Fund manager skill: Does selling matters more than buying?

Liang Jin and Richard Taffler*

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ABSTRACT

This study explores whether mutual fund managers have "bad" skill that can persistently affect fund performance. By decomposing aggregate characteristic-timing performance into buying and selling components we show that, while on average fund managers are able to generate positive characteristic-timing returns when buying stocks, they exhibit a "striking" ability to sell stocks at the wrong time. A closer look reveals that fund managers making purely valuation-motivated purchases generate significant timing returns, but are not able to do so when compelled to work off excess cash from investor inflows. More importantly, fund managers do not demonstrate any timing performance from their selling decisions, even when they are mostly motivated by valuation beliefs. Further results show that fund managers who possess superior selling ability are also significantly better at buying stocks than other fund managers and, as a result, earn significantly greater aggregate characteristic-timing returns. Surprisingly, fund managers who appear to buy stocks well are not able to outperform other funds when selling stocks, and overall are unable to generate superior returns.

Keywords: mutual funds, characteristic-timing ability, trade motivation, investment performance, valuation beliefs

* Both authors from the Finance Group, University of Warwick, Warwick Business School, Coventry, CV4 7AL, United Kingdom, Respective e-mail addresses are Liang.Jin@warwick.ac.uk and Richard.Taffler@wbs.ac.uk.

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1. Introduction

Despite the vast amount of resource fund managers expend, and the high management fees charged to fund investors, whether fund managers have investment skills or talents to deliver exceptional returns to fund investors still remains an open question. Prior literature on the performance of actively managed mutual funds paints a disheartening picture of active funds on average failing to outperform passive benchmarks and failing to add value for fund investors.[2] The consensus view is that only a small number of fund managers, if any at all, are able to identify and profit from mispriced stocks,[3] and there is little evidence of fund manager timing ability. Early studies such as Treynor and Mazuy (1966), Chang and Lewellen (1984), and Henriksson (1984) suggest that significant market timing ability is rare among mutual fund managers. The most puzzling aspect of the empirical evidence in most of such studies is that average timing performance across mutual funds is negative, and that mutual fund managers who exhibit superior market timing ability show negative performance more often than positive performance. Using more sophisticated tests, more recent studies such as Becker *et al* (1999) and Jiang (2003) still fail to provide convincing evidence that funds have superior timing ability.

Extant studies identify and measure timing ability by running non-linear regressions of realized fund returns against contemporaneous market returns (return-based measure). However, this approach can lead to misleading inferences regarding market timing ability. First, in a non-linear regression framework, spurious timing ability can appear to exist due to factors other than active timing strategies of fund managers. Jagannathan and Korajczyk (1986) demonstrate that certain dynamic trading strategies by mutual funds might give rise to a negative non-linear relationship between fund and market returns. Second, most existing studies assume that market timing strategies are implemented in a specific way. Elton *et al* (2012) argue that fund managers might choose to time in a more complicated way. Third, Goetzmann, *et al* (2000) and Bollen and Busse (2001) argue that return-based methods employ monthly return information, and thus ignore active timing and trading between observations of fund returns, leading to negatively-biased timing ability. Recent studies such as Jiang *et al* (2007) and

[2] See e.g., Jensen (1968), Friend *et al* (1970), Lehmann and Modest (1987), Elton et al (1993), Malkiel (1995), Carhart (1997), Fama and French (2010) and others.
[3] See e.g., Pástor and Stambaugh (2002), Kacperczyk et al (2005, 2008), Kosowski et al (2006), Cremers and Petajisto (2009), Barras et al (2010), Huang *et al* (2011) and others.

Kaplan and Sensoy (2008) propose alternative market timing measures based on mutual fund portfolio holdings (holding-based measure). Using a single-index model, these authors find that mutual fund managers have significant timing ability, which is opposite to what has been found in prior return-based studies. However, Elton *et al* (2012) show that the positive timing ability identified by the single-index model actually turns out to be negative timing ability. Overall, there is also little empirical evidence to suggest that mutual fund managers are able to time the market or exploit time-varying stock characteristic returns.

One possible reason for this unfavourable view of fund manager timing ability is that extant work on timing ability has concentrated on investigating whether mutual fund managers or a subset of them have timing ability by testing the market timing performance in aggregate which might not necessarily be a good indicator of the timing skills mutual fund managers really possess. Mutual fund managers might be able to perform some tasks well, but they might be not good at other tasks. As a result, superior performance deriving from positive skill can be cancelled out by poor performance from negative skill, which perhaps explains the lack of evidence of fund managers' timing skills documented in the literature.

One set of potential candidates for such distinct investment skills consists of buying and selling abilities. Sell decisions are assumed in traditional finance literature to be the other side of the coin to buy decisions, but investment practitioners often find themselves tending to have more trouble with sell decisions than they do with buy decisions. Norris (2002) expresses concern that behavioral and emotional biases can be highly influential in shaping investors' decisions to sell stocks and argues that a decision to sell stocks involves changing investors' minds about the prospects of their investments, which can be particularly difficult in the investment world, where investors are swamped with incomplete information. The behavioral finance literature recognizes the existence of such differential investment behaviors, and explains how sell decisions are more likely to be susceptible to the operation of cognitive heuristics and biases. It suggests that buy decisions may be more forward looking in terms of prospective performance while sell decisions may be more backward looking focusing on past performance. In particular, several studies of selling behavior in natural and experimental markets provide evidence that investors are more reluctant to realize losses than gains (Odean, 1998; Weber and Camerer, 1998). Shefrin and Statman (1985) label this phenomenon the "disposition effect". Working with a discount brokerage database, Odean (1998) finds that retail investors tend to selling winning stocks rather than losing stocks using the original purchase price as a reference point. A similar pattern can also be found in other markets such as the housing market (Genesove and Mayer, 2001). Genesove and Mayer (2001) show that house sellers tend to set an asking price that exceeds the asking price of other sellers with comparable houses when the expected selling price is below their original purchase price. Researchers find that it is very hard to explain the tendency of selling winners over losers in a rational trading framework (e.g., Barberis and Thaler, 2003). On the other hand, a number of behavioral explanations have been suggested such as the concavity (convexity) of the value function in the domain of gains (losses) from prospect theory (e.g., Kahneman and Tversky, 1979).

These studies mostly provide evidence that retail investors tend to have difficulty to make sell decisions in a disciplined way. While there is little doubt that behavioral biases can play an adverse role in sell decisions and therefore can be harmful to investment performance from the individual investors' point view, there is rare empirical evidence on the more critical question of whether professional investors such as mutual fund managers who play a dominating role in financial market are also bad at selling. A survey conducted by Cabot Research and the CFA Institute provides direct evidence that mutual fund managers have to rely on subjective judgment to shape their sell decisions, rather than more quantitative or research based methods (Cabot Research, 2007). In particular, more than 80% of participants in their survey indicate that judgment plays an important role in making sell decisions and over 70% of the respondents indicate that their decisions are formed from experience, trial and error, and advice from past mentors. If it is more difficult to make disciplined investment decisions in the sell domain than the buy domain, then the lack of evidence of overall mutual fund performance along the market-timing and characteristic-timing dimensions documented in the literature might mask the existence of positive buying but negative selling skills.

To investigate whether mutual fund managers exhibit distinct trading skills, this study evaluates the timing ability of mutual fund managers by employing the characteristic-timing measure of Daniel *et al* (1997) decomposing estimated aggregate characteristic-timing performance into its buying and selling components. Specifically, we utilise mutual fund holdings to explore directly whether increases or decreases in portfolio weightings along the three stock characteristics of size, book-to-market, and momentum effect, are able to forecast future returns. This approach not only allows researchers to better capture the dynamic aspects of actively managed portfolios but also avoid the "artificial timing" bias that is usually found in return-based measures. Using the CRSP Mutual Fund Holdings Dataset with a broad sample of 3,384 unique U.S. actively managed domestic equity funds from September 2003 to December 2013, this study finds no evidence that mutual fund managers exhibit significant aggregate characteristic-timing performance, which is consistent with the literature (e.g., Daniel *et al*, 1997). However, there is strong evidence that fund managers possess distinct trading abilities. In particular, mutual fund managers on average earn characteristic-timing returns of 1.42% per year when adding stocks to their portfolios, indicating that fund managers possess abilities in the buy domain. On the other hand, fund managers appear to exhibit negative characteristic-timing skill when selling stocks with average characteristic-timing returns of no less than -1.78% per year, significant at the 5% level.

This study also examines whether characteristic timing abilities persist over time by sorting mutual fund portfolios into quintiles based on their past characteristic-timing performance and then tracking the future performance of each performance quintile. There is strong persistence of aggregate characteristic-timing performance in the negative domain, at least over the following four quarters, suggesting that mutual fund managers do not possess characteristic-timing ability in aggregate. A subset of fund managers tend to have poor timing ability that persistently hurts their overall portfolio performance. More importantly, results reveal that fund managers who exhibit superior characteristic-timing performance when buying stocks in the past tend to continue performing buying tasks well in the near term, while those who were the worst performers for selling stocks tend to underperform in the selling domain over the following quarter. In other words, a small number of mutual fund managers have "hot" hands in buying stocks, while another subset of fund managers have "icy" hands in selling stocks in the short term. Any apparent extreme negative (positive) performance for buying (selling) seems to be due to bad (good) luck.

In further examination of potential distinct trading skills, this study considers the fact that the natural structure of open-end mutual funds can often force fund managers to trade for reasons other than their valuation beliefs, which is mostly overlooked by previous studies in the literature. In fact, not only mutual fund managers provide investors with valuation expertise and diversified equity positions, but also offer low direct costs for liquidity to investors. They are required by law to pay a proportional share of the net asset value of the fund to investors who choose to redeem fund shares. This unique structural design of open-end mutual funds actually allows fund investors to buy and redeem fund shares without paying a large premium for immediate liquidity needs. However, this provision of low cost liquidity imposes significant indirect trading costs on open-end funds (e.g., Chordia, 1996; Edelen, 1999; and Nanda *et al*, 2000). Fund managers themselves must engage in costly trades in response to significant fund flows. Significant investor inflows can compel fund managers to work off excessive cash by purchasing stocks, even if none of these stocks are believed to be undervalued at the time; similarly, significant investor outflows will constrain fund managers by forcing them to control liquidity in their portfolio by disposing of stocks, even if these stocks are perceived to be under-priced. In effect, such liquidity-driven trades play the role of uninformed trades and cause fund managers to act as noisy traders who should experience losses to other informed traders in a rational expectation framework.[4] Grossman and Stiglitz (1980) suggest that uninformed trades should underperform informed trades that represent fund managers' valuation beliefs. Thus, any performance metric that does not account for funds' flow-induced trading can yield negatively biased inferences regarding fund manager trading skills that they really possess (e.g., Edelen, 1999). In particular, the adverse effect of fund flows on sell decisions can be particularly severe. This is because fund managers with large inflows might have more flexibility in their investment decisions: they can temporarily accumulate cash for unexpected redemption needs and postpone their equity investment decisions, and can immediately open new positions or expand their current holdings. On the other hand, when experiencing significant outflows,

[4] See e.g., Grossman (1976); Hellwig (1980); and Verrcecchia (1982).

fund managers without enough cash reserves have no other options available but to sell their assets immediately at fire sale prices (Coval and Stafford, 2007; Zhang, 2010).

A more appropriate indicator of fund managers' skill should be based only on trades motivated by valuation beliefs (e.g., Alexander *et al*, 2007). However fund managers' beliefs are not observable, and consequently the key challenge in studies on mutual fund performance is to identify ex ante valuation-motivated trades. Cohen *et al* (2011) label each manager's highest estimated alpha holding as his "best idea" and show fund managers' "best idea" generate superior performance. Similarly, Pomorski (2009) shows that when multiple funds in the same fund family trade the same stock in the same direction, that stock outperforms. In order to separate various trading motivations, this study follows the approach of Alexander *et al* (2007) to condition trades on the direction and magnitude of concurrent realised net fund flows. The rationale is that fund managers who face severe outflows would buy stocks that are perceived to be significantly undervalued, and thus a larger proportion of the purchases they make in their portfolios are likely to be motivated by valuation beliefs. On the other hand, when experiencing significant inflows, fund managers are compelled to work off excess cash, and thus a smaller proportion of the purchases in their portfolios are likely to be valuation-based ones. Symmetrical intuition applies to fund managers' sales of stocks.

Indeed, our analysis shows that the performance of mutual fund trades 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 1.90% per year (t = 2.19), but are not able to do so when they are compelled to work off excessive cash from investor inflows. On the other hand, valuation-motivated sales significantly outperform liquidity-driven sales by an average of 0.69% per year at the 5% significance level. More importantly, fund managers appear to have a striking ability to sell stocks at the wrong time. Sales of stocks are associated with negative and significant characteristic-timing returns of -1.57% per year (t = 1.94), even when sells are most likely to be motivated by their valuation beliefs. These results are robust when using multivariate regressions to control for other mutual fund characteristics that might be related to the performance of fund trades. These findings confirm that observed fund managers' distinct trading skills are not driven by the adverse effect of fund flows, and that fund managers are not able to generate characteristic-timing performance from their selling decisions.

In addition, 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 possess different trading skills. A group of fund managers might specialize in buying decisions and another group of fund managers might be expert at selling decisions, or a small subset of fund managers might successfully perform both buying and selling tasks. In particular, since selling decisions are susceptible to behavioral bias, fund managers who can manage to make sell decisions in a more disciplined and research-based way may be more likely to possess general investment ability. By identifying the top 25% of funds in terms of their selling (buying) ability, this study provides strong evidence that these "good sellers" outperform other fund managers when selling stocks on a statistically significant basis by an average of 1.35% per year, and they also significantly outperform others when purchasing stocks by an average of 0.87% per year. On the other hand, although "good buyers" by construction do exhibit good characteristic-timing performance when adding stocks to their portfolios, they are unable to do the same when selling stocks, and give their buying returns back as a result. Whereas "good sellers" exhibit statistically and economically significant outperformance of 0.31% per year in aggregate characteristic-timing performance terms, good buyers do not. These results are consistent with the notion that sell decisions are particularly susceptible to behavioral bias, and are not made in a way as disciplined as buying decisions might be. Our analysis suggests that a small subset of fund managers skilled in selling possess investment ability that can lead to significant outperformance.

Our study contributes to the literature on mutual fund performance. While the majority of prior studies evaluate fund managers' skills using the conventional approach which only considers aggregate mutual fund performance, this study decomposes overall timing performance into different trading components and reveals that fund managers appear to possess positive buying skill and negative selling skills. In this way we are able to offer a potential explanation for the lack of evidence of overall mutual fund performance documented in the literature.

