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Chandra Sekhar Mangipudi Date

Three Essays in Mutual Funds

By

Chandra Sekhar Mangipudi

Doctor of Philosophy

Business

____

Narasimhan Jegadeesh, Ph.D.
Advisor

____

Jeffrey Busse, Ph.D.
Committee Member

____

Tarun Chordia, Ph.D.
Committee Member

____

Ilia Dichev, Ph.D.
Committee Member

Accepted:

____

Lisa A. Tedesco, Ph.D.
Dean of the James T. Laney School of Graduate Studies

____

Date

Three Essays in Mutual Funds

By

Chandra Sekhar Mangipudi
B.Tech., Indian Institute of Technology, Madras, 2007

Advisor: Narasimhan Jegadeesh, Ph.D.

An abstract of
A dissertation submitted to the Faculty of the
James T. Laney School of Graduate Studies of Emory University
in partial fulfillment of the requirements for the degree of
Doctor of Philosophy
in Business
2020

Abstract

Three Essays in Mutual Funds

By Chandra Sekhar Mangipudi

My dissertation is focused on understanding the investment decisions of retail investors in the mutual funds market. In the first essay, I find that levels of purchases and redemptions are higher at the turn of the year, i.e. December and January, compared to other months. In tests studying the role of distribution channel on these patterns, I find that broker-sold funds experience a pull in purchases from January to December of previous year compared to direct-sold funds. This is consistent with the incentives selling brokers in the distribution channel to meet their annual sales quotas. In tests studying the role of tax-loss selling, I find that higher redemptions in December are concentrated in funds with poor performance but are not systematically different in years with negative and positive aggregate market returns. In the second essay co-authored with Narasimhan Jegadeesh, we investigate the validity of the claim in the recent literature that fund flows reveal the true asset pricing model. Based on the finding that market model alphas are stronger predictors of mutual fund flows than alphas with other models, Berk and van Binsbergen (2016) claim that CAPM is the best asset pricing model but Barber, Huang and Odean (2016) (BHO) claim it is evidence against investor sophistication. We evaluate the merits of these mutually exclusive interpretations. We show, theoretically and through simulations, that inference about the true asset pricing model is not tenable. The rejection of investor sophistication is tenable, but the appropriate benchmark to judge sophistication is different from the one that BHO use. In the third essay, I study the revealed preferences of equity mutual fund investors to examine the horizon of past performance that matters for buying and selling decisions separately. I find that current buying and selling decisions are sensitive to 52 and 37 months of past performance respectively. I compare the ability of long-horizon information in identifying superior funds next period with that of a simple metric such as prior one-month net return. The performance of portfolios formed using these two information sets indicates that investors' dependence on long horizons of performance is not optimal.

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Seasonality in Fund Flows at the Turn of the Year: Role of Performance and Distribution Channel*

Chandra Sekhar Mangipudi†

Abstract: Investment decisions of retail investors in equity mutual funds are significantly different at the turn of the year, i.e. December and January. My results indicate that levels of purchases and redemptions are higher at the turn of the year compared to other months. I study the role of distribution channel and tax-loss selling on these seasonal patterns. Intermediaries such as selling brokers in the distribution channel of a fund can influence the timing of purchases at the turn of the year due to their compensation incentives for meeting annual sales quotas. Compared to direct-sold funds, broker-sold funds experience a shift in purchases from January of next year to the December of current year. Higher redemptions in December are concentrated in funds with poor performance but are not systematically different in years with negative and positive aggregate market returns.

Keywords: Fund flows, calendar seasonality, turn of the year, selling brokers, distribution channel, flow timing.

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† Goizueta Business School, Emory University, email: chandra.sekhar.mangipudi@emory.edu.

1. Introduction

Mutual funds are an important avenue for retail investors to access the equity markets. The ICI fact book for 2019 reports that 44% of the households in the United States hold mutual funds and that 88% of such households own equity mutual funds. Accordingly, the criteria investors use to select funds and the factors that influence these choices are studied widely in the literature on fund flows. In this paper, I study the timing aspect of investor flows in equity mutual funds. The central aim of this paper is to understand if investors in equity mutual funds are more likely to transact at certain times of the year and the role of distribution channel on these timing decisions. From a consumer finance perspective, this study complements the earlier literature which focuses on the fund selection decisions of households.

Flows in mutual funds are a result of the cumulative preferences of investors, fund managers, and intermediaries such as financial brokers through which investors make their transactions. These factors can also play a role in impacting the timing of flows into funds within a year, both in systematic and idiosyncratic ways. In this paper, I focus on the turn of the year which yields specific testable hypotheses for the trading outcomes based on the behavior of investors and the incentives of intermediaries. For instance, if investors' trades in equity mutual funds are impacted by tax-loss selling or holiday-liquidity motives at the year-end, fund flows at this time would be systematically different. The incentives of selling brokers of funds can also impact the timing of flows in funds that are sold through brokers. If the selling brokers service their own interests in the form of quota related bonuses at year-end, this can result in altering the timing of flows between the months of December and January and can lead to systematic differences between funds with and without selling brokers. I explore the implications of these factors on equity mutual fund flows in December and January.

Understanding the timing of flows is important from a practitioner standpoint to the fund management. It is well-established that abnormal fund flows impose externalities on portfolio performance through forced sales and liquidity costs (Chordia, 1996; Edelen, 1999; Coval and Stafford, 2007; Alexander, Cici, and Gibson, 2007 etc.) Therefore, identifying if investors have systematically higher propensity to trade at certain times can help funds manage their portfolios more efficiently. Studying flow decisions at the turn of the year are also important from a theoretical perspective for the literature on mutual fund tournaments (Brown, Harlow, and Starks, 1996; Chevalier and Ellison, 1997; Basak, Pavlova, and Shapiro, 2007; Schwarz, 2012 etc.) In these studies, flows from investors towards the end of the year hold special significance for the compensation incentives of fund managers. Hence, investor behavior in funds at the turn of the year and the factors that impact it such as the role of intermediaries have direct implications for studies in the tournament literature.

The first hypothesis I examine empirically is that the level of buying and selling by retail investors in equity mutual funds would be systematically different at the turn of the year. While mutual funds provide liquidity at the daily level, many retail investors remain inattentive to their portfolios for long periods of time distracted by other pursuits.[1] Year-end marks an opportunity for such investors to take stock of the winning and losing positions in their portfolios and to reallocate their invested wealth across assets. To study the buying and selling behaviors separately in a clean way, I collect disaggregated data on purchases and redemptions of mutual funds at a monthly level from Morningstar Direct and N-SAR files. I match the CRSP Mutual Funds database with these two databases using a sequence of automated and manual approaches. In the end, almost

[1] Duffie (2010) models the asset pricing implications of investors rebalancing their portfolios infrequently, driven by attention to non-investment activities. He also discusses the literature showing evidence of infrequent rebalancing by both retail and institutional investors.

80% of the equity funds in CRSP MF database during 1994 to 2017 have a mapping with the purchases and redemptions data from the above two databases. I filter and use the funds catered to retail investors for the empirical analyses in this study.

Using this data, I first report that inflows and outflows (i.e. purchases and redemptions as percentage of TNA) are markedly different in December and January compared to other months. Inflows and outflows in January are higher by 21%, 12% compared to other months. In December, inflows and outflows are higher by 13% and 20% compared to other months. Prior literature has shown that funds flows are driven by a host of fund characteristics such as past performance, expenses, family affiliation etc.[2] To alleviate concerns that time-variation in some of these characteristics could be driving my results, I repeat the analysis with abnormal flows, computed as the residuals from regression of flows on these explanatory variables. I find qualitatively similar results affirming that seasonal variation in investor trading behavior is behind the turn-of-the-year patterns in flows.

I next examine the role of marketing & distribution channel on the timing of flows at the turn of the year due to the compensation incentives of the selling brokers of funds. Distribution channel of a fund determines the mode through which investors can transact in that fund.[3] At a very broad

[2] Survey evidence from Investment Company Institute (https://www.ici.org/pdf/per25-08.pdf) indicates that past performance is a very important factor in influencing the investment decisions of investors. Ippolito (1992), Patel, Zeckhauser, and Hendricks (1994) and many other studies establish that flows chase past performance in equity funds. Jain and Wu (2002), Gallaher, Kaniel, and Starks (2006), Kaniel and Parham (2017) show that advertising attracts flows. Sirri and Tufano (1998), Barber, Odean, and Zheng (2005), Roussanov, Ruan, and Wei (2018) show that flows are positively associated with marketing and distribution activities. Finally, Del Guercio and Tkac (2008), Ben-David et. al. (2019) show that fund flows are positively correlated with Morningstar's proprietary star ratings.

[3] Distribution channel is the mode through which a product reaches the consumer from the manufacturer. This is an important ingredient in the marketing decision of any product and the main objective is to reduce the 'search cost' for the consumer. In direct-market channel, such as telemarketing for example, investors can transact directly with the manufacturer to buy or sell the product. Alternatively, the product can go through one or more intermediaries such as wholesalers, dealers, retailers etc. through which the end consumer can access it. Distribution channel of a product is a strategic choice of the manufacturer and it can have a huge influence on its revenues.

level, retail investors can access funds in one of two possible ways: the direct-market channel or the broker-sold channel. In the former, investors can transact either directly with the fund management company or through a discount brokerage. In both cases, there are no explicit advisory services offered to investors either by the fund or by the brokerage platform. Therefore, the timing of flows in these funds is solely a product of investors' decisions. In the broker-sold channel, investors use the services of brokers or financial advisors for transacting in funds. Because investors receive advice along with transaction facilitation, the monetary incentives of these intermediaries can play a role in the ultimate trading outcomes in this channel.

The monetary incentives of the selling brokers who interact with the end-consumers are strongly tied to the volume of transactions they bring to the firm that employs them. Their compensation packages are very similar to those of sales agents in any industry with a small fixed component and a large bonus-based component. A common compensation structure for these agents involves a periodic bonus payout for meeting quarterly and annual sales quotas.[4] Oyer (1998) and Jensen (2003) argue that such quota-based non-linear compensation structures can incentivize agents to game the system to their own advantage by altering the timing of sales. Since agents get paid at the end of the period for the effort expended during the period, they optimally push their efforts closer to the end of the period at which the reward is paid (effort gaming). And, at the end of the year, they face a choice between pushing new sales to the next year and pulling sales from next year to the current year (timing gaming).[5]

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[4] For example, there is payment grid for brokers that encourages them to involve in asset gathering. Firms also use sales contests to motivate brokers to increase their asset base (see the SEC report on compensation practices: https://www.sec.gov/news/studies/bkrcomp.txt). The SEC has recently come up with 'Regulation Best Interest' or RegBI which explicitly bans such sales quotas etc.

[5] For example, if sales agents fall short of a yearly quota, they might influence clients to book a sale at the end of current year which would ordinarily have been made in January (this leads to "pulling"). If the sales reps hit their quota in the current year, they might influence customers to "push" December sales into January to get a head start on the next year's sales targets.

Since brokerage firms' revenues are directly related to the amount of assets bought through them, they encourage their brokers to engage in asset gathering through sales contests, sales-quota based bonuses etc. If these quota-based incentives cause brokers to engage in timing gaming at the turn of the year, then the inflows in broker-sold funds would be systematically different compared to direct-sold funds at the turn of the year. To test this prediction empirically, I compare the month-on-month changes in inflows at the turn of the year in broker-sold vs. direct-sold funds. Since timing gaming involves pulling-in or pushing-out sales from one month to the other, comparing the month-on-month changes across distribution channels and calendar months can reveal the presence or absence of timing gaming at the turn of the year.

Using data on the shareclass type indicator, I split my sample of retail-oriented equity mutual funds into funds sold through broker and direct channels. My empirical results using month-on-month changes in inflows indicates strong evidence of timing gaming at the turn of the year between December and January. Specifically, I find that there is a strong pulling-in of inflows from January to December in broker-sold funds compared to the direct-sold funds. That is, there is a bunching of new sales at the end of a calendar year and drop in new sales at the beginning of a calendar year in broker-sold funds compared to the direct-sold ones. While both pulling-in and pushing-out are both possible under gaming outcomes, Oyer (1998) shows that pulling-in sales from next year to current year is more probable under the conditions in which sales agents normally operate, and my results are consistent with this narrative. These findings lend support to the hypothesis on the role of brokers' incentives in influencing the timing of flows at the turn of the year.

Year-end trading activities of retail investors are widely studied in the context of equities. To explain the high abnormal returns on small-cap stocks in January, Ritter (1988) proposed the 'parking the proceeds' hypothesis which states that retail investors are more likely to engage in selling in December and wait until January to reinvest their selling proceeds. Ritter (1988), Dyl and Maberly (1992) find empirical evidence consistent with this hypothesis in equity markets. The first set of results I document in this paper show that retail investors in equity mutual funds are also more active in trading in the months of December and January. However, my second set of results indicate that financial intermediaries can impact the timing and reallocation of flows at the turn of the year. In the direct-market channel with no financial intermediaries, the trading behavior of investors is consistent with the 'parking the proceeds' hypothesis. But, in the broker-sold channel, inflows are pulled from January to December due to the incentives of the intermediaries. To the best of my knowledge, this is the first study to highlight the role of financial intermediaries on the timing of trading outcomes in financial markets.

My hypotheses relate investor behavior and broker behavior to turn of the year seasonal patterns in flows. I run additional tests to alleviate concerns that fund management might influence investor behavior or the behavior of brokers to exert higher efforts in a particular calendar month and confound the results. Fund management's incentives to do so would be highest in months which coincide with fiscal year ends. Therefore, I repeat my analysis in a sub-sample by dropping funds which have their fiscal month-end coinciding with the calendar month. The inferences are qualitatively similar to the full sample which indicates that management's efforts are not the major reason behind my results.

The increased propensity to sell in December across different asset classes is consistent with multiple potential explanations such as tax-loss selling, seasonal liquidity needs, seasonally varying attention to personal portfolios etc. In the United States, December coincides with the end of tax-year for retail investors. And tax laws in the US are realization-based with different rates for short-term and long-term capital gains. All these factors can lead to seasonal tax-motivated trading behavior as argued in Constantinides (1984). Motivated by these arguments, I next examine if higher outflows that I find at the turn of the year are consistent with a seasonal tax-loss selling motive by conducting both cross-sectional and time-series analyses.

Seasonal tax-loss selling motivation for trading leads to a specific set of predictions for the relation between outflows and past performance of the funds at the turn of the year. Since December marks the end of a tax-year in the US, redemptions in both December and January could be impacted by past performance in a different way compared to the rest of the year. In case of equity markets, Badrinath and Lewellen (1991), Barber and Odean (2004), Ivkovic, Poterba, and Weisbenner (2005) show that the propensity to realize a capital loss is higher in December compared to other months and Chordia, Goyal, and Jegadeesh (2016) show that seasonal tax-loss trading can influence the relation between order flows and past performance at the turn of the year. If investors in equity mutual funds trade in a similar way and defer loss realization till the end of the year, then funds performing poorly have a higher likelihood of experiencing redemptions in December. Redemptions in January could also be impacted by past performance in a different way from other months and reasoning is as follows. Redemptions in January cannot be used to offset any capital gains from the prior calendar year. However, investors who plan to redeem their investments that are performing well are more likely to do so in January compared to other times in order to postpone potential tax consequences on these trades till the end of the new year. In this case, any increased redemptions in January would be concentrated in relatively good performing funds.

I test the above predictions by comparing the flow-performance sensitivity in the cross-section of funds at the turn of the year vs. other months. While the gain or loss of an investment with reference to the purchase price is the most relevant metric for tax purposes, identifying these using aggregate fund returns is not possible. Therefore, I focus on losing funds in the cross-section to identify the effect of tax-loss selling if it indeed exists. Funds that are performing very poorly by the turn of the year, even in terms of a simple metric like prior one-year return, are highly likely to be registering losses on many investor accounts and funds performing extremely well are likely to be at a gain in many investor accounts. My empirical analyses indicate that the sensitivity of outflows (i.e. redemptions/TNA) to market-model alpha in the low performance region is 112% higher in December than the average value in remaining months and is statistically significant. However, the sensitivity of outflows to market-model alpha in January in the high performance is not statistically different from the other months.

In the time-series analysis, I use the variation in aggregate market return as an instrument to identify the role of tax-loss selling on year-end outflows. Tax-loss selling must be particularly predominant in down-market years when most of the assets in investors' portfolios are registering losses. I use the compounded return on the CRSP value-weighted market index over a calendar year to define down-market years as those in which this return is negative. I conduct my time-series analyses by comparing the relative level of outflows in December to other months in up-market vs. down-market years. My empirical results show that the incremental outflows in December (over other months of the calendar year) in down-market years are 47% higher than those in up-market years. However, the difference is not statistically significant. Repeating the analyses using only the years in the top and bottom most terciles in terms of market return yield similar results. This indicates that tax-loss selling might only be a partial explanation for the increased outflows at the turn of the year.

I conduct various robustness checks for sensitivity of my results to various empirical choices. I find that my results are very similar in the two half sub-samples based on the sample period, and in sub-samples based on style categories. My results are also robust to the choice of performance metric used to compute abnormal flows and in flow-performance regressions. Finally, I also show that all my inferences about the seasonal trading behavior and the role of brokers are similar when using net flows computed from CRSP and without dropping the funds that do not have a match with the purchases and redemptions data.

The key contribution of my study is to show that the investment behavior of investors in equity mutual funds at the turn of the year is significantly different from other months. In addition, I show that the turn-of-the-year patterns are different across distribution channels where incentive gaming by sales agents can alter the timing of investments in broker-sold funds at the turn of the year. Recent studies by Barber, Odean, and Zheng (2005), Zhao (2008), and Christoffersen, Evans, and Musto (2013) show that brokers try to maximize their own revenue when suggesting funds to their investors. While these studies show that brokers influence fund selection decision of investors, my results indicate that broker can also game the timing of flows to cater to their own interests. These findings complement the results in studies that look at the advantages and disadvantages of brokers in the mutual fund industry. To my knowledge, my study is the first to explore the implications of seasonal selling efforts of intermediaries on retail trading activity in financial markets.

2. Literature

My study contributes to the findings in three branches of literature. First is the literature on seasonality in investor trading behavior, particularly the year-end behavior of retail investors. Studies in equity markets document many abnormal return patterns in calendar time associated with weekends, beginning of the month, holidays, January etc.[6] The huge abnormal returns on small stocks and illiquid stocks in January drew widespread attention to the January seasonality phenomenon in the literature.[7] Ritter (1988), Dyl and Maberly (1992), Sias and Starks (1997) document abnormal trading activity at the turn of the year and use it to explain the January effect. Starks, Yong, and Zheng (2006) show similar pattern in trades of retail investors in municipal bond closed-end funds.

While equity market data uses prices determined in equilibrium by supply and demand forces, mutual fund flows measure the quantities traded at a fixed price. Using aggregate mutual fund flows by asset categories such as equity, money market etc. Kamstra et. al. (2017) study calendar-time seasonal patterns in the trading behavior of investors. They find that money flows out of equity mutual funds in aggregate and into money market funds during summer and fall seasons. The opposite happens in winter and spring seasons. They attribute these fluctuations to seasonal changes in trading behavior of individual investors due to changes in sentiment related to risk aversion. Although they control for turn-of-the-year seasonal effects in their analysis, they do not analyze these effects in detail which is the main objective of my study. Moreover, they study asset allocation across asset categories by focusing on aggregate flows by categories while I study the cross-sectional implications within equity mutual funds at the turn of the year.

Another notable deviation from Kamstra et. al. (2017) is the use of disaggregated purchases and redemptions data in this study, while they use net flows [defined as (purchases-redemptions)/TNA]. When I study the calendar seasonal patterns in net flows using my data, I find

[6] Jacobs and Levy (1988) discuss some of these empirical regularities. Bouman and Jacobsen (2002) document the Halloween effect, Hong and Yu (2009) document the summer vacation effect, and Kamstra, Kramer, and Levi (2003) discuss the role of Seasonal Affective Disorder in equity return variation over calendar year.

[7] In addition to size and illiquidity characteristics, anomalies associated with momentum, long-horizon reversals, book to market, asset growth also display different patterns in January compared to other months.

a monotonic drop from January to December in an approximately linear fashion. Without studying purchases and redemptions separately, one cannot infer if lower net flows in December are driven by a drop in purchases or an increase in redemptions or both. My results show that both purchases and redemptions increase at the turn of the year compared to other months. But redemptions are higher than purchases in December leading to lower net flows and purchases are higher than redemptions in January leading to higher net flows on average.

Ivkovic and Weisbenner (2009) study the trading behavior of retail investors in mutual funds. However, their sample is a subset of retail investors at one discount brokerage firm. Although they note that tax related effects play a role at the year-end, they do not focus on the trading behavior at the turn of the year. My sample covers larger set of equity funds over a longer time span and uses all the transactions in these funds, although it doesn't identify trades at the investor level. I study the buying and selling behavior of investors in funds aggregated across all investors. The relation between past performance and order flows of buyers and sellers in equity markets is studied by Chordia, Goyal, and Jegadeesh (2016). They report an increase in both seller- and buyer-initiated trades at the turn of the year. And, they also find evidence of heavy tax-motivated selling at this time. My findings on the level of inflows and outflows at the turn of the year and relation of inflows and outflows to past performance at the turn of the year echo their findings. However, my findings on the role of brokers in turn-of-the-year trading activity are novel and have not been studied either in equity markets or mutual fund literature before.

The second branch of literature my study is connected to is the role of brokers and advisors in financial markets. Current literature on the role of brokers and financial advisors in the financial marketplace indicates that conflicts of interests plague the market.[8] Commission-based compensation arrangement in the broker-sold channel results in brokers aggressively selling products that maximize their own revenues. In case of mutual funds, Barber, Odean, and Zheng (2005), Zhao (2008), Bergstresser, Chalmers, and Tufano (2008), Christoffersen, Evans, and Musto (2013) report that flows are directed more towards funds with higher commissions. In my study, I focus on a different aspect of brokers' compensation structure – sales quotas – that induce seasonal selling efforts as shown in Asch (1990) and Oyer (1998). While revenue from commissions goes to the brokerage firm that employs the brokers and creates a conflict of interest, I focus on a different conflict of interest – the one between the broker and the brokerage firm – that leads to an aggressive end-of-year selling.

My study also relates to the literature on agency issues in fund management that appeal to the turn-of-the-year trading behavior of investors such as 'mid-year risk shifting'. Turn of the year holds special significance for the motives behind these agency issues. Studies that appeal to cash flow based tournaments in funds use the calendar year as a decision window of investors and test if mid-year poor performers increase their portfolio risk during the second half. This setup is used in Brown, Harlow, and Starks (1996), Chevalier and Ellison (1997), Basak, Pavlova, and Shapiro (2007), Kempf, Ruenzi, and Thiele (2009), Schwarz (2012) etc. The extent to which investors' behavior at the turn of the year lines up with the assumptions in these studies has significant implication for the interpretation of results in these studies.

My findings on the increased level of flows at the turn of the year provides a rationale for the assumption in the tournaments literature that managers compete during a calendar year for

[8] Burke et. al. (2015) review a large literature on the conflicts of interest in the financial advisory industry.

investors’ flows at the turn of the year. However, I find that funds performing relatively poorly are likely to experience higher redemptions in December which casts doubt on the mid-year risk-shifting incentives of managers. Since increased risks can also end up damaging the performance of the fund further and poor performing funds experience heavy redemptions in December, some managers may be wary of this consequence. That is, all losing funds by mid-year are not equally likely to engage in risk shifting. Despite the significance of year-end trading behavior for the narratives in this literature, there are no studies that examine this aspect. My study fills this gap.

