneath the corresponding estimates. $\overline{\lvert\alpha\rvert}$ represents the mean absolute alpha for each set of quintiles, and the p-value from the GRS test on the null hypothesis that the alphas across the quintiles are jointly zero is presented in brackets.

Table 3.5.1 Properties of Expected Investment Growth Factor (Part 1)

Panel A: Factor-model regressions of expected investment growth factor, R_{Eg}

$\bar{R}_{Eg}$	α_{CAPM}	β_{Mkt}	R^2					
0.34	0.70	-0.45	0.32					
(2.01)	(4.27)	(-4.61)						
	α_{FF3}	β_{Mkt}	β_{SMB3}	β_{HML}	R^2			
	0.85	-0.36	-0.73	-0.41	0.60			
	(3.83)	(-5.64)	(-6.29)	(-3.89)				
	$\alpha_{Carhart4}$	β_{Mkt}	β_{SMB4}	β_{HML}	β_{UMD}	R^2		
	0.51	-0.23	-0.35	-0.26	0.42	0.72		
	(2.78)	(-4.48)	(-4.91)	(-3.02)	(9.60)			
	α_{FF5}	β_{Mkt}	β_{SMB5}	β_{HML}	β_{CMA}	β_{RMW}	R^2	
	0.54	-0.24	-0.60	-0.20	0.03	0.47	0.68	
	(3.90)	(-6.28)	(-5.99)	(-2.12)	(0.35)	(4.95)		
	α_{FF6}	β_{Mkt}	β_{SMB6}	β_{HML}	β_{CMA}	β_{RMW}	β_{UMD}	R^2
	0.36	-0.16	-0.30	-0.18	0.00	0.35	0.34	0.76
	(2.75)	(-4.28)	(-5.33)	(-1.86)	(0.03)	(4.17)	(5.59)	
	α_{HXZq}	β_{Mkt}	β_{Me}	$\beta_{I/A}$	β_{Roa}	R^2		
	0.67	-0.33	-0.69	-0.01	0.30	0.62		
	(3.70)	(-5.22)	(-8.35)	(-0.06)	(3.66)			
	α_{BX3}	β_{Mkt}	$\beta_{I/A\_}$	$\beta_{Roa\_}$	R^2			
	0.61	-0.41	-0.09	0.38	0.41			
	(4.08)	(-4.08)	(-0.53)	(2.74)				

Panel B: Correlations of R_{Eg} with model factors

R_{Mkt}	R_{SMB6}	R_{HML}	R_{UMD}	R_{CMA}	R_{RMW}	R_{Me}	$R_{I/A}$	R_{Roa}	$R_{I/A\_}$	$R_{Roa\_}$
-0.56	-0.54	-0.39	0.77	-0.28	0.68	-0.61	-0.28	0.52	-0.11	0.38
(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.06)	(0.00)

The expected investment growth factor, R_{Eg}, is constructed using an independent two-way (2 × 3) monthly sort based on size and $E_{it}[d^1I/A]$. At the beginning of each month t, I split REITs into two groups, small and large, using the end-of-prior-month median market equity. Independently, I divide all REITs into three groups—low, median, and high—based on the lowest 30%, middle 40%, and highest 30% of the ranked $E_{it}[d^1I/A]$ values. The intersection of the two size groups and the three $E_{it}[d^1I/A]$ groups forms six benchmark portfolios. I calculate value-weighted portfolio returns for the current month t and rebalance the portfolios at the beginning of month t+1. The expected investment growth factor is the difference (high-minus-low) each month between the simple average returns of the two high $E_{it}[d^1I/A]$ portfolios and the simple average returns of the two low $E_{it}[d^1I/A]$ portfolios. I conduct time-series factor-model regressions of the expected investment growth factor, including the CAPM, FF3, Carhart4, FF5, FF6, HXZq, and BX3. Panel A presents the time-series average of the expected investment growth factor, $\bar{R}_{Eg}$, alongside the model alphas, factor loadings, and R^2 values from the regressions. The t-values, adjusted for heteroskedasticity and autocorrelations, are reported in parentheses. Panel B provides the correlations of the expected investment growth factor with the model factors.

Table 3.5.2 Properties of Expected Investment Growth Factor (Part 2)

Panel A: HXZq factor-model regressions of expected investment growth factor, with augmented factors

$\bar{R}_{Eg}$	α	β_{Mkt}	β_{Me}	$\beta_{I/A}$	β_{Roa}	R^2				
0.34	0.67	-0.33	-0.69	-0.01	0.30	0.62				
(2.01)	(3.70)	(-5.22)	(-8.35)	(-0.06)	(3.66)					
	α	β_{Mkt}	β_{Me}	$\beta_{I/A}$	β_{Roa}	$\beta_{\log(q)}$	R^2			
	0.62	-0.31	-0.58	0.19	0.18	0.35	0.65			
	(3.90)	(-6.27)	(-6.36)	(1.33)	(3.28)	(3.79)				
	α	β_{Mkt}	β_{Me}	$\beta_{I/A}$	β_{Roa}	β_{Gp}	R^2			
	0.51	-0.25	-0.58	-0.13	0.16	0.52	0.69			
	(3.80)	(-6.15)	(-6.39)	(-1.66)	(1.67)	(3.88)				
	α	β_{Mkt}	β_{Me}	$\beta_{I/A}$	β_{Roa}	β_{dRoa}	R^2			
	0.61	-0.32	-0.62	-0.02	0.24	0.22	0.63			
	(2.95)	(-5.00)	(-6.49)	(-0.19)	(3.01)	(1.53)				
	α	β_{Mkt}	β_{Me}	$\beta_{I/A}$	β_{Roa}	$\beta_{Ret^{11}}$	R^2			
	0.50	-0.23	-0.38	-0.06	0.11	0.35	0.71			
	(2.86)	(-4.11)	(-6.56)	(-0.91)	(1.11)	(6.01)				
	α	β_{Mkt}	β_{Me}	$\beta_{I/A}$	β_{Roa}	$\beta_{\log(q)}$	β_{dRoa}	R^2		
	0.55	-0.30	-0.50	0.18	0.11	0.36	0.26	0.67		
	(3.20)	(-6.12)	(-4.62)	(1.23)	(2.04)	(4.05)	(2.13)			
	α	β_{Mkt}	β_{Me}	$\beta_{I/A}$	β_{Roa}	β_{Gp}	$\beta_{Ret^{11}}$	R^2		
	0.31	-0.14	-0.24	-0.20	-0.05	0.57	0.38	0.79		
	(2.57)	(-4.51)	(-3.51)	(-3.78)	(-0.66)	(5.80)	(7.28)			
	α	β_{Mkt}	β_{Me}	$\beta_{I/A}$	β_{Roa}	$\beta_{\log(q)}$	β_{Gp}	β_{dRoa}	$\beta_{Ret^{11}}$	R^2
	0.26	-0.13	-0.14	-0.03	-0.16	0.29	0.52	0.09	0.37	0.81
	(2.16)	(-5.15)	(-3.12)	(-0.41)	(-2.68)	(3.48)	(6.75)	(0.85)	(9.23)	

Panel B: Correlations of R_{Eg} with augmented factors

$R_{\log(q)}$	R_{Gp}	R_{dRoa}	$R_{Ret^{11}}$
0.60	0.63	0.51	0.77
(0.00)	(0.00)	(0.00)	(0.00)

I perform time-series HXZq factor-model regressions of the expected investment growth factor, R_{Eg}, augmented with factors on Tobin's q ($R_{\log(q)}$), gross profitability (R_{Gp}), changes in return on assets (R_{dRoa}), and prior 11-month returns ($R_{Ret^{11}}$). Analogous to the expected investment growth factor, factors on $\log(q)$, Gp, $dRoa$, and Ret^{11} are formed by interacting each of them separately with size in 2 × 3 monthly sorts. Panel A reports the time-series averages of the expected investment growth factor, $\bar{R}_{Eg}$, alongside the model alphas, factor loadings, and R^2 values from the regressions. The t-values adjusted for heteroskedasticity and autocorrelations are presented in parentheses. Panel B reports the correlations of the expected investment growth factor with the augmented factors.

Table 3.6 Properties of Alternative Expected Investment Growth Factor Formed with Composite Score

Panel A: Factor-model regressions of alternative expected investment growth factor, R^C_{Eg}

$\bar{R}^C_{Eg}$	α	β_{Eg}	R^2			
0.49	0.19	0.91	0.75			
(2.65)	(1.75)	(15.12)				
	α	β_{Mkt}	β_{Me}	$\beta_{I/A}$	β_{Roa}	R^2	
	0.65	-0.22	-0.60	0.02	0.63	0.68	
	(3.98)	(-3.78)	(-6.72)	(0.22)	(7.91)		
	α	β_{Mkt}	β_{Me}	$\beta_{I/A}$	β_{Roa}	β_{Eg}	R^2
	0.20	-0.00	-0.14	0.03	0.42	0.68	0.84
	(1.78)	(-0.02)	(-1.96)	(0.44)	(6.68)	(14.14)	
$\bar{R}_{Eg}$	α	β^C_{Eg}	R^2				
0.34	-0.07	0.83	0.75				
(2.01)	(-0.79)	(20.13)					
	α	β_{Mkt}	β_{Me}	$\beta_{I/A}$	β_{Roa}	β^C_{Eg}	R^2
	0.19	-0.16	-0.24	-0.02	-0.16	0.74	0.81
	(1.43)	(-4.95)	(-5.70)	(-0.38)	(-1.92)	(14.52)	

Panel B: Correlations of R^C_{Eg} with R_{Eg} and HXZq model factors

R_{Eg}	R_{Mkt}	R_{Me}	$R_{I/A}$	R_{Roa}
0.87	-0.47	-0.60	-0.28	0.70
[0.00]	[0.00]	[0.00]	[0.00]	[0.00]

I form a composite score using the log of Tobin's q ($\log(q)$), gross profitability (Gp), changes in return on assets ($dRoa$), and prior 11-month returns (Ret^{11}.). For each portfolio formation month, I create the composite score by equal-weighting a stock's percentage rankings across these four variables, ensuring each is realigned to yield a positive slope in forecasting returns. I compute the composite score for a stock only if it has non-missing values for all component variables. At the beginning of each month t, I use the median market equity to split stocks into two groups: small and big, based on their beginning-of-month market equity. Independently, I sort all stocks into three groups—low, median, and high—based on the low 30%, middle 40%, and high 30% of the ranked composite score values at the beginning of month t. By intersecting the two size groups with the three composite score groups, I form six portfolios. I calculate value-weighted portfolio returns for the current month t and rebalance the portfolios at the beginning of month t+1. R^C_{Eg} is an alternative expected investment growth factor, defined as the difference (high-minus-low) each month between the simple average of the returns on the two high composite score portfolios and the simple average of the returns on the two low composite score portfolios. Panel A reports for R^C_{Eg}: its average return ($\bar{R}^C_{Eg}$), alongside alphas, factor loadings, and R^2s from a single-factor model that includes only the benchmark expected investment growth factor (R_{Eg}), the HXZq, and the HXZq augmented with R_{Eg}. The t-values, adjusted for heteroskedasticity and autocorrelation, are presented in parentheses. Panel A also reports for R_{Eg} for reference: its average return ($\bar{R}_{Eg}$), alongside alphas, factor loadings, and R^2s from a single-factor model that includes only R^C_{Eg} and the HXZq augmented with R^C_{Eg}. Panel B reports the correlations of R^C_{Eg} with R_{Eg} and HXZq model factors.

Table 3.7.1 Cross-Sectional Forecasts of Future Changes in Log Gross Asset Growth or Non-Cash Asset Growth

τ	$\log(q)$	Gp	$dRoa$	Ret^{11}	R^2	Pearson	Rank
Panel A: τ-year-ahead changes in the log of gross asset growth, $d^\tau \log(1+I/A)$							
1	0.046	0.801	1.029	0.121	0.086	0.134	0.164
	(3.31)	(6.22)	(2.70)	(6.27)		[0.00]	[0.00]
2	0.009	0.957	1.745	0.150	0.093	0.123	0.138
	(0.53)	(5.67)	(4.03)	(7.67)		[0.00]	[0.00]
Panel B: τ-year-ahead changes in non-cash asset growth, $d^\tau I/A_{NCA}$							
τ	$\log(q)$	Gp	$dRoa$	Ret^{11}	R^2	Pearson	Rank
1	0.050	0.721	0.539	0.100	0.084	0.125	0.150
	(3.37)	(5.75)	(1.53)	(5.83)		[0.00]	[0.00]
2	0.012	0.957	1.543	0.175	0.098	0.129	0.151
	(0.73)	(5.83)	(3.43)	(9.83)		[0.00]	[0.00]

I estimate monthly Fama-MacBeth cross-sectional regressions of τ-year-ahead changes in the log of gross asset growth, $d^\tau \log(1+I/A)$, where τ = 1 and 2, and τ-year-ahead changes in non-cash asset growth, $d^\tau I/A_{NCA}$, where τ = 1 and 2, on the log of Tobin's q ($\log(q)$), gross profitability (Gp), changes in return on assets ($dRoa$), and prior 11-month returns (Ret^{11}). At the beginning of each month t, I measure current gross asset growth, $1 + I/A$, as total assets (Compustat annual item AT) from the most recent fiscal year end at least four months ago divided by total assets from one year prior. The τ-year-ahead changes in the log of gross asset growth, $d^\tau \log(1 + I/A)$, are calculated as the log of gross asset growth from the τth fiscal year after the most recent fiscal year end minus the current log of gross asset growth. Current non-cash asset growth, I/A_{NCA}, is defined as non-cash assets (item AT minus CHE) from the most recent fiscal year end at least four months ago minus non-cash assets from one year prior, scaled by the average non-cash assets. The τ-year-ahead changes in non-cash asset growth, $d^\tau I/A_{NCA}$, are calculated as the non-cash asset growth from the τth fiscal year after the most recent fiscal year end minus the current non-cash asset growth. I winsorize all variables at the 1st and 99th percentiles of their distributions. I report the time-series average slopes, the t-values adjusted for heteroskedasticity and autocorrelations (in parentheses), and goodness-of-fit coefficients (R^2). Additionally, I form out-of-sample forecasts of τ-year-ahead changes in the log of gross asset growth, $E_{it}[d^\tau \log(1+I/A)]$, where τ = 1 and 2, and τ-year-ahead changes in non-cash asset growth, $E_{it}[d^\tau I/A_{NCA}]$, where τ = 1 and 2. At the beginning of each month t, I combine the most recent winsorized predictors with the average slopes estimated from the prior 120-month rolling window (minimum 30 months). The calculation of $E_{it}[d^\tau \log(1+I/A)]$ or $E_{it}[d^\tau I/A_{NCA}]$ is analogous to that of $E_{it}[d^\tau I/A]$. I report time-series averages of cross-sectional Pearson and Rank correlations between $E_{it}[d^\tau \log(1+I/A)]$ (or $E_{it}[d^\tau I/A_{NCA}]$) calculated at the beginning of month t and the realized τ-year-ahead changes in the log of gross asset growth (or non-cash asset growth). The p-values testing whether a given correlation is zero are presented in brackets.

Table 3.7.2 Properties of Alternative Expected Investment Growth Factors Formed with Expected Changes in Log Gross Asset Growth or Non-Cash Asset Growth

Panel A: HXZq factor-model regressions of alternative expected investment growth factors, R_{Eg}^{L}, and R_{Eg}^{NCA}

	$\bar{R}$	α	β_{Mkt}	β_{Me}	$\beta_{I/A}$	β_{Roa}	R^2
R_{Eg}	0.34	0.67	-0.33	-0.69	-0.01	0.30	0.62
	(2.01)	(3.70)	(-5.22)	(-8.35)	(-0.06)	(3.66)	
R_{Eg}^{L}	0.37	0.70	-0.32	-0.68	-0.01	0.30	0.62
	(2.09)	(3.82)	(-5.00)	(-8.44)	(-0.07)	(3.89)	
R_{Eg}^{NCA}	0.39	0.71	-0.34	-0.64	0.09	0.31	0.61
	(1.88)	(3.01)	(-4.05)	(-8.84)	(1.09)	(3.98)	

Panel B: Correlations of R_{Eg}^{L} and R_{Eg}^{NCA} with R_{Eg} and HXZq model factors

	R_{Eg}	R_{Mkt}	R_{Me}	$R_{I/A}$	R_{Roa}
R_{Eg}^{L}	0.99	-0.56	-0.62	-0.29	0.52
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
R_{Eg}^{NCA}	0.96	-0.58	-0.58	-0.23	0.52
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]

R_{Eg}^{L} is an alternative expected investment growth factor derived from an independent two-way (2 × 3) monthly sort on size and the expected one-year-ahead changes in the log of gross asset growth, $E_{it}[d^1 \log(1 + I/A)]$. Similarly, R_{Eg}^{NCA} is an alternative expected investment growth factor derived from an independent two-way (2 × 3) monthly sort on size and the expected one-year-ahead changes in non-cash asset growth, $E_{it}\left[d^1\, I/A_{NCA}\right]$. The construction of R_{Eg}^{L} and R_{Eg}^{NCA} is analogous to that of the benchmark expected investment growth factor, R_{Eg}. For each alternative expected growth factor, Panel A reports its average returns ($\bar{R}$), alongside alphas, factor loadings, and R^2 from the HXZq model. The t-values adjusted for heteroskedasticity and autocorrelations are presented in parentheses. For reference, the panel also reports for R_{Eg}: its average return, alongside alphas, factor loadings, and R^2 from the HXZq model. Panel B reports the correlations of R_{Eg}^{L} and R_{Eg}^{NCA} with R_{Eg} and HXZq model factors.

Table 3.8.1 Cross-Sectional Forecasts of Future Investment Growth Using Alternative Predictors

Panel A: Operating profitability, Opp							
τ	$\log(q)$	Opp	$dRoa$	Ret^{11}	R^2	Pearson	Rank
1	0.022	1.130	1.147	0.116	0.088	0.141	0.169
	(1.57)	(6.53)	(3.44)	(6.84)		[0.00]	[0.00]
2	-0.023	1.514	1.960	0.148	0.102	0.130	0.145
	(-1.29)	(6.22)	(4.95)	(8.64)		[0.00]	[0.00]
Panel B: Change in return on equity, $dRoe$							
τ	$\log(q)$	Gp	$dRoe$	Ret^{11}	R^2	Pearson	Rank
1	0.040	0.739	0.167	0.121	0.083	0.136	0.163
	(3.11)	(6.10)	(1.77)	(6.97)		(0.00)	(0.00)
2	0.008	0.863	0.394	0.150	0.093	0.124	0.133
	(0.50)	(5.46)	(3.90)	(8.59)		[0.00]	[0.00]
Panel C: Prior 11-month abnormal returns, $Aret^{11}$							
τ	$\log(q)$	Gp	$dRoa$	$Aret^{11}$	R^2	Pearson	Rank
1	0.043	0.523	1.360	0.097	0.074	0.131	0.144
	(3.90)	(4.92)	(4.52)	(6.51)		[0.00]	[0.00]
2	0.015	0.666	1.541	0.117	0.082	0.107	0.111
	(1.14)	(4.30)	(4.63)	(6.65)		[0.00]	[0.00]

I estimate monthly Fama-MacBeth cross-sectional predictive regressions of τ-year-ahead investment-to-assets changes, $d^{\tau}I/A$, where τ = 1 and 2, using operating profitability (Opp), changes in return on equity ($dRoe$), and prior 11-month abnormal returns ($Aret^{11}$) as alternative predictors. At the beginning of each month t, I measure current operating profitability, Opp, as total revenue (Compustat annual item REVT) minus cost of goods sold (item COGS), minus selling, general, and administrative expenses (item XSGA), plus research and development expenditures (item XRD, set to zero if missing), scaled by book assets—all from the most recent fiscal year end at least four months ago. Changes in return on equity, $dRoe$, are calculated as Roe minus the four-quarter-lagged Roe. Roe is defined as income before extraordinary items (Compustat quarterly item IBQ) scaled by one-quarter-lagged book equity. Quarterly book equity is computed as shareholders' equity plus balance sheet deferred taxes and investment tax credit (item TXDITCQ) if available, minus the book value of preferred stock. Depending on availability, I use stockholders' equity (item SEQQ), or common equity (item CEQQ) plus the carrying value of preferred stock (item PSTKQ), or total assets (item ATQ) minus total liabilities (item LTQ), in that order, as shareholders' equity. For the book value of preferred stock, I use redemption value (item PSTKRQ) if available, otherwise the carrying value. I compute $dRoe$ using earnings from the most recent announcement dates (item RDQ) and, if unavailable, from the fiscal quarter end at least four months ago. To calculate abnormal returns, I use a prior 60-month rolling window (minimum 24 months) to estimate the CAPM regression and measure abnormal returns as the intercept plus residuals. Prior 11-month abnormal returns, $Aret^{11}$, are the cumulative abnormal returns from month t−12 to month t−2. I winsorize all variables at the 1st and 99th percentiles of their distributions. Missing $dRoe$ values are set to zero in the cross-sectional predictive regressions. I report the time-series average slopes, the t-values adjusted for heteroskedasticity and autocorrelations (in parentheses), and goodness-of-fit coefficients (R^2). Additionally, I form out-of-sample forecasts of τ -year-ahead investment-to-assets changes, $E_{it}[d^{\tau}I/A]$, where τ = 1 and 2. At the beginning of each month t, I combine the most recent winsorized predictors with the average slopes estimated from the prior 120-month rolling window (minimum 30 months). I report time-series averages of cross-sectional Pearson and rank correlations between $E_{it}[d^{\tau}I/A]$ calculated at the beginning of month t and the realized τ-year-ahead investment-to-asset changes. The p-values testing whether a given correlation is zero are presented in brackets.

Table 3.8.2 Properties of Alternative Expected Investment Growth Factors Formed with Alternative Predictors

Panel A: HXZq factor-model regressions of alternative expected investment growth factors, R_{Eg}^{Opp}, R_{Eg}^{dRoe}, and $R_{Eg}^{Aret^{11}}$

	$\bar{R}$	α	β_{Mkt}	β_{Me}	$\beta_{I/A}$	β_{Roa}	R^2
R_{Eg}	0.34	0.67	-0.33	-0.69	-0.01	0.30	0.62
	(2.01)	(3.70)	(-5.22)	(-8.35)	(-0.06)	(3.66)	
R_{Eg}^{Opp}	0.38	0.68	-0.31	-0.61	-0.02	0.34	0.62
	(2.02)	(3.40)	(-4.47)	(-7.04)	(-0.17)	(4.96)	
R_{Eg}^{dRoe}	0.36	0.70	-0.33	-0.69	-0.02	0.32	0.62
	(2.05)	(3.61)	(-5.02)	(-7.59)	(-0.20)	(4.12)	
$R_{Eg}^{Aret^{11}}$	0.32	0.66	-0.34	-0.68	0.03	0.33	0.64
	(1.75)	(3.47)	(-4.77)	(-7.79)	(0.32)	(4.65)	

Panel B: Correlations of R_{Eg}^{Opp}, R_{Eg}^{dRoe}, and $R_{Eg}^{Aret^{11}}$ with R_{Eg} and HXZq model factors

	R_{Eg}	R_{Mkt}	R_{Me}	$R_{I/A}$	R_{Roa}
R_{Eg}^{Opp}	0.97	-0.56	-0.60	-0.29	0.55
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
R_{Eg}^{dRoe}	0.99	-0.56	-0.62	-0.29	0.53
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
$R_{Eg}^{Aret^{11}}$	0.95	-0.58	-0.61	-0.27	0.54
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]

I form three alternative expected one-year-ahead investment-to-asset changes: $E_{it}[d^1I/A]\_Opp$, $E_{it}[d^1I/A]\_dRoe$, and $E_{it}[d^1I/A]\_Aret^{11}$, where operating profitability, changes in return on equity, and prior 11-month abnormal returns are used as alternative predictors in the cross-sectional predictive regressions, respectively. R_{Eg}^{Opp}, R_{Eg}^{dRoe}, and $R_{Eg}^{Aret^{11}}$ are alternative expected investment growth factors formed by interacting the alternative expected one-year-ahead investment-to-asset changes with size in monthly two-way (2 × 3) sorts. The construction of R_{Eg}^{Opp}, R_{Eg}^{dRoe}, and $R_{Eg}^{Aret^{11}}$ is analogous to that of the benchmark expected investment growth factor, R_{Eg}. For each alternative expected investment growth factor, Panel A reports its average returns ($\bar{R}$), alongside alphas, factor loadings, and R^2 from the HXZq model. The t-values adjusted for heteroskedasticity and autocorrelations are presented in parentheses. For reference, the panel also reports for R_{Eg}: its average return, alongside alphas, factor loadings, and R^2 from the HXZq model. Panel B reports the correlations of R_{Eg}^{Opp}, R_{Eg}^{dRoe}, and $R_{Eg}^{Aret^{11}}$ with R_{Eg} and HXZq model factors.

Table 3.9.1 Cross-Sectional Forecasts of Future Investment Growth Using Augmented Predictors

Panel A: The first difference of the ratio of after-tax corporate profits to sales, $dNis$

τ	$\log(q)$	Gp	$dRoa$	Ret^{11}	$dNis$	R^2	Pearson	Rank
1	0.051	0.684	1.111	0.115	0.048	0.103	0.141	0.169
	(3.74)	(6.17)	(3.65)	(7.14)	(2.79)		[0.00]	[0.00]
2	0.013	0.877	1.778	0.143	0.027	0.106	0.129	0.148
	(0.84)	(5.92)	(4.85)	(8.49)	(1.74)		[0.00]	[0.00]

Panel B: The annual growth rate of sales, $gSale$

τ	$\log(q)$	Gp	$dRoa$	Ret^{11}	$gSale$	R^2	Pearson	Rank
1	0.036	0.523	0.876	0.110	-0.154	0.185	0.298	0.292
	(3.10)	(6.09)	(2.96)	(7.67)	(-10.41)		[0.00]	[0.00]
2	0.003	0.658	1.462	0.130	-0.202	0.220	0.312	0.298
	(0.25)	(6.14)	(3.95)	(9.89)	(-14.19)		[0.00]	[0.00]

Panel C: The current investment-to-asset changes, $lag0d^1\,I/A$

τ	$\log(q)$	Gp	$dRoa$	Ret^{11}	$lag2d^1\,I/A$	R^2	Pearson	Rank
1	0.064	0.507	0.783	0.125	-0.394	0.261	0.437	0.374
	(6.54)	(5.13)	(2.77)	(8.47)	(-22.19)		[0.00]	[0.00]
2	0.044	0.457	0.833	0.154	-0.359	0.244	0.378	0.322
	(3.22)	(4.07)	(2.83)	(9.92)	(-16.10)		[0.00]	[0.00]

Panel D: The one-year-lagged investment-to-asset changes, $lag1d^1\,I/A$

τ	$\log(q)$	Gp	$dRoa$	Ret^{11}	$lag2d^1\,I/A$	R^2	Pearson	Rank
1	0.050	0.554	0.995	0.122	-0.020	0.091	0.135	0.157
	(4.01)	(5.36)	(3.25)	(7.65)	(-2.08)		[0.00]	[0.00]
2	0.023	0.507	1.307	0.129	-0.040	0.099	0.098	0.102
	(1.57)	(3.41)	(3.38)	(6.58)	(-2.96)		[0.00]	[0.00]

I estimate monthly Fama-MacBeth cross-sectional predictive regressions of τ-year-ahead investment-to-asset changes, $d^\tau I/A$, where τ = 1 and 2, with the augmentation of the first difference of the ratio of after-tax corporate profits to sales ($dNis$), the annual growth rate of sales ($gSale$), and the current or the one-year-lagged investment-to-asset changes ($lag0d^1\,I/A$ or $lag1d^1\,I/A$) as predictors. At the beginning of each month t, I measure $dNis$ as the first difference of the ratio of after-tax corporate profits (Compustat annual item NI) to sales (item SALE) from the fiscal year end at least four months ago, and $gSale$ as the annual growth rate of sales from the fiscal year end at least four months ago. I winsorize all variables at the 1st and 99th percentiles of their distributions. Missing $dRoa$ values are set to zero in the cross-sectional predictive regressions. I report the time-series average slopes, the t-values adjusted for heteroskedasticity and autocorrelations (in parentheses), and goodness-of-fit coefficients (R^2). Additionally, I form out-of-sample forecasts of τ-year-ahead investment-to-asset changes, $E_{it}[d^\tau I/A]$, where τ = 1 and 2. At the beginning of each month t, I combine the most recent winsorized predictors with the average slopes estimated from the prior 120-month rolling window (minimum 30 months). I report time-series averages of cross-sectional Pearson and Rank correlations between $E_{it}[d^\tau I/A]$ calculated at the beginning of month t and the realized τ-year-ahead investment-to-asset changes. The p-values testing whether a given correlation is zero are presented in brackets.

Table 3.9.2 Properties of Alternative Expected Investment Growth Factors Formed with Augmented Predictors

Panel A: HXZq factor-model regressions of alternative expected growth factors, R_{Eg}^{dNis}, R_{Eg}^{gSale}, $R_{Eg}^{lag0d^1I/A}$, and $R_{Eg}^{lag1d^1I/A}$

	$\bar{R}$	α	β_{Mkt}	β_{Me}	$\beta_{I/A}$	β_{Roa}	R^2
R_{Eg}	0.34	0.67	-0.33	-0.69	-0.01	0.30	0.62
	(2.01)	(3.70)	(-5.22)	(-8.35)	(-0.06)	(3.66)	
R_{Eg}^{dNis}	0.44	0.79	-0.36	-0.69	0.06	0.30	0.64
	(2.35)	(3.77)	(-3.94)	(-9.80)	(0.66)	(4.64)	
R_{Eg}^{gSale}	0.20	0.51	-0.30	-0.66	0.23	0.19	0.57
	(1.91)	(3.91)	(-5.24)	(-8.10)	(2.66)	(2.55)	
$R_{Eg}^{lag0d^1I/A}$	0.13	0.23	-0.13	-0.31	0.14	0.24	0.31
	(1.20)	(2.13)	(-3.76)	(-1.97)	(1.26)	(3.08)	
$R_{Eg}^{lag1d^1I/A}$	0.25	0.65	-0.36	-0.74	0.01	0.35	0.66
	(2.01)	(3.16)	(-4.16)	(-9.06)	(0.10)	(4.08)	

Panel B: Correlations of R_{Eg}^{dNis}, R_{Eg}^{gSale}, $R_{Eg}^{lag0d^1I/A}$ and $R_{Eg}^{lag1d^1I/A}$ with R_{Eg} and HXZq model factors

	R_{Eg}	R_{Mkt}	R_{Me}	$R_{I/A}$	R_{Roa}
R_{Eg}^{dNis}	0.97	-0.59	-0.61	-0.25	0.52
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
R_{Eg}^{gSale}	0.93	-0.56	-0.58	-0.14	0.44
	[0.00]	[0.00]	[0.00]	[0.02]	[0.00]
$R_{Eg}^{lag1d^1I/A}$	0.73	-0.36	-0.41	-0.10	0.43
	[0.00]	[0.00]	[0.00]	[0.09]	[0.00]
$R_{Eg}^{lag2d^1I/A}$	0.95	-0.59	-0.63	-0.29	0.55
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]

I form four alternative expected one-year-ahead investment-to-asset changes: $E_{it}[d^1I/A]\_dNis$, $E_{it}[d^1I/A]\_gSale$, $E_{it}[d^1I/A]\_lag0d^1I/A$, and $E_{it}[d^1I/A]\_lag1d^1I/A$, where the first difference of the ratio of after-tax corporate profits to sales, the annual growth rate of sales, and the current and the one-year-lagged investment-to-asset changes are used as augmented predictors in the cross-sectional predictive regressions, respectively. R_{Eg}^{dNis}, R_{Eg}^{gSale}, $R_{Eg}^{lag0d^1I/A}$, and $R_{Eg}^{lag1d^1I/A}$ are alternative expected investment growth factors formed by interacting the alternative expected one-year-ahead investment-to-asset changes with size in monthly two-way (2 × 3) sorts. The construction of R_{Eg}^{dNis}, R_{Eg}^{gSale}, $R_{Eg}^{lag0d^1I/A}$, and $R_{Eg}^{lag1d^1I/A}$ is analogous to that of the benchmark expected investment growth factor, R_{Eg}. For each alternative expected investment growth factor, Panel A reports its average returns ($\bar{R}$), alongside alphas, factor loadings, and R^2 from the HXZq model. The t-values adjusted for heteroskedasticity and autocorrelations are presented in parentheses. For reference, the panel also reports for R_{Eg}: its average return, alongside alphas, factor loadings, and R^2 from the HXZq model. Panel B reports the correlations of R_{Eg}^{dNis}, R_{Eg}^{gSale}, $R_{Eg}^{lag0d^1I/A}$, and $R_{Eg}^{lag1d^1I/A}$ with R_{Eg} and HXZq model factors.