Our research is closely related to Chen *et al* (2013) who identify differential trading skills for a small number of "star" growth-oriented mutual fund managers. However, their study can be subject to some criticisms. Chen *et al* (2013) use at least 36 months of past monthly fund returns data to identify superior performing funds. This sample selection procedure not only excludes young mutual funds that do not have a sufficiently long return history, but also induces survivorship bias. Their analysis might also overestimate the trading skills along both buying and selling dimensions because their small group of growth-oriented mutual fund managers are more likely to possess genuine skill, rather than luck (Kosowski *et al*, 2006). Our findings therefore support and complement their argument with direct evidence that such distinct buying and selling characteristics-timing abilities exist in a much broader sample of virtually all U.S. domestic actively managed equity funds, and these trading skills are not driven by luck.

Our study also makes a significant contribution over and above Chen *et al* (2013) and others by considering the potential adverse effect of flow-induced trading on trade performance. First, although the academic literature recognises that liquidity-induced trades are costly (Edelen, 1999), there are few empirical studies that directly investigate the costs of liquidity provision on actual fund trades. One notable exception is Alexander *et al* (2007) who place emphasis on fund managers' stock picking ability and show that valuation-motivated trades outperform liquidity-driven trades. Our study contributes to the literature by showing that trade motivation also matters for characteristic-timing ability, even after controlling for fund characteristics and time fixed effects. Second, our results show that fund managers appear to exhibit significantly negative characteristic-timing performance from their selling decisions, even when most of these sales are motivated by fund managers' valuation beliefs. Third, our study contributes to the literature by showing that a small subset of fund managers who specialise in making sell decisions (good sellers) also possess buying skill and exhibit superior aggregate performance while those who have the best record of buying performance (good buyers) exhibit negative selling ability, suggesting that the performance deriving from fund managers' selling activities is a more powerful indicator of overall fund manager skills.

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

2. Methodology

2.1 Measuring Characteristic-Timing Performance

The "characteristic timing" measure of Daniel *et al* (1997) allows researchers to capture fund performance driven by fund managers' ability to time the three different investment styles of size, book-to-market, and momentum. 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 returns. The *CT* for month *t* measure is defined as:

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

where $\tilde{\omega}_{j,t-1}$ is the portfolio weight of stock j at the end of month *t-1*, $\tilde{\omega}_{j,t-13}$ is the portfolio weight of stock j at the end of month *t-13*, $\tilde{R}_t^{b_{j,t-1}}$ is the month t return of the characteristic-based passive benchmark portfolio that is matched to individual stock *j* according its size, book to market and momentum during the month *t-1*, $\tilde{R}_t^{b_{j,t-13}}$ is the month *t* return of the characteristic-based benchmark portfolio that is matched to stock *j* during month *t-13*. To illustrate the rationale behind the *CT* 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 *CT* performance for that month. A significant positive time series average of the *CT* measure of a fund indicates superior characteristic-timing ability by this fund.

This characteristic-based approach requires the construction of passive benchmark portfolios that are matched to individual stocks in the mutual fund portfolios with the dimensions of market value of equity (size), book-to-market ratio (btm), and momentum effect (mom). This paper constructs passive benchmark portfolios according to the procedure detailed in Daniel *et al* (1997). Briefly, at the end of June each year, the common stocks listed from the NYSE, AMEX, and NASDAQ are categorized into three quintile groups based on individual stock size, book to market ratio and prior year return and consequently $5 \times 5 \times 5$ sorted characteristic-based portfolios are formed. The monthly returns of these benchmark portfolios are calculated as the monthly value weighted returns of the stocks in the 125 portfolios. The detailed procedure is provided in Daniel *et al* (1997).

2.2 Measuring Buying and Selling Performance

Chen *et al* (2013) point out that the traditional *CT* measure, which is simply calculated by aggregating the characteristic timing performance of all holdings, would mask the distinct characteristic timing ability of buying and selling. This study follows Chen *et al* (2013) in decomposing the aggregate CT performance into different trading components. Specifically, for each fund, we measure the changes in number of shares held in each stock from the end of quarter *t-1* to the end of quarter *t* for each quarter in the sample period. Increases in the number of shares are treated as buys and aggregated to form the buy portfolio, and decreases are aggregated to form the sell portfolio, for each fund each quarter. This study then calculates the characteristic-timing performance for each trading portfolio.

2.3 Estimating Fund Flows

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

$$FLOW_{i,t} = \frac{TNA_{i,t} - TNA_{i,t-1} * \left(1 + RET_{i,t}\right) - MGN_{i,t}}{TNA_{i,t-1}} \quad (2)$$

where $TNA_{i,t}$ is the total net assets for individual fund share class *i* at time t; $RET_{i,t}$ is the gross return before expense ratio for individual fund share class *i* at time t; $MGN_{i,t}$ is the increase in total net assets for individual fund share class *i* at time t due to fund mergers. Since the CRSP Mutual Fund Database does not provides the exact date on which fund mergers occur, this paper follows Lou (2012) and uses the last net asset value (NAV) report date as the initial estimate of the merger date and in order to avoid the obvious mismatches generated by this initial estimate, this paper matches 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. Then the month in which the acquirer has the smallest absolute percentage flow, after subtracting the merger, is assigned as the merge event month. After adjusting for mutual fund mergers, monthly estimated net flows for all share classes belonging to their common fund are summed to obtain the total fund level monthly estimated flow. Monthly fund flows during the corresponding quarter are then aggregated into the quarter flow. This paper assumes that investor inflows and outflows take place at the end of each quarter, and investors reinvest their dividends and capital appreciation distributions in the same fund.

2.4 Measuring Trade Motivation

To measure trade motivation, this paper follows Alexander *et al* (2007) and divides fund manager trading activities into different types and track the characteristic-timing performance of trades, based on the various motivations driving them. Specifically, for each fund *i*, trade in stock *j* made by the fund manager is estimated as the change in the number of shares held in stock *j* between two consecutive reports from time *t-1* and time *t* in the sample period and trade dollar volume for each stock *j* is calculated by multiplying each change by the appropriate stock price which is the average daily closing stock price between the two consecutive report dates when the trade is assumed to occur. Trades associated with increased number of shares are treated as buys and then summed to obtain total purchase volume $BUY_{i,t}$ for fund *i* at time *t* and trades associated with decreased number of shares are aggregated to form the total sell volume $SELL_{i,t}$ for fund *i* at time t. Buy flow score ($BF_{i,t}$) and sell flow score ($SF_{i,t}$) that are used as proxies for trade motivation are defined respectively as:

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

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

where $FLOW_{i,t}$ is the estimated net investor flow into/out of fund *i* during quarter t, and $TNA_{i,t-1}$ is fund *i* total net assets under management at the end of quarter *t-1*. This paper follows Alexander *et al* (2007) in dividing the time series of portfolios of each fund's holdings that existed during the sample period into five quintiles. The $BF_{i,t}$ metric assigns buy portfolios of funds with high total buy dollar volume and high investor outflows to the top quintile, *BF1*, and buy portfolios with low total buy dollar volume and high investor inflow to the bottom quintile, *BF5*. This ranking procedure, according to Alexander *et al* (2007), deals appropriately with possible serial and cross-sectional trading patterns and correlations that might be present in the holdings data and therefore could bias results in unexpected ways.

BF1 refers to cases where despite a need to raise cash to meet investors outflows, mutual funds will only purchase stocks that are strongly believed to be undervalued, which infers that a large proportion of the buys in these buy portfolios are likely to be motivated by valuation considerations. On the other hand, *BF5* refers to those cases where mutual fund managers might be forced to invest the excess cash from large investor inflows into stocks that are not perceived to be undervalued, and therefore a small proportion of buys in these buy portfolios are likely to be valuation motivated. Similarly, $SF_{i,t}$ assigns sell portfolios with high total sell dollar volume with high investor inflows when a large proportion of sells in these sell portfolios are likely to be driven by valuation motivation to the top quintile, *SF1*, and sell portfolios with low total sell dollar volume with high investor outflows when a small proportion of sells in these sell portfolios are likely to be driven by valuation motivation to the bottom quintile, *SF5*

For illustration purposes, consider an example of the two scenario used by Alexander *et al* (2007) where a fund holds total net assets of $100 million at the beginning of two quarterly report dates. During the quarter of the first report, the fund undergoes net outflows of $10 million and purchase $5 million worth of stocks, while during the quarter of the second report, this fund experiences inflows of $15 million and buys $10 million worth of stocks. The $BF_{i,t}$ metric assigns the higher score of 0.15 = [5 - (-10)] / 100 to buy portfolios for the first report that are more likely to have a larger proportion of valuation-motivated trades, while it assigns a lower score of -0.05 = (10 - 15) / 100 for the second report which has a larger proportions of liquidity-motivated trades. Symmetrical intuition also applies to the $SF_{i,t}$ metric.

2.5 Measuring Active Style Drift

The characteristic-timing measure is designed to see whether, and by how much mutual fund managers are able to generate additional performance by increasing (or decreasing) portfolio weights on stock characteristics along the dimensions of size, book to market, and momentum when trading strategies focused on these stock characteristics are most profitable (or unprofitable). However, the characteristic-timing measure is not able to reflect how and to what extent mutual fund managers adjust their portfolio weights across these three different characteristics. In particular, characteristic-timing performance can be generated from passively holding the same stocks in portfolios over time because of fund managers' preference for certain overall stock characteristics, or from active engagement in chasing stock characteristics when they become profitable, or even from aggressive style drift from one equity style category to another one.

In order to investigate the relationship between style drift and characteristic-timing performance, this study employs the non-parametric measure developed by Wermers (2012) which allows us to identify the style characteristics of each stock held by mutual funds over time and to track the difference in overall stock style, in each of the three dimensions of size, book-to-market and momentum, in mutual fund portfolio holdings between two periods.

The total style drift of a managed portfolio in style dimension *l* (where *l* = size, book-to-market, or momentum) at portfolio reporting date is measured as:

$$TSD_q^l = \sum_{j=1}^{N} \left(\widetilde{w}_{j,q} \tilde{C}_{j,q}^l - \widetilde{w}_{j,q-1} \tilde{C}_{j,q-1}^l \right) \quad (5)$$

where $\widetilde{\omega}_{j,q}$ is the portfolio weight on stock j at the end of quarter q and $\widetilde{\omega}_{j,q-1}$ is the portfolio weight on stock j at the end of quarter *q-1*, while $\tilde{C}_{j,q}^l$ equals the non-parametric style characteristic of stock *j* in style dimension *l* at the end of quarter q and $\tilde{C}_{j,q-1}^l$ equals the non-parametric style characteristic of stock *j* in style dimension *l* at the end of quarter *q-1*.

The total style drift can be further decomposed into active style drift that results from active changes in the portfolio through trades of stocks, and passive style drift that results from passively holding stocks with changing holding weights and stock characteristics:

$$\mathrm{TSD}_q^l = PSD_q^l + ASD_q^l \quad (6)$$

where PSD_q^l measures the change in style dimension *l* assuming that the manager passively hold the portfolio during quarter *q-1* to quarter q while ASD_q^l measures the change in style dimension *l* through buys and sales of stocks during quarter *q-1* to quarter *q*.

PSD_q^l or passive style drift in dimension *l* during quarter *q-1* to quarter *q* is measured as:

$$PSD_q^l = \sum_{j=1}^{N} \left(\widetilde{w}'_{j,q} \tilde{C}_{j,q}^l - \widetilde{w}'_{j,q-1} \tilde{C}_{j,q-1}^l \right) \quad (7)$$

where $\widetilde{w}'_{j,q}$ denotes the portfolio weight of stock j of quarter q when a manager buys and holds the entire portfolio during quarter *q-1* to quarter *q*, while $\tilde{C}_{j,q}^l$ equals the non-parametric style characteristic of stock *j* in style dimension *l* at the end of quarter q and $\tilde{C}_{j,q-1}^l$ equals the non-parametric style characteristic of stock *j* in style dimension *l* at the end of quarter *q-1*.

The remainder of total style drift is captured by ASD_q^l or the active style drift:

$$ASD_q^l = \sum_{j=1}^{N} \left(\widetilde{w}_{j,q} \tilde{C}_{j,q}^l - \widetilde{w}'_{j,q} \tilde{C}_{j,q}^l \right) \quad (8)$$

Where $\widetilde{\omega}_{j,q}$ is the portfolio weight on stock *j* at the end of quarter *q* while $\widetilde{w}'_{j,q}$ denotes the portfolio weight of stock *j* at the end of quarter *q* when a manager buys and holds the entire portfolio during quarter *q-1* to quarter *q* and $\tilde{C}_{j,q}^l$ equals the non-parametric style characteristic of stock *j* in style dimension *l* at the end of quarter *q*.

Total, passive and active style drifts are then aggregated across all three dimensions of size, book-to-market and momentum effects for a fund during the period between quarter *q-1* to quarter *q* as:

$$TSD_q = \left|TSD_q^{size}\right| + \left|TSD_q^{btm}\right| + \left|TSD_q^{mom}\right| \tag{9}$$

$$PSD_q = \left|PSD_q^{size}\right| + \left|PSD_q^{btm}\right| + \left|PSD_q^{mom}\right| \tag{10}$$

$$ASD_q = \left|ASD_q^{size}\right| + \left|ASD_q^{btm}\right| + \left|ASD_q^{mom}\right| \tag{11}$$

A non-zero value of active style drift would primarily occur due to active changes in portfolio weights of stocks through buys and sells. For example, in the style dimension of book-to-market, a fund manager who believes that the book-to-market effect would be unusually strong for the following month could allocate a higher portfolio weight to high book-to-market stocks by purchasing high book-to-market stocks or selling low book-to-market stocks in his portfolios.

3. Data and Sample

3.1 Mutual Fund Holdings Data

Our portfolio holdings data from September 2003 to December 2013 for U.S. actively managed domestic equity funds is 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 (RET), monthly total net assets (TNA), monthly net assets value (NAV) different types of fees including 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. The CRSP Mutual Fund Database also provides information on reported portfolio holdings of mutual funds since September 2003, including the identification of portfolios (crsp_portno), holdings report date (report_dt), the effectiveness date of the report (eff_dt), stock identification number (permno), number of shares held in the portfolio (nbr_shares), and market value of the stocks held (market_val). The holdings data in the CRSP Mutual Fund Database is collected both from reports filed with the SEC and from voluntary reports generated by the mutual funds themselves. The CRSP mutual fund characteristic/returns dataset for each share class of every common mutual fund is linked to the holdings dataset of mutual fund portfolios by using the map (portnomap) provided by the CRSP mutual fund database. The map dataset contains information on the identification of individual share classes (crsp_fundno) and their common funds (crsp_portno) over time, as well as other share class characteristics including delist date, delist type, and the identification of the acquirer share classes and the latest available date for monthly net assets value for target share classes.

3.2 Price and Accounting Data

Data on stock identification, stock return, delist return, share price, trading volume, cumulative price adjustment factors, cumulative shares adjustment factors, and shares outstanding as well as other stock characteristics are obtained from the CRSP stock price database. This CRSP price dataset[5] is then merged with the CRSP Mutual Fund database by matching stock identification (permno) and holding report date (report_dt). This study estimates mutual fund trades by tracking changes in holdings from report to report. In order to follow changes in stock holdings correctly, the number of shares held in portfolios is adjusted by the CRSP cumulative shares adjustment factors.[6] Data used to estimate book value of equity for stocks in the way by Daniel and Titman (1997) are retrieved from Compustat, including shareholders' equity (SEQ), deferred taxes (TXDB), investment tax credit (ITCB), and preferred stock (PREF). Industry classifications (SIC) are obtained from the CRSP stock file and Compustat whenever available.

3.3 Sample Selection

This study follows and modifies the procedure of Kacperczyk *et al* (2008) to select U.S. domestic equity mutual funds.[7] This study starts with all mutual fund samples in the CRSP Mutual Fund Database universe. Since the focus of the analysis is on actively managed U.S. domestic equity mutual funds for which holdings data are most complete and reliable, this study eliminates 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. This screening procedure generates a sample of 109054 fund-report observations with a total of 3384 unique U.S. domestic equity mutual fund samples from September 2004 to December 2013. Table 1 reports the summary statistics relating to our sample of mutual funds and Appendix A provides the detailed screening procedure.

4. Empirical Results

4.1 Aggregate Characteristic-Timing Performance

This study first reports an overview of fund performance of our sample of U.S. domestic equity mutual funds over the 10-year period from 2004 to 2013. Column (2) to column (4) of Table 2 provide a year-by-year comparison of the average gross returns of all mutual funds in the sample with the average buy-and-hold monthly return for the CRSP value weighted and equally weighted NYSE/AMEX/NASDAQ portfolios without distribution. Comparisons indicate that at first glance, mutual fund managers appear to outperform the two passive portfolios of the CRSP stock universe. For instance, the average gross

[5] Stock return is adjusted for delist events, share price is adjusted by cumulative price adjustment factors, and share outstanding is adjusted by cumulative shares adjustment factors.

[6] The CRSP Mutual Fund Holdings Database changed its data source since October 2010. Before October 2010, the reported number of shares in portfolio for stock distribution events such as splits is already adjusted and therefore we need to re-adjust it back before calculating changes in shares and market value of holdings.

[7] This report also follows a note written by Glushkov and Moussawi (2010) from WRDS on selecting actively managed U.S. domestic equity mutual funds.

return of mutual funds before any expense and commissions is 11.29%, while the value-weighted (equally-weighted) hypothetical portfolio of all stocks in CRSP universe is only 7.39% (9.23%) for the period from 2004 to 2013 in our study. However, this outperformance does not hold when we control for the cross-sectional differences in stock returns, due to stock characteristics of size, book-to-market and momentum effects by using the Daniel *et al* (1997) performance measures.

In particular, the last three columns on the right of Table 2 report the three different performance attributes proposed by Daniel *et al* (1997). "CS Performance" captures the stock picking ability of mutual fund managers by mitigating performance generated due to cross-sectional differences in stocks returns attributable to the size, book-to-market, and momentum anomalies. Results in Table 2 indicate that on average mutual fund managers have a negative but insignificant stock selectivity ability over the sample period from 2004 to 2013, with statistically insignificant -2 basis point per year before expense. Yearly results also show that, on average, stocks held in mutual fund portfolios could not outperform passive characteristic-benchmark portfolios. Overall, these results are consistent with the consensus view in the literature that on average mutual fund managers are not able to outperform their passive benchmarks. Recent empirical studies in the U.S. market suggest little or no evidence of superior mutual fund performance.[8]

The CT measure is designed to detect any additional performance from successfully timing stock characteristics. Overall, we can see that on average, CT performance is -37 basis points per year but is statistically insignificant with a t-statistic -1.57 from 2004 to 2013, consistent with the results of Daniel *et al* (1997). In other words, mutual fund managers do not exhibit any characteristic timing skills, but instead, there is weak evidence to show that they actually have negative timing performance at a marginally significant level. Separate yearly results show that CT measure is negative but insignificant in eight years except for year 2008. Sub-period results confirm that there is no evidence of timing skills: average CT performance is -42 basis points per year but is insignificant with a t-statistic of -1.61 before the recession, while average CT performance is -46 basis points per year, statistically significant at 10% level, with t-statistic of -1.82, after the recession. Fund managers tend to have economically significant and negative characteristic-timing performance during expansion period. Interestingly, during the recession from December 2007 to June 2009, CT performance is only -3 basis points per year, and it is not statistically different from zero. The difference in characteristic-timing performance between recession and expansion market conditions is economically meaningful and it is mainly driven by the poor performance during the expansion periods. In other words, fund managers appear to have some timing abilities, at least showing non-negative characteristic-timing performance, during the recession. This finding is consistent with Kacperczyk *et al* (2014) who find that fund managers have time-varying

[8] See e.g., Blake and Timmermann, 1998; Blake et al 1999; Thomas and Tonks, 2001, Cuthbertson *et al*, 2008.

skills. Fund managers tend to perform stock picking well in expansions and time the market well in recessions.

Table 3 reports the CS, CT, and AS performance attribution components for funds in different investment categories. Panel A shows that in the analysis of the entire sample period on average, CS performance for all mutual fund investment categories is never statistically significant, indicating that none of the mutual fund categories on average is able to outperform their passive benchmark portfolios. In terms of characteristic-timing ability, only Micro-Cap mutual funds exhibit negative and statistically significant CT performance, with an average -79 basis points per year, while the other investment objectives have negative but insignificant CT performance. Sub-period analysis provides strong evidence that no investment category of fund managers possesses positive characteristic-timing skills while fund managers in some investment categories exhibit positive stock-picking performance in expansions but significantly negative performance in recessions.

To summarize, we find that on average, mutual fund managers exhibit no superior investment performance. In particular, mutual fund managers have negative but insignificant stock selection ability over our sample period, indicating that fund managers are not able to pick stocks that deliver risk-adjusted abnormal performance. More interestingly, there is some evidence to show that fund managers appear to have, if any, negative characteristic-timing performance. In other words, fund managers tend to change the weights on the characteristics of the stocks held in the portfolios along the dimensions of size, book to market, and momentum in the wrong way, or at least they are not able to exploit the time-varying expected returns of these stock characteristics.

4.2 Buying and Selling Abilities

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 the domain. Chen *et al* (2013) point out that the traditional CT measure, which is simply calculated by aggregating the characteristic timing performance of all holdings, would mask the distinct trading skills where the CT performance for buying and selling are calculated separately.

To explore distinct trading abilities, this study follows Chen *et al* (2013) to decompose aggregate CT performance into different trading components. Specifically, for each fund, we measure the changes in number of shares held in each stock from the end of quarter *t-1* to the end of quarter *t* for each quarter in the sample period. Increases in the number of shares are treated as buys and aggregated to form the buy portfolio and decreases are aggregated to form the sell portfolio, for each fund each quarter. Additionally, we aggregate stocks with no changes in number of shares between two quarters into the passive holding portfolio. This study then calculates the characteristic-timing performance for each trading portfolio. If a fund's purchases of stocks are associated with subsequent performance above prior average returns from stock characteristics, the characteristic-timing performance for the buy portfolio will be positive; if sales of stocks are associated with subsequent returns higher than prior average returns from stock characteristics, the characteristic-timing performance for the sell portfolio will also be positive. Similarly, if passive holdings are effective in terms of subsequent performance, the characteristic-timing performance for passive holdings will equally be positive. If a fund exhibits positive time series average characteristic-timing performance along buying (selling) dimension, this indicates that this fund manager possesses superior buying (selling) skill.

Panel A in Table 4 reports the CT performance for buying, selling and passive holdings for equity mutual funds during the whole sample period from September 2004 to December 2013. The second column reveals that whereas no overall characteristic-timing ability measured by aggregate characteristic-timing performance is found, this masks different skills along buying and selling dimensions. In general, mutual fund managers (All Funds) appear to exhibit significant timing ability when purchasing stocks. For example, mutual fund managers earn an average return of 1.42% per year (t-statistic=1.65) greater than the average across the three characteristic styles from their purchases, indicating that mutual fund managers possess skills in this domain. When breaking down mutual funds by their investment objectives, we find some evidence to show that growth oriented mutual funds (Growth and Mid-Cap funds) possess significant timing ability for buying stocks, while income oriented mutual funds (Growth & Income and Income funds) exhibit no statistically significant characteristic-timing performance when purchasing stocks. The difference of buying performance between growth and income funds is economically significant.

Our results show that none of the investment categories of mutual funds earn significant characteristic-timing performance from holding the same stocks. This is consistent with the literature, suggesting that passive holdings represent fund managers' past investment beliefs and are not useful measures for detecting investment ability (e.g., Chen *et al*, 2000). Our findings therefore contribute to the literature by showing a similar result in terms of characteristic-timing ability.

More interestingly, mutual fund managers exhibit poor characteristic-timing abilities when disposing of stocks in their portfolios. In general, the stocks mutual fund managers sell are associated with subsequent negative characteristic-timing returns of -1.78% per year (t-statistic=-1.86). None of the fund investment categories shows positive characteristic-timing performance for selling. These results indicate that on average, mutual fund managers are not able to generate characteristic-timing performance when selling their stocks but instead destroy the characteristic-timing performance generated from their buying activities.

To summarize, our results show that fund managers appear to possess significant timing ability over stock characteristics when purchasing stocks. In particular, growth oriented funds have greater stock buying skills than other income oriented funds. We also reveal that mutual fund managers seem to systematically fail to time the stock characteristic styles when selling stocks. None of the investment categories exhibit significant and positive characteristic-timing skills for selling. Overall, these findings are consistent with the fundamental asymmetry between buy and sell decisions in terms of trading disciplines found in the investment community. This study also offers empirical support to the theoretical predictions from the behavioral finance literature that sell decisions are susceptible to behavioral biases and heuristics that might affect investment performance.

4.3 Characteristic-timing Performance Persistence

To test for persistence of characteristic-timing performance, this study first sorts mutual funds into five performance quintiles each quarter based on aggregate, buying and selling CT measures respectively. We report the average characteristic-timing performance of each of the performance quintile portfolios during the formation quarter and track the performance over the subsequent four quarters. Panel A in Table 5 summarises the persistence results for aggregate performance while Panel B and Panel C present persistence results for trading activities.

There is weak evidence in Panel A to show that the difference in aggregate performance between past winners and losers continues to remain positive in the following four quarters after portfolio formation, suggesting that aggregate characteristic-timing performance is persistent. Surprisingly, a closer look reveals that such persistence of aggregate performance is mainly driven by the persistence of characteristic-timing performance in the negative domain. In particular, losers in performance quintile 1 who exhibit the worst characteristic-timing performance (-7.64% per year) in the formation quarter continue to have negative quarterly characteristic-timing performance of -0.87%, -0.46%, -0.87% and -0.75% per year in the following four quarters, while the future performance of past winners (7.26% per year) turn out to be negative immediately after the formation quarter. These results are consistent with recent studies such as Teo and Woo (2001) and Cuthbertson *et al* (2008) who observe strong persistence among poorly performing funds.

Panel B shows that the characteristic-timing performance when buying stocks is persistent. In particular, on average mutual funds in the performance quintile 1 that have the worst CT_{buy} performance in the formation quarter have positive CT_{buy} performance of 1.00%, 1.53%, 1.36%, and 1.41% per year in the subsequent four quarters. On the other hand, mutual funds that are particularly successful in buying stocks continue to have positive and statistically significant CT_{buy} performance of 2.39%, 1.85%, 1.94%, and 1.67% per year in the following four quarters. The performance difference between past winners and losers remain positive over four quarters and the outperformance of past winning funds is a statistically and economically significant average of 1.38% per year for at least the following quarter Q+1. These results suggest that a small number of fund managers have “hot hands” to buys stocks: fund managers who have the best past buying performance continue outperform those who display the worst buying ability in near term.

Similarly, results in Panel C report that mutual fund managers seem to have persistently bad characteristic-timing ability for selling. Mutual funds with the lowest CT_{sell} performance in the quintile formation quarter display negative performance of -2.83%, -2.28%, -2.56%, and -2.14% per year while mutual funds with highest past CT_{sell} performance exhibit negative performance of -1.44%, -1.90%, -1.55%, and -1.74% per year during the following four quarters. Past losers continue to underperform past winners by a statistically significant amount of 1.43% in quarter Q+1. This underperformance is also economically meaningful. These results suggest that there is a small number of mutual fund managers who exhibit "icy hands" in selling stocks in short term.

This study documents the strong persistence of aggregate characteristic-timing performance in the negative domain over the following four quarters, indicating that mutual fund managers do not possess characteristic-timing ability in aggregate but instead a subset of fund managers tend to have poor timing ability that persistently destroys portfolio value. We also find strong evidence to show that characteristic-timing performance along both buying and selling dimensions is persistent in near term. In particular, mutual fund managers who exhibit superior characteristic-timing performance when buying stocks in the past tend to continue performing buying tasks well, while those who were the worst performers in selling stocks tend to underperform in the sell domain in short term. Extreme positive (negative) performance for selling (buying) is due to good (bad) luck. These results reinforce our main hypothesis that mutual fund managers have distinct trading skills.

4.5 Do Investor Flows Act as Drag of Characteristic-Timing Performance?

The structure of open-end mutual funds forces fund managers to trade in response to fund flows. First, an important role of open-end mutual funds is to provide liquidity to investors. Fund managers are required by law to pay a proportional share of the net asset value of the fund to each investor who chooses to redeem their investment. Second, since fund managers' compensation depends on their ability to track and beat their benchmark portfolios (e.g., Chevalier and Ellison, 1997; Sirri and Tufano, 1998), they have strong incentives to trade to counteract flow shocks so that they can maintain the efficient fraction of equity investment in their portfolios.

One might naturally ask whether, and to what extent, fund flows affect fund performance. In the context of timing performance, consider a mutual fund manager who initially holds some target efficient portfolio in terms of level of risk exposure toward the three stock characteristics. Unanticipated fund flows would then force this fund manager make trades that could his fund portfolio to shift away from his initial efficient target portfolio. When experiencing fund outflows, fund managers often have to sell some of their existing holdings to fulfil investor redemption requirements. In extreme cases, they can also be forced to engage in fire sales (Coval and Stafford, 2007). These liquidity-driven sales can move fund portfolios away from fund managers' intended exposure to style factors because fund managers might need to sell down their liquid positions to avoid a high liquidity premium. On the other hand, despite the need to maintain an efficient fraction of equity investment in their portfolios, fund managers who have fund inflows have more flexibility in their trading: they can accumulate cash for cash redemption needs; they can postpone their equity investment decisions; and they can immediately open new positions or expand their current holdings. If fund managers can take advantage of the financial flexibility provided by investor flows, one should observe better, at least not worse performance by those fund managers with fund inflows compared with those who experience significant outflows.

In contrast with expectations, Table 6 shows that mutual fund managers who experience heavy investor inflows (*NF5*) exhibit statistically and economically significant characteristic-timing returns of -0.85% per year (t-statistic=-2.86), while those who have heavy investor outflows exhibit no characteristic-timing performance. The difference in characteristic-timing performance between *NF1* and *NF5* is significantly positive 0.78% per year (t-statistic=2.80) with this difference driven by the underperformance of mutual funds that experiencing heavy inflows. Moreover, no mutual fund investment objective subgroups exhibits any characteristic-timing performance when experiencing heavy outflows while all subgroups exhibit negative characteristic-timing performance when facing heavy inflows. In particular, income mutual funds appear to have the worst performance when they face extreme investor inflows.

In a further refinement, mutual fund portfolios within each flow quintile are sorted and categorised into another 5 quintile groups based on their active style drift at the end of each quarter. *SD1* refers to portfolios which engage in large active style drift and *SD5* refers to the portfolios which engage in small style drift. The rationale is that when facing investor flows, fund managers could simply proportionally adjust current holdings to minimise the impact of inflow shock to portfolio risk exposure and control liquidity. They will engage in active style drift along the three stock characteristics by buying (selling) stocks, when and only when they strongly believe that these stocks will have good (poor) future characteristic-timing performance. In other words, managers who strongly believe that certain stock characteristics would have superior future performance will make active style changes moving their portfolio equity style factors from one category to another over the quarter. But managers who need to control for liquidity will make smaller adjustments across the three characteristics. If this is the case, one should observe that the portfolios with high level of active style drift when experiencing heavy unanticipated flows have better subsequent characteristic-timing performance. However, if these style bets are motivated by reasons other than valuation beliefs, a negative relationship should be observed.

Table 7 reports aggregate characteristic-timing performance results for mutual fund portfolios categorized by active style drift and concurrent investor flows. The first three rows and three columns of each panel report results from two way sorting on net investor flows and active style drift. The fourth row and fourth column present results from one-way sorting only on active style drift and net investor flows, respectively. The fifth row and fifth column report the difference between the extreme investor flow and active style drift quintiles.

Consider now the upper left-hand corner of Panel A where we find *NF1/SD1* (i.e., large active style drift concurrent with heavy outflows), the fund portfolios that should reflect managers' strong beliefs about the future performance of certain stock characteristics. Inconsistent with the expectation, *NF1/SD1* exhibits a negative but marginally significant -0.92% characteristic-timing return per year. Similarly, as we move down to *NF5/SD1* (i.e., large active style drift concurrent with heavy inflows), reflecting the large style bets of mutual fund managers when they have financial flexibility. These portfolios are associated with economically and statistically significant characteristic-timing returns of -1.76% per year (t-statistics=-2.78). These results therefore provide evidence for the competing hypothesis that active timing decisions might be motivated by reasons other than valuation beliefs, such as overconfidence.

Small style drifts could be simply motivated by the need to control liquidity. When fund managers face heavy outflows, they could proportionally reduce their existing holdings to raise cash. These sales are more likely to be driven by liquidity needs, and thus are less likely to reflect managers' valuation beliefs. Consistent with our expectation, *NF1/SD5* (i.e., small active style drift concurrent with heavy outflows) shows a statistically and economically insignificant -0.02% characteristic-timing return per year. Similarly, fund managers could proportionally expand their holdings when experiencing significant inflows. *NF5/SD5* (i.e., small active style drift concurrent with heavy inflows) exhibits a negative statistically significant -0.90% characteristic-timing return per year. We interpret these results as consistent with no significant characteristic-timing ability.

Inconsistent with Simutin (2014) who argue that financial flexibility allows fund managers to satisfy redemption requests and capture investment opportunities quickly, our results suggest that fund managers seem to be not able to take advantages of the financial flexibility provided by fund inflows. Instead, excessive cash holdings from fund inflows impose a significant drag on characteristic-timing performance. This argument is confirmed by the results of further investigation conditioning portfolios based on the magnitude of active style drifts as a proxy for fund manager conviction. Large style bets that should reflect the strong valuation beliefs when managers have excess cash from investor flows are associated with significantly negative characteristic-timing returns. Furthermore, these surprising results are consistent with the free cash flows hypothesis that is well documented in the corporate finance literature. Free cash flow hypothesis suggests that firms' managers tend to use free cash flows to finance low-return projects (e.g., Jensen, 1986).

4.6 Does Trade Motivation Relate to Trade Performance?

4.6.1 Conditioning on Motivation Score

Chen *et al* (2013) document that mutual fund managers exhibit distinct trading skills by decomposing their aggregate characteristic-timing performance into buying and selling components. Their study, however, gives no consideration to the fact that fund managers provide a great deal of liquidity to investors and that this provision of liquidity forces fund managers to engage in costly trading. Thus, the inference regarding fund manager trading skills in their study can be significantly negatively biased. One might naturally ask whether negative characteristic-timing performance when selling stocks is driven by liquidity-induced sales. This sub-section attempts to address this question.

To increase the test power of the standard characteristic-timing performance measure, we separate fund managers' motivations for trading by conditioning fund purchases and sales on the motivation score metrics of Alexander *et al* (2007). Intuitively, the 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). This approach has several advantages over realised net fund flows. First, motivation score metrics not only consider realised net investor flows between two quarters, but also capture total trading volume from buying and selling actives during the corresponding period. Second, the ranking procedure based on motivation score breaks down possible serial and cross-sectional trading patterns and correlations that might be present in the stock holdings data and therefore could bias results in unexpected ways (Alexander *et al,* 2007).

Panel A of Table 8 provides evidence that buying characteristic-timing ability is strongly related to trade motivations. Consistent with the expectation that mutual fund managers (All Funds) possess positive buying skill, in the case of *BF1* (i.e., large total purchase volume concurrent with heavy outflows), buy portfolios that have the highest proportion of valuation-motivated buys show a statistically and economically significant characteristic-timing return of 1.90% per year higher than the average across the three different characteristic styles. When moving down the rows from *BF1*, one can observe generally decreasing returns because buy portfolios are characterized by a decreasing proportion of valuation-motivated buys and an increasing proportion of liquidity-induced buys. In particular, in the case of *BF5* (i.e., low total purchase volume concurrent with heavy inflows), buy portfolios that consist of the highest proportion of liquidity-driven buys exhibit no statistically significant characteristics-timing returns. As expected, valuation-motivated buys outperform liquidity-driven buys (*BF1*-*BF5*) by an average of 0.93% per year, statistically significant at the 1% level. While this pattern holds for all investment categories, there is some evidence to show that income oriented mutual funds appear to have lower characteristic-timing returns from their valuation-motivated purchases.

In Panel B, the results for sell portfolios are organised in the same ways as for the buy portfolios. Consistent with mutual fund managers (All Funds) having negative selling skill, *SF1* (i.e., high total stock sales concurrent with high inflows), sell portfolios that have the highest proportion of valuation-motivated sales have a statistically and economically significant characteristic-timing return of -1.57% per year. On the other hand, in the case of *SF5* (i.e., low total stock sales concurrent with high outflows), the sell portfolios that have the highest proportion of liquidity-driven sales show an average characteristic-timing returns of -2.24% per year, significant at the 5% level. The difference between valuation-motivated sales and liquidity-driven sales (*SF1-SF5*) is statistically and economically significant at 0.69% per year. This suggests that despite lacking selling ability in general, trade motivation still matters in terms of subsequent characteristic-timing performance. The remaining columns in Panel B demonstrate a similar story, namely that none of the investment categories exhibits positive selling skill and that valuation-motivated sales outperform liquidity-induced sales.

4.6.2 Multivariate Regression Evidence

In this section, we further extend our analysis of fund manager trading skills using multivariate regressions. This approach differs from the above portfolio approach in three major respects. First, a multivariate regression framework can simultaneously control for mutual fund characteristics that might be related to trade motivations or/and fund manager trading performance. Second, fund managers might be motivated to trade due to other reasons, such as for tax management and window-dressing purpose. According to the mutual fund tournament literature, these trades typically occur before the fiscal year end. Regression analysis can effectively control these effects by introducing year-end dummy variables. Third, the portfolio approach aggregates mutual funds of similar trade motivation scores into quintile groups, while the regression approach allows researchers to take advantage of the rich panel structure to directly look at individual mutual funds.

We begin with sorting fund-month observations for each fund based on motivation scores for purchase (*BF*) and divide these observations into high, mid and low motivation score subgroups. An indicator variable, $Valuation_t^i$, is constructed to capture the purchases that are the most likely to be motivated by valuation beliefs, and the other dummy variable $Liquidity_t^i$ is used to identify liquidity-induced purchases. This procedure is repeated for selling skills. 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:

$$Ability_t^i = a_0 + a_1 Valuation_{t-1}^i + a_2 Liquidity_{t-1}^i + a_3 Control_{t-1}^i + \epsilon_t^i$$

where $Ability$ denotes either $Selling$ or $Buying$; $Valuation_{t-1}^i$ is an indicator variable equal to one if the mutual fund *i* is categorised as being more likely to be motivated by valuation beliefs at time *t-1*, and zero otherwise; $Liquidity_{t-1}^i$ is an indicator variable equal to one if the mutual fund *i* is categorised as being more likely to be motivated by liquidity needs at time *t-1*, and zero otherwise. $Control_{t-1}^i$ is mainly a vector of lagged fund-specific control variables, including age (natural logarithm of age in years since first offer date, *log(AGE)*), size (natural logarithm of total net assets under management in millions of dollars, *log(TNA)*), expense ratio (in percent per year, *Expenses*), turnover rate (in percentage per year, *Turnover*), percentage flow (the ratio of $TNA_{i,t} - TNA_{i,t-1} * \left(1 + RET_{i,t}\right) - MGN_{i,t}$ to $TNA_{i,t-1}$, *Flow*), management fee (in percentage 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 trades when fund managers are "normally" motivated, and a_1 indicates how much skills increase when fund managers are motivated by valuation beliefs, while a_2 indicates how much skills decrease when fund managers are motivated by liquidity needs. In addition to these control variables mainly from Kacperczyk *et al* (2014), We also include two variables to control the effect of the financial crisis (defined by the NBER, *Recession*) and the fourth calendar quarter (*4th Quarter*). The latter is motivated by Alexander *et al* (2007) and others working in tournament literature who argue that there is the possibility that some trades may be motivated by tax management or window-dressing reasons which typically occur just before the fund's fiscal year end.

Table 9 examines the variation in buying and selling skills based on trade motivations. Column (1) to Column (3) show the coefficients on trade motivation from the panel regression using the characteristic-timing returns of buy portfolios as the dependent variable. The sign and magnitude of the coefficients on both motivation indicator variables are consistent with the previous analysis based on the trade motivation quintile portfolios across all three model specifications. For example, in Column (3), valuation-motivated purchases are associated with 7 basis points per month or approximately 0.85% per year higher returns than others purchases while liquidity-driven purchases are associated with 4.7 basis points per month or 0.56% per year lower returns than others purchases, after controlling for fund-specific characteristics and time fixed effects. The effects of trade motivation on subsequent performance are economically and statistically significant. Likewise, Column (4) to Column (6) reports that valuation-motivated sales outperform other sales by an average of 4.3 basis points per month or 0.52% per year, while liquidity-induced sales substantially underperform other sales by a statistically and economically significant 12 basis points per month or about 1.43% per year. Again, signs and magnitudes of the coefficients are consistent with previous portfolio analysis.

4.6.3. Conditioning on Motivation Score and Trade Size

Another test of managers' timing ability is attainable by studying their individual stock trades. Trades within each motivation score categorized portfolio are further split into another 5 quintile groups on the basis of their dollar volume. Alexander *et al* (2007) argue that large trades are more likely to be driven by valuation motivation, whereas small trades are more likely to be liquidity motivated. The rationale is that fund managers would want to buy a relatively large amount of stocks that they believe are undervalued, but they are more likely to make smaller-size purchases when dealing excess liquidity from unanticipated investor inflows. Similarly, fund managers would want to sell a relative large amount of stocks when they no longer believe that these stocks are attractive while they might spread the smaller-size sales across the stocks in their the portfolios to meet investor redemption requests.

Panel A of Table 10 summarizes characteristic-timing performance for buy portfolios categorized by net investor flows and trade size. Stocks mutual fund managers purchase in the *BF1/TS1* group (i.e., large buys concurrent heavy outflows) are associated with subsequent significantly positive characteristic-timing returns of 1.61% per year. Moving down the rows from *BF1* to *BF5* and across the columns from *TS1* to *TS5*, generally decreasing trends of characteristic-timing returns are reported as these portfolios are characterised by a decreasing proportion of valuation-motivated, but an increased percentage of liquidity-motivated buys. Difference of characteristic-timing performance between large buys (*TS1*) and small buys (*TS5*) is 1.45% per year in the group where buys are most likely valuation-motivated. This difference goes down to 0.58% per year in the group of lowest valuation-motivated buys. A similar pattern holds when the difference in characteristic-timing performance between valuation-motivated buys and liquidity-motivated buys is conditional on trade size. The difference between the two extreme groups: *BF1/TS1*, which contain the highest proportion of valuation-buys, and *BF5/TS5*, which have the highest proportion of liquidity-motivated buys, is statistically and economically significant with characteristic-timing returns of 1.56% per year. These results are consistent with previous findings that fund managers possess positive buying skill, and that valuation-based purchases outperform liquidity-driven purchases.

Panel B presents the subsequent characteristic-timing returns of fund managers' sells, which are categorized by the *SF* metric and trade size. Characteristic-timing performance for selling in the category *SF1/TS1* (i.e., large sells and high total sales concurrent with heavy inflows) is statistically significant but negative or -0.87% per year. There is a decreasing trend in characteristic-timing performance for sell portfolios characterised by the decreasing proportions of valuation-motivated sells and increasing proportions of liquidity motivated sells from *SF1* to *SF5*. Difference between the category *SF1/TS1* and *SF5/TS1* is significantly positive or 1.91% per year, indicating that even though mutual fund managers have negative characteristic-timing selling ability, trade motivation still matters.

However, when moving across columns from large sells (*TS1*) to small sells (*TS5*), an increasing trend of characteristic-timing performance is observed, which is inconsistent with the expectation that large sells that are more likely to be motivated by valuation beliefs should outperform small sells. Instead, within any net investor flow category from *SF1* to *SF5*, large sells tend to underperform small sells in terms of subsequent characteristic-timing returns. When experiencing heavy investor outflows, mutual fund managers appear to exhibit significantly negative characteristic-timing returns of -2.73% per year from large sells (*SF5/TS1*), while insignificant but positive characteristic-timing performance of 0.03%

per year from small sells (*SF5/TS5*). The difference between these two groups is statistically and economically significant. We interpret this finding as consistent with the notion that mutual fund managers have negative timing ability when selling stocks. Large bets when selling stocks might be more likely to reflect other reasons than valuation beliefs, such as behavioral bias.

Overall, by segmenting trades based on the motivation for making them, we find evidence that trade motivations are strongly related to subsequent trade performance. In particular, valuation-motivated trades significantly outperform liquidity-induced trades, and this pattern holds for both buying and selling dimensions. However, fund managers appear to exhibit negative selling ability even when they are highly motivated by valuation beliefs, which directly supports and extends the argument of Chen *et al* (2013) who show that in general mutual fund managers exhibit poor selling characteristic-timing abilities. These findings are robust when using a multivariate regression approach to control for fund characteristics and time fixed effects.

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

Findings reported thus far show that mutual fund managers on average possess apparent buying skill but exhibit negative selling skill which is consistent with Chen *et al* (2013). By conditioning on trade motivations, further evidence does not improve this unfavourable finding regarding selling ability. Instead, valuation-based sales are associated with significantly negative subsequent characteristic-timing returns, indicating that on average fund managers exhibit negative selling skill even when these sales are motivated by valuation beliefs. However, such underperformance in general does not necessarily mean that no mutual fund managers possess good selling skills. Most studies in the literature on mutual fund performance treat fund managers as a homogeneous class of professional investor, and have not yet explored whether one group of fund managers is better at buying and another group of fund managers specialise in selling, or that a small subset of managers can perform both buying and selling well.

To examine whether different groups of fund managers possess different skills, we begin by testing the prediction that the same mutual funds that exhibit good selling skills display good buying skills. Since valuation-motivated trades are more likely to reflect the true trading skills of fund managers, we first identify "good sellers", those mutual funds with superior selling ability when they are most likely to be motivated by valuation beliefs. To achieve this, for each fund, we divide all fund-month observations into three subsamples according to motivation scores for selling (*SF*). Within the subsamples of fund-month observations that are mostly likely to have the highest proportion of valuation-motivated sales (high motivation score), we select fund-month observations that are in the highest 25% of the $Selling_t^i$ distribution. Then, an indicator variable *Top* ($Top_i \in \{0, 1\}$) is formed to identify those managers who have the best record for valuation-motivated selling, which is equal one for the 25% of funds with the highest fraction of observations (months) in that group, relative to the total number of observations for that fund in the high motivation score subsample. Next we estimate the following pooled panel data regression model:

$$Ability_t^i = c_0 + c_1 Top_t^i + c_2 Control_{t-1}^i + \epsilon_t^i$$

Where $Ability$ denotes either $Selling$ or $Buying$, Top denotes either "good sellers" or "good buyers", and $Control$ is a vector of previously defined control variables. The coefficient of interest is c_1.

Table 11 summarises the pooled panel data regression estimates with different model specifications. Column (3) shows that on average "good sellers" are significantly better at characteristic-timing when selling stocks than all other funds, after controlling for fund characteristics and other time effects. The coefficient of the indicator variable Top is statistically and economically significant. This is true given the way "good sellers" are identified. When mutual fund managers are highly motivated by valuation beliefs, $Selling$ is 11.2 basis points per months or 1.35% higher for "good sellers" than for the remaining funds. The main point of Table 11 is that the same "good sellers" are on average also better at $Buying$ when they are motivated by valuation beliefs. Column (6) presents the positive coefficient on the indicator variable Top, which is statistically significant at the 1% level. The effect is also economically meaningful. $Buying$ is 7.2 basis points per month or 0.87% per year higher for the same "good sellers" than for all other funds. In sum, these results suggest that there are a small number of mutual fund managers who possess selling skill and also exhibit positive buying skill.

We repeat the above analysis procedure for "good buyers" who are the funds in the top 25% of the buying skill distribution. In Table 12, Column (3) shows that on average "good buyers" are significantly better at buying stocks than all other funds, after controlling for fund characteristics and other time effects, which follows the construction of the "good buyer" set of funds. These successful buyers exhibit 30.7 basis points per month or 3.75% per year higher characteristic-timing performance when buying stocks based on valuation beliefs. Strikingly, these "good buyers" are not able to outperform the other funds when selling stocks. This result is evident from the negative but statistically insignificant coefficient on Top in column (6). Overall, it is very interesting to see that "good sellers" who by construction are good at selling ability also possess good buying ability, while "good buyers" who by construction are significantly successful at characteristic-timing when buying stocks are not able to outperform all other funds when selling stocks. In other words, "good sellers" are also "good buyers" but "good buyers" are not "good sellers".

If the same "good sellers" are able to time stock characteristics well when buying and selling stocks in their portfolios, then these fund managers should also outperform unskilled funds in terms of aggregate characteristic-timing, whereas "good buyers" who are good at buying but are not capable of selling might not be able to exhibit superior aggregate characteristic-timing ability. To investigate this, we estimate the above pooled panel data regression with aggregate characteristic-timing performance as dependent variables for "good sellers" and "good buyers" separately. Consistent with expectation, Column (3) of Table 13 shows that aggregate characteristic-timing performance is 2.6 basis points per month or 31.2 basis points per year higher for "good sellers" than all other funds, which is statistically significant at the 1% level after controlling for fund characteristics and time effects. Column (6) shows that the coefficient of Top for "good buyers" is economically and statistically insignificant, indicating that on average "good buyers" exhibit no aggregate characteristic-timing ability. These results indicate that there are a small number of mutual fund managers that possess timing abilities, and the superior characteristic-timing performance is mainly attributed to their selling skills.

These findings are robust to changing the cut-off levels for inclusion in the Top portfolio and using an alternative way to identify "good sellers" or "good buyers" by conditioning on trade motivation based on net investor flows. The main findings that good sellers are also good buyers but good buyers are not necessarily good seller and that good sellers possess superior aggregate characteristic-timing ability hold.

To summarise, we find strong evidence to suggest that there are a small number of mutual funds in our sample that possess both good buying and selling skills in timing stock characteristics along the size, book-to-market, and momentum dimensions. By estimating panel data regressions of characteristic-timing performance on the indicator variable for "good sellers", our results reveal that "good sellers", namely mutual fund managers who by construction have the best performance record for selling, also have superior characteristic-timing performance when buying stocks compared with all other funds, after controlling for fund characteristics and time effects. However, there is no evidence to show that "good buyers" who by construction are good at buying exhibit superior characteristic-timing performance when selling stocks than all other funds. Furthermore, "good sellers" exhibit superior aggregate characteristic-timing performance, while "good buyers" do not have outperformance. We interpret this as being consistent with the behavioral finance literature which shows that sell decisions are particularly difficult because they are more likely to be susceptible to behavioral biases and heuristics, even for mutual fund managers who are skilled at buying. Fund managers who are good at the difficult task of selling stocks perhaps possess genuine investment talents so that not only do they outperform other funds when buying stocks, but they also exhibit superior aggregate characteristic-timing performance.

4.8 The Characteristics of Good Sellers

Table 14 summarises the fund characteristics of "good sellers" in comparison with the remaining funds. Several interesting differences emerge. First, "good sellers" are younger than other fund managers in our sample. Second, they have less assets under management, suggestive decreasing returns to scale at the fund level (e.g., Berk and Green, 2004). Third, "good sellers" appear to charge higher expenses and management fees to fund investors, perhaps reflecting higher rents to their customers for their superior skills. Fourth, they exhibit higher portfolio turnover, indicating that these mutual funds are more active than other funds. Fifth, they tend to hold portfolios with a smaller number of stocks, and therefore, tend to be somehow more concentrated. Finally, they are more likely to actively engage in style drift, suggesting that their superior characteristic-timing performance comes from active style drift along the size, book-to-market, momentum dimensions. In sum, in line with previous studies that find there does exist a subset of skilled managers, "good sellers" seem to be younger, manage smaller funds and are more active as measured by turnover ratio, diversification, and active style drift than all other funds, but they also charge higher expenses and management fees to compensate for their superior skills.

5. Conclusion

This study examines whether mutual fund managers, a representative group of professional investors, exhibit investment abilities, and in particular, whether they possess the skill to produce performance from adjusting portfolio exposure to the risk factors of size, book-to-market and momentum effects. Consistent with Daniel *et al* (1997) and others, we find no evidence of significant aggregate characteristic-timing skill. However, we show strong persistence of aggregate characteristic-timing performance in the negative domain. Mutual fund managers do not possess characteristic-timing ability in aggregate but instead a subset of fund managers tend to have poor timing ability that persistently destroys overall portfolio value.

In an attempt to explain such underperformance from characteristic-timing decisions, this study disaggregates overall characteristic-timing performance into different trading components. Consistent with Chen *et al* (2013), our results show that in general mutual fund managers possess positive characteristic-timing ability when buying stocks but negative trading ability when selling stocks. Performance persistence tests confirm that these distinct trading "skills" are driven by systematic factors. Mutual fund managers who were successful in buying stocks tend to continue generating superior characteristic-timing performance when purchasing stocks, while those who were the worst sellers tend to remain underperforming when disposing of stocks in near term. In other words, there are a small number of mutual funds exhibiting "hot hands" ("icy hands") in buying (selling) stocks.

By conditioning trades on the motivation for making them, our results shows that valuation-motivated trades are associated with higher subsequent characteristic-timing performance than liquidity-driven trades, which is consistent with predications from the literature. Perhaps more interestingly, stocks sold by managers who have excess liquidity following significant investor inflows, which are expected to have a higher proportion of valuation-motivated sales, are on average still associated with statistically significant negative characteristic-timing returns. These results suggest that average managers seem to be unable to generate positive characteristic-timing performance when selling stocks, even when these sales are valuation-motivated.

This study further investigates the proposition that there is a group of fund managers who are particularly good at selling, while another group of managers have strong buying skills, or alternatively, the same group of managers can perform both tasks well, or badly. We find clear evidence that there are a small number of mutual funds in our sample that possess both good buying and selling skills in timing stock characteristics along the size, book-to-market, and momentum dimensions. Results reveal that “good sellers”, those fund managers who have the best performance records for selling, also show superior characteristic-timing performance when buying stocks compared with all other funds. However, there is no evidence to show that “good buyers” exhibit any superior characteristic-timing performance when selling stocks over and above all other funds. Furthermore, “good sellers” exhibit significant aggregate characteristic-timing performance, while “good buyers” do not outperform other funds in aggregate. Comparing fund-specific characteristics with other funds, “good sellers” appear to be younger, smaller in size, and more active in managing their portfolios as measured by turnover ratio, diversification, and active style drift. However, they also tend to charger higher expenses and management fees to compensate for their superior skills.

Overall, our study contributes to the ongoing debate about whether professional investors possess special investment skills or talents. Our findings suggest that the lack of evidence of overall mutual fund performance documented in the literature masks distinct trading abilities. In particular, while fund managers are able to perform buy decisions well, they seem to possess negative selling ability. This finding is consistent with the hypothesis that sell decisions are more likely to be susceptible to behavioral bias. Even for professional investors, sell decisions are particularly difficult.

Future work might explore the mechanisms by which behavioral biases 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 documented in recent studies (e.g., Cuthbertson et al, 2008) which suggest the inferior performance of most poorly performing funds is not merely due to bad luck, but to “bad skill”. These questions are left for future research.

Table 1 Summary Statistics of Mutual Fund Samples

The table below reports the summary statistics of a total of 3384 unique U.S. domestic equity mutual fund samples from September 2004 to December 2013. The mutual fund data with self-reporting investment objectives including Growth, Growth & Income, Income, 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. CRSP investment objective variable (crsp_obj_cd) is used to filter U.S. domestic equity mutual funds from the CRSP mutual funds universe in CRSP mutual fund database. The mutual funds are broken down by the CRSP investment objectives, including growth, growth & income, income, micro-cap, small-cap, and mid-cap. Total number of funds is the total number of unique mutual funds that exist during the sample periods. Avg number of stocks is the times series average of cross-sectional average of the number of unique stocks held by mutual funds during the sample periods. Avg TNA is times series average of cross-sectional average of total net assets under management of mutual funds. Avg Flow is time series average of cross-sectional average of estimated percentage change in TNA adjusted for investment return and mutual fund mergers. Avg Turnover is time series average of cross-sectional average of mutual fund turnover ratio. Avg Exp is time series average of cross-sectional average expense ratio 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.

	Total Number of Funds	**Avg Number of Stocks**	**Avg TNA (in $ Million)**	**Median TNA (in $ Million)**	**Avg Flow (%/Month)**	**Avg Turnover (%/Year)**	**Avg Exp Ratio (%/Year)**
Panel A: Summary statistics of all mutual fund samples over time							
2004	1360	126.94	$1,327.63	$178.00	7.24	89.54	1.34
2005	1459	120.09	$1,354.98	$197.80	5.56	86.17	1.29
2006	1479	112.61	$1,512.18	$224.40	3.95	86.13	1.28
2007	1638	114.71	$1,483.71	$202.20	2.63	91.09	1.25
2008	2046	115.75	$821.48	$124.40	0.31	88.76	1.19
2009	2022	122.04	$1,059.28	$162.75	1.89	100.46	1.20
2010	2727	109.65	$1,097.55	$210.40	3.05	90.41	1.18
2011	2612	103.05	$1,011.80	$201.85	1.57	83.66	1.16
2012	2577	117.82	$1,105.19	$218.70	1.19	79.77	1.12
2013	2454	120.80	$1,502.37	$321.85	7.29	72.94	1.10
Panel B: summary statistics of mutual fund with different investment objectives							
All	3384	115.90	$1,217.94	$205.20	7.25	87.19	1.22
Growth	1529	100.48	$1,933.87	$254.50	10.89	92.59	1.22
Growth&Income	576	103.45	$1,332.02	$181.00	4.68	71.76	1.11
Income	191	78.90	$1,508.81	$317.60	14.48	48.60	1.09
Micro-Cap	50	111.93	$187.91	$101.65	2.71	92.92	1.66
Small-Cap	679	170.93	$843.47	$233.75	1.55	89.91	1.29
Mid-Cap	470	113.35	$728.33	$201.60	5.99	97.00	1.24

Table 2 Mutual Fund Performance in Aggregate, All Samples

This table below reports the average buy-and-hold monthly return for the Centre for Research in Security Prices value weighted and equally weighted NYSE/AMEX/NASDAQ portfolio without distribution and equally weighted portfolio of all mutual funds existing during the years with a self-declared investment objectives of growth, growth & income, income, micro-cap, small-cap, and mid-cap over time from 2004 to 2013. The gross return is estimated based on the monthly returns of the holdings of mutual funds before management fees and commissions. The CS performance, the CT performance, and the AS performance are calculated as Daniel *et al* (1997). Specifically, the CS performance is measured as the difference between the time t return of the portfolio held at time t-1 and the time t return of the time t-1 matching benchmark portfolio. The CT performance is calculated as the difference between the time t value weighted return of benchmark portfolio of stocks held at time t-1 and the time t value weighted return of benchmark portfolio of stocks held at time t-13. The AS performance is the time t value weighted return of benchmark portfolio of stocks held at time t-13. The time series average of annualized monthly returns and t-statistics are presented below (t-statistics in parentheses).

Year	CRSP VW	CRSP EW	Gross Return	CS Performance	CT Performance	AS Performance
2004	39.86%	73.82%	28.96%	0.67%	-1.15%**	28.58%
				(0.72)	(-2.27)	
2005	5.77%	4.40%	17.89%	1.86%*	-0.45%	15.63%
				(1.99)	(-1.06)	
2006	14.28%	17.28%	10.54%	-1.46%	-0.58%	12.53%
				(-1.51)	(-1.31)	
2007	5.78%	-4.53%	-2.40%	0.55%	-0.05%	-2.82%
				(0.33)	(-0.09)	
2008	-37.97%	-42.53%	-36.99%	2.95%	1.54%*	-39.02%
				(1.36)	(1.79)	
2009	31.10%	65.88%	41.87%	-6.30%	-1.74%	51.99%
				(-1.37)	(-1.20)	
2010	17.20%	24.91%	30.50%	0.75%	-0.22%	29.35%
				(0.80)	(-0.67)	
2011	-1.78%	-9.39%	6.09%	0.17%	-0.03%	5.84%
				(0.19)	(-0.05)	
2012	13.54%	14.78%	17.38%	0.52%	-0.69%	17.30%
				(0.59)	(-1.29)	
2013	27.66%	28.58%	34.38%	1.02%*	-0.86%	33.24%
				(1.72)	(-1.31)	
2004-2007	11.35%	10.89%	12.99%	0.78%	-0.42%	12.17%
				(1.51)	(-1.61)	
2007-2009	-23.68%	-18.00%	-15.84%	-2.80%	-0.03%	-13.04%
				(-0.80)	(-0.03)	
2009-2013	16.60%	18.11%	21.46%	0.43%	-0.46%*	21.06%
				(1.08)	(-1.82)	
2004-2013	7.39%	9.23%	11.29%	-0.01%	-0.37%	11.44%
				(-0.01)	(-1.57)	

* Significant at the 10% level.

** Significant at the 5% level.

*** Significant at the 1% level.

Table 3 Mutual Fund Performance in Aggregate, by Investment Objectives

This table below reports the average buy-and-hold monthly return for the Centre for Research in Security Prices value weighted and equally weighted NYSE/AMEX/NASDAQ portfolio without distribution and equally weighted portfolio of all mutual funds existing during the years with a self-declared investment objectives. The mutual funds are broken down by the CRSP investment objectives, including growth, growth & income, income, micro-cap, small-cap, and mid-cap. Panel A reports average mutual funds' performance during the whole sample period from 2004 to 2013. In order to examine the difference of mutual fund performance for time-varying market conditions, Panel B, Panel C, and Panel D presents the average performance of mutual funds for sub-sample periods from September 2004 to December 2007, from December 2007 to June 2009, and from June 2009 to December 2013. The gross return is estimated based on the monthly returns of the holdings of mutual funds before management fees and commissions. The CS performance, the CT performance, and the AS performance are calculated as Daniel *et al* (1997). Specifically, the CS performance is measured as the difference between the time t return of the portfolio held at time t-1 and the time t return of the time *t-1* matching benchmark portfolio. The CT performance is calculated as the difference between the time t value weighted return of benchmark portfolio of stocks held at time *t-1* and the time t value weighted return of benchmark portfolio of stocks held at time *t-13*. The AS performance is the time t value weighted return of benchmark portfolio of stocks held at time *t-13*. The time series average of annualized monthly returns and t-statistics are presented below (t-statistics in parentheses).

Objective	Gross Return	CS Performance	CT Performance	AS Performance
Panel A September 2004-December 2013				
All	11.29%	-0.01%	-0.37%	11.44%
		(-0.01)	(-1.57)	
Growth	10.67%	0.07%	-0.28%	10.69%
		(0.11)	(-0.95)	
Growth&Income	9.89%	-0.26%	-0.58%	10.71%
		(-0.60)	(-1.61)	
Income	9.86%	-0.21%	-0.66%	10.72%
		(-0.27)	(-1.43)	
Micro-Cap	12.19%	1.00%	-0.79%**	12.19%
		(0.85)	(-1.98)	
Small-Cap	12.97%	-0.15%	-0.40%	13.09%
		(-0.15)	(-1.12)	
Mid-Cap	12.48%	0.21%	-0.20%	12.12%
		(0.23)	(-0.74)	
Panel B September 2004-December 2007				
All	12.99%	0.78%	-0.42%	12.17%
		(1.51)	(-1.61)	
Growth	12.73%	0.03%	-0.49%	12.32%
		(0.96)	(-1.39)	
Growth&Income	11.90%	0.24%	-0.38%	11.94%
		(0.50)	(-0.73)	
Income	11.56%	-0.01%	0.22%	11.20%
		(-0.04)	(0.36)	
Micro-Cap	13.15%	2.83%**	-0.96%*	10.27%
		(2.08)	(-1.91)	
Small-Cap	13.27%	0.99%	-0.24%	11.68%
		(1.55)	(-0.78)	
Mid-Cap	15.09%	1.56%**	-0.55%***	13.36%
		(2.01)	(-3.03)	

Table 3 *continued*

Objective	Gross Return	CS Performance	CT Performance	AS Performance
Panel C December 2007-June 2009 (Recession)				
All	-13.04%	-2.80%	-0.03%	-13.04%
		(-0.80)	(-0.03)	
Growth	-16.57%	-1.79%	0.41%	-15.14%
		(-0.60)	(0.33)	
Growth&Income	-17.06%	-2.45%	0.05%	-14.85%
		(-1.17)	(0.04)	
Income	-16.33%	-1.67%	-0.05%	-14.78%
		(-0.45)	(-0.03)	
Micro-Cap	-17.06%	-9.47%**	-0.05%	-7.66%
		(-2.15)	(-0.03)	
Small-Cap	-13.47%	-4.60%	-0.96%	-7.90%
		(-0.89)	(-0.51)	
Mid-Cap	-15.71%	-2.75%	0.06%	-12.88%
		(-0.59)	(0.05)	
Panel D June 2009-December 2013				
All	21.46%	0.43%	-0.46%*	21.06%
		(1.08)	(-1.82)	
Growth	20.63%	0.37%	-0.37%	20.28%
		(0.68)	(-1.06)	
Growth&Income	19.78%	0.18%	-0.95%**	20.49%
		(0.57)	(-2.35)	
Income	19.60%	0.14%	-1.53%***	21.05%
		(0.18)	(-2.77)	
Micro-Cap	25.77%	3.63%***	-0.92%**	21.73%
		(3.05)	(-2.08)	
Small-Cap	23.88%	0.65%	-0.32%	22.75%
		(1.13)	(-1.14)	
Mid-Cap	22.47%	0.29%	-0.04%	21.60%
		(0.46)	(-0.14)	

* Significant at the 10% level.
** Significant at the 5% level.
*** Significant at the 1% level.

Note: recession during the financial crisis is defined by NBER

Table 4 Mutual Fund CT Performance for Buying, Sizing, and Selling

This table below reports the characteristic-timing attributes of all mutual funds The mutual funds are broken down by the CRSP investment objectives, including growth, growth & income, income, micro-cap, small-cap, and mid-cap. Panel A reports the average performance of mutual funds during the whole sample period from 2004 to 2013. Panel B, Panel C, and Panel D presents the average performance of mutual funds for sub-sample periods from September 2004 to December 2007, from December 2007 to June 2009, and from June 2009 to December 2013. The aggregate CT performance (CT) is calculated as the difference between the time t value-weighted return of benchmark portfolio of stocks held at time *t-1* and the time t value weighted return of benchmark portfolio of stocks held at time *t-13*. The aggregate CT performance is decomposed into three components for buying, sizing, and selling, based on the changes in shares held between two reports. CT_{buy} measures the monthly characteristic-timing performance at time t when mutual funds increase holdings of stocks at time *t-1*; CT_{size} measures the monthly characteristic-timing performance at time t when mutual funds remain the same holdings of stocks at time *t-1*; CT_{sell} measures the monthly characteristic-timing performance at time t when mutual funds decrease holdings of stocks at time *t-1*. The time series average of annualized monthly returns and t-statistics are presented below (t-statistics in parentheses).

	All Funds	Growth	Growth &Income	Income	Micro-Cap	Small-Cap	Mid-Cap
Panel A September 2004-December 2013							
CT	-0.37%	-0.28%	-0.58%	-0.66%	-0.79%*	-0.40%	-0.20%
	(-1.57)	(-0.95)	(-1.61)	(-1.43)	(-1.98)	(-1.12)	(-0.74)
CT_{buy}	1.42%*	1.39%*	1.02%	0.86%	1.48%	1.67%	1.69%*
	(1.65)	(1.71)	(1.41)	(1.54)	(1.43)	(1.58)	(1.77)
CT_{size}	-0.02%	0.06%	-0.04%	-0.20%	-0.37%*	-0.15%	0.09%
	(-0.24)	(0.62)	(-0.30)	(-0.75)	(-1.89)	(-1.29)	(0.76)
CT_{sell}	-1.78%*	-1.73%**	-1.57%**	-1.48%**	-1.95%	-1.94%	-1.96%*
	(-1.86)	(-1.89)	(-2.14)	(-2.30)	(-1.53)	(-1.58)	(-1.84)
Panel B September 2004-December 2007							
CT	-0.42%	-0.49%	-0.38%	0.22%	-0.96%*	-0.24%	-0.55%***
	(-1.61)	(-1.39)	(-0.73)	(0.36)	(-1.91)	(-0.78)	(-3.03)
CT_{buy}	2.08%**	2.15%**	1.80%**	1.33%**	1.71%	2.16%	2.36%*
	(1.97)	(2.21)	(2.23)	(2.07)	(1.16)	(1.54)	(1.84)
CT_{size}	0.04%	0.05%	0.06%	0.26%	-0.30%	-0.07%	0.16%
	(0.43)	(0.42)	(0.32)	(0.93)	(-1.27)	(-0.76)	(1.49)
CT_{sell}	-2.53%**	-2.67%***	-2.23%***	-1.41%**	-2.47%	-2.35%	-3.02%**
	(-2.2)	(-2.58)	(-2.71)	(-2.05)	(-1.26)	(-1.48)	(-2.21)
Panel C December 2007-June 2009 (Recession)							
CT	-0.03%	0.41%	0.05%	-0.05%	-0.05%	-0.96%	0.06%
	(-0.03)	(0.33)	(0.04)	(-0.03)	(-0.03)	(-0.51)	(0.05)
CT_{buy}	-2.29%	-2.56%	-2.29%	-1.13%	-1.34%	-2.10%	-2.24%
	(-0.64)	(-0.75)	(-0.73)	(-0.51)	(-0.32)	(-0.48)	(-0.59)
CT_{size}	0.01%	0.12%	0.23%	0.12%	-0.09%	-0.41%	0.08%
	(0.04)	(0.34)	(0.38)	(0.10)	(-0.11)	(-0.69)	(0.15)
CT_{sell}	2.24%	2.88%	2.18%	0.86%	1.41%	1.48%	2.23%
	(0.52)	(0.72)	(0.68)	(0.29)	(0.27)	(0.26)	(0.47)
Panel D June 2009-December 2013							
CT	-0.46%*	-0.37%	-0.95%**	-1.53%***	-0.92%**	-0.32%	-0.04%
	(-1.82)	(-1.06)	(-2.35)	(-2.77)	(-2.08)	(-1.14)	(-0.14)
CT_{buy}	2.28%**	2.29%**	1.66%**	1.23%**	2.34%**	2.68%**	2.63%**
	(2.39)	(2.52)	(2.06)	(1.77)	(2.00)	(2.31)	(2.38)
CT_{size}	-0.07%	0.05%	-0.22%	-0.65%**	-0.52%**	-0.12%	0.04%
	(-0.72)	(0.33)	(-1.21)	(-2.39)	(-2.44)	(-1.02)	(0.28)
CT_{sell}	-2.64%***	-2.65%***	-2.40%***	-2.36%***	-2.74%**	-2.84%**	-2.64%**
	(-2.62)	(-2.63)	(-2.98)	(-3.40)	(-2.11)	(-2.39)	(-2.41)

* Significant at the 10% level.
** Significant at the 5% level.
*** Significant at the 1% level.

Table 5 Mutual Fund Characteristic-Timing Performance Persistence

This table presents the persistence of mutual fund characteristic-timing performance. The aggregate CT performance (CT) is calculated as the difference between the time t value-weighted return of benchmark portfolio of stocks held at time *t-1* and the time *t* value weighted return of benchmark portfolio of stocks held at time *t-13*. The aggregate CT performance is decomposed into three components for buying, and selling, based on the changes in shares held between two reports. CT_{buy} measures the monthly characteristic-timing performance at time t when mutual funds increase holdings of stocks at time *t-1*while CT_{sell} measures the monthly characteristic-timing performance at time t when mutual funds decrease holdings of stocks at time *t-1*. At the end of each quarter, all existing mutual funds are divided into five quintiles based on the average monthly aggregate, buying, and selling characteristic-timing performance. The characteristic-timing performance for the formation quarter and subsequent four quarters are reported. All returns are annualized monthly returns. Numbers in parentheses are t-statistics, which are computed based on two-way clustered standard errors.

Current Quarter Performance Quintiles	Quarters				
	Q+0	Q+1	Q+2	Q+3	Q+4
Panel A: Aggregate CT Performance					
q1 (Loser)	-7.64%***	-0.87%***	-0.46%	-0.87%***	-0.75%***
	(-16.25)	(-2.74)	(-1.37)	(-3.46)	(-3.03)
q2	-2.80%***	-0.48%**	-0.45%*	-0.64%**	-0.50%**
	(-12.46)	(-2.33)	(-1.90)	(-3.04)	(-1.96)
q3	-0.44%**	-0.35%	-0.34%	-0.30%	-0.37%
	(-2.23)	(-1.58)	(-1.52)	(-1.50)	(-1.49)
q4	1.99%***	-0.21%	-0.46%*	-0.25%	-0.23%
	(7.13)	(-0.75)	(-1.95)	(-0.94)	(-0.98)
q5 (Winner)	7.26%***	-0.10%	-0.41%	-0.09%	-0.15%
	(12.74)	(-0.24)	(-1.32)	(-0.25)	(-0.58)
q5-q1	16.02%***	0.77%*	0.05%	0.78%*	0.61%**
	(15.78)	(1.72)	(0.1)	(1.84)	(2.31)
Panel B: Buying CT Performance					
q1 (Loser)	-5.69%***	1.00%	1.53%	1.36%	1.41%*
	(-4.69)	(0.99)	(0.76)	(1.44)	(1.73)
q2	-0.94%	1.17%	1.25%*	1.24%	1.27%*
	(-1.28)	(1.52)	(1.74)	(1.54)	(1.73)
q3	1.23%**	1.32%**	1.29%*	1.44%*	1.16%
	(1.91)	(1.96)	(1.79)	(1.95)	(1.56)
q4	3.71%***	1.56%**	1.48%*	1.52%**	1.40%*
	(5.40)	(2.10)	(1.91)	(2.07)	(1.71)
q5 (Winner)	10.00%***	2.39%**	1.85%*	1.94%**	1.67%
	(9.39)	(2.42)	(1.85)	(2.1)	(1.58)
q5-q1	16.54%***	1.38%*	0.31%	0.58%	0.26%
	(12.87)	(1.68)	(0.56)	(0.99)	(0.48)
Panel C: Selling CT Performance					
q1 (Loser)	-10.05%***	-2.83%***	-2.28%**	-2.56%**	-2.14%*
	(-9.40)	(-2.69)	(-2.13)	(-2.57)	(-1.83)
q2	-4.16%***	-1.89%**	-1.80%**	-2.04%**	-1.71%*
	(-5.65)	(-2.37)	(-2.12)	(-2.45)	(-1.85)
q3	-1.60%**	-1.54%*	-1.67%**	-1.70%**	-1.61%**
	(-2.27)	(-1.94)	(-2.08)	(-2.04)	(-1.93)
q4	0.84%	-1.51%	-1.65%*	-1.58%*	-1.60%*
	(1.02)	(-1.80)	(-2.01)	(-1.80)	(-1.97)
q5 (Winner)	6.06%***	-1.44%	-1.90%*	-1.55%	-1.74%*
	(4.21)	(-1.28)	(-1.88)	(-1.45)	(-1.92)
q5-q1	17.74%***	1.43%*	0.38%	1.02%	0.42%
	(13.02)	(1.71)	(0.68)	(1.59)	(0.77)

* Significant at the 10% level.
** Significant at the 5% level.
*** Significant at the 1% level.

Table 6 Aggregate Characteristic-Timing Performance, Conditioning on Net Flows

This table reports the aggregate characteristic-timing performance conditioning on net investor flows. Net investor flows are calculated as estimated percentage change in TNA adjusted for investment return and mutual fund mergers. For each month, mutual funds are divided into five quintiles based on net investor flows. The mutual funds are broken down by the CRSP investment objectives, including growth, growth & income, income, micro-cap, small-cap, and mid-cap. The t-statistics are presented below in parentheses.

	All Funds	Growth	Growth &Income	Income	Micro-Cap	Small-Cap	Mid-Cap
NF1	-0.07%	-0.14%	-0.40%	0.41%	-0.32%	-0.32%	0.43%
	(-0.23)	(-0.36)	(-0.92)	(0.57)	(-0.58)	(-0.94)	(1.16)
NF2	-0.26%	0.09%	-0.93%**	-0.63%	-0.62%	0.17%	-0.13%
	(-1.04)	(0.27)	(-2.05)	(-0.89)	(-1.32)	(0.47)	(-0.31)
NF3	-0.18%	-0.36%	-0.31%	-0.35%	-0.85%	-0.04%	-0.23%
	(-0.59)	(-1.00)	(-0.60)	(-0.63)	(-1.43)	(-0.10)	(-0.52)
NF4	-0.53%	-0.43%	-0.40%	-0.81%	-0.78%	-0.41%	-0.24%
	(-1.68)	(-1.08)	(-0.84)	(-1.61)	(-1.22)	(-1.16)	(-0.67)
NF5	-0.85%***	-0.81%**	-0.87%*	-1.28%*	-0.29%	-0.56%	-0.37%
	(-2.86)	(-2.07)	(-1.94)	(-1.88)	(-0.49)	(-1.68)	(-1.09)
NF1-NF5	0.78%***	0.68%*	0.48%	1.71%***	-0.04%	0.24%	0.80%**
	(2.80)	(1.66)	(1.10)	(2.74)	(-0.06)	(0.88)	(2.31)

* Significant at the 90 percent confidence level.
** Significant at the 95 percent confidence level.
*** Significant at the 99 percent confidence level.

Table 7 Aggregate Characteristic-Timing Performance, Conditioning on Net Investor Flows and Active Style Drift

This table reports the aggregate characteristic-timing performance conditioning on net investor flows and active style drift. Net investor flows are calculated as estimated percentage change in TNA adjusted for investment return and mutual fund mergers. Active style drift is calculated following Wermers (2012) as the difference of style quintile numbers along size, book-to-market and momentum dimensions. For each month, mutual funds are divided into five quintiles based on net investor flows. For each of net investor flows portfolio, mutual funds are then divided into quintiles according to active style drift. The t-statistics are presented below in parentheses.

	SD1 (Large Drift)	**SD2-SD4**	**SD5 (Small Drift)**	**ALL**	**SD1-SD5**
NF1 (Outflow)	-0.92%	0.21%	-0.02%	-0.07%	-0.91%
	(-1.63)	(0.64)	(-0.05)	(-0.23)	(-1.32)
NF2-NF4	-0.04%	-0.38%	-0.29%	-0.30%	0.25%
	(-0.12)	(-1.43)	(-0.82)	(-1.11)	(0.79)
NF5 (Inflow)	-1.76%***	-0.54%*	-0.90%**	-0.85%***	-0.88%
	(-2.78)	(-1.75)	(-2.46)	(-2.86)	(-1.34)
ALL	-0.66%**	-0.17%	-0.57%*	-0.37%	-0.08%
	(-2.31)	(-0.70)	(-1.80)	(-1.57)	(-0.26)
NF1-NF5	0.86%	0.75%**	0.88%**	0.78***	-
	(1.21)	(2.58)	(2.50)	(2.80)	-

* Significant at the 90 percent confidence level.
** Significant at the 95 percent confidence level.
*** Significant at the 99 percent confidence level.

Table 8 Characteristic-Timing Performance for Buying and Selling Are Related to Trade Motivations (1)

This table reports the characteristic-timing performance for buying and selling, conditioning on motivation scores including buy flow score (*BF*) and sell flow score (*SF*). Based on Alexander *et al* (2007), the proximities for buying and selling motivation are calculated based on the net investor flows, total buying volume and total selling volume. Specifically, buy flow score for fund i at time t is measured as the difference between total dollar volume for buying at time t and net investor flows at time t, divided by total net assets at time t-1. And sell flow score for fund i at time t is calculated as the sum of total dollar volume for selling at time t and net investor flow at time t, divided by total net assets at time t-1. For each month, mutual funds are divided into five quintiles based on the buy flow score and the sell flow score. The times series average of cross-sectional average of buying and selling characteristic-timing performance are reported for all mutual fund samples and sub-samples of different investment objectives. The t-statistics are presented below in parentheses.

	All Funds	Growth	Growth &Income	Income	Micro-Cap	Small-Cap	Mid-Cap
				Buying			
BF1	1.90%**	2.04%**	1.76%**	1.66%*	2.02%**	2.21%**	2.27%**
	(2.19)	(2.25)	(2.25)	(1.95)	(1.99)	(2.16)	(2.12)
BF2	1.15%*	0.87%	0.77%	1.10%*	1.39%	1.66%**	2.09%**
	(1.70)	(1.45)	(1.08)	(1.71)	(1.54)	(2.17)	(2.28)
BF3	0.97%*	0.77%	1.03%*	0.80%	1.00%	1.16%*	1.66%*
	(1.76)	(1.23)	(1.72)	(1.48)	(1.01)	(1.79)	(1.78)
BF4	0.93%	0.58%	0.53%	1.14%*	1.00%	1.18%*	1.05%
	(1.61)	(0.96)	(1.06)	(1.83)	(1.09)	(1.83)	(1.38)
BF5	0.95%	0.31%	0.97%	0.79%	1.04%	1.58%*	1.80%*
	(1.16)	(0.43)	(1.30)	(0.84)	(0.84)	(1.80)	(1.93)
BF1-BF5	0.93%***	1.70%**	0.78%**	0.86%**	0.96%	0.63%**	0.46%
	(4.03)	(2.49)	(2.01)	(2.33)	(1.47)	(2.09)	(0.91)
				Selling			
SF1	-1.57%*	-1.36%	-1.80%***	-1.67%**	-1.11%	-1.62%*	-1.97%*
	(-1.94)	(-1.49)	(-2.69)	(-2.53)	(-0.84)	(-1.79)	(-1.95)
SF2	-1.21%*	-1.40%**	-0.72%	-0.91%*	-1.34%	-1.44%*	-1.25%*
	(-1.92)	(-2.01)	(-1.33)	(-1.81)	(-1.14)	(-1.90)	(-1.71)
SF3	-1.45%**	-1.31%*	-1.60%***	-1.36%**	-1.32%	-1.32%*	-2.10%*
	(-2.20)	(-1.86)	(-2.66)	(-2.11)	(-1.21)	(-1.85)	(-1.81)
SF4	-1.63%**	-1.29%*	-1.76%**	-1.82%**	-1.95%*	-1.93%**	-2.39%**
	(-2.08)	(-1.65)	(-2.29)	(-2.35)	(-1.78)	(-2.21)	(-2.19)
SF5	-2.24%**	-2.13%**	-2.36%***	-2.23%**	-2.08%	-2.70%**	-2.64%**
	(-2.16)	(-2.00)	(-2.68)	(-2.14)	(-1.57)	(-2.13)	(-2.10)
SF1-SF5	0.69%**	0.78%*	0.58%	0.58%	0.99%	1.11%**	0.69%
	(2.01)	(1.80)	(1.40)	(0.83)	(1.13)	(2.29)	(1.42)

* Significant at the 90 percent confidence level.
** Significant at the 95 percent confidence level.
*** Significant at the 99 percent confidence level.

Table 9 Characteristic-Timing Performance for Buying and Selling Are Related to Trade Motivations (2)

The dependent variables are the characteristic-timing performance for buy and sell portfolio for mutual funds. Valuation is an indicator variable equal to one for every month the mutual fund is identified as valuation motivated (high flow score for buying and selling, respectively), zero otherwise; Liquidity is an indicator variable equal to one for every month the mutual fund is identified as liquidity driven (low flow score for buying and selling, respectively), zero otherwise. *log(AGE)* is the natural logarithm of age in years since first offer date. *log(TNA)* is the natural logarithm of total net assets under management in millions of dollars. *Expenses* is fund expense ratio in percentage per year. *Turnover* is the fund turnover ratio in percentage per year. *Flow* is estimated investor flows as the ratio of $TNA_{i,t} - TNA_{i,t-1} * (1 + RET_{i,t}) - MGN_{i,t}$ to $TNA_{i,t-1}$. *Fee* is the fund management fee in percentage per year. *Size*, *btm*, and *Momentum* are quintile number of fund style characteristics along the size, book-to-market and momentum dimensions. All these control variables are demeaned. *Flow* and *Turnover* are winsorized at 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 every month is in the fourth quarter, and zero otherwise. The data are monthly and cover the period from 2003 to 2013. Standard errors (in parentheses) are clustered by fund and time.

	Buying			Selling		
	(1)	(2)	(3)	(4)	(5)	(6)
Valuation	0.065***	0.070***	0.070***	0.012*	0.030***	0.043***
	(0.008)	(0.008)	(0.008)	(0.007)	(0.008)	(0.007)
Liquidity	-0.025***	-0.033***	-0.047***	-0.110***	-0.124***	-0.121***
	(0.006)	(0.006)	(0.006)	(0.009)	(0.010)	(0.009)
Log(AGE)		0.107***	0.086***		-0.124***	-0.104***
		(0.014)	(0.013)		(0.015)	(0.014)
Log(TNA)		-0.093***	-0.123***		0.104***	0.136***
		(0.007)	(0.007)		(0.080)	(0.007)
Expenses		6.983	-3.421		-5.850	5.223
		(4.708)	(3.689)		(4.500)	(3.540)
Turnover		0.052***	0.064***		-0.032***	-0.045***
		(0.010)	(0.009)		(0.012)	(0.012)
Flow		0.205***	0.159***		-0.277***	-0.232***
		(0.043)	(0.042)		(0.043)	(0.041)
Fee		-0.019***	-0.015***		0.017***	0.013**
		(0.003)	(0.004)		(0.004)	(0.006)
Size		0.110***	0.107***		-0.136***	-0.129***
		(0.028)	(0.027)		(0.030)	(0.029)
btm		-0.065***	-0.052***		0.108***	0.094***
		(0.020)	(0.019)		(0.020)	(0.019)
Momentum		-0.110***	-0.060***		0.115***	0.062***
		(0.014)	(0.014)		(0.015)	(0.015)
Recession			-0.360***			0.388***
			(0.011)			(0.012)
4th Quarter			-0.001			-0.025***
			(0.005)			(0.005)
Constant	0.101***	0.100***	0.166***	-0.110***	-0.108***	-0.172***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)
Obs	144,926	141,767	141,767	144,926	141,767	141,767

Table 10 Characteristic-Timing Performance for Buying and Selling, Conditioning on Flow Score and Trade Size

This table reports the buying and selling characteristic-timing performance conditioning on flow metrics and trade size. Following Alexander *et al* (2007), the flow metrics for buying and selling motivation are calculated based on the net investor flows, total buying volume and total selling volume. Specifically, buy flow score for fund i at time *t* is measured as the difference between total dollar volume for buying at time t and net investor flows at time *t*, divided by total net assets at time *t-1*. Sell flow score for fund i at time t is measured as the sum of total dollar volume for sell at time *t* and net investor flows at time *t*, divided by total net assets at time *t-1*. The net investor flows are calculated based on the changes total net assets under management adjusted for investment returns and mutual fund mergers. For each month, mutual funds are divided into five quintiles based on the buy and sell flow score. For each of the buy and selling portfolio, trades are divided into quintiles according to their dollar value. The t-statistics are presented below in parentheses.

	TS1 (Large)	**TS2**	**TS3**	**TS4**	**TS5 (Small)**	**TS1-TS5**	
Panel A Buy							
BF1	1.61%**	1.06%**	0.65%**	0.45%**	0.16%*	1.45%**	
	(1.99)	(2.42)	(2.11)	(2.31)	(1.68)	(1.97)	
BF2	1.14%*	0.67%*	0.49%*	0.25%	0.12%*	1.01%*	
	(1.85)	(1.95)	(1.89)	(1.38)	(1.77)	(1.80)	
BF3	0.80%	0.53%*	0.36%*	0.27%*	0.05%	0.75%	
	(1.54)	(1.93)	(1.70)	(1.93)	(0.88)	(1.56)	
BF4	0.74%*	0.43%*	0.26%	0.15%	0.03%	0.71%**	
	(1.88)	(1.94)	(1.61)	(1.22)	(0.45)	(2.05)	
BF5	0.64%*	0.30%	0.28%**	0.17%*	0.05%	0.58%*	
	(1.83)	(1.56)	(2.10)	(1.87)	(1.15)	(1.83)	
BF1-BF5	0.96%*	0.76%**	0.37%*	0.28%**	0.11%	-	
	(1.77)	(2.55)	(1.74)	(2.13)	(1.26)	-	
BF1/TS1-BF5/TS5							1.56%*
							(1.98)
Panel B Sell							
SF1	-0.87%**	-0.42%*	-0.35%**	-0.26%**	-0.14%**	-0.73%**	
	(-2.13)	(-1.74)	(-2.01)	(-2.24)	(-1.99)	(-2.08)	
SF2	-1.11%**	-0.49%*	-0.29%	-0.18%*	-0.11%	-1.00%**	
	(-2.21)	(-1.75)	(-1.43)	(-1.68)	(-1.45)	(-2.29)	
SF3	-1.11%*	-0.55%*	-0.32%	-0.19%	-0.10%	-1.02%*	
	(-1.78)	(-1.67)	(-1.32)	(-1.36)	(-1.44)	(-1.78)	
SF4	-1.32%*	-0.75%*	-0.51%**	-0.29%**	-0.10%	-1.24%*	
	(-1.76)	(-1.94)	(-2.02)	(-2.29)	(-1.44)	(-1.75)	
SF5	-2.73%***	-1.29%***	-0.87%***	-0.44%**	0.03%	-2.76%***	
	(-2.90)	(-2.82)	(-3.03)	(-2.39)	(0.44)	(-3.03)	
SF1-SF5	1.91%***	0.88%***	0.53%***	0.17%	-0.17%**	-	
	(3.04)	(3.11)	(3.21)	(1.56)	(-2.50)	-	
SF1/TS1-SF5/TS5							-0.89%**
							(-2.37)

* Significant at the 90 percent confidence level.
** Significant at the 95 percent confidence level.
*** Significant at the 99 percent confidence level.

Table 11 Characteristic-Timing Performance of Good Sellers

The dependent variables are the characteristic-timing performance for buy and sell portfolio for mutual funds. *Top* is the indicator variable equal to one for all funds whose selling performance when sales are valuation motivated is in the highest 25th percentile of the distribution, and zero otherwise. *log(AGE)* is the natural logarithm of age in years since first offer date. *log(TNA)* is the natural logarithm of total net assets under management in millions of dollars. *Expenses* is fund expense ratio in percentage per year. *Turnover* is the fund turnover ratio in percentage per year. *Flow* is estimated investor flows as the ratio of $TNA_{i,t} - TNA_{i,t-1} * \left(1 + RET_{i,t}\right) - MGN_{i,t}$ to $TNA_{i,t-1}$. *Fee* is the fund management fee in percentage per year. *Size*, *btm*, and *Momentum* are quintile number of fund style characteristics along the size, book-to-market and momentum dimensions. All these control variables are demeaned. *Flow* and *Turnover* are winsorized at 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 every month is in the fourth quarter, and zero otherwise. The data are monthly and cover the period from 2003 to 2013. Standard errors (in parentheses) are clustered by fund and time.

	Selling			Buying		
	(1)	(2)	(3)	(4)	(5)	(6)
Top	0.135***	0.135***	0.112***	0.096***	0.087***	0.072***
	(0.011)	(0.011)	(0.011)	(0.017)	(0.017)	(0.016)
Log(AGE)		-0.049***	-0.046***		0.218***	0.205***
		(0.017)	(0.017)		(0.031)	(0.028)
Log(TNA)		0.067***	0.083***		-0.145***	-0.186***
		(0.009)	(0.009)		(0.016)	(0.015)
Expenses		5.567	11.807***		11.664	-3.353
		(4.090)	(3.763)		(8.255)	(5.921)
Turnover		0.004	-0.009		0.098***	0.111***
		(0.019)	(0.018)		(0.023)	(0.022)
Flow		-0.254***	-0.245***		0.097	0.022
		(0.048)	(0.046)		(0.092)	(0.090)
Fee		-0.013	-0.016		-0.016***	-0.013***
		(0.014)	(0.013)		(0.003)	(0.005)
Size		-0.063	-0.054		0.162***	0.168***
		(0.039)	(0.039)		(0.061)	(0.058)
btm		0.035	0.025		-0.170***	-0.143***
		(0.024)	(0.023)		(0.040)	(0.038)
Momentum		0.065***	0.034*		-0.175***	-0.091***
		(0.019)	(0.019)		(0.032)	(0.031)
Recession			0.277***			-0.509***
			(0.019)			(0.024)
4th Quarter			-0.079***			-0.084***
			(0.008)			(0.011)
Constant	-0.130***	-0.113***	-0.127***	0.143***	0.145***	-0.265***
	(0.004)	(0.005)	(0.005)	(0.007)	(0.009)	(0.008)
Obs	46,868	46,202	46,202	46,676	46,094	46,094

Table 12 Characteristic-Timing Performance of Good Buyers

The dependent variables are the characteristic-timing performance for buy and sell portfolio for mutual funds. *Top* is the indicator variable equal to one for all funds whose buying performance when purchases are valuation motivated is in the highest 25th percentile of the distribution, and zero otherwise. *log(AGE)* is the natural logarithm of age in years since first offer date. *log(TNA)* is the natural logarithm of total net assets under management in millions of dollars. *Expenses* is fund expense ratio in percentage per year. *Turnover* is the fund turnover ratio in percentage per year. *Flow* is estimated investor flows as the ratio of $TNA_{i,t} - TNA_{i,t-1} * \left(1 + RET_{i,t}\right) - MGN_{i,t}$ to $TNA_{i,t-1}$. *Fee* is the fund management fee in percentage per year. *Size*, *btm*, and *Momentum* are quintile number of fund style characteristics along the size, book-to-market and momentum dimensions. All these control variables are demeaned. *Flow* and *Turnover* are winsorized at 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 every month is in the fourth quarter, and zero otherwise. The data are monthly and cover the period from 2003 to 2013. Standard errors (in parentheses) are clustered by fund and time.

	Buying			Selling		
	(1)	(2)	(3)	(4)	(5)	(6)
Top	0.315***	0.310***	0.307***	-0.020	-0.017	-0.011
	(0.017)	(0.017)	(0.016)	(0.012)	(0.012)	(0.012)
Log(AGE)		0.213***	0.200***		-0.049***	-0.046***
		(0.030)	(0.027)		(0.017)	(0.017)
Log(TNA)		-0.137***	-0.180***		0.070***	0.086***
		(0.015)	(0.014)		(0.009)	(0.009)
Expenses		12.035	-2.999		6.332	12.915***
		(7.799)	(5.621)		(4.155)	(3.807)
Turnover		0.079***	0.091***		0.001	-0.012
		(0.023)	(0.021)		(0.019)	(0.019)
Flow		0.068	-0.012		-0.245***	-0.237***
		(0.089)	(0.087)		(0.049)	(0.047)
Fee		-0.017***	-0.013***		-0.015	-0.018
		(0.003)	(0.005)		(0.015)	(0.013)
Size		0.164***	0.172***		-0.067	-0.057
		(0.060)	(0.057)		(0.040)	(0.040)
btm		-0. 177***	-0.152***		0.029	0.020
		(0.039)	(0.037)		(0.025)	(0.024)
Momentum		-0.173***	-0.090***		0.069***	0.035*
		(0.032)	(0.031)		(0.020)	(0.020)
Recession			-0.512***			0.292***
			(0.024)			(0.020)
4th Quarter			-0.083***			-0.079***
			(0.011)			(0.008)
Constant	0.091***	0.092***	0.210***	-0.092***	-0.076***	-0.100***
	(0.006)	(0.007)	(0.007)	(0.004)	(0.005)	(0.005)
Obs	46,676	46,094	46,094	46,868	46,202	46,202

Table 13 Aggregate Characteristic-Timing performance, Good Sellers V.S. Good Buyers

The dependent variables are the aggregate characteristic-timing performance for top sellers and top buyers, respectively. *Top* is the indicator variable equal to one for all funds whose selling (buying) performance when sales (purchases) are valuation motivated is in the highest 25th percentile of the distribution, and zero otherwise. *log(AGE)* is the natural logarithm of age in years since first offer date. *log(TNA)* is the natural logarithm of total net assets under management in millions of dollars. *Expenses* is fund expense ratio in percentage per year. *Turnover* is the fund turnover ratio in percentage per year. *Flow* is estimated investor flows as the ratio of $TNA_{i,t} - TNA_{i,t-1} * \left(1 + RET_{i,t}\right) - MGN_{i,t}$ to $TNA_{i,t-1}$. *Fee* is the fund management fee in percentage per year. *Size*, *btm*, and *Momentum* are quintile number of fund style characteristics along the size, book-to-market and momentum dimensions. All these control variables are demeaned. *Flow* and *Turnover* are winsorized at 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 every month is in the fourth quarter, and zero otherwise. The data are monthly and cover the period from 2003 to 2013. Standard errors (in parentheses) are clustered by fund and time.

	Good seller			Good buyer		
	(1)	(2)	(3)	(4)	(5)	(6)
Top	0.025***	0.026***	0.026***	0.009	0.008	0.008
	(0.005)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Log(AGE)		-0.019**	-0.024***		-0.019**	-0.024***
		(0.008)	(0.008)		(0.008)	(0.008)
Log(TNA)		0.010**	0.012***		0.010**	0.013***
		(0.004)	(0.004)		(0.004)	(0.004)
Expenses		0.519	1.205		0.486	1.186
		(1.955)	(1.980)		(1.957)	(1.982)
Turnover		0.024***	0.023***		0.024***	0.023***
		(0.008)	(0.008)		(0.008)	(0.008)
Flow		-0.010	-0.010		-0.010	-0.010
		(0.026)	(0.026)		(0.026)	(0.026)
Fee		-0.000	-0.000		-0.000	-0.000
		(0.002)	(0.002)		(0.002)	(0.002)
Size		-0.031**	-0.025*		-0.031**	-0.025*
		(0.014)	(0.014)		(0.014)	(0.014)
btm		0.049***	0.049***		0.049***	-0.049***
		(0.014)	(0.014)		(0.014)	(0.014)
Momentum		0.003	0.000		0.004	0.000
		(0.010)	(0.010)		(0.010)	(0.010)
Recession			0.031***			0.031***
			(0.008)			(0.008)
4th Quarter			-0.035***			-0.035***
			(0.005)			(0.005)
Constant	-0.034***	-0.034***	-0.030***	-0.030***	-0.030***	-0.026***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Obs	144,926	141,767	141,767	144,926	141,767	141,767

Table 14 Fund Characteristics for Good Sellers

Top is the indicator variable equal to one for all funds whose selling performance when sales are valuation motivated is in the highest 25th percentile of the distribution, and zero otherwise. *AGE* is age in years since first offer date. *TNA* is the total net assets under management in millions of dollars. *Expenses* is fund expense ratio in percentage per year. *Turnover* is the fund turnover ratio in percentage per year. *Fee* is the fund management fee in percentage per year. *ASD* is the active style drift calculated according to Wermers (2012) as the changes in quintile number of fund style characteristics along the size, book-to-market and momentum dimensions. *Stock Number* is the total number of stock held by mutual funds. *Top1-Top0* is the difference between the mean values of the groups for which *Top* equals to one and zero, respectively. *p*-value measure statistical significance of the difference. The data are monthly and cover the period from 2003 to 2013.

	Good seller			Others			Difference	
	Mean	Stdev.	Median	Mean	Stdev.	Median	Top1-Top0	*p*-value
Age	14.65	13.01	11	15.30	12.55	12	-0.65	0.000
TNA	1397.58	4072.90	246.60	1567.89	6592.69	288.4	-170.31	0.000
Expenses	1.24	0.45	1.20	1.19	0.37	1.20	0.05	0.000
Fee	0.73	0.35	0.75	0.71	0.36	0.74	0.02	0.000
Turnover	105.38	103.13	81.00	73.17	66.29	58.00	32.21	0.000
ASD	0.27	0.27	0.18	0.19	0.23	0.13	0.07	0.000
Stock Number	116.96	132.73	82	136.70	172.31	88	-19.74	0.000

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Appendix A

The screening procedure for U.S. domestic equity mutual funds builds on Kacperczyk *et al* (2008). I start with a sample of all mutual funds in the CRSP Mutual Fund Database and eliminate funds with the Investment Objective Codes (IOC) of International funds (IOC=1), Municipal Bonds funds (IOC=5), Bond and Preferred funds (IOC=6) and Balanced funds (IOC=7). Then, I exclude funds with CRSP policy codes for Canadian and international (C&I), Balanced (Bal), Bonds (Bonds), Preferred stocks (Pfd), Bonds and preferred stocks (B&P), Government securities (GS), Money market fund (MM), and Tax-free money market fund (TFM). After these two screening steps, I select funds with Lipper Class codes of, if available, "EIEI", "G", "LCCE", "LCGE", "LCVE", "MCCE", "MCGE", "MCVE", "MLCE", "MLGE", "MLVE", "SCCE", "SCGE", and "SCVE" or with Lipper Objective codes of, if available, "CA", "EI", "G", "GI", "MC", "MR", and "SG". If neither Lipper Class codes nor Lipper Objective codes are available, I include funds with Strategic Insight Objective Code (si_obj_cd) of "AGG", "GMC", "GRI", "GRO", "ING", and "SCG". If Strategic Insight Objective codes are missing, then funds with Wiesenberger Fund Type codes of "G", "G-I", "AGG", "GCI", "GRI", "GRO", "LTG", "MCG", and "SCG" are included. If none of the above objective codes are available, funds with a CS policy are included. If CS policy is not available, I exclude funds with average stock holdings less than 80% or more than 105% and fund that hold less than 10 stocks and that managed asset less than $5 million in previous month. In addition, I search for keywords in the fund full name and eliminate funds with keywords of "index", "idx", "S&P", "DFA", "program", "ETF", "exchange traded", "exchange-traded", "target", and target date funds. Following Alexander *et al* (2007), funds with less than four holdings reports that were each preceded by another report in the previous quarter are excluded from my final sample.