3. Hypotheses

3.1. Level of retail trading activity in equity funds at the turn of the year

The months of December and January constitute a special time for retail investors in the United States. First, December coincides with the end of tax-year for individuals in the US. Next, December and January also coincide with the largest holiday season in the US. These factors can impact the consumption and trading decisions of investors in a different way compared to other times.

Retail investor trades at the turn of the year are studied widely in the context of equity markets. Ritter (1988), Dyl and Maberly (1992), Barber and Odean (2004) and others find that retail investors trade more actively at the turn of the year (i.e. December and January). Chordia, Goyal, and Jegadeesh (2016) document a similar finding using order flow data of all investors from the TAQ database. It is not readily apparent if this evidence from equities can be readily extrapolated to infer the turn-of-the-year trading behavior of retail investors in equity mutual funds. Bailey, Kumar, and Ng (2011) show that investors in mutual funds are more sophisticated compared to investors in equities. And, Chang, Solomon, and Westerfield (2016) argue that investors in equity mutual funds do not display the well-documented disposition effect in case of equity market trades.

Therefore, my first hypothesis on the level of retail trading in equity mutual funds at the turn of the year is:

H1: Outflows are higher in December compared to other months and inflows are higher in January compared to other months.

This prediction would be borne out in the data if retail investors display similar seasonal variations in trading preferences across asset classes. Alternatively, if retail investors in equity mutual funds are more likely to trade uniformly throughout the year, then the above prediction would be rejected.

3.2. Role of distribution channel on turn-of-the-year trading activity in equity funds

Mutual funds are not traded on an exchange and can only be bought and sold through a distribution channel chosen by the fund to make its product available to investors. At a broad level, there are Direct, Advice, Retirement Plan, Supermarket, and Institutional channels through which funds are sold to investors.[9] In the direct-market channel investors can transact directly with the fund management to buy or sell units. In the supermarket channel investors buy or sell units through discount brokerage platforms which list funds from a variety of asset management companies. In the advisory channel, funds use the services of firms that have a distribution channel in place to sell their units. The distributor firm employs brokers or advisors who prospect for new clients and also advise the existing clients on various financial matters. Most investors transacting through direct-market and supermarket channels rely on their own personal judgement to make their buying and selling decisions. In the advisory channel, investors use services of the broker/advisor for

[9] The ICI report at https://www.ici.org/pdf/per09-03.pdf covers more details on mutual fund distribution channels.

choosing the right product as well as to get financial advice on other aspects of their wealth and portfolios.

The individual brokers who work for the brokerage division of the distributing firm act in the capacity of salesmen. The typical compensation arrangement for these brokers involves a fixed salary and a large bonus component. Bonuses are tied to the new assets they gather for their employer by meeting sales quotas that are set typically on a quarterly basis and an annual quota. Meeting or exceeding the quota usually leads to a large sales bonus. Brokerage firms' revenues depend on the asset size of assets they manage and hence they have an incentive to push their brokers to engage in asset gathering and compensate them through quotas.[10]

Literature on sales and marketing discusses the business seasonality implications of such compensation arrangements. Oyer (1998) discusses two potential effects of quota-based sales compensation: effort gaming and timing gaming. When salesmen are compensated at the end of a fiscal period for meeting or exceeding the quota anytime during the period, they have an incentive to increase their selling effort gradually over the period and bunch most of the selling towards the end of the period (effort gaming). When brokers compute utility based on the reward less the effort and discount it to present time, their optimal action is to delay their effort closer to the end of period when the reward is paid. Similarly, at the end of the fiscal year, brokers can either push some sales to next fiscal year to maximize revenues next period or pull in sales from next fiscal year to maximize revenues in the current period. The trade-off in waiting for the next year is a potential loss due to moving away from the current market that the broker is operating in. Under standard conditions, Oyer (1998) shows that it is more likely for brokers to pull in sales from the

[10] The SEC has recently adopted Regulation Best Interest (Reg BI) that explicitly prohibits compensation practices based on sales quotas, sales contests etc. More details are available at: https://www.sec.gov/info/smallbus/secg/regulation-best-interest

beginning of next fiscal to the end of current fiscal year resulting in increased sales at the end of current fiscal year and decreased sales at the beginning of the next period (timing gaming). Based on these arguments, the specific hypothesis to test is as follows:

H2: Seasonal efforts of sales agents lead them to shift inflows from January to December in funds distributed through the broker-sold channel.

If selling brokers of funds display incentives to game the timing of new money just like other sales agents, then the prediction in hypothesis 2 should reflect in the inflow patterns at the turn of the year.[11] Alternatively, if selling brokers in financial markets are not prone to such incentives at the turn of the year, then there should be no significant difference in inflow patterns across distribution channels in the months of December and January.

4. Data and Descriptive Statistics

4.1. Sample Selection

I construct the final sample used in this study by merging the survivorship bias free CRSP Mutual Fund database (CRSP MF hereafter) with Morningstar Direct (MS Direct hereafter) and N-SAR filings. The sample period is 1994 to 2017. I get the monthly data on funds' net returns, TNA, expense related variables, styles etc. from CRSP MF which is at the share-class level. I use the comprehensive style code provided by CRSP MF to filter out actively managed US domestic equity funds. I use MS Direct to obtain monthly share-class level data on Morningstar rating, share-class type and fund level data on gross purchases and gross redemptions.[12] Mutual funds report

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[11] Although Oyer (1998)'s argument applies to fiscal year cut-offs, I expect it to hold for a calendar year in the sample of mutual funds. Most firms in the financial services industry (SIC 6000 to 6799) use calendar year as their fiscal year as shown by Huberman and Kandel (1989).

[12] My sample does not suffer from survivorship bias since Morningstar Direct provides data on both surviving and dead funds unlike Morningstar data on disks and the Internet.

monthly purchases and redemptions at the fund level in their semi-annual N-SAR filings for the six months covered by the filing and MS direct provides this data beginning 1999. I merge CRSP MF and MS Direct following the approach in Pastor, Stambaugh, and Taylor (2015) along with some additional manual steps. To get data on monthly purchases and redemptions for the earlier period, I download and parse the N-SAR files from SEC EDGAR database. These files are available in electronic format starting 1993 but the coverage improves from 1994 as more funds started complying. I provide a detailed description of the steps involved in filtering, cleaning, and merging all these datasets in Appendix 1A.

Since purchases and redemptions are the fund level, I conduct all my analyses at this level. I aggregate the share class level data from CRSP MF and Morningstar Direct to fund level using WFICN as the identifier which is provided by WRDS. I compute the fund-level returns and expense related metrics as weighted average values of the constituent share classes, with the beginning-of-month TNA as the weight. I compute fund-level TNA as the sum of TNA across share classes, fund-level dividend distributions and capital gains distributions as sum of these values across share classes and fund-level age using the minimum offer date across all share classes and time periods. I consider a fund to be ‘no-load’ if data on both front-end, back-end loads exists and takes values of zero for all its share classes. I construct fund-level qualitative metrics such as style, management code, fiscal year etc. using the corresponding values from the share class with the largest TNA. Using the comprehensive style code from CRSP MF, I group funds into four different styles: growth, growth & income, mid-cap and small-cap.[13]

[13] Since micro-cap funds (EDCI) are small in number, I group them with small caps (EDCS). Similarly, I group income funds (EDYI) which are small in number with growth & income funds (EDYB). Mid-cap and growth funds are identified by the CRSP style codes EDCM and EDYG respectively.

I assign a distribution channel at the fund level by first computing the percentage of TNA held in broker-sold, direct-sold, institutional, retirement, other categories across all share classes each month. Following Del Guercio and Reuter (2014), if a fund holds 75% or more of its assets in one of the above categories, I assign that category in that month. Funds which do not have 75% in any particular category get assigned to ‘other’. I drop fund-month observations that are categorized as Institutional or Retirement class from my analyses for two reasons. First, I expect the trading behavior of institutions to be different from that of retail investors, especially at the year-end, because gains and losses in these accounts are not tied to their immediate consumption requirements. Second, as James and Karceski (2006) document using information from fund prospectuses, institutional funds serve a wide-variety of clients ranging from 401(k) plan participants, foundations and endowments, customers of a bank trust or custodial account, or investors with more than $100,000 to invest in the fund. Therefore, a portion of Institutional funds and all of Retirement funds are essentially tax-deferred accounts. Ivkovic, Poterba, and Weisbenner (2005) show that the behavior of investors in these accounts is significantly different from taxable accounts. Therefore, I exclude these funds from this study. I drop records before the fund’s first offer date to avoid incubation bias documented in Evans (2010). And to avoid survivorship bias associated with reporting conventions in smaller funds documented in Elton, Gruber, and Blake (1996a), I drop the fund-month observations with TNA less than $15 million.

Table 2 shows the mapping statistics between the CRSP MF database and the purchases and redemptions data from Morningstar Direct, N-SAR files. Panel A reports the percentage of funds from CRSP that have a mapping by each year in the sample. These statistics indicate that mapping coverage increases over time and is not widely available in the beginning years. Post 2002, almost 80% of the equity funds in CRSP MF get mapped to the purchases and redemptions data. Panel B of Table 2 compares the characteristics of equity funds which get a mapping with those of all equity funds from CRSP. This panel reveals some systematic differences between the two sets of funds. The funds that do not get a mapping are smaller, younger, and have poor performance compared to those that get a mapping. However, these funds constitute only 20% of the sample in CRSP MF database.

4.2. Variable Construction

For each fund i in month t, I construct inflows, outflows, and net flows as percentage of TNA as:

$$\text{Inflow}_{\text{i,t}} = \frac{\text{Purchases}_{\text{i,t}} * 100}{\text{TNA}_{\text{i,t-1}}},$$

$$\text{Outflow}_{\text{i,t}} = \frac{\text{Redemptions}_{\text{i,t}} * 100}{\text{TNA}_{\text{i,t-1}}}, \quad (1.1)$$

$$\text{Net Flow}_{\text{i,t}} = \frac{\left(\text{Purchases}_{\text{i,t}}\text{-Redemptions}_{\text{i,t}}\right) * 100}{\text{TNA}_{\text{i,t-1}}}.$$

Since the dollar values of purchases and redemptions would vary to a great extent depending on the size of the fund, scaling by fund size allows easy comparison of the flow metrics across funds. And, to reduce the effect of extreme outliers in the above metrics (due to data coding errors in purchases and redemptions), I winsorize them at the 1% level. Computing net flows using purchases and redemptions data as in equation (1.1) avoids the influence of dividend payout policy of the fund on the definition of flows. Because most equity funds distribute a large portion of capital gains and dividends accrued during the year in December, defining net flows following prior literature might pose a problem for studying seasonal flow patterns at the turn of the year.[14]

[14] Most studies in the prior literature on flows construct *net flows* using only the data from CRSP as: $Net\,flow_{i,t} = \left(TNA_{i,t} - TNA_{i,t-1}(1 + R_{i,t})\right)/TNA_{i,t}$, where $R_{i,t}$ is the net returns for month t reported in CRSP. The inherent assumptions underlying this metric are that all the new money enters or leaves the fund at the end of the month and that all distributions during the month are reinvested into the fund. The second assumption is required because CRSP computes and reports net returns under the assumption that all distributions are reinvested into the fund. To the extent

I construct monthly family size as the sum of TNA of all funds within a family in that month after dropping the institutional and retirement funds. Similarly, the number of retail funds in a family each month gives the monthly number of funds in the family. And, I sum the purchases and redemptions across all funds in a family each month and subtract the contribution of the fund itself to get the numerator of family level flow metrics. Dividing these by lagged family TNA gives the family level inflow, outflow, and net flow. To construct style category level flow metrics, I use the sum of purchases, redemptions, and lagged TNA across all funds in a style category each month.

I construct various factor-based performance metrics each month using rolling window time series regressions. For each fund-month with at least 24 observations on past returns in the prior 36 months, I run time-series OLS regressions of funds' excess net returns on common factor returns in equities.[15] I use the OLS intercepts from the market model, Fama French 3-factor model, Fama French Carhart 4-factor model as different proxies of performance. Finally, I begin my sample in 1994 based on the availability of purchases and redemptions data from N-SAR filings.

4.3. Descriptive Statistics

The final sample of actively managed US domestic equity funds used in this study spans the time period Jan-1994 to Dec-2017. After dropping fund-month observations in institutional and retirement categories and the observations with missing purchases and redemptions data, the sample contains 2,026 funds. There are 1011, 414, 299 and 458 funds in the style groups growth, growth & income, mid-cap, and small-cap respectively.

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that some investors retain a portion of their distributions at the year-end for other purposes, the CRSP based net flow metric understates the actual net flow. Specifically, if the actual reported TNA at the end of December does not contain all the distributions that are disbursed during the month, then by assuming that all the distributions are reinvested into the fund and using the reported TNA at the month end to compute net flows will lead to a downward bias in this estimate in December. Therefore, the dividend policy of the fund and the reinvestment behavior of investors can contaminate inferences on flow seasonality at the turn of the year using this proxy for flows.

[15] Data on common factor returns is from Prof. Kenneth French's website. I thank him for sharing this data.

Table 4 shows the sample averages of the main variables in my final sample. The first three columns show the statistics within the distribution channels and the last column shows the full sample averages. The average fund has $1.5 billion in assets and is 13 years old. The average number of share classes per fund is 3 which is consistent with the fact that a lot of funds shifted to a multi-class structure during the 1990s as discussed in Nanda, Wang, and Zheng (2009). The average fund in my sample trades 83% of its portfolio over a year as seen from the turnover ratio statistic. In terms of performance after expenses, the average fund in this sample returns the same as the CRSP VW market index with a market excess return of -0.01% per month. After adjusting for exposures to the common factors using the Fama-French-Carhart 4-factor model, the average 4-factor net alpha is -0.07% per month. This is consistent with the evidence of underperformance from a large body of literature on mutual fund performance evaluation. All the statistics in my sample correspond well with the statistics in samples of actively managed US domestic equity funds from other studies (see for e.g. Amihud and Goyenko, 2013).

A comparison of sample means across broker-sold and direct-sold funds reveals some interesting patterns. Direct-sold funds are larger on average and have smaller expense ratios compared to broker-sold funds. More importantly, broker-sold funds underperform their counterparts even before fees and expenses. Broker-sold funds return 0.68% on average per month before expenses while direct-sold funds return 0.79%. The puzzling underperformance of broker-sold funds on a gross-returns basis is also documented and studied in Bergstresser, Chalmers, and Tufano (2009), Christoffersen, Evans, and Musto (2013), and Del Guercio and Reuter (2014). These studies use the distribution channel classification provided by Financial Research Corporation. However, the statistics for broker-sold and direct-sold funds in my sample are comparable to the values tabulated in Del Guercio and Reuter (2014) which ensures the validity of my distribution channel classification.[16]

The last three rows of Table 4 report the sample averages of the flow proxies. There is a positive net flow per month on average across all funds. Purchases and redemptions as percentages of TNA (i.e. inflows and outflows) average to 3.30% and 2.96% respectively, while net flow as percentage of TNA averages to 0.30%. The contrast in the magnitudes of net flow vis-à-vis disaggregated inflows, outflows indicates that buying and selling activities are substantially correlated within and across funds in this sample each month. O'Neal (2004) studies inflows, outflows separately and reports similar patterns.

5. Empirical Analysis of Turn-of-the-year Seasonality in Flows

5.1. Level of retail trading activity in equity funds at the turn of the year

To test hypothesis 1 (H1), I examine the level of trading activity of retail investors in equity mutual funds at the turn of the year using different flow proxies defined in equation (1.1). Kamstra et. al. (2017) study calendar seasonality in fund flows and document that aggregate net flows across all equity funds in December are lower than average while those in January are high and above average. Figure 1 shows the variation of average net flows by calendar month in my sample. The pattern in this figure resembles the result in Kamstra et. al. (2017) (Figure 2 in their paper). Net flows are lower starting from June and continue to be so till December. And the opposite occurs from January to May. These patterns on net flows would indicate a subdued trading activity in December in equity funds.

[16] They report the summary statistics for actively managed funds in panel B of table 1. Their sample period is 1992 to 2004 which is different from mine.

While net flows are informative and are used commonly in the literature on fund flows, they do not give a complete picture of the buying and selling behavior. A net flow value close to zero could indicate a lack of trading activity or an equal magnitude of buying and selling in the same month within a fund. And if outflows from one fund are allocated to another fund, averaging net flows across funds would mask this rebalancing activity because net flows are signed metrics. To understand buying and selling behaviors separately and verify if these are different on average at the turn of the year compared to other months, I look at disaggregated inflows and outflows by calendar month. Figures 2 and 3 show the variation in selling and buying activities in equity mutual funds by calendar month. While average net flows in December indicates a low trading activity, studying inflows and outflows separately reveals different results.

Figure 2 indicates higher selling activity in December. Increased redemptions in December could be driven by higher demand for liquidity at the year-end due to holidays as well as with tax-loss harvesting. Apart from December, redemptions are also high in January which could also be due to liquidity needs or due to reallocation of invested wealth across assets. This would result if at least some investors who are making profits on their portfolios want to lock-in capital gains early in the year and defer paying taxes on these gains for longer time. Figure 3 indicates that January has the highest amount of purchases across all months in my sample. Inflows are also high in December with magnitude that is third highest among all months. Higher inflows at the turn of the year could be due to investing year-end cash bonuses or reinvesting proceeds from tax-loss harvesting. The patterns in Figures 2 and 3 indicate that both buying and selling activities are higher at the turn of the year[17] just as in the case of equity markets.

[17] I recently became aware that this result was documented earlier by Choi (2015).

5.2. Is the turn-of-the-year seasonality statistically significant?

To test if the turn of the year patterns in Figures 1 to 3 represents systematic effects, I run a regression of the flow metrics on dummy variables for January and December months. Statistically significant coefficients on the dummy variables indicate that the pattern is not driven by a few outlier years. The constant in these tests represents the average trading activity in the months February to November across years while the coefficients on the dummy variables for December and January indicate the average additional trading activity in the respective months. I use net flows, inflows, and outflows as measures of trading activity in these regressions, where each metric represents a different aspect of the trading activity. Studying inflows and outflows informs about the aggregate buying and selling behavior separately and across all funds in a month while net flows inform about the net buying activity for each fund in a month. I also run separate tests for positive net flow sub-samples and negative net flow sub-samples on the dummy to test if there is predominance of funds experiencing net flows in a particular direction at the turn of the year.

Table 5 reports the results from these regressions. To account for both cross-sectional correlations in flows across funds within a month and for autocorrelation in flows at fund level, I estimate standard errors that are double-clustered by fund and by month. The results in panel A of Table 5 with all funds in the sample show statistically significant coefficients on both the dummies in most of the specifications. The coefficients on the dummies in columns (2) and (3) indicate that buying and selling activities in January are higher by 20.5%, 12.5% compared to other months and by 13.1%, 20.2% in December. Results in columns (4) and (5) indicate similar magnitudes among funds that experience positive and negative net flows in a month. For a fund with an average size of $1,468 million, the above values indicate that buying and selling are higher in January by $9.65 million, $5.28 million and in December by $6.15 million, $8.53 million respectively. Therefore, turn of the year marks higher trading activity in equity funds which is statistically and economically significant.

Apart from investors' and sales agents' incentives, fund management might also play a role in affecting the turn of the year trading patterns from the supply side. Funds can involve in practices such as 'portfolio pumping' that artificially enhance the performance as of fiscal quarter ends and fiscal year ends. Since fund managers' compensation and bonus are tied to performance as of the end of a fiscal year, they are incentivized to shift performance from next period to the current period as argued in Carhart et. al. (2002). Fund management can also push their brokers to engage in excessive selling at strategic times such as quarter ends and fiscal year ends. I assume that any such practices of fund management would be concentrated more at the ends of fiscal years. Bonus payouts, annual shareholder letters etc. are related to fiscal year end of a fund and hence this time is more important from the fund's perspective.[18] To alleviate the concern that fund's supply side effect is causing the seasonal patterns, I repeat my analysis in a sub-sample obtained by dropping funds with fiscal month ending in December or January or is missing. By only considering funds that have fiscal years ending in other calendar months, I can reduce the effect of fund management's role in the flow outcomes.[19]

In panel B of Table 5, I report the results in a sub-sample obtained by dropping funds with fiscal years ending in December, January or if the fiscal year is missing. Results in panel B are qualitatively very similar to those in panel A implying little role of fund management in investor behavior at this time. Overall, the evidence from Table 5 indicates that trading preferences of

[18] Note that fiscal year end of a fund need not be the same as the fiscal year end of the firm that distributes its shares. Funds within a fund family choose different fiscal year ends so as to spread out the paper work related to filing requirements over the course of a calendar year.

[19] The distribution of fiscal months is skewed. Table 3 presents the frequency tabulation by fiscal months. Most observations fall in October which is followed by December and September.

investors are different at the turn of the year in equity mutual funds which reflects in a higher level of trading activity.

5.3. Is the turn-of-the-year seasonality driven by fund characteristics?

Flows into mutual funds are affected by a variety of fund-specific, investor-specific, and macroeconomic factors.[20] If some of these factors exhibit systematic variation within a calendar year, then they could be potentially driving the turn of the year patterns in flows. Therefore, I next try to isolate the role of investor preferences in turn-of-the-year patterns over and above the fund-level characteristics that determine flows.

5.3.1. Estimating abnormal flows

By projecting flows on the standard determinants that are documented in the literature, I estimate the unexplained portion each month and study if these abnormal flows exhibit systematic variation over calendar months in a manner similar to the evidence in Table 5. Specifically, I estimate the following linear regression specification.

$$\text{Flow}_{i,t} = \alpha + \boldsymbol{\beta}.\boldsymbol{X} + \mu_t + \epsilon_{i,t} \tag{1.2}$$

I use three proxies of flows which are defined in equation (1.1): net flows, inflows, and outflows when estimating the specification in equation (1.2). In this specification μ_t denotes month fixed effects which account for time specific demand shocks to flows and $\boldsymbol{X}$ denotes the set of explanatory variables that affect flows. I measure of abnormal flows in each month as the sum of the estimated values of the fixed effect and the residual in that month.[21]

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[20] Christoffersen, Musto, and Wermers (2014) provide a comprehensive review of the literature discussing these determinants.

[21] Estimates of month fixed effects obtained from equation (1.2) are only relative values with respect to an omitted month which forms the base category and whose month fixed effect estimate is captured in the intercept. Since I use the estimated abnormal flows to compare trading activity at the turn of the year with other months, the value of the unknown constant for the base month cancels out, leaving my inferences unaffected when using such relative estimates.

$$\text{Abnormal Flow}_{i,t} = \hat{\mu}_t + \hat{\epsilon}_{i,t} \quad (1.3)$$

To choose the relevant explanatory variables that go into $\boldsymbol{X}$**,** I rely on the evidence from an extensive literature on fund flows. Ippolito (1992), Patel, Zeckhauser, and Hendricks (1994) and many other studies establish that flows chase past performance in equity funds. Sirri and Tufano (1998), Barber, Odean, and Zheng (2005) and others show flows are positively associated with marketing and distribution activities and negatively related to expense ratios.

When choosing the appropriate performance metric to include in estimating (1.2), it is desirable to use a metric that is representative of investors' choice so that the residual portion of (1.2) captures the part orthogonal to fund characteristics in the best way. Although the literature on fund performance evaluation proposed a host of metrics (viz. alphas from various factor models, Sharpe ratio, appraisal ratio etc.), a recent study by Barber, Huang, and Odean (2016) documents that market model alpha has highest correlation with net flows. Based on this finding, I report all my main analyses using the 1-factor alpha. Since most multi-factor performance metrics and fund returns are highly correlated in the cross-section, my results are robust to using other performance metrics as well.

To allow for non-linearity in the flow-performance relation, I estimate a piece-wise linear specification following the approach in Sirri and Tufano (1998). I first assign percentile ranks to each fund within a style group each month based on ranks of the performance metric. Next, I generate the following three variables to allow for kinks at the 20th and 80th percentiles.

$$\begin{aligned} &\text{LOW}_{i,t} = \min(\text{Rank}_{i,t}, 20), \\ &\text{MID}_{i,t} = \min(60, \text{Rank}_{i,t} - \text{LOW}_{i,t}), \quad (1.4) \\ &\text{HIGH}_{i,t} = \text{Rank}_{i,t} - \text{LOW}_{i,t} - \text{MID}_{i,t}. \end{aligned}$$

This procedure normalizes performance variables and facilitates comparison across different segments of the performance groups as well as across months.

The 12b-1 Fees (which is quoted as a % of TNA) captures the marketing and distribution costs of a fund. The fees are named after Rule 12b-1 of the Investment Advisers Act of 1940 which allows funds to use a portion of assets to compensate the broker-dealers for their distribution service or for shareholder account maintenance services along with any front-end or back-end loads. To avoid conflicts related to using existing assets for advertising, the rule limits 12b-1 fee to a maximum of 1% of TNA per annum. Prior to this act, loads are the only ways to compensate the broker-dealers for recommending a fund to their clients. Loads are deducted directly from the client's investment and do not impact the entire fund portfolio as opposed to 12b-1 fee which is deducted from the fund's assets and considered an operating expense. Fund units sold through direct-market channel typically do not incur 12b-1 fees since there is no intermediary in this case. But funds that charge a 12b-1 fee of less than 0.25% of TNA can advertise themselves as No-Load funds. These funds are not sold through broker-dealers but use the 12b-1 fees for advertising, paying a discount brokerage platform etc. In general, higher 12b-1 fee represents higher marketing and distribution efforts for a fund, particularly through broker-dealers. And, expense ratio from CRSP includes management fees, administration expenses, and 12b-1 fees in it.

Apart from performance and expense related variables, I include a host of other fund characteristics that influence flows. I add the log of fund size to control for non-linear effects of size on flows since bigger funds might grow (in terms of new money) at a different rate than smaller ones. I also control for fund's age and total risk measured by the standard deviation of returns over past 12 months which impact flows as shown in prior literature. To allow for the possibility that fund flows can depend on much longer horizons of performance than captured by the alpha, I use lagged flows from previous month as a control. This variable also captures the persistence of flows for reasons orthogonal to performance such as systematic investment plans. I also include contemporaneous flows into funds of the same objective code to account for style-specific demand shocks. Nanda, Wang, and Zheng (2004) document positive spillover of flows to funds belonging to a family which has a star fund. To control for such spillovers, I use contemporary flows to the family (after excluding the contribution of the fund itself) as an explanatory variable. I include lagged turnover to control for the effect of capital gains distributions on flow. I also include the contemporary capital gains payout and dividend payout variables to allow for the possibility that purchases and redemptions in a month could be influenced by such payouts during that month. When analyzing purchases and redemptions separately, I use a slightly different set of control variables. In tests involving purchases (redemptions), I use contemporary redemptions (purchases) as a control variable since purchases and redemptions are contemporarily correlated as shown in O'Neil (2004). I also include category level purchases and redemptions, family level purchases and redemptions as controls in this specification.

5.3.2. Seasonality in abnormal flows

I repeat the analysis in Section 5.2, but I now estimate a regression of the abnormal flow metrics on the dummy variables for January and December months. The constant from these regressions represents the average abnormal trading activity in the months February to November across years while the coefficients on the dummy variables for December and January indicate the average additional abnormal trading activity in the respective months. To account for both cross-sectional correlations in flows across funds within a month and for autocorrelation in flows at fund level, I estimate standard errors that are double-clustered by fund and by month. Table 6 reports the results from this estimation. The results in panel A of Table 6 with all funds in the sample show results that are qualitatively very similar to those of Table 5. Inflows are abnormally high in both the months of December and January and outflows are abnormally high in the month of December. The results in panel B of Table 6 after dropping funds with fiscal years ending in December, January or if the fiscal year is missing are also in accordance with the prior evidence. These results indicate that turn of the year patterns in inflows and outflows are not driven by seasonal patterns in fund characteristics and that trading preferences of retail investors in equity mutual funds are indeed systematically different at the turn of the year.

6. Empirical Analysis on the Role of Distribution Channel on Turn-of-the-year Flows

I now present my empirical analysis related to hypothesis 2 (H2) which predicts that timing gaming by financial brokers at the turn of the year leads to a shift of inflows from January to December of previous year. To identify the role of brokers on the turn-of-the-year patterns, I split my sample of retail-oriented equity mutual funds based on their distribution channel into funds sold through brokers and those sold through the direct-market channel. Trading outcomes in the latter group are a result of just the investors' decisions. Therefore, funds in direct-market channel can serve as a control group to compare the trading outcomes in the broker-sold channel where intermediaries such as the selling brokers can potentially affect the outcomes.

The analyses in Section 5 related to hypothesis 1 use levels of various flow proxies each month as the dependent variable. Figure 4 presents a comparison of calendar seasonal patterns in inflows and outflows by distribution channel. Looking at the patterns within each distribution channel reveals a strong turn-of-the-year seasonality in both channels. Although investors in broker-sold channel are considered to be relatively less sophisticated, the pattern of increased redemptions in December in broker-sold funds indicates that investors in these funds could be receiving valuable tax-related advice from their financial advisors as shown in Cici, Kempf, and Sorhage (2017). Comparing the patterns across the two channels indicates slight differences in the months of December and January as against the remaining months. For example, inflows in broker-sold funds are greater in magnitude compared to that in direct-sold funds in all the months expect January where the pattern reverses. Even in the months of June and December, the difference between inflows in broker-sold and direct-sold funds is slightly higher than in the remaining months. Outflow patterns across the two channels also exhibit a slight difference in December and January months compared to other months.

While the evidence from Figure 4 indicates difference in turn-of-the-year patterns across distribution channels, it is not a clean and direct test of hypothesis 2. The prediction in hypothesis 2 is for a shift of inflows between the months of December and January. Therefore, I construct month-on-month changes for each of the flow proxy in equation (1.1). To understand the reasoning behind this, consider the following example. Suppose that the inflows in two consecutive months are x and y when there is no timing gaming. Consider an alternate scenario where, under hypothesis 2, inflows in these two months are $x + d$ and $y - d$. In this scenario, inflows worth d are shifted between the two months. A month-on-month difference computed backwards would yield values $y - x$ and $y - x - 2d$ under the two scenarios. Therefore, this difference would be systematically different when inflows are indeed affected as predicted by hypothesis 2.

6.1. Analysis using month-on-month changes in flow proxies

To test the implications of hypothesis for shift in inflows due to incentives of brokers, I compare the month-on-month changes in various flow proxies across the two distribution channels at the turn of the year vs. other months. If timing gaming is particularly predominant at the turn of the year, then month-on-month changes in inflows at this time must be systematically different compared to the differences in other periods. Figure 5 plots the month-on-month changes in inflows and outflows for each pair of sequential calendar months and across distribution channels. Within each distribution channel, there is a spike for the difference in inflows from November to December and from February to March. And there is a similar pattern for outflows as well. However, comparing across the two channels indicates a difference in pattern for inflows in the months of January and June. The pattern for changes in outflows is very similar across the two channels. To compare if the month-on-month changes at the turn of the year are significantly different compared to the changes in other sequential month pairs, I run the following regression.

$$\Delta\text{Flow}_{i,t} = \alpha + \beta * I_{January} + \epsilon_{i,t}, \tag{1.5}$$

where $I_{January}$ is a dummy for the month of January. Table 7 shows results from this estimation within each distribution channel. The constant in this regression represents the average value for month-on-month changes across all sequential month pairs other than December and January. By way of construction, the month-on-month change in a flow proxy in the month of January equals the change at the turn of the year, i.e. difference in the flow proxy between January and December of previous year. Therefore, the coefficient on the January dummy in Table 7 indicates how the month-on-month change in a flow proxy varies at the turn of the year compared to other sequential month pairs.

Panel A of Table 7 shows the results for direct-sold funds. The coefficient on January dummy in column (2) for inflows indicates a positive significant value while the constant in this specification is negative. Month-on-month changes in inflows in the direct-sold channel are negative in general as shown by the constant while the change from December to January at the turn of the year is hugely positive. That is, investors in direct-sold funds are more likely to invest in the markets in January compared to December. This indicates that the behavior of investors in direct-sold funds at the turn of the year is consistent with the prediction of ‘parking the proceeds’ hypothesis of Ritter (1988). In contrast, the negative coefficient on January dummy in column (2) of panel B for broker-sold funds indicates a difference in trading behavior. Coefficients in column (3) for outflows do not indicate any systematic difference at the turn of the year in either channels.

In Table 8, I repeat the analysis with month-on-month change in abnormal flows. After estimating abnormal flows as described in Section 5.3.1, I compute a backward difference each month (i.e. month ‘t’ value minus month ‘t-1’ value) to get the month-on-month changes in abnormal flows. The results in column (2) for inflows in both panels of Table 8 reinforce the findings from Table 7. Particularly, the direction of shift in abnormal inflows at the turn of the year is completely opposite across the two distribution channels.

6.2. Difference in difference estimation using month-on-month changes in flow proxies

I compare the coefficient on January dummy in Table 7 across the distribution channels to test if the difference is statistically significant. This is equivalent to a difference-in-difference estimation that compares the dependent variable (which is the month-on-month changes in flow proxies in this case) at the turn of the year with other months in broker-sold funds vs. direct-sold funds. Specifically, I estimate the following regression.

$$\Delta\text{Flow}_{i,t} = \alpha + \beta_1 * I_{January} + \beta_2 * I_{broker\ sold} + \beta_3 * I_{January} * I_{broker\ sold} + \epsilon_{i,t}, \quad (1.6)$$

where $I_{broker\ sold}$ is a dummy variable that take a value of one for broker-sold funds and zero otherwise. In equation (1.6), the estimate of β_3 is the coefficient of interest. Comparing the dependent variable across the two distribution channels and between the turn of the year and other month pairs helps in controlling for heterogeneity in investor behavior and therefore in teasing out the role of brokers’ incentives at the turn of the year. Table 9 reports the results from estimating

(1.6) with standard errors double clustered by fund and month to account for both cross-sectional correlations in the dependent variable across funds within a month and for autocorrelation at fund level. Panel A shows the results with month-on-month changes in various flow proxies and panel B reports the results with month-on-month changes in various abnormal flow proxies.

The results in Table 9 indicate that the difference-in-difference coefficient β_3 in equation (1.6) is statistically significant using both normal flows and abnormal flow proxies. Month-on-month changes in inflows from December to January are significantly lower in broker sold funds compared to direct-sold funds and other sequential month pairs. This result is consistent with the prediction of hypothesis 2 that financial intermediaries can impact the timing of flows at the turn of the year in line with their incentives. The coefficient on the interaction term β_3 in column (3) with Δinflows as the dependent variable in panel A is -0.641 which is significantly different from zero with a p-value less than 1%. This estimate provides a measure of the extent of shift of inflows between January and December due to brokers' incentives at the turn of the year after controlling for heterogeneity in investor behavior across channels and across time. A broker-sold fund with an average size of $1029 million receives dollar inflows of $36 million per month on average. For this fund, the difference-in-difference estimate translates to a shift of inflows of $6.6 million between the months of January and December. This represents 18% (=6.6/36) of the average inflows in this fund in a month which is a reasonably big magnitude.

Table 9 also reports the results from estimating equation (1.6) by including fund and month fixed effects. This alleviates concerns that the results discussed above could be driven by unobserved fund-specific factors other than broker-affiliation and month-specific factors beyond marking of the year-end. Columns (2), (4), and (6) report the results using the two sets of fixed effects. In this estimation, coefficient β_1 is not identified anymore since it is collinear with the month dummies. But β_2 is identified because some funds switch their distribution channel over time based on the proportion of assets held in each channel across all share classes. As before, β_3 is the coefficient of interest. The results with fixed effects still indicate a negative and statistically significant coefficient for the interaction term. More importantly, there is only a slight change in the coefficient magnitudes from the specification without fixed effects implying little role for other unobserved factors on these results.

7. Tax-loss Selling and Outflows at the Turn of the year

The first result documented in this paper shows that both outflows and inflows are high in both the months of December and January in retail-oriented equity mutual funds. Increased selling in December could be driven either by tax-loss selling motive of retail investors or by seasonally varying liquidity needs. In this section, I try to pin down the reason behind higher selling activity at the turn of the year.

Calendar year coincides with the end of tax-year for retail investors in the US. And, the tax-code allows investors to offset taxes on realized capital gains with capital losses realized during the calendar year. While losses realized any time during the year can be used to offset taxes on gains, investors might postpone the loss realization till the end of the year due to uncertainty in the amount of capital gains they accrue by the end of the year. Moreover, features in the tax-code such as different tax rates for long-term vs. short-term gains and the transaction costs in the markets can all push investors to concentrate their selling behavior in the months of December and January as argued in Constantinides (1984). I study if the seasonal selling behavior I document in this paper is driven by seasonal tax-loss selling motives of investors as documented in equity markets. I conduct both cross-sectional and time-series analyses to identify the role of tax-loss selling as I discuss next.

7.1. Cross-sectional tests for tax-loss selling at the turn of the year

In December, selling for tax-loss purpose implies that investments that are making loss on investor accounts would register higher outflows. The data I compile for this study is at the aggregate fund level which does not identify individual investor holding details. Therefore, multiple investors in the same fund can have different rates of return on their personal accounts in the same month depending on when they begin their position with the fund. Moreover, data on fund flows is also aggregated across all the investors and, therefore, it does not allow identifying trades made by investors who are facing losses from the fund versus those who trade for other reasons. Therefore, I resort to cross-sectional variation in the fund performance in a given month to identify flows that are driven by tax-loss motivation.

Funds that are performing very poorly by the end of the year, even in terms of a simple metric like prior one-year return, are highly likely to be registering losses on the personal accounts of most investors in those funds and are, therefore, likely to face more redemptions. Hence, I expect seasonal tax-loss selling in December to be concentrated in relatively poor performing funds in the cross-section. In other words, seasonal tax-loss selling predicts increased sensitivity of outflows to poor performance in December.

In January, investors whose portfolios are at a gain relative to their purchase price could be encouraged to sell and capture the gains in order to postpone paying taxes on these realized gains for an entire year. Such trades are also motivated by the fact that calendar year serves the base for retail investors' tax computation. Since funds performing extremely well in the cross-section are likely to be at a gain in many investor accounts, I expect that seasonal tax-loss selling leads to higher outflows in January to be predominantly concentrated in funds with good performance. This predicts a higher sensitivity of outflows to good performance in January.

To test the above implications of tax-loss selling on the flow performance sensitivity at the turn of the year, I estimate a linear regression of flow proxies on the three performance rank variables shown in equation (1.4) and allowing for the coefficients on the performance variables to vary in the months of December and January. By interacting the performance rank variables with dummy variables for the months of December, January I can test if there are statistically significant differences in the flow-performance sensitivity in these two months from remaining months. Table 10 reports the results from these regressions. Columns (5) and (6) show the results with outflows as the dependent variable. The coefficients of interest are on 'LOW Perf*December dummy' and 'HIGH Perf*January dummy' in column (6).

The results in column (6) of Table 10 support the role of tax-loss selling in December outflows but not much for January outflows. The coefficients on interaction terms of LOW, MID, and HIGH performance rank variables with December dummy indicate statistically and economically significant effect only for the LOW performance group on outflows. In other words, abnormal outflows in December are mostly concentrated in the low performance group. In Table 11, I report additional tests by including other variables that affect flows and allowing for these to change in the months of December and January. The results in column (6) of Table 11 indicate similar evidence on the role of tax-loss selling on December outflows.

7.2. Time-series tests for tax-loss selling at the turn of the year

Apart from the cross-sectional tests, I run additional analyses to pin down the role of tax-loss selling on the turn-of-the-year outflows based on time-series variation in the market-wide returns. In years when the aggregate market portfolio performs poorly by the end of the year, a lot of investor accounts register losses resulting in more tax-loss selling motivated outflows in such years. Moreover, in states of the world with lower market returns, the tax-saving benefit arising from selling the losers would be more valuable to investors, thus propelling such behavior. Similar tests were used by Dyl and Maberly (1992) to identify the role of tax-loss selling on year-end selling behavior of investors in equity markets.

Using the return on the CRSP value-weighted aggregate market portfolio as a proxy for market returns, I test if outflows in December are higher in down-market years compared to other times. I classify the years in which the compounded return on the above market proxy from January to December of a year is negative as down-market year. In my sample of 24 years, the 10 calendar years with negative market returns are 1994, 2000, 2001, 2002, 2005, 2007, 2008, 2011, 2014, 2015. If a calendar year has negative return on the market as discussed, I consider the months February to December of that year and the January of the next year to be a part of down market. I repeat my main analyses in Tables 5 and 6 with normal flow proxies and abnormal flow proxies by including additional interaction terms with a dummy for down market years. Table 12 presents the results from these estimations. Panels A and B show the results with normal flow metrics and abnormal flow metrics respectively.

Column (3) of Table 12 show results with outflows as the dependent variable. The coefficient on 'December Dummy*Down market dummy' is positive in both the panels but is not statistically significant. Although the sign of this coefficient is consistent with the prediction for tax-loss selling, lack of statistical significance casts a doubt on this explanation. Particularly, the coefficient on the interaction term in panel B indicates a very small magnitude for the increase in abnormal December selling in down-market years. The lack of results in this specification could also be due to lower power for this test due to a noisy proxy for the down-market years. To address this concern, I use an alternative proxy for down-market years by splitting the 24 years in my sample into terciles. I re-run my analyses by retaining only the top-most and bottom-most eight years with the bottom-most classified as down-market years. Table 16 reports these results which are very similar to the results in Table 12. These results indicate that tax-loss selling might not be the sole reason behind the increased outflows in December.

8. Robustness Tests

I now explore the sensitivity of my results to assumptions about various empirical choices. First, I study if the patterns I document in this paper are robust to sample period chosen. If behavioral biases are driving the documented patterns and investors learn and correct their biases, then the patterns should weaken over time. I run my analyses on sub-samples by splitting my sample into two halves. The results presented in the Tables 13 and 14 show that the patterns are qualitatively similar in both halves. In unreported results, I explore the sensitivity of my results to choice of performance metric such as market adjusted return, four factor alpha and find that the results are similar. I also repeat my analyses in sub-samples by style category. In unreported results, I find that my results are qualitatively similar.

Finally, I check the sensitivity of my results to the definition of flows. Most studies in the literature on fund flows use the net flow metric computed using the data on TNA and net returns available from CRSP MF database. Although this way of computing flows does not allow studying the buying and selling trades separately, it increases the size of the sample with data on net flows compared to using purchases and redemptions data as evident from the mapping statistics in Table 1. Therefore, I replicate my main results using CRSP based net flows as the dependent variable to mitigate concerns related to the systematic differences between the two sets of samples and also to relate my findings to previous literature on net flows. Figure 6 and Table 15 in the Appendix report these results. All the results are qualitatively very similar to the net flow computed using purchases and redemptions. Therefore, my findings are relatable to the prior literature on fund flows and contribute to them by exploring the dimension of seasonality at the turn of the year.

9. Discussion and Conclusion

In this paper I study equity mutual fund flows at the turn-of-the-year and address two main research questions. First is whether the trading behavior of investors in equity mutual funds is uniform across all calendar months. Retail investors, who comprise a large chunk of the investor base of equity mutual funds, rebalance their portfolios on an infrequent basis distracted by other pursuits. Year-end is associated with holidays and cash flow infusions in the form of bonuses to many investors and also coincides with the end of tax-year in the United States. Therefore, the attention to personal portfolios might be higher at this time resulting in higher rebalancing activities. Consistent with this narrative I find that the levels of buying and selling are significantly higher at the turn of the year, i.e. in December and January.

The second question I ask is if marketing & distribution efforts of selling brokers in financial markets differ at the turn of the year and influence the seasonal patterns flows. This question is motivated the incentives of selling agents to influence timing of flows due to their sales quotas. Sales agents are usually compensated through bonus payments that are tied to periodic sales quotas. Meeting or exceeding an annual sales quota results in an annual bonus payment which is a predominant part of their income. Literature on compensation design argues that such plans can lead to incentive gaming and hurt the firm that employs these agents. During the year, agents have an incentive to push their efforts towards the end of the period where the bonus payouts happen. And, at the turn of the year where the quotas are reset, they have an incentive to pull new sales from the beginning of next year to the end of current year by influencing their clients if they fall short of their quotas in the current period. Such incentives can distort the timing of flows in funds sold through brokers who essentially act as sales agents of the distributing firm.

Based on this theory, I study if higher distribution effort leads to increased inflows at the end of the year and lower inflows at the beginning of a year (i.e. pulling-in of sales from next year to end of current year). I split my sample into broker-sold and direct-sold funds and compare the month-on-month change in inflows in these two channels at the turn of the year with other months. I find that in broker-sold funds, there is a shift of inflows from January to December lending support to the argument on the role of selling brokers in influencing the timing of flows.

The patterns I document in this paper indicate that trading behavior of investors differs significantly at the turn of the year and that intermediaries such as selling brokers can influence investor behavior due to their compensation structures. While both types engage in higher selling in December, direct-sold investors defer their buying to the beginning of next year consistent with 'parking the proceeds' hypothesis of Ritter (1988). Investors in broker-sold funds actively invest at the year-end itself along with higher selling at this time. These findings complement the literature studying the timing ability of mutual fund investors. These studies document that mutual fund investors display poor timing ability in picking winners and that broker-sold funds are especially worse. My findings suggest that brokers might have a role to play in the poor timing ability of these investors. Therefore, studies that make economic inferences based on investors' flow behavior in equity funds must consider the impact of change in trading motives, behavioral biases, and incentives of various intermediaries in influencing the flows.

Appendix

Appendix 1A: Cleaning and Merging CRSP with Morningstar Direct and N-SAR files

In this appendix, I discuss my approach to clean and merge the CRSP mutual fund data with MS Direct data and N-SAR data. I also discuss my approach to identify distribution channel and fund family affiliation. I get the data from MS Direct by setting the Domicile to 'United States of America' and Global Broad Category Group to 'Equity'. I collect data on both surviving and dead funds starting from 1990. CRSP data is from WRDS and I filter actively managed domestic equity funds using the comprehensive style code provided by CRSP. Specifically, I consider records with crsp_obj_cd values in ('EDC', 'EDY') and then exclude records with crsp_obj_cd values 'EDYH' and 'EDYS'. To drop index funds, ETFs and target date funds, I use the CRSP index fund flag combined with a fund name search for the strings 'index', 's&p', 'idx', 'dfa', 'program', 'etf', 'exchange traded', 'exchange-traded', 'target', '2005', '2010', '2015', '2020', '2025', '2030', '2035', '2040', '2045', '2050, '2055'. I begin this sample in 1990 as well. Both CRSP and MS Direct are at the share class level and I merge them at this level. I scrape the EDGAR database to collect N-SAR files of all mutual funds and parse them to get data on monthly purchases and redemptions.

I parse the share class names in CRSP to identify the fund name and share class codes separately following the procedure discussed in the Appendix to Berk, van Binsbergen (2015).[22] I clean up the expense related variables following the Data Appendix in Pastor, Stambaugh, Taylor (2015).[23] I set expense ratio to missing if the reported value is less than 10 bps per year or if the difference between expense ratio and 12b-1 fee is less than 5 bps per year. Within each share class,

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[22] This is accessible from http://jfe.rochester.edu/Berk_vanBinsbergen_skill_data_app.pdf
[23] This is accessible from https://faculty.chicagobooth.edu/lubos.pastor/research/Data_Appendix_Aug_2013_V3.pdf

I fill any gaps in expense ratio, 12b-1 fee, loads, styles and management code with the most recently available values. And, I forward-fill and backward-fill fund names to deal with records having blank names. I set 12b-1 fee to 1% if the reported value is greater than 1% per year. I compute monthly gross returns by adding back monthly expense ratio (obtained by dividing the reported annual expense ratio by 12) to the reported values of monthly net returns. I separately sum all the capital gains distributions and dividend distributions by each share class within a month to construct the values at share class-month level.

Share class names in MS Direct are not standardized as in CRSP. Therefore, cleaning these share class names to identify the fund name and share class code involves some manual work. As a first step, I parse the share class names to separate the last word and verify if it represents a valid share class identifier. After correcting any mistaken assignments, I manually check the full names of the remaining records. In some cases, multiple words at the end of the name are used to identify a share class and in some other cases the share class type is combined with some other words without any separators. I identify and assign the share class types and fund names to these records after manual verification. For the remaining unassigned records, I leave the share class blank and consider them to represent funds with single share class.

I merge the cleaned MS Direct data with CRSP MF data using both ticker and CUSIP codes following the Data Appendix of Pastor, Stambaugh, Taylor (2015). For unmatched records, I match the fund names (that are cleaned and parsed for share class types) in CRSP with those in MS Direct. I use both automated and manual approaches for the text match. To validate the match quality, I use the same criteria as with CUSIP matches. Overall, I could match 88% of equity share classes in MS Direct with those in CRSP and 77% of the equity share classes in CRSP with those in MS Direct.

After the merge, I assign each share-class to one of the following distribution channels: broker-sold, direct-sold, institutional, retirement, other. Del Guercio and Reuter (2014) use the classification provided by Financial Research Corporation which is proprietary. In lieu of this, Sun (2014) uses data on 12b-1 fees and loads from CRSP for the classification. Since this data is missing for a lot of records in CRSP, I use the share class type from Morningstar to assign the channel.[24] I classify the types 'A', 'B', 'C', 'M', 'T', 'Adv' as broker-sold; 'D', 'Inv', 'N', 'No Load', 'S' as direct-sold. 'Retirement', 'Inst', 'Other' are classified accordingly. When this field is missing, I use the share class code parsed from the CRSP fund names. I classify codes A, B, C, Advisor and variants of these into broker-sold channel; classes N, D, M, S, T, Retail, No-Load, Investor into direct-sold channel; classes I, Y, X, K, Institutional share, Inst, Trust Class, Premier Class, Fiduciary Class, Consultant Class and their variants into institutional channel; classes R, Investor R, Retirement, R-1, R-2, R-3, R-4, R-5 and their variants into retirement channel; and all other non-blank share class codes into "other" channel. If the share class code parsed from the CRSP fund names is blank, I categorize that share class into direct-sold channel. Next, I use the information on loads and 12b-1 to classify some more share classes that are assigned to "other". If there is a non-zero front load or non-zero rear load or the actual 12b-1 is greater than 25 bps, I reclassify the share class from "other" to broker-sold. And, if there is zero front load and zero rear load and either actual 12b-1 or maximum 12b-1 is less than 25 bps, I reclassify the share class from "other" to direct-sold.

Data on purchases and redemptions is available in Morningstar beginning in 1999. To extend my sample, I update purchases and redemptions data for pre-1999 records with the data from the

[24] A description of MS share class types is available at
https://morningstardirect.morningstar.com/clientcomm/Share_Class_Types.pdf

parsed N-SAR files. I use name-based matching to merge N-SAR records to CRSP records. I use both automatic and manual approaches for matching the family name in N-SAR with family name in CRSP and then matching fund name in N-SAR with fund name from CRSP (which is parsed to remove share class identifier) within the matched families. I ensure match quality in two ways: 1) through manual verification, 2) by tallying the purchases redemptions data in the year 1999 between the CRSP-MS Direct matched data and the N-SAR data. The number of equity funds from CRSP that have a matching N-SAR record changes from each year from 1994 to 1998. Although N-SAR files are available electronically starting from 1993, the number of firms that started complying increased starting 1994 and hence I do not use the records from 1993. These details are discussed in the Internet Appendix of Christoffersen, Evans, and Musto (2013).[25]

To identify a fund's family affiliation, I use the management code variable provided by CRSP (mgmt_cd). CRSP reports management names starting from 1993 and management codes starting from 1999. I clean up the management codes before using them in my sample. In the post-1999 period, if a share class contains the same management name across time but has missing management codes for some periods, I fill the management code with the most recent non-missing value. If two share classes of a fund identified by WFICN have different values for management code, I retain these values as is. But if some share classes have a missing value in a given month, I fill these using the management code entry from the non-missing share classes in that month. For the records that still have blank values for management code, I try to identify the fund family by manually checking the names in CRSP and assign a code based on the value for these families in

[25] This is accessible from https://www.afajof.org/wp-content/uploads/files/supplements/IA-7929-Feb_2013.pdf

other records. For records which do not match any family name, I assign a temporary code in my sample.

What do fund flows reveal about asset pricing models and investor sophistication?

Narasimhan Jegadeesh and Chandra Sekhar Mangipudi†

Goizueta Business School

Emory University

Abstract: Recent evidence indicates that market model alphas are stronger predictors of mutual fund flows than alphas with other models. Berk and van Binsbergen (2016) claim that this evidence indicates CAPM is the best asset pricing model but Barber, Huang and Odean (2016) (BHO) claim it is evidence against investor sophistication. We evaluate the merits of these mutually exclusive interpretations. We show that no tenable inference about the true asset pricing model can be drawn from this evidence. The rejection of investor sophistication hypothesis is tenable, but the appropriate benchmark to judge sophistication is different from the one that BHO use.

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† Narasimhan Jegadeesh is the Dean's Distinguished Professor at the Goizueta Business School, Emory University, Atlanta, GA 30322, Ph: 404-727-4821, email: Jegadeesh@emory.edu., Chandra Sekhar Mangipudi is a Doctoral student at Emory University, email: chandra.sekhar.mangipudi@emory.edu . We would like to thank Jonathan Berk, Kent Daniel, Amit Goyal, Cliff Green, Ravi Sastry, Jay Shanken, and the seminar participants at the 2018 SFS Cavalcade North America, 2019 American Finance Association Meetings, 2019 Eastern Finance Association Meetings, Baruch College - CUNY, Louisiana State University, Virginia Tech and Case Western Reserve University for helpful discussions, comments, and suggestions.

1. Introduction

An extensive literature documents that net fund flows into mutual funds are driven by funds' past performance. For example, Patel, Zeckhauser, and Hendricks (1994) document that equity mutual funds with bigger returns attract more cash inflows and they offer various explanations for this phenomenon. Other papers that document a positive relation between fund flows and past performance include Ippolito (1992), Chevalier and Ellison (1997), and Sirri and Tufano (1998).

Some papers in the early literature also examine whether abnormal performance (or alphas) measured with some benchmarks better predict fund flows than others. For example, Gruber (1996) compares the mutual fund flow-performance relation for alphas measured with one- and four-factor models, while Del Guercio and Tkac (2002) compares sensitivity of flows to raw returns with that to market model alphas for mutual funds and pension funds. Fung et. al. (2008) makes similar comparisons with a different set of factor models for hedge funds.

While comparison of flow-alpha relations across models was not the primary focus of earlier papers, recent papers in this area have shown a renewed interest in such comparisons using a broader range of asset pricing and factor models. The primary driving force for this resurgence is the idea that these comparisons can potentially help us answer important economic questions that extend beyond a descriptive analysis of mutual fund flows. For example, Barber, Huang and Odean (2016) (hereafter "BHO") compare the relation between fund flows and alphas measured with various models to evaluate whether mutual fund investors are sophisticated, or equivalently whether they rationally use all available information. They hypothesize that sophisticated investors should use alphas computed with a model with all common factors to evaluate fund performance regardless of the underlying true asset pricing model, but they find that market model alphas are the strongest predictors of mutual fund flows. BHO conclude that therefore investors in aggregate are not sophisticated in how they use past returns to assess fund performance.

Berk and van Binsbergen (2016) (hereafter "BvB"), however, claim that such flow-alpha comparisons serve as a new and fundamentally different test of asset pricing models and the results can reveal the true asset pricing model. Because of potential asset pricing model implications, BvB's comparisons include multifactor models and several versions of consumption-CAPM. Agarwal, Green and Ren (2017) and Blocher and Molyboga (2017) carry out similar tests with hedge funds.

BvB also find that fund flows are most highly correlated with alphas computed with the market model in their tests. They conclude that therefore the CAPM is "the best method to use to compute the cost of capital of an investment opportunity" (Berk and van Binsbergen 2016, p. 17). The true asset pricing model has been a holy grail of the finance literature and hence BvB's findings potentially have broad implications that go well beyond the mutual fund literature. For instance, Berk and van Binsbergen (2017) prescribe that practitioners should use the CAPM to make capital budgeting decisions based on BvB's evidence.

Although BHO's and BvB's flow-alpha horse races yield similar results, their inferences are mutually exclusive. Specifically, BvB's asset pricing model interpretation assumes rational expectations but BHO's interpretation implies that investors' actions violate the rational expectations hypothesis. Because the inferences in BHO, BvB and related papers have far-reaching implications, we examine whether such inferences are conceptually and empirically tenable.

We address the conceptual issues using a rational expectations model where investors extract information about mutual fund manager skills from funds' past performance and optimally decide on investments into and withdrawals from mutual funds. Our model augments Berk and Green's (2004) model with a multifactor return generating process and allows investors the flexibility to compute alphas with respect to any factor model to update their priors about fund skills. Investors in the model know the true asset pricing model, and therefore which factors are priced. Although investors can compute alphas with only the priced factors, we show that investors optimally use alphas computed with the model with all common factors, both priced and unpriced, to decide on fund flows.

We then consider the flow-alpha horse race that empiricists run when they do not have all the information that agents in the model economy possess. Specifically, unlike the agents in the model, empiricists do not know the true asset pricing model. Also, empiricists do not know true factor betas and they can only estimate them with error. We show that empiricists' alphas that most precisely estimate funds' skills will win the empiricists' horse race under the rational expectations hypothesis.

We use the results from our model to assess empirically whether we can identify the true asset pricing model based on the flow-alpha horse race with a sample of actively managed mutual funds. We use a seven-factor model as in BHO in our empirical analysis where the seven factors are Fama-French factors (market, SMB, HML), momentum factor (UMD) proposed by Carhart (1997) based on Jegadeesh (1990) and Jegadeesh and Titman (1993) and three industry factors. We compute the precision of alphas with models that include all seven factors and with subsets of these factors under the hypothesis that each of the following asset pricing models is true: (i) None of the risk factors are priced (or true expected returns are unrelated to factors betas), (ii) CAPM, (iii) Fama-French three factor model and (iv) Fama-French-Carhart four-factor model.

We find that four-factor alphas are the most precise when true betas are unknown. Therefore, if fund flows are determined under the rational expectations hypothesis, four-factor alpha should win the empiricists' horse race regardless of which asset pricing model is true. For instance, four-factor alphas should win the horse race whether the CAPM or the Fama-French three-factor model is the true asset pricing model.

We also conduct simulation experiments with parameters that match the data. We generate simulated fund flows according to our model and we examine the small sample performance of model predictions. We also conduct a number of robustness tests. The simulation results are similar to our empirical results. Specifically, the four-factor model alphas are the most precise estimates when we estimate betas using traditional time-series regressions.[26] When flows are generated according to the rational expectations model, the most precise estimator always wins that horse race. In addition, the precision of the alpha estimator and the winner of the horse race does not depend on the true asset pricing model.

The results of our model and our empirical results indicate that the horse race cannot uniquely identify the true underlying asset pricing model. Therefore, flow-alpha horse is not a tenable test of asset pricing models. Because our conclusions are contrary to BvB's, we take a closer look at their model to resolve the contradiction. We show that a faulty foundational assumption in BvB's model is the source of their mistaken inference.

[26] Our empirical tests and the main tests in the simulation estimate betas using OLS regressions as in BHO. However, when we use the more precise Vasicek (1973) shrinkage estimator to estimate betas in the simulation, we find that the alphas computed with all factors are the most precise estimates. We also find similar results when we replace BHO's three industry factors with the first three principal components that we compute from the four-factor model residuals for the mutual fund sample.

Our empirical findings also contradict BHO's hypothesis that alphas with a model that includes all common factors will win the horse race under the investor sophistication hypothesis. The main reason why four-factor alpha is more precise than seven factor alpha, and therefore wins the horse race, is that estimation errors in the three industry factor betas are relatively large. However, even if we use the four-factor model as the benchmark BHO's finding that the single factor alpha wins their horse race rejects the investor sophistication hypothesis.

2. Fund flows and alphas: Foundation for empirical tests and inferences

This section presents a model that forms the basis for our analysis of the implications of flow-alpha relations as tests of asset pricing models and investor sophistication. Broadly, we use the model to answer the following questions:

(a) How do investors optimally update their priors about unobservable skills of fund managers when they observe fund returns?

(b) How are equilibrium fund flows related to the information investors use to update their priors?

(c) What are the implications of the answers to the above questions for interpreting the results of a flow-alpha horse race with alphas computed using different multifactor models?

We answer these questions using a rational expectations model as in Berk and Green (2004) augmented with a multifactor return generating process and an equilibrium asset pricing model.

2.1. Asset pricing model and return generating process

The following *K*-factor model is the true asset pricing model:

$$E[r_i] = \sum_{k=1}^{K} \beta_{k,i} \gamma_k, \tag{2.1}$$

where r_i is the return in excess of the risk-free rate or excess returns, $E[r_i]$ is the expected excess return on asset *i*, $\beta_{k,i}$ is the beta of asset *i* with respect to factor *k*, and γ_k is the premium for a unit of factor risk. For the CAPM, $K = 1$ and for Fama-French three-factor model, which we refer to as FF3, $K = 3$. We also define a model with $K = 0$ where the expected returns are equal for all assets regardless of any differences in their factor betas, i.e. $\gamma_k = 0\ \forall k$ in Eq. (2.1). Because there is no beta risk premium under this model we abbreviate it as "NBRP."

Asset returns follow the *J*-factor model below:[27]

$$r_{i,t} = \mathrm{E}[r_i] + \sum_{k=1}^{J} \beta_{k,i}\, f_{k,t} + \xi_{i,t}, \qquad (2.2)$$

where $f_{k,t}$ is the realization of the common factor *k*, and $\xi_{i,t}$ is asset specific return at time *t*. Factor realization $f_{k,t}$ is the innovation or the unexpected component of factor *k*. For instance, let $F_{k,t}$ be the total factor realization of the k^{th} factor, then $f_{k,t} = F_{k,t} - \mathrm{E}\left[F_{k,t}\right]$ and $\mathrm{E}\left[f_{k,t}\right] = 0$. Because we consider only traded factors, $\mathrm{E}\left[F_{k,t}\right] = \gamma_k\ \forall\ k \le K$ and for the unpriced factors $\mathrm{E}\left[F_{k,t}\right] = 0\ \forall\ k > K$.

In general, the J factors in the multifactor model (2.2) include the K priced factors from the asset pricing model as well as additional unpriced factors that describe realized returns. For example, the J factors could include industry factors that are unpriced because they are not correlated with future investment opportunity set or with consumption. Therefore, in general $J \ge K$. Factor returns and asset specific returns are all normally distributed.

[27] Eq. (2.2) imposes the condition that the intercept of the return generating process for each asset equals its expected return from the asset pricing model.

2.2.The Model

This subsection presents a rational expectations model that identifies alphas that investors use to make their mutual fund investment decisions. The following are our assumptions:

(a) **Rational Economy:** All agents in the rational expectations economy are symmetrically informed.

(b) **Mutual funds and skill:** There are *N* mutual funds in the economy and $N \longrightarrow \infty$. Fund p is endowed with stock selection skills that allow it to generate a gross return of Φ_p in excess of the *K*-factor asset pricing benchmark. Investors know the true asset pricing model. Fund manager skill $\Phi_p \sim N(\phi_0, 1/\nu)$, where ϕ_0 is average skill and ν is the precision of the distribution of skill at the time of a fund's inception. ϕ_0 and ν are common knowledge, and Φ_p is constant over time.

(c) **Costs of active management:** Funds incur certain costs for active management which is a function of total assets under management (AUM), denoted as q, and $c_t(q)$ is the total cost per unit of AUM at time *t*. The cost $c_t(q)$ includes fund fees and administrative costs, brokerage costs and price impact of trades. Funds experience decreasing returns to scale and hence $c_t(q)$ is an increasing function of q.

(d) **Gross and net returns:** Let $R_{p,t}$ and $r_{p,t}$ be fund p's gross and net excess returns at time t, respectively. $R_{p,t} = r_{p,t} + c_{t-1}(q_{p,t-1})$. Funds' net returns are observable by both investors in the model economy and econometricians. Investors can also compute $R_{p,t}$ since they know $q_{p,t-1}$ and $c_{t-1}(q_{p,t-1})$ but econometricians observe only $q_{p,t-1}$.

(e) **Competitive Market:** The mutual fund market is perfectly competitive. Therefore, expected alpha net of fees and costs for an investment in any mutual fund equals zero in equilibrium:

$$\phi_{p,t} - c_t(q_{p,t}) = 0. \tag{2.3}$$

where $\phi_{p,t}$ is the mean of investors' posterior about fund manager skill at time *t*.

(f) **Expected return and return generating process:** Eqs. (2.1) and (2.2) specify expected returns and the return generating process in this economy, which are both common knowledge. Fund betas are constant and common knowledge as well. The net return at time *t* is:[28]

$$r_{p,t} = \Phi_p + \underbrace{\sum_{k=1}^{K} \beta_{k,p} \mathrm{E}[F_{k,t}]}_{\text{Expected return, Eq. (2.1)}} + \underbrace{\sum_{k=1}^{J} \beta_{k,p} f_{k,t} + \xi_{p,t}}_{\text{Unexpected return, Eq. (2.2)}} - c_{t-1}(q_{p,t-1}). \tag{2.4}$$

Assumptions (a) through (e) are the same as in Berk and Green (2004). We add assumption (f) about expected asset returns and the return generating factor model.[29]

Investors make their mutual fund investment decisions based on their assessment of fund manager skills. Investors assign a skill of ϕ_0 to all funds at their origin. Subsequently, investors observe net fund returns and factor realizations each period and optimally update their priors. To update their priors, investors could compute alphas relative to any η-factor model, which we denote as $\hat{\alpha}_{p,\eta,t}$, as follows:

$$\hat{\alpha}_{p,\eta,t} = r_{p,t} - r_{market,t} \text{ if } \eta = 0 \text{ and} \tag{2.5}$$

$$\hat{\alpha}_{p,\eta,t} = r_{p,t} - \sum_{k=1}^{\eta} \beta_{k,p} F_{k,t} \text{ , if } \eta > 0, \tag{2.6}$$

[28] Funds' gross returns follow the return generating process (2.2) plus Φ_p. Investors earn net returns in (2.4) after all costs.

[29] Φ_p in Eq. (2.4) denotes managerial skill in our model which is denoted as α in Berk and Green. We use α to denote ex-post abnormal returns following a common practice in the empirical mutual fund literature.

where $F_{k,t}$ is realized factor returns.

The proposition below describes the Bayesian rule that investors use to update their priors recursively, conditional on using a particular η-factor model to compute alphas.

Proposition 2.1: Let $\phi_{p,\eta,t-1}$ be investors' assessment of fund p's skill prior to the realization of $r_{p,t}$ and let $\phi_{p,\eta,t}$ be the mean of investors' posterior after observing $r_{p,t}$. Suppose the competitive market condition in Eq. (2.3) holds and suppose investors compute $\hat{\alpha}_{p,\eta,t}$ with an η-factor model in Eq. (2.5) or Eq. (2.6) to recursively update their priors about fund manager skills. Then:

$$\phi_{p,\eta,t} = \phi_{p,\eta,t-1} + \frac{\vartheta_{\hat{\alpha},\eta}}{\nu + Age_{p,t} \times \vartheta_{\hat{\alpha},\eta}} \times \hat{\alpha}_{p,\eta,t}, \tag{2.7}$$

where $Age_{p,t}$ is the fund's age at time t. The precision of investors' posterior is $\nu + Age_{p,t} \times \vartheta_{\hat{\alpha},\eta}$, where $\vartheta_{\hat{\alpha},\eta} = \frac{1}{\sigma^2_{\hat{\alpha},\eta}}$.

Proof: See Appendix 2A.

Which particular η-factor model would investors use to compute alphas? We examine the properties of the posteriors with different alphas next to determine the answer to this question.

Proposition 2.2: (a) Investors obtain an unbiased estimate of true skill conditional on factor realizations if and only if they use $\hat{\alpha}_{p,J,t}$ to update their priors; (b) $\mathrm{Var}(\hat{\alpha}_{p,J,t}) < \mathrm{Var}(\hat{\alpha}_{p,\eta,t})\ \forall\ \eta < J$.

Proof: See Appendix 2A.

Proposition 2.3: Investors optimally use $\hat{\alpha}_{p,J,t}$ to minimize mean squared error risk.

Proof: From Proposition 2.1, investors' posterior of fund p's skill is distributed $N(\phi_{p,\eta,t}, 1/\nu_{p,\eta,t})$. From Proposition 2.2, $\phi_{p,J,t}$ is unbiased and has the smallest variance and hence the smallest MSE.

Proposition 2.4: In a competitive equilibrium, investors update their priors using $\hat{\alpha}_{p,J,t}$.

Proof: Suppose the contrapositive that a competitive equilibrium obtains when investors use $\hat{\alpha}_{p,\eta,t}$ with $\eta < J$ to update their priors and determine fund flows. The competitive market condition under the contrapositive implies $\phi_{p,\eta,t} - c(q_{p,t}) = 0$. But, suppose $f_{k^*,t} \neq 0$ for some $k^* > \eta$. For any fund with $\beta_{p,k^*} \neq 0$, $\mathrm{E_t}(\Phi_p | f_{k^*}) = \phi_{p,\eta,t} - \beta_{p,k^*} f_{k^*,t}$ and $\mathrm{E_t}(\Phi_p | f_{k^*}) - c(q_{p,t}) \neq 0$. Hence under the contrapositive, non-zero NPV investments exist which violate the competitive market condition. Therefore, the contrapositive is not consistent with a competitive market equilibrium.

Both Propositions 2.3 and 2.4 indicate that in equilibrium investors use $\hat{\alpha}_{p,J,t}$, the *J*-factor alpha, to update their priors about fund manager skills. Intuitively, investors know the true asset pricing model, betas and factor realizations and what they do not know is what portion of a fund's benchmark-adjusted return is due to the difference between its true skill and investors' priors $(\Phi_p - \phi_{p,\eta,t-1})$ and what portion is due to $\xi_{p,t}$. Investors optimally use $\hat{\alpha}_{p,J,t}$ because it is orthogonal to the information that they already know. Because $\hat{\alpha}_{p,J,t}$ is orthogonalized to both priced and unpriced factors it does not contain any information to differentiate between them.

2.3.Alphas and fund flows

Investors update their priors each period using $\hat{\alpha}_{p,J,t}$ and make their investment decisions each period. In a competitive equilibrium $\phi_{p,J,t} = c_t(q_{p,t})$ where $q_{p,t}$ is fund p's AUM after time *t* net fund flows. Therefore, $c_t(q_t)$ also follows a recursive equation analogous to Eq. (2.7). Specifically,

$$c_t(q_{p,t}) = c_{t-1}(q_{p,t-1}) + \frac{\vartheta_{\hat{\alpha},J}}{\nu + Age_{p,t} \times \vartheta_{\hat{\alpha},J}} \times \hat{\alpha}_{p,J,t}. \quad (2.8)$$

The net flow $\Gamma_{p,t}$ into mutual fund p in each period is given by:

$$\Gamma_{p,t} = \frac{q_{p,t} - q_{p,t-1}(1 + r_{p,t})}{q_{p,t-1}} = \frac{q_{p,t} - q_{p,t-1}}{q_{p,t-1}} - r_{p,t}. \quad (2.9)$$

To determine a functional relation between $\hat{\alpha}_{p,J,t}$ and fund flows, we assume that the cost function is given by:

$$c_{p,t}(q_{p,t}) = \delta_{p,t} \times q_{p,t}, \quad (2.10)$$

where δ_t is a time-varying cost per unit of AUM.

We specify the time-varying cost function as:

$$\delta_{p,t} = \frac{\delta_{p,t-1}}{(1 + r_{p,t})}. \quad (2.11)$$

This cost function assumes that the total cost of active management does not change with changes in fund size due to funds' own returns and any change in total cost is only due to net fund flows.[30] With this cost function and Eqs. (2.8) and (2.9), equilibrium fund flows are:

$$\Gamma_{p,t} = \frac{q_{p,t} - q_{p,t-1}(1 + r_{p,t})}{q_{p,t-1}} = \frac{\vartheta_{\hat{\alpha},J}}{\nu + Age_{p,t} \times \vartheta_{\hat{\alpha},J}} \times \frac{(1 + r_{p,t})}{\delta_{t-1} q_{p,t-1}} \times \hat{\alpha}_{p,J,t}. \quad (2.12)$$

[30] Since $q_t = q_{t-1}(1 + r_t) + q_{t-1}\Gamma_t$, total cost of active management at t under this specification is $c_t(q_t) = \delta_{t-1} q_{t-1} + \delta_t q_{t-1} \Gamma_t = c_{t-1}(q_{t-1}) + \delta_t q_{t-1} \Gamma_t$. Therefore, change in total cost from $t - 1$ to t is only due to new money. In contrast, a time-invariant cost function (e.g. $\delta_t \equiv$ constant) would imply that aggregate fund flows would be negatively correlated with market returns because average alpha is zero and costs vary with aggregate AUM regardless of whether the change in AUM is due to fund returns or due to flow of new funds. Also, because expected fund returns are positive, a time-invariant cost function would result in an average net outflow of funds to offset funds' capital gains.

Eq. (2.12) indicates that in addition to $\hat{\alpha}_{p,J,t}$, fund flow is a function of fund's marginal cost and the precision of investors' posterior distribution. As we noted earlier, $\hat{\alpha}_{p,J,t}$ does not differentiate between priced and unpriced factors. Therefore, $\Gamma_{p,t}$ also does not differentiate between priced and unpriced factors and it contains no information to identify which factors are priced or unpriced in the true asset pricing model.

2.4.Econometricians' information set and Alpha-fund flows horse race

The literature runs a horse race based on the relation between fund flows and alphas computed under various η-factor models. Because the horse race is run by empiricists, alphas should only use information available to them. Empiricists have the same information as investors in the model except that empiricists do not know (i) the true asset pricing model and (ii) true betas. Therefore, the η-factor model alpha computed by empiricists is:

$$\hat{\alpha}^{E}_{p,\eta,t} = r_{p,t} - \sum_{k=1}^{\eta} \hat{\beta}_{k,p} F_{k,t}, \tag{2.13}$$

where $\hat{\beta}_{k,p}$'s are empiricists' unbiased beta estimates. The superscript *E* on alpha denotes that it is computed with the econometrician's information set.

The literature typically runs the following horse race regression between flow and $\hat{\alpha}^{E}_{p,\eta,t}$ to draw inferences about the true asset pricing model and investor sophistication:

$$\Gamma_p = a_\eta + b_\eta \times \hat{\alpha}^{E}_{p,\eta,t} + \omega_{p,\eta,t}. \tag{2.14}$$

The probability limit of the OLS estimate of the slope coefficient is:

$$plim\ b_\eta = \frac{Cov\left(\Gamma_{p,t}, \hat{\alpha}^{E}_{p,\eta,t}\right)}{\sigma^2_{\hat{\alpha}^{E}_{p,\eta,t}}}, \tag{2.15}$$

where $\sigma^2_{\hat{\alpha}^E_{p,\eta,t}}$ is cross-sectional variance of $\hat{\alpha}^E_{p,\eta,t}$. Our empirical tests follow the Fama-MacBeth approach and fit Regression (2.14) for each t and the time-series average of monthly slope coefficients is the sample estimate of b_η. The winner of the horse race regression (2.14) is the η-factor model with the biggest b_η.

Which η-factor model would have the biggest b_η? Since flow in the model is determined by $\hat{\alpha}_{p,J,t}$, heuristically the winner of the horse race would depend on how accurately $\hat{\alpha}^E_{p,\eta,t}$ measures $\hat{\alpha}_{p,J,t}$. From Eqs. (2.4) and (2.13) $\hat{\alpha}^E_{p,\eta,t}$ is:

$$\hat{\alpha}^E_{p,\eta,t} = \begin{cases} \hat{\alpha}_{p,J,t} + \sum_{k=\eta+1}^{J} \beta_{k,p} f_{k,t} - \left(\sum_{k=K+1}^{\eta} \beta_{k,p} \bar{F}_k + \sum_{k=1}^{\eta} \left(\hat{\beta}_{k,p,t} - \beta_{k,p}\right) F_{k,t} \right) & \text{for } \eta \geq K, \\ \hat{\alpha}_{p,J,t} + \left(\sum_{k=\eta+1}^{K} \beta_{k,p} \bar{F}_k + \sum_{k=\eta+1}^{J} \beta_{k,p} f_{k,t} \right) - \sum_{k=1}^{\eta} \left(\hat{\beta}_{k,p,t} - \beta_{k,p}\right) F_{k,t} & \text{for } \eta < K, \end{cases} \tag{2.16}$$

where $\bar{F}_k$ is the sample mean of factor k. The unconditional factor mean equals the corresponding factor risk premium for all priced factors.

In a frictionless economy, unconditional mean for unpriced factors (i.e. for $k > K$) should equal zero to preclude arbitrage. Empirically, however, the sample mean of unpriced factors could differ from zero because arbitrage is costly. For example, if CAPM were the true asset pricing model then the fact that the mean of HML is positive is an anomaly and $\beta_{HML,p}\bar{F}_{HML}$ is not a component of expected returns. Because empiricists do not know the true asset pricing model and whether the k^{th} factor is priced, the measurement error in $\hat{\alpha}^E_{p,\eta,t}$ due to model misspecification is $\beta_{k,p}\bar{F}_k$ if $\eta < K$ and $-\beta_{k,p}\bar{F}_k$ if $\eta > K$.

From Eq. (2.16) $\sigma^2_{\hat{\alpha}^E_{p,\eta,t}}$, the denominator of Eq. (2.15), is:

$$\sigma^2_{\hat{\alpha}^E_\eta} = \sigma^2_{\hat{\alpha}_J} + \sum_{k=K+1}^{\eta} \sigma^2_{\beta_k} \bar{F}^2_k + \sum_{k=1}^{\eta} \sigma^2_{\hat{\beta}_k-\beta_k} E\left(F^2_{k,t}\right) + \sum_{k=\eta+1}^{J} \sigma^2_{\beta_k} \sigma^2_{f_k} + \sum_{k=\eta+1}^{J} \sigma^2_{f_k} [E(\beta_k)]^2 , \tag{2.17}$$

where $\sigma^2_{\beta_k}$ is the cross-sectional variance of factor beta, $\sigma^2_{f_k}$ is factor variance, $\sigma^2_{\hat{\beta}_k-\beta_k}$ is the variance of beta measurement error, $\bar{F}_k$ is the expected value of factor k and $\bar{\beta}_k$ is the cross-sectional average of corresponding factor beta.[31] Eq. (2.17) assumes that betas on various factors are uncorrelated in the cross-section for expositional convenience. For example, this assumption implies that the market beta of a fund relative to other funds has no information for the relative HML beta of that fund. However, when we later empirically estimate the components of $\sigma^2_{\hat{\alpha}^E_\eta}$ we estimate all cross-sectional covariances of betas from the data.

The first term on the right-hand side is the variance of alphas across the cross-section of funds if one could estimate alphas with investors' information set. The remaining terms are sources of incremental error because empiricists do not have all of investors' information. Consider each of these three terms:

- **Asset Pricing Model (APM) Misspecification error:** Because factors $k > K$ are unpriced according to the true asset pricing model, realized fund returns are driven only by the unexpected component of these factors and not by $\bar{F}_k$. Suppose K factors are priced under the true asset pricing model but we use η-factor model to compute alphas, variance due to

[31] When $\eta = 0$, Eq. (2.5) subtracts market return from fund returns and hence the last term in Eq. (2.17) should be modified as $\sigma^2_{market}[E(\beta_1 - 1)]^2 + \sum_{k=2}^{J} \sigma^2_{f_k} [E(\beta_k)]^2$.

APM misspecification equals $\sum_{k=K+1}^{\eta} \sigma_{\beta_k}^2 \bar{F}_k^2$.[32] Empiricists compute alphas with all priced factors but without any unpriced factor when $\eta = K$ and in this case this term equals zero.

- **Beta measurement error:** Because empiricists estimate betas from the data, the factors used to compute alphas in Eq. (2.13) contribute an incremental error that equals $\sum_{k=1}^{\eta} \sigma_{\hat{\beta}_k - \beta_k}^2 E\left(F_{k,t}^2\right)$.
- **Omitted factors:** Common factors that investors use but are omitted from Eq. (2.13) add $\sum_{k=\eta+1}^{J} \sigma_{\beta_k}^2 \sigma_{f_k}^2 + \sum_{k=\eta+1}^{J} \sigma_{f_k}^2 \left[E\left(\beta_k\right)\right]^2$ to alpha estimation errors. The first part of this sum is due to the cross-sectional variance of betas. This part would be zero if the factor betas of all funds are the same because in this case adjusting for betas would not affect the cross-sectional rank of a fund's performance. The second part is a function of the cross-sectional mean of factor betas. For $\eta = J$, all factors are used to compute alphas and hence this component is zero.

Because $\sigma_{\hat{\alpha}_{p,\eta,t}^E}^2$ is the denominator of Eq. (2.15), the η-factor model that yields the most precise alpha estimator would win the horse race, ceteris paribus.[33] From Eq. (2.17), estimation error in $\hat{\alpha}_{p,\eta,t}^E$ due to omitted factors increases with the exclusion of any factor. However, inclusion of unpriced factors to compute alphas makes the estimate less precise because each unpriced factor adds to APM misspecification error and to beta-measurement error. The trade-offs between these two opposite effects will determine whether inclusion of a particular factor leads to a less or more precise alpha estimator.

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[32] When $\eta < K$, the limits of the summation for the second term in Eq. (2.17) is from $\eta + 1$ to K. For brevity, we present formulas for $\eta \geq K$ and analogous changes yield the corresponding formulas for $\eta < K$.

[33] One component of $\sigma_{\hat{\alpha}_{p,\eta,t}^E}^2$ is the cross-sectional variance of true skill of fund managers. Because this component is common across all η's, the most precise alpha estimator also has the smallest $\sigma_{\hat{\alpha}_{p,\eta,t}^E}^2$.

BHO hypothesize that sophisticated investors would optimally use all J factors to compute alphas. Investors in our model do use all J factors because they know the true asset pricing model and true betas. However, because empiricists do not have the same information their most precise estimator would exclude some of the J factors if their beta measurement errors and APM misspecification errors are sufficiently large.

The winner of the horse race also depends on the numerator in Eq. (2.15). However, as we prove in Appendix 2B, the numerator does not vary with η. Specifically,

$$Cov\left(\Gamma_{p,t}, \hat{\alpha}^{E}_{p,\eta,t}\right) = Cov\left(\Gamma_{p,t},\ \hat{\alpha}_{p,J,t}\right)\ \forall\, \eta. \tag{2.18}$$

This result may seem somewhat counterintuitive because Eq. (2.12) shows that $\Gamma_{p,t}$ is a function of $r_{p,t}$, and therefore it shares some of the common factors with $\hat{\alpha}^{E}_{p,\eta,t}$ for $\eta < J$, but $\hat{\alpha}_{p,J,t}$ is orthogonal to all common factors. Therefore, how is $Cov\left(\Gamma_{p,t}, \hat{\alpha}^{E}_{p,\eta,t}\right)$ the same for all η when the common factors included in $\hat{\alpha}^{E}_{p,\eta,t}$ vary with η? Eq. (2.18) obtains because of some key features of our results. One important feature is that $r_{p,t}$ enters $\Gamma_{p,t}$ only in the product form $\left(1 + r_{p,t}\right) \times \hat{\alpha}_{p,J,t}$ in Eq. (2.12), and another is that $\hat{\alpha}_{p,J,t}$ is uncorrelated with any of the other components of $\hat{\alpha}^{E}_{p,\eta,t}$ in Eq. (2.16). These features and the fact that $E\left[\hat{\alpha}_{p,J,t}\right] = 0$ yield Eq. (2.18) and Appendix 2B contains the technical details. Therefore, $Cov\left(\Gamma_{p,t}, \hat{\alpha}^{E}_{p,\eta,t}\right)$ is the same for all η-factor models. Because the numerator of Eq. (2.15) does not depend on η, the winner of the horse race is determined by the denominator $\sigma^2_{\hat{\alpha}^E_\eta}$. Therefore, the most precise alpha estimator based on empiricists' information set will win the flow-alpha horse race under the hypothesis that a rational expectations equilibrium determines fund flows.

3. Empirical Tests

Our first set of tests examine the precision of alphas estimated using Eq. (2.13) with various η-factor models with a sample of mutual funds. The results in the last section indicate that the most precise alpha estimator will win the flow-alpha horse race under the hypothesis that a rational expectations equilibrium determines fund flows. The horse race could be used as a test of asset pricing models if alphas with only the *K* priced factors are the most precise. Because we do not know the true asset pricing model, we compute the precision under each of the following candidate asset pricing models: NBRP, CAPM, FF3 and FFC4, i.e. *K*=0, 1, 3 and 4.

We use the seven factor model from BHO as the *J*-factor model that generates returns. The seven factors are the three Fama-French factors (market $(mkt - r_f)$, SMB and HML), Carhart (1997) momentum factor (UMD), and three industry factors (IND_1, IND_2 and IND_3). We construct the three industry factors as the first three principal components of residuals from regressing Fama-French 17 equal weighted industry portfolios on FFC4 factors, as in BHO.

We obtain our sample of mutual funds from the CRSP survivor-bias free mutual fund database. Our sample is comprised of all actively managed domestic equity funds excluding sector funds. Specifically, we consider funds that CRSP refers to as style-based or cap-based and assigns objective codes 'EDC', 'EDYG', 'EDYB' or 'EDYI'. When a fund has multiple share classes, we add assets in all share classes to compute its TNA and we compute fund level return as the weighted average of returns of individual share classes with lagged TNA as weights.

Our sample period is from January 1990 to June 2017. Our sample includes all funds with at least $10 million assets under management as of the end of the previous month. Also, the sample for month *t* includes only funds that have returns data for all months from *t*-60 to *t*-1.[34] We follow BHO and exclude funds that had flows smaller than -90% or greater than 1000% in any month from the sample to avoid the effect of outliers.

Table 17 presents sample summary statistics. The sample is comprised of 2,969 funds with 1,224 funds per month on average. The average monthly fund flow into a fund is 0.25% of its TNA the previous month.

3.1.Precision of alphas

The decomposition in Eq. (2.17) indicates that one important determinant of precision of alpha is $\sigma^2_{\beta_k}\sigma^2_{f_k}$, which when normalized by the variance of fund returns equals the incremental R^2_{adj} attributable to common factor k. The other determinant is beta measurement error. To evaluate the individual contribution of each factor to the precision of alpha estimates we first examine these two components separately. We then empirically estimate the variance of alphas from each η-factor model and the contribution of various components.

3.1.1. R^2_{adj} and Beta estimation error

We fit the following time series regression with η factors for month *t* using data for each fund from months $t-60$ to $t-1$ and compute average R^2_{adj} for each model:

$$r_{p,\tau} = a_{p,\eta,t} + \sum_{k=1}^{\eta} \beta_{k,p,t}\, F_{k,\tau} + e_{p,\eta,\tau}, \qquad \tau = t-60 \text{ to } t-1. \qquad (2.19)$$

Table 18 reports average OLS R^2_{adj} of Eq. (2.19). We compute average R^2_{adj} across all funds each month and the table reports the time-series average. R^2_{adj} for the single factor market model

[34] This criterion excludes funds from the sample during the first 60 months of their existence. Therefore, our sample is not exposed to potential incubation bias that Evans (2010) and Elton, Gruber and Blake (2001) document.

is 0.820 and it increases to 0.892 for the three-factor model, but the increase is fairly gradual as we go from the three-factor model to the seven factor model. Table 18 also reports R^2_{adj} that we compute based on the explanatory power of $\hat{\alpha}^E_{p,\eta}$, which we define as $R^2_{adj} = 1 - \frac{\mathrm{Var}(\hat{\alpha}^E_{p,\eta})\times(T_p-1)}{\mathrm{Var}(r_p)\times(T_p-\eta-1)}$ where T_p is number of months the fund is in the sample. Market-adjusted returns have the smallest R^2_{adj} of 0.761 and R^2_{adj} for the single factor market model is bigger at 0.829. R^2_{adj} increases to 0.883 for the three-factor model and then marginally to 0.884 for the seven factor model.

Another important component of alpha measurement error is the variance of measurement error in betas across funds $\left(\sigma^2_{\hat{\beta}-\beta}\right)$. The term $\sigma^2_{\hat{\beta}-\beta}$ includes OLS estimation error. Additionally, it also includes any difference between average betas during the estimation period and month *t+1* beta because of any time-variation in betas due to turnover of funds' holdings.

To estimate the magnitude of this error we first estimate the following regressions for each fund for each month:

$$(r_{p,\tau} - r_{f,\tau}) = \alpha^{past}_{p,k,t} + \sum_{k=1}^{7} \beta^{past}_{p,k,t} F_{k,\tau} + e_{p,k,\tau} \qquad \tau = t - 60 \text{ to } t - 1,$$
$$(r_{p,\tau} - r_{f,\tau}) = \alpha^{future}_{p,k,t} + \sum_{k=1}^{7} \beta^{future}_{p,k,t} F_{k,\tau} + e_{p,k,\tau} \qquad \tau = t \text{ to } t + 11 \qquad (2.20)$$

where $F_{k,\tau}$ is the factor with respect to which betas are estimated. Suppose betas for a particular fund are constant over time.

$$\hat{\beta}^{past}_{p,k,t} = \beta_{p,k} + u^{past}_{p,k,t}, \text{ and}$$
$$\hat{\beta}^{future}_{p,k,t} = \beta_{p,k} + u^{future}_{p,k,t}, \qquad (2.21)$$

where $\beta_{p,k}$ is fund p's true beta with respect to factor k.

Consider the following cross-sectional regression for month t:

$$\hat{\beta}_{p,k,t}^{future} = a_t + b_t \times \hat{\beta}_{p,k,t}^{past} + e_{p,t}. \quad (2.22)$$

Because we use non-overlapping sample periods to estimate $\beta_{p,k,t}^{past}$ and $\beta_{p,k,t}^{future}$, $u_{p,k,t}^{past}$ and $u_{p,k,t}^{future}$ are uncorrelated. The probability limit of the slope coefficient is:

$$\text{plim}\, b_t = \frac{var(\beta_{p,k})}{var(\beta_{p,k}) + var\left(u_{p,k,t}^{past}\right)}. \quad (2.23)$$

Therefore, the slope coefficient of regression (2.22) is the ratio of the cross-sectional variance of the factor betas divided by the sum of this variance plus the variance of the measurement error.

We fit regression (2.22) each month for each of the betas estimated using multiple regressions of fund returns on the seven factors. Table 19 reports the time-series averages of the slope coefficients for each beta. The slope coefficients are bigger with respect to the three Fama-French factors and UMD compared with industry factor betas. This result combined with the evidence that the incremental R_{adj}^2 from adding the three industry factors is small suggests that the incremental benefit of adding industry factors is likely small as well.

3.1.2. Precision of alpha estimates and implications

This subsection compares the precision of various η-factor model alphas $\left(\sigma_{\hat{\alpha}_\eta^E}^2\right)$. We use OLS estimates of Regression (2.19) and compute $\hat{\alpha}_{p,\eta,t}^E$ using Eq. (2.13). We compute the cross-sectional variance of $\hat{\alpha}_{p,\eta,t}^E$ each month and the time-series average of monthly variance is our estimate of $\sigma_{\hat{\alpha}_\eta^E}^2$.

Table 20 presents $\sigma^2_{\hat{\alpha}^E_\eta}$ for each η-factor model. The variance monotonically declines from 650.5 to 357.7 as we go from the single factor model to the four factor model but increases to 363.2 for the seven factor model.[35] Therefore, the four factor alpha is the most precise estimate. What does this result imply for interpretations about the true asset pricing model? For instance, can we conclude that the four-factor model is the true asset pricing model based on this result? Also, why is the seven factor model alpha not the most precise estimator as hypothesized by BHO?

To answer these questions, we need to know the components of $\sigma^2_{\hat{\alpha}^E_\eta}$ that we discussed earlier. For example, one component of $\sigma^2_{\hat{\alpha}^E_\eta}$ is APM misspecification error and the alpha-fund flow horse race can be used as a test of asset pricing models as proposed by BvB only if this component is sufficiently large to make the other models less precise. A sufficiently large misspecification component could also explain why the seven factor model alpha is not the most precise.

We empirically estimate each component of $\sigma^2_{\hat{\alpha}^E_\eta}$ to examine these issues. Eq. (2.17) presents the components of $\sigma^2_{\hat{\alpha}^E_\eta}$, but for expositional convenience that equation assumes funds' factor betas are not cross-sectionally correlated. Empirically, however, funds' factor betas are cross-sectionally correlated. For example, funds with bigger market betas on average have smaller HML betas in the data. Allowing for beta correlations, $\sigma^2_{\hat{\alpha}^E_{\eta,t}}$ conditional on a K-factor model being the true asset pricing model is:

[35] The table reports variances multiplied by 10^6.

$$
\begin{aligned}
&\sigma^2_{\hat{\alpha}^E_{\eta,t}}|K \\
&= \sigma^2_{\hat{\alpha}_{J,t}} + \underbrace{\overline{\boldsymbol{F}}'_{(K+1,\eta)} \left(Cov(\boldsymbol{\beta}'_{(K+1,\eta)}, \boldsymbol{\beta}_{(K+1,\eta)})\right) \overline{\boldsymbol{F}}_{(K+1,\eta)}}_{APM\ Misspecification} \\
&+ \underbrace{\boldsymbol{f}'_{(\eta+1,J),t} \left(Cov(\boldsymbol{\beta}'_{(\eta+1,J)}, \boldsymbol{\beta}_{(\eta+1,J)})\right) \boldsymbol{f}_{(\eta+1,J),t} + \boldsymbol{E}[\boldsymbol{\beta}_{(\eta+1,J)}]' (\boldsymbol{f}_{(\eta+1,J),t}\boldsymbol{f}'_{(\eta+1,J),t}) E[\boldsymbol{\beta}_{(\eta+1,J)}]}_{Omitted\ factors} \qquad (2.24) \\
&- \underbrace{\boldsymbol{f}'_{(\eta+1,J),t} \left(Cov(\boldsymbol{\beta}'_{(\eta+1,J)}, \boldsymbol{\beta}_{(K+1,\eta)})\right) \overline{\boldsymbol{F}}_{(K+1,\eta),t}}_{Covariance} \\
&+ \underbrace{\boldsymbol{F}'_{(1,\eta),t} \left(Cov\left([\widehat{\boldsymbol{\beta}}_{(1,\eta),t} - \boldsymbol{\beta}_{(1,\eta)}]', [\widehat{\boldsymbol{\beta}}_{(1,\eta),t} - \boldsymbol{\beta}_{(1,\eta)}]\right)\right) \boldsymbol{F}_{(1,\eta),t}}_{\widehat{\beta}\ measurement\ error}
\end{aligned}
$$

Eq. (2.24) expresses factors and factor betas as vectors. We use the same notations for vectors as the corresponding scalars but boldface denotes vectors. Also, the subscripts for vectors within parentheses indicate their first and last items. For example, $\boldsymbol{\beta}'_{(\eta+1,J)} \equiv [\beta_{\eta+1},\ \beta_{\eta+2}, \dots, \beta_J]$. Eq. (2.24) obtains for $\eta \geq K$ and an analogous expression with dimensions of vectors with subscripts $(K+1,\eta)$ replaced by $(\eta+1,K)$ obtains for $\eta < K$.

Eq. (2.24) is a straightforward generalization of Eq. (2.17) with the addition of terms that include cross-sectional covariance of factor betas. The term labelled “covariance” captures the potential effect of any cross-sectional covariance between betas of unpriced factors included in η and omitted factors that are part of fund returns. This term is non-zero when betas on factors are correlated in the cross-section.

We compute the components of $\sigma^2_{\hat{\alpha}^E_{\eta,t}}$ in Eq. (2.24) as follows: because we use OLS estimates, $Cov\left([\widehat{\boldsymbol{\beta}}_{(1,\eta)p,t} - \boldsymbol{\beta}_{(1,\eta),p,t}]', [\widehat{\boldsymbol{\beta}}_{(1,\eta),p,t} - \boldsymbol{\beta}_{(1,\eta),p,t}]\right)$ is $\sigma^2_{e_{p,t}}\left(X'_{(1,\eta),t}X_{(1,\eta),t}\right)^{-1}$ where $X_{(1,\eta),t}$ is the matrix of factors used in regression (2.19). The quadratic product of this estimate with $\boldsymbol{F}_{(1,\eta),t}$ is the $\hat{\beta}$ measurement error component for that month. We need the covariance matrix of true betas to compute the APM misspecification error, which is:

$$Cov\left(\boldsymbol{\beta}'_{(1,\eta)}, \boldsymbol{\beta}_{(1,\eta)}\right) = \frac{1}{T}\sum_{\boldsymbol{t}}\left(Cov\left(\widehat{\boldsymbol{\beta}}'_{(1,\eta),t}, \widehat{\boldsymbol{\beta}}_{(1,\eta),t}\right) - \left\{\frac{1}{P_t}\sum_{\boldsymbol{P}}\sigma^2_{e_{p,t}}\left(X'_{(1,\eta),t}X_{(1,\eta),t}\right)^{-1}\right\}\right), \tag{2.25}$$

where P_t is the number of funds in the sample in month *t*, and *T* is the number of months in the sample period. We compute $Cov\left(\widehat{\boldsymbol{\beta}}'_{(1,\eta)}, \widehat{\boldsymbol{\beta}}_{(1,\eta)}\right)$ by taking the average of the cross-sectional covariance of $\widehat{\boldsymbol{\beta}}_{(1,\eta),p,t}$ each month. The APM misspecification component of variance is the quadratic product of $\overline{\boldsymbol{F}}_{(K+1,\eta)}$ with the corresponding submatrix of $Cov\left(\boldsymbol{\beta}'_{(1,\eta)}, \boldsymbol{\beta}_{(1,\eta)}\right)$. Appendix 2C describes how we compute the other components.

Table 21 presents sample means and standard deviations of market, SMB, HML and UMD, which are all significantly positive.[36] Therefore, if CAPM were the true model the non-zero means of the other factors contribute to APM misspecification error in alphas computed using a four-factor model. Table 21 also presents the covariance matrix of true betas estimated using the procedure described above for the case $\eta = 7$.

Table 22 presents the estimates of various components in Eq. (2.24). To evaluate the net effect of using unpriced factors to compute alphas on $\sigma^2_{\hat{\alpha}^E_\eta}$, consider the NBRP model where all *J*-factors are unpriced. When η=0, the benefit of excluding all unpriced factors is that APM misspecification error is zero, but the cost is added variance due to omitted factors, which equals 340.9.[37] When

[36] Industry factors are arbitrarily scaled and hence their means and variances have no particular economic meaning. Therefore, we do not report them in the table.
[37] As η increases above *K*, unpriced factors are added to the model and the contribution of omitted factors to $\sigma^2_{\hat{\alpha}^E_\eta}$ declines monotonically. But the contribution of APM misspecification declines when we go from $\eta = 1$ to $\eta = 3$

η=J, variance due to omitted factors is zero but now the APM misspecification error variance is 1.94. While the contributions from omitted factors and APM misspecification typically go in opposite directions, the contribution of the former is orders of magnitude bigger than that from the latter.

Column (1) of the Table 6 presents $\sigma^2_{\hat{\alpha}_J}$ for each asset pricing model. $\sigma^2_{\hat{\alpha}_J}$ varies across K because $\sigma^2_{\hat{\alpha}^E_\eta}$ is the empirical cross-sectional variance (therefore independent of hypothesized K) but its components vary across K. Column (7) presents the sum of the four components excluding $\sigma^2_{\hat{\alpha}_J}$, which ranges from 48.0 to 340.9 as we vary η from 0 to 7 for K=0. For any given η, this sum varies little with changes in the hypothesized "true" asset pricing model.

The results in Table 20 indicate that the four factor alpha estimator is empirically the most precise when we estimate beta from the data using the time-series regression (2.19) regardless of the true asset pricing model. What would be the most precise alpha estimator if we know true betas but not the true asset pricing model? To answer this question we can compare the sum of the components of variance excluding the beta measurement error component and $\sigma^2_{\hat{\alpha}_J}$ under each of the hypothesized asset pricing models.

Column (6) reports this sum, which ranges from 1.9 to 340.9 as we vary η from 0 to 7 for K=0. We get the most precise estimator with η=7 regardless of the true asset pricing model. Therefore, if fund flows are determined under the rational expectations hypothesis the four factor alpha will win the horserace when betas are estimated from the data using the conventional approach, but the

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because of the negative cross-sectional covariance between market and HML betas. APM misspecification error increases as η becomes bigger than 3.

seven factor model will win if true betas are known or if factor betas can be estimated with sufficient precision.

The results in Table 22 quantify the tradeoffs among the components of measurement error as we add more factors to compute alphas. For example, when NBRP is the true asset pricing model, each common factor used to compute alphas increases the APM misspecification error but decreases the omitted factor component. The biggest contribution of the APM misspecification component is 1.94 when η=7, but the omitted factor component decreases from 340.9 to 0 as η varies from 0 to 7. The APM misspecification component is at least an order of magnitude smaller than the omitted factor component if any factor is excluded from the alpha estimator. Therefore, APM misspecification makes a trivial contribution to the overall precision of alpha estimators.

The beta measurement error component also increases with η because the number of factor betas that are estimated increase with η. The marginal change in this component is bigger than that for the omitted factor component only when η increases from four to seven. Therefore, alpha estimation error is smaller with the four-factor model.

4. Simulation Experiment

We simulate the rational expectations economy we model with parameters that match the data. We generate fund flows in the simulation according to our model and test the predictions of the model under each of the candidate asset pricing models. Specifically, we compute the precision of alphas with various η-factor models and test the model prediction that the most precise alpha will win the flow-alpha horse race. We also test BvB's and BHO's hypotheses that imply either the *K*- or *J*-factor model would win the horse race. Additionally, we conduct a number of robustness checks by changing various parameters of the model economy and estimation methodology.

4.1.Simulation: Experimental design

The simulation generates fund returns with a seven factor model with parameters determined from the data. The number of funds in the simulated sample exactly matches the data each month. Mutual fund skill is unobservable and investors start with priors about the unconditional distribution of fund manager skills and recursive update their priors after observing fund returns and make their investment decisions as the model describes.

The following are the simulation details:

a. **Fund origin:** We start the simulation with the number of funds equal to that in the sample on January 1985.

b. **Skill (Φ_p):** When a fund enters the sample, we randomly draw its skill from a normal distribution with mean (ϕ_0) equal to 0.15% and standard deviation of 0.2% per month. The average four factor alpha in our sample of domestic equity funds, gross of fund fees and expenses is around 5 bps per month and we add 10 bps per month to this estimate to account for average trading costs incurred by actively managed funds.[38] The standard deviation of fund skill matches the estimate we obtain from the data.[39] Our results are not sensitive to the choice of these parameters.

[38] Edelen et. al. (2013) report that the transaction costs are of the same order of magnitude as expense ratios which average to around 10 bps per month.

[39] The monthly cross-sectional variance of $\hat{\alpha}$s in the real data is the variance of true alphas plus the measurement error of alphas. The measurement error variance in $\hat{\alpha}$s is the average squared OLS standard errors from the time-series regressions used to estimate alphas. The average difference of cross-sectional variance and measurement error variance in $\hat{\alpha}$s across models results in the standard deviation of true alphas to be around 0.2% per month.

c. **Betas**: We generate the seven factor betas $[\beta_{mkt}, \beta_{SMB}, \beta_{HML}, \beta_{UMD}, \beta_{IND1}, \beta_{IND2}, \beta_{IND3}]'$ jointly for each fund from a multivariate normal distribution with the mean vector $[1,0,0,0,0,0,0]'$ and covariance matrix of true betas reported in Table 21.[40]

d. **Fund specific return**: We draw $\epsilon_{p,t}$ for each fund from a normal distribution with mean zero and standard deviation equal to 1.75%, which matches our estimates from the data.

e. **Asset pricing model and expected returns**: We conduct simulations under four asset pricing models and expected excess returns under each model are computed as follows:

- NBRP risk model: $E^{NR}(r_p - r_f) = 0.699\%$,
- CAPM: $E^{CAPM}(r_p - r_f) = \beta_{p,m} \times (\overline{mkt - r_f})$,
- Fama-French three factor model (FF3): $E^{FF3}(r_p - r_f) = \beta_{p,m} \times (\overline{mkt - r_f}) + \beta_{p,smb} \times (\overline{SMB}) + \beta_{p,hml} \times (\overline{HML})$, (2.26)
- Fama-French-Carhart four factor model (FFC4): $E^{FFC4}(r_p - r_f) = \beta_{p,m} \times (\overline{mkt - r_f}) + \beta_{p,smb} \times (\overline{SMB}) + \beta_{p,hml} \times (\overline{HML}) + \beta_{p,umd} \times (\overline{UMD})$.

The overbars above common factor returns indicate sample means. The average fund excess returns under all asset pricing models equal average of market excess returns.

f. **Net fund returns:** Fund net returns each period is given by the following seven-factor model:

[40] The average fund betas in the sample are [1, 0.245, 0.012, 0.015, -0.003, 0.016, -0.001] which we approximate with the factor betas for the market portfolio. None of our results are sensitive to changes in average betas.

$$r_{p,t} = \Phi_p - c_{t-1}(q_{t-1}) + E^{model}(r_p) + \beta_{p,m} \times \left(\widetilde{mkt - r_f}\right)_t + \beta_{p,smb} \times \widetilde{SMB}_t + \beta_{p,hml} \times \widetilde{HML}_t + \beta_{p,umd} \times \widetilde{UMD}_t + \beta_{p,ind1} \times \widetilde{IND1}_t + \beta_{p,ind2} \times \widetilde{IND2}_t + \beta_{p,ind3} \times \widetilde{IND3}_t + \epsilon_{p,t}, \quad (2.27)$$

where Φ_p is the fund manager skill, $c_{t-1}(q_{t-1})$ is the cost per unit size, the variables under $tilde$ are demeaned realizations of the seven common factors. We do not observe $c_{t-1}(q_{t-1})$ but the competitive equilibrium condition implies $c_{t-1}(q_{t-1}) = \phi_{p,J,t-1}$.

The simulations start with $\phi_{p,J,0} = \phi_0$ at *t*=0 for all funds. Total unexpected return for *t*=1 is the sum of beta times unexpected factor realizations for that month and $\epsilon_{p,1}$. We add $\Phi_p - \phi_0 + E^{model}(r_p)$ to compute $r_{p,1}$. We then compute alpha $\hat{\alpha}_{p,J,1}$ using Eq. (2.5) and $\phi_{p,J,1}$ using Eq. (2.7). We follow these steps recursively for each month.

g. **Fund flow:** Investors observe $r_{p,t}$ and update their priors using Eq. (2.7). Fund flow is given by Eq. (2.12).

h. **Fund exit and entry:** If $\phi_{p,t}$, the posterior of fund skill, drops below a critical value the fees fund earns will not be sufficient to cover its fixed costs and therefore the fund shuts down. We set this critical value to $\phi_0/100$.[41]

To match the number of funds in the simulation to the number of funds in the actual sample, we add new funds when the number of funds in simulated sample in any month is smaller than that in the actual sample. If it is greater, the appropriate number of funds with the smallest values of $\phi_{p,t}$ exit the simulated sample for month t.

[41] The critical value is non-zero for any positive fixed costs. We choose a small positive value here and we examine robustness with respect to changes in critical value later.

4.2.Simulation: Tests and results

We first examine the relation between fund flows and alphas under various asset pricing models. Table 8 presents $\sigma^2_{\hat{\alpha}^E_\eta}$ in the simulations and its components from Eq. (2.24). Because we know the true asset pricing model, fund skill and factor betas in the simulation, we use them when necessary to compute the components in the simulation experiment.

Variance due to omitted factors decreases monotonically from 324.1 to 0 as η increases from 0 to 7. In comparison, APM misspecification variance ranges from .93 to 1.95 when we set *K*=0. These results are similar to that in Table 22 and they confirm that the contribution of APM misspecification component is orders of magnitude smaller than that due to omitted factors. Total variance in addition to $\sigma^2_{\hat{\alpha}_J}$ excluding the beta measurement error component ranges from 2 to 324.1 when *K*=0.

We find similar results for simulations under the other asset pricing models.[42] When we ignore the beta measurement error component, the most precise alpha estimator is with $\eta = 7$ for all asset pricing models. When we estimate factor betas from simulated returns, the variance of beta measurement error increases monotonically from 0 to 56.7 as we increase η and now four-factor alpha is the most precise estimator. These results indicate that $\sigma^2_{\hat{\alpha}^E_\eta}$ and its components in the simulation are similar in magnitude and pattern to what we find in Tables 20 and 22. Therefore, our decomposition of alpha measurement errors based on asymptotic analytics holds in finite samples.[43]

[42] The total variance for a given η varies slightly as we change *K* because $E^{model}(r_p)$ in Eq. (2.27) varies with *K*.
[43] Overall, the distribution of fund returns in the simulation also matches the data. For example, average R^2_{adj} in the simulation varies from 76.9 to 86.3 as η varies from 0 to 7 which is close the corresponding statistics in Table 18.

We next generate fund flows using Eq. (2.12) each period, and we fit the horse race regression using Fama-MacBeth approach. Table 25 reports the slope coefficients. When we compute alphas using true betas, the slope coefficient increases monotonically as we add factors. For example, under the CAPM, the slope increases from 2.19 for $\eta = 0$ to 3.50 for $\eta = 7$. The seven factor alpha is the winner under all asset pricing models.

Panel B reports the slope coefficients when we use betas estimated from simulated returns to compute alphas. Now we get the biggest slope coefficient for $\eta = 4$ and not for $\eta = 7$. For example, for the CAPM, the slope coefficients are 3.05 and 3.02 for $\eta = 4$ and $\eta = 7$, respectively. The four-factor alpha wins the horse race under all asset pricing models.

Overall, the simulation results indicate that four- and seven-factor alphas are the most precise estimators depending on whether factors betas are estimated with error or whether true betas are known. The horse race results indicate that when flows are generated under the rational expectations hypothesis the most precise alpha wins the horse race. The simulation results also indicate that the outcome of the horse race does not depend on the true asset pricing model. For example, FFC4 wins the horse race in Table 25 when the true asset pricing model is FFC4 and when the true asset pricing model is NBRP, CAPM or FF3. Therefore, the winner of empiricists' horse race does not contain any information about the true asset pricing model. All these results confirm our model predictions.

4.3.Robustness Tests

4.3.1. Simulation Parameters

We conduct a number of robustness tests to evaluate the sensitivity of the simulation results including the following: a) vary the mean and variance of Φ_p, b) set the critical value of posterior about fund skill for exit to $\frac{\phi_0}{50}$ or $\frac{\phi_0}{10}$ and c) vary the variance of true factor betas from 1/4th of the variance in the main simulation to twice the variance. Our conclusion that the true asset pricing model has no effect on the precisions of alpha estimates or on the winner of the horse race is robust to all these changes.

Our result that the seven-factor model wins the horse race if betas are measured without error is also robust. However, when we set the variance of true factor betas to 150% of the variance in Table 21 or larger, the seven factor model is always the winner even when betas are measured with error. Intuitively, at this level the benefit of including an unpriced factor because of the omitted factor effect, i.e. the effect of $\sigma_{\beta_k}^2 \sigma_{f_k}^2$ in Eq. (2.17), outweighs the cost due to beta measurement error. These findings are consistent with our analytic results that the benchmark for investor sophistication depends on the properties of betas of the assets in the sample and therefore must be determined from the sample under consideration.

4.3.2. Time-varying betas

Factor betas of funds could vary over time as they turnover their holdings. To capture such time variation, we assume that true factor betas follow an AR(1) process as specified below:

$$\boldsymbol{\beta}_{(1,J),p,t} = (1-\rho)\overline{\boldsymbol{\beta}}_{(1,J),p} + \rho\boldsymbol{\beta}_{(1,J),p,t-1} + \boldsymbol{\varsigma}_{(1,J),p,t}, \qquad (2.28)$$

where $Cov\left(\boldsymbol{\varsigma}_{(1,J)}\right) = (1-\rho^2)Cov\left(\boldsymbol{\beta}_{(1,J)}\right)$ and $\overline{\boldsymbol{\beta}}_{(1,J),p}$ is unconditional mean of factor betas. We consider values of ρ ranging from 0.2 to 0.9 and set the covariance of $\boldsymbol{\varsigma}$ to match the average covariance of fund level betas. We draw the first value of $\overline{\boldsymbol{\beta}}_{(1,J),p}$ for a fund 60 months before its entry date from a normal distribution with the mean vector $[1,0,0,0,0,0,0]'$ and covariance equal to the covariance reported in Panel B of Table 21 minus covariance of $\boldsymbol{\varsigma}$.

In untabulated results, we find that the relative precision of alphas and the winner of the horse race were identical to what we found with constant betas. Specifically, the winner is always the seven factor model when we use true betas to run the horse race and the four factor model when we estimate betas from the data with time-series regression. The true asset pricing model has a trivial effect on the precision of alphas or on the slope coefficients of the horse race regression.

4.3.3. Precision of alpha estimators: Beta shrinkage and alternative factors

We find that the four factor model wins the horse race over the seven factor model when betas are measured with error. Would this result change if we estimate betas more precisely? Vasicek (1973) shows that market betas shrunk towards one are more precise estimates of future betas than OLS betas. To examine whether such shrinkage increases precision, we shrink the betas towards their population means with weights equal to the corresponding slope coefficients in Table 19 and compute alphas in the data for various factor models.[44] With the shrunk beta, $\sigma^2_{\hat{\alpha}^E_\eta}$ for the four- and seven factor models are 350.2 and 345.6 compared with 357.7 and 363.2 in Table 20. Therefore, alphas are more precisely estimated in the data with shrunk betas and also seven factor alphas are more precise than four-factor alphas.

We could also potentially improve the precision of alpha estimates by suitably modifying the return generating process that we assume. The first four factors, i.e. market, SMB, HML and UMD are specified by theoretical or empirical asset pricing models. However, the industry factors are statistically defined. It is possible that statistical factors identified from the sample would better identify the common factors in the sample.

[44] For instance, for market beta the shrinkage estimator equals $(1-.656)\times 1+.656\times\ \beta^{past}_{market}$, where β^{past}_{market} is the estimate from the time-series regression with past returns.

To identify these common factors from the sample, we first fit a time-series regression analogous to regression (2.19) with η=4 for each fund over its entire life. We extract the principal components of covariance matrix of the residuals using the approach in Connor, Korajczyk (1987). We use the first three principal components in place of the industry factors in the return generating process.

With this model, $\sigma^2_{\hat{\alpha}^E_\eta}$ for the seven factor model is 321.4 which is smaller than 363.2 for the corresponding model with industry factors in Table 20. Alphas estimated with this model are also more precise than that with the four factor model in Table 20. Therefore, sample specific common factors could potentially increase the precision of alpha estimates.[45]

We also run our simulation experiments using these modifications. First, we use shrunk betas to compute alpha in the simulation and fit horse race regression (2.14). In untabulated results we find that the seven factor model wins the horse race with shrunk betas. Similarly, we simulate returns with factors from fund principal components in place of industry factors and fit the horse race regression. Here again the seven factor alpha wins the horse race.[46]

Overall, the robustness test results are consistent with our analytic results that the winner of the horse race under the rational expectations hypothesis depends on the characteristics of the sample such as dispersion of factor betas and measurement error in betas. Specifically, when betas are estimated more precisely with Vasicek (1973) shrunk betas and when cross-sectional dispersion of betas is bigger than in our sample, the optimal alpha estimator includes more factors and the seven factor model wins. But large beta measurement errors, for instance due to time

[45] However, an advantage with industry factors is that they are not specific to particular samples.
[46] One could also improve the precision of beta estimates using daily returns data that are available on CRSP starting September 1998.

varying betas, and smaller dispersion in factor betas favor a model with fewer factors and the four factor model wins. The true asset pricing model has no effect on the outcome of the horse race.

4.3.4. Fund Flows

When we generate fund flows according to our model in the simulation, the slope coefficient on the seven factor alpha in horse race regression in Panel B of Table 25 is about 3.02. We fit the following regression with actual data to compare the empirical and model flow alpha relations:

$$\Gamma_{p,t} = a + b \times \hat{\alpha}^{E}_{p,7,t} + \psi_{p,t}. \quad (2.29)$$

The slope coefficient of this regression is 0.198. The smaller empirical correlation indicates that investors' decisions are based on factors other than funds' past performance. Ibert et. al. (2017) document that past performance does not fully explain fund flows and suggest that factors such as managerial fundraising skill, advertising and broker-intermediated flows could also affect fund flows. Additional factors such as investors' personal liquidity demands and recommendations by advisory services such as Morningstar also potentially drive a wedge between empirical and model flows.[47]

We assume that investors who optimally extract information about fund skills are aware of flows due to other factors and their effect on funds' costs and they adjust their flows so that we get to a competitive equilibrium. Propositions 2.1 through 2.3 apply in a competitive equilibrium regardless of the underlying factors that drive flows. To examine the effect of how empirical flows affect the horse race, we match simulated flows with empirical flows. Regression (2.29) uses $\hat{\alpha}^{E}_{p,7,t}$

[47] For example, Jain and Wu (2000), Gallaher, Kaniel, and Starks (2006), Kaniel and Parham (2017) find that fund flows are positively related to advertising activities, Del Guercio and Tkac (2008), Ben-David et al. (2019) find that fund flows are correlated with Morningstar ratings, Christoffersen, Evans, and Musto (2013) find that flows in broker-sold funds are impacted by the incentives of the brokers.

as the explanatory variable but for the simulation we need the relation between $\hat{\alpha}_{p,7,t}$ that investors in the model use and fund flows. Because $\hat{\alpha}^E_{p,7,t}$ is $\hat{\alpha}_{p,7,t}$ with additional error, we can get the slope coefficient with respect to the latter by scaling up the slope coefficient estimate from regression (2.29) by a factor equal to $\sigma^2_{\hat{\alpha}^E_{p,7,t}}/\sigma^2_{\hat{\alpha}_{p,7,t}}$ from Tables 20 and 22. With this scaling, we generate fund flows in the simulation using the following equation:

$$\Gamma_{p,t} = -.00225 + .232 \times \hat{\alpha}_{p,7,t} + \psi_{p,t}. \tag{2.30}$$

We randomly draw $\psi_{p,t}$ from a mean zero normal distribution with variance equal to 9.33%, to match the empirical variance.

Because fund returns are generated using the same parameters as before, the precision of alpha estimates is same as that in Table 24. For the horse race regression, the untabulated results are similar to that in Table 25. Specifically, the true asset pricing model has a negligible effect on the slope coefficient estimates, the seven factor alpha wins without beta estimation error and the four factor model wins when betas are measured with error.

5. Binary variable regression

Our analyses so far use a linear regression for the alpha-fund flow horse race but the true relation need not be linear. For example, the coefficient on alpha in Eq. (2.12) varies cross-sectionally with fund returns and fund age. Also, in Berk and Green (2004) the equilibrium relation between alpha and fund flow is nonlinear. Because of potential non-linearity, BvB transform flows and alpha estimates to binary variables and run the horse race with these transformed variables. Specifically, the transformed binary variables are defined as follows:

$$Q_x = \begin{cases} 1 \text{ if } x \geq 0 \\ -1 \text{ if } x < 0 \end{cases}, \tag{2.31}$$

where x is any random variable. BvB run the following OLS regression:

$$Q_{\Gamma_p} = A_\eta + B_\eta \times Q_{\hat{\alpha}^E_{p,\eta}} + o_{p,\eta}, \tag{2.32}$$

and compare $\hat{B}_\eta$. To relate the analyses based on Regressions (2.14) and (2.32), we first establish the following proposition:

Proposition 2.5: Let $\hat{\alpha}^E_{p,\eta_1}$ and $\hat{\alpha}^E_{p,\eta_2}$ be the alphas computed by the empiricist with respect to η_1- and η_2-factor models using Equation (2.13) and suppose the model misspecification term is sufficiently small.[48] $\hat{b}_{\eta_1}$ and $\hat{b}_{\eta_2}$ are the corresponding Regression (2.14) slope coefficients and $\hat{B}_{\eta_1}$ and $\hat{B}_{\eta_2}$ are the corresponding Regression (2.32) slope coefficients. Under the assumptions of our model, if $\hat{b}_{\eta_1} > \hat{b}_{\eta_2}$ then $\hat{B}_{\eta_1} > \hat{B}_{\eta_2}$, when the number of funds in the sample is sufficiently large.

Proof: See Appendix 2D.

Corollary: The ordering of the slope coefficients of Regressions (2.14) and (2.32) are identical.

Proposition 2.5 and its corollary show that our analysis of the horse race based on Regression (2.14) applies exactly to that of the horse race based on Regression (2.32) if we ignore the model misspecification term, and we find that this term is indeed empirically small. Nevertheless, we

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[48] We can show that this proposition also obtains when we replace the supposition that "the model misspecification term is sufficiently small" with an assumption that average factor betas of funds equal corresponding betas for the market portfolio.

directly run a horse race with Eq. (2.32) to examine whether Proposition 2.3 holds if we do not ignore the model misspecification term.

Table 26 reports the slope coefficients of Regression (2.32). As Proposition 2.5 predicts, the ordering of the slope coefficients in Table 26 is identical to that for Regression (2.14) in Table 25. Therefore, our results are not sensitive to regression specifications.[49]

6. Model Robustness

Our analytic results have two broad parts. The first part shows that rational investors use the most precise alpha to update their priors and inform their investment decisions. We derive this result under the assumptions that fund skills are unobservable but constant and investors know fund betas. This section considers generalizations of these assumptions along dimensions proposed in the literature.

Roussanov et al. (2019) assume that fund manager skill follows an AR(1) process while skill is constant in BG. Investors' posterior in Roussanov et al. is also a linear function of their priors and alphas as in Proposition 2.1, but their weights are different. Proposition 2.3 does not depend on the weights assigned to alphas and therefore the result that investors use $\hat{\alpha}_{p,J,t}$ to update priors in a competitive equilibrium applies in this case as well.

Franzoni and Schmalz (2017) consider a model where investors do not know true factor betas but learn about them through funds' past performance. Investors' posterior in this model is also a linear function of their priors and alphas as in Eq. (2.7) but the coefficient of alpha includes a term related to the uncertainty about betas. We need to specify investors' uncertainty about factor betas

[49] Asymptotically, regression slope coefficients do not vary with the horizon over which alphas and model flows are computed because model flows are uncorrelated with lagged alphas. Therefore, we present the results only for monthly regressions.

to determine the exact factor model that investors would use to update their priors. However, whether or not investors use a particular factor to compute alphas depends on the uncertainty about its betas and not the true asset pricing model.

To examine the effect of investors' uncertainty about true betas, we run a modified simulation experiment. We let betas follow the AR(1) process as in Eq. (2.28) but we assume that at time *t* investors observe $\boldsymbol{\beta}_{(1,J),p,t-1}$ but not $\boldsymbol{\beta}_{(1,J),p,t}$. Investors' optimal estimate of time *t* factor betas is $(1-\rho)\overline{\boldsymbol{\beta}}_{(1,J),p} + \rho\boldsymbol{\beta}_{(1,J),p,t-1}$, which they use to compute alphas. We find in untabulated results that none of our conclusions from earlier simulations change.

Koijen (2014) presents a structural model where funds actively manage a time-varying fraction of their AUM and passively index the rest. Fund betas in this model could vary through time if factor betas of the actively managed portion of the fund are different from the passively indexed portion. In our robustness tests we find virtually the same results with time-varying betas and constant betas. Although our robustness tests model beta time-variation as an AR(1) process, our results with a wide range of AR(1) coefficients suggest that beta time-variation per se is unlikely to qualitatively change our main results.

Fund managers in BG also actively manage a time-varying fraction of their AUM and passively index the rest and funds also set their fees to maximize their revenues. Propositions 2.1, 2.2 and 2.3 depend only on competitive market equilibrium and they do not depend on how exactly funds manage their AUM. Therefore, our result that investors use $\hat{\alpha}_{p,J,t}$ to inform their investment decisions is not sensitive to BG's model of funds' investment decisions.

7. Results in Perspective

BvB, BHO, Agarwal, Green and Ren (2017) and Blocher and Molyboga (2017) report that single factor alpha wins their horse race with samples of mutual funds and hedge funds. BvB and some other papers conclude that these results indicate that the CAPM is the true asset pricing model. However, BHO conclude that these results indicate that investors lack sophistication because they do not use a model with all common factors to estimate alphas to inform their investment decisions. Are such inferences tenable?

A fundamental concept in finance is that investors make investment decisions based on their assessment of future risk-adjusted returns. Therefore, it may appear on the surface that one could identify the particular asset pricing model that investors use for risk-adjustment from their investments into and out of mutual funds. While rational investors indeed make decisions based on expected *future* risk-adjusted performance, we show that they optimally extract information from *past* returns with alphas orthogonalized to both priced and unpriced factors. Therefore, alphas that investors use do not contain any information to differentiate between priced and unpriced factors.

BvB justify their inferences about asset pricing model based on a proposition built on their assumption that "if a true risk model exists, any false risk model cannot have additional explanatory power" (p. 6) for fund flows. BvB's Eq. (7) presents a mathematical representation of this assumption, which in our notations is:[50]

$$\text{Probability}\left[\Gamma_{p,t} > 0 \middle| \, \hat{\alpha}_{p,K,t} > 0,\, \hat{\alpha}_{p,k^*,t} > 0\right] = \text{Probability}\left[\Gamma_{p,t} > 0 \middle| \, \hat{\alpha}_{p,K,t} > 0\right], \quad (2.33)$$

[50] BvB's Equation (7) defines the conditioning variables in Eq. (2.33) as fund net return minus benchmark returns and BvB's Eq. (9) defines benchmark returns for various single- and multifactor models. Monthly fund return minus benchmark return in their Eq. (9) is the same as alphas in our Eq. (2.13).

where $\hat{\alpha}_{p,K,t}$ is alpha computed with only the *K* priced factors in the true asset pricing model and $\hat{\alpha}_{p,k^*,t}$ is alpha computed with respect to any other model. Is this assumption tenable? We show that investors optimally use $\hat{\alpha}_{p,J,t}$ to update their priors about manager skills and hence flows are determined by $\hat{\alpha}_{p,J,t}$ and not by alpha with respect to the true asset pricing model. Therefore, $\hat{\alpha}_{p,J,t}$ and $\Gamma_{p,t}$ have the same sign and $\text{Probability}\left[\Gamma_{p,t} > 0 | \, \hat{\alpha}_{p,J,t} > 0\right] = 1$. If $K \neq J$, i.e. if there is at least one unpriced factor, then BvB's assumption represented by Eq. (2.33) is false. BvB's assumption holds in a rational expectations economy if and only if all common factors are priced. But such an assumption would predetermine the true asset pricing model and render any asset pricing model test moot.

Our empirical results also indicate that the true asset pricing model has a negligible effect on the outcome of the horse race. For example, the four factor model alpha is empirically the most precise estimate when betas are estimated from the data and our empirical decomposition of the components of alpha measurement error indicates that this model would win the horse race under the rational expectations hypothesis even if the true asset pricing model were CAPM or FF3. Our results in a simulated rational expectations economy confirm this result. So, the winner does not reveal the true asset pricing model and there is neither a theoretical nor an empirical justification to use the horse race as a test of asset pricing models.

BHO, citing Grinblatt and Titman (1989) and Pastor and Stambaugh (2002), hypothesize that if investors are sophisticated then the *J*-factor model alpha should win the horse race and use this model alpha as the benchmark for investor sophistication. However, we show that the *J*-factor model alpha need not win empiricists' horse race under the rational expectations hypothesis because empiricists do not know the true asset pricing model and true factor betas. Our empirical results indicate that when empiricists follow the common practice of estimating betas using time-series regressions with 60 months of data four-factor model alphas win the horse race under the rational expectations hypothesis and not seven factor model alphas. Even with the four-factor model as the benchmark, however, BHO's result that the single factor model alpha wins the horse race suggests rejection of the investor sophistication hypothesis.[51, 52]

8. Conclusion

Investors reveal their preferences for mutual funds through investments in or withdrawals from them. In a rational expectations economy, investors update their priors about fund manager skills based on funds' past performance and make their investment decisions. Because flows reveal the model that investors use to update their priors, recent literature proposes that a comparison of relations between fund flows and alphas computed with different models can be used to test asset pricing models and also to assess investor sophistication. We examine whether these proposals are conceptually and empirically tenable.

To examine the conceptual issues, we build a rational expectations model where investors extract information about mutual fund manager skills from funds' past performance and optimally decide on fund flows. We show that investors use alphas computed with a multifactor model that includes all priced and unpriced factors to update their priors. Because alphas that determine fund flows are orthogonal to both priced and unpriced factors, flows do not contain any information to

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[51] Mathematically, BHO's findings indicate that $Cov\left(\Gamma_{p,t}, \hat{\alpha}^E_{p,1,t}\right)$, the numerator in Eq. (2.15) is bigger than the covariance between flow and alphas computed with more than one factor because empirically $\sigma^2_{\hat{\alpha}^E_{p,\eta,t}} < \sigma^2_{\hat{\alpha}^E_{p,1,t}}$ for $\eta > 1$. If investors use $\hat{\alpha}_{p,1,t}$ to inform their investment decisions they conflate abnormal performance due to skill with that due to omitted factor realization. Therefore, $Cov\left(\Gamma_{p,t}, \hat{\alpha}^E_{p,1,t}\right) = Cov\left(\Gamma_{p,t}, \left[\hat{\alpha}^E_{p,\eta,t} + \sum_{k=2}^{\eta} \beta_{p,k} f_k\right]\right) > Cov\left(\Gamma_{p,t}, \hat{\alpha}^E_{p,\eta,t}\right)$.

[52] Ben-David et al. (2019) report that investors rely on Morningstar ratings and recent fund returns and not on market model alphas as suggested by BHO and BvB and suggest that investors outsource risk assessment to Morningstar.

differentiate between factors that are priced under the true asset pricing model and unpriced factors.

We then analyze the flow-alpha horse race that the literature runs under the hypothesis that flows are generated in a rational expectations economy. Unlike the investors in the economy, empiricists who run the horse race do not know the true asset pricing model and true betas. We show that the most precise alphas based on empiricists' information set will win the flow-alpha horse race under the rational expectations hypothesis.

We empirically examine the precision of alphas computed with various models with a sample of actively managed mutual funds. Our empirical tests use BHO's seven-factor model with Fama-French factors (market, SMB, HML), momentum factor (UMD) and three industry factors. We compute the precision of alphas under the hypothesis that each of the following asset pricing models is true: (i) None of the risk factors are priced (or true expected returns are unrelated to factors betas), (ii) CAPM (iii) Fama-French three factor model or (iv) Fama-French-Carhart four factor model.

We find that alphas with a four-factor model that excludes the three industry factors are the most precise regardless of the true asset pricing model. Therefore, our model implies that a four-factor alpha will always win the horse race if flows are determined in a rational expectations economy. We also conduct a simulation experiment with parameters that match the data. We generate fund flows in the simulation according to our model under each candidate asset pricing model, and test our predictions. We find that four-factor alphas are the most precise in our simulations as well, and they always win the flow-alpha horse race regardless of the true asset pricing model.

Our findings show that the winner of the flow-alpha horse race cannot be used to identify the true asset pricing model. In contrast, BvB present a model to justify their inference that CAPM is the best asset pricing model based on their evidence that the market model alpha wins the horse race. We show that a faulty foundational assumption in BvB's model is the source of their mistaken inference.

Our finding is also contrary to BHO's hypothesis that alphas computed with all seven factors will win the horse race under the investor sophistication hypothesis, or equivalently, the rational expectations hypothesis. We show that four-factor alphas are more precise than seven factor alphas because of estimation errors in industry betas. Even with the four-factor model as the benchmark, however, BHO's finding that the single factor model alpha wins the horse race suggests rejection of the investor sophistication hypothesis.

Appendix

Appendix 2A: Proofs of Propositions 2.1 and 2.2

This appendix presents the proofs of Propositions 2.1 and 2.2.

A. Proof of Proposition 2.1.

At time t investors observe the history of net returns and fund size $\{r_s, q_s\}_{s=0}^{t}$ over the life of each fund. Let $Age_{p,t}$ denote the age of a fund as of time t and $c_t(q)$ denote the cost per unit size of the fund. Since $c_t(q)$ is in the investors' information set, they back out the history of gross returns on each fund $\{R_s\}_{s=0}^{t}$. Investors' prior on managerial skill at $t = 0$ is given by $N(\phi_0, 1/\nu)$. They use the gross returns history up to the end of period t and update their prior on managerial skill using an η-factor model benchmark to compute abnormal returns. Let $X_{p,\eta,t}$ denote the benchmark adjusted gross returns for fund p at time t, i.e. $X_{p,\eta,t} = \hat{\alpha}_{p,\eta,t} + c_{t-1}(q_{p,t-1})$, and $\bar{X}_{p,\eta,t}$ denote its sample mean over t periods. Note that for each fund, the sample size of return history as of time t is equal to the age of the fund as of t ($Age_{p,t}$).

Under the assumption that all returns are all normally distributed, using Theorem 1 of DeGroot (1970, p. 167), the posterior distribution is normal with mean $\phi_{p,\eta,t}$ given by:

$$\phi_{p,\eta,t} = \frac{\nu\,\phi_0 + t\vartheta_{\hat{\alpha},\eta}\,\bar{X}_{p,\eta,t}}{\nu + t\vartheta_{\hat{\alpha},\eta}}, \qquad (2A.1)$$

and precision given by $\left(\nu + t\vartheta_{\hat{\alpha},\eta}\right)$, where $\vartheta_{\hat{\alpha},\eta} = \frac{1}{\sigma^2_{\hat{\alpha},\eta}}$.

Equation (2A.1) follows DeGroot and specifies investors' cumulative update from time 0 to t. This result, in conjunction with the competitive equilibrium condition yields the recursive update described by Eq. (2.7) in Proposition 2.1. Under the competitive equilibrium condition in Eq. (2.3):

$$c_t(q_{p,t}) = \mathrm{E_t}(\Phi_p) = \phi_{p,\eta,t} \qquad (2A.2)$$

Rewriting $t\bar{X}_{p,\eta,t}$ as $(t-1)\bar{X}_{p,\eta,t-1} + X_{p,\eta,t}$ which can further be written as $(t-1)\bar{X}_{p,\eta,t-1} + \hat{\alpha}_{p,\eta,t} + c_{t-1}(q_{p,t-1})$, Eq. (2A.1) becomes:

$$\phi_{p,\eta,t} = \frac{\nu\,\phi_0 + (t-1)\vartheta_{\hat{\alpha},\eta}\,\bar{X}_{p,\eta,t-1} + \vartheta_{\hat{\alpha},\eta}c_{t-1}(q_{p,t-1})}{\nu + t\vartheta_{\hat{\alpha},\eta}} + \frac{\vartheta_{\hat{\alpha},\eta}}{\nu + t\vartheta_{\hat{\alpha},\eta}}\hat{\alpha}_{p,\eta,t}\,. \qquad (2A.3)$$

From (2A.2), the competitive equilibrium condition for period $t-1$ will be $c_{t-1}(q_{p,t-1}) = \phi_{p,\eta,t-1}$ and from (2A.1), $\phi_{p,\eta,t-1} = \frac{\nu\,\phi_0 + (t-1)\vartheta_{\hat{\alpha},\eta}\,\bar{X}_{p,\eta,t-1}}{\nu + (t-1)\vartheta_{\hat{\alpha},\eta}}$. Substituting these two results in (2A.3) gives:

$$\phi_{p,\eta,t} = \frac{[\nu + (t-1)\vartheta_{\hat{\alpha},\eta}]\phi_{p,\eta,t-1} + \vartheta_{\hat{\alpha},\eta}\phi_{p,\eta,t-1}}{\nu + t\vartheta_{\hat{\alpha},\eta}} + \frac{\vartheta_{\hat{\alpha},\eta}}{\nu + t\vartheta_{\hat{\alpha},\eta}}\hat{\alpha}_{p,\eta,t}$$

Further simplification yields:

$$\phi_{p,\eta,t} = \phi_{p,\eta,t-1} + \frac{\vartheta_{\hat{\alpha},\eta}}{\nu + t\vartheta_{\hat{\alpha},\eta}}\hat{\alpha}_{p,\eta,t}. \qquad (2A.4)$$

Finally, substituting the age of the fund as of time t ($Age_{p,t}$) for the sample size at t, Eq. (2A.4) becomes:

$$\phi_{p,\eta,t} = \phi_{p,\eta,t-1} + \frac{\vartheta_{\hat{\alpha},\eta}}{\nu + Age_{p,t} \times \vartheta_{\hat{\alpha},\eta}}\hat{\alpha}_{p,\eta,t}, \qquad (2A.5)$$

which is the result in Proposition 2.1.

Note that Proposition 2.1 implies that the precision of the posterior after each t (which represents the prior for *t+1*) is $\nu + Age_{p,t} \times \vartheta_{\hat{\alpha},\eta}$ which differs across η. Therefore, although $1/\nu$ is the precision at *t*=0, precision of priors differs across η for *t*>0.

Using the competitive equilibrium condition in (2A.2), we can also write a recursive relation for the cost function as:

$$c_t(q_{p,t}) = c_{t-1}(q_{p,t-1}) + \frac{\vartheta_{\hat{\alpha},\eta}}{\nu + Age_{p,t} \times \vartheta_{\hat{\alpha},\eta}} \hat{\alpha}_{p,\eta,t}. \qquad (2A.6)$$

B. Proof of Proposition 2.2

For part (a) of the proposition, to prove the "if" condition, substitute Eqs. (2.4) and (2.5) in Eq. (2.7) to get:

$$\mathrm{E}_t[\phi_{p,J,t} - \phi_{p,J,t-1} | f_{k,\tau},\ \forall k, \tau \leq t] = \frac{\vartheta_{\hat{\alpha},J}}{\nu + t\vartheta_{\hat{\alpha},J}} \times \mathrm{E}_t[\xi_{p,t} | f_{k,\tau},\ \forall k, \tau \leq t] = 0.$$

So, if investors start with an unbiased prior that skill equals $\phi_0\ \forall p$ at time 0, then their posterior is unbiased in every subsequent period. To prove the "only if" condition, suppose the contrapositive $\mathrm{E}_t[\phi_{p,\eta,t} | f_{k,\tau},\ \forall k, \tau \leq t\ ] = \Phi_p\ \forall t$ is true for some $\eta < J$. Consider a fund p with $\beta_{p,k^*} \neq 0$ for some $k^* > \eta$. Substituting Eqs. (2.4) and (2.5) in Eq. (2.7) we get:

$$\mathrm{E}_t[\phi_{p,\eta,t} - \phi_{p,\eta,t-1} | f_{k,\tau}, \forall k, \tau \leq t]$$
$$= \frac{\vartheta_{\hat{\alpha},\eta}}{\nu + Age_t \times \vartheta_{\hat{\alpha},\eta}} \times \mathrm{E}_t\left[\sum_{k=\eta+1}^{J} \beta_{p,k} f_{k,t} + \xi_{p,t} | f_{k,\tau}, \forall k, \tau \leq t\right] \neq 0. \qquad (2A.7)$$

Therefore, if $\phi_{p,\eta,t-1}$ is an unbiased estimate of Φ_p then $\phi_{p,\eta,t}$ is not an unbiased estimate because $\beta_{p,k^*} f_{k^*,t} \neq 0$, which leads to a contradiction of the contrapositive.

For part (b): From Eqs. (2.4) and (2.5), we get: $\hat{\alpha}_{p,\eta,t} = \hat{\alpha}_{p,J,t} + \sum_{k=\eta+1}^{J} \beta_{p,k} f_{k,t}$. Therefore, $Var(\hat{\alpha}_{p,\eta,t}) = Var(\hat{\alpha}_{p,J,t}) + \boldsymbol{\beta}'_{(\eta+1,J)} \boldsymbol{E}[\boldsymbol{f}'_{(\eta+1,J)} \boldsymbol{f}_{(\eta+1,J)}] \boldsymbol{\beta}_{(\eta+1,J)}$ where $\boldsymbol{\beta}_{(\eta+1,J)}$ and $\boldsymbol{f}_{(\eta+1,J)}$ are vectors of betas and factors from $\eta + 1$ to J. Because no factor is redundant, $E\left[\boldsymbol{f}'_{(\boldsymbol{\eta}+\mathbf{1},\boldsymbol{J})}\boldsymbol{f}_{(\boldsymbol{\eta}+\mathbf{1},\boldsymbol{J})}\right]$ is positive definite and therefore $\boldsymbol{\beta}'_{(\eta+1,J)}\boldsymbol{E}\left[\boldsymbol{f}'_{(\eta+1,J)}\boldsymbol{f}_{(\eta+1,J)}\right]\boldsymbol{\beta}_{(\eta+1,J)} > 0$ for any non-zero vector $\boldsymbol{\beta}_{(\eta+1,J)}$. Therefore, $Var\left(\hat{\alpha}_{p,\eta,t}\right) > Var\left(\hat{\alpha}_{p,J,t}\right)$.

Appendix 2B: Covariance of Flows with Empiricist's Alpha

This appendix derives the result presented in Eq. (2.18) for the covariance of flows with the empiricist's alpha estimate. The relation between the empiricist's estimate of alpha from an η-factor model and investors' estimate of alpha from J-factor model is given by Eq. (2.16). We rewrite this equation as $\hat{\alpha}^{E}_{p,\eta,t} = \hat{\alpha}_{J,t} + \nu_{p,\eta,t}$ where $\nu_{p,\eta,t}$ denotes the remaining terms on the right hand side of Eq. (2.16). Because $\hat{\alpha}_{J,t}$ is uncorrelated with each individual term in $\nu_{p,\eta,t}$, $Cov(\hat{\alpha}_{J,t}, \nu_{p,\eta,t}) = 0$. Rewrite Eq. (2.12) as:

$$\Gamma_{p,t} = \mathcal{K}_{p,t} \times (1 + r_{p,t}) \times \hat{\alpha}_{p,J,t},$$

where $\mathcal{K}_{p,t} = \frac{\vartheta_{\hat{\alpha},J}}{\nu + Age_{p,t} \times \vartheta_{\hat{\alpha},J}} \times \frac{1}{\delta_{t-1} q_{p,t-1}}$.

With these notations:

$$Cov(\Gamma_{p,t}, \hat{\alpha}^{E}_{p,\eta,t}) = Cov(\Gamma_{p,t}, \hat{\alpha}_{p,J,t}) + Cov(\mathcal{K}_{p,t}\hat{\alpha}_{p,J,t}(1 + r_{p,t}), \nu_{p,\eta,t}). \qquad (2B.1)$$

Since $\mathcal{K}_{p,t}$ is a deterministic function of time, the second term on the RHS becomes $\bar{\mathcal{K}}_t Cov(\hat{\alpha}_{p,J,t}(1 + r_{p,t}), \nu_{p,\eta,t})$ where the overbar represents cross-sectional average. The covariance term can be equivalently written as $Cov(\hat{\alpha}_{p,J,t}(1 + r_{p,t}), \tilde{\nu}_{p,\eta,t})$ where $\tilde{\nu}_{p,\eta,t} = \nu_{p,\eta,t} - \bar{\nu}_{\eta,t}$ and $\bar{\nu}_{\eta,t}$ is the mean.

We can evaluate the covariance using the following identity:

$$Cov(ab, c) = Cov(a, bc) - Cov(a, b)E(c) + E(a)Cov(b, c). \qquad (2B.2)$$

With $a = \hat{\alpha}_{p,J,t}, b = (1 + r_{p,t}), c = \tilde{\nu}_{p,\eta,t}$ and using $(\hat{\alpha}_{p,J,t}) = 0$, $Cov(\hat{\alpha}_{p,J,t}, \tilde{\nu}_{p,\eta,t}) = 0$, $E(\tilde{\nu}_{p,\eta,t}) = 0$, we get:

$$Cov(\hat{\alpha}_{p,J,t}(1 + r_{p,t}), \tilde{\nu}_{p,\eta,t}) = Cov(\hat{\alpha}_{J,t}, r_{p,t}\tilde{\nu}_{p,\eta,t}). \qquad (2B.3)$$

From Eqs. (2.4) and (2.5) we get:

$$r_{p,t} = \hat{\alpha}_{J,t} + \sum_{k=1}^{K} \beta_{k,p} \mathrm{E}[F_{k,t}] + \sum_{k=1}^{J} \beta_{k,p}\, f_{k,t} \equiv \hat{\alpha}_{J,t} + \theta_{p,t}, \qquad (2B.4)$$

where $\hat{\alpha}_{J,t}$ and $\theta_{p,t}$ are independent.

From Eqs. (2B.3) and (2B.4) we get

$$Cov\left(\hat{\alpha}_{p,J,t}(1 + r_{p,t}), \tilde{v}_{p,\eta,t}\right) = Cov\left(\hat{\alpha}_{J,t}, \hat{\alpha}_{J,t}\tilde{v}_{p,\eta,t}\right) + Cov\left(\hat{\alpha}_{J,t}, \theta_{p,t}\tilde{v}_{p,\eta,t}\right). \qquad (2B.5)$$

Since $\hat{\alpha}_{J,t}$ is independent of all factors and factor betas, the second term on the RHS Eq. (2B.5) equals zero and the first term equals $Var(\hat{\alpha}_{J,t})E(\tilde{v}_{p,\eta,t})$ using the identity in (2B.2). Since $E(\tilde{v}_{p,\eta,t}) = 0$ in every time period, (2B.5) equals zero.

Substituting this result in Eq. (2B.1), we get:

$$Cov\left(\Gamma_{p,t}, \hat{\alpha}^{E}_{p,\eta,t}\right) = Cov\left(\Gamma_{p,t}, \hat{\alpha}_{p,J,t}\right).$$

Appendix 2C: Estimating Measurement Error Components

This appendix presents the steps to empirically estimate various components of $\sigma^2_{\hat{\alpha}^E_\eta}$ conditional on the true asset pricing model. For brevity, the table below presents the components of $\sigma^2_{\hat{\alpha}^E_\eta}$ from Eq. (2.24) with *J*=2 and for $\eta = 0, 1, 2$ and $K = 0, 1$.

		Variance due to:					
		$\sigma^2_{\hat{\alpha}_J}$	APM Misspecification	Omitted factors	Covariance of omitted factors with APM misspecification	Beta measurement error	Total
K	η	(1)	(2)	(3)	(4)	(5)	(6)
0	0	IV	0	V	0	0	I
	1	IV	III	V	VI	II	I
	2	IV	III	0	0	II	I
1	0	IV	III	V	VI	0	I
	1	IV	0	V	0	II	I
	2	IV	III	0	0	II	I

We first fill cells that are zero by definition. These cells are:

a. APM Misspecification, when $\eta = K$.

b. Omitted Factors, when $\eta = J$.

c. Covariance of omitted factors with APM misspecification, when $\eta = J$ or K.

d. Beta measurement error, when $\eta = 0$.

Next, we fill the remaining columns of the above table using the sequence of steps discussed below. Numbers I to VI in the table correspond to the respective step numbers below and denote the order in which we estimate each component of the variance decomposition labeled in the column heading.

I. Using estimates from the time-series OLS regression (2.19), we compute $\hat{\alpha}^{E}_{p,\eta,t}$ for each fund-month under each η-factor model and then compute the cross-sectional variance $\sigma^2_{\hat{\alpha}^E_{\eta,t}}$. We average this across months to get $\sigma^2_{\hat{\alpha}^E_{\eta}} = \frac{1}{T}\sum_t \sigma^2_{\hat{\alpha}^E_{\eta,t}}$.

II. From the time-series OLS regression (2.19) for each fund-month and η-factor model, we get the covariance matrix of $\hat{\boldsymbol{\beta}}$ estimates: $Cov\left(\left[\hat{\boldsymbol{\beta}}_{(1,\eta),p,t} - \boldsymbol{\beta}_{(1,\eta),p,t}\right]', \left[\hat{\boldsymbol{\beta}}_{(1,\eta),p,t} - \boldsymbol{\beta}_{(1,\eta),p,t}\right]\right) = \sigma^2_{e_{p,t}}\left(X'_{(1,\eta),t}X_{(1,\eta),t}\right)^{-1}$, where $\boldsymbol{\beta}_{(1,\eta),p,t}$ is the vector of true factor betas for fund p for month t, $X_{(1,\eta),t}$ is the data matrix of corresponding factors and $\sigma^2_{e_p}$ is the variance of residuals. We compute the variance due to beta measurement error component as:

$$\frac{1}{T}\sum_t \frac{1}{P_t}\sum_{\boldsymbol{P}} \boldsymbol{F}'_{(1,\eta),t} Cov\left(\left[\hat{\boldsymbol{\beta}}_{(1,\eta),p,t} - \boldsymbol{\beta}_{(1,\eta),p,t}\right]', \left[\hat{\boldsymbol{\beta}}_{(1,\eta),p,t} - \boldsymbol{\beta}_{(1,\eta),p,t}\right]\right) \boldsymbol{F}_{(1,\eta),t}, \qquad (2C.1)$$

where P_t is the number of funds in the cross-section at time t.

III. For $\eta > K$, misspecification error variance = $\overline{\boldsymbol{F}}'_{(K+1,\eta)} Cov\left(\boldsymbol{\beta}'_{(K+1,\eta)}, \boldsymbol{\beta}_{(K+1,\eta)}\right)\overline{\boldsymbol{F}}_{(K+1,\eta)}$, where $\overline{\boldsymbol{F}}_{(K+1,\eta)}$ is the sample mean of unpriced factors, $Cov\left(\boldsymbol{\beta}'_{(K+1,\eta)}, \boldsymbol{\beta}_{(K+1,\eta)}\right)$ is the covariance matrix of true betas of corresponding factors. We estimate the covariance of true betas of an η-factor model as:

$$Cov\left(\boldsymbol{\beta}'_{(1,\eta)}, \boldsymbol{\beta}_{(1,\eta)}\right) = \frac{1}{T}\sum_{\boldsymbol{t}}\left(Cov\left(\hat{\boldsymbol{\beta}}'_{(1,\eta),t}, \hat{\boldsymbol{\beta}}_{(1,\eta),t}\right) - \left\{\frac{1}{P_t}\sum_{\boldsymbol{P}} \sigma^2_{e_{p,t}}\left(X'_{(1,\eta),t}X_{(1,\eta),t}\right)^{-1}\right\}\right). \qquad (2C.2)$$

We use the sub-matrix of the above matrix starting at row $K+1$ to compute $\overline{\boldsymbol{F}}'_{(K+1,\eta)} Cov\left(\boldsymbol{\beta}'_{(K+1,\eta)}, \boldsymbol{\beta}_{(K+1,\eta)}\right)\overline{\boldsymbol{F}}_{(K+1,\eta)}$. For $\eta < K$, we use the covariance matrix of true betas from the case $\eta \geq K$ for the corresponding factors since these betas are not estimated in this case. For example, with $\eta = 1, K = 3$ we use the covariance matrix of true betas for SMB, HML estimated for the case $\eta = 3, K = 1$.

IV. For $\eta = J$, from Eq (2.24),

$$\sigma^2_{\hat{\alpha}_{J,t}} = \sigma^2_{\hat{\alpha}^E_{\eta,t}} - \left(\overline{\boldsymbol{F}}'_{(K+1,\eta)} \left(Cov\left(\boldsymbol{\beta}'_{(K+1,\eta)}, \boldsymbol{\beta}_{(K+1,\eta)}\right)\right) \overline{\boldsymbol{F}}_{(K+1,\eta)}\right) - \left(\boldsymbol{F}'_{(1,\eta),t} Cov\left(\left[\widehat{\boldsymbol{\beta}}_{(1,\eta),p,t} - \boldsymbol{\beta}_{(1,\eta),p,t}\right]', \left[\widehat{\boldsymbol{\beta}}_{(1,\eta),p,t} - \boldsymbol{\beta}_{(1,\eta),p,t}\right]\right) \boldsymbol{F}_{(1,\eta),t}\right). \quad (2C.3)$$

We computed each term on the RHS of the equation using steps I, II and III[53] and hence we can determine $\sigma^2_{\hat{\alpha}_{J,t}}$ which is the variance of alphas computed by investors in the economy using their information set. Empiricists do not know true asset pricing model, but under the hypothesis that the K-factor model is the true asset pricing model, $\sigma^2_{\hat{\alpha}_{J,t}}$does not depend on the η-factor model used to estimate alpha. Therefore, $\sigma^2_{\hat{\alpha}_{J,t}}$ is constant across all rows with the same K. $\sigma^2_{\hat{\alpha}_J}$ is the time-series average of $\sigma^2_{\hat{\alpha}_{J,t}}$.

V. To compute the variance due to omitted factors, let $\eta = K$. From Eq. (2.24), we get

$$\boldsymbol{f}'_{(\eta+1,J),t} \left(Cov\left(\boldsymbol{\beta}'_{(\eta+1,J)}, \boldsymbol{\beta}_{(\eta+1,J)}\right)\right) \boldsymbol{f}_{(\eta+1,J),t} + \boldsymbol{E}\left[\boldsymbol{\beta}_{(\eta+1,J)}\right]' \left(\boldsymbol{f}_{(\eta+1,J),t} \boldsymbol{f}'_{(\eta+1,J),t}\right) E\left[\boldsymbol{\beta}_{(\eta+1,J)}\right]$$
$$= \sigma^2_{\hat{\alpha}^E_{\eta,t}} - \sigma^2_{\hat{\alpha}_{J,t}} - \left(\overline{\boldsymbol{F}}'_{(K+1,\eta)} \left(Cov\left(\boldsymbol{\beta}'_{(K+1,\eta)}, \boldsymbol{\beta}_{(K+1,\eta)}\right)\right) \overline{\boldsymbol{F}}_{(K+1,\eta)}\right) \quad (2C.4)$$
$$- \left(\boldsymbol{F}'_{(1,\eta),t} \left(Cov\left(\left[\widehat{\boldsymbol{\beta}}_{(1,\eta),t} - \boldsymbol{\beta}_{(1,\eta)}\right]', \left[\widehat{\boldsymbol{\beta}}_{(1,\eta),t} - \boldsymbol{\beta}_{(1,\eta)}\right]\right) \boldsymbol{F}_{(1,\eta),t}\right)\right).$$

We know all the variables on the RHS using steps I through IV and hence we can compute the LHS.[54] The terms on the LHS are a function of η, true betas and unexpected factor realizations and it is not dependent on true K. Therefore, the value we compute for $\eta = K$ applies to all

[53] We consider $\eta = J$ to compute $\sigma^2_{\hat{\alpha}_{J,t}}$ because the other remaining cells after steps I, II and III are zero for this case.

[54] We consider $\eta = K$ to estimate this term because the remaining cell after steps I through IV is zero for this case.

rows with the same η. The variance due to omitted factors is the time-series average of the LHS in Eq. (2C.4).

VI. We have now computed all terms of Eq. (2.24) except the covariance term, and hence we can now compute this term as well.

Appendix 2D: Proof of Proposition 2.5

This appendix proves the result in Proposition 2.5 for the ordering of coefficients in the horse race regression with binary transformation. From Regression (2.32), we have:

$$B_\eta = \mathrm{E}\left[Q_{\Gamma_p}|Q_{\hat{\alpha}^E_{p,\eta}}\right] = \Pr\left(\Gamma_p \geq 0\middle|Q_{\hat{\alpha}^E_{p,\eta}}\right) - \Pr\left(\Gamma_p < 0\middle|Q_{\hat{\alpha}^E_{p,\eta}}\right)$$

When $Q_{\hat{\alpha}^E_{p,\eta}} = 1$, this term can be expanded as:

$$\begin{aligned} &\mathrm{E}\left[Q_{\Gamma_p}|Q_{\hat{\alpha}^E_{p,\eta}} = 1\right] \\ &= \left\{\Pr\left(\Gamma_p \geq 0\middle|\hat{\alpha}^E_{p,\eta} \geq 0, \hat{\alpha}_{p,J} \geq 0\right) - \Pr\left(\Gamma_p < 0\middle|\hat{\alpha}^E_{p,\eta} \geq 0, \hat{\alpha}_{p,J} \geq 0\right)\right\} \\ &\times \Pr\left(\hat{\alpha}_{p,J} \geq 0\middle|\hat{\alpha}^E_{p,\eta} \geq 0\right) \qquad (2D.1) \\ &+ \left\{\Pr\left(\Gamma_p \geq 0\middle|\hat{\alpha}^E_{p,\eta} \geq 0, \hat{\alpha}_{p,J} < 0\right) - \Pr\left(\Gamma_p < 0\middle|\hat{\alpha}^E_{p,\eta} \geq 0, \hat{\alpha}_{p,J} < 0\right)\right\} \\ &\times \Pr\left(\hat{\alpha}_{p,J} < 0\middle|\hat{\alpha}^E_{p,\eta} \geq 0\right). \end{aligned}$$

From Eq. (2.12), the sign of flow is determined only by sign of $\hat{\alpha}_{p,J}$ since all other terms are positive. Therefore, $\hat{\alpha}^E_{p,\eta} \geq 0$ has no additional information about sign of flows being positive conditioning on sign of $\hat{\alpha}_{p,J}$. The model also implies that flow is always positive (negative) when $\hat{\alpha}_{p,J}$ is positive (negative). Substituting these conditions, we can simplify (2D.1) as:

$$\begin{aligned} &\mathrm{E}\left[Q_{\Gamma_p}|Q_{\hat{\alpha}^E_{p,\eta}} = 1\right] \\ &= \Pr\left(\Gamma_p \geq 0\middle|\hat{\alpha}_{p,J} \geq 0\right)\Pr\left(\hat{\alpha}_{p,J} \geq 0\middle|\hat{\alpha}^E_{p,\eta} \geq 0\right) \qquad (2D.2) \\ &- \Pr\left(\Gamma_p < 0\middle|\hat{\alpha}_{p,J} < 0\right)\Pr\left(\hat{\alpha}_{p,J} < 0\middle|\hat{\alpha}^E_{p,\eta} \geq 0\right). \end{aligned}$$

From Eq. (2.16), $\hat{\alpha}^E_{p,\eta} = \hat{\alpha}_{p,J} + \nu_{p,\eta}$ and $Var\left(\hat{\alpha}^E_{p,\eta}\right) = Var\left(\hat{\alpha}_{p,J}\right) + Var\left(\nu_{p,\eta}\right)$. Since the average betas of funds on various factors are equal to betas of market portfolio by assumption, the unconditional average of the bias term in $\nu_{\eta,t}$ is zero for all η-factor models considered in our study. Therefore, $\hat{\alpha}_{p,\eta}$ is Normally distributed with mean zero for all η, and $\Pr\left(\hat{\alpha}^E_{p,\eta} \geq 0\right) = \Pr\left(\hat{\alpha}_{p,J} \geq 0\right) = 0.5$. Using this along with Bayes rule gives:

$$\begin{aligned} \Pr\left(\hat{\alpha}_{p,J} \geq 0 \middle| \hat{\alpha}^E_{p,\eta} \geq 0\right) &= \Pr\left(\hat{\alpha}^E_{p,\eta} \geq 0 \middle| \hat{\alpha}_{p,J} \geq 0\right), \\ \Pr\left(\hat{\alpha}_{p,J} < 0 \middle| \hat{\alpha}^E_{p,\eta} \geq 0\right) &= \Pr(\hat{\alpha}^E_{p,\eta} \geq 0 | \hat{\alpha}_{p,J} < 0). \end{aligned} \qquad (2D.3)$$

It can be easily verified that $\Pr\left(\hat{\alpha}^E_{p,\eta} \geq 0 \middle| \hat{\alpha}_{p,J} \geq 0\right)$ is decreasing in the variance of $\nu_{p,\eta}$ while $\Pr(\hat{\alpha}^E_{p,\eta} \geq 0 | \hat{\alpha}_{p,J} < 0)$ is increasing in the variance of $\nu_{p,\eta}$. Therefore, from (2D.2) and (2D.3) we can infer that $\mathrm{E}\left[Q_{\Gamma_p} | Q_{\hat{\alpha}^E_{p,\eta}} = 1\right]$ is decreasing with the variance of $\hat{\alpha}^E_{p,\eta}$. We obtain similar inference with $\mathrm{E}\left[Q_{\Gamma_p} | Q_{\hat{\alpha}^E_{p,\eta}} = -1\right]$.

Therefore, we can conclude that $\sigma^2_{\hat{\alpha}^E_{p,\eta_1}} < \sigma^2_{\hat{\alpha}^E_{p,\eta_2}} \Rightarrow B_{\eta_1} > B_{\eta_2}$. We established earlier for the horse race Regression (2.14) that $\hat{b}_{\eta_1} > \hat{b}_{\eta_2} \Rightarrow \sigma^2_{\hat{\alpha}^E_{p,\eta_1}} < \sigma^2_{\hat{\alpha}^E_{p,\eta_2}}$. Therefore, $\hat{b}_{\eta_1} > \hat{b}_{\eta_2} \Rightarrow B_{\eta_1} > B_{\eta_2}$.

Fund flow sensitivity to long-horizon performance*

Chandra Sekhar Mangipudi†

Abstract: I study the revealed preferences of equity mutual fund investors to examine the horizon of past performance that matters for buying and selling decisions separately. Using purchases and redemptions data, I find that current buying and selling decisions are sensitive to 52 and 37 months of past performance respectively. Cross-sectional performance predictability regressions of monthly alphas on past performance reveal higher explanatory power for specifications with more lags. However, the performance of portfolios formed using long-horizons of past performance indicates that a simple metric such as one-month net return from previous month outperforms long-horizon models. This indicates that investors' dependence on long horizons of performance is sub-optimal.

Keywords: Fund flows, inflows, outflows, past performance, persistence, long-horizon.

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† Goizueