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ORIGINAL RESEARCH

Fund manager skill: selling matters more!

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Abstract
We examine whether mutual fund managers have differential skill in the buy and sell domains. Although they have characteristic-timing ability in aggregate, we show they exhibit asymmetric ability when buying and selling. Our key finding is that fund managers with superior selling ability are significantly better at buying stocks and, as a result, earn significantly higher aggregate returns. However, fund managers who buy stocks successfully do not necessarily have parallel selling skills, leading to lower returns overall. Thus, we provide strong evidence that selling skill is the key determinant of overall mutual fund timing performance.

Keywords Mutual funds · Timing ability · Trade motivation · Investment performance · Attention

JEL Classification C15 · G11

1 Introduction

> "If you ask any fund manager what his or her weakest point is, I'd say it is probably selling." (fund manager interviewed in Tuckett and Taffler 2012, p.18)

The investment community tends to place most emphasis on decisions relating to how and when to buy stocks. The finance literature equally focuses on buy decisions, and

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valuation methods, and stock investment styles in the buy domain have been intensively investigated and empirically tested in prior work. However, selling skill, which is necessary to exploit returns resulting from good buy decisions, has received much less empirical research attention to date (Faugere et al. 2004). The limited evidence there is on such asymmetry in attention given to buying and selling is largely of an anecdotal nature (e.g., Norris 2002). In this paper, we explore whether professional investors such as mutual fund managers possess distinct buying and selling skills and, if so, whether this might help explain the general lack of evidence of fund outperformance in the literature.

While most portfolio managers are aware of the importance of selling and often claim to follow explicit sell disciplines, the process of selling is, in fact, much less rigorous compared to buying (Ervolini 2014). Buy decisions tend to be highly disciplined and involve rigorous analysis and structured research processes (e.g., Tuckett and Taffler 2012) and, most importantly, place the fund manager mentally in the prospective "gain" domain. In contrast, sell decisions are predominantly subjective and often undisciplined in nature (Ervolini 2014, chs. 7, 8). In addition, if stocks underperform, the portfolio manager is now mentally in the "loss" domain, making it more difficult to sell down such stocks in line with the operation of the disposition effect.[1] If it is more difficult to make disciplined investment decisions in the sell domain than in the buy domain, we would expect to observe distinct fund manager buying and selling abilities with clear implications for measuring overall fund manager skill which is typically addressed in the literature by exploring aggregate portfolio returns.

In our examination of differential buying and selling skills, we focus on the ability of fund managers to capitalize on different market conditions by exploiting the time-varying expected returns of stock characteristics including the size, book-to-market, and momentum factors. This is because, such timing ability is a key determinant of overall fund performance, as is clearly recognised by the industry in their promotion of smart beta products (e.g., Glushkov 2015; Asness 2016). However, despite factor timing strategies becoming increasingly popular, the literature suggests a perverse tendency of fund managers to mistime the market.[2] One possible reason for the lack of evidence supportive of fund manager timing performance is that existing research has concentrated on investigating whether mutual fund managers have timing ability by testing timing performance in aggregate. This approach might not be able to capture the differential abilities that mutual fund managers really possess, such as buying and selling skills.

In this paper, we break down fund manager timing ability into its buying and selling components, using the "characteristic timing" (CT) measure of Daniel et al. (1997). Specifically, we examine mutual fund holdings directly to explore whether increases or decreases

[1] Several empirical studies on selling behavior show such loss-aversion-related tendencies mostly among retail investors (e.g., Shefrin and Statman, 1985; Odean, 1998; Grinblatt and Keloharju, 2001) and in the house market (e.g., Genesove and Mayer, 2001). Similar behavioral tendencies among professional money managers have been receiving growing attention (e.g., Wermers, 2003; Frazzini, 2006; O'Connell and Teo, 2009; Jin and Scherbina, 2011). Cici (2012) shows that when experiencing outflows, team-managed funds tend to sell disproportionately more winners than losers, however, the author does not find observable impact of such disposition-driven trades on overall fund performance. See also Luo and Qiao (2020).

[2] See e.g., Treynor and Mazuy (1966); Chang and Lewellen (1984); Henriksson and Merton (1981); Ferson and Schadt (1996) who explore fund manager timing ability by investigating a potential non-linear relation-ship between fund returns and market returns. Using more sophisticated tests, more recent studies such as Becker, Ferson, Myers, and Schill (1999), Jiang (2003), Lam and Li (2004); Zheng et al. (2020); Song (2020); Jiang et al. (2021); and Argyle (2021) still fail to provide convincing evidence that fund managers have superior timing ability. This can, *inter alia*, explain the anxiety-generating environment of the fund management industry (Taffler, Spence, Eshraghi, 2017).

in portfolio weightings along the three stock characteristics of size, book-to-market and momentum effect, can forecast future fund returns. This approach allows us to better capture the dynamic aspects of actively managed portfolios, and also avoid the potential "artificial timing" and other biases that are usually found in return-based measures (e.g., Jagannathan and Korajczyk 1986). Working with a broad sample of 5,661 U.S. actively managed domestic equity funds from 2003 to 2019 drawn from the CRSP mutual fund holdings database in line with the extant literature (e.g., Daniel et al. 1997; Elton et al. 2012) we find evidence mutual fund managers exhibit significant characteristic-timing abilities in aggregate. On average, they earn characteristic-timing returns of 29 basis points/annum when adding stocks to their portfolios, suggesting clear ability in the buy domain. Interestingly, the same fund managers manifest similar positive performance when selling down stocks, earning average characteristic-timing returns of 35 basis points/annum. However, more importantly, when we investigate trading performance persistence in the buy and sell domains separately, we find that good buyers (sellers) continue to be good buyers (sellers) over the following three quarters, while in the case of bad buyers (sellers) negative buying (selling) ability does not persist. In other words, whereas inferior characteristic-timing performance seems to be due to bad luck in both buy and sell domains, superior characteristic-timing returns appear to be driven by skill.

The structure of open-end mutual funds can often force fund managers to trade for reasons other than their valuation beliefs.[3] A more appropriate indicator of fund manager skill should be based only on trades motivated by their valuation beliefs. However, these are not directly observable, and consequently the key challenge in studies on mutual fund performance is to identify ex ante valuation-motivated trades. We follow the approach of Alexander et al. (2007) who condition stock trades on the direction and magnitude of concurrent realized net fund flows. Consistent with Alexander et al. (2007) and Popescu and Xu (2017), we find mutual fund characteristic-timing performance is significantly related to the motivation behind fund managers' trading decisions. In particular, fund managers making purely valuation-based buys generate significant characteristic-timing performance of about 0.25% ($=0.021\times 12$) per year, but they underperform about 0.65% ($=-0.054\times 12$) per year when their buy decisions are liquidity-driven. On the other hand, fund managers appear to sell stocks at the right time regardless of whether such decisions are valuation-motivated or liquidity-motivated exhibiting positive and significant characteristic-timing returns of 1.63% ($=0.136\times 12$) and 1.37% ($=0.114\times 12$) per year, respectively.

Most studies on mutual fund performance view fund managers as a homogeneous class of professional investor, and to the best of our knowledge the literature has not yet explored whether different groups of fund managers might possess different trading skills and whether buying/selling ability might be informative about other dimensions of investment decision-making. We speculate that, since selling decisions are arguably more prone to behavioral biases such as the disposition effect and loss aversion, fund managers who are more skilled at selling may also have better buying ability. Consistent with this, we find that best sellers also outperform other fund managers when purchasing stocks by an average of 0.43% ($=0.036\times 12$) per year. On the other hand, even the best buyers are not able to make money in the sell domain. Interestingly, compared to skilled sellers, fund managers with best buying ability show no evidence of characteristic-timing performance in the sell domain. To summarise our results, there is a subset of fund managers skilled in selling who also possess superior characteristic-timing ability when buying stocks leading to

[3] See e.g., Chordia (1996); Edelen (1999); Nanda, Narayanan, and Warther (2000); Rohleder, Schulte, and Wilkens (2017); Koutmos et al. (2020); and, An and Argyle (2021).

significant fund outperformance. This has clear implications for fund manager selection decisions.

Firstly, this paper contributes to style-timing studies such as Chen et al. (2013) which are limited to “star" growth-oriented mutual fund managers. Using a related methodology, we provide direct evidence that distinct buying and selling characteristic-timing abilities exist among the generality of actively managed equity funds, and these trading skills are not driven by luck. We also consider the potential adverse effect of investor flows on trading performance, and demonstrate that trade motivation affects fund managers’ buying and selling skills and, more importantly, that both liquidity driven and valuation-motivated sells earn positive returns on average. Employing the “characteristic selection” (CS) measure, Chen et al. (2000) and Alexander et al. (2007) report that fund managers’ buy decisions outperform their sell decisions in aggregate. However, these studies examine the trading performance at the individual stock level, and thus consequently don’t explore whether certain fund managers are more skilled in trading than others at the portfolio level, the principal research question of this paper.

Secondly, our results also contribute to finance literature by providing strong evidence that selling skill is the key determinant of overall mutual fund timing performance, thus making a direct contribution to Lam and Li (2004); Zheng et al. (2020); and Jiang et al. (2021) among others. *Thirdly*, the empirical findings is consistent with the hypothesis that sell decisions are more likely to be susceptible to behavioral heuristics and biases. Therefore, we contribute important empirical evidence to studies such as Akepanidtaworn et al. 2021 who provide heuristic explanations for the underperformance of selling decisions.

The remainder of this study is organized as follows. Section 2 describes the data sources and sample construction. Section 3 describes fund performance, and other relevant fund characteristics measurements used in this study. Section 4 discusses our findings and Sect. 5 concludes.

2 Data and sample construction

In this section, we first introduce our mutual fund returns and holdings data, and then describe our sample selection procedure. Our mutual fund portfolio holdings data are created by merging the CRSP Survivorship Bias Free Mutual Fund Database with the CRSP stock price database. The CRSP Mutual Fund Database provides information on monthly fund net returns, monthly total net assets, monthly net assets value, annual expense ratio and management fee, turnover ratio, investment objectives, first offer date and other fund characteristics for each share class of every U.S. open-end mutual fund.[4] The CRSP Mutual Fund Database also provides information on mutual fund portfolio holdings typically reported on a monthly basis. Information on the returns of each fund in our dataset

[4] Share class data belonging to the same fund portfolio composition are aggregated into one observation.

is matched to the fund's holdings using the map provided by CRSP.[5] We then link each reported stock holding in our mutual fund portfolios to the CRSP stock price database.[6]

We mainly follow and modify the procedure of Kacperczyk et al. (2008) to select our U.S. domestic equity mutual funds. We start with all mutual fund samples in the CRSP Mutual Fund Database universe and eliminate balanced, bond, money market, international, sector, index, ETF, exchange target, and target date funds as well as those funds not invested primarily in equity securities. In order to address potential incubation bias, we also exclude funds with less than $5 million in total assets under management or holding fewer than 10 stocks. This screening procedure generates a sample of 282,934 fund-report observations representing a total of 5,661 unique U.S. domestic equity mutual funds from January 2003 to December 2019.

Table 1 reports summary statistics relating to our sample. Panel A shows an increase in number of funds until 2009 followed by a decrease until 2012 where the number of funds started to rise again together with mean and median assets under management each year. In Panel B of Table 1, we categorize our sample by investment style. It is clear that funds investing in smaller stocks (Micro-Cap, Small-Cap and Mid-Cap) and Growth funds are more active in terms of portfolio turnover, and they charge higher fees to their investors.

3 Methodology

We adopt a holdings-based timing performance measurement approach to explore whether mutual fund managers have distinct trading skills. In this section, we describe the characteristic-timing evaluation method we employ, and how we decompose aggregate timing performance into its buying and selling components. In order to increase the power of our tests on trading performance, we also consider other fund characteristics in further analysis, including fund flows and trade motivation.

3.1 Measuring buying and selling characteristic-timing performance

Extant timing studies, which almost exclusively focus on fund manager general market timing ability, mostly employ non-linear regressions of realized fund returns against contemporaneous market returns (return-based measures). However, such approaches have been challenged due to potential estimation problems.

First, most existing studies assume that timing strategies are implemented in a specific way, which can limit the test power of return-based measures to detect timing ability if fund managers choose to time in a more complex manner. Second, negative timing

[5] The CRSP fund-portfolio map contains information on the identification of individual share classes and their common funds over time, as well as other characteristics including delist date and delist type.

[6] Data include stock identification, stock return, delist return, share price, trading volume, cumulative price adjustment factors, cumulative share adjustment factors, and shares outstanding as well as other stock characteristics. We follow the approach of Daniel and Titman (1997) to estimate book value of equity for stocks by using shareholders' equity (SEQ), deferred taxes (TXDB), investment tax credit (ITCB), and preferred stock (PREF), retrieved from Compustat. Industry classifications (SIC) are obtained from the CRSP stock file and Compustat whenever available. In addition, we adjust numbers of shares held in portfolios using CRSP cumulative share adjustment factors, and estimate mutual fund trades by tracking changes in holdings from report to report. The CRSP Mutual Fund Holdings Database changed its data source in October 2010. Before October 2010, the reported numbers of shares in a portfolio are already adjusted for stock distribution events such as splits, and therefore we need to re-adjust it back before calculating changes in numbers of shares and market value of holdings.

Table 1 Descriptive statistics of mutual fund samples

Year	Number of funds	Number of stocks	Average assets	Median assets	Average turnover	Average expenses	Average fee
Panel A: Descriptive statistics by year							
2003	2610	65.67	1241.96	172.05	91.53%	1.57%	0.74%
2004	1813	72.02	1434.41	213.75	85.76%	1.55%	0.75%
2005	1936	74.06	1705.52	210.86	84.23%	1.52%	0.74%
2006	2219	75.05	1419.53	201.52	88.26%	1.47%	0.75%
2007	3940	81.28	1556.13	204.97	91.04%	1.42%	0.75%
2008	3099	92.65	810.23	110.22	96.40%	1.37%	0.70%
2009	2549	105.03	1379.33	200.87	92.53%	1.36%	0.69%
2010	2938	107.59	1387.50	217.05	81.10%	1.31%	0.71%
2011	2818	106.62	1402.54	221.36	78.58%	1.27%	0.71%
2012	2932	109.94	1411.95	219.11	74.01%	1.25%	0.71%
2013	3270	111.45	1602.65	238.48	69.69%	1.21%	0.71%
2014	3375	110.86	1814.52	259.37	65.90%	1.18%	0.71%
2015	3560	113.37	1865.62	263.20	66.62%	1.16%	0.70%
2016	3552	120.88	1768.69	263.24	66.15%	1.14%	0.70%
2017	3698	127.12	1898.80	269.64	64.15%	1.10%	0.69%
2018	3709	128.57	2000.45	275.28	64.78%	1.07%	0.67%
2019	3501	131.93	2133.15	271.74	65.24%	1.06%	0.67%
Panel B: Descriptive statistics by style							
All funds	5661	111.08	1693.67	242.57	73.54%	1.22%	0.70%
Growth	2257	110.70	1690.30	242.11	73.68%	1.22%	0.70%
Growth and income	905	109.68	1672.72	240.13	74.39%	1.23%	0.70%
Income	328	114.14	1733.46	248.22	71.35%	1.19%	0.70%
Hedged	320	117.32	1775.71	252.22	69.85%	1.17%	0.70%
Micro-cap	58	106.27	169.77	119.79	75.02%	1.25%	0.71%

Table 1 Continued

Year	Number of funds	Number of stocks	Average assets	Median assets	Average turnover	Average expenses	Average fee
Small-cap	1066	111.25	565.51	242.75	73.59%	1.22%	0.70%
Mid-cap	727	110.65	560.61	241.33	74.01%	1.23%	0.70%

The table reports the summary statistics of a total of 5661U.S. domestic equity mutual fund samples from January 2003 to December 2019. The mutual fund data with self-reporting investment objectives including Growth Growth & Income, Income, Hedged, Micro-Cap, Small-Cap, and Mid-Cap are obtained from the merged CRSP mutual fund holdings databases and CRSP mutual fund characteristics databases in CRSP Survivor-Bias-Free U.S. Database. Number Funds is the total number of mutual funds that exist during the sample periods. Number Stocks is the times series average of cross-sectional average of the number of stocks held by mutual funds during the sample periods. Average (Median) Assets is times series average of cross-sectional median of total net assets under management of mutual funds. Average Turnover is time series average of cross-sectional average of mutual fund turnover ratio. Average Expense is time series average of cross-sectional average expense ratio of mutual fund. Average Fee is time series average of cross-sectional average management fee of mutual fund. Panel A reports the summary statistics of all mutual fund samples over time and Panel B reports the summary statistics of mutual fund with different investment objectives ability can appear to exist for reasons other than fund managers' active timing strategies. For example, Jagannathan and Korajczyk (1986) demonstrate that certain dynamic trading strategies might give rise to a negative non-linear relationship be-tween fund and market returns. While recent studies attempt to overcome such estimation problems by estimating fund manager timing ability based on mutual fund portfolio holdings (holdings-based measures), there is still no convincing empirical evidence to show that mutual fund managers are able to successfully time the market. For instance, although Jiang et al. (2007) find positive timing ability using single-index models, Elton et al. (2012) show that such findings do not hold when using multi-index models.

More importantly, market-timing studies overlook the possibility that fund managers might possess factor-timing ability to exploit time-varying stock characteristic returns, the focus of this paper. The "characteristic timing" (CT) measure of Daniel et al. (1997) allows researchers to capture that part of fund performance reflecting manager ability to time the three different investment styles of size, book-to-market, and momentum.[7] Unlike factor-based methods, this characteristic measure of timing performance directly looks at whether changes in the relative portfolio weights of these styles can forecast future fund returns. The CT for month t measure is defined as:

$$CT_t = \sum_{j=1}^{N} (\tilde{w}_{j,t-1}\tilde{R}_t^{b_{j,t-1}} - \tilde{w}_{j,t-13}\tilde{R}_t^{b_{j,t-13}}) \tag{1}$$

where $\tilde{w}_{j,t-1}$ is portfolio weight of stock *j* at the end of month *t-1*, $\tilde{w}_{j,t-13}$ is portfolio weight of stock *j* at the end of month *t-13*, $\tilde{R}_t^{b_{j,t-1}}$ is month *t* return of the characteristic-based passive benchmark portfolio that is matched to individual stock *j* according to its size, book to market and momentum at the end of month *t-1*, $\tilde{R}_t^{b_{j,t-13}}$ is month *t* return of the characteristic-based passive benchmark portfolio that is matched to stock *j* at the end of month *t-13*. To illustrate the rationale behind the characteristic-timing measure, suppose that a fund increases its weight in high book-to-market stocks at the beginning of the month in which the book-to-market effect is unusually strong, then this fund would have positive characteristic-timing performance for that month. A significant positive time series average of the characteristic-timing measure of a fund indicates superior characteristic-timing ability by this fund.

To explore distinct trading abilities, we break down aggregate characteristic-timing performance into its buying and selling components. Specifically, for each fund-month in our sample, we measure changes in number of shares held in each stock from the end of month *t-1* to the end of month *t*. Increases in number of shares are treated as buys, and aggregated to form the buy sub-portfolio, and decreases are aggregated to form the sell sub-portfolio. We then calculate the characteristic-timing performance for each trading sub-portfolio. Intuitively, if a fund's purchases (sales) of stocks in a month are associated with subsequent above average return, the characteristic-timing performance of its buy (sell) sub-portfolio will be positive. On this basis, if a fund exhibits positive average characteristic-timing performance along the buy (sell) dimension, it indicates this fund manager possesses superior buying (selling) skill.

[7] This characteristic-based approach requires the construction of passive benchmark portfolios matched with the individual stocks in the mutual fund portfolios along the dimensions of market value of equity, book-to-market ratio and momentum effect. This paper constructs passive benchmark portfolios according to the procedure detailed in Daniel et al. (1997). Brie y, at the end of June each year, all common stocks listed on the NYSE, AMEX, and NASDAQ are triple-sorted based on stock size, book to market ratio and prior year return, and then categorized into 125 (5 5 5) characteristic-based portfolios. Monthly returns of these 125 benchmark portfolios are then derived based on value-weighted returns of their constituent stocks.

3.2 Estimating fund flows

Following prior literature (e.g., Chevalier and Ellison 1997; Sirri and Tufano 1998; Lou 2012), investor net flow for individual fund share class i at time t is estimated as:

$$FLOW_{i,t} = \frac{TNA_{i,t} - TNA_{i,t-1} \times \left(1 - RET_{i,t}\right) - MNG_{i,t}}{TNA_{i,t-1}} \tag{2}$$

where $TNA_{i,t}$ is total net assets for individual fund share class i at time t; $RET_{i,t}$ is the gross return before expenses for individual fund share class i at time t; $MNG_{i,t}$ is the increase in total net assets for individual fund share class i at time t due to fund mergers.[8] After adjusting for mutual fund mergers, monthly estimated net flows for all share classes in a fund are summed to obtain total monthly estimated net flow. We assume that investor inflows and outflows take place at the end of each month, and investors reinvest their dividends and capital gains distributions in the same fund.

3.3 Measuring trade motivation

This paper follows Alexander et al. (2007) in segmenting fund manager trading activity depending on trade motivation. Specifically, for each fund i, trade in stock j is estimated as the change in the number of shares held in stock j between two consecutive report dates. Trade dollar volume for stock j is calculated by multiplying each change in number of shares by the appropriate stock price calculated as the average daily closing stock price between the two consecutive report dates during which the trade is assumed to occur. Trades by fund i in month m associated with an increase in number of shares are treated as buys, and then summed to obtain total purchase volume $BUY_{i,m}$, and trades associated with a decrease in number of shares are aggregated to form total sell volume $SELL_{i,m}$. Buy Flow score ($BF_{i,m}$) and Sell Flow score ($SF_{i,m}$) used as proxies for trade motivation are defined respectively as:

$$BF_{i,m} = \frac{BUY_{i,m} - FLOW_{i,m}}{TNA_{i,m-1}} \tag{3}$$

$$SF_{i,m} = \frac{SELL_{i,m} + FLOW_{i,m}}{TNA_{i,m-1}} \tag{4}$$

where $FLOW_{i,m}$ is the estimated net investor flow into/out of fund i during month m, and $TNA_{i,m-1}$ is fund i total net assets under management at the end of month $m-1$.

Using the $BF_{i,m}$ metric, buy sub-portfolios of funds with high total buy dollar volume and high investor outflows are assigned to the top quintile, $BF1$, and buy sub-portfolios with low total buy dollar volume and high investor inflow to the bottom quintile, $BF5$. $BF1$ refers to cases where despite a need to raise cash to meet investor outflows, fund managers

[8] The CRSP Mutual Fund Database does not provide the exact date on which fund mergers occur. This paper follows Lou (2012), and starts with the last net asset value (NAV) report date as the initial estimate of the merger date. Then, in order to avoid the obvious mismatches generated by this initial estimate, we match a target individual share class to its acquirer from one month before its last NAV report date to five months later, a total matching period of 7 months. Finally, the month in which the acquirer has the smallest absolute percentage net flow, after subtracting the merger, is assigned as the merger event month.

will only purchase stocks they strongly believe to be undervalued, which infers that a large proportion of the buys in these buy sub-portfolios are likely to be motivated by valuation considerations. On the other hand, *BF*5 refers to those cases where mutual fund managers might be forced to invest excess cash from large investor inflows into stocks that are not perceived to be undervalued, and therefore only a small proportion of buys in these buy sub-portfolios are likely to be valuation motivated.

Similarly, the $SF_{i,m}$ metric assigns sell sub-portfolios with high sell dollar volume and high investor inflows to the top quintile, *SF*1, and sell sub-portfolios with low sell dollar volume and high investor outflows to the bottom quintile, *SF*5. *SF*1 indicates that fund managers who hold excess cash from investor inflows will only sell over-valued stocks, and thus a large proportion of their sells are likely to be valuation motivated, while *SF*5 suggests a small proportion of sells are likely to be motivated by fund managers' valuation beliefs.[9]

4 Empirical results

This section presents our empirical results. We begin by examining the aggregate characteristic-timing performance of the mutual funds in our sample. Then we decompose this aggregate characteristic-timing performance into its buying and selling components to test the main proposition of this paper. This is that the lack of overall fund manager timing performance documented in the previous literature is masked by distinct buy and sell trading skills. We also investigate whether observed trading performance is due to chance or skill. By segmenting trades depending on trading motivation, we are able to explore the subsequent characteristic-timing performance of valuation-motivated and liquidity-driven trades. Finally, we consider whether different groups of fund managers possess different trading skills and whether there exists a small set of fund managers with both buying and selling skills.

4.1 Do fund managers possess distinct buying and selling skills?

Although a large number of studies in the literature find that mutual fund managers do not possess timing ability, there is no convincing evidence that directly explains why mutual fund managers underperform in this domain. These studies typically measure timing ability in aggregate terms and thus overlook the possibility that fund managers might be skilled along certain dimensions but not others. In particular, considering the fundamental asymmetry between buy and sell decisions in terms of trading disciplines found in the investment community, we conjecture that fund managers might exhibit distinct buying and selling abilities, and that any potential positive buying or negative selling skill might be masked by aggregate timing performance documented in the literature.

In Panel A of Table 2 we first report that the average aggregate characteristic-timing performance of our mutual funds (All Funds) from 2003 to 2019 is 33 basis points per year, which is statistically significant at the 1% level. However, in Panel B, average

[9] This approach has several advantages over using realized net fund flows to measure trade motivation. First, Alexander et al. (2007)'s motivation score metrics not only consider realized net investor flows between two quarters, but also take into account total trading volume from buying and selling activities. Second, the motivation score ranking procedure deals appropriately with potential biases resulting from serial and cross-sectional trading patterns.

characteristic-timing performance is -6 basis points per year during the Global Financial Crisis. We conclude, on this basis, fund managers possess characteristic-timing ability under normal market conditions.[10]

In this paper, we explore, in particular, whether fund managers exhibit differential abilities in the buy and sell domains. To start with we examine whether their aggregate buying and selling performance diverge. Table 2 Panel A shows our mutual fund managers exhibit significant ability when adding stocks to their portfolios earning an average characteristic-timing return of 0.29% per year from their purchases, significant at the 1% level, consistent with them potentially possessing skill in the buy domain. This finding is consistent across all fund styles. On the other hand, probably expectedly, we observe that fund managers fail to buy stocks appropriately during the Global Financial Crisis underperforming by 7 basis points per year compared to the benchmark.

More interestingly, however, Table 2 shows mutual fund managers sell stocks from their portfolios appropriately on average. In fact, stocks they sell are associated with subsequent positive characteristic-timing returns of 0.35% (Panel A) and 0.04% (Panel B) per year regardless of whether market conditions are normal or in crisis. Again, positive selling skill is consistent across all fund styles. Our empirical results differ from earlier characteristic-timing papers which suggest fund managers underperform overall and exhibit particularly poor ability in the sell domain.

4.2 Luck versus skill

To explore whether our results so far can be accounted for by luck or skill, we test for fund manager characteristic-timing performance persistence. Each quarter, we sort our mutual funds into five performance quintiles. Table 3 reports aggregate, buying, and selling characteristic-timing performance for each of the performance quintile portfolios in the formation quarter, and then over the subsequent three quarters. Panel A summarises persistence results for aggregate performance, while Panels B and C present separately our buying and selling persistence results.

Panel A provides some evidence showing that aggregate characteristic-timing performance is persistent, the difference in aggregate characteristic-timing performance between past winners and past losers (q5-q1) continues to remain positive over the following three quarters after portfolio formation. In particular, the worst losers in characteristic-timing performance terms (q1) (-0.25%) do not continue to underperform manifesting very similar characteristic-timing returns to the fund average of 0.22%, 0.26%, and 0.21% per year in the following three quarters consistent with the bad luck argument. On the other hand, past winners (q5) (1.90%) continue to outperform in the post-portfolio-formation quarters consistent with skill.

Panel B of Table 3 which reports buying performance shows that mutual fund managers in the loser quintile (q1) who exhibit the worst buying performance of -0.53% annualized characteristic-timing returns in the formation quarter revert effectively back to average fund returns of 0.25%, 0.14%, and 0.07% on an annualized basis in the subsequent three quarters. In contrast to losers in the buy domain, mutual funds that have been successful in buying stocks earning an annualized return of 2.12% in the formation

[10] This finding is in line with Kacperczyk et al. (2014) who find that fund managers have time-varying skills: they tend to perform stock picking well in non-recession periods and time the market well in recessions.

Table 2 Mutual fund characteristic-timing performance

	All funds	Growth	Growth and income	Income	Hedged	Micro-cap	Small-cap	Mid-cap
Panel A: All times (January 2003–December 2019)								
Aggregate	0.33%***	0.35%***	0.25%***	0.22%***	0.31%***	0.33%***	0.34%***	0.42%***
Buying	0.29%***	0.32%***	0.21%***	0.16%***	0.23%***	0.26%***	0.29%***	0.37%***
Selling	0.35%***	0.36%***	0.27%***	0.25%***	0.26%***	0.23%***	0.38%***	0.42%***
Panel B: Crisis times (January 2008–June 2009)								
Aggregate	− 0.06%**	− 0.12%***	− 0.16%***	− 0.23%**	0.05%	0.38%*	0.05%	0.09%
Buying	− 0.07%***	− 0.09%***	− 0.17%***	− 0.20%**	0.09%	0.32%*	0.01%	0.03%
Selling	0.04%**	0.08%***	− 0.05%	− 0.01%	0.07%	0.14%	− 0.01%	0.08%**

This table below reports the characteristic-timing attributes of all mutual funds and also broken down by CRSP investment objectives: growth, growth & income, income, hedged, micro-cap, small-cap, and mid-cap. Panel A reports the average annualized performance of mutual funds as returns during the whole sample period from 2003 to 2019. Panels B presents the average annualized performance as returns for the sub-sample period January 2008 to June 2009. Aggregate characteristic-timing performance is calculated as the difference between month t value-weighted return of the benchmark portfolio of stocks held at month $t-1$ and month t value-weighted return of benchmark portfolio of stocks held at month $t-13$. Aggregate characteristic-timing performance is decomposed into its buying and selling components based on changes in holdings between two consecutive reports. *Buying* measures the characteristic-timing performance of stocks at time t when a mutual fund increases its stock holdings during period $t-1$; *Selling* measures the characteristic-timing performance of stocks at time t when a mutual fund reduces its stock holdings during period $t-1$. Significance levels are denoted by *, **, and ***, and indicate whether the results are statistically different from zero at the 10%, 5%, and 1% significance levels quarter continue to manifest positive and statistically significant annualized returns of 0.61%, 0.29%, and 0.29% in the following three quarters. However, taken together with the performance difference between past winners and past losers (q5-q1), our evidence is consistent with the idea that top performing funds in a quarter do demonstrate skill but only in the short term (one quarter ahead). Overall, in the buy domain, fund manager underperformance seems to be driven more by bad luck than bad skill. Similarly, Panel C shows that, in the sell domain poor selling is only short-lived. Of particular interest are the characteristic-timing returns for the winner quintile (q5) which shows parallel evidence of short-term skill as in the buy domain earning 0.60% on an annualized-basis in the first post-portfolio formation quarter but only average returns subsequently.

4.3 Does trade motivation relate to trade performance?

An important role played by mutual funds is to provide liquidity to investors, allowing them to redeem their investment when they wish. However, this need to provide liquidity forces fund managers to engage in costly trading. In particular, when experiencing fund outflows, fund managers often have no other option but to sell some of their existing holdings to fulfil investor redemption requirements, even when they might believe that these stocks are undervalued. In extreme cases, they can also be forced to engage in a "re-sale" (e.g., Coval and Stafford 2007). As such, if not explicitly taken into account, any inferences regarding fund manager trading skill can be significantly negatively biased (e.g., Chen et al. 2013). The important question is whether negative characteristic-timing performance when selling stocks is driven by liquidity-induced sales. This sub-section attempts to address this question. In particular, we separate fund managers' motivations for trading by conditioning fund purchases and sales on the motivation score metrics of Alexander et al. (2007) to increase the test power of the standard characteristic-timing performance measure. Intuitively, this flow-based motivation score metric assigns a higher score to buy (sell) portfolios of funds that are more likely comprised of larger proportions of valuation-motivated purchases (sales).

In Table 4, we extend our analysis of fund manager trading skills by controlling for potential confounding variables. For each fund, we sort monthly motivation observations and construct quintile-trade-motivation subgroups. The dummy indicator variable, Valuation, identifies trades that are the most likely to be motivated by valuation beliefs, and the dummy variable, Liquidity, indicates liquidity-induced trades. More specifically, Valuation is an indicator variable equal to one for each month a mutual fund is identified as valuation motivated (i.e., high buy flow score or high sell flow score), zero otherwise; Liquidity is an indicator variable equal to one for each month a mutual fund is identified as liquidity driven (i.e., low buy flow score or low sell flow score), zero otherwise. We test the hypothesis that trade motivations are related to subsequent characteristic-timing performance by estimating the following fixed effect panel data regression model separately for buying and selling skills:

$$Performance_{i,t} = a_0 + a_1 Valuation_{i,t-1} + a_2 Liquidity_{i,t-1} + a_3 Controls_{i,t-1} + \epsilon_{i,t} \quad (5)$$

where $Performance_{i,t}$ denotes either buying or selling trading performance; $Valuation_{i,t-1}$ is an indicator variable equal to one if trades by mutual fund i are categorised as being motivated by valuation beliefs at time *t-1*, and zero otherwise; $Liquidity_{i,t-1}$ is an indicator variable equal to one if trades by mutual fund i are categorised as being driven by liquidity needs at time *t-1*, and zero otherwise. $Controls_{i,t-1}$ is mainly a vector of lagged

Table 3 Mutual fund characteristic-timing performance persistence

	Quarters			
Quintiles	Q+0	Q+1	Q+2	Q+3
Panel A: Aggregate performance				
q1	− 0.25%***	0.22%***	0.26%***	0.21%***
q3	0.59%***	0.31%***	0.11%***	0.30%***
q5	1.90%***	0.73%***	0.38%***	0.38%***
q5–q1	2.14%***	0.52%***	0.12%***	0.17%***
Panel B: Buying performance				
q1	− 0.53%***	0.25%***	0.14%***	0.07%***
q3	0.56%***	0.32%***	0.08%***	0.34%***
q5	2.12%***	0.61%***	0.29%***	0.29%***
q5–q1	2.64%***	0.36%***	0.15%***	0.21%***
Panel B: Selling performance				
q1	− 0.27%***	0.24%***	0.26%***	0.18%***
q3	0.63%***	0.36%***	0.13%***	0.30%***
q5	2.43%***	0.60%***	0.33%***	0.32%***
q5–q1	2.70%***	0.36%***	0.07%***	0.14%***

This table presents the persistence of mutual fund characteristic-timing performance. Aggregate characteristic-timing performance is calculated as the difference between month t value-weighted return of the benchmark portfolio of stocks held at month $t-1$ and month t value-weighted return of benchmark portfolio of stocks held at month $t-13$. Aggregate characteristic-timing performance is decomposed into its buying and selling components based on changes in holdings between two consecutive report dates. At the end of each quarter, all existing mutual funds are divided into five quintiles based on average aggregate buying, and selling characteristic-timing performance. The characteristic-timing performance for the first quarter and subsequent three quarters are reported. Significance levels are denoted by *, **, and ***, and indicate whether the results are statistically different from zero at the 10%, 5%, and 1% significance levels

fund-specific control variables, including age (natural logarithm of age of fund in years since first o er date, log(Age)), size (natural logarithm of total net assets under management in millions of dollars, log(TNA)), expense ratio (in % per year, Expenses), turnover ratio (in % per year, Turnover), fund flow (in % per month, Flow), management fee (in % per year, Fee), and fund style characteristics along the size, book-to-market and momentum dimensions (in quintile number, size, btm, and momentum).

To mitigate the impact of outliers on our estimates, we winsorize Flow and Turnover at the 1% level. We demean all these control variables so that the constant a_0 measures the performance of non-valuation-motivated and non-liquidity-induced trades, a_1 indicates how much trade performance increases when motivated by valuation beliefs, and a_2 indicates how this decreases when fund managers have to meet liquidity needs. In addition to these control variables, following Kacperczyk et al. (2014) we include a dummy variable to control for the impact of the Global Financial Crisis (Recession). Motivated by Alexander et al. (2007) and others working in the tournament literature who argue that some fund manager trades may be motivated by tax management or window-dressing reasons which typically occur just before fund fiscal year end, we also include a dummy variable to indicate the fourth calendar quarter (4th Quarter). To further control other fund manager characteristics, we construct four variables. *Solo* is a dummy equal to one if mutual fund *i* is managed by a single manager during the period *t-1* to *t*, and 0 otherwise. *Female* is an indicator variable equal to one for female managers. *Tenure* is the natural logarithm of current manager's tenure at the fund in years. *Log(Busy)* is the natural logarithm of the number of different funds managed by the same manager in that month. The model includes time and fund fixed effects.

Table 4 examines variation in buying and selling performance broken down by trade motivation. Columns (1) to (3) report trade motivation coefficients derived from panel regressions with the characteristic-timing returns of buy sub-portfolios as the dependent variable. Statistically very significant results imply that buying performance is strongly related to trade motivation and valuation-motivated buys outperform liquidity-driven buys. In column (3), valuation-motivated buys are associated with 2.1 basis points per month or approximately 0.25% ($=0.021\times12$) per year higher returns than non-valuation-driven buys, while liquidity-driven buys are associated with 5.4 basis points per month or 0.65% (=—0.054 × 12) per year lower returns than non-liquidity-induced buys, after controlling for fund- and manager specific characteristics and time fixed effects.

Columns (4) to (6) of Table 4 summarise our selling performance results. Fund managers appear to sell stocks at the right time regardless of whether such decisions are valuation-motivated or driven by liquidity requirements. In particular, column (6) reports that valuation-motivated sells outperform non-valuation-driven sells by an average of 13.6 basis points per month or 1.36% ($=0.136\times12$) per year, while liquidity-induced sales have a statistically and economically significant 11.4 basis points per month or 1.37% ($=0.114\times12$) per year higher returns than non-liquidity-driven sales.[11]

Our sample includes "2008–2009 Sub-prime Mortgage Crisis". One can argue that large losses and highly volatile nature of this period may have an impact on the buying and selling performance of fund managers through their trade motivation. Moreover, a significant event like this may even influence their motivation in such a way that their buying and selling strategies can be different before and after this crisis. To investigate these possibilities further, we divide our sample into three periods and repeat the main exercise in Table 4 with these sub-samples. Before (After) crisis period is from January 2003 to December 2007 (from July 2009 to December 2019). Outside the crisis period is from January 2003 to December 2019, excluding the period from January 2008 to June 2009. Table 5 provides the results similar to the ones in Table 4. Particularly, buying performance is strongly linked to trade motivation and valuation-motivated buys outperform liquidity-driven buys, regardless of whichever period we consider. Sub-prime Mortgage Crisis seems to have no considerable impact on fund managers because they appear to also sell stocks at the right time before and after the crisis. Their sell decision can be valuation-driven or liquidity-induced, they perform exceptionally well in either case.

4.4 Are there managers who possess both good buying and good selling skills?

Findings reported thus far show that mutual fund managers possess both positive buying and selling skills, and these results are unchanged even controlling for fund characteristics and trade motivation. Most studies to date treat fund managers as a homogeneous class of professional investor and do not explore whether different fund managers may have

[11] We have no reason to believe that the samples with U.S. domestic equity mutual funds and with international equity mutual funds produce substantially different results within the scope of this paper considering the characteristics of those funds (Cumby and Glen, 1990; Droms and Walker, 1994).

Table 4 Buying and selling characteristic-timing performance broken down by trade motivations: multivariate analysis

	Buying Performance			Selling Performance		
	(1)	(2)	(3)	(4)	(5)	(6)
Valuation	0.026***	0.020**	0.021**	0.119***	0.137***	0.136***
	(0.009)	(0.010)	(0.010)	(0.012)	(0.012)	(0.012)
Liquidity	− 0.052***	− 0.055***	− 0.054***	0.119***	0.115***	0.114***
	(0.009)	(0.010)	(0.010)	(0.011)	(0.012)	(0.012)
Log(Age)		− 0.171***	− 0.083**		− 0.159***	− 0.174***
		(0.028)	(0.032)		(0.029)	(0.033)
Log(TNA)		− 0.039***	− 0.036***		− 0.011	− 0.012
		(0.013)	(0.014)		(0.014)	(0.015)
Expenses		15.370**	14.040*		6.212	4.229
		(7.521)	(7.815)		(8.292)	(8.783)
Turnover		0.130***	0.129***		0.092***	0.093***
		(0.016)	(0.017)		(0.017)	(0.018)
Flow		0.316***	0.296***		− 0.353***	− 0.354***
		(0.064)	(0.070)		(0.077)	(0.083)
Fee		− 0.233***	− 0.222***		− 0.115	− 0.080
		(0.078)	(0.084)		(0.080)	(0.088)
Size		0.017	0.018		0.020	0.022
		(0.014)	(0.015)		(0.015)	(0.016)
BTM		− 0.022***	− 0.020***		− 0.022***	− 0.022***
		(0.003)	(0.004)		(0.004)	(0.004)
Momentum		0.003	0.002		0.006*	0.005
		(0.003)	(0.003)		(0.003)	(0.003)
Recession			0.198			0.033
			(0.455)			(0.227)
4^{th} Quarter			− 0.110			− 0.799***
			(0.067)			(0.131)
Solo			− 0.017			− 0.048**
			(0.020)			(0.021)
Female			0.058**			0.011
			(0.026)			(0.025)
Tenure			− 0.069***			− 0.009
			(0.013)			(0.013)
Log(Busy)			− 0.027*			− 0.025
			(0.016)			(0.020)
Observations	282,934	281,438	266,626	282,934	281,438	266,626
Adj. R^2	0.432	0.433	0.434	0.322	0.322	0.323

Dependent variables are mutual fund buying and selling characteristic-timing performance. *Valuation* is an indicator variable equal to one for each month a mutual fund is identified as valuation motivated (i.e., high buy flow score or high sell flow score), zero otherwise; *Liquidity* is an indicator variable equal to one for each month a mutual fund is identified as liquidity driven (i.e., low buy flow score or low sell flow score), zero otherwise. *Log(age)* is the natural logarithm of fund age in years since the first offer date. *Log(TNA)* is the natural logarithm of total net assets under management in millions of dollars. *Expenses* is the fund expense ratio in percent per year. *Turnover* is the fund turnover ratio in percent per year. *Flow* is the esti-

Table 4 (continued)

mated investor flows as the ratio of $TNA_{i,t} - TNA_{i,t-1} \times (1+RET_{i,t}) - MGN_{i,t}$ to $TNA_{i,t-1}$. *Fee* is the fund management fee in percent per year. All control variables are demeaned. *Flow* and *Turnover* are winsorized at the 1% level. *Recession* is an indicator variable equal to one for every month the economy is in a recession according to the NBER, and zero otherwise. *4th Quarter* is an indicator variable equal to one for each month is in the fourth quarter, and zero otherwise. *Solo* is a dummy equal to one if mutual fund *i* is managed by a single manager during the period $t-1$ to t, and 0 otherwise. *Female* is an indicator variable equal to one for female managers. Data are monthly and cover the period from 2003 to 2019. The model includes time and fund fixed effects

different trading abilities. For example, one group of fund managers might have superior buying skill whereas another group might be good at selling, or a small subset of fund managers might even perform both tasks successfully. In this subsection, we test whether best buyers may nonetheless have good selling skill, even if on average selling performance is negative, and similarly, whether best sellers do not underperform in the buy domain.

Since valuation-motivated trades are more likely to reflect the true trading skills of fund managers, we first identify best buyers (best sellers), those fund managers with superior buying (selling) ability when their trades are motivated by valuation beliefs. To achieve this, again we divide all fund-month observations for each fund into quintile sub-samples according to trade motivation scores. An indicator variable Best is next constructed to identify those fund managers who have the best buying (selling) performance which equals one for funds with valuation-motivated buying performance in the highest quintile of the distribution, zero otherwise. Finally, the following pooled panel data regression model is run:

$$Performance_{i,t} = c_0 + c_1 Best_{i,t} + c_2 Controls_{i,t-1} + \epsilon_{i,t} \tag{6}$$

where $Performance_{i,t}$ denotes either *buying* or *selling* performance for fund *i* at time *t*, $Best_{i,t}$ denotes either "best buyers"and $Controls_{i,t-1}$ is a vector of previously defined control variables. The model includes time and fund fixed effects. The coefficient of interest is c_1.

Table 6 reports buying performance for our best buyer mutual funds in columns (1) to (3) and selling performance in columns (4) to (6). In line with the construction of the best buyers set of funds, column (3) shows that on average best buyers are significantly better at buying stocks than all other funds in our sample after controlling for fund characteristics and time fixed effects. These successful buyers exhibit 4.5 basis points per month or 0.54% (=0.045×12) per year higher characteristic-timing performance when buying stocks based on their valuation beliefs. However, strikingly, these best buyers are not able to outperform other funds when selling stocks, with the coefficient on Best in column (6) insignificantly different from zero.

We repeat this analysis procedure for best sellers with superior valuation-motivated selling performance and report the results in Table 7. For this exercise, Best is an indicator variable equal to one for funds with valuation-motivated selling performance in the highest quintile of the distribution, zero otherwise. Again, by construction, column (3) shows that on average our best sellers are significantly better at characteristic-timing when selling stocks than other funds. The coefficient on the indicator variable Best is statistically and economically significant. Valuation-motivated selling performance for our best seller mutual funds is 6.3 basis points per month or 0.76% (=0.063×12) per year more than for the remaining funds. However, the main point Table 7 makes is that our best sellers are also on average better at buying. Column (6) demonstrates this clearly, with the coefficient on the indicator variable Best

Table 5 Buying and selling characteristic-timing performance broken down by trade motivation: analysis considering the crisis period

	Buying performance			Selling performance		
	Before crisis period	After crisis period	Outside the crisis period	Before crisis	After crisis	Outside the crisis period
	(1)	(2)	(3)	(4)	(5)	(6)
Valuation	0.132***	0.021**	0.020**	0.327***	0.131***	0.142***
	(0.035)	(0.011)	(0.010)	(0.039)	(0.013)	(0.012)
Liquidity	− 0.065*	− 0.063***	− 0.058***	0.161***	0.109***	0.112***
	(0.036)	(0.011)	(0.010)	(0.035)	(0.013)	(0.012)
Log(Age)	− 0.445	− 0.073**	− 0.081**	− 0.423	− 0.169***	− 0.164***
	(0.326)	(0.034)	(0.033)	(0.286)	(0.034)	(0.034)
Log(TNA)	− 0.061	− 0.038***	− 0.036***	− 0.012	− 0.012	− 0.010
	(0.084)	(0.014)	(0.014)	(0.091)	(0.016)	(0.016)
Expenses	− 52.310	19.850**	18.461**	− 49.451	20.780**	18.190**
	(38.400)	(8.5101)	(8.179)	(36.160)	(9.165)	(8.943)
Turnover	− 0.096*	0.150***	0.131***	− 0.086	0.113***	0.101***
	(0.049)	(0.019)	(0.018)	(0.054)	(0.020)	(0.019)
Flow	− 0.237	0.351***	0.334***	− 0.065	− 0.342***	− 0.347***
	(0.313)	(0.073)	(0.070)	(0.316)	(0.086)	(0.083)
Fee	− 0.248	− 0.242***	− 0.204**	0.667	− 0.076	− 0.067
	(0.398)	(0.089)	(0.085)	(0.436)	(0.089)	(0.087)
Size	0.001	0.022	0.019	0.044	0.018	0.017
	(0.062)	(0.015)	(0.014)	(0.069)	(0.017)	(0.016)
BTM	− 0.014	− 0.023***	− 0.022***	− 0.037**	− 0.025***	− 0.025***
	(0.014)	(0.004)	(0.004)	(0.015)	(0.004)	(0.004)
Momentum	0.008	− 0.003	− 0.001	0.005	0.004	0.004
	(0.009)	(0.003)	(0.002)	(0.009)	(0.003)	(0.003)
Recession		− 0.504***	2.882***		2.414***	3.129***
		(0.143)	(0.140)		(0.189)	(0.196)

Table 5 (continued)

	Buying performance			Selling performance		
	Before crisis period	After crisis period	Outside the crisis period	Before crisis	After crisis	Outside the crisis period
	(1)	(2)	(3)	(4)	(5)	(6)
4th Quarter	2.978***	− 2.287***	− 0.361***	− 0.781***	0.755***	− 0.260*
	(0.261)	(0.154)	(0.055)	(0.234)	(0.179)	(0.156)
Solo	0.126	− 0.041*	− 0.026	0.158**	− 0.076***	− 0.068***
	(0.086)	(0.021)	(0.020)	(0.065)	(0.022)	(0.021)
Female	0.218*	0.071***	0.065***	0.044	0.022	0.026
	(0.116)	(0.027)	(0.025)	(0.116)	(0.025)	(0.024)
Tenure	0.202***	− 0.077***	− 0.077***	0.207***	− 0.019	− 0.013
	(0.078)	(0.014)	(0.013)	(0.057)	(0.014)	(0.013)
Log(Busy)	0.243***	− 0.032*	− 0.018	0.156***	− 0.043**	− 0.034*
	(0.061)	(0.017)	(0.016)	(0.059)	(0.021)	(0.020)
Observations	23,137	237,169	260,306	23,137	237,169	260,306
Adj. R^2	0.530	0.352	0.361	0.472	0.302	0.309

Dependent variables are mutual fund buying and selling characteristic-timing performance. *Valuation* is an indicator variable equal to one for each month a mutual fund is identified as valuation motivated (i.e., high buy flow score or high sell flow score), zero otherwise; *Liquidity* is an indicator variable equal to one for each month a mutual fund is identified as liquidity driven (i.e., low buy flow score or low sell flow score), zero otherwise. The control variables and model specifications are the same as in our main analysis in Table 4. The exercise is repeated for three different time periods. Before sub-prime mortgage crisis period is from January 2003 to December 2007. After sub-prime mortgage crisis period is from July 2009 to December 2019. Outside the crisis period is from January 2003 to December 2019, excluding the period from January 2008 to June 2009 statistically and economically significant. In particular, valuation-motivated buying performance for best seller funds is, on average, 3.6 basis points per month or 0.43% (=0.036×12) higher than for other funds. In summary, fund managers with the best selling ability also possess superior buying ability. On the other hand, best buyers who by construction are successful at buying stocks have no ability in the sell domain. In other words, good sellers are also good buyers but good buyers are not good sellers.

4.5 The characteristics of best sellers

Who are these best sellers? In this final sub-section we compare the characteristics of “best seller" funds with all other funds. Table 8 shows first that those funds demonstrating superior selling skill are smaller on average which, we speculate, may help explain decreasing returns to scale at the overall fund level (e.g., Ang and Lin 2001; Chen et al. 2004; Berk and Green 2004; Liu et al 2021). Second, such funds are younger, and appear to charge lower expenses and management fees on average to fund investors, although medians do not differ. Interestingly, our “best seller" funds exhibit lower portfolio turnover, indicating lower levels of trading activity. Consistent with this feature, these fund managers also hold less stocks in their portfolios. Based on this analysis we speculate whether superior selling skill may be a potential source of the observed outperformance of smaller, newer funds over larger more mature funds found in previous studies (e.g., Kacperczyk et al. 2014).

5 Conclusions

This study examines whether mutual fund managers, a representative group of professional investors, exhibit investment abilities, and in particular whether they have factor-timing skill, i.e., they are able to adjust portfolio exposure to the risk factors of size, book-to-market and momentum effects appropriately. Consistent with Daniel et al. (1997), Elton et al. (2012), and others, we find no evidence of significant characteristic-timing skill in aggregate. We disaggregate overall characteristic-timing performance into its buying and selling components. On average, fund managers seem to earn positive characteristic-timing returns from their buying activities consistent with skill in this domain. However, fund managers exhibit a striking ability to sell stocks at the wrong time: their selling decisions are subsequently associated with negative characteristic-timing performance.

Further, we demonstrate that such differential buying and selling performance is not driven by chance but due to skill (good and bad). Fund managers who are successful in buying stocks in the past tend to continue generating superior returns from their purchase decisions, while those who performed badly in the sell domain tend to continue to underperform when disposing of stocks. In further ex-amination of these distinct trading skills, we take account of the adverse effects of fund flows on fund manager behavior (e.g., Chordia 1996; Edelen 1999; Nanda et al. 2000; Rohleder et al. 2017). We find that when making valuation-driven buying decisions fund managers generate significant positive characteristic-timing performance, but they are not able to do so when compelled to work o excess cash from fund inflows. However, more importantly, our results reveal that, even when motivated by valuation beliefs, fund managers appear unable to earn characteristic-timing returns from their selling decisions, and again exhibit negative selling skill.

Table 6 Best buyer performance

	Buying performance			Selling performance		
	(1)	(2)	(3)	(4)	(5)	(6)
Best	0.069***	0.047**	0.045**	− 0.021	− 0.028	− 0.030
	(0.021)	(0.022)	(0.022)	(0.024)	(0.025)	(0.026)
Log(Age)		− 0.109**	− 0.022		− 0.217***	− 0.134**
		(0.048)	(0.052)		(0.053)	(0.061)
Log(TNA)		− 0.015	− 0.021		0.004	0.002
		(0.021)	(0.021)		(0.025)	(0.026)
Expenses		12.430	15.320		19.090	18.620
		(15.750)	(16.611)		(15.081)	(16.060)
Turnover		0.121***	0.124***		0.080**	0.074**
		(0.029)	(0.030)		(0.032)	(0.033)
Flow		0.269***	0.255***		− 0.089	− 0.134
		(0.082)	(0.088)		(0.100)	(0.107)
Fee		− 0.266*	− 0.308**		0.047	0.029
		(0.139)	(0.149)		(0.135)	(0.145)
Size		− 0.008	− 0.005		− 0.029	− 0.026
		(0.022)	(0.023)		(0.026)	(0.027)
BTM		− 0.018***	− 0.017***		− 0.019***	− 0.016**
		(0.006)	(0.006)		(0.007)	(0.007)
Momentum		0.004	0.001		0.012**	0.015**
		(0.004)	(0.005)		(0.006)	(0.006)
Recession			2.197***			0.457**
			(0.170)			(0.197)
4th Quarter			− 4.186***			− 4.578***
			(0.458)			(0.350)
Solo			0.012			− 0.078**
			(0.032)			(0.035)
Female			0.014			− 0.054
			(0.042)			(0.041)
Tenure			− 0.033			− 0.108***
			(0.022)			(0.025)
Log(Busy)			− 0.033			0.004
			(0.030)			(0.038)
Observations	58,581	58,203	53,848	58,581	58,203	53,848
Adj. R^2	0.444	0.445	0.446	0.416	0.417	0.418

Dependent variables are mutual fund buying and selling characteristic-timing performance. *Best* is an indicator variable equal to one for funds with valuation-motivated buying performance in the highest quintile of the distribution, zero otherwise. *Log(age)* is the natural logarithm of fund age in years since the first offer date. *Log(TNA)* is the natural logarithm of total net assets under management in millions of dollars. *Expenses* is the fund expense ratio in percent per year. *Turnover* is the fund turnover ratio in percent per year. *Flow* is the estimated investor flows as the ratio of $TNA_{i,t} - TNA_{i,t-1} \times (1 + RET_{i,t}) - MGN_{i,t}$ to $TNA_{i,t-1}$. *Fee* is the fund management fee in percent per year. *Size, BTM*, and *Momentum* are quintile number of fund style characteristics along the size, book-to-market, and momentum dimensions. All control variables are demeaned. *Flow* and *Turnover* are winsorized at the 1% level. *Recession* is an indicator variable equal to one for every month the economy is in a recession according to the NBER, and zero otherwise. *4th Quarter* is an indicator variable equal to one for each month is in the fourth quarter, and zero otherwise. *Solo* is a dummy equal to one if mutual fund *i* is managed by a single manager during the period $t-1$ to t, and 0

Table 6 (continued)

otherwise. *Female* is an indicator variable equal to one for female managers. *Tenure* is the natural logarithm of current manager's tenure at the fund in years. *Log(Busy)* is the natural logarithm of the number of different funds managed by the same manager in that month. Data are monthly and cover the period from 2003 to 2019. The model includes time and fund fixed effects. Standard errors (in parentheses) are clustered. Significance levels at 10%, 5%, and 1% are denoted by *, **, and ***, respectively

More interestingly, this study investigates the proposition that different fund managers may have different trading skills. Focusing on valuation-motivated trades, we find that fund managers who have the greatest selling ability also exhibit superior characteristic-timing performance when buying stocks compared with all other funds, and not surprisingly, these “best seller" funds significantly outperform other funds in terms of their aggregate timing returns. In contrast, our “best buyers” give back all their buying returns through poor selling, and consequently, do not exhibit any superior overall characteristic-timing performance. Nonetheless, we find clear evidence that a small set of fund managers in our sample are skilled in both buy and sell domains, and their superior characteristic-timing performance is mainly attributable to their good selling skills. Comparing the characteristics of “best sellers" with all other funds, such funds appear to be younger and smaller in size but are far more active in managing their portfolios in terms of their turnover ratio, smaller number of stocks held, and active style drift. However, there is no real evidence that they tend to charge higher expenses and management fees to compensate for their superior skills.

Overall, our study contributes to the ongoing debate on whether active fund managers possess special investment skill (see, e.g., Jin et al. 2020). Our findings suggest the lack of evidence for overall mutual fund performance documented in the literature masks positive buying and negative selling abilities. This empirical finding is consistent with the hypothesis that sell decisions are more likely to be susceptible to behavioral heuristics and biases (see, e.g., Akepanidtaworn et al. 2021). Even for professional investors sell decisions are particularly di cult. Future work might explore the mechanisms by which behavioral factors could drive poor selling performance. In addition, it would be interesting to examine whether the inability to sell down stocks well contributes to the strong negative performance persistence among poorly performing fund managers (e.g. Kosowski et al. 2006; Cuthbertson et al. 2008; Barras et al. 2010). These are fruitful avenues for future research.

Table 7 Best Seller Performance. Dependent variables are mutual fund buying and selling characteristic-timing performance

	Selling performance			Buying performance		
	(1)	(2)	(3)	(4)	(5)	(6)
Best	0.083***	0.076***	0.063**	0.070***	0.036**	0.036*
	(0.028)	(0.029)	(0.030)	(0.024)	(0.019)	(0.021)
Log(Age)		– 0.451***	– 0.520***		– 0.333***	– 0.375***
		(0.049)	(0.059)		(0.025)	(0.053)
Log(TNA)		– 0.020	– 0.031		– 0.062***	– 0.063**
		(0.032)	(0.034)		(0.017)	(0.028)
Expenses		– 2.755	– 8.575		– 13.390	– 37.350*
		(17.720)	(18.490)		(8.938)	(19.150)
Turnover		0.082**	0.101**		0.164***	0.172***
		(0.042)	(0.044)		(0.021)	(0.041)
Flow		– 0.233*	– 0.272**		0.215**	0.156
		(0.130)	(0.138)		(0.092)	(0.123)
Fee		0.185	0.221		– 0.303***	– 0.144
		(0.157)	(0.167)		(0.099)	(0.180)
Size		0.003	0.005		0.023	0.027
		(0.034)	(0.035)		(0.019)	(0.030)
BTM		– 0.014	– 0.014		– 0.021***	– 0.015*
		(0.009)	(0.009)		(0.005)	(0.008)
Momentum		0.001	– 0.001		– 0.003	– 0.011*
		(0.007)	(0.007)		(0.003)	(0.006)
Recession			– 0.448***			– 0.646***
			(0.129)			(0.123)
4th Quarter			– 0.024			0.021
			(0.022)			(0.020)
Solo			– 0.048			0.021
			(0.044)			(0.040)
Female			– 0.046			0.015
			(0.054)			(0.052)
Tenure			0.033			0.064**
			(0.031)			(0.028)
Log(Busy)			0.003			– 0.040
			(0.048)			(0.037)
Observations	58,581	58,203	53,848	58,581	58,203	53,848
Adj. R^2	0.002	0.003	0.004	0.001	0.003	0.005

Best is an indicator variable equal to one for funds with valuation-motivated selling performance in the highest quintile of the distribution, zero otherwise. *Log(age)* is the natural logarithm of fund age in years since the first offer date. *Log(TNA)* is the natural logarithm of total net assets under management in millions of dollars. *Expenses* is the fund expense ratio in percent per year. *Turnover* is the fund turnover ratio in percent per year. *Flow* is the estimated investor flows as the ratio of $TNA_{i,t} - TNA_{i,t-1} \times (1+RET_{i,t}) - MGN_{i,t}$ to $TNA_{i,t-1}$. *Fee* is the fund management fee in percent per year. *Size, BTM*, and *Momentum* are quintile number of fund style characteristics along the size, book-to-market, and momentum dimensions. All control variables are demeaned. *Flow* and *Turnover* are winsorized at the 1% level. *Recession* is an indicator variable equal to one for every month the economy is in a recession according to the NBER, and zero otherwise. *4th Quarter* is an indicator variable equal to one for each month is in the fourth quarter, and zero otherwise. *Solo* is a dummy equal to one if mutual fund *i* is managed by a single manager during the period $t-1$ to

Table 7 (continued)

t, and 0 otherwise. *Female* is an indicator variable equal to one for female managers. *Tenure* is the natural logarithm of current manager's tenure at the fund in years. *Log(Busy)* is the natural logarithm of the number of different funds managed by the same manager in that month. Data are monthly and cover the period from 2003 to 2019. The model includes time and fund fixed effects. Standard errors (in parentheses) are clustered. Significance levels at 10%, 5%, and 1% are denoted by *, **, and ***, respectively

Table 8 Fund characteristics for best sellers

	Best sellers			Others			Difference	
	Mean	Standard deviation	Median	Mean	Standard deviation	Median	Mean	*p*-value
Age	8.81	8.89	6.00	10.95	9.76	9.00	− 2.14	0.000
TNA	1,515.09	4,136.44	232.15	1,689.17	7,934.97	235.80	− 174.08	0.000
Expenses	1.15	0.44	1.06	1.23	0.49	1.14	− 0.08	0.000
Fee	0.68	0.20	0.68	0.70	0.24	0.70	− 0.03	0.000
Turnover	54.63	45.24	44.00	72.33	61.13	56.00	− 17.70	0.000
Stocks	101.02	113.69	72.00	110.99	151.00	74.00	− 9.97	0.000

Best sellers are identified as those funds with valuation-motivated selling performance in the highest quintile of the distribution. *Age* is the fund age in years since the first offer date. *TNA* is the total net assets under management in millions of dollars. *Expenses* is the fund expense ratio in percent per year. *Fee* is the fund management fee in percent per year. *Turnover* is the fund turnover ratio in percent per year. *Stocks* is the total number of stocks held by mutual funds. p-value measures statistical significance of the difference. The data cover the period from 2003 to 2019

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References

Akepanidtaworn K, Di Mascio R, Imas A, Schmidt L (2021) Selling fast and buying slow: heuristics and trading performance of institutional investors (No. w29076). National Bureau of Economic Research

Alexander GJ, Cici G, Gibson S (2007) Does motivation matter when assessing trade performance? An analysis of mutual funds. Rev Financ Stud 20:125–150

An L, Argyle B (2021) Overselling winners and losers: How mutual fund managers' trading behavior affects asset prices. J Financ Mark 55:100580

Ang JS, Lin JW (2001) A fundamental approach to estimating economies of scale and scope of financial products: the case of mutual funds. Rev Quant Financ Acc 16(3):205–222

Asness CS (2016) The siren song of factor timing aka “smart beta timing” aka “style timing.” J Portf Manag 1:1–6
Barras L, Scaillet O, Wermers R (2010) False discoveries in mutual fund performance: measuring luck in estimated alphas. J Finance 65:179–216
Becker C, Ferson W, Myers DH, Schill MJ (1999) Conditional market timing with benchmark investors. J Financ Econ 52:119–148
Berk JB, Green RC (2004) Mutual fund flows and performance in rational markets. J Polit Econ 112:1269–1295
Chang EC, Lewellen WG (1984) Market timing and mutual fund investment performance. J Bus 57:57–72
Chen H-L, Jegadeesh N, Wermers R (2000) The value of active mutual fund management: an examination of the stockholdings and trades of fund managers. J Financ Quant Anal 35:343–368
Chen J, Hong H, Huang M, Kubik JD (2004) Does fund size erode mutual fund performance? The role of liquidity and organization. Am Econ Rev 94:1276–1302
Chen L-W, Adams A, Taffler R (2013) What style-timing skills do mutual fund “stars" possess? J Empir Financ 21:156–173
Chevalier J, Ellison G (1997) Risk taking by mutual funds as a response to incentives. J Polit Econ 105:1167–1200
Chordia T (1996) The structure of mutual fund charges. J Financ Econ 41:3–39
Cici G (2012) The prevalence of the disposition effect in mutual funds’ trades. J Financ Quant Anal 47:795–820
Coval J, Stafford E (2007) Asset fire sales (and purchases) in equity markets. J Financ Econ 86:479–512
Cumby RE, Glen JD (1990) Evaluating the performance of international mutual funds. J Finance 45:497–521
Cuthbertson K, Nitzsche D, O’Sullivan N (2008) UK mutual fund performance: skill or luck? J Empir Financ 15:613–634
Daniel K, Grinblatt M, Titman S, Wermers R (1997) Measuring mutual fund performance with characteristic-based benchmarks. J Finance 52:1035–1058
Daniel K, Titman S (1997) Evidence on the characteristics of cross sectional variation in stock returns. J Finance 52:1–33
Droms WG, Walker DA (1994) Investment performance of international mutual funds. J Financ Res 17:1–14
Edelen RM (1999) Investor flows and the assessed performance of open-end mutual funds. J Financ Econ 53:439–466
Elton EJ, Gruber MJ, Blake CR (2012) An examination of mutual fund timing ability using monthly holdings data. Rev Finance 16:619–645
Ervolini MA (2014) Managing equity portfolios: a behavioral approach to improving skills and investment processes. MIT Press, Cambridge
Faugere C, Shawky HA, Smith DM, Spring (2004) Sell discipline and institutional money management. J Portf Manag 30:95–105
Ferson WE, Schadt RW (1996) Measuring fund strategy and performance in changing economic conditions. J Finance 51:425–461
Frazzini A (2006) The disposition effect and underreaction to news. J Finance 61:2017–2046
Genesove D, Mayer C (2001) Loss aversion and seller behavior: evidence from the housing market. Quart J Econ 116:1233–1260
Glushkov D (2015) How smart are ’smart beta’ ETFs? Analysis of relative performance and factor exposure. SSRN Scholarly Paper ID 2594941, Social Science Research Network, Rochester, NY
Grinblatt M, Keloharju M (2001) What makes investors trade? J Finance 56:589–616
Henriksson RD, Merton RC (1981) On market timing and investment performance. II. Statistical procedures for evaluating forecasting skills. J Bus 54:513–533
Jagannathan R, Korajczyk RA (1986) Assessing the market timing performance of managed portfolios. J Bus 59:217–235
Jiang GJ, Zaynutdinova GR, Zhang H (2021) Stock-selection timing. J Bank Finance 125:106089
Jiang GJ, Yao T, Tong Yu (2007) Do mutual funds time the market? Evidence from portfolio holdings. J Financ Econ 86:724–758
Jiang W (2003) A nonparametric test of market timing. J Empir Financ 10:399–425
Jin Li, Scherbina A (2011) Inheriting losers. Rev Financ Stud 24:786–820
Jin L, Taffler R, Eshraghi A, Tosun OK (2020) Fund manager conviction and investment performance. Int Rev Financ Anal 71:101550
Kacperczyk M, Van Nieuwerburgh S, Veldkamp L (2014) Time-varying fund manager skill. J Finance 69:1455–1484

Kacperczyk M, Sialm C, Zheng Lu (2008) Unobserved actions of mutual funds. Rev Financ Stud 21:2379–2416

Kosowski R, Timmermann A, Wermers R, White H (2006) Can mutual fund “stars" really pick stocks? New evidence from a bootstrap analysis. J Finance 61:2551–2595

Koutmos D, Wu B, Zhang Q (2020) In search of winning mutual funds in the Chinese stock market. Rev Quant Financ Acc 54(2):589–616

Lam K, Li W (2004) Is the ‘perfect’ timing strategy truly perfect? Rev Quant Financ Acc 22(1):39–51

Liu LX, Jiang F, Li J, Farooque OA (2021) Antecedents of equity fund performance: a contingency perspective. Rev Pac Basin Financ Mark Policies 24(01)

Lou D (2012) A flow-based explanation for return predictability. Rev Financ Stud 25:3457–3489

Luo J, Qiao Z (2020) Individual commitment and team performance: evidence from mutual fund managers. J Financ Quant Anal 55(6):2073–2098

Nanda V, Narayanan MP, Warther VA (2000) Liquidity, investment ability, and mutual fund structure. J Financ Econ 57:417–443

Norris J (2002) How to take your emotions out of the sell decision. Am Assoc Ind Invest J 24:15–18

O’Connell PGJ, Teo M (2009) Institutional investors, past performance, and dynamic loss aversion. J Financ Quant Anal 44:155–188

Odean T (1998) Are investors reluctant to realize their losses? J Finance 53:1775–1798

Popescu M, Zhaojin Xu (2017) Leading the herd: evidence from mutual funds’ buy and sell decisions. Rev Quant Financ Acc 50:1131–1146

Rohleder M, Schulte D, Wilkens M (2017) Management of flow risk in mutual funds. Rev Quant Financ Acc 48:31–56

Shefrin H, Statman M (1985) The disposition to sell winners too early and ride losers too long: theory and evidence. J Finance 40:777–790

Sirri ER, Tufano P (1998) Costly search and mutual fund flows. J Finance 53:1589–1622

Song Y (2020) The mismatch between mutual fund scale and skill. J Financ 75(5):2555–2589

Taffler RJ, Spence C, Eshraghi A (2017) Emotional economic man: calculation and anxiety in fund management. Acc Organ Soc 61:53–67

Treynor JL, Mazuy KK (1966) Can mutual funds outguess the market? Harv Bus Rev 44:131–136

Tuckett D, Taffler RJ (2012) Fund management: an emotional finance perspective. Research Foundation of CFA Institute

Wermers R (2003) Is money really ‘smart’? New evidence on the relation between mutual fund flows, manager behavior, and performance persistence. SSRN Scholarly Paper ID 414420, Social Science Research Network, Rochester, NY.

Zheng Y, Osmer E, Zheng L (2020) Can mutual funds time investor sentiment? Rev Quant Financ Acc 54(4):1449–1486

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