Table 3.10 Explaining Expected Investment Growth Quintiles with a REIT-Based HMXZq^5 model

	Low	2	3	4	High	H-L
			Panel A: τ = 1 ($\overline{\lvert\alpha\rvert}$ = 0.10 and p = 0.18)			
α	-0.03	0.24	-0.06	0.00	0.19	0.21
β_{Mkt}	0.89	0.96	0.99	0.99	0.87	-0.02
β_{Me}	0.00	0.08	-0.04	0.08	-0.15	-0.16
$\beta_{I/A}$	0.44	0.16	0.33	0.11	0.27	-0.17
β_{Roa}	-0.16	-0.12	0.07	-0.08	-0.27	-0.11
β_{Eg}	-0.62	-0.30	-0.04	0.17	0.53	1.16
t_{α}	-0.21	2.12	-0.65	0.00	1.84	1.74
t_{Mkt}	23.20	33.93	42.03	42.24	25.04	-0.55
t_{Me}	0.04	1.82	-0.63	1.97	-1.88	-1.08
$t_{I/A}$	4.11	2.41	3.03	1.52	2.13	-1.12
t_{Roa}	-2.93	-2.77	1.71	-1.88	-4.76	-1.94
t_{Eg}	-9.42	-6.41	-0.63	2.97	6.64	21.39
			Panel B: τ = 2 ($\overline{\lvert\alpha\rvert}$ = 0.10 and p = 0.43)			
α	-0.04	0.17	-0.04	-0.04	0.19	0.23
β_{Mkt}	0.94	0.96	0.98	0.97	0.83	-0.11
β_{Me}	-0.14	0.17	0.08	0.05	-0.21	-0.07
$\beta_{I/A}$	0.39	0.15	0.29	0.17	0.25	-0.14
β_{Roa}	-0.01	-0.12	0.01	-0.05	-0.31	-0.30
β_{Eg}	-0.64	-0.28	-0.01	0.25	0.52	1.16
t_{α}	-0.34	1.84	-0.43	-0.34	1.62	2.10
t_{Mkt}	32.96	40.39	38.53	38.73	28.87	-3.05
t_{Me}	-0.82	3.61	1.79	0.80	-2.47	-0.33
$t_{I/A}$	3.05	2.41	2.11	2.65	2.27	-0.77
t_{Roa}	-0.08	-2.45	0.28	-1.15	-5.16	-3.06
t_{Eg}	-8.43	-4.48	-0.11	4.77	6.96	17.76

I form a REIT-based HMXZq^5 model. In this model, the expected excess return of a REIT is described by its loadings on the expected premium of five factors: the market factor (R_{Mkt}), the size factor (R_{Me}), the investment factor ($R_{I/A}$), the return on assets factor (R_{Roa}), and the expected investment growth factor (R_{Eg}); $E\left[R_i - R_f\right] = \beta_{Mkt}^i E[R_{Mkt}] + \beta_{Me}^i E[R_{Me}] + \beta_{I/A}^i E\left[R_{I/A}\right] + \beta_{Roa}^i E[R_{Roa}] + \beta_{Eg}^i E\left[R_{Eg}\right]$, where $E[R_{Mkt}]$, $E[R_{Me}]$, $E\left[R_{I/A}\right]$, $E[R_{Roa}]$, and $E\left[R_{Eg}\right]$ are the expected premium of the five factors, respectively, and β_{Mkt}^i, β_{Me}^i, $\beta_{I/A}^i$, β_{Roa}^i, and β_{Eg}^i are the corresponding factor loadings. For each expected investment growth quintile, I perform time-series HMXZ q^5 factor-model regressions. Appendix 3.1 details the factor construction and the factor model regression specifications. I report the model alphas and factor loadings. The t-values are adjusted for heteroskedasticity and autocorrelations. $\overline{\lvert\alpha\rvert}$ represents the mean absolute alpha for a given set of quintiles, and the p-value is from the GRS test on the null hypothesis that the alphas across the quintiles are jointly zero.

Table 3.11 Spanning Tests: HXZq and HMXZq^5 versus FF5 And FF6

Panel A: Explaining the HXZq and HMXZq^5 factors

	$\bar{R}$	α	β_{Mkt}	β_{SMB}	β_{HML}	β_{CMA}	β_{RMW}	β_{UMD}	R^2
R_{Me}	0.19	-0.04	0.01	0.98	0.09	-0.02	-0.02		0.99
	(1.58)	(-2.83)	(2.57)	(62.20)	(5.99)	(-2.63)	(-2.30)		
		-0.01	0.02	1.03	0.03	-0.01	-0.02	-0.04	0.99
		(-0.34)	(4.30)	(58.37)	(2.48)	(-1.32)	(-1.85)	(-4.16)	
R_{Roa}	0.21	0.01	0.06	-0.15	-0.18	-0.05	0.67		0.52
	(0.99)	(0.07)	(1.73)	(-1.40)	(-1.53)	(-0.33)	(13.95)		
		-0.10	0.11	0.08	-0.18	-0.07	0.59	0.21	0.58
		(-0.61)	(2.25)	(1.03)	(-1.74)	(-0.44)	(10.37)	(3.04)	
R_{Eg}	0.34	0.54	-0.24	-0.60	-0.20	0.03	0.47		0.68
	(2.01)	(3.90)	(-6.28)	(-5.99)	(-2.12)	(0.35)	(4.95)		
		0.36	-0.16	-0.30	-0.18	0.00	0.35	0.34	0.76
		(2.75)	(-4.28)	(-5.33)	(-1.86)	(0.03)	(4.17)	(5.59)	

Panel B: Explaining the FF5 and FF6 factors

	$\bar{R}$	α	β_{Mkt}	β_{Me}	$\beta_{I/A}$	β_{Roa}	β_{Eg}	R^2
R_{SMB6}	0.19	0.04	-0.03	0.90	0.01	0.02		0.98
	(1.65)	(2.62)	(-5.29)	(45.07)	(0.66)	(1.48)		
		0.02	-0.02	0.92	0.01	0.01	0.04	0.98
		(0.93)	(-4.47)	(49.88)	(0.73)	(0.54)	(4.37)	
R_{HML}	0.08	0.06	-0.00	0.12	0.51	-0.22		0.35
	(0.54)	(0.41)	(-0.13)	(0.67)	(3.74)	(-2.81)		
		0.15	-0.05	0.02	0.51	-0.17	-0.14	0.37
		(0.91)	(-1.46)	(0.09)	(3.50)	(-2.02)	(-1.72)	
R_{RMW}	0.30	0.37	-0.20	-0.18	0.12	0.53		0.59
	(1.64)	(1.83)	(-4.32)	(-2.27)	(1.16)	(6.20)		
		0.17	-0.10	0.02	0.12	0.44	0.29	0.64
		(0.90)	(-2.46)	(0.39)	(1.40)	(4.94)	(3.12)	
R_{UMD}	0.22	0.48	-0.27	-0.87	0.17	0.53		0.56
	(1.01)	(3.07)	(-3.75)	(-4.09)	(0.66)	(3.87)		
		0.05	-0.06	-0.42	0.17	0.34	0.65	0.66
		(0.35)	(-0.93)	(-2.18)	(0.82)	(2.08)	(7.37)	

Panel C: GRS statistics and their p-values testing that the alphas of a key set of factors are jointly zero

$\alpha_{Roa}, \alpha_{Eg} = 0$		$\alpha_{HML}, \alpha_{RMW}, \alpha_{UMD} = 0$	
FF5	FF6	HXZq	$HMXZq^5$
5.59	3.31	3.87	0.97
[0.00]	[0.04]	[0.01]	[0.41]

In Panel A and B, $\bar{R}$ is the time-series average factor returns, α is the alpha from factor-model regressions, and R^2 is the goodness of fit from the regressions. R_{Mkt}, R_{Me}, $R_{I/A}$, and R_{Roa} are the market, size, investment, and return on assets factors in the REIT-based Hou-Xue-Zhang q-factor model (HXZq). R_{Eg} is the expected investment growth factor in the REIT-based Hou-Mo-Xue-Zhang q^5 model (HMXZq^5). R_{Mkt}, R_{SMB}, R_{HML}, R_{CMA}, and R_{RMW} are the market, size, value, investment, and operating profitability factors in the REIT-based Fama-French five-factor model (FF5). R_{UMD} is the momentum factor in the REIT-based Fama-French six-factor model (FF6). The t-values (presented in parentheses) are adjusted for heteroskedasticity and autocorrelations. Panel C reports the statistics and the corresponding p-values from GRS tests.

Table 3.12 Spanning Tests: HMXZq^5 versus FF5*, FF6*, HXZq*, and HMXZq^5*

Panel A: FF5* and FF6* regressions

	$\bar{R}$	α	β_{MKT^*}	β_{SMB^*}	β_{HML^*}	β_{CMA^*}	β_{RMW^*}	β_{UMD^*}	R^2
R_{Mkt}	0.81	0.09	0.79	0.33	0.42	0.11	0.24		0.49
	(2.63)	(0.43)	(6.13)	(3.20)	(1.72)	(0.68)	(2.31)		
		0.12	0.75	0.35	0.36	0.13	0.26	-0.08	0.49
		(0.58)	(6.59)	(3.02)	(1.77)	(0.89)	(2.44)	(-1.09)	
R_{Me}	0.19	0.08	0.04	0.41	0.23	-0.09	0.04		0.26
	(1.58)	(0.70)	(0.81)	(4.78)	(7.50)	(-1.00)	(0.62)		
		0.16	-0.04	0.46	0.10	-0.04	0.10	-0.21	0.37
		(1.35)	(-0.86)	(5.74)	(1.54)	(-0.48)	(1.11)	(-3.54)	
$R_{I/A}$	0.10	-0.05	0.12	0.21	0.23	0.00	0.08		0.23
	(0.68)	(-0.32)	(2.10)	(2.25)	(1.99)	(0.05)	(1.17)		
		-0.06	0.12	0.20	0.23	0.01	0.08	0.01	0.22
		(-0.35)	(2.27)	(2.08)	(2.17)	(0.08)	(1.12)	(0.28)	
R_{Roa}	0.21	0.41	-0.31	-0.21	0.03	-0.08	0.19		0.29
	(0.99)	(2.63)	(-4.18)	(-2.08)	(0.40)	(-0.67)	(1.57)		
		0.33	-0.23	-0.27	0.16	-0.13	0.14	0.21	0.36
		(1.82)	(-3.18)	(-2.65)	(1.50)	(-1.13)	(1.18)	(3.16)	
R_{Eg}	0.34	0.59	-0.28	-0.35	-0.50	0.17	-0.05		0.27
	(2.01)	(3.08)	(-3.06)	(-2.67)	(-7.30)	(1.41)	(-0.46)		
		0.48	-0.19	-0.40	-0.33	0.10	-0.10	0.27	0.35
		(2.02)	(-2.39)	(-3.20)	(-4.61)	(0.68)	(-0.75)	(3.16)	

Panel B: HXZq* and HMXZq^5* regressions

	$\bar{R}$	α	β_{Mkt^*}	β_{Me^*}	β_{I/A^*}	β_{Roe^*}	β_{Eg^*}	R^2
R_{Mkt}	0.81	0.08	0.80	0.27	0.61	0.05		0.44
	(2.63)	(0.29)	(5.39)	(2.54)	(2.90)	(0.31)		
		-0.00	0.82	0.28	0.62	0.00	0.13	0.44
		(-0.01)	(4.96)	(2.64)	(3.00)	(0.00)	(0.73)	
R_{Me}	0.19	0.19	-0.02	0.24	0.29	-0.33		0.28
	(1.58)	(1.42)	(-0.28)	(2.64)	(2.69)	(-2.42)		
		0.24	-0.03	0.23	0.29	-0.30	-0.08	0.28
		(2.00)	(-0.50)	(2.52)	(2.68)	(-1.85)	(-0.68)	
$R_{I/A}$	0.10	-0.05	0.12	0.14	0.36	-0.06		0.18
	(0.68)	(-0.30)	(1.83)	(1.40)	(4.22)	(-0.62)		
		0.09	0.09	0.11	0.34	0.03	-0.26	0.21
		(0.64)	(1.49)	(1.29)	(4.91)	(0.35)	(-1.47)	
R_{Roa}	0.21	0.23	-0.21	-0.07	-0.14	0.52		0.38
	(0.99)	(1.20)	(-3.17)	(-1.20)	(-1.47)	(3.76)		
		0.13	-0.18	-0.05	-0.13	0.46	0.16	0.38
		(0.81)	(-3.08)	(-0.92)	(-1.39)	(2.88)	(1.49)	
R_{Eg}	0.34	0.51	-0.25	-0.18	-0.49	0.36		0.24
	(2.01)	(2.66)	(-2.81)	(-1.54)	(-2.78)	(1.85)		
		0.36	-0.21	-0.15	-0.48	0.27	0.26	0.24
		(1.73)	(-2.24)	(-1.47)	(-2.66)	(1.35)	(1.64)	

Table 3.12 Continued

Panel C: GRS statistics and their p-values testing that the alphas of a set of factors are jointly zero			
$\alpha_{Mkt}, \alpha_{Me}, \alpha_{I/A}, \alpha_{Roa}, \alpha_{Eg} = 0$		$\alpha_{Mkt}, \alpha_{Me}, \alpha_{I/A}, \alpha_{Roa}, \alpha_{Eg} = 0$	
FF5*	FF6*	HXZq*	HMXZq5*
2.89	2.72	3.21	2.12
[0.02]	[0.02]	[0.01]	[0.06]

In Panel A and B, $\bar{R}$ is the time-series average factor returns, α is the alpha from factor-model regressions, and R^2 is the goodness of fit from the regressions. R_{Mkt}, R_{Me}, $R_{I/A}$, R_{Roa}, and R_{Eg} are the market, size, investment, return on assets, and expected investment growth factors in the REIT-based Hou-Mo-Xue-Zhang q^5 model (HMXZq^5). R_{MKT^*}, R_{SMB^*}, R_{HML^*}, R_{CMA^*}, and R_{RMW^*} are the market, size, value, investment, and operating profitability factors in the common stock-based Fama-French five-factor model (FF5*). R_{UMD^*} is the momentum factor in the common stock-based Fama-French six-factor model (FF6*). R_{Mkt^*}, R_{Me^*}, R_{I/A^*}, and R_{Roe^*} are the market, size, investment, and return on equity factors in the common stock-based Hou-Xue-Zhang q-factor model (HXZq*). R_{Eg^*} is the expected investment growth factor in the common stock-based Hou-Mo-Xue-Zhang q^5 model (HMXZq^5*). The FF5* and FF6* model factors are obtained from Kenneth French's website, while the HXZq* and HMXZq^5* model factors are sourced from Global-q.org. The t-values (presented in parentheses) are adjusted for heteroskedasticity and autocorrelations. Panel C reports the statistics and the corresponding p-values from GRS tests.

Table 3.13 Spanning Tests: FF6 versus FF5*, FF6*, HXZq*, and HMXZq^5*

Panel A: FF5* and FF6* regressions

	$\bar{R}$	α	β_{MKT^*}	β_{SMB^*}	β_{HML^*}	β_{CMA^*}	β_{RMW^*}	β_{UMD^*}	R^2
R_{Mkt}	0.81	0.09	0.79	0.33	0.42	0.11	0.24		0.49
	(2.63)	(0.43)	(6.13)	(3.20)	(1.72)	(0.68)	(2.31)		
		0.12	0.75	0.35	0.36	0.13	0.26	-0.08	0.49
		(0.58)	(6.59)	(3.02)	(1.77)	(0.89)	(2.44)	(-1.09)	
R_{SMB6}	0.19	0.10	0.01	0.37	0.18	-0.06	0.05		0.24
	(1.65)	(0.93)	(0.16)	(5.20)	(5.46)	(-0.78)	(0.75)		
		0.16	-0.05	0.41	0.07	-0.02	0.09	-0.16	0.32
		(1.49)	(-1.11)	(6.37)	(1.25)	(-0.32)	(1.27)	(-3.69)	
R_{HML}	0.08	0.01	0.14	0.17	0.25	0.02	-0.17		0.20
	(0.54)	(0.04)	(2.57)	(1.40)	(2.68)	(0.13)	(-1.82)		
		0.04	0.11	0.19	0.20	0.04	-0.15	-0.08	0.21
		(0.23)	(1.62)	(1.39)	(2.59)	(0.30)	(-1.34)	(-1.12)	
R_{CMA}	0.10	-0.05	0.12	0.21	0.23	0.00	0.08		0.23
	(0.68)	(-0.32)	(2.10)	(2.25)	(1.99)	(0.05)	(1.17)		
		-0.06	0.12	0.20	0.23	0.01	0.08	0.01	0.22
		(-0.35)	(2.27)	(2.08)	(2.17)	(0.08)	(1.12)	(0.28)	
R_{RMW}	0.30	0.41	-0.22	-0.21	-0.18	0.00	0.25		0.27
	(1.64)	(2.20)	(-2.79)	(-2.57)	(-1.98)	(0.00)	(3.67)		
		0.38	-0.19	-0.24	-0.12	-0.02	0.23	0.08	0.28
		(2.00)	(-2.63)	(-2.46)	(-1.91)	(-0.21)	(2.61)	(1.06)	
R_{UMD}	0.22	0.53	-0.43	-0.24	-0.48	0.16	0.02		0.22
	(1.01)	(2.62)	(-3.13)	(-1.38)	(-4.17)	(0.85)	(0.11)		
		0.28	-0.20	-0.38	-0.09	0.02	-0.12	0.63	0.47
		(1.16)	(-1.95)	(-2.49)	(-0.86)	(0.13)	(-0.79)	(3.39)	

Panel B: HXZq* and HMXZq^5* regressions

	$\bar{R}$	α	β_{Mkt^*}	β_{Me^*}	β_{I/A^*}	β_{Roe^*}	β_{Eg^*}	R^2
R_{Mkt}	0.81	0.08	0.80	0.27	0.61	0.05		0.44
	(2.63)	(0.29)	(5.39)	(2.54)	(2.90)	(0.31)		
		-0.00	0.82	0.28	0.62	0.00	0.13	0.44
		(-0.01)	(4.96)	(2.64)	(3.00)	(0.00)	(0.73)	
R_{SMB6}	0.19	0.20	-0.04	0.23	0.24	-0.26		0.25
	(1.65)	(1.55)	(-0.64)	(2.92)	(2.71)	(-2.33)		
		0.25	-0.05	0.22	0.24	-0.23	-0.08	0.25
		(2.06)	(-0.88)	(2.77)	(2.78)	(-1.82)	(-0.84)	
R_{HML}	0.08	0.06	0.10	0.09	0.23	-0.32		0.20
	(0.54)	(0.39)	(1.60)	(0.91)	(2.65)	(-2.76)		
		0.16	0.07	0.07	0.22	-0.26	-0.18	0.21
		(0.95)	(1.23)	(0.67)	(2.37)	(-2.00)	(-1.08)	
R_{CMA}	0.10	-0.05	0.12	0.14	0.36	-0.06		0.18
	(0.68)	(-0.30)	(1.83)	(1.40)	(4.22)	(-0.62)		
		0.09	0.09	0.11	0.34	0.03	-0.26	0.21
		(0.64)	(1.49)	(1.29)	(4.91)	(0.35)	(-1.47)	
R_{RMW}	0.30	0.46	-0.21	-0.23	-0.18	0.23		0.27
	(1.64)	(2.25)	(-2.82)	(-3.56)	(-1.41)	(2.25)		
		0.37	-0.19	-0.22	-0.17	0.18	0.15	0.28
		(1.79)	(-2.40)	(-3.40)	(-1.31)	(1.37)	(1.57)	
R_{UMD}	0.22	0.24	-0.29	0.06	-0.52	0.80		0.29
	(1.01)	(1.01)	(-2.56)	(0.50)	(-2.15)	(2.52)		
		0.15	-0.27	0.07	-0.51	0.74	0.16	0.30
		(0.73)	(-2.30)	(0.72)	(-2.07)	(1.91)	(0.53)	

Table 3.13 Continued

Panel C: GRS statistics and their p-values testing that the alphas of a set of factors are jointly zero			
$\alpha_{Mkt}, \alpha_{SMB6}, \alpha_{HML}, \alpha_{CMA}, \alpha_{RMW}, \alpha_{UMD} = 0$		$\alpha_{Mkt}, \alpha_{SMB6}, \alpha_{HML}, \alpha_{CMA}, \alpha_{RMW}, \alpha_{UMD} = 0$	
FF5*	FF6*	HXZq*	HMXZq5*
1.90	1.76	2.26	1.60
[0.08]	[0.11]	[0.04]	[0.15]

In Panel A and B, $\bar{R}$ is the time-series average factor returns, α is the alpha from factor-model regressions, and R^2 is the goodness of fit from regressions. R_{Mkt}, R_{SMB6}, R_{HML}, R_{CMA}, R_{RMW}, and R_{UMD} are the market, size, value, investment, operating profitability, and momentum factors in the REIT-based Fama-French six-factor model (FF6). R_{MKT^*}, R_{SMB^*}, R_{HML^*}, R_{CMA^*}, and R_{RMW^*} are the market, size, value, investment, and operating profitability factors in the common stock-based Fama-French five-factor model (FF5*). R_{UMD^*} is the momentum factor in the common stock-based Fama-French six-factor model (FF6*). R_{Mkt^*}, R_{Me^*}, R_{I/A^*}, and R_{Roe^*} are the market, size, investment, and return on equity factors in the common stock-based Hou-Xue-Zhang q-factor model (HXZq*). R_{Eg^*} is the expected investment growth factor in the common stock-based Hou-Mo-Xue-Zhang q^5 model (HMXZq^5*). The FF5* and FF6* model factors are obtained from Kenneth French's website, while the HXZq* and HMXZq^5* model factors are sourced from Global-q.org. The t-values (presented in parentheses) are adjusted for heteroskedasticity and autocorrelations. Panel C reports the statistics and the corresponding p-values from GRS tests.

Table 3.14 Correlation Matrix

	R_{Mkt}	R_{Me}	$R_{I/A}$	R_{Roa}	R_{Eg}	R_{SMB6}	R_{HML}	R_{CMA}	R_{RMW}	R_{UMD}	R_{Mkt^*}	R_{Me^*}	R_{I/A^*}	R_{Roe^*}	R_{Eg^*}	R_{MKT^*}	R_{SMB6^*}	R_{HML^*}	R_{CMA^*}	R_{RMW^*}
R_{Me}	0.21																			
	(0.00)																			
$R_{I/A}$	0.14	0.39																		
	(0.02)	(0.00)																		
R_{Roa}	-0.27	-0.38	-0.23																	
	(0.00)	(0.00)	(0.00)																	
R_{Eg}	-0.56	-0.61	-0.28	0.52																
	(0.00)	(0.00)	(0.00)	(0.00)																
R_{SMB6}	0.14	0.99	0.38	-0.34	-0.54															
	(0.02)	(0.00)	(0.00)	(0.00)	(0.00)															
R_{HML}	0.14	0.37	0.51	-0.39	-0.39	0.33														
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)														
R_{CMA}	0.14	0.39	1.00	-0.23	-0.28	0.38	0.51													
	(0.02)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)													
R_{RMW}	-0.49	-0.40	-0.14	0.69	0.68	-0.32	-0.32	-0.14												
	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)												
R_{UMD}	-0.45	-0.60	-0.21	0.56	0.77	-0.51	-0.23	-0.21	0.52											
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)											
R_{Mkt^*}	0.60	0.16	0.23	-0.47	-0.34	0.11	0.29	0.23	-0.40	-0.38										
	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.05)	(0.00)	(0.00)	(0.00)	(0.00)										
R_{Me^*}	0.31	0.40	0.26	-0.30	-0.29	0.39	0.26	0.26	-0.37	-0.20	0.27									
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)									
R_{I/A^*}	0.06	0.15	0.23	0.08	-0.12	0.15	0.06	0.23	0.01	-0.05	-0.28	-0.01								
	(0.32)	(0.01)	(0.00)	(0.20)	(0.05)	(0.01)	(0.33)	(0.00)	(0.89)	(0.41)	(0.00)	(0.85)								
R_{Roe^*}	-0.31	-0.40	-0.20	0.57	0.37	-0.36	-0.40	-0.20	0.41	0.49	-0.51	-0.40	0.20							
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)							
R_{Eg^*}	-0.33	-0.33	-0.33	0.49	0.38	-0.30	-0.37	-0.33	0.41	0.39	-0.54	-0.41	0.12	0.65						
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.04)	(0.00)						
R_{MKT^*}	0.60	0.16	0.23	-0.47	-0.34	0.11	0.29	0.23	-0.40	-0.38	1.00	0.27	-0.28	-0.51	-0.54					
	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.05)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)					
R_{SMB6^*}	0.31	0.44	0.28	-0.36	-0.31	0.43	0.31	0.28	-0.38	-0.24	0.28	0.97	-0.05	-0.52	-0.48	0.28				
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.42)	(0.00)	(0.00)	(0.00)				
R_{HML^*}	0.29	0.26	0.34	0.08	-0.32	0.23	0.21	0.34	-0.07	-0.22	-0.06	0.08	0.64	0.12	-0.06	-0.06	0.03			
	(0.00)	(0.00)	(0.00)	(0.19)	(0.00)	(0.00)	(0.00)	(0.00)	(0.22)	(0.00)	(0.33)	(0.17)	(0.00)	(0.05)	(0.31)	(0.33)	(0.59)			

Table 3.14 Continued

	R_{Mkt}	R_{Me}	$R_{I/A}$	R_{Roa}	R_{Eg}	R_{SMB6}	R_{HML}	R_{CMA}	R_{RMW}	R_{UMD}	R_{Mkt^*}	R_{Me^*}	R_{I/A^*}	R_{Roe^*}	R_{Eg^*}	R_{MKT^*}	R_{SMB6^*}	R_{HML^*}	R_{CMA^*}	R_{RMW^*}
R_{CMA^*}	0.03	0.10	0.15	0.12	-0.06	0.11	0.07	0.15	0.04	0.00	-0.31	0.07	0.91	0.19	0.15	-0.31	0.02	0.60		
	(0.64)	(0.10)	(0.01)	(0.04)	(0.28)	(0.07)	(0.23)	(0.01)	(0.49)	(1.00)	(0.00)	(0.25)	(0.00)	(0.00)	(0.01)	(0.00)	(0.75)	(0.00)		
R_{RMW^*}	-0.10	-0.09	0.02	0.38	0.07	-0.08	-0.20	0.02	0.34	0.10	-0.39	-0.45	0.33	0.71	0.53	-0.39	-0.48	0.41	0.28	
	(0.10)	(0.11)	(0.79)	(0.00)	(0.26)	(0.16)	(0.00)	(0.79)	(0.00)	(0.08)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	
R_{UMD^*}	-0.33	-0.39	-0.14	0.36	0.43	-0.33	-0.26	-0.14	0.24	0.63	-0.33	0.04	-0.06	0.48	0.34	-0.33	-0.03	-0.27	-0.01	0.04
	(0.00)	(0.00)	(0.02)	(0.00)	(0.00)	(0.00)	(0.00)	(0.02)	(0.00)	(0.00)	(0.00)	(0.53)	(0.33)	(0.00)	(0.00)	(0.00)	(0.59)	(0.00)	(0.86)	(0.47)

R_{Mkt}, R_{Me}, $R_{I/A}$, R_{Roa}, and R_{Eg} are the market, size, investment, return on assets, and expected investment growth factors in the REIT-based Hou-Mo-Xue-Zhang q^5 model (HMXZq^5). R_{Mkt}, R_{SMB6}, R_{HML}, R_{CMA}, R_{RMW}, and R_{UMD} are the market, size, value, investment, operating profitability, and momentum factors in the REIT-based Fama-French six-factor model (FF6). R_{Mkt^*}, R_{Me^*}, R_{I/A^*}, R_{Roe^*}, and R_{Eg^*} are the market, size, investment, return on equity, and expected investment growth factors in the common stock-based Hou-Mo-Xue-Zhang q^5 model (HMXZq^5*). The data for R_{Mkt^*}, R_{Me^*}, R_{I/A^*}, R_{Roe^*}, and R_{Eg^*} are sourced from Global-q.org. R_{MKT^*}, R_{SMB6^*}, R_{HML^*}, R_{CMA^*}, R_{RMW^*}, and R_{UMD^*} are the market, size, value, investment, operating profitability, and momentum factors in the common stock-based Fama-French six-factor model (FF6**). The data for R_{MKT^*}, R_{SMB6^*}, R_{HML^*}, R_{CMA^*}, R_{RMW^*}, and R_{UMD^*} are obtained from Kenneth French's website. The p-values testing whether a given correlation equals zero are presented in parentheses beneath the correlations.

Table 3.15 Properties of Momentum Quintiles

	Low	2	3	4	High	H-L
Panel A: Average excess returns, $\bar{R}$						
$\bar{R}$	0.32	0.87	0.84	0.93	0.86	0.54
$t_{\bar{R}}$	0.60	2.68	2.73	2.75	2.73	1.80
Panel B: The CAPM ($\overline{\lvert\alpha_{CAPM}\rvert}$ = 0.22 and p_{CAPM} = 0.06)						
α_{CAPM}	-0.55	0.00	0.09	0.21	0.24	0.78
β_{Mkt}	1.07	1.07	0.93	0.88	0.77	-0.31
t_{CAPM}	-2.00	0.02	1.17	3.39	2.39	2.72
t_{Mkt}	10.77	16.63	32.05	15.42	15.00	-2.78
Panel C: The Fama-French three-factor model ($\overline{\lvert\alpha_{FF3}\rvert}$ = 0.26 and p_{FF3} = 0.02)						
α_{FF3}	-0.57	-0.08	0.08	0.25	0.30	0.88
β_{Mkt}	1.02	1.03	0.92	0.90	0.80	-0.22
β_{SMB3}	0.07	0.45	0.07	-0.17	-0.34	-0.41
β_{HML}	0.63	0.10	0.06	-0.03	-0.07	-0.70
t_{FF3}	-2.11	-0.54	1.02	3.27	2.83	2.97
t_{Mkt}	15.36	27.81	36.23	19.22	22.00	-2.76
t_{SMB3}	0.19	2.55	1.03	-3.00	-4.77	-1.10
t_{HML}	2.71	0.94	0.96	-0.89	-0.98	-2.66
Panel D: The Carhart four-factor model ($\overline{\lvert\alpha_{Carhart4}\rvert}$ = 0.16 and $p_{Carhart4}$ = 0.12)						
$\alpha_{Carhart4}$	-0.27	0.26	0.10	0.14	0.03	0.31
β_{Mkt}	0.86	0.88	0.91	0.95	0.92	0.07
β_{SMB4}	-0.33	-0.05	0.05	-0.06	-0.01	0.32
β_{HML}	0.58	0.01	0.05	0.01	0.02	-0.56
β_{UMD}	-0.40	-0.43	-0.03	0.13	0.35	0.75
$t_{Carhart4}$	-0.74	2.37	1.23	2.13	0.39	0.92
t_{Mkt}	13.54	24.60	36.86	24.12	36.26	1.07
t_{SMB4}	-1.59	-0.69	0.85	-1.03	-0.13	1.36
t_{HML}	2.61	0.17	0.88	0.15	0.34	-2.41
t_{UMD}	-1.42	-12.36	-0.82	5.93	11.62	2.75
Panel E: The Fama-French five-factor model ($\overline{\lvert\alpha_{FF5}\rvert}$ = 0.19 and p_{FF5} = 0.13)						
α_{FF5}	-0.44	-0.01	0.04	0.17	0.29	0.73
β_{Mkt}	0.96	1.00	0.94	0.93	0.79	-0.16
β_{SMB5}	-0.08	0.42	0.10	-0.18	-0.40	-0.33
β_{HML}	0.49	-0.04	0.05	-0.04	-0.08	-0.56
β_{CMA}	0.26	0.11	0.03	0.16	0.19	-0.07
β_{RMW}	-0.22	-0.10	0.07	0.12	-0.01	0.21
t_{FF5}	-1.74	-0.06	0.43	2.21	2.70	2.98
t_{Mkt}	13.29	35.34	43.78	32.20	25.14	-2.32
t_{SMB5}	-0.22	2.42	1.34	-4.13	-4.88	-0.92
t_{HML}	2.27	-0.39	0.97	-0.94	-1.15	-2.53
t_{CMA}	0.82	1.20	0.64	2.24	1.46	-0.18
t_{RMW}	-0.85	-0.98	1.75	3.28	-0.11	0.82
Panel F: The Fama-French six-factor model ($\overline{\lvert\alpha_{FF6}\rvert}$ = 0.14 and p_{FF6} = 0.27)						
α_{FF6}	-0.23	0.22	0.06	0.11	0.10	0.33
β_{Mkt}	0.84	0.89	0.93	0.96	0.89	0.05
β_{SMB6}	-0.51	-0.04	0.06	-0.08	-0.06	0.45
β_{HML}	0.51	-0.04	0.05	-0.03	-0.07	-0.58
β_{CMA}	0.27	0.15	0.03	0.16	0.16	-0.11
β_{RMW}	-0.02	0.06	0.09	0.08	-0.16	-0.13
β_{UMD}	-0.45	-0.43	-0.04	0.11	0.37	0.82
t_{FF6}	-0.58	1.96	0.65	1.53	1.39	0.92
t_{Mkt}	8.91	26.62	44.25	31.67	31.74	0.63
t_{SMB6}	-2.41	-0.47	1.07	-1.55	-0.57	1.75
t_{HML}	2.20	-0.66	0.95	-0.85	-1.05	-2.33
t_{CMA}	1.02	2.20	0.79	2.04	1.60	-0.34
t_{RMW}	-0.12	1.28	1.84	2.69	-2.98	-0.75
t_{UMD}	-1.88	-12.24	-1.24	4.56	12.68	3.68

Table 3.15 Continued

Panel G: The Hou-Xue-Zhang q-factor model ($\overline{\lvert\alpha_{HXZq}\rvert}$ = 0.22 and p_{HXZq} = 0.03)						
α_{HXZq}	-0.42	0.06	0.10	0.22	0.28	0.70
β_{Mkt}	0.98	0.99	0.91	0.90	0.80	-0.18
β_{Me}	-0.08	0.31	0.05	-0.23	-0.41	-0.33
$\beta_{I/A}$	0.47	0.05	0.06	0.16	0.15	-0.33
β_{Roa}	-0.41	-0.27	-0.04	0.03	-0.02	0.39
t_{HXZq}	-1.48	0.48	1.28	2.93	2.68	2.51
t_{Mkt}	14.99	31.78	38.18	23.27	26.49	-2.35
t_{Me}	-0.26	2.26	0.74	-3.83	-4.44	-0.94
$t_{I/A}$	1.27	0.38	1.36	2.74	1.27	-0.74
t_{Roa}	-1.55	-2.98	-0.99	0.78	-0.20	1.51
Panel H: The Bond-Xue investment-based three-factor model ($\overline{\lvert\alpha_{BX3}\rvert}$ = 0.20 and p_{BX3} = 0.08)						
α_{BX3}	-0.40	0.06	0.10	0.20	0.22	0.63
β_{Mkt}	1.02	1.04	0.92	0.88	0.77	-0.26
$\beta_{I/A\_}$	0.01	0.15	0.04	0.06	0.04	0.03
$\beta_{Roa\_}$	-0.51	-0.29	-0.06	0.02	0.03	0.54
t_{BX3}	-1.45	0.43	1.31	2.91	2.13	2.13
t_{Mkt}	12.44	19.53	35.94	15.74	16.74	-2.80
$t_{I/A\_}$	0.02	1.76	1.41	1.37	0.34	0.07
$t_{Roa\_}$	-2.60	-2.78	-1.11	0.54	0.36	2.45
Panel I: The Hou-Mo-Xue-Zhang q^5 model ($\overline{\lvert\alpha_{HMXZq^5}\rvert}$ = 0.08 and p_{HMXZq^5} = 0.69)						
α_{HMXZq^5}	-0.07	0.17	0.05	0.08	-0.02	0.05
β_{Mkt}	0.81	0.94	0.94	0.97	0.94	0.13
β_{Me}	-0.45	0.20	0.10	-0.08	-0.11	0.34
$\beta_{I/A}$	0.47	0.04	0.06	0.16	0.15	-0.32
β_{Roa}	-0.25	-0.22	-0.06	-0.04	-0.15	0.10
β_{Eg}	-0.53	-0.16	0.08	0.21	0.44	0.97
t_{HMXZq^5}	-0.29	1.49	0.53	1.13	-0.12	0.22
t_{Mkt}	11.54	28.55	40.94	33.04	30.23	1.65
t_{Me}	-1.19	1.25	2.24	-1.34	-1.32	0.90
$t_{I/A}$	1.35	0.40	1.30	2.47	1.78	-0.83
t_{Roa}	-0.83	-2.16	-1.77	-1.13	-1.54	0.35
t_{Eg}	-2.91	-2.32	1.66	6.46	6.68	6.02
Panel J: Average expected τ-year-ahead investment-to-asset changes, $E[d^\tau I/A]$						
$E[d^1 I/A]$	-4.68	-3.77	-2.77	-1.41	1.45	6.13
t	-5.80	-4.60	-3.60	-1.83	2.08	9.06
$E[d^2 I/A]$	-6.59	-5.31	-4.41	-2.65	1.19	7.78
t	-5.37	-4.39	-3.48	-2.21	1.03	9.95

At the beginning of each month t, I sort all firms into quintiles based on prior 11-month returns from month t−12 to t−2, Ret^{11}, and compute value-weighted quintile excess returns for the current month t, using the beginning-of-month market equity as the weights. The quintiles are rebalanced at the beginning of month t+1. For each quintile, I perform time-series REIT-based factor model regressions, including the Capital Asset Pricing Model (CAPM), the Fama-French three-factor model (FF3), the Carhart four-factor model (Carhart4), the Fama-French five-factor model (FF5), the Fama-French six-factor model (FF6), the Hou-Xue-Zhang q-factor model (HXZq), the Bond-Xue investment-based three-factor model (BX3), and the Hou-Mo-Xue-Zhang q^5 model (HMXZq^5). I report the time-series average of quintile excess returns, alphas and factor loadings from the factor model regressions, as well as their heteroskedasticity-and-autocorrelation-adjusted t-statistics. $\overline{\lvert\alpha\rvert}$ is the mean absolute alpha for a given set of quintiles, and the p-value from the GRS test on the null hypothesis that the alphas across the quintiles are jointly zero. Additionally, I report the time-series average of quintile expected τ-year-ahead investment-to-asset changes, $E[d^\tau I/A]$, where τ = 1 and 2.

Table 3.16 Properties of Standardized Unexpected Earnings Quintiles

	Low	2	3	4	High	H-L
Panel A: Average excess returns, $\bar{R}$						
$\bar{R}$	0.61	0.61	0.79	0.94	0.90	0.30
$t_{\bar{R}}$	1.88	1.88	2.50	3.07	2.83	3.24
Panel B: The CAPM ($\overline{\lvert\alpha_{CAPM}\rvert}$ = 0.17 and p_{CAPM} = 0.05)						
α_{CAPM}	-0.22	-0.14	0.06	0.20	0.22	0.44
β_{Mkt}	1.02	0.93	0.91	0.92	0.85	-0.17
t_{CAPM}	-2.35	-1.26	0.74	1.96	2.68	3.50
t_{Mkt}	25.28	24.91	28.35	20.17	17.10	-2.15
Panel C: The Fama-French three-factor model ($\overline{\lvert\alpha_{FF3}\rvert}$ = 0.18 and p_{FF3} = 0.01)						
α_{FF3}	-0.27	-0.11	0.07	0.21	0.26	0.53
β_{Mkt}	1.00	0.94	0.91	0.92	0.87	-0.13
β_{SMB3}	0.26	-0.16	-0.07	-0.07	-0.22	-0.48
β_{HML}	-0.01	0.06	0.03	0.08	-0.03	-0.02
t_{FF3}	-2.66	-1.06	0.99	1.95	3.42	3.97
t_{Mkt}	40.00	34.23	34.66	23.02	21.51	-2.41
t_{SMB3}	3.18	-2.48	-1.39	-1.67	-3.69	-4.62
t_{HML}	-0.13	0.95	0.63	1.65	-0.72	-0.20
Panel D: The Carhart four-factor model ($\overline{\lvert\alpha_{Carhart4}\rvert}$ = 0.12 and $p_{Carhart4}$ = 0.11)						
$\alpha_{Carhart4}$	-0.09	-0.09	0.03	0.22	0.18	0.27
β_{Mkt}	0.92	0.92	0.93	0.91	0.90	-0.03
β_{SMB4}	0.02	-0.23	-0.01	-0.12	-0.13	-0.15
β_{HML}	-0.06	0.08	0.04	0.09	0.02	0.08
β_{UMD}	-0.22	-0.04	0.04	-0.02	0.10	0.32
$t_{Carhart4}$	-1.11	-1.02	0.43	2.18	2.22	1.98
t_{Mkt}	28.42	31.72	38.46	23.31	29.79	-0.68
t_{SMB4}	0.31	-2.57	-0.15	-2.05	-1.78	-1.95
t_{HML}	-1.13	1.46	0.80	2.17	0.41	1.19
t_{UMD}	-4.29	-0.75	1.49	-0.60	3.38	5.99
Panel E: The Fama-French five-factor model ($\overline{\lvert\alpha_{FF5}\rvert}$ = 0.14 and p_{FF5} = 0.09)						
α_{FF5}	-0.19	-0.07	0.09	0.18	0.16	0.35
β_{Mkt}	0.97	0.92	0.90	0.92	0.91	-0.06
β_{SMB5}	0.22	-0.20	-0.11	-0.10	-0.21	-0.42
β_{HML}	-0.12	0.04	0.02	0.02	0.01	0.13
β_{CMA}	0.12	0.08	0.06	0.23	0.09	-0.03
β_{RMW}	-0.11	-0.09	-0.05	0.04	0.15	0.27
t_{FF5}	-2.44	-0.88	1.42	1.99	2.25	2.99
t_{Mkt}	41.83	23.99	36.93	28.68	35.66	-1.78
t_{SMB5}	3.09	-2.69	-1.60	-3.01	-3.51	-5.22
t_{HML}	-1.74	0.66	0.29	0.36	0.26	1.81
t_{CMA}	1.23	0.84	0.80	2.55	1.09	-0.25
t_{RMW}	-2.16	-0.68	-1.51	1.49	3.14	4.88
Panel F: The Fama-French six-factor model ($\overline{\lvert\alpha_{FF6}\rvert}$ = 0.10 and p_{FF6} = 0.22)						
α_{FF6}	-0.08	-0.05	0.07	0.19	0.13	0.21
β_{Mkt}	0.92	0.90	0.91	0.91	0.92	0.00
β_{SMB6}	0.00	-0.26	-0.06	-0.15	-0.15	-0.16
β_{HML}	-0.12	0.05	0.02	0.02	0.02	0.14
β_{CMA}	0.14	0.08	0.05	0.23	0.08	-0.05
β_{RMW}	-0.03	-0.07	-0.06	0.05	0.13	0.17
β_{UMD}	-0.21	-0.04	0.04	-0.03	0.07	0.28
t_{FF6}	-1.14	-0.64	1.01	2.14	1.70	1.71
t_{Mkt}	29.75	22.03	39.32	27.35	36.44	0.13
t_{SMB6}	0.06	-2.84	-0.87	-3.03	-1.84	-2.06
t_{HML}	-2.16	0.95	0.35	0.58	0.41	2.12
t_{CMA}	1.69	0.86	0.72	2.60	0.90	-0.47
t_{RMW}	-0.87	-0.55	-1.97	2.20	2.81	3.15
t_{UMD}	-3.71	-1.10	1.57	-1.57	2.90	5.30

Table 3.16 Continued

Panel G: The Hou-Xue-Zhang q-factor model ($\overline{\lvert\alpha_{HXZq}\rvert}$ = 0.14 and p_{HXZq} = 0.04)						
α_{HXZq}	-0.14	-0.05	0.10	0.21	0.20	0.35
β_{Mkt}	0.96	0.92	0.90	0.91	0.88	-0.08
β_{Me}	0.12	-0.24	-0.13	-0.13	-0.22	-0.35
$\beta_{I/A}$	0.02	0.07	0.05	0.24	0.12	0.10
β_{Roa}	-0.25	-0.20	-0.11	-0.03	0.09	0.34
t_{HXZq}	-1.50	-0.55	1.42	2.09	2.47	2.34
t_{Mkt}	45.05	29.52	35.27	26.75	30.62	-2.30
t_{Me}	2.07	-2.61	-1.67	-3.86	-3.78	-5.02
$t_{I/A}$	0.15	0.59	0.76	2.87	1.81	0.87
t_{Roa}	-3.99	-1.97	-3.01	-0.88	1.72	3.79
Panel H: The Bond-Xue investment-based three-factor model ($\overline{\lvert\alpha_{BX3}\rvert}$ = 0.15 and p_{BX3} = 0.11)						
α_{BX3}	-0.17	-0.10	0.09	0.17	0.20	0.37
β_{Mkt}	0.99	0.92	0.90	0.91	0.85	-0.14
$\beta_{I/A\_}$	0.08	-0.02	-0.03	0.18	0.01	-0.07
$\beta_{Roa\_}$	-0.22	-0.14	-0.10	-0.01	0.05	0.28
t_{BX3}	-1.76	-0.98	1.20	1.84	2.21	2.53
t_{Mkt}	28.87	21.73	29.19	23.82	18.85	-1.98
$t_{I/A\_}$	0.75	-0.21	-0.62	2.03	0.10	-0.50
$t_{Roa\_}$	-5.24	-1.78	-1.96	-0.47	1.32	4.44
Panel I: The Hou-Mo-Xue-Zhang q^5 model ($\overline{\lvert\alpha_{HMXZq^5}\rvert}$ = 0.12 and p_{HMXZq^5} = 0.28)						
α_{HMXZq^5}	-0.16	-0.14	0.04	0.14	0.09	0.25
β_{Mkt}	0.97	0.96	0.93	0.94	0.94	-0.04
β_{Me}	0.14	-0.15	-0.06	-0.06	-0.11	-0.25
$\beta_{I/A}$	0.02	0.07	0.05	0.24	0.12	0.11
β_{Roa}	-0.26	-0.24	-0.14	-0.06	0.04	0.30
β_{Eg}	0.03	0.14	0.10	0.10	0.17	0.14
t_{HMXZq^5}	-1.58	-1.73	0.63	1.84	0.98	1.60
t_{Mkt}	28.42	41.71	30.83	40.35	30.16	-0.62
t_{Me}	1.49	-1.73	-0.60	-1.75	-1.69	-2.07
$t_{I/A}$	0.15	0.58	0.80	2.82	1.72	0.92
t_{Roa}	-3.64	-2.29	-3.66	-1.45	0.64	2.55
t_{Eg}	0.39	2.96	1.67	1.93	3.35	1.29
Panel J: Average expected τ-year-ahead investment-to-asset changes, $E[d^{\tau}I/A]$						
$E[d^1I/A]$	-2.64	-2.26	-2.47	-1.68	-0.91	1.72
t	-3.62	-2.77	-3.01	-2.28	-1.30	4.16
$E[d^2I/A]$	-5.10	-3.86	-3.83	-2.73	-0.98	4.12
t	-4.13	-3.19	-3.04	-2.68	-0.88	6.14

At the beginning of each month t, I sort all firms into quintiles based on the beginning-of-month standardized unexpected earnings, Sue, and compute value-weighted quintile excess returns for the current month t, using the beginning-of-month market equity as the weights. The quintiles are rebalanced at the beginning of month t+1. For each quintile, I perform time-series REIT-based factor model regressions, including the Capital Asset Pricing Model (CAPM), the Fama-French three-factor model (FF3), the Carhart four-factor model (Carhart4), the Fama-French five-factor model (FF5), the Fama-French six-factor model (FF6), the Hou-Xue-Zhang q-factor model (HXZq), the Bond-Xue investment-based three-factor model (BX3), and the Hou-Mo-Xue-Zhang q^5 model (HMXZq^5). I report the time-series average of quintile excess returns, alphas and factor loadings from the factor model regressions, as well as their heteroskedasticity-and-autocorrelation-adjusted t-statistics. $\overline{\lvert\alpha\rvert}$ is the mean absolute alpha for a given set of quintiles, and the p-value from the GRS test on the null hypothesis that the alphas across the quintiles are jointly zero. Additionally, I report the time-series average of quintile expected τ-year-ahead investment-to-asset changes, $E[d^{\tau}I/A]$, where τ = 1 and 2.

Table 3.17 Properties of Idiosyncratic Volatility Quintiles

	Low	2	3	4	High	H-L
Panel A: Average excess returns, $\bar{R}$						
	Low	2	3	4	High	H-L
$\bar{R}$	0.88	0.85	0.95	0.70	0.53	-0.34
$t_{\bar{R}}$	2.95	2.61	3.15	2.06	0.98	-0.89
Panel B: The CAPM ($\overline{\lvert\alpha_{CAPM}\rvert}$ = 0.22 and p_{CAPM} = 0.03)						
α_{CAPM}	0.24	0.12	0.18	-0.14	-0.43	-0.68
β_{Mkt}	0.78	0.90	0.96	1.04	1.20	0.42
t_{CAPM}	3.15	1.50	2.58	-1.00	-1.28	-1.93
t_{Mkt}	14.81	17.02	48.16	27.08	8.00	2.07
Panel C: The Fama-French three-factor model ($\overline{\lvert\alpha_{FF3}\rvert}$ = 0.28 and p_{FF3} = 0.00)						
α_{FF3}	0.29	0.15	0.17	-0.18	-0.60	-0.88
β_{Mkt}	0.81	0.90	0.95	1.02	1.12	0.31
β_{SMB3}	-0.22	-0.13	0.03	0.19	0.84	1.06
β_{HML}	-0.08	0.04	0.11	0.06	0.19	0.27
t_{FF3}	3.43	1.66	2.89	-1.31	-1.70	-2.35
t_{Mkt}	20.05	22.06	55.85	31.99	10.85	2.25
t_{SMB3}	-3.00	-1.76	0.72	1.17	2.02	2.19
t_{HML}	-1.89	0.79	2.44	0.58	0.73	0.94
Panel D: The Carhart four-factor model ($\overline{\lvert\alpha_{Carhart4}\rvert}$ = 0.11 and $p_{Carhart4}$ = 0.05)						
$\alpha_{Carhart4}$	0.20	0.09	0.19	-0.00	-0.05	-0.25
β_{Mkt}	0.84	0.93	0.94	0.95	0.89	0.05
β_{SMB4}	-0.11	-0.06	0.00	-0.08	0.09	0.20
β_{HML}	-0.04	0.06	0.11	0.03	0.02	0.07
β_{UMD}	0.11	0.07	-0.02	-0.21	-0.67	-0.78
$t_{Carhart4}$	2.26	0.98	2.86	-0.04	-0.20	-0.83
t_{Mkt}	23.39	30.84	45.56	23.80	10.67	0.49
t_{SMB4}	-1.45	-1.52	0.12	-0.56	0.24	0.49
t_{HML}	-0.95	1.42	2.58	0.29	0.11	0.27
t_{UMD}	5.00	1.87	-0.73	-5.05	-4.92	-5.48
Panel E: The Fama-French five-factor model ($\overline{\lvert\alpha_{FF5}\rvert}$ = 0.13 and p_{FF5} = 0.08)						
α_{FF5}	0.21	0.08	0.13	-0.16	0.05	-0.16
β_{Mkt}	0.84	0.93	0.96	1.02	0.85	0.02
β_{SMB5}	-0.21	-0.14	0.04	0.17	0.52	0.73
β_{HML}	-0.06	0.01	0.10	-0.01	-0.15	-0.09
β_{CMA}	0.10	0.18	0.06	0.10	-0.03	-0.13
β_{RMW}	0.12	0.10	0.06	-0.02	-1.03	-1.15
t_{FF5}	2.89	0.96	2.24	-1.18	0.21	-0.59
t_{Mkt}	27.35	34.81	56.03	30.98	13.34	0.23
t_{SMB5}	-2.99	-2.83	0.98	0.99	1.40	1.69
t_{HML}	-1.40	0.46	1.79	-0.04	-0.64	-0.37
t_{CMA}	1.34	2.10	0.95	0.89	-0.17	-0.58
t_{RMW}	2.97	2.91	1.80	-0.27	-4.73	-5.67
Panel F: The Fama-French six-factor model ($\overline{\lvert\alpha_{FF6}\rvert}$ = 0.15 and p_{FF6} = 0.11)						
α_{FF6}	0.16	0.06	0.15	-0.04	0.33	0.17
β_{Mkt}	0.85	0.94	0.95	0.96	0.72	-0.13
β_{SMB6}	-0.13	-0.10	0.01	-0.08	-0.01	0.12
β_{HML}	-0.05	0.02	0.10	-0.00	-0.15	-0.10
β_{CMA}	0.09	0.17	0.06	0.12	0.02	-0.07
β_{RMW}	0.09	0.08	0.07	0.07	-0.84	-0.92
β_{UMD}	0.08	0.05	-0.03	-0.23	-0.52	-0.60
t_{FF6}	2.22	0.63	2.35	-0.36	1.37	0.63
t_{Mkt}	26.90	41.62	47.03	28.87	8.88	-1.41
t_{SMB6}	-1.70	-3.19	0.31	-0.49	-0.04	0.31
t_{HML}	-1.27	0.64	1.87	-0.02	-0.79	-0.50
t_{CMA}	1.23	1.96	0.96	1.20	0.08	-0.36
t_{RMW}	2.15	2.27	1.89	0.94	-4.77	-5.81
t_{UMD}	3.53	1.77	-1.25	-3.98	-5.76	-6.31

Table 3.17 Continued

Panel G: The Hou-Xue-Zhang q-factor model ($\overline{\lvert\alpha_{HXZq}\rvert}$ = 0.13 and p_{HXZq} = 0.00)						
α_{HXZq}	0.25	0.10	0.20	-0.05	-0.06	-0.31
β_{Mkt}	0.81	0.91	0.94	0.98	0.97	0.16
β_{Me}	-0.25	-0.14	-0.00	0.05	0.40	0.64
$\beta_{I/A}$	0.08	0.21	0.11	0.06	-0.31	-0.40
β_{Roa}	0.04	0.08	-0.08	-0.27	-1.14	-1.18
t_{HXZq}	3.26	1.44	3.07	-0.48	-0.30	-1.40
t_{Mkt}	20.33	31.48	62.02	33.92	17.24	1.79
t_{Me}	-2.63	-2.23	-0.08	0.32	1.08	1.43
$t_{I/A}$	1.26	2.83	1.99	0.53	-1.51	-1.59
t_{Roa}	0.69	2.98	-2.20	-4.67	-6.16	-5.51
Panel H: The Bond-Xue investment-based three-factor model ($\overline{\lvert\alpha_{BX3}\rvert}$ = 0.15 and p_{BX3} = 0.02)						
α_{BX3}	0.23	0.09	0.19	-0.08	-0.14	-0.37
β_{Mkt}	0.79	0.90	0.94	1.01	1.11	0.32
$\beta_{I/A\_}$	-0.02	0.12	0.11	0.07	-0.10	-0.08
$\beta_{Roa\_}$	0.06	0.05	-0.12	-0.26	-0.96	-1.02
t_{BX3}	2.87	1.15	3.03	-0.60	-0.61	-1.47
t_{Mkt}	13.52	19.27	66.40	29.61	8.50	1.72
$t_{I/A\_}$	-0.54	2.18	2.19	1.35	-0.45	-0.34
$t_{Roa\_}$	0.77	2.07	-2.57	-3.78	-6.22	-5.29
Panel I: The Hou-Mo-Xue-Zhang q^5 model ($\overline{\lvert\alpha_{HMXZq^5}\rvert}$ = 0.11 and p_{HMXZq^5} = 0.23)						
α_{HMXZq^5}	0.12	0.07	0.15	-0.11	-0.10	-0.22
β_{Mkt}	0.88	0.93	0.96	1.01	0.99	0.12
β_{Me}	-0.11	-0.11	0.05	0.10	0.44	0.55
$\beta_{I/A}$	0.09	0.21	0.11	0.06	-0.31	-0.40
β_{Roa}	-0.02	0.06	-0.10	-0.30	-1.16	-1.14
β_{Eg}	0.20	0.05	0.08	0.08	0.07	-0.13
t_{HMXZq^5}	1.81	0.92	2.07	-0.85	-0.56	-1.00
t_{Mkt}	31.82	42.95	48.44	31.50	13.13	1.28
t_{Me}	-1.44	-2.03	2.04	0.77	1.17	1.26
$t_{I/A}$	1.48	2.76	2.21	0.52	-1.48	-1.65
t_{Roa}	-0.25	2.15	-3.17	-4.76	-6.30	-5.17
t_{Eg}	5.26	1.46	1.68	1.42	0.66	-1.34
Panel J: Average expected τ-year-ahead investment-to-asset changes, $E[d^{\tau}I/A]$						
$E[d^1I/A]$	-1.33	-2.35	-2.47	-1.85	-1.90	-0.56
t	-1.70	-2.86	-3.06	-2.45	-2.26	-0.53
$E[d^2I/A]$	-2.61	-3.78	-3.71	-3.13	-2.74	-0.13
t	-2.85	-3.23	-2.82	-2.33	-1.85	-0.10

At the beginning of each month t, I sort all firms into quintiles based on the beginning-of-month idiosyncratic volatility per REIT-based Fama-French three-factor model, $Ivff$, and compute value-weighted quintile excess returns for the current month t, using the beginning-of-month market equity as the weights. The quintiles are rebalanced at the beginning of month t+1. For each quintile, I perform time-series REIT-based factor model regressions, including the Capital Asset Pricing Model (CAPM), the Fama-French three-factor model (FF3), the Carhart four-factor model (Carhart4), the Fama-French five-factor model (FF5), the Fama-French six-factor model (FF6), the Hou-Xue-Zhang q-factor model (HXZq), the Bond-Xue investment-based three-factor model (BX3), and the Hou-Mo-Xue-Zhang q^5 model (HMXZq^5). I report the time-series average of quintile excess returns, alphas and factor loadings from the factor model regressions, as well as their heteroskedasticity-and-autocorrelation-adjusted t-statistics. $\overline{\lvert\alpha\rvert}$ is the mean absolute alpha for a given set of quintiles, and the p-value from the GRS test on the null hypothesis that the alphas across the quintiles are jointly zero. Additionally, I report the time-series average of quintile expected τ-year-ahead investment-to-asset changes, $E[d^{\tau}I/A]$, where τ = 1 and 2.

Table 3.18 Properties of Share Turnover Quintiles

	Low	2	3	4	High	H-L
			Panel A: Average excess returns, $\bar{R}$			
$\bar{R}$	1.00	0.75	0.97	0.90	0.39	-0.61
$t_{\bar{R}}$	3.78	2.61	3.33	2.81	0.79	-2.13
			Panel B: The CAPM ($\overline{\lvert\alpha_{CAPM}\rvert}$ = 0.26 and p_{CAPM} = 0.00)			
α_{CAPM}	0.47	0.11	0.25	0.11	-0.34	-0.81
β_{Mkt}	0.66	0.79	0.89	0.97	0.90	0.24
t_{CAPM}	4.92	1.40	2.88	1.18	-1.37	-2.89
t_{Mkt}	9.67	12.75	15.72	66.67	9.94	3.92
			Panel C: The Fama-French three-factor model ($\overline{\lvert\alpha_{FF3}\rvert}$ = 0.27 and p_{FF3} = 0.00)			
α_{FF3}	0.50	0.14	0.25	0.11	-0.34	-0.84
β_{Mkt}	0.67	0.81	0.89	0.97	0.87	0.20
β_{SMB3}	-0.16	-0.15	-0.04	0.02	-0.02	0.14
β_{HML}	0.00	-0.07	0.04	0.06	0.39	0.39
t_{FF3}	4.86	1.60	2.69	1.24	-1.44	-3.11
t_{Mkt}	10.83	16.74	18.08	66.35	14.07	3.89
t_{SMB3}	-1.83	-1.48	-0.49	0.24	-0.07	0.45
t_{HML}	0.06	-1.30	0.49	1.01	2.00	1.62
			Panel D: The Carhart four-factor model ($\overline{\lvert\alpha_{Carhart4}\rvert}$ = 0.24 and $p_{Carhart4}$ = 0.00)			
$\alpha_{Carhart4}$	0.36	0.06	0.28	0.16	-0.32	-0.68
β_{Mkt}	0.73	0.84	0.88	0.94	0.86	0.12
β_{SMB4}	0.05	-0.04	-0.11	-0.07	-0.05	-0.10
β_{HML}	0.03	-0.04	0.05	0.06	0.39	0.36
β_{UMD}	0.17	0.10	-0.03	-0.06	-0.03	-0.20
$t_{Carhart4}$	3.99	0.76	3.55	1.87	-0.91	-1.95
t_{Mkt}	16.31	20.35	20.97	56.57	18.47	1.77
t_{SMB4}	0.76	-0.39	-1.56	-0.85	-0.25	-0.47
t_{HML}	0.59	-0.90	0.76	1.24	2.40	1.91
t_{UMD}	4.40	3.25	-0.57	-1.95	-0.13	-1.02
			Panel E: The Fama-French five-factor model ($\overline{\lvert\alpha_{FF5}\rvert}$ = 0.21 and p_{FF5} = 0.00)			
α_{FF5}	0.39	0.05	0.21	0.11	-0.27	-0.66
β_{Mkt}	0.72	0.84	0.91	0.97	0.84	0.12
β_{SMB5}	-0.13	-0.13	-0.07	0.00	-0.17	-0.04
β_{HML}	0.05	-0.05	-0.02	0.04	0.25	0.19
β_{CMA}	0.04	0.10	0.21	0.06	0.37	0.33
β_{RMW}	0.17	0.15	0.07	0.00	-0.12	-0.29
t_{FF5}	3.32	0.52	3.03	1.39	-1.19	-2.95
t_{Mkt}	15.63	26.27	27.23	76.90	15.47	2.60
t_{SMB5}	-1.56	-1.62	-0.92	0.03	-0.60	-0.13
t_{HML}	0.87	-0.86	-0.28	0.60	1.58	1.03
t_{CMA}	0.42	1.36	2.33	1.00	2.61	2.00
t_{RMW}	2.14	2.77	1.18	0.09	-0.75	-1.95
			Panel F: The Fama-French six-factor model ($\overline{\lvert\alpha_{FF6}\rvert}$ = 0.19 and p_{FF6} = 0.00)			
α_{FF6}	0.31	0.01	0.24	0.14	-0.26	-0.57
β_{Mkt}	0.75	0.86	0.89	0.95	0.82	0.07
β_{SMB6}	0.04	-0.06	-0.14	-0.08	-0.20	-0.24
β_{HML}	0.05	-0.04	-0.01	0.04	0.26	0.20
β_{CMA}	0.02	0.09	0.22	0.07	0.36	0.34
β_{RMW}	0.12	0.12	0.09	0.03	-0.10	-0.22
β_{UMD}	0.15	0.07	-0.05	-0.07	-0.03	-0.18
t_{FF6}	2.84	0.11	3.71	1.81	-0.81	-1.89
t_{Mkt}	18.08	27.25	28.83	51.34	13.63	1.02
t_{SMB6}	0.50	-0.70	-2.36	-0.80	-1.22	-1.21
t_{HML}	0.88	-0.83	-0.15	0.75	1.72	1.18
t_{CMA}	0.28	1.30	2.41	1.13	2.57	2.26
t_{RMW}	1.75	2.46	1.52	0.69	-0.68	-1.49
t_{UMD}	4.63	2.62	-1.40	-2.18	-0.16	-0.94

Table 3.18 Continued

Panel G: The Hou-Xue-Zhang q-factor model ($\overline{\lvert\alpha_{HXZq}\rvert}$ = 0.24 and p_{HXZq} = 0.00)						
α_{HXZq}	0.44	0.12	0.27	0.16	-0.21	-0.64
β_{Mkt}	0.69	0.81	0.89	0.95	0.83	0.15
β_{Me}	-0.12	-0.19	-0.14	-0.06	-0.26	-0.14
$\beta_{I/A}$	0.09	0.09	0.21	0.07	0.47	0.38
β_{Roa}	0.11	0.03	-0.05	-0.13	-0.38	-0.49
t_{HXZq}	4.41	1.40	3.41	2.17	-0.77	-2.24
t_{Mkt}	12.20	17.81	21.32	90.18	17.78	2.30
t_{Me}	-1.38	-1.61	-2.42	-0.93	-1.04	-0.59
$t_{I/A}$	0.88	1.99	2.23	1.68	2.24	1.77
t_{Roa}	1.70	0.61	-1.37	-2.24	-2.27	-3.06
Panel H: The Bond-Xue investment-based three-factor model ($\overline{\lvert\alpha_{BX3}\rvert}$ = 0.23 and p_{BX3} = 0.00)						
α_{BX3}	0.45	0.11	0.24	0.14	-0.22	-0.67
β_{Mkt}	0.67	0.79	0.88	0.96	0.85	0.18
$\beta_{I/A\_}$	-0.01	-0.01	0.11	0.03	0.08	0.09
$\beta_{Roa\_}$	0.09	-0.00	-0.06	-0.12	-0.45	-0.54
t_{BX3}	4.75	1.46	3.04	1.91	-0.87	-2.32
t_{Mkt}	9.78	12.23	17.29	85.93	11.03	3.40
$t_{I/A\_}$	-0.17	-0.38	1.73	0.68	0.46	0.44
$t_{Roa\_}$	1.40	-0.09	-1.08	-2.44	-2.91	-2.99
Panel I: The Hou-Mo-Xue-Zhang q^5 model ($\overline{\lvert\alpha_{HMXZq^5}\rvert}$ = 0.15 and p_{HMXZq^5} = 0.01)						
α_{HMXZq^5}	0.23	-0.01	0.22	0.12	-0.18	-0.41
β_{Mkt}	0.79	0.87	0.91	0.97	0.82	0.03
β_{Me}	0.09	-0.07	-0.09	-0.02	-0.29	-0.38
$\beta_{I/A}$	0.09	0.09	0.21	0.07	0.47	0.38
β_{Roa}	0.01	-0.03	-0.07	-0.15	-0.37	-0.39
β_{Eg}	0.32	0.18	0.07	0.06	-0.04	-0.35
t_{HMXZq^5}	2.08	-0.06	3.44	1.58	-0.64	-1.59
t_{Mkt}	22.37	27.69	29.80	59.83	12.81	0.47
t_{Me}	1.08	-0.64	-1.99	-0.28	-1.16	-1.70
$t_{I/A}$	1.01	1.94	2.19	1.70	2.26	1.94
t_{Roa}	0.25	-0.57	-2.15	-2.75	-2.20	-2.67
t_{Eg}	6.74	4.03	0.99	1.91	-0.29	-2.90
Panel J: Average expected τ-year-ahead investment-to-asset changes, $E[d^{\tau}I/A]$						
$E[d^1 I/A]$	-0.79	-1.11	-2.35	-2.54	-2.12	-1.33
t	-0.76	-1.59	-3.26	-3.57	-3.21	-1.19
$E[d^2 I/A]$	-2.36	-2.39	-3.99	-3.66	-2.85	-0.48
t	-1.95	-2.40	-3.63	-3.19	-2.16	-0.35

At the beginning of each month t, I sort all firms into quintiles based on the beginning-of-month share turnover, Tur, and compute value-weighted quintile excess returns for the current month t, using the beginning-of-month market equity as the weights. The quintiles are rebalanced at the beginning of month t+1. For each quintile, I perform time-series REIT-based factor model regressions, including the Capital Asset Pricing Model (CAPM), the Fama-French three-factor model (FF3), the Carhart four-factor model (Carhart4), the Fama-French five-factor model (FF5), the Fama-French six-factor model (FF6), the Hou-Xue-Zhang q-factor model (HXZq), the Bond-Xue investment-based three-factor model (BX3), and the Hou-Mo-Xue-Zhang q^5 model (HMXZq^5). I report the time-series average of quintile excess returns, alphas and factor loadings from the factor model regressions, as well as their heteroskedasticity-and-autocorrelation-adjusted t-statistics. $\overline{\lvert\alpha\rvert}$ is the mean absolute alpha for a given set of quintiles, and the p-value from the GRS test on the null hypothesis that the alphas across the quintiles are jointly zero. Additionally, I report the time-series average of quintile expected τ-year-ahead investment-to-asset changes, $E[d^{\tau}I/A]$, where τ = 1 and 2.

Table 3.19 Expected Investment Growth and Future Profitability

τ		Low	2	3	4	High	H-L
Panel A: Average τ-year-ahead sale growth, $g^{\tau}Sale$							
1	$g^{\tau}Sale$	1.08	1.09	1.25	1.56	2.22	1.14
	t	3.97	5.56	6.66	9.04	8.36	2.98
2	$g^{\tau}Sale$	1.83	1.70	2.16	2.77	4.92	3.10
	t	5.20	6.68	8.98	9.86	7.51	4.45
Panel B: Average τ-year-ahead gross profit growth, $g^{\tau}GP$							
1	$g^{\tau}GP$	0.31	0.28	0.41	0.60	1.01	0.70
	t	2.00	2.58	4.61	8.25	9.08	3.71
2	$g^{\tau}GP$	0.53	0.30	0.77	1.05	2.09	1.55
	t	2.99	2.04	6.33	10.34	8.49	6.25

At the beginning of each month t, I sort all firms into quintiles based on the ranked values of the expected τ-year-ahead investment-to-asset changes, $E_{it}[d^{\tau}I/A]$, where τ = 1 and 2. The quintiles are value-weighted using the end-of-prior-month market equity as weights and are rebalanced at the beginning of month t+1. I report the time-series averages of quintile τ-year-ahead sales growth and gross profit growth, as well as their heteroskedasticity-and-autocorrelation-adjusted t-statistics (presented beneath the corresponding estimates). At the beginning of each month t, I measure current sales as Compustat annual item SALE from the most recent fiscal year end at least four months ago. The τ-year-ahead sales growth, $g^{\tau}Sale$, is calculated as the sales from the τ-th fiscal year after the most recent fiscal year end minus current sales, scaled by average total assets. I measure current gross profit as Compustat annual item REVT minus item COGS, both from the most recent fiscal year end at least four months ago. The τ-year-ahead gross profit growth, $g^{\tau}GP$, is calculated as gross profit from the τ-th fiscal year after the most recent fiscal year end minus current gross profit, scaled by average total assets.

Table 3.20 Expected Investment Growth and Future Leverage

τ		Low	2	3	4	High
Panel A: τ-year-ahead degree of operating leverage, DOL$^{\tau}$						
0	DOL$^{\tau}$	1.23	1.20	1.20	1.13	1.47
		(4.64)	(6.80)	(6.52)	(8.05)	(5.78)
1	DOL$^{\tau}$	1.19	1.14	1.00	1.23	1.57
		(5.81)	(8.28)	(3.99)	(8.12)	(5.89)
2	DOL$^{\tau}$	1.39	1.17	1.25	0.92	0.92
		(5.33)	(5.90)	(6.61)	(2.52)	(3.73)
Panel B: τ-year-ahead degree of financial leverage, DFL$^{\tau}$						
0	DFL$^{\tau}$	0.55	0.59	0.62	0.74	1.02
		(2.93)	(4.47)	(5.27)	(4.05)	(3.57)
1	DFL$^{\tau}$	0.58	0.61	0.91	0.74	1.05
		(3.53)	(3.29)	(4.26)	(3.21)	(2.90)
2	DFL$^{\tau}$	0.69	0.58	0.61	0.79	1.07
		(3.81)	(2.91)	(3.14)	(3.28)	(2.61)

At the beginning of each month t, I sort all firms into quintiles based on the ranked values of the expected one-year-ahead investment-to-asset changes, $E_{it}[d^1I/A]$. The quintiles are rebalanced at the beginning of month t+1. In Panel A, for each quintile, I run panel firm-month OLS regressions of the annual growth rate of operating income, OIG, on the contemporaneous annual growth rate of sales, $SALEG$, both from the τ-th year after the beginning of month t: $OIG_{it+12\tau}= \beta_{0,t+12\tau} + \beta_{1,t+12\tau}SALEG_{it+12\tau} + \varepsilon_{it+12\tau}$, where τ = 0, 1, and 2. In Panel B, for each quintile, I perform panel firm-month OLS regressions of the annual growth rate of net income, NIG, on the contemporaneous annual growth rate of operating income, OIG, both from the τ-th year after the beginning of month t: $NIG_{it+12\tau}= \beta_{0,t+12\tau} + \beta_{1,t+12\tau}OIG_{it+12\tau} + \varepsilon_{it+12\tau}$, where τ = 0, 1, and 2. At the beginning of each month t, I measure current sales as Compustat annual item SALE from the most recent fiscal year end at least four months ago. The annual growth rate of sales, $SALEG$, is calculated as the current sales minus sales from one year ago, divided by sales from one year ago. Current operating income is measured as Compustat annual item EBIT from the most recent fiscal year end at least four months ago. The annual growth rate of operating income, OIG, is calculated as the current operating income minus operating income from one year ago, divided by operating income from one year ago. Current net income is measured as Compustat annual item NI from the most recent fiscal year end at least four months ago. The annual growth rate of net income, NIG, is calculated as the current net income minus net income from one year ago, divided by net income from one year ago. Each variable is winsorized at the 1% and 99% levels. Panel A reports the operating income elasticity to sales, denoted as the degree of operating leverage. Panel B reports the net income elasticity to operating income, denoted as the degree of financial leverage. The t-statistics (presented in parentheses beneath the corresponding estimates) are based on robust standard errors clustered at both firm and month levels.

Table 3.21 Expected Investment Growth and Future Cash-Flow Risk

	Panel A		Panel B		Panel C		Panel D	
τ	1	2	1	2	1	2	1	2
$E[d^1I/A]$	0.051	0.077	0.052	0.078	0.068	0.061	0.063	0.056
	(4.37)	(4.22)	(4.56)	(3.85)	(7.69)	(4.39)	(6.35)	(3.65)
$GDPG$	0.049	0.305						
	(2.09)	(8.03)						
$E[d^1I/A] * GDPG$	0.865	-0.769						
	(2.18)	(-1.36)						
$PCEG$			-0.002	0.199				
			(-0.15)	(5.43)				
$E[d^1I/A] * PCEG$			0.707	-0.843				
			(2.12)	(-1.30)				
IPG					0.035	0.148		
					(2.19)	(6.52)		
$E[d^1I/A] * IPG$					0.279	-0.242		
					(1.19)	(-0.88)		
MTSG							0.036	0.186
							(1.90)	(6.45)
$E[d^1I/A] * MTSG$							0.353	-0.139
							(1.32)	(-0.41)
R^2	0.016	0.040	0.016	0.023	0.016	0.040	0.016	0.038

I perform panel firm-month OLS regressions of future τ-year-ahead net income growth, $g^{\tau}NI$, where τ = 1 and 2, on expected one-year-ahead investment-to-assets change, $E[d^1I/A]$, future one-year-ahead economic growth, EG, and their interaction term.

$$g^{\tau}NI_{it+12\tau} = \beta_{0,t+12\tau} + \beta_{1,t+12\tau}E[d^1I/A]_{it} + \beta_{2,t+12\tau}EG_{t+12} + \beta_{3,t+12\tau}E[d^1I/A]_{it} * EG_{t+12} + \varepsilon_{it+12\tau}$$

At the beginning of each month t, I measure current net income as Compustat annual item NI from the most recent fiscal year end at least four months ago. The τ-year-ahead net income growth, $g^{\tau}NI$, is measured as the net income from the τ-th fiscal year after the most recent fiscal year end minus the current net income, scaled by average total assets. I use four proxies for economic growth: gross domestic product growth (GDPG), personal consumption expenditure growth (PCEG), industrial production growth (IPG), and real manufacturing and trade sales growth (MTSG). I obtain quarterly data on real gross domestic product (GDP), real personal consumption expenditures (PCE), industrial production: total index (IP), and real manufacturing and trade industries sales (MTS) from the Federal Reserve Bank of St. Louis website. At the beginning of each month t, I measure GDPG as the GDP from the most recent quarter end minus the GDP from four quarters ago, divided by the GDP from four quarters ago; PCEG as the PCE from the most recent quarter end minus the PCE from four quarters ago, divided by the PCE from four quarters ago; IPG as the IP from the most recent quarter end minus the IP from four quarters ago, divided by the IP from four quarters ago; MTSG as the MTS from the most recent quarter end minus the MTS from four quarters ago, divided by the MTS from four quarters ago. All variables are winsorized at the 1% and 99% levels. I report the main regression coefficients, the t-values based on robust standard errors clustered at the firm level (presented in parentheses), and goodness-of-fit coefficients (R^2).

Appendices

Appendix 3.1 REIT-Based Factor Model Construction

Standard Factor Models

Let $E[R_i]$ denote the expected returns of REIT i, and R_f the risk-free rate.

The Capital Asset Pricing Model (CAPM) consists of a market factor, R_{Mkt}:

$$E[R_i - R_f] = \beta^i_{Mkt} E[R_{Mkt}].$$

In the Fama and French three-factor model (FF3), the expected excess returns are described by the loadings of its returns to three factors: a market factor, R_{Mkt}, a size factor, R_{SMB3}, and a value factor, R_{HML}:

$$E[R_i - R_f] = \beta^i_{Mkt} E[R_{Mkt}] + \beta^i_{SMB3} E[R_{SMB3}] + \beta^i_{HML} E[R_{HML}].$$

The Carhart four-factor model (Carhart4) augments the FF3 with a momentum factor, R_{UMD}:

$$E[R_i - R_f] = \beta^i_{Mkt} E[R_{Mkt}] + \beta^i_{SMB4} E[R_{SMB4}] + \beta^i_{HML} E[R_{HML}] + \beta^i_{UMD} E[R_{UMD}].$$

The Fama and French five-factor model (FF5) augments the FF3 with an investment factor, R_{CMA}, and an operating profitability factor, R_{RMW}:

$$E[R_i - R_f] = \beta^i_{Mkt} E[R_{Mkt}] + \beta^i_{SMB5} E[R_{SMB5}] + \beta^i_{HML} E[R_{HML}] + \beta^i_{CMA} E[R_{CMA}] + \beta^i_{RMW} E[R_{RMW}].$$

The Fama and French six-factor model (FF6) augments the FF5 with a momentum factor, R_{UMD}:

$$E[R_i - R_f] = \beta^i_{Mkt} E[R_{Mkt}] + \beta^i_{SMB6} E[R_{SMB6}] + \beta^i_{HML} E[R_{HML}] + \beta^i_{CMA} E[R_{CMA}] + \beta^i_{RMW} E[R_{RMW}] + \beta^i_{UMD} E[R_{UMD}].$$

Here, $E[R_{Mkt}]$, $E[R_{SMB}]$, $E[R_{HML}]$, $E[R_{CMA}]$, $E[R_{RMW}]$, and $E[R_{UMD}]$ represent the expected premiums of the market, size, value, investment, operating profitability, and momentum factors, respectively, and β^i_{Mkt}, β^i_{SMB}, β^i_{HML}, β^i_{CMA}, β^i_{RMW}, and β^i_{UMD} the corresponding factor loadings.

The factor construction procedure largely follows Fama and French (2018). The market factor, R_{Mkt}, is the excess returns on the FTSE NAREIT All Equity REIT Index over the one-month Treasury bill rate. The value factor, R_{HML}, is constructed from an independent two-way (2 × 3) monthly sort on size and book-to-market ratio (B/M).[41] At the beginning of each month t, I use the median size or market equity to split stocks into two groups: small and big, based on the beginning-of-month size or market equity. Independently, I sort all stocks into three B/M groups: low, median, and high, based on the lowest 30%, middle 40%, and highest 30% of their ranked B/M values at the beginning of month t. By taking the intersections of these two sorts, I form six size-B/M portfolios. I calculate value-weighted portfolio returns for the current month t and rebalance the portfolios at the beginning of month t+1. The value factor, R_{HML}, is the monthly difference between the simple average returns of the two high B/M portfolios and the simple average returns of the two low B/M portfolios (high-minus-low).

From an independent two-way (2 × 3) monthly sort on size and Ret^{11}, the momentum factor, R_{UMD}, is defined as the monthly difference between the simple average returns of the two high Ret^{11} portfolios and the simple average returns of the two low Ret^{11} portfolios (high-minus-low). From an independent two-way (2 × 3) monthly sort on size and I/A, the investment factor, R_{CMA}, is defined as the monthly difference between the simple average returns of the two low I/A portfolios and the simple average returns of the two high I/A portfolios (low-minus-high). From an independent two-way (2 × 3) monthly sort on size and Opp, the profitability factor, R_{RMW}, is defined as the monthly difference between the

[41] The expected τ-year-ahead investment-to-asset change quintiles are formed monthly. I adopt the same sorting frequency in factor construction. Compared to annual sorts, monthly sorts exploit more up-to-date information. Asness and Frazzini (2013) construct a monthly sorted value factor, which is later included in the six-factor model of Barillas and Shanken (2018). Hou et al. (2019) reconstruct their q factors using monthly sorts on all three characteristics, including size and investment. They demonstrate that monthly formed size and investment factors earn higher premiums compared to the original annual formed size and investment factors. Bond and Xue (2017) also use monthly sorts when constructing their REIT-based factors.

simple average returns of the two high Opp portfolios and the simple average returns of the two low Opp portfolios (high-minus-low).[42]

Each independent sort above yields a size factor, R_{SMB}, which is the simple average returns of the three small portfolios minus the simple average returns of the three big portfolios. In the FF3, the size factor, R_{SMB3}, is derived from the sort on size and B/M. In the Carhart4, the size factor, R_{SMB4}, is the average of two size factors: one from the sort on size and B/M, and the other from the sort on size and Ret^{11}. In the FF5, the size factor, R_{SMB5}, is the average of three size factors, which are derived from the sorts on size and B/M, size and I/A, and size and Opp. In the FF6, the size factor, R_{SMB6}, is the average of four size factors: those from the sorts on size and B/M, size and I/A, size and Opp, and size and Ret^{11}.

q and q^5 Factor Models

In the Hou-Xue-Zhang q-factor model (HXZq), the expected excess returns are described by the loadings of its returns to four factors: a market factor, R_{Mkt}, a size factor, R_{Me}, an investment factor, $R_{I/A}$, and a return on assets factor, R_{Roa}:

$$E[R_i - R_f] = \beta^i_{Mkt}E[R_{Mkt}] + \beta^i_{Me}E[R_{Me}] + \beta^i_{I/A}E[R_{I/A}] + \beta^i_{Roa}E[R_{Roa}].$$

The Hou-Mo-Xue-Zhang q^5 model (HMXZ q^5) augments the HXZq with an expected investment growth factor, R_{Eg}:

$$E[R_i - R_f] = \beta^i_{Mkt}E[R_{Mkt}] + \beta^i_{Me}E[R_{Me}] + \beta^i_{I/A}E[R_{I/A}] + \beta^i_{Roa}E[R_{Roa}] + \beta^i_{Eg}E[R_{Eg}].$$

Here, $E[R_{Mkt}]$, $E[R_{Me}]$, $E[R_{I/A}]$, $E[R_{Roa}]$, and $E[R_{Eg}]$ are the expected premium of the market, size, investment, return on assets, and expected investment growth factors, respectively, and β^i_{Mkt}, β^i_{Me}, $\beta^i_{I/A}$, β^i_{Roa}, and β^i_{Eg} are the corresponding factor loadings.

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[42] At the beginning of each month t, I measure operating profitability, Opp, as total revenue (Compustat annual item REVT) minus cost of goods sold (item COGS), minus selling, general, and administrative expenses (item XSGA), plus research and development expenditures (item XRD, zero if missing), scaled by book assets, all from the most recent fiscal year end at least four months ago.

Hou et al. (2015) construct their q factors from an independent triple-way (2 × 3 × 3) sort on size, investment, and return on equity. However, due to limited REIT sample size, I adopt a two-way sort to ensure that portfolios are reasonably diversified. Specifically, the investment factor, $R_{I/A}$, is derived from an independent two-way (2 × 3) monthly sort on size and I/A and defined as the monthly difference between the simple average returns of the two low I/A portfolios and the simple average returns of the two high I/A portfolio (low-minus-high). The two-way sort on size and I/A makes the investment factor equivalent to the investment factor in the FF5 and FF6 models.

Hou et al. (2015) measure profitability as return on equity. I adopt return on assets as the profitability proxy. Both book equity and book asset have been applied to deflate earnings in the REIT literature, e.g., Bond and Xue (2017) and Ling et al. (2019). Using book asset as the deflator is to maintain a consistency with the measurement of other variables in this study. I find similar results when using earnings deflated by book equity. Derived from an independent two-way (2 x 3) monthly sort on size and Roa, the return on asset factor, R_{Roa}, is defined as the monthly difference between the simple average returns of the two high Roa portfolios and the simple average returns of the two low Roa portfolio (high-minus-low). The size factor, R_{Me}, is the average of the two size factors derived from the sorts on size and I/A and the sort on size and Roa.

The expected investment growth factor, R_{Eg}, is derived from an independent two-way (2 × 3) monthly sort on size and expected one-year-ahead investment-to-asset changes, $E_{it}[d^1 I/A]$. At the beginning of each month t, I use the end-of-prior-month median market equity to split stocks into two groups: small and large. Independently, I divide all stocks into three groups—low, median, and high—based on the lowest 30%, middle 40%, and highest 30% of their ranked $E_{it}[d^1 I/A]$ values. I then intersect the two size groups with the three $E_{it}[d^1 I/A]$ groups to form six portfolios. I calculate monthly value-weighted portfolio returns for the current month t and rebalance the portfolios at the beginning of month t+1. The expected investment growth factor is the monthly difference between the simple average returns of the two high $E_{it}[d^1 I/A]$ portfolios and the simple average returns of the two low $E_{it}[d^1 I/A]$ portfolios (high-minus-low).

Investment-Based Three-Factor Model

The Bond and Xue investment-based three-factor model (BX3) consists of a market factor, R_{Mkt}, an alternative investment factor, $R_{I/A\_}$, and an alternative return on asset factor, $R_{Roa\_}$:

$$E[R_i - R_f] = \beta^i_{Mkt}E[R_{Mkt}] + \beta^i_{I/A\_}E[R_{I/A\_}] + \beta^i_{Roa\_}E[R_{Roa\_}].$$

Here, $E[R_{I/A\_}]$ and $E[R_{Roa}]$ are the expected premium of the alternative investment and return on asset factors, respectively, and $\beta^i_{I/A\_}$ and $\beta^i_{Roa\_}$ are the corresponding factor loadings.

Different from Hou et al. (2015), Bond and Xue (2017) form their investment-based factors from an independent two-way (3 x 3) sort on investment and return on equity. They exclude size in their sorting due to the limited sample size of REITs. Without the presence of size in their sorting, their model excludes a size factor. I reproduce their sorting and generate the alternative investment and return on asset factors. Using returns on assets rather than returns on equity serves for the model comparison between the HMXZq^5 and the BX3. $R_{I/A\_}$ is defined as the monthly difference between the simple average returns of the three low I/A portfolios and the simple average returns of the three high I/A portfolios (low-minus-high). $R_{Roa\_}$ is defined as the monthly difference between the simple average returns of the three high Roa portfolios and the simple average returns of the three low Roa portfolios (high-minus-low).

Alternatively, I augment the Bond-Xue investment-based three-factor model (BX3) with the expected investment growth factor, R_{Eg}, to form an investment-based four-factor model (BX4). This alternative model produces similar results. However, I argue that it is more appropriate to add the R_{Eg} to the HXZq rather than to the BX3. This is because R_{Eg} is derived from a two-way (2 × 3) sort on size and expected one-year-ahead investment-to-assets changes, aligning with the factor construction of $R_{I/A}$ and R_{Roa} in the HXZq model. In contrast, the BX3 model utilizes the alternative factors, $R_{I/A\_}$ and $R_{Roa\_}$, which are derived from a two-way (3 × 3) sort on investment and return on assets. Also, the model excludes a size factor.

Time-Series Factor Model Regression Specification

For time-series factor model regressions, I use the following specifications:

The CAPM:

$$R_t^i - R_t^f = \alpha_{CAPM}^i + \beta_{Mkt}^i R_{Mkt,t} + \epsilon_t^i.$$

The FF3:

$$R_t^i - R_t^f = \alpha_{FF3}^i + \beta_{Mkt}^i R_{Mkt,t} + \beta_{SMB3}^i R_{SMB3,t} + \beta_{HML}^i R_{HML,t} + \epsilon_t^i.$$

The Carhart4:

$$R_t^i - R_t^f = \alpha_{Carhart4}^i + \beta_{Mkt}^i R_{Mkt,t} + \beta_{SMB4}^i R_{SMB4,t} + \beta_{HML}^i R_{HML,t} + \beta_{UMD}^i R_{UMD,t} + \epsilon_t^i.$$

The FF5:

$$R_t^i - R_t^f = \alpha_{FF5}^i + \beta_{Mkt}^i R_{Mkt,t} + \beta_{SMB5}^i R_{SMB5,t} + \beta_{HML}^i R_{HML,t} + \beta_{CMA}^i R_{CMA,t} + \beta_{RMW}^i R_{RMW,t} + \epsilon_t^i.$$

The FF6:

$$R_t^i - R_t^f = \alpha_{FF6}^i + \beta_{Mkt}^i R_{Mkt,t} + \beta_{SMB6}^i R_{SMB6,t} + \beta_{HML}^i R_{HML,t} + \beta_{CMA}^i R_{CMA,t} + \beta_{RMW}^i R_{RMW,t} + \beta_{UMD}^i R_{UMD,t} + \epsilon_t^i.$$

The HXZq:

$$R_t^i - R_t^f = \alpha_{HXZq}^i + \beta_{Mkt}^i R_{Mkt,t} + \beta_{Me}^i R_{Me,t} + \beta_{I/A}^i R_{I/A,t} + \beta_{Roa}^i R_{Roa,t} + \epsilon_t^i.$$

The HMXZq^5:

$$R_t^i - R_t^f = \alpha_{HMXZq^5}^i + \beta_{Mkt}^i R_{Mkt,t} + \beta_{Me}^i R_{Me,t} + \beta_{I/A}^i R_{I/A,t} + \beta_{Roa}^i R_{Roa,t} + \beta_{Eg}^i R_{Eg,t} + \epsilon_t^i.$$

The BX3:

$$R_t^i - R_t^f = \alpha_{BX3}^i + \beta_{Mkt}^i R_{Mkt,t} + \beta_{I/A\_}^i R_{I/A\_,t} + \beta_{Roa\_}^i R_{Roa\_,t} + \epsilon_t^i.$$

α_{CAPM}, α_{FF3}, $\alpha_{Carhart4}$, α_{FF5}, α_{FF6}, α_{HXZq}, α_{HMXZq^5}, and α_{BX3} are the corresponding model alphas for the CAPM, the FF3, the Carhart4, the FF5, the FF6, the HXZq, the HMXZq^5, and the BX3.

Chapter 4 Climate Change Exposure, Green Investment, and Financial Performance: The Case of Publicly Listed Real Estate

Abstract

I examine the real and financial implications of climate change exposure among publicly listed real estate firms. Exposure reflects earnings call participants' attention to a firm's climate-related opportunities, as well as regulatory and physical shocks. I find that firms with higher climate change exposure allocate more capital towards green building initiatives over the subsequent year. Additionally, tenants of high-exposure firms tend to achieve superior aggregate environmental scores in the future. The overall exposure effects are primarily attributable to firms with higher regulatory exposure. However, doing good may not mean doing well. High-exposure firms experience lower future operating and rental performance. The effect is primarily due to the reduced cash flows in firms with higher opportunity exposure. Furthermore, the opportunity exposure negatively predicts subsequent market valuations and stock returns, suggesting that investors may overlook the adverse signal of exposure for firms' future fundamentals, or may have non-financial preferences, accepting lower expected returns.

4.1 Introduction

Climate change has emerged as a critical issue garnering widespread attention. The real estate industry, in particular, is highly vulnerable to the impacts of climate change. The increasing frequency, duration, severity, and scope of climate-related hazards have resulted in significant damage to physical structures and escalating economic losses.[43] Concurrently, the industry faces more stringent climate regulatory interventions, as evidenced by the fact that in 2022, buildings accounted for 34% of global energy demand and 37% of global carbon dioxide emissions.[44] In response to the imperative to decarbonize, the industry has committed to adopting energy-efficient and green building practices aimed at creating more sustainable, resilient, and efficient built environments.[45] The presence of climate-related risks and opportunities can substantially influence business operations within the industry.

This study investigates the extent to which climate change exposure affects green investment, transition enabling, operational performance, rental performance, valuation, and stock returns among firms within the industry. To quantify these effects, I utilize the firm-level climate change exposure measures developed by Sautner et al. (2023a). Leveraging a keyword discovery algorithm, these authors analyse quarterly earnings conference call transcripts to construct time-varying indicators of the attention call participants devote to firms' climate change exposures. Specifically, they quantify each firm's climate change exposure as the proportion of discussion during an earnings call that pertains to this topic. Their measures encompass a firm's exposure to climate change in a broadly defined sense as well as three distinct facets: physical threats, regulatory interventions, and technological opportunities.

Earnings conference calls are pivotal corporate events during which financial analysts engage with managers to discuss significant current and future developments within firms (Chen et al., 2018). Consequently, the climate change exposure measures developed by Sautner et al. (2023a) capture market participants' perceptions of how climate change impacts individual firms.

[43] See the State of the Global Climate 2023, World Meteorological Organization, https://wmo.int/publication-series/state-of-global-climate-2023.
[44] See the Global Status Report for Buildings and Construction 2024, UN Environmental Programme and the Global Alliance for Buildings and Construction, https://www.unep.org/resources/report/global-status-report-buildings-and-construction.
[45] See the Green Building Principles: The Action Plan for Net-Zero Carbon Buildings, World Economic Forum, in collaboration with JLL, https://www.weforum.org/realestate/green-buildings/.

Assessing these perceptions within a financial context is essential, as market participants play a critical role in resource allocation and the price discovery process (Brochet et al., 2018; Rennekamp et al., 2022). Additionally, these measures encompass "soft" information derived from the interactions between managers and analysts. This characteristic enables this study to complement existing research that mostly utilizes climate change exposure measures based on "hard" information, such as green building certifications, environmental performance or disclosures, and climate- and weather-related events. [46]

The initial sample comprises data from 639 publicly listed real estate firms across 34 countries spanning the period from 2002 to 2022. To examine the characteristics of the climate change exposure measures, I conduct several analyses. First, I find that compared to regulatory and physical shocks, opportunities, on average, dominate climate change discussions during firms' earnings calls. This finding aligns with the progress being made by REITs and other publicly listed real estate companies in enhancing the resiliency of their buildings to achieve sustainable outcomes.[47] Second, I identify discernible patterns related to property types in the exposure measures. When aggregating exposure at the property-type level, Specialty properties (including Energy Infrastructure, Land, Timber, Data Centres, etc.) exhibit the highest overall exposure, followed by Office, Diversified, and Industrial properties. Specialty properties lead the exposure ranking for opportunities, whereas Office and Industrial properties top the rankings for regulatory and physical risks, respectively. Third, consistent with the assertion that climate concerns have emerged as a recent phenomenon in financial markets (Krueger et al., 2020), the attention allocated by call participants to climate-related regulations and opportunities has surged only since the late 2020s. In contrast, attention to physical hazards has exhibited greater volatility over the sample period, often spiking following major hurricanes.

Fourth, the climate change exposure is positively correlated with public climate change attention, as measured by Engle et al. (2020) Wall Street Journal Climate Change News Index

[46] Although limited, recent literature offers valuable insights into the relationships between "hard" information and the financial outcomes of publicly listed real estate firms. For environmental certifications, studies include Eichholtz et al. (2012), Sah et al. (2013), Eichholtz et al. (2018), Eichholtz et al. (2019b), and Devine and Yönder (2023). Research on ESG performance, and in particular environmental performance, encompasses Cajias et al. (2014), Brounen and Marcato (2018), Fan et al. (2022), Erol et al. (2023), Chacon et al. (2024), and Neo and Sing (2024). Studies focusing on ESG disclosure include Devine et al. (2023) and Feng and Wu (2023). Additionally, literature addressing climate hazards such as hurricanes, extreme temperatures, and multiple climate hazards comprises Rehse et al. (2019), Nguyen (2023), Feng et al. (2024), Zhu and Fuerst (2023), and Ling et al. (2024).
[47] See the 2024 REIT industry sustainability report, NAREIT, https://www.reit.com/investing/reits-sustainability/2024-reit-sustainability-report

and Howe et al. (2015) Yale Climate Change Opinion Map. This correlation is primarily driven by the opportunity exposure. The findings indicate a convergence in climate change attention between financial market participants and the general public. Fifth, there is a positive correlation between the overall exposure measure and the environmental component of the S&P Global ESG Score, wherein a higher score signifies that a firm is more environmentally friendly. This relationship is largely attributable to the positive association between the environmental score and the opportunity exposure measure. Indeed, the environmental scores provided by ESG data vendors appear to more accurately capture certain aspects of firms' climate change exposure, particularly opportunities and regulatory risks, rather than physical risks (Engle et al., 2020).

As a robustness check, the climate change exposure measure is also positively correlated with an alternative measure proposed by Nagar and Schoenfeld (2022), who develop a firm-level weather exposure metric by quantifying the occurrence of weather and weather-related terms in firms' annual 10-K filings. This weather exposure measure exhibits positive correlations with both the opportunity and physical exposure measures. These findings demonstrate consistency in the climate change attention paid by market participants during earnings calls and by firm managers in financial reporting.

Finally, I examine the heterogeneity of climate change exposure among the sample firms. It is somewhat surprising to discover that the effects of climate change on firms within the same property type are heterogeneous, given that climate change is typically perceived as a market risk factor associated with global alterations in weather patterns and climate systems (Venturini, 2022). To investigate this heterogeneity, I conduct a variance analysis that differentiates the relative contributions of aggregate, sectoral, and firm-level exposures by incorporating an appropriate set of fixed effects. The analysis reveals that firm-level variation accounts for a substantial portion of the variation in the exposure measures, ranging from 58% to 93%. Furthermore, more than half of the variation in the exposure measures is attributable to potential firm-specific time-variant factors. I interpret the significant firm-level variance as an indication of economically meaningful heterogeneity, which is likely driven primarily by firms' idiosyncratic climate change exposure (Sautner et al., 2023a).[48]

[48] One could contend that a portion of the firm-level variation in the climate change exposure measures may result from idiosyncratic measurement error. This concern is addressed by demonstrating robust associations between the exposure measures and both real and financial outcomes, including green building investment, tenants' environmental performance, firms' operating and rental performance, valuation, and stock performance.

After establishing the properties of the measured climate change exposures, I investigate their real and financial implications among U.S. publicly listed real estate firms. Concerning real economic impacts, I demonstrate that climate change exposure positively predicts green building investment—a transformative strategy in the real estate industry aimed at enhancing resilience and sustainability in response to climate change. Utilizing a matched panel between firms' portfolio properties and LEED and Energy Star certifications, I show that firms with higher climate change exposure invest in a greater number of certified properties in the subsequent year, compared to those with lower climate change exposure. This overall exposure effect is driven by more sustainable building investments among firms exhibiting higher regulatory exposure.

Shifting to green building technologies and practices not only aids in decarbonizing the real estate sector but also supports the low-carbon transition of other economic sectors. For instance, these enabling activities benefit tenants occupying sustainable spaces by reducing the environmental impacts of their business operations. Specifically, I find that firms with high climate change exposure are not only investing more in certified buildings but also facilitating their tenants' efforts to become more environmentally friendly. Tenants of high-exposure firms tend to achieve superior environmental scores in aggregate over the subsequent year.[49] This overall exposure effect is primarily driven by firms with higher regulatory exposure.

Next, I examine the relationship between climate change exposure and operating performance. I demonstrate that climate change exposure negatively predicts operating profits and funds from operations over the subsequent three years. This negative effect is plausible, as green opportunities—such as energy-efficient or low-carbon buildings—entail high initial costs and require extended periods to complete. Despite the significant environmental and economic gains that green buildings can offer relative to traditional (non-green) buildings (Eichholtz et al., 2010; Fuerst and McAllister, 2011; Eichholtz et al., 2013; Devine and Kok, 2015; Eichholtz et al., 2019a), the higher upfront development or acquisition costs and longer construction times remain substantial barriers to the widespread adoption of the economically rational sustainable investments (Hwang and Tan, 2012; Chegut et al., 2019). Indeed, I find that the

[49] The observed effect is modest in magnitude yet highly statistically significant. This limited effect may be attributable to the composite nature of the S&P Global Environmental Score, which encompasses multiple criteria, including biodiversity, climate strategy, decarbonization strategy, energy, among others. Each criterion is assessed based on a series of specific questions. Consequently, the climate change exposure measure may only capture certain components of the Environmental Score, potentially diluting the overall effect size.

negative overall exposure effect is largely driven by lower operating profitability at firms with higher opportunity exposure.

The results for operating performance broadly extend to rental performance. Firms with high climate change exposure exhibit lower rental net operating incomes over the subsequent three years compared to firms with low exposure. This overall exposure effect primarily arises from firms with higher opportunity exposure, indicating the negative impact of green retrofits on rental profits. Additionally, firms with high climate change exposure experience lower future occupancy rates than their low-exposure counterparts. This overall exposure effect is largely attributable to firms with high regulatory exposure, underscoring the adverse impact of climate regulations on tenant occupancy.

I finally examine the impact of climate change exposure on financial market outcomes. The negative prediction of future fundamentals implies that climate change exposure should be priced into the market. If investors fail to anticipate the lower future profits associated with high climate change exposure, subsequent cash-flow shocks will result in reduced stock prices and returns. Alternatively, if investors allocate capital to stocks with high climate change exposure for non-pecuniary reasons (Pástor et al., 2021; Pedersen et al., 2021), the resulting capital allocation could lead to zero or even negative risk premium for climate change exposure. I find that firms with high climate change exposure exhibit lower Tobin's Q in the subsequent year compared to firms with low exposure. This overall exposure effect primarily arises from the lower market valuations among firms with higher opportunity and regulatory exposures.

I further demonstrate that climate change exposure negatively predicts stock returns in the subsequent year. Specifically, the stock returns in the next year decrease by 1.3% for a one-standard-deviation increase in the overall exposure. This overall exposure effect primarily arises from firms with high opportunity exposure.[50] When examining the time-series dynamics, I find that the return predictability does not emerge until the mid-2010s, shortly after the conclusion of the 2009 Copenhagen UN Climate Change Conference. Additionally, the return

[50] This result is consistent with the ESG-efficient frontiers framework proposed by Pedersen et al. (2021). In their model, asset prices depend on both the ESG-driven prediction of fundamentals and investor demand for ESG characteristics. Presumably, ESG scores negatively predict future fundamentals. If investors disregard ESG information or accept lower expected returns due to their ESG preferences, a higher ESG score will be associated with lower future valuations and returns. I demonstrate that climate change exposure, and in particular the opportunity exposure, is positively correlated with the environmental component of the S&P ESG score and negatively predicts future cash flows.

predictability persists during the post-Copenhagen period. The overall exposure consistently negatively predicts stock returns over the subsequent one to five years. Correspondingly, cumulative stock returns decrease by 1.9%, 3.7%, 5.7%, 8.3%, and 10.0%, respectively, for a one-standard-deviation increase in the overall exposure. This enduring overall exposure effect is also attributable to firms with higher opportunity exposure.

Finally, I find that the return predictability extends to the portfolio level. The high-minus-low quintile sorted on climate change exposure generates an average return of –0.26% per month. The negative high-minus-low premium is not accounted for by a range of asset pricing factor models, including the Capital Asset Pricing Model (CAPM), the Fama and French (1993) three-factor model, the Carhart (1997) model, the Fama and French (2015) five-factor model, Fama and French (2018) six-factor model, Hou et al. (2015) q-factor model, and Hou et al. (2021) q^5 model. For instance, the six-factor model produces a high-minus-low alpha of –0.32%, leaving the bulk of average returns unexplained. The factor loadings are minimal, indicating that the high-minus-low quintile has limited exposure to the pricing factors.[51]

This study first contributes to the literature on climate change, sustainability, and real estate. Recent literature has increasingly analysed how climate change and sustainability affect the financial performance of publicly listed real estate firms. Some studies focus on firms' environmental performance based on green building certifications (e.g., Eichholtz et al., 2012; Sah et al., 2013; Eichholtz et al., 2018; Eichholtz et al., 2019b; Devine and Yönder, 2023), while others examine firms' broader environmental performance using metrics from ESG data providers such as MSCI, GRESB, or LSEG (e.g., Cajias et al., 2014; Brounen and Marcato, 2018; Fan et al., 2022; Devine et al., 2023; Erol et al., 2023; Feng and Wu, 2023; Chacon et al., 2024; Neo and Sing, 2024). Additionally, some research highlights the impact of physical climate change by measuring firms' exposure to climate or climate-related hazards at the asset level (e.g., Rehse et al., 2019; Nguyen, 2023; Zhu and Fuerst, 2023; Feng et al., 2024; Ling et al., 2024).

[51] I do not intend to propose a climate factor to explain the cross-section of stock returns. The conditional model framework employed does not aim to interpret the return pattern associated with climate change exposure as an asset pricing anomaly. Instead, the primary objective is to demonstrate that earnings call participants' perceptions of a firm's climate change exposure are linked to systematic risk and that shocks to these perceptions are priced into the cross-section.

This study distinguishes itself from previous research by employing the firm-level climate change exposure measures proposed by Sautner et al. (2023a), which categorizes exposure into opportunities, regulatory shocks, and physical shocks and reflects investor attention to these climate-related topics. The exposure measures offer some significant advantages. First, whereas earlier measures primarily focus on climate risks—either regulatory or physical—the exposure measures developed by Sautner et al. encompass both the upside and downside factors associated with climate change. This feature enables a more comprehensive analysis of the impacts of climate change.[52] Additionally, the exposure measures capture how market participants perceive a firm's exposure to climate change. I provide evidence that such perceptions are relevant not only to firms' green building investment policies but also to investors' decisions regarding firm stocks, demonstrating information flows from earnings calls into real and financial outcomes.

This study also contributes to the literature on climate change exposure and corporate green investment. Firms' investments in green human capital and green patent inventions facilitate the net-zero transition. Sautner et al. (2023a) demonstrate that firms with higher climate change exposure create more jobs in disruptive green technologies and generate more green patents. Similarly, Cohen et al. (2020) identify an ESG-innovation disconnect in the oil, gas, and energy-producing sector—the sector that tops the ranking for climate change exposure in Sautner et al. (2023a). They find that firms with lower ESG scores are more innovative, producing more and significantly higher-quality green innovations. In the real estate industry, firms typically invest in green building practices to reduce their environmental footprints. This study reveals that real estate firms with higher climate change exposure invest more in sustainable buildings, primarily driven by firms with higher regulatory exposure.[53] Moreover, the adoption of low-carbon solutions by these firms enables their tenants to enhance environmental performance. However, doing good may not necessarily mean doing well. I demonstrate that higher-exposure firms experience lower future operating and rental

[52] The Task Force on Climate-related Financial Disclosures (TCFD) emphasizes that financial markets require information on both risks and opportunities to effectively evaluate the impacts of climate change (see https://www.fsb-tcfd.org). Indeed, the environmental performance scores developed by ESG providers may more closely reflect regulatory risks rather than physical risks (Engle et al., 2020).

[53] This finding is consistent with Brounen and Marcato (2018) and Erol et al. (2023), which suggest that REITs tend to increase green building investments when confronted with environmental regulation compliance and/or investor demands.

performance, an effect originating from the lower cash flows in firms exhibiting higher opportunity and/or regulatory exposures.[54]

This study further contributes to the literature on climate change exposure and asset prices. Using option-implied expected return proxies, Sautner et al. (2023a and 2023b) find a positive premium based on a sample of S&P 500 stocks. In contrast, I identify a negative premium extracted from realized returns using a sample of SNL U.S. publicly listed real estate firms. Despite the opposite sign, a consistent finding is that the premium for high-exposure stocks is largely attributable to their high opportunity exposure. Sautner et al. align the positive premium with the models that incorporate "uncertainty about the path of climate change" (Giglio et al., 2021). They argue that climate change uncertainty complicates investors' ability to evaluate the climate impacts on individual stocks, thereby necessitating a premium for high climate change exposure. For example, it is challenging to predict whether technological opportunities that facilitate the low-carbon transition will succeed. Conversely, the negative premium documented in this study can be linked to the ESG-efficient frontier framework of Pedersen et al. (2021). I demonstrate that climate change exposure, and in particular opportunity exposure, are positively correlated with environmental score. Also, climate change exposure negatively predicts real estate firms' future operating and rental profits. To the extent that investors fail to predict the lower cash flows or tolerate lower expected returns for holding high exposure stocks due to their demands for ESG and responsible investing, the resulting relationship between the exposure measures and future returns should be negative.[55]

The findings of this study have practical implications for firm managers, investors, lenders, and policymakers. Climate discussions during earnings calls influence future green investments, transition facilitation, operating performance, rental performance, valuation, and stock returns. Firm managers should strategically allocate resources toward green opportunities to mitigate their potential erosion on firm profitability. In the real estate sector, green building investments signify firms' commitment to transitioning toward a new green economy. However, such investment commitments heavily rely on the capital provision from investors and lenders.

[54] Indeed, green building opportunities are both expensive and time-consuming (Dwaikat and Ali, 2016; Vyas and Jha, 2018) and may even lead to higher operating costs (Reichardt, 2014; Scofield and Doane, 2018), straining firm capital and other resources.

[55] In accordance with Pedersen et al. (2021), Fan et al. (2022) suggest that institutional investors do not fully incorporate environmental information into their investments in U.S. publicly listed REITs. This omission occurs either because investors disregard the information or because they are motivated by ESG preferences and choose not to divest from "green" REITs, even though the greenness is negatively related to future fundamentals.

Despite the increasing awareness of climate-related topics among stakeholders and policymakers, this study advocates for incentives for those firms committed to green building investments to encourage the continuation of such good practices.

The rest of this chapter proceeds as follows. Section 4.2 describes the data and variable measurements. Section 4.3 presents the properties of climate change exposure measures. Section 4.4 discusses the real outcomes of climate change exposure. Section 4.5 examines the financial outcomes of climate change exposure. Section 6 concludes.

4.2 Data and Variable Measurements

Firm-Level Climate Change Exposure

I use the firm-level climate change exposure data from Sautner et al. (2023a) (hereafter referred to as SvLVZ), which are derived from quarterly earnings conference call transcripts.[56] Earnings calls are significant corporate events during which market participants listen to firm managers' presentations and pose questions about firms' current and future developments (Chen et al., 2018). Specifically, market participants utilize earnings calls to inquire about various risks and opportunities facing firms, including those related to climate change. SvLVZ define "exposure" to climate change as the proportion of conversations during an earnings call dedicated to that topic.[57]

To measure such climate change exposure, SvLVZ pinpoint when manager-analyst conversations during earnings calls shift to climate change. Their algorithm identifies such conversations by detecting key word combinations commonly used in climate change discussions. This step is challenging to implement because firms tailor the language used in earnings calls to their unique business models and ecosystems. To address this issue, SvLVZ modify King et al. (2017)'s keyword discovery algorithm to generate a collection of bigrams $\mathbb{C}$ specific to climate change. Moreover, these authors distinguish three categories of climate change bigram: opportunity, regulatory shocks, and physical shocks ($\mathbb{C}^{Opp}$, $\mathbb{C}^{Reg}$, and $\mathbb{C}^{Phy}$, respectively). Using these bigram sets, they construct four variables to measure an individual firm's exposure to climate change for each quarter. These variables reflect the frequency of climate change bigrams appearing in an earnings call transcript, adjusted for the transcript's length:

$$CCExposure_{i,t} = \frac{1}{B_{i,t}} \sum_{b=1}^{B_{i,t}} (1[b \in \mathbb{C}]) \quad (4.1),$$

[56] SvLVZ's climate change exposure data are publicly accessible at https://osf.io/fd6jq/ and cover the period from January 2002 onward.

[57] This definition of "exposure" is distinct from the traditional definition of risk exposure in the asset pricing literature. Specifically, the climate change exposure measures developed by SvLVZ are not designed to capture the covariance with aggregate market fluctuations. Instead, they focus on the proportion of climate-related discussions during earnings calls, reflecting investor attention to climate-related topics. Hassan et al. (2019) explore the relationship between these two domains of literature.

where b = 1, $\ldots B_{i,t}$ represent the bigrams appearing in the transcript of firm i in quarter t; $1[\cdot]$ is the indicator function; and $\mathbb{C}$ denotes climate change bigram set ($\mathbb{C}$, $\mathbb{C}^{Opp}$, $\mathbb{C}^{Reg}$, or $\mathbb{C}^{Phy}$). The overall climate change exposure measure is labelled as $CCExposure$, while the three topic-specific measures are designated as $CCExposure^{Opp}$, $CCExposure^{Reg}$, and $CCExposure^{Phy}$, respectively. Since most of the other data in this study are measured at annual level, I aggregate the quarterly exposure measures by average them for each firm-year.

I initially focus on a sample of publicly listed real estate firms classified within the SNL real estate industry and covered by the SvLVZ algorithm. The initial sample comprises 5,776 firm-year observations from 639 firms headquartered in 34 countries over the period from 2002 to 2022. The sample period starts from 2002 because climate change exposure data from SvLVZ start from 2002. The global sample is used to analyse the properties of climate change exposure, including summary statistics, property-type variations, and variance decomposition. It is also employed to conduct empirical tests on (tenant) environmental score.

Subsequently, I focus on a U.S. subsample, which comprises 3,268 firm-year observations from 297 firms spanning from 2002 to 2022. The U.S. subsample serves as the primary data source for the remainder of the empirical analysis. This selection is justified by the fact that the data and variables introduced as followed, such as public attention to climate change, weather exposure, and green building investment, are predominantly relevant to the U.S.. Furthermore, prior studies investigating the impacts of climate change and sustainability on the financial performance of publicly listed real estate firms have predominantly focused on the U.S..

Public Attention to Climate Change

I employ the $WSJ\ Climate\ Change\ (CC)\ News\ Index$ developed by Engle et al. (2020), which captures the time-series variation in public attention to climate change. The index is constructed based on climate-related news coverage in *The Wall Street Journal* (WSJ). Engle et al. measure the intensity of climate news coverage by comparing the WSJ's content to a repository of seventy-four authoritative texts on climate change. Consequently, the index quantifies the proportion of WSJ content dedicated to climate change topics each day. For the purposes of this study, I utilize the average annual values of the index, which are available from 2002 to 2017.

Additionally, I incorporate state-level data from *the Yale Climate Opinion (CO) Map* (Howe et al., 2015) to measure the extent to which local respondents perceive climate change. Specifically, I focus on survey responses to the question: "How often do you discuss global warming with your friends and family?" Respondents could choose from four options: "Often," "Occasionally," "Rarely," and "Never." I use the proportion of respondents in each state who discuss global warming at least occasionally to construct a time-varying, cross-state measure of public attention to climate change. This variable is available for the years 2010 to 2022.

Environmental Score

Data on the environmental score are sourced from the environmental component of the S&P Global ESG Score. The environmental dimension of the S&P Global ESG rating system is evaluated based on a set of environmental criteria, some of which are directly related to climate change, including energy, climate strategy, and decarbonization strategy. A higher environmental score, $Esore$, indicates that a firm is more environmentally friendly or resilient to climate change. I utilize lagged values because ESG scores assessed for fiscal year $t-1$ are reported in year t. This variable is available from 2014 to 2022.

Weather Exposure

To validate the SvLVZ physical exposure measure, I employ the weather exposure measure, $Weather$, developed by Nagar and Schoenfeld (2022) using part-of-speech tagging techniques. These authors quantify firms' weather exposure by counting the number of times the term "weather" or weather-related terms appear in their 10-K reports. While SvLVZ utilize transcripts of earnings calls to construct their climate exposure measure, Nagar and Schoenfeld rely on firms' annual financial reports. They argue that, to the extent that managers understand the impacts of severe weather-related events, it is plausible to extract quantitative insights about a firm's exposure to these events by analysing such qualitative firm information. I use lagged values because financial reports for fiscal year $t-1$ are available in year t. The variable is available from 2002 to 2019.[58]

[58] Nagar and Schoenfeld (2022) make their weather exposure data publicly available on https://michiganross.umich.edu/news/new-online-tool-measures-firms-exposure-severe-weather-events. The data are from fiscal year 1994 to 2018.

Green Building Investment

In the U.S., the two primary asset-level environmental certification programs are LEED and Energy Star. LEED is developed by the U.S. Green Building Council (USGBC), while Energy Star is managed by the U.S. Environmental Protection Agency (EPA). I collect property-level sustainability information from S&P Global Market Intelligence, including whether a property has achieved LEED or Energy Star certification and the year in which the building underwent the certification process. These property-level sustainability data are then matched with the sampled U.S. firms' property portfolio.[59] I measure the share of buildings in firm portfolios with a LEED certification, Energy Star label, or both, referred to as $Green\ Ppty$. This variable is available from 2003 to 2023. Consistent with Eichholtz et al. (2019b), the average share of environmentally certified buildings is relatively small (approximately 6.8%) compared to the share of non-green buildings. Additionally, I use the number of green buildings ($\#Green\ Ppty$) and the number of non-green buildings ($\#\mathrm{Non}green\ Ppty$)) in firm portfolios.

Tenant Environmental Score

Tenants refer to the occupants of the spaces within buildings in firm portfolios. I collect information on the sampled U.S. firms' top tenants from S&P Global Market Intelligence, including tenant identifiers and tenant revenues. Each tenant, where available, is matched with an environmental score from the S&P Global ESG Score. $TEscore$ represents an equally weighted average of tenant environmental scores for each firm-year. $TEscore\_w$ denotes a value-weighted average of tenant environmental scores, using tenant revenues as weights. Both variables are available for the years 2013 to 2023.

Operating Performance

I measure firm-level operating performance using both a GAAP-standard indicator and an industry-standard indicator. Operating profitability (Opp) is calculated as total revenue (Compustat NA Fundamentals Annual item REVT) minus cost of goods sold (item COGS),

[59] LEED and Energy Star certification data are publicly available on the USGBC and Energy Star websites, https://www.usgbc.org and https://www.energystar.gov/buildings, respectively. Eichholtz et al. (2019b) identify LEED and Energy Star labelled buildings in the portfolio of REITs by matching the address of REIT-owned assets with the LEED and Energy Star certification data.

minus selling, general, and administrative expenses (item XSGA), plus research and development expenses (item XRD, zero if missing), scaled by total assets (item AT). This variable is available for the years 2003 to 2023. In the REIT and public real estate industries, companies commonly use funds from operations (FFO) to define cash flows from their operations and disclose the figure in their income statements. This indicator is calculated as GAAP net income excluding gains or losses from property sales or debt restructuring and adding back real estate depreciation. FFO is scaled by total assets and is available from 2003 to 2023. I obtain data on funds from operations from S&P Global Market Intelligence. Both variables are winsorized at the 1% level to mitigate the influence of outliers.

Rental Performance

I also assess a firm's operating performance through its properties' rental performance. Rent level and occupancy rate are two key indicators of operating performance at real estate asset level. I obtain data on a firm's rental net operating income ($RNOI$) and occupancy rate (Occ) from S&P Global Market Intelligence. $RNOI$ is calculated as total rental revenue, net of property operating expenses and excluding depreciation and amortization, scaled by total assets. Occ represents the percentage of all leased properties that are occupied or leased at a given time. Both variables are winsorized at the 1% level and are available from 2003 to 2023.

Valuation and Stock Return

Firm valuation is measured using Tobin's Q, Q, which is calculated as market equity (Compustat NA Fundamentals Annual item PRCC_F times item CSHO) plus long-term debt (item DLTT) and debt in current liabilities (item DLC), scaled by total assets. The variable is available for the years 2003 to 2023.

Monthly stock returns, including dividends, are sourced from the CRSP Monthly Stock File. Monthly Excess Stock Returns are calculated by subtracting the risk-free rate from the monthly stock returns. I measure annual excess returns (R) by compounding monthly excess returns from July of year t to June of year t+1. The six-month lag ensures that financial variables are publicly available as of the end of June in year t, thereby avoiding look-ahead bias. The variable is available for the years 2003 to 2022.

Control Variables

In examining the real impacts of climate change exposure, I control for a set of financial variables suggested by SvLVZ. $Assets$ represent total assets (Compustat NA/Global Fundamentals Annual item AT). $Debt/Assets$ is calculated as the sum of long-term debt (item DLTT) and debt in current liabilities (item DLC) divided by total assets. $Cash/Assets$ is the ratio of cash and short-term investments (item CHE) to total assets. $EBIT/Assets$ is earnings before interest and taxes (item EBIT) divided by total assets. I utilize lagged values because financial variables for fiscal year t−1 are reported in year t. These variables are winsorized at the 1% level to mitigate the influence of outliers and are available from 2002 to 2022.

In the annual Fama-MacBeth excess return predictive regressions, I include a set of well-known return predictors as control variables. Me (Market Equity) is calculated as the product of the share price (CRSP Monthly Stock File item PRC) and the number of shares outstanding (item CSHO). B/M (Book-to-Market Ratio) is computed as book equity scaled by market equity, where book equity is defined as stockholders' book equity plus deferred taxes and investment tax (item TXDITC) if available, minus the book value of preferred stocks. If stockholders' equity (Compustat item SEQ) is unavailable, it is derived as the book value of common equity (item CEQ) plus the par value of preferred stock (PSTK), or as the book value of assets (item AT) minus total liabilities (item LT). Depending on data availability, I use the redemption value (item PSTKRV), liquidating value (item PSTKL), or par value (item PSTK) for the book value of preferred stock.

Mom (Momentum) is measured as the cumulative monthly returns (CRSP Monthly Stock File item RET) from July of year t−1 to May of year t, excluding June of year t to eliminate the bid-ask bounce effect. I/A (Investment-to-Assets Ratio) is calculated as the change in total assets from one year prior, scaled by the average of total assets. Opp (Operating Profitability) is computed as total revenue (Compustat NA Fundamentals Annual item REVT) minus cost of goods sold (item COGS), minus selling, general, and administrative expenses (item XSGA), plus research and development expenses (item XRD, zero if missing), all scaled by total assets (item AT). These financial variables are winsorized at the 1% level and are available for the years 2002 to 2021.

Standard and q factors

In the monthly factor-model regressions, I utilize monthly data on standard factors from Ken French's data library. Specifically, MKT, SMB, HML, RMW, CMA, and UMD represent the market factor, size factor, value factor, profitability factor, investment factor, and momentum factor, respectively. Additionally, I incorporate the monthly q factors from Hou et al. (2015) and the augmented factor from Hou et al. (2021). The corresponding factors are labelled as R_{Mkt} (market factor), R_{Me} (size factor), $R_{I/A}$ (investment factor), R_{Roe} (return on equity factor), and R_{Eg} (expected growth factor). All factors are available from July 2003 to December 2023.

4.3 Properties of Climate Change Exposure

4.3.1 Summary Statistics

I examine the properties of climate change exposure using a multifaceted approach. First, I analyse the summary statistics for the exposure measures. As shown in Table 4.1, the average climate change exposure is 0.524, indicating that bigrams related to climate change occur at a relative frequency of approximately 0.5 per 1,000 bigrams in earnings calls. Compared to other climate-related topics, opportunities dominate the climate discussions during earnings calls. The average opportunity exposure measure is 0.112, compared to 0.035 and 0.010 for the regulatory and physical exposure measures, respectively. The prominence of opportunity discussions aligns with the developments in the public real estate industry, where firms are increasingly embracing energy efficiency, green buildings, and the net-zero transition in their business models.

[Insert Table 4.1]

4.3.2 Property-Type Variation

I calculate the average values of the exposure measures by property types and present a ranking of the means in Table 4.2. In Panel A, for $CCExposure$, the property type with the highest exposure is Specialty. The top-ranked sub-property types within Specialty include Energy Infrastructure, Land, Timber, and Data Centre. Specialty is followed by Office and Diversified. It is worthwhile to comment on several property types in Panels B to D, which report the topic-based exposure measures. Specialty also ranks highest for $CCExposure^{Opp}$ (Panel B). This ranking position is somewhat surprising; nevertheless, it is consistent with Cohen et al. (2020), who report that oil, gas, and energy-producing firms are key innovators in green patents. Among Specialty, Energy Infrastructure has the highest opportunity exposure.

Office displays the highest climate change exposure related to regulatory shocks (Panel C). This high regulatory exposure is expected given the large energy consumption associated with office building operations (Devine and Kok, 2015). The top two property types for $CCExposure^{Phy}$ (Panel D) are Industrial and Self-Storage, reflecting the closer proximity of these property types to climate hazards.

The exposure measures exhibit large standard deviations within each property type, indicating significant heterogeneity. For instance, Specialty has a standard deviation of 1.480 for the overall exposure measure, compared to the mean of 1.001. More broadly, the substantial variation within property types suggests the presence of both "winners" and "losers" in terms of climate change exposure. Consequently, investors might manage climate risks and opportunities more effectively by maintaining broad diversification across property types rather than excluding specific ones. This approach allows investors to apply negative screening selectively to filter out the climate change "losers" while retaining the "winners."

[Insert Table 4.2]

4.3.3 Time-Series Variation

In Figure 4.1, Panels A to D, I calculate the cross-sectional averages for the exposure measures and display their trends over time. For each measure, I focus on the U.S. sub-sample. This figure also highlights significant moments in public perception of climate change, including climate issues relevant to opportunities and regulatory shocks (Panels B and C), salient physical shocks (Panel D), or both (Panel A).

As shown in Panel A, $CCExposure$ exhibits a general increase over the sample period, particularly since the late 2010s. The dramatic rise in recent years indicates that market participants in earnings calls have increasingly discussed climate-related issues later than one might have anticipated. Nevertheless, this late surge in climate concerns aligns with the argument that climate issues are a relatively recent phenomenon in financial markets (Krueger et al., 2020). By the end of the sample period, $CCExposure$ reaches its peak, with earnings calls on average containing approximately 0.7 climate change bigrams per 1,000 bigrams.

In Panels B and C, the time series for $CCExposure^{Opp}$ and $CCExposure^{Reg}$ closely mirror that of $CCExposure$. Both trends upward, especially towards the end of the sample period. In Panel D, $CCExposure^{Phy}$ exhibits more fluctuations compared to the other measures. The physical exposure measure does not strongly reflect prominent climate hazards in the U.S. For instance, although there are significant increases in the exposure measure following major hurricanes such as Katrina, Ike, and Sandy, these increases occur with a delay of one to two years. This pattern suggests that the measure primarily captures firm-specific exposures to extreme weather events.

[Insert Figure 4.1]

4.3.4 Climate Change Exposure and Public Attention to Climate Change

I explore how well the exposure measures relate to public attention to climate change, which has been documented to influence financial market participants (e.g., Choi et al., 2020; Ilhan et al., 2021). One might expect that the prominence of climate topics in public discussions would prompt reactions in earnings call conversations. I utilize two proxies for public perception of climate change: the $WSJ\ CC\ News\ Index$ from Engle et al. (2020) and the $Yale\ CO\ Map$ from Howe et al. (2015). Table 4.3, Panels A and B, demonstrate that climate change exposure tends to increase during periods when public attention to climate issues is heightened.

In Panel A, this effect reflects a positive relationship between the $WSJ\ CC\ News\ Index$ and the opportunity exposure. Panel B additionally shows a positive association between the $Yale\ CO\ Map$ and both the opportunity and regulatory exposure. Therefore, when public interest in climate issues is elevated, earnings calls are more likely to address climate opportunities and regulatory shocks. In contrast, increased values of both the $WSJ\ CC\ News\ Index$ and the $Yale\ CO\ Map$ do not correspond to more discussions of physical shocks. This result implies that the physical exposure measure primarily captures firm-specific physical shocks rather than broader economic innovations reflected by the two proxies.

[Insert Table 4.3]

4.3.5 Climate Change Exposure and Environmental Score

I evaluate the extent to which the exposure measures correlate with firms' environmental performance scores constructed by ESG data provider S&P Global. ESG investing is closely related to climate change considerations by investors (Pedersen et al., 2021). Environmental scores serve as a proxy for firms' climate risk exposure but may better capture exposure to regulatory risk than to physical risk (Engle et al., 2020). A higher score suggests that a firm is more environmentally friendly. One might expect that discussions about climate regulations would be less prevalent in the earnings calls of firms with high environmental scores. Conversely, highly scored firms would likely feature more conversations in earnings calls related to green technologies and practices that provide firms with marketplace opportunities. Finally, environmental scores should be unrelated to a firm's exposure to physical shocks.

I test these predictions by regressing the exposure measures on the environmental score. Table 4.4, Panel A, reports the results. In Column (1), I observe a significant positive association between the environmental score and the climate change exposure measure. As predicted, this association stems from a positive correlation between the environmental score and the opportunity exposure measure (Column (2)). It is perhaps surprising that in Column (3), I find no association between the environmental score and the regulatory exposure measure. This may be because S&P Global evaluates firms' environmental scores are based on several criteria that primarily capture positive environmental performance. Finally, as expected, firms' environmental scores exhibit no association with the physical exposure measure (Column (4)).

[Insert Table 4.4]

4.3.6 Climate Change Exposure and Weather Exposure

I examine the relationship between the exposure measures and the weather exposure measure developed by Nagar and Schoenfeld (2022). These authors quantify firm-level weather exposure as the count of "weather" and weather-related terms appearing in firms' annual 10-K filings. Their measure offers an alternative assessment of firms' exposure to climate and weather-related events. One might expect that management discussions and analyses of weather events in firms' annual financial reports would be scrutinized by market participants during earnings calls, as managers' discussions of these events may raise analysts' concerns about their material effects. Indeed, Table 4.4, Panel B, Column (4) shows that the weather exposure is positively correlated with the physical exposure. Additionally, the weather exposure exhibits a positive correlation with the opportunity exposure and the overall climate change exposure. This result suggests that the weather exposure may capture a broader aspect of climate change, beyond the physical dimension.

[Insert Table 4.4]

4.3.7 Variance Decomposition

I conduct a variance analysis to evaluate how effectively $CCExposure$ and its components quantify firm-level variation in climate change exposure. Table 4.5, Panel A illustrates the increase in explanatory power when the exposure measures are conditioned on fixed effects that likely contribute to their variation. The explanatory power from time fixed effects varies across the exposure measures, with an incremental R^2 ranging from 0.43% ($CCExposure^{Phy}$) to 12.04% ($CCExposure$). Additionally, the exposure measures exhibit a modest property-type component, with the largest incremental R^2 of 4.54% ($CCExposure$) and the smallest of 0.80% ($CCExposure^{Phy}$). Similarly, country fixed effects contribute minimally to the explanatory power. In contrast, the interaction between property-type and time fixed effects accounts for a greater portion of the variation, yielding an incremental R^2 ranging from 5.24% ($CCExposure^{Phy}$) to 19.44% ($CCExposure$).

Depending on the exposure measures, 58% ($CCExposure$) to 93% ($CCExposure^{Phy}$) of the variation remains unexplained by the fixed effects. This suggests that the variation primarily occurs at firm level rather than across countries, property types, or over time. The substantial unexplained variation in the physical exposure is expected, as firms' exposure to physical shocks is heavily dependent on the geographic locations of their real estate assets. Panel B further incorporates firm fixed effects. The results indicate that permanent differences among firms within the same property type and country explain 50.67%, 41.28%, 31.66%, and 25.85% of the variation in $CCExposure$, $CCExposure^{Opp}$, $CCExposure^{Reg}$, and $CCExposure^{Phy}$, respectively. The rest 49.33%, 58.72%, 68.34%, and 74.15% represent the variation in the exposure measures that cannot be explained by firm, property type × time, and country fixed effects. Specifically, this unexplained variation may include firm-specific time-varying effects or other unobserved factors.

[Insert Table 4.5]

4.4 Real Outcomes

4.4.1 Green Building Investment

The net-zero transitions by 2050 necessitate substantial climate-related innovations. For the real estate sector, this entails significant investments by firms in both building construction and operations. Specifically, increased investments are required in energy-efficient and green buildings. Given the critical role of sustainable building practices in enabling the industry to achieve climate targets, I investigate the extent to which firms' exposure to climate change influences their future investments in green buildings.

For each firm-year within the sampled U.S. firms, I estimate the following regression model:

$$Green\ Ppty_{i,t+1} = \alpha + \beta CCExposure_{i,t} + \gamma \mathbf{X}_{i,t} + \delta_j + \delta_t + \varepsilon_{i,t+1} \text{ (4.2)},$$

where $Green\ Ppty_{i,t+1}$ is the share of buildings in firm i's portfolio with a LEED certification, Energy Star label, or both in year $t+1$, and $CCExposure_{i,t}$ is the climate change exposure measure for firm i in year t (including the overall and the three topic-based exposure measures). The vector $\mathbf{X}_{i,t}$ comprises control variables: $log(Assets)$, $Debt/Assets$, $Cash/Assets$, and $EBIT/Assets$. The terms δ_j and δ_t represent property-type and year fixed effects, respectively.[60] The error term is defined by $\varepsilon_{i,t+1}$.

The estimation results are reported in Table 4.6. In Column (1), the estimates indicate that firms with higher climate change exposure invest more in green buildings in the subsequent year. Specifically, a one-standard-deviation increase in $CCExposure$ is associated with an increase in $Green\ Ppty$ over the next year equivalent to 5.0% of its standard deviation (based on values from the regression sample). Columns (2) to (4) examine the topic-based exposure measures. As anticipated, the effect of the overall exposure is primarily driven by firms with high regulatory exposure (Column (3)). Conversely, firms with high opportunity exposure or physical exposure do not exhibit a significant tendency to invest more in low-carbon buildings compared to firms with low exposure (Columns (2) and (4)). In Column (5), I find

[60] The term δ_j represent a firm's property type. The sampled firms are categorized into nine types, including office, industrial, retail, residential, hotel, healthcare, self-storage, diversified, and specialty.

that $CCExposure$ continues to positively predict investment in sustainable buildings when substituting $Green\ Ppty$ with log1plus $\#Green\ Ppty$, which measures the number of green buildings in a firm's portfolio.

Column (6) addresses the concern that firms with higher climate change exposure might generally invest more in buildings without specifically focusing on those certified by LEED, Energy Star, or both. Specifically, I replace $\#Green\ Ppty$ with $\#Nongreen\ Ppty$, which measures the number of nongreen buildings in a firm's portfolio, and re-estimate the regression from Column (1). I observe no positive predictive effects from the overall exposure measure. In fact, high-exposure firms invest less, rather than more, in nongreen buildings. This result helps alleviate concerns about potential spurious relationships, suggesting a shift in investment from nongreen to green buildings, rather than a general expansion of building investments by high-exposure firms.

[Insert Table 4.6]

4.4.2 Tenant Environmental Score

The shift to green buildings not only enhances efficiency, resilience and sustainability within the real estate sector but also facilitates the green transition of other economic sectors. The supply of energy-efficient buildings, such as office buildings and industrial facilities, enables the service sector and manufacturing to reduce their carbon footprints. For tenants and occupants of commercial properties, the environmental performance of buildings has become an increasingly important concern, as buildings constitute a tangible and significant component of their ESG profiles and strategies (Devine and Kok, 2015). Given such transition enabling activities, I investigate the extent to which firms' exposure to climate change influences their tenants' environmental profiles.

For each firm-year within the sampled firms, I estimate the following regression model:

$$TEscore_{i,t+1} = \alpha + \beta CCExposure_{i,t} + \gamma \mathbf{X}_{i,t} + \delta_j + \delta_t + \varepsilon_{i,t+1} \text{ (4.3)},$$

where $TEscore_{i,t+1}$ is equally-weighted average of firm i's tenant environmental scores from the S&P Global ESG Score in year $t+1$, and $CCExposure_{i,t}$ is the climate change exposure measure for firm i in year t (including the overall and the three topic-based exposure measures). The vector $\mathbf{X}_{i,t}$ includes control variables: $log(Assets)$, $Debt/Assets$, and $EBIT/Assets$. The terms δ_j and δ_t represent property-type and year fixed effects, respectively. The error term is denoted by $\varepsilon_{i,t+1}$.

The results for the aggregate tenant environmental score are reported in Table 4.7. In Column (1), tenants of firms with greater climate change exposure exhibit higher aggregate environmental scores in the following year. Specifically, a one-standard-deviation increase in $CCExposure$ is associated with an increase in $TEscore$ equivalent to 3.3% of its standard deviation (based on values from the regression sample). The modest magnitude of this effect is unsurprising, given that the environmental dimension of the S&P Global ESG Score is evaluated based on multiple criteria, including climate change. Column (3) further demonstrates that the overall exposure effect predominantly originates from firms with high regulatory exposure. This finding is consistent with the impact of regulatory exposure on firms' investments in green buildings. Conversely, tenants of firms with higher opportunity or physical exposure do not achieve significantly higher environmental performance in the subsequent year (Columns (2) and (4)).

In Columns (5) and (6), I continue to find that $CCExposure$ and $CCExposure^{Reg}$ positively predict tenant environmental score when substituting $TEScore$ with a value-weighted measure, $TEscore\_w$. Overall, the results suggest that tenants' environmental profiles benefit from their landlords' exposure to climate change, particularly regulatory shocks, and the subsequent investments in portfolio greenness.

[Insert Table 4.7]

4.5 Financial Outcomes

4.5.1 Operating Performance

I now shift focus from real outcomes to examine the financial outcomes of climate change exposure. This analysis involves several steps. In the first step, I investigate the extent to which firms' exposure to climate change impacts their operating performance. In real estate sector, the occurrence of extreme weather events can lead to increased maintenance and repair expenditures and even cause business interruptions. Additionally, the implementation of regulations to combat carbon emissions can result in significant compliance costs and operational restrictions. Although green buildings offer energy efficiency (Eichholtz et al., 2019a) and economic benefits (Eichholtz et al., 2010 and 2013), transitioning to these green practices is an expensive and time-consuming process (Dwaikat and Ali, 2016; Vyas and Jha, 2018). Therefore, one might expect a negative relationship between climate change exposure and future operating performance.

To quantify operating performance, I utilize both a GAAP-standard measure, Operating Profitability (Opp), and an industry-standard measure, Funds from Operations (FFO). For each of these variables, I run the following regression model:

$$Operating\ Perf_{i,t+1:t+3} = \alpha + \beta CCExposure_{i,t} + \gamma Operating\ Perf_{i,t-1} + \delta_j + \varepsilon_{i,t+1:t+3} \quad (4.4),$$

where $Operating\ Perf_{i,t+1:t+3}$ represents the alternative operating performance measures for firm i in year $t+1$, $t+2$, or $t+3$, and $CCExposure_{i,t}$ denotes firm i's climate change exposure in year t (including the overall and the three topic-based exposure measures). The lagged value, $Operating\ Perf_{i,t-1}$, is included to control for time-series persistence in operating performance. The term δ_j represents property-type fixed effect. The error term is denoted by $\varepsilon_{i,t+1:t+3}$.

Table 4.8 presents the regression results for operating profitability. In Panel A, Columns (1) to (3), $CCExposure$ negatively predicts future operating profitability, and this negative relationship persists from year t+1 to year t+3. Specifically, a one-standard-deviation increase in $CCExposure$ is associated with a decrease in Opp over year t+1 equivalent to 3.4% of its standard deviation (based on values from the regression sample). Panels B to D examine the topic-based exposure measures. The overall exposure effect is largely driven by firms with higher opportunity exposure (Panel B, Column (1)). Additionally, firms with higher regulatory exposure exhibit lower operating profitability in the subsequent year (Panel C, Column (1)). However, firms with higher physical exposure do not experience a significant decline in future operating profitability (Panel D).

The results for operating profitability are also broadly applicable to funds from operations as reported in Table 4.9. Notably, the negative association between $CCExposure$ and future FFO is not statistically significant until year t+2 (Panel A, Columns (2) to (3)). A one-standard-deviation increase in $CCExposure$ is related to a decrease in FFO over year t+2 equivalent to 5.2% of its standard deviation (based on values from the regression sample). Another key observation is that the overall exposure effect on future FFO can only be attributed to firms with high opportunity exposure (Panel B, Columns (2) to (3)). In contrast, firms with higher regulatory exposure do not show a significant negative impact on future FFO (Panel C). Furthermore, the physical exposure measure does not exhibit any significant associations with firms' future FFO (Panel D).

Overall, the findings show the negative impact of climate change exposure, and in particular opportunity exposure, on firms' future operating performance. The findings suggest that the materialization of opportunities, such as green buildings, can deteriorate firm profits, at least in the short term.

[Insert Table 4.8]

[Insert Table 4.9]

4.5.2 Rental Performance

I next examine the impacts of climate change exposure on firms' rental business activities, as asset-level metrics may more accurately capture climate change's effects (Gostlow, 2021; Hsu et al., 2023). I utilize two key measures of firms' rental performance: Rental Net Operating Income ($RNOI$) and Occupancy Rate (Occ). For each of these measures, I estimate the following regression model:

$$Rental\ Perf_{i,t+1:t+3} = \alpha + \beta CCExposure_{i,t} + \gamma Rental\ Perf_{i,t-1} + \delta_j + \varepsilon_{i,t+1:t+3} \quad (4.5),$$

where $Rental\ Perf_{i,t+1:t+3}$ represents the alternative rental performance measures for firm i in year $t+1$, $t+2$, or $t+3$, and $CCExposure_{i,t}$ denotes firm i's climate change exposure in year t (including the overall and the three topic-based exposure measures). The lagged value, $Rental\ Perf_{i,t-1}$, is included to control for time-series persistence in rental performance. The term δ_j represents property-type fixed effect. The error term is denoted by $\varepsilon_{i,t+1:t+3}$.

Table 4.10, Panel A, Columns (1) to (3), demonstrate that $CCExposure$ is negatively associated with $RNOI$ over years t+1, t+2, and t+3. Specifically, a one-standard-deviation increase in $CCExposure$ is related to a decrease in $RNOI$ over year t+1 equivalent to 3.3% of its standard deviation (based on values from the regression sample). Panels B to D examine the topic-based exposure measures. If a firm is retrofitting green practices into its building portfolio, its earnings calls might include discussions about these climate-related opportunities. However, the green retrofit could lead to significant expenses and take several years to complete. Panel B, Columns (1) to (3), confirm this intuition: firms with high opportunity exposure experience lower future $RNOI$ than firms with low exposure. This finding is consistent with earlier evidence that high-opportunity-exposure firms face reduced operating performance due to the potential erosion of green building investment on short-term cash flows. In Panel C, Column (2), the pattern for $CCExposure^{Reg}$ is similar to that for $CCExposure^{Opp}$, though the magnitudes are much smaller. In Panel D, the effects of $CCExposure^{Phy}$ are not statistically significant.

Table 4.11 reports the results for occupancy rate. In Panel A, Columns (2) to (3), $CCExposure$ negatively predicts Occ over years t+2 and t+3. Specifically, the occupancy rate over year t+2 decreases by 3.5% of its standard deviation for a one-standard-deviation increase in the overall exposure measure. This effect is largely driven by firms with higher regulatory exposure (Panel C, Column (2)). A one-standard-deviation increase in $CCExposure^{Reg}$ is related to a decrease in Occ over year t+2 equivalent to 4.0% of its standard deviation. Additionally, the effect of $CCExposure^{Opp}$ is also significantly negative, though with smaller magnitudes (2.7%). These results collectively suggest the negative impact of firms' regulatory exposure on tenant occupancy. As economies decarbonize, tighter regulatory interventions may compel firms to adopt costly green practices. To cover the costs of greening their properties, firms may need to raise property rental rates, prompting tenants to reconsider their occupancies. Alternatively, firms with high regulatory exposure may have building portfolios that are more carbon intensive. Due to an increasing concern on environmental impacts, tenants may shift to buildings with less carbon footprint. Finally, I do not observe any significant negative effects for physical exposure in Panel D.

Overall, the results suggest that climate change exposure negatively affects not only future firm-level operating performance but also property-level operation.

[Insert Table 4.10]

[Insert Table 4.11]

4.5.3 Market Valuation

The negative predictions regarding future operating and rental performance suggest that climate change exposure should be appropriately priced in the market. If investors fail to anticipate the decline in firms' profitability associated with higher climate change exposure, they may be disappointed by the subsequent realization of lower profits. This cash-flow shock can lead to declines in stock prices and returns. Additionally, the broader societal shifts toward ESG criteria and impact investing may influence the risk premium associated with climate change exposure. Some investors may choose to invest in stocks exposed to climate change for non-pecuniary reasons, such as ethical considerations (Pástor et al., 2021; Pedersen et al., 2021). For instance, they might accept lower expected returns in exchange for holding stocks with high opportunity exposure. Consequently, this capital allocation behavior could result in a zero or even negative risk premium for climate change exposure.

I now investigate the financial market outcomes of climate change exposure. My first analysis examines the relationship between climate change exposure and firms' future market valuation. For each firm-year within the sampled U.S. firms, I estimate the following regression model:

$$Q_{i,t+1} = \alpha + \beta CCExposure_{i,t} + \gamma \mathbf{X}_{i,t} + \delta_j + \delta_t + \varepsilon_{i,t+1} \text{ (4.6)},$$

where $Q_{i,t+1}$ represents Tobin's Q for firm i in year $t+1$, and $CCExposure_{i,t}$ denotes the climate change exposure measure for firm i in year t (including the overall and the three topic-based exposure measures). The vector $\mathbf{X}_{i,t}$ includes control variables: $log(1+Me)$, B/M, Mom, Opp, and I/A (all in year t). The terms δ_j and δ_t represent property-type and year fixed effects, respectively. The error term is denoted by $\varepsilon_{i,t+1}$.

Table 4.12 presents the estimation results for market valuation. In Column (1), the estimates indicate that firms with higher climate change exposure have lower Tobin's Q in the subsequent year. Specifically, a one-standard-deviation increase in $CCExposure$ is associated with a decrease in Q over the next year equivalent to 5.4% of its standard deviation (based on values from the regression sample). Columns (2) to (4) examine the topic-based exposure measures. As anticipated, the overall exposure effect is partly attributable to firms with higher opportunity exposure (Column (2)). Additionally, firms with high regulatory exposure experience lower future valuation compared to firms with low exposure (Column (3)). A one-standard-deviation increase in $CCExposure^{Opp}$ and $CCExposure^{Reg}$ is associated with a decline in Q over year t+1 equivalent to 2.9% and 3.2% of its standard deviation, respectively. However, firms with larger physical exposure do not exhibit lower valuation in the following year (Column (4)).

[Insert Table 4.12]

4.5.4 Stock Returns

I next examine the extent to which firms' exposure to climate change affects their stock return performance. For each firm-year within the sampled U.S. firms, I estimate the following Fama and MacBeth (1973) cross-sectional annual excess return predictive regression:

$$R_{i,t+1} = \alpha_{t+1} + \beta_{t+1} CCExposure_{i,t} + \gamma_{t+1}\mathbf{X}_{i,t} + \delta_j + \varepsilon_{i,t+1} \text{ (4.7)},$$

where $R_{i,t+1}$ represents the compounded monthly excess returns from July in year $t+1$ to June in year $t+2$, and $CCExposure_{i,t}$ denotes firm i's climate change exposure measure in year t (including the overall and the three topic-based exposure measures). The vector $\mathbf{X}_{i,t}$ includes control variables: $log(1+Me)$, B/M, Mom, Opp, and I/A (all in year t). The term δ_j represents property-type fixed effect. The error term is denoted by $\varepsilon_{i,t+1}$.

Table 4.13 presents the estimation results. Panel A displays the results for the full sample period. In Column (1), I find that climate change exposure over year t+1 negatively predicts stock returns in the following year. Specifically, the stock returns decrease by 1.3% (the mean value of stock returns for the regression sample is 9.3%) for a one-standard-deviation increase in $CCExposure$. The negative impact of the overall exposure is primarily driven by firms with high opportunity exposure as shown in Column (2), where a one-standard-deviation increase in $CCExposure^{Opp}$ is associated with a decrease of 1.8% in R over the subsequent year. In Columns (3) and (4), I do not observe any significant negative associations between regulatory or physical exposure and future stock returns.

Table 4.13, Panels B to D illustrate the time-series dynamics of the return predictability of climate change exposure. I divide the sample into three periods and re-estimate equation (4.7). Panel B presents the estimation results prior to the financial crisis, revealing that none of the exposure measures significantly predict stock returns in the following year. This non-significance extends to the subsample during the financial crisis (Panel C). The return predictability emerges not until the mid-2010, shortly after the conclusion of the 2009 Copenhagen UN Climate Change Conference, which generated unprecedented public attention to climate change (Engle et al., 2020). The return predictability documented for the full sample period in Panel A is largely attributable to that for the post-Copenhagen period in Panel D.

Specifically, a one-standard-deviation increase in $CCExposure$ and $CCExposure^{Opp}$ is associated with a decrease of 1.9% and 1.7% in stock returns over the subsequent year, respectively.

I further replace $R_{i,t+1}$ in equation (4.7) with cumulative annual stock returns for up to five years, $R_{i,t+1:t+5}$, to examine the persistence of the return predictability of climate change exposure during the post-Copenhagen period. Table 4.14 reports the estimation results. In Panel A, Columns (1) to (5), the overall exposure measure negatively predicts stock returns over the subsequent one to five years. Specifically, the cumulative annual stock returns decrease by 1.9%, 3.7%, 5.7%, 8.3%, and 10.0%, respectively, for a one-standard-deviation increase in $CCExposure$. As anticipated, the enduring negative effect of the overall exposure is largely attributable to firms with high opportunity exposure. A one-standard-deviation increase in $CCExposure^{Opp}$ is associated with a decline of 1.7%, 2.7%, 3.6%, 6.1%, and 9.8% in cumulative annual stock returns over the subsequent one to five years, respectively. In contrast, the regulatory and physical exposure measures do not significantly predict future cumulative annual stock returns across multiple periods.

[Insert Table 4.13]

[Insert Table 4.14]

4.5.5 Portfolio Returns

I finally investigate whether the negative risk premium documented at firm level extends to the portfolio level. Beginning each month from July 2003, I sort all sampled U.S. firms into quintiles based on the ranked values of climate change exposure measure, $CCExposure$. I then compute value-weighted quintile excess returns for the current month, using the end-of-prior-month market equity as weights. The quintiles are rebalanced at the beginning of each subsequent month.

Table 4.15, Panels A and B, display the time-series averages of quintile climate change exposure and excess returns. While the average climate change exposure increases from 0.06 to 0.80 per 1,000 bigrams across quintiles from low to high, the average excess returns decrease from 1.00% to 0.74%. The high-minus-low quintile earns, on average, -0.26% per month (t-statistic = -2.17) during the period from July 2003 to December 2023. This negative risk premium observed in the single-sort long-short portfolio is consistent with the return patterns documented in the Fama-MacBeth cross-sectional predictive regressions.

To evaluate the performance of asset pricing factor models to explain the negative high-minus-low premium, I draw on a set of conventional and more recent models. For each quintile, I estimate the following time-series factor model regressions,

The CAPM,

$R_t^i - R_t^f = \alpha_{CAPM}^i + \beta_{MKT}^i MKT_t + \varepsilon_t^i$ (4.8);

The Fama and French (1993) three-factor model (FF3),

$R_t^i - R_t^f = \alpha_{FF3}^i + \beta_{MKT}^i MKT_t + \beta_{SMB3}^i SMB3_t + \beta_{HML}^i HML_t + \varepsilon_t^i$ (4.9);

The Carhart (1997) model (Carhart),

$R_t^i - R_t^f = \alpha_{Carhart}^i + \beta_{MKT}^i MKT_t + \beta_{SMB3}^i SMB3_t + \beta_{HML}^i HML_t + \beta_{UMD}^i UMD_t + \varepsilon_t^i$ (4.10);

The Fama and French (2015) five-factor model (FF5),

$R_t^i - R_t^f = \alpha_{FF5}^i + \beta_{MKT}^i MKT_t + \beta_{SMB5}^i SMB5_t + \beta_{HML}^i HML_t + \beta_{RMW}^i RMW_t + \beta_{CMA}^i CMA_t + \varepsilon_t^i$ (4.11);

The Fama and French (2018) six-factor model (FF6),

$R_t^i - R_t^f = \alpha_{FF6}^i + \beta_{MKT}^i MKT_t + \beta_{SMB5}^i SMB5_t + \beta_{HML}^i HML_t + \beta_{RMW}^i RMW_t + \beta_{CMA}^i CMA_t + \beta_{UMD}^i UMD_t + \varepsilon_t^i$ (4.12);

The Hou et al. (2015) q-factor model (HXZq),

$R_t^i - R_t^f = \alpha_{HXZq}^i + \beta_{Mkt}^i R_{Mkt,t} + \beta_{Me}^i R_{Me,t} + \beta_{I/A}^i R_{I/A,t} + \beta_{Roe}^i R_{Roe,t} + \varepsilon_t^i$ (4.13);

The Hou et al. (2021) q^5 model (HMXZq^5),

$R_t^i - R_t^f = \alpha_{HMXZq^5}^i + \beta_{Mkt}^i R_{Mkt,t} + \beta_{Me}^i R_{Me,t} + \beta_{I/A}^i R_{I/A,t} + \beta_{Roe}^i R_{Roe,t} + \beta_{Eg}^i R_{Eg,t} + \varepsilon_t^i$ (4.14);

where $R_t^i - R_t^f$ is excess returns for each quintile; MKT, SMB, HML, RMW, CMA, and UMD are the standard market factor, size factor, value factor, profitability factor, investment factor, and momentum factor; R_{Mkt}, R_{Me}, $R_{I/A}$, R_{roe}, and R_{Eg} are the alternative market factor, size factor, investment factor, return on equity factor, and expected growth factor. α_{CAPM}, α_{FF3}, $\alpha_{Carhart}$, α_{FF5}, α_{FF6}, α_{HXZq}, and α_{HMXZq^5} are the corresponding model alphas for the CAPM, the FF3, the Carhart, the FF5, the FF6, the HXZq, and the HMXZq^5.

Table 4.15, Panels C to I, present the estimation results for the high-minus-low quintile using various asset pricing models. In Panel C, the CAPM fails to explain the high-minus-low quintile, yielding an alpha of -0.22% (t = -1.83). The loading of the market factor is statistically indistinguishable from zero. Moving to the FF3 in Panel D, the alpha decreases to -0.27% (t = -2.52) for the high-minus-low quintile. While the size and value factors load statistically significant coefficients of -0.19 and -0.26, respectively, their magnitudes in absolute value are small.

Incorporating a momentum factor as in the Carhart in Panel E does not enhance the model's explanatory power for the high-minus-low quintile, resulting in an alpha of -0.28% (t = -2.58). Panel F examines the FF5, adding an investment factor and a profitability factor. This addition further reduces the high-minus-low alpha to -0.31% (t = -2.58), with an investment factor loading of 0.36 (t = 2.18). However, the FF5 model fails to explain quintile 2. Adding all the standard factor together as in FF6 (Panel G) brings the high-minus-low alpha down to -0.32% (t = -2.65).

Panels H and I explore the alternative factor models, HXZq and HMXZq^5, which show less explanatory power for the high-minus-low quintile, producing an alpha of -0.34% (t = -2.60) and -0.40% (t = -2.26), respectively. The further decline in alpha can be partly attributed to the significant positive loadings on the return on equity factor, despite the small magnitudes. Additionally, both models fail to explain the low quintile, with an alpha of 0.29% (t = 1.76) and 0.30% (t = 2.27), respectively.

Overall, I find that the return predictability of climate change exposure extends from firm level to portfolio level and is not explained by a set of traditional and more recent factor models. However, as in Sautner et al. (2023a and 2023b), this study does not intend to propose a climate factor to explain the cross section of stock returns. While one may interpret the return pattern associated with climate change exposure as an asset pricing anomaly, this study echo Sautner et al. that earnings call participants' perception of a firm's climate change exposure may be linked to systematic risk and shocks to those perceptions are priced into the cross section.

[Insert Table 4.15]

4.6 Conclusion

I investigate the real and financial implications of firm-level climate change exposure among publicly listed real estate firms. The climate change exposure measures are from Sautner et al. (2023a), who utilize quarterly earnings calls to assess the attention paid by market participants to a firm's climate-related opportunities, regulatory shocks, and physical shocks. The measured climate change exposure varies across property types and has increased over time. It also positively correlates with public climate change attention, firm environmental scores, and alternative weather exposure.

My analysis reveals that firms with higher climate change exposure invest more in green buildings in the subsequent year, and tenants of these high-exposure firms achieve higher future environmental scores in aggregate. These positive exposure effects are primarily driven by firms with higher regulatory exposure. However, engaging in environmentally responsible practices does not uniformly translate to better financial performance. I demonstrate that high-exposure firms experience lower future operating and rental performance. These negative exposure effects are attributable to firms with higher opportunity and/or regulatory exposures. Furthermore, driven by the opportunity exposure, climate change exposure negatively predicts subsequent market valuations and stock returns. The results suggest that investors may ignore the negative prediction of firm cash flows, or they have non-financial preference and have low expected returns.

This study makes several contributions to the literature. It first adds to the growing literature on climate change exposure and corporate green investment. Among others, Sautner et al. (2023a and 2023b) find that firms with high climate change exposure invest more in green jobs and green patents. This study provides new evidence on green buildings as well as transition enabling, Second, this study contributes to the literature on climate change exposure and asset prices. Saunter et al. document a positive premium related to climate change exposure, using option-implied expected returns and a sample of S&P 500 stocks. They align the positive premium with the model of "uncertainty about the path of climate change"(Giglio et al., 2021). This study finds contrasting evidence of a negative premium based on realized returns and a sample of SNL U.S. publicly traded real estate firms. The negative premium can be linked to the ESG-efficient frontier framework (Pedersen et al., 2021).

This study thirdly adds to the literature on climate change, sustainability, and real estate. A growing number of studies have examined the effects of green building certifications, environmental or broader ESG performance or disclosure, and physical climate hazards on the financial performance of publicly traded real estate firms. This study differs from previous studies by using the firm-level climate change exposure from Sautner et al. Compared with previous interest, this study provides a more comprehensive analysis, covering both climate risks and opportunities, and offers new insight from market participant perceptions of firms' climate change exposure. In additional, this study provides new evidence on green building investment and transition enabling as well as contrasting evidence on financial performance.

This study also has practical implications for investors, professionals, and policymakers. Regarding the real economic outcomes, the findings suggest that the introduction of climate regulation and policies can facilitate the shift to sustainable practices in real estate sector. Also, the findings suggests that the adaption of low-carbon buildings can promote the net-zero transition of other economic sectors. For policymakers, the findings endorse potential incentives for green building investment—such as tax credits, grants, or favourable financing terms—to encourage the continuation of the green practices. Regarding the financial outcomes, the findings can inform those investors who ignore climate change exposure and its negative signal of firm fundamentals. For firm managers, the findings highlight the importance of strategic planning and resource allocation on green opportunities to mitigate their potential erosion on future cash flows.

It is crucial to acknowledge the limitations of this study. One primary limitation is data constraint. Firm-level climate change exposure, as defined by Sautner et al. (2023a), is measured by the proportion of climate change discussions during earnings conference calls. While this approach provides an innovative method to capture firms' exposure to climate-related risks and opportunities, it is limited by the quality and completeness of earnings call transcripts. Not all firms consistently discuss climate change during their quarterly earnings calls, which may lead to potential underestimation or overestimation of their actual exposure. Indeed, Sautner et al.'s data encounter instances where specific earnings calls in a given year do not mention climate change, even though the topic is addressed in surrounding calls. These incidental gaps in quarterly data may not accurately reflect the firms' true engagement with climate-related issues.

Another data-related limitation is the reliance on selective green building proxies. The use of LEED certifications and Energy Star labels as proxies for green buildings, while widely adopted in the literature, may not capture all aspects of a firm's commitment to sustainable building practices. Other forms of green building initiatives—such as regional certifications, unregistered sustainable projects, or internal sustainability programs—are not reflected in the measure, potentially leading to an incomplete picture of firms' green building holdings.

The limitation related to methodology is the use of fixed-effect regression models. The analysis of the real and financial impacts of climate change exposure primarily relies on linear regression models with multiple fixed effects, such as property types and years. While this approach effectively identifies the relationships between climate change exposure and real and financial outcomes, it does not reflect the time-series dynamics of the relationships over time. Indeed, the effects of climate change exposure may evolve over time as meteorological conditions, regulatory frameworks, and technological advancements change. However, given the relatively short period and low frequency of the climate change exposure measures, a dynamic analysis face limited degree of freedom. Furthermore, even if the time period were extended further into the past, it remains unclear whether additional data would aid in uncovering potential dynamics, given that climate change has recently been a significant concern for investors.

Finally, the scope and generalizability of the findings are of concern. The geographical focus on the United States, while relevant for understanding the U.S. publicly listed real estate firms, limits the generalizability of the findings to international markets. Real estate markets in other countries may be subject to different economic, political, and regulatory conditions. Therefore, the real and financial impacts of climate change exposure could be different from that in a U.S. context.

Figures

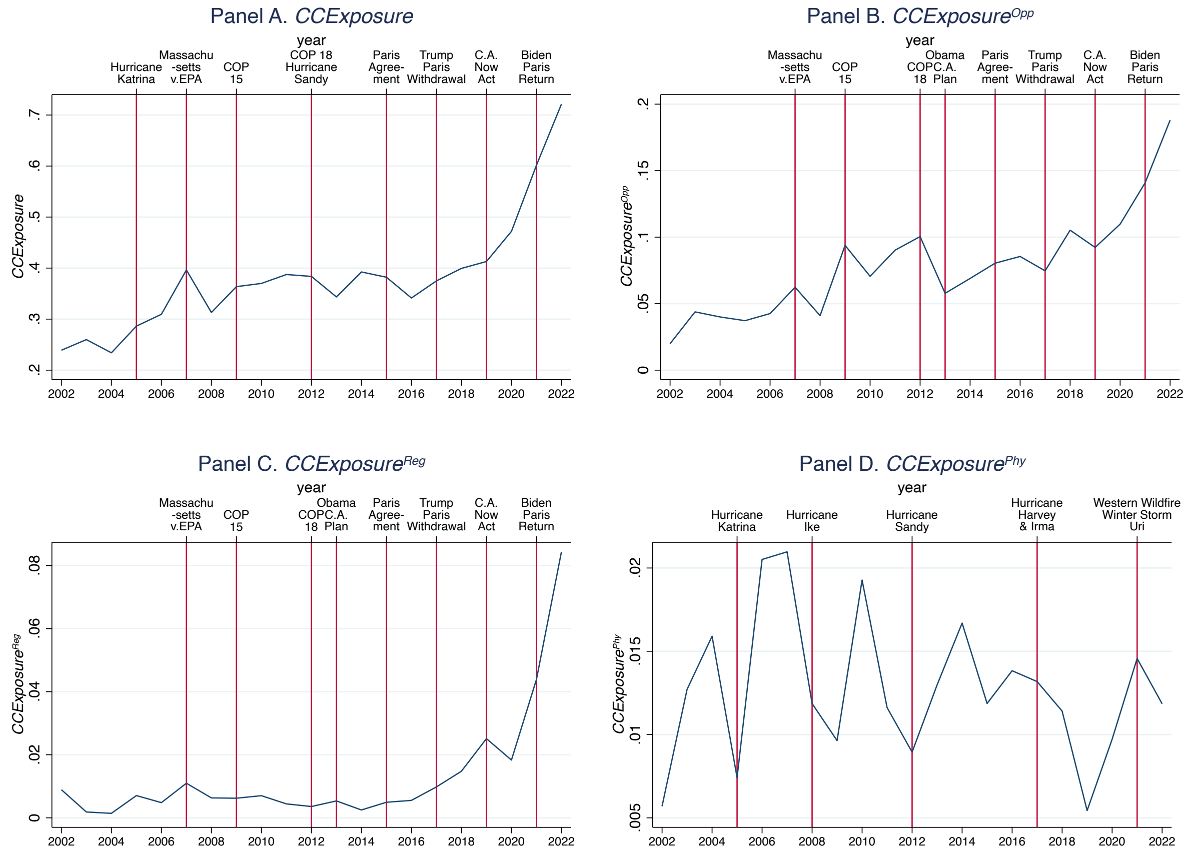

Figure 4.1 Climate Change Exposure over Time

This figure shows firms' average climate change exposure over time. $CCExposure$ measures the share of climate change bigrams in earnings call transcripts. $CCExposure^{Opp}$ measures the share of bigrams that capture opportunities related to climate change in earnings call transcripts. $CCExposure^{Reg}$ measures the share of bigrams that capture regulatory shocks related to climate change in earnings call transcripts. $CCExposure^{Phy}$ measures the share of bigrams that capture physical shocks related to climate change in earnings call transcripts. For each exposure measure, I construct the time series using the firm-year observations from the U.S. sub-sample. Appendix 4.1 provides detailed variable definitions.

Tables

Table 4.1 Climate Change Exposure: Summary Statistics

This table reports summary statistics for climate change exposure measures at firm-year level. $CCExposure$ measures the share of climate change bigrams in earnings call transcripts. $CCExposure^{Opp}$ measures the share of bigrams that capture opportunities related to climate change in earnings call transcripts. $CCExposure^{Reg}$ measures the share of bigrams that capture regulatory shocks related to climate change in earnings call transcripts. $CCExposure^{Phy}$ measures the share of bigrams that capture physical shocks related to climate change in earnings call transcripts. For all exposure measures, I average quarterly measures for each firm-year and scale the annual measures by a factor of 1,000 for the purpose of exposition. The sample includes 639 unique firms from 34 countries over the period 2002 to 2022. Appendix 4.1 provides detailed variable definitions.

	Mean	SD	25%	Median	75%	N
$CCExposure$	0.524	0.896	0.000	0.245	0.596	5776
$CCExposure^{Opp}$	0.112	0.307	0.000	0.000	0.101	5776
$CCExposure^{Reg}$	0.035	0.173	0.000	0.000	0.000	5776
$CCExposure^{Phy}$	0.010	0.056	0.000	0.000	0.000	5776

Table 4.2 Property Type Distribution of Climate Change Exposure

This table reports firms' climate change exposure measures for property types. Statistics are reported at the firm-year level across different property types. $CCExposure$ measures the share of climate change bigrams in earnings call transcripts. $CCExposure^{Opp}$ measures the share of bigrams that capture opportunities related to climate change in earnings call transcripts. $CCExposure^{Reg}$ measures the share of bigrams that capture regulatory shocks related to climate change in earnings call transcripts. $CCExposure^{Phy}$ measures the share of bigrams that capture physical shocks related to climate change in earnings call transcripts. For each exposure measure, I rank property types by the average values of the exposure measure. Appendix 4.1 provides detailed variable definitions.

Panel A: $CCExposure$

Type	Mean	SD	Median	*N*
Specialty	1.0013	1.4796	0.5497	503
Office	0.6134	1.0298	0.2684	720
Diversified	0.5988	0.9276	0.2927	1462
Industrial	0.5391	0.7884	0.2736	380
Residential	0.5331	0.7792	0.3253	556
Self-Storage	0.3912	0.5368	0.2411	99
Retail	0.3719	0.6931	0.1696	974
Health Care	0.3717	0.6452	0.1851	400
Hotel	0.2230	0.2851	0.1442	682

Panel B: $CCExposure^{Opp}$

Type	Mean	SD	Median	*N*
Specialty	0.2340	0.5198	0.0754	503
Industrial	0.1773	0.4114	0.0000	380
Diversified	0.1364	0.3358	0.0000	1462
Office	0.1152	0.2929	0.0000	720
Self-Storage	0.0967	0.2225	0.0000	99
Residential	0.0847	0.2030	0.0000	556
Retail	0.0722	0.2270	0.0000	974
Health Care	0.0653	0.2157	0.0000	400
Hotel	0.0356	0.0854	0.0000	682

Panel C: $CCExposure^{Reg}$

Type	Mean	SD	Median	*N*
Office	0.0533	0.2036	0.0000	720
Diversified	0.0488	0.2146	0.0000	1462
Specialty	0.0403	0.2634	0.0000	503
Residential	0.0332	0.1408	0.0000	556
Retail	0.0315	0.1517	0.0000	974
Industrial	0.0162	0.0690	0.0000	380
Health Care	0.0157	0.0773	0.0000	400
Hotel	0.0131	0.0618	0.0000	682
Self-Storage	0.0057	0.0438	0.0000	99

(Continued)

Table 4.2 – Continued

Panel D: $CCExposure^{Phy}$				
Type	Mean	SD	Median	*N*
Industrial	0.0198	0.0982	0.0000	380
Self-Storage	0.0191	0.0859	0.0000	99
Specialty	0.0179	0.0613	0.0000	503
Residential	0.0171	0.0628	0.0000	556
Diversified	0.0084	0.0611	0.0000	1462
Health Care	0.0081	0.0465	0.0000	400
Retail	0.0075	0.0439	0.0000	974
Hotel	0.0066	0.0332	0.0000	682
Office	0.0046	0.0308	0.0000	720

Table 4.3 Climate Change Exposure: Effect of Public Attention to Climate Change

This table reports regressions that relate public climate change attention to climate change exposure. Regressions are estimated at firm-year level. $CCExposure$ measures the share of climate change bigrams in earnings call transcripts. $CCExposure^{Opp}$ measures the share of bigrams that capture opportunities related to climate change in earnings call transcripts. $CCExposure^{Reg}$ measures the share of bigrams that capture regulatory shocks related to climate change in earnings call transcripts. $CCExposure^{Phy}$ measures the share of bigrams that capture physical shocks related to climate change in earnings call transcripts. For all exposure measures, I average quarterly measures for each firm-year and scale the annual measures by a factor of 1,000. $WSJ\ CC\ New\ Index$ is a time-series index developed in Engle et al. (2020) that captures climate change news in the *Wall Street Journal*. I scale the index by a factor of 100. $Yale\ CO\ Map$ is a time-series, cross-state, index developed in Howe et al. (2015) that captures local survey respondents' perceptions of climate change. In both Panel A and B, the regressions control for Log($Asset$), $Debt/Assets$, $Cash/Assets$, and $EBIT/Assets$ (all in $t-1$), as well as property-type fixed effects. Standard errors are in parentheses. Appendix 4.1 defines all variables in detail. *p < 0.1; **p < 0.05; ***p < 0.01.

Panel A: Wall Street Journal Climate Change News Index				
	$CCExposure_{i,t}$	$CCExposure_{i,t}^{Opp}$	$CCExposure_{i,t}^{Reg}$	$CCExposure_{i,t}^{Phy}$
	(1)	(2)	(3)	(4)
$WSJ\ CC\ News\ Index_t$	0.299***	0.067*	0.003	0.016
	(0.104)	(0.037)	(0.008)	(0.010)
Controls	Yes	Yes	Yes	Yes
Type FE	Yes	Yes	Yes	Yes
N	2280	2280	2280	2280
Adj. R^2	0.134	0.052	0.003	0.013
Panel B: Yale Climate Opinion Map				
	$CCExposure_{i,t}$	$CCExposure_{i,t}^{Opp}$	$CCExposure_{i,t}^{Reg}$	$CCExposure_{i,t}^{Phy}$
	(1)	(2)	(3)	(4)
$Yale\ CO\ Map_{s,t}$	0.661**	0.402***	0.120**	0.019
	(0.324)	(0.122)	(0.057)	(0.025)
Controls	Yes	Yes	Yes	Yes
Type FE	Yes	Yes	Yes	Yes
N	2264	2264	2264	2264
Adj. R^2	0.141	0.072	0.010	0.017

Table 4.4 Climate Change Exposure: Effects of Environmental Score and Weather Exposure

This table reports regressions that relate environmental score and weather exposure to climate change exposure. Regressions are estimated at firm-year level. $CCExposure$ measures the share of climate change bigrams in earnings call transcripts. $CCExposure^{Opp}$ measures the share of bigrams that capture opportunities related to climate change in earnings call transcripts. $CCExposure^{Reg}$ measures the share of bigrams that capture regulatory shocks related to climate change in earnings call transcripts. $CCExposure^{Phy}$ measures the share of bigrams that capture physical shocks related to climate change in earnings call transcripts. For all exposure measures, I average quarterly measures for each firm-year and scale the annual measures by a factor of 1,000. $Escore$ is a firm's environmental score, which comes from the environmental component of the S&P Global ESG Score. I divide the $Escore$ by 100. $Weather$ is the firm-level weather exposure measure developed by Nagar and Schoenfeld (2022), which measures the count of "weather" or weather-related terms in a firm's 10K reports. I divide the $Weather$ by 1,000. In Panel A, the regressions control for Log($Asset$), $Debt/Assets$, and $EBIT/Assets$ (all in $t-1$), as well as country, property-type, and year fixed effects. In Panel B, the regressions control for Log($Asset$), $Debt/Assets$, $Cash/Assets$, and $EBIT/Assets$, as well as time-varying property-type effects. Standard errors are in parentheses. Appendix 4.1 defines all variables in detail. *p < 0.1; **p < 0.05; ***p < 0.01.

Panel A: Environmental Score				
	$CCExposure_{i,t}$	$CCExposure_{i,t}^{Opp}$	$CCExposure_{i,t}^{Reg}$	$CCExposure_{i,t}^{Phy}$
	(1)	(2)	(3)	(4)
$Escore_{i,t}$	0.653***	0.196***	0.062	-0.005
	(0.158)	(0.054)	(0.039)	(0.009)
Controls	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Type FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	1641	1641	1641	1641
Adj. R^2	0.267	0.153	0.127	0.012

Panel B: Weather Exposure				
	$CCExposure_{i,t}$	$CCExposure_{i,t}^{Opp}$	$CCExposure_{i,t}^{Reg}$	$CCExposure_{i,t}^{Phy}$
	(1)	(2)	(3)	(4)
$Weather_{i,t}$	11.096***	3.601***	0.103	0.574**
	(2.689)	(1.074)	(0.177)	(0.246)
Controls	Yes	Yes	Yes	Yes
Type x Year FE	Yes	Yes	Yes	Yes
N	2262	2262	2262	2262
Adj. R^2	0.113	0.031	-0.011	0.043

Table 4.5 Climate Change Exposure: Variance Decomposition

This table provides a variance decomposition of the climate change exposure measures. Regressions are estimated at firm-year level. In Panel A, the table reports the incremental R^2 from adding a specific fixed effect. In Panel B, the table decomposes the variation into a set of fixed effects and a residual component. $CCExposure$ measures the share of climate change bigrams in earnings call transcripts. $CCExposure^{Opp}$ measures the share of bigrams that capture opportunities related to climate change in earnings call transcripts. $CCExposure^{Reg}$ measures the share of bigrams that capture regulatory shocks related to climate change in earnings call transcripts. $CCExposure^{Phy}$ measures the share of bigrams that capture physical shocks related to climate change in earnings call transcripts. For all exposure measures, I average quarterly measures for each firm-year and scale the annual measures by a factor of 1,000. Appendix 4.1 defines all variables in detail.

Panel A: Incremental R^2

	$CCExposure_{i,t}$	$CCExposure_{i,t}^{Opp}$	$CCExposure_{i,t}^{Reg}$	$CCExposure_{i,t}^{Phy}$
	(1)	(2)	(3)	(4)
Year FE	12.04%	6.95%	7.83%	0.43%
Type FE	4.54%	2.82%	0.58%	0.80%
Type x Year FE	19.44%	12.14%	11.32%	5.24%
Country FE	5.36%	2.90%	3.68%	1.08%
"Firm Level"	58.62%	75.19%	76.59%	92.45%
Sum	100%	100%	100%	100%

Panel B: Fraction of Variation

	$CCExposure_{i,t}$	$CCExposure_{i,t}^{Opp}$	$CCExposure_{i,t}^{Reg}$	$CCExposure_{i,t}^{Phy}$
	(1)	(2)	(3)	(4)
Type x Year FE Country FE Firm FE	50.67%	41.28%	31.66%	25.85%
Residual	49.33%	58.72%	68.34%	74.15%
Sum	100%	100%	100%	100%

Table 4.6 Green Building Investment and Climate Change Exposure

This table reports regressions that relate green building investment to climate change exposure. Regressions are estimated at firm-year level. $Green\ Ppty$ is the share of buildings in a firm's portfolio with a LEED certification, Energy Star label, or both. $\#Green\ Ppty$ is the number of environmentally certified buildings in a firm's portfolio. $\#Nongreen\ Ppty$ is the number of buildings in a firm's portfolio without those environmental certifications. $CCExposure$, $CCExposure^{Opp}$, $CCExposure^{Reg}$, and $CCExposure^{Phy}$ are the overall and three topic-based exposure measures defined as in previous tables. The regressions control for $log\ (Assets)$, $Debt/Assets$, $Cash/Assets$, and $EBIT/Assets$ (all in t), as well as property-type and year fixed effects. Standard errors are in parentheses. Appendix 4.1 defines all variables in detail. *p < 0.1; **p < 0.05; ***p < 0.01.

	$Green\ Ppty_{i,t+1}$				$Log(1 + \#Green\ Ppty_{i,t+1})$	$\log(1 + \#Nongreen\ Ppty_{i,t+1})$
	(1)	(2)	(3)	(4)	(5)	(6)
$CCExposure_{i,t}$	0.014***				0.107***	-0.467***
	(0.004)				(0.039)	(0.053)
$CCExposure_{i,t}^{Opp}$		0.009				
		(0.010)				
$CCExposure_{i,t}^{Reg}$			0.086**			
			(0.035)			
$CCExposure_{i,t}^{Phy}$				-0.023		
				(0.037)		
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Type FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	2622	2622	2622	2622	2622	2622
Adj. R^2	0.470	0.468	0.469	0.468	0.420	0.456

Table 4.7 Tenant Environmental Score and Climate Change Exposure

This table reports regressions that relate tenant environmental score to climate change exposure. Regressions are estimated at firm-year level. $TEscore$ is the equally-weighted average of a firm's tenant environmental score from S&P Global ESG Score. $TEscore_w$ is the value-weighted average of a firm's tenant environmental score using tenant revenues as the weight. $CCExposure$, $CCExposure^{Opp}$, $CCExposure^{Reg}$, and $CCExposure^{Phy}$ are the overall and three topic-based exposure measures defined as in previous tables. The regressions control for $log\ (Assets)$, $Debt/Assets$, and $EBIT/Assets$ (all in t), as well as property-type and year fixed effects. Standard errors are in parentheses. Appendix 4.1 defines all variables in detail. *p < 0.1; **p < 0.05; ***p < 0.01.

	$TEscore_{i,t+1}$				$TEscore\_w_{i,t+1}$	
	(1)	(2)	(3)	(4)	(5)	(6)
$CCExposure_{i,t}$	0.017***				0.017***	
	(0.005)				(0.006)	
$CCExposure_{i,t}^{Opp}$		0.015				
		(0.012)				
$CCExposure_{i,t}^{Reg}$			0.081***			0.069***
			(0.029)			(0.035)
$CCExposure_{i,t}^{Phy}$				-0.002		
				(0.074)		
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Type FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	1537	1537	1537	1537	1256	1256
Adj. R^2	0.249	0.244	0.247	0.244	0.227	0.225

Table 4.8 Operating Profitability and Climate Change Exposure

This table reports regressions that relate operating profitability to climate change exposure. Regressions are estimated at firm-year level. Opp is operating profitability (in time $t+1$ to $t+3$). $CCExposure$, $CCExposure^{Opp}$, $CCExposure^{Reg}$, and $CCExposure^{Phy}$ are the overall and three topic-based exposure measures defined as in previous tables. The regressions control for a lagged value of Opp (in $t-1$), as well as property-type fixed effect. Standard errors are in parentheses. Appendix 4.1 defines all variables in detail. *p < 0.1; **p < 0.05; ***p < 0.01.

Panel A: $CCExposure$			
	$Opp_{i,t+1}$	$Opp_{i,t+2}$	$Opp_{i,t+3}$
	(1)	(2)	(3)
$CCExposure_{i,t}$	-0.002***	-0.002**	-0.002**
	(0.001)	(0.001)	(0.001)
$Opp_{i,t-1}$	0.755***	0.674***	0.663***
	(0.016)	(0.019)	(0.023)
Type FE	Yes	Yes	Yes
N	2007	1610	1267
Adj. R^2	0.633	0.582	0.599
Panel B: $CCExposure^{Opp}$			
	$Opp_{i,t+1}$	$Opp_{i,t+2}$	$Opp_{i,t+3}$
	(1)	(2)	(3)
$CCExposure_{i,t}^{Opp}$	-0.006***	-0.001	-0.005*
	(0.002)	(0.003)	(0.003)
$Opp_{i,t-1}$	0.753***	0.674***	0.661***
	(0.016)	(0.019)	(0.023)
Type FE	Yes	Yes	Yes
N	2007	1610	1267
Adj. R^2	0.633	0.581	0.599
Panel C: $CCExposure^{Reg}$			
	$Opp_{i,t+1}$	$Opp_{i,t+2}$	$Opp_{i,t+3}$
	(1)	(2)	(3)
$CCExposure_{i,t}^{Reg}$	-0.019*	-0.004	-0.002
	(0.010)	(0.012)	(0.018)
$Opp_{i,t-1}$	0.756***	0.675***	0.664***
	(0.016)	(0.019)	(0.023)
Type FE	Yes	Yes	Yes
N	2007	1610	1267
Adj. R^2	0.632	0.581	0.598
Panel D: $CCExposure^{Phy}$			
	$Opp_{i,t+1}$	$Opp_{i,t+2}$	$Opp_{i,t+3}$
	(1)	(2)	(3)
$CCExposure_{i,t}^{Phy}$	-0.002	-0.006	-0.001
	(0.009)	(0.010)	(0.012)
$Opp_{i,t-1}$	0.755***	0.674***	0.664***
	(0.016)	(0.019)	(0.023)
Type FE	Yes	Yes	Yes
N	2007	1610	1267
Adj. R^2	0.632	0.581	0.598

Table 4.9 Funds from Operations and Climate Change Exposure

This table reports regressions that relate funds from operations to climate change exposure. Regressions are estimated at firm-year level. FFO is funds from operations (in time $t+1$ to $t+3$). $CCExposure$, $CCExposure^{Opp}$, $CCExposure^{Reg}$, and $CCExposure^{Phy}$ are the overall and three topic-based exposure measures defined as in previous tables. The regressions control for a lagged value of FFO (in $t-1$), as well as property-type fixed effect. Standard errors are in parentheses. Appendix 4.1 defines all variables in detail. *p < 0.1; **p < 0.05; ***p < 0.01.

Panel A: $CCExposure$			
	$FFO_{i,t+1}$	$FFO_{i,t+2}$	$FFO_{i,t+3}$
	(1)	(2)	(3)
$CCExposure_{i,t}$	-0.002	-0.003***	-0.004**
	(0.001)	(0.001)	(0.002)
$FFO_{i,t-1}$	0.604***	0.533***	0.517***
	(0.018)	(0.022)	(0.026)
Type FE	Yes	Yes	Yes
N	2015	1654	1337
Adj. R^2	0.393	0.334	0.309
Panel B: $CCExposure^{Opp}$			
	$FFO_{i,t+1}$	$FFO_{i,t+2}$	$FFO_{i,t+3}$
	(1)	(2)	(3)
$CCExposure_{i,t}^{Opp}$	-0.003	-0.007**	-0.007*
	(0.002)	(0.003)	(0.004)
$FFO_{i,t-1}$	0.604***	0.533***	0.515***
	(0.018)	(0.022)	(0.026)
Type FE	Yes	Yes	Yes
N	2015	1654	1337
Adj. R^2	0.393	0.333	0.307
Panel C: $CCExposure^{Reg}$			
	$FFO_{i,t+1}$	$FFO_{i,t+2}$	$FFO_{i,t+3}$
	(1)	(2)	(3)
$CCExposure_{i,t}^{Reg}$	-0.008	-0.008	-0.010
	(0.009)	(0.010)	(0.013)
$FFO_{i,t-1}$	0.604***	0.533***	0.516***
	(0.018)	(0.022)	(0.026)
Type FE	Yes	Yes	Yes
N	2015	1654	1337
Adj. R^2	0.393	0.331	0.305
Panel D: $CCExposure^{Phy}$			
	$FFO_{i,t+1}$	$FFO_{i,t+2}$	$FFO_{i,t+3}$
	(1)	(2)	(3)
$CCExposure_{i,t}^{Phy}$	0.007	0.007	0.009
	(0.008)	(0.009)	(0.012)
$FFO_{i,t-1}$	0.605***	0.533***	0.515***
	(0.018)	(0.022)	(0.026)
Type FE	Yes	Yes	Yes
N	2015	1654	1337
Adj. R^2	0.393	0.331	0.306

Table 4.10 Rental Net Operating Income and Climate Change Exposure

This table reports regressions that relate rental net operating incomes to climate change exposure. Regressions are estimated at firm-year level. $RNOI$ is rental net operating incomes (in time $t+1$ to $t+3$). $CCExposure$, $CCExposure^{Opp}$, $CCExposure^{Reg}$, and $CCExposure^{Phy}$ are the overall and three topic-based exposure measures defined as in previous tables. The regressions control for a lagged value of $RNOI$ (in $t-1$), as well as property-type fixed effect. Standard errors are in parentheses. Appendix 4.1 defines all variables in detail. *p < 0.1; **p < 0.05; ***p < 0.01.

Panel A: $CCExposure$			
	$RNOI_{i,t+1}$	$RNOI_{i,t+2}$	$RNOI_{i,t+3}$
	(1)	(2)	(3)
$CCExposure_{i,t}$	-0.002***	-0.003***	-0.002***
	(0.000)	(0.001)	(0.001)
$RNOI_{i,t-1}$	0.868***	0.847***	0.833***
	(0.010)	(0.012)	(0.014)
Type FE	Yes	Yes	Yes
N	2319	1909	1544
Adj. R^2	0.890	0.866	0.848
Panel B: $CCExposure^{Opp}$			
	$RNOI_{i,t+1}$	$RNOI_{i,t+2}$	$RNOI_{i,t+3}$
	(1)	(2)	(3)
$CCExposure_{i,t}^{Opp}$	-0.003***	-0.004***	-0.003*
	(0.001)	(0.002)	(0.002)
$RNOI_{i,t-1}$	0.871***	0.851***	0.836***
	(0.010)	(0.012)	(0.014)
Type FE	Yes	Yes	Yes
N	2319	1909	1544
Adj. R^2	0.890	0.865	0.847
Panel C: $CCExposure^{Reg}$			
	$RNOI_{i,t+1}$	$RNOI_{i,t+2}$	$RNOI_{i,t+3}$
	(1)	(2)	(3)
$CCExposure_{i,t}^{Reg}$	-0.003	-0.011**	-0.006
	(0.002)	(0.006)	(0.008)
$RNOI_{i,t-1}$	0.872***	0.852***	0.838***
	(0.010)	(0.012)	(0.014)
Type FE	Yes	Yes	Yes
N	2319	1909	1544
Adj. R^2	0.890	0.865	0.847
Panel D: $CCExposure^{Phy}$			
	$RNOI_{i,t+1}$	$RNOI_{i,t+2}$	$RNOI_{i,t+3}$
	(1)	(2)	(3)
$CCExposure_{i,t}^{Phy}$	-0.003	-0.003	-0.006
	(0.005)	(0.006)	(0.007)
$RNOI_{i,t-1}$	0.872***	0.853***	0.837***
	(0.010)	(0.012)	(0.014)
Type FE	Yes	Yes	Yes
N	2319	1909	1544
Adj. R^2	0.890	0.865	0.847

Table 4.11 Occupancy Rate and Climate Change Exposure

This table reports regressions that relate occupancy rates to climate change exposure. Regressions are estimated at firm-year level. Occ is occupancy rate (in time $t+1$ to $t+3$). $CCExposure$, $CCExposure^{Opp}$, $CCExposure^{Reg}$, and $CCExposure^{Phy}$ are the overall and three topic-based exposure measures defined as in previous tables. The regressions control for a lagged value of Occ (in $t-1$), as well as property-type fixed effect. Standard errors are in parentheses. Appendix 4.1 defines all variables in detail. *p < 0.1; **p < 0.05; ***p < 0.01.

Panel A: $CCExposure$			
	$OCC_{i,t+1}$	$OCC_{i,t+2}$	$OCC_{i,t+3}$
	(1)	(2)	(3)
$CCExposure_{i,t}$	-0.002	-0.006**	-0.007*
	(0.002)	(0.003)	(0.004)
$OCC_{i,t-1}$	0.585***	0.460***	0.378***
	(0.022)	(0.028)	(0.038)
Type FE	Yes	Yes	Yes
N	1363	1098	872
Adj. R^2	0.800	0.750	0.721
Panel B: $CCExposure^{Opp}$			
	$OCC_{i,t+1}$	$OCC_{i,t+2}$	$OCC_{i,t+3}$
	(1)	(2)	(3)
$CCExposure_{i,t}^{Opp}$	-0.004	-0.010*	-0.010
	(0.005)	(0.006)	(0.007)
$OCC_{i,t-1}$	0.584***	0.458***	0.375***
	(0.022)	(0.028)	(0.038)
Type FE	Yes	Yes	Yes
N	1363	1098	872
Adj. R^2	0.800	0.749	0.721
Panel C: $CCExposure^{Reg}$			
	$OCC_{i,t+1}$	$OCC_{i,t+2}$	$OCC_{i,t+3}$
	(1)	(2)	(3)
$CCExposure_{i,t}^{Reg}$	-0.038**	-0.059***	-0.037
	(0.018)	(0.022)	(0.027)
$OCC_{i,t-1}$	0.585***	0.461***	0.380***
	(0.022)	(0.028)	(0.038)
Type FE	Yes	Yes	Yes
N	1363	1098	872
Adj. R^2	0.800	0.750	0.721
Panel D: $CCExposure^{Phy}$			
	$OCC_{i,t+1}$	$OCC_{i,t+2}$	$OCC_{i,t+3}$
	(1)	(2)	(3)
$CCExposure_{i,t}^{Phy}$	0.002	0.000	-0.008
	(0.016)	(0.020)	(0.026)
$OCC_{i,t-1}$	0.584***	0.460***	0.377***
	(0.022)	(0.028)	(0.038)
Type FE	Yes	Yes	Yes
N	1363	1098	872
Adj. R^2	0.800	0.749	0.720

Table 4.12 Tobin's Q and Climate Change Exposure

This table reports regressions that relate Tobin's Q to climate change exposure. Regressions are estimated at firm-year level. Q is Tobin's q. $CCExposure$, $CCExposure^{Opp}$, $CCExposure^{Reg}$, and $CCExposure^{Phy}$ are the overall and three topic-based exposure measures defined as in previous tables. The regressions control for $log\ (1 + Me)$, B/M, Mom, Opp, and I/A (all in t), as well as property-type and year fixed effects. Standard errors are in parentheses. Appendix 4.1 defines all variables in detail. *p < 0.1; **p < 0.05; ***p < 0.01.

	$Q_{i,t+1}$			
	(1)	(2)	(3)	(4)
$CCExposure_{i,t}$	-0.038***			
	(0.009)			
$CCExposure_{i,t}^{Opp}$		-0.057**		
		(0.026)		
$CCExposure_{i,t}^{Reg}$			-0.205**	
			(0.082)	
$CCExposure_{i,t}^{Phy}$				0.119
				(0.098)
Controls	Yes	Yes	Yes	Yes
Type FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	2742	2742	2742	2742
Adj. R^2	0.576	0.574	0.575	0.574

Table 4.13 Excess Returns and Climate Change Exposure

This table reports annual Fama-MacBeth cross-sectional predictive regressions of excess returns on climate change exposure. Regressions are estimated at firm-year level. R is compounding monthly excess returns from July in year $t+1$ to June in year $t+2$. $CCExposure$, $CCExposure^{Opp}$, $CCExposure^{Reg}$, and $CCExposure^{Phy}$ are the overall and three topic-based exposure measures defined as in previous tables. The regressions control for $log\ (1+Me)$, B/M, Mom, Opp, and I/A (all in t), as well as property-type fixed effect. Standard errors are in parentheses. Appendix 4.1 defines all variables in detail. *p < 0.1; **p < 0.05; ***p < 0.01.

Panel A: July 2003 – June 2023				
	$R_{i,t+1}$			
	(1)	(2)	(3)	(4)
$CCExposure_{i,t}$	-0.020**			
	(0.007)			
$CCExposure_{i,t}^{Opp}$		-0.083**		
		(0.034)		
$CCExposure_{i,t}^{Reg}$			-0.306	
			(0.192)	
$CCExposure_{i,t}^{Phy}$				-0.057
				(0.059)
Controls	Yes	Yes	Yes	Yes
Type FE	Yes	Yes	Yes	Yes
N	2686	2686	2686	2686
Average Adj. R^2	0.331	0.326	0.327	0.323

Panel B: July 2003 – June 2008				
	$R_{i,t+1}$			
	(1)	(2)	(3)	(4)
$CCExposure_{i,t}$	-0.006			
	(0.031)			
$CCExposure_{i,t}^{Opp}$		-0.063		
		(0.116)		
$CCExposure_{i,t}^{Reg}$			-0.271	
			(0.244)	
$CCExposure_{i,t}^{Phy}$				0.017
				(0.055)
Controls	Yes	Yes	Yes	Yes
Type FE	Yes	Yes	Yes	Yes
N	504	504	504	504
Average Adj. R^2	0.352	0.348	0.348	0.346

(Continued)

Table 4.13 – Continued

Panel C: July 2008 – June 2010				
	$R_{i,t+1}$			
	(1)	(2)	(3)	(4)
$CCExposure_{i,t}$	-0.010			
	(0.015)			
$CCExposure_{i,t}^{Opp}$		-0.274		
		(0.222)		
$CCExposure_{i,t}^{Reg}$			-2.161	
			(1.514)	
$CCExposure_{i,t}^{Phy}$				0.100
				(0.653)
Controls	Yes	Yes	Yes	Yes
Type FE	Yes	Yes	Yes	Yes
N	229	229	229	229
Average Adj. R^2	0.329	0.332	0.359	0.340

Panel D: July 2010 – June 2023				
	$R_{i,t+1}$			
	(1)	(2)	(3)	(4)
$CCExposure_{i,t}$	-0.027***			
	(0.008)			
$CCExposure_{i,t}^{Opp}$		-0.068**		
		(0.024)		
$CCExposure_{i,t}^{Reg}$			-0.065	
			(0.107)	
$CCExposure_{i,t}^{Phy}$				-0.110
				(0.073)
Controls	Yes	Yes	Yes	Yes
Type FE	Yes	Yes	Yes	Yes
N	1953	1953	1953	1953
Average Adj. R^2	0.324	0.318	0.316	0.313

Table 4.14 Cumulative Excess Returns and Climate Change Exposure

This table reports annual Fama-MacBeth cross-sectional predictive regressions of cumulative excess returns on climate change exposure. Regressions are estimated at firm-year level. R is cumulative annual excess returns from year $t+1$ to year $t+2$, $t+3$, $t+4$, or $t+5$. $CCExposure$, $CCExposure^{Opp}$, $CCExposure^{Reg}$, and $CCExposure^{Phy}$ are the overall and three topic-based exposure measures defined as in previous tables. The regressions control for $log\ (1+Me)$, B/M, Mom, Opp, and I/A (all in t), as well as property-type fixed effect. Standard errors are in parentheses. Appendix 4.1 defines all variables in detail. *p < 0.1; **p < 0.05; ***p < 0.01.

Panel A: $CCExposure$					
	$R_{i,t+1}$	$R_{i,t+1:t+2}$	$R_{i,t+1:t+3}$	$R_{i,t+1:t+4}$	$R_{i,t+1:t+5}$
	(1)	(2)	(3)	(4)	(5)
$CCExposure_{i,t}$	-0.027***	-0.053***	-0.087***	-0.123***	-0.142***
	(0.008)	(0.013)	(0.019)	(0.019)	(0.031)
Controls	Yes	Yes	Yes	Yes	Yes
Type FE	Yes	Yes	Yes	Yes	Yes
N	1953	1743	1539	1339	1146
Average Adj. R^2	0.324	0.339	0.370	0.384	0.397
Panel B: $CCExposure^{Opp}$					
	$R_{i,t+1}$	$R_{i,t+1:t+2}$	$R_{i,t+1:t+3}$	$R_{i,t+1:t+4}$	$R_{i,t+1:t+5}$
	(1)	(2)	(3)	(4)	(5)
$CCExposure_{i,t}^{Opp}$	-0.068**	-0.113***	-0.165***	-0.274***	-0.426**
	(0.024)	(0.028)	(0.046)	(0.052)	(0.144)
Controls	Yes	Yes	Yes	Yes	Yes
Type FE	Yes	Yes	Yes	Yes	Yes
N	1953	1743	1539	1339	1146
Average Adj. R^2	0.318	0.334	0.365	0.375	0.391
Panel C: $CCExposure^{Reg}$					
	$R_{i,t+1}$	$R_{i,t+1:t+2}$	$R_{i,t+1:t+3}$	$R_{i,t+1:t+4}$	$R_{i,t+1:t+5}$
	(1)	(2)	(3)	(4)	(5)
$CCExposure_{i,t}^{Reg}$	-0.065	-0.130	-0.047	0.012	-0.166
	(0.107)	(0.243)	(0.268)	(0.564)	(0.912)
Controls	Yes	Yes	Yes	Yes	Yes
Type FE	Yes	Yes	Yes	Yes	Yes
N	1953	1743	1539	1339	1146
Average Adj. R^2	0.316	0.330	0.361	0.371	0.384
Panel D: $CCExposure^{Phy}$					
	$R_{i,t+1}$	$R_{i,t+1:t+2}$	$R_{i,t+1:t+3}$	$R_{i,t+1:t+4}$	$R_{i,t+1:t+5}$
	(1)	(2)	(3)	(4)	(5)
$CCExposure_{i,t}^{Phy}$	-0.110	-0.070	0.164	0.391	0.587
	(0.073)	(0.117)	(0.165)	(0.322)	(0.438)
Controls	Yes	Yes	Yes	Yes	Yes
Type FE	Yes	Yes	Yes	Yes	Yes
N	1953	1743	1539	1339	1146
Average Adj. R^2	0.313	0.329	0.360	0.370	0.386

Table 4.15 Properties of Monthly Climate Change Exposure Quintiles

	Low	2	3	4	High	H-L
Panel A: Average climate change exposure, $\overline{CCExposure}$						
$\overline{CCExposure}$	0.06	0.14	0.22	0.34	0.80	0.74
$t_{\overline{CCExposure}}$	6.90	14.36	22.54	25.56	15.35	15.99
Panel B: Average excess returns, $\overline{R}$						
$\overline{R}$	1.00	0.80	0.85	1.02	0.74	-0.26
$t_{\overline{R}}$	6.16	3.84	4.21	4.44	4.36	-2.17
Panel C: The CAPM						
α_{CAPM}	0.16	-0.19	-0.01	0.10	-0.07	-0.22
β_{MKT}	1.04	1.23	1.05	1.12	1.00	-0.05
t_{CAPM}	0.88	-1.26	-0.03	0.52	-0.42	-1.83
t_{MKT}	8.30	7.25	9.98	6.80	6.55	-0.91
Panel D: The Fama-French three-factor model						
α_{FF3}	0.22	-0.13	0.02	0.15	-0.05	-0.27
β_{MKT}	0.94	1.12	1.01	1.06	0.96	0.02
β_{SMB3}	0.28	0.29	0.10	0.11	0.09	-0.19
β_{HML}	0.37	0.41	0.17	0.35	0.12	-0.26
t_{FF3}	1.62	-1.08	0.11	0.79	-0.29	-2.52
t_{MKT}	11.60	9.50	12.31	10.10	8.87	0.46
t_{SMB3}	3.86	2.55	1.67	0.81	0.89	-3.08
t_{HML}	2.23	3.29	1.88	1.84	0.59	-3.12
Panel E: The Carhart model						
$\alpha_{Carhart}$	0.26	-0.05	0.07	0.21	-0.02	-0.28
β_{MKT}	0.90	1.05	0.96	1.01	0.93	0.04
β_{SMB3}	0.27	0.27	0.09	0.10	0.08	-0.19
β_{HML}	0.32	0.32	0.11	0.29	0.08	-0.24
β_{UMD}	-0.15	-0.25	-0.16	-0.18	-0.10	0.05
$t_{Carhart}$	1.82	-0.41	0.35	1.02	-0.11	-2.58
t_{MKT}	14.69	12.57	16.95	13.48	10.77	0.96
t_{SMB3}	3.16	2.29	1.26	0.68	0.76	-3.43
t_{HML}	2.30	3.84	1.64	1.94	0.50	-3.05
t_{UMD}	-2.08	-2.22	-2.04	-1.77	-1.18	1.35
Panel F: The Fama-French five-factor model						
α_{FF5}	0.26	-0.20	-0.02	0.18	-0.05	-0.31
β_{MKT}	0.92	1.11	0.99	1.04	0.97	0.06
β_{SMB5}	0.28	0.39	0.16	0.12	0.08	-0.21
β_{HML}	0.41	0.37	0.21	0.39	0.06	-0.35
β_{RMW}	-0.03	0.23	0.17	-0.02	-0.04	-0.01
β_{CMA}	-0.24	-0.09	-0.19	-0.15	0.12	0.36
t_{FF5}	1.48	-1.90	-0.08	0.94	-0.26	-2.58
t_{MKT}	13.50	8.88	12.68	11.90	11.54	1.89
t_{SMB5}	5.78	3.95	4.26	0.84	0.72	-2.30
t_{HML}	1.78	2.17	1.37	1.65	0.21	-2.80
t_{RMW}	-0.23	1.62	1.24	-0.15	-0.55	-0.07
t_{CMA}	-1.19	-0.59	-1.08	-0.78	0.46	2.18

(Continued)

Table 4.15 – Continued

Panel G: The Fama-French six-factor model						
α_{FF6}	0.30	-0.14	0.02	0.22	-0.02	-0.32
β_{MKT}	0.88	1.05	0.96	1.00	0.94	0.06
β_{SMB5}	0.27	0.37	0.15	0.10	0.07	-0.20
β_{HML}	0.34	0.24	0.13	0.30	0.00	-0.34
β_{RMW}	-0.04	0.22	0.16	-0.03	-0.04	-0.01
β_{CMA}	-0.17	0.03	-0.11	-0.07	0.17	0.35
β_{UMD}	-0.14	-0.25	-0.15	-0.18	-0.11	0.03
t_{FF6}	1.62	-1.20	0.10	1.12	-0.11	-2.65
t_{MKT}	16.22	10.79	16.54	15.46	13.27	2.18
t_{SMB5}	4.82	3.39	4.06	0.66	0.57	-2.39
t_{HML}	1.78	2.29	1.14	1.70	0.00	-2.72
t_{RMW}	-0.30	1.45	1.24	-0.21	-0.64	-0.06
t_{CMA}	-1.05	0.31	-0.79	-0.45	0.76	2.14
t_{UMD}	-2.10	-2.18	-1.92	-1.88	-1.70	0.99
Panel H: The Hou-Xue-Zhang q model						
α_{HXZq}	0.29	0.00	0.08	0.23	-0.05	-0.34
β_{Mkt}	0.91	1.08	0.98	1.03	0.97	0.06
β_{Me}	0.30	0.22	0.11	0.12	0.09	-0.21
$\beta_{I/A}$	0.16	0.33	0.02	0.24	0.17	0.02
β_{Roe}	-0.27	-0.44	-0.19	-0.31	-0.06	0.21
t_{HXZq}	1.76	-0.02	0.35	0.97	-0.26	-2.60
t_{Mkt}	12.57	13.59	16.32	14.35	11.78	2.24
t_{Me}	2.84	2.20	1.48	0.78	0.83	-3.33
$t_{I/A}$	2.36	4.19	0.42	2.70	1.76	0.22
t_{Roe}	-2.07	-1.84	-0.89	-1.27	-0.27	2.06
Panel I: The Hou-Mo-Xue-Zhang q^5 model						
α_{HMXZq5}	0.30	0.02	0.13	0.22	-0.10	-0.40
β_{Mkt}	0.91	1.08	0.97	1.03	0.98	0.07
β_{Me}	0.29	0.20	0.08	0.13	0.11	-0.17
$\beta_{I/A}$	0.14	0.31	-0.02	0.25	0.21	0.07
β_{Roe}	-0.25	-0.41	-0.13	-0.32	-0.11	0.15
β_{Eg}	-0.05	-0.08	-0.13	0.04	0.12	0.17
t_{HMXZq5}	2.27	0.18	0.68	1.17	-0.43	-2.26
t_{Mkt}	10.68	11.59	13.83	11.68	11.67	3.64
t_{Me}	2.07	1.59	0.91	0.66	1.07	-3.35
$t_{I/A}$	1.15	2.18	-0.29	1.64	2.18	0.65
t_{Roe}	-1.23	-1.26	-0.46	-0.98	-0.55	2.26
t_{Eg}	-0.24	-0.36	-0.63	0.14	1.03	0.73

At the beginning of each month, I sort all firms into quintiles based on the ranked values of $CCExposure$, and compute value-weighted quintile excess returns for the current month, with the end-of-prior-month market equity as weights. The quintiles are rebalanced at the beginning of next month. For each quintile, I perform time-series factor model regressions, including the CAPM, the Fama-French three-factor model, the Carhart model (Carhart), the Fama-French five-factor model, the Fama-French six-factor model, the Hou-Xue-Zhang q-factor model, and the Hou-Mo-Xue-Zhang q^5 model. I report the time-series average of quintile $CCExposure$ and excess returns; alphas and factor loadings from the factor model regressions; as well as their heteroskedasticity-and-autocorrelation-adjusted t-statistics.

Appendices

Appendix 4.1Variable Definitions, Data Sources, and Construction

Variable	Year	Definition
$CCExposure$	2002 to 2022	Relative frequency with which bigrams related to climate change occur in the transcripts of earnings conference calls. SvLVZ count the number of such bigrams and divide by the total number of bigrams in the transcripts. Source: Sautner et al. (2023a).
$CCExposure^{Opp}$	2002 to 2022	Relative frequency with which bigrams that capture opportunities related to climate change occur in the transcripts of earnings conference calls. SvLVZ count the number of such bigrams and divide by the total number of bigrams in the transcripts. Source: Sautner et al. (2023a).
$CCExposure^{Reg}$	2002 to 2022	Relative frequency with which bigrams that capture regulatory shocks related to climate change occur in the transcripts of earnings conference calls. SvLVZ count the number of such bigrams and divide by the total number of bigrams in the transcripts. Source: Sautner et al. (2023a).
$CCExposure^{Phy}$	2002 to 2022	Relative frequency with which bigrams that capture physical shocks related to climate change occur in the transcripts of earnings conference calls. SvLVZ count the number of such bigrams and divide by the total number of bigrams in the transcripts. Source: Sautner et al. (2023a).
$WSJ\ CC\ News\ Index$	2002 to 2017	Time-series index of the fraction of the Wall Street Journal dedicated to the topic of climate change. Source: Engle et al. (2020).
$Yale\ CO\ Map$	2010 to 2022	Time-varying, cross-state, measure of the proportion of respondents who discuss global warming at least occasionally. Source: Howe et al. (2015).
$EScore$	2014 to 2022	Firms' environmental score from the environmental component of the S&P Global ESG Score. Source: S&P Global ESG Score.
$Weather$	2002 to 2019	The number of times the "weather" or weather-related terms appeared in a firm's 10k reports. Source: Nagar and Schoenfeld (2022).
$Green\ Ppty$	2003 to 2023	The share of buildings in firm portfolios with a LEED certification, Energy Star label, or both. Source: S&P Global Market Intelligence
$\#Green\ Ppty$	2003 to 2023	The number of buildings in firm portfolios with a LEED certification, Energy Star label, or both. Source: S&P Global Market Intelligence
#Non$green\ Ppty$	2003 to 2023	The number of buildings in firm portfolios without a LEED certification, Energy Star label, or both. Source: S&P Global Market Intelligence
TEscore	2013 to 2023	Equally-weighted average of tenant environmental score. Source: S&P Global ESG Score.
TEscore_w	2013 to 2023	Value-weighted average of tenant environmental score, using tenant revenues as weights. Source: S&P Global ESG Score.
Opp	2003 to 2023	Total revenue (item REVT) minus cost of goods sold (item COGS), minus selling, general, and administrative expense (item XSGA), plus research and development expense (item XRD, zero if missing), scaled by total assets (item AT). Winsorized at the 1%. Source: Compustat NA Fundamentals Annual.

(Continued)

Appendix 4.1 – Continued

Variables	Year	Definition
FFO	2003 to 2023	Net income excluding gains or losses from sales of properties or debt restructuring and adding back real estate depreciation. Winsorized at the 1%. Source: S&P Global Market Intelligence.
$RNOI$	2003 to 2023	The total rental revenue, net of property operating expenses, excluding the effect of depreciation and amortization, scaled by total assets. Winsorized at the 1%. Source: S&P Global Market Intelligence.
Occ	2003 to 2023	The percent of all leased properties that are occupied or leased at a given time. Winsorized at the 1%. Source: S&P Global Market Intelligence.
Q	2003 to 2023	Market equity (item PRCC_F times item CSHO) plus long-term debt (item DLTT) and total debt in current liabilities (item DLC), scaled by total assets. Source: Compustat NA Fundamentals Annual.
R	2003 to 2022	Compounding monthly excess returns from July in year t to June in year t+1. Source: CRSP Monthly Stock File.
$Assets$	2002 to 2022	Total Assets (item AT). Winsorized at the 1%. Source: Compustat NA/Global Fundamentals Annual item.
$Debt/Assets$	2002 to 2022	Sum of long-term debt (item DLTT) and debt in current liabilities (item DLC) divided by total assets. Winsorized at the 1%. Source: Compustat NA/Global Fundamentals Annual item.
$Cash/Assets$	2002 to 2022	Cash and short-term investments (item CHE) divided by total assets. Winsorized at the 1%. Source: Compustat NA/Global Fundamentals Annual item.
$EBIT/Assets$	2002 to 2022	Earnings before interest and taxes (item EBIT) divided by total assets. Winsorized at the 1%. Source: Compustat NA/Global Fundamentals Annual item.
Me	2002 to 2021	Price (item PRC) times number of shares outstanding (item SHROUT). Winsorized at the 1%. Source: CRSP Monthly File.
B/M	2002 to 2021	Book equity scaled by market equity (item PRCC_F times item CSHO). Book equity is stockholders' book equity, plus deferred taxes and investment tax (item TXDITC) if available, minus the book value of preferred stocks. Stockholders equity is the value reported by Compustat (item SEQ), if available. Otherwise, I use the book value of common equity (item CEQ) plus the par value of preferred stock (PSTK), or the book value of assets (item AT) minus total liabilities (item LT). Depending on availability, I use redemption value (item PSTKRV), liquidating value (item PSTKL), or par value (item PSTK) for the book value of preferred stock. Winsorized at the 1%. Source: Compustat NA Fundamentals Annual item.
Mom	2002 to 2021	Cumulative monthly returns (item RET) from July in year t-1 to May in year t. Winsorized at the 1%. Source: CRSP Monthly Stock File.
I/A	2002 to 2021	Total assets (item AT) minus the total assets from one year prior, scaled by the average of total assets. Winsorized at the 1%. Source: Compustat NA Fundamentals Annual item.
Standard factors	Jul. 2003 to Dec. 2023	MKT, SMB, HML, RMW, CMA, and UMD are the market factor, size factor, value factor, profitability factor, investment factor, and momentum factor respectively. Source: Ken French's data library.
q and q^5 factors	Jul. 2003 to Dec. 2023	R_{Mkt}, R_{Me}, $R_{I/A}$, R_{roe}, and R_{Eg} are the corresponding market factor, size factor, investment factor, return on equity factor, and expected growth factor. Source: Hou et al. (2015) and Hou et al. (2021).

Chapter 5 Conclusion

5.1 Summary of Key Findings

This thesis, consisting of three interrelated essays, uncovers the property investment behaviour of commercial real estate market players and the return patterns of the asset class. The first essay, "Real Estate Investment and Asset Return Dynamics: Evidence from REITs," probes whether aggregate corporate investment in commercial properties serves as a predictor of future returns on commercial real estate. The analysis reveals a novel finding: aggregate REIT property investment negatively predicts future returns on the NAREIT index. The predictive power remains robust after controlling for financial ratios, term-structure variables, investor sentiment measures, net equity issues, and operating accruals. In addition, aggregate REIT investment is weakly related to investor sentiment measures and fails to predict firm cash-flow shock indicators. Instead, aggregate investment is strongly tied to discount rate proxies and positively predicts macroeconomic growth indicators. And the investment's return predictability is not subsumed by the future materialization of firm cash-flow shocks and macroeconomic fundamentals. These additional analyses suggest that the predictive relationship is mainly driven by the time variation in expected returns rather than investor sentiment.

The second essay, "Real Estate Investment Plans and the Cross-Section of Asset Returns: Evidence from REITs," explores the expected return implications of real estate investment plans in the cross section. I form cross-sectional forecasts of future investment growth using such predictors as the log of Tobin's q, gross profitability, changes in return on assets, and prior stock returns. The forecasted future investment growth generates a significant positive premium at both firm and portfolio levels. To capture the return variation, I construct a factor-mimicking portfolio. With the factor, an augmented REIT-based investment-based factor model not only compares favourably against competing REIT-based and common stock-based factor models in spanning tests but also outperforms them in explaining prominent REIT return patterns. I finally propose an alternative risk-based explanation for the documented premium, highlighting the role of operating and financial leverages. Firms with high expected investment growth demonstrate higher future profitability yet also exhibit a greater degree of future operating and financial leverage and increased sensitivity of future cash flows to economic conditions, resulting in higher discount rates.

The third essay, "Climate Change Exposure, Green Investment, and Financial Performance: The Case of Publicly Listed Real Estate," investigates the real and financial impacts of climate change exposure among publicly listed real estate firms. Exposure reflects the attention paid by market participants during earnings calls to a firm's climate-related opportunities, regulatory challenges, and physical risks. I find that firms with higher climate change exposure invest more in green buildings over the subsequent year, and tenants of high-exposure firms achieve higher future environmental scores in aggregate. The overall exposure effects are primarily driven by firms with higher regulatory exposure. However, engaging in environmentally responsible practices does not always translate into better financial performance. High-exposure firms experience lower future operating and rental performance. The effect largely originates from the reduced cash flows at firms with higher green opportunities. Additionally, driven by opportunity exposure, climate change exposure negatively predicts subsequent market valuations and stock returns. The results suggest that investors may either ignore the negative signal of firm fundamentals or be willing to accept lower returns due to their non-financial preferences.

5.2 Main Contributions

This thesis makes contributions to the fields of empirical asset pricing, real estate finance, and climate finance. For the first essay, it first extends the literature on aggregate stock return predictability based on investment-related variables. Previous studies have predominantly focused on productive capital investment and aggregate stock market returns. This study provides new evidence from commercial real estate investment and its public market returns. In addition, previous studies have debated the economic force behind the investment's return predictability. This study provides new evidence strengthening the rational explanation of time-varying expected returns. Second, the first essay contributes to the literature on aggregate REIT return predictability, which has been addressed with different interests in previous studies. This study approaches the topic with new insight from the investment-based asset pricing models and suggests that aggregate REIT property investment is an alternative and possibly shaper measure of expected returns. Third, the first essay adds to the growing literature on REIT real investment decisions. Previous studies have documented the effects of biased managers or investors on REIT property investment at the firm level. This study shows contrasting evidence that at the aggregate level, investor sentiment is, in effect, a sideshow to REIT investment, conveying a signal of collective rationality.

For the second essay, it first extends the literature on investment plans and asset returns. Previous studies have focused on productive capital investment plans and stock returns at either the aggregate or cross-sectional level. This study provides new evidence from commercial real estate investment plans and the cross-section of REIT returns. In addition, despite the dynamic investment CAPM, it remains an open question of why high expected investment growth commands high expected returns in the cross-section. This study proposes an alternative risk-based explanation that focuses on the risk amplification effect of operating and financial leverages heightened by expected investment growth. Second, the second essay contributes to the literature on real estate finance. The cross-section of REIT returns has long attracted various interests from real estate researchers. This study provides evidence of a new return pattern related to expected investment growth, which is not only a reincarnation of several existing return patterns but also an extension of them. Also, there is an ongoing debate on the integration or segmentation of REIT returns with or from stock returns. This study provides new evidence strengthening the segmentation argument.

For the third essay, it first adds to the growing literature on climate change exposure and corporate green investment. Among others, Sautner et al. (2023a and 2023b) find that firms with high climate change exposure invest more in green jobs and green patents. This study provides new evidence on green buildings as well as transition enabling. Second, the third essay contributes to the literature on climate change exposure and asset prices. Saunter et al. document a positive premium related to climate change exposure, using option-implied expected returns and a sample of S&P 500 stocks. They align the positive premium with the model of "uncertainty about the path of climate change"(Giglio et al., 2021). This study finds contrasting evidence of a negative premium based on realized returns and a sample of SNL U.S. publicly traded real estate firms. The negative premium can be linked to the ESG-efficient frontier framework (Pedersen et al., 2021). Third, the third essay adds to the literature on climate change, sustainability, and real estate. A growing number of studies have examined the effects of green building certifications, environmental or broader ESG performance or disclosure, and physical climate hazards on the financial performance of publicly traded real estate firms. This study differs from previous studies by using the firm-level climate change exposure from Sautner et al. Compared with previous interest, this study provides a more comprehensive analysis, covering both climate risks and opportunities, and offers new insight from market participant perceptions of firms' climate change exposure. In addition, this study provides new evidence on green building investment and transition enabling as well as contrasting evidence on financial performance.

In general, this thesis makes theoretical contributions. The theoretical predictions from the investment-based asset pricing models or the ESG-efficient frontier framework ultimately rest on how and whether capital market prices investment, expected investment growth, or climate change exposure. This thesis provides new evidence from commercial real estate through asset pricing tests of public real estate equity returns. Also, this thesis sheds light on the potential channels that investors are using to price those factors of interest in commercial real estate markets through economic mechanism analysis. The findings would be of importance in the formation of hypotheses aimed at equilibrium model development.

5.3 Practical Implications

This thesis has practical implications for investors, professionals, and policymakers. The first two essays provide insights into investment-based asset pricing in commercial real estate, particularly public traded equity. The first essay finds that aggregate REIT property investment closely tracks future market return dynamics. This finding can inform the investment management of commercial real estate investors. For example, they can assess the market expected returns on public commercial real estate equity by examining the aggregate property investment of key commercial real estate market players, such as real estate investment trusts and real estate operating companies, etc. The second essay shows that with the presence of expected investment growth factor, the augmented investment-based factor model provides superior information on the cross section of expected REIT returns. This finding suggests that in addition to standard factor models, the factor model can be used as an alternative benchmark for REIT asset pricing. For example, the model can be applied to evaluate REIT risk-adjusting performance as well as the performance of dedicated REIT mutual funds.

The third essay uncovers the real and financial impacts of climate change exposure on publicly listed real estate firms. Regarding the real economic outcomes, the third essay finds that firms with higher regulatory exposure tend to invest more in green buildings. This finding suggests that the introduction of climate regulation and policies can facilitate the shift to sustainable practices in the real estate sector. The third essay also finds that tenants of high-exposure firms achieve higher subsequent environmental scores in aggregate. This finding suggests that the adaption to low-carbon buildings can promote the net-zero transition of other economic sectors. For policymakers, the findings endorse potential incentives for green building investment—such as tax credits, grants, or favourable financing terms—to encourage the continuation of the green practices. Regarding the financial outcomes, the third study finds that a high opportunity exposure is indicative of a low future profit, valuation, and return. This finding can inform those investors who ignore climate change exposure and its negative signal of firm fundamentals. For firm managers, the finding highlights the importance of strategic planning and resource allocation on green opportunities to mitigate their potential erosion on future cash flows.

5.4 Limitations

It is essential to acknowledge certain limitations of this thesis, which arise from data constraints, methodological choices, and the scope of research questions.

Data Constraints and Availability

One of the primary limitations of this thesis pertains to data constraints, particularly regarding the availability and quality of data on real estate investment, real estate investment plans, climate change exposure, and green buildings. The analysis in the first essay relies heavily on non-cash asset growth rate as a proxy for equity REIT property investment. While this proxy provides a feasible measurement of real estate investment, as suggested by Bond and Xue (2017), its quality may vary across the sample period from 1972 to 2018. In the earlier years, the REIT industry has experienced significant structural changes, such as the Revenue Reconciliation Act of 1993. These changes could introduce inconsistencies into the rules governing the composition of firms' assets.

The measure of real estate investment plans in the second essay is based on cross-sectional forecasts of future investment growth. While this approach offers a novel method for capturing REIT planned real estate investment, it is inherently dependent on chosen predictors and forecasting methods. Additionally, REITs may have broader investment plans, beyond planned acquisition and development, including planned expansion and renovation. However, the future materialization of planned expansion or renovation is typically treated as expenses rather than capitalized as assets in financial statements. As a result, forecasting investment-to-asset changes may underestimate firms' actual planned investment.

In the third essay, firm-level climate change exposure, as defined by Sautner et al. (2023a), is measured by the proportion of climate change discussions during earnings conference calls. While this approach provides an innovative method to capture firms' exposure to climate-related risks and opportunities, it is limited by the quality and completeness of earnings call transcripts. Not all firms consistently discuss climate change during their quarterly earnings calls, which may lead to potential underestimation or overestimation of their actual exposure. Indeed, Sautner et al.'s data encounter instances where specific earnings calls in a given year do not mention climate change, even though the topic is addressed in surrounding calls. These incidental gaps in quarterly data may not accurately reflect the firms' true engagement with climate-related issues.

Another data-related limitation is the reliance on selective green building proxies. The use of LEED certifications and Energy Star labels as proxies for green buildings, while widely adopted in the literature, may not capture all aspects of a firm's commitment to sustainable building practices. Other forms of green building initiatives—such as regional certifications, unregistered sustainable projects, or internal sustainability programs—are not reflected in the measure, potentially leading to an incomplete picture of firms' green building holdings.

Methodological Limitations

While the methodologies employed in this thesis are rigorous, they also present certain limitations. The predictive regression models used in the first essay to examine the relationship between investment and future returns are based on linear assumptions. Although these models are effective in capturing general trends and relationships between variables, statistical complications can arise when predictors are persistent and their innovations are correlated with residuals, leading to small-sample bias in coefficient estimation. To address this potential bias, I adjust coefficient estimates using the Stambaugh (1999) correction. However, alternative estimation procedures could have been applied to ensure the robustness of the results.

Additionally, the REIT-based asset pricing factors used in the second essay are subject to the reconstruction process. I reconstruct a set of standard factors, as well as the q and q^5 factors, specifically for REITs. The factor reconstruction is motivated by the ongoing debate on the integration or segmentation of REIT returns with or from common stock returns. Although the reconstruction largely follows the original procedure, it makes necessary adjustments regarding variable measurements and sorting methods to generate factors applicable in a REIT context. For instance, when forming the q factors, I adopt an independent two-way sort instead of the original three-way sort due to the smaller REIT sample size, to ensure that the portfolios are reasonably diversified.

In the third essay, the analysis of the real and financial impacts of climate change exposure primarily relies on linear regression models with multiple fixed effects, such as property types and years. While this approach effectively identifies the relationships between climate change exposure and real and financial outcomes, it does not reflect the time-series dynamics of the relationships over time. Indeed, the effects of climate change exposure may evolve over time as meteorological conditions, regulatory frameworks, and technological advancements change. However, given the relatively short period and low frequency of the climate change exposure measures, a dynamic analysis faces limited degree of freedom. Furthermore, even if the time period were extended further into the past, it remains unclear whether additional data would aid in uncovering potential dynamics, given that climate change has recently been a significant concern for investors.

Scope and Generalizability

Another limitation of this thesis pertains to the scope and generalizability of the findings. The focus on public commercial real estate equity, while providing rich and relevant datasets, limits the applicability of the results to other types of commercial real estate equity, such as private commercial real estate equity. Moreover, REITs are subject to specific regulatory requirements, market dynamics, and investor behaviors, which are less representative of the broader commercial real estate market. Consequently, the conclusions drawn from this thesis may not be fully applicable to other segments of commercial real estate, in particular, commercial real estate debt. The geographical focus on the United States, while relevant for understanding the U.S. public commercial real estate equity market, limits the generalizability of the findings to international markets. Real estate markets in other countries may be subject to different economic, political, and regulatory conditions, which could influence asset pricing in ways that differ from the U.S. context.

Potential Biases and Endogeneity

The inevitable limitations of this thesis pertain to potential biases and endogeneity issues. Although grounded in robust asset pricing theories and employing predictive regressions with control variables wherever possible, this thesis acknowledges the persistent possibility of omitted variables or endogeneity, which could affect the validity of results.

5.5 Further Research Directions

The findings of this thesis open several avenues for future research, particularly in advancing the application of investment-based real estate asset pricing and exploring the financial implications of climate change exposure.

One promising direction is to examine the investment-based costs of equity for publicly listed real estate equities. While prior studies have predominantly relied on accounting-based implied costs of equity for real estate firms, including REITs, this approach has faced criticism for its imprecision and weak correlations. Applying the q^5-characteristics model to estimate costs of equity offers a competitive alternative to traditional accounting-based methods.

Another avenue involves investigating the performance of dedicated REIT mutual funds through an investment-based lens. Dynamic investment-based asset pricing suggests that expected investment growth provides valuable insights into future fund returns—insights often overlooked by standard benchmarks. Consequently, funds favoring REITs with high expected investment growth tend to outperform, while those favoring the opposite underperform. Developing new benchmarks that incorporate expected investment growth could better account for the cross-section of REIT returns and more accurately track dedicated REIT mutual fund performance.

Regarding climate change exposure, future research could explore its financial impact on the cost of capital. Market participants' perceptions of firms' exposure to climate change may influence the capital financing costs of publicly listed real estate firms. Investigating whether and how climate change exposure affects the cost of equity and debt—including commercial mortgages and corporate bonds—could yield valuable insights into the underlying climate issues driving these effects.

Additionally, future research could examine the potential for hedging climate change risk using public real estate. Although direct instruments for hedging climate risks remain limited, investors can construct hedging portfolios using assets exposed to climate risks. By leveraging climate exposure data, such as that from Sautner et al. (2023a), researchers could employ a mimicking portfolio approach to build climate change hedging portfolios. It would be valuable to assess whether such portfolios perform effectively when climate risks materialize, both in and out of sample.

5.6 Final Thoughts

Through an examination of the implications of investment-based asset pricing and the real and financial consequences of climate change exposure, this thesis reveals the investment behaviour of commercial real estate market participants and the return pattern of the asset class. The findings underscore the paramount importance of informed investment strategies and the necessity for a holistic approach to managing risks in an increasingly intricate and uncertain market environment.

This thesis not only advances academic knowledge in the domains of empirical asset pricing, real estate finance, and climate finance but also provides practical recommendations for investors, professionals, and policymakers. This thesis serves as a foundation for future research and offers valuable tools for addressing the challenges and opportunities that lie ahead in the ever-evolving market. As the global economy increasingly prioritizes sustainability and resilience, this thesis will continue to guide decision-making and contribute to the development of a more sustainable and financially stable real estate sector.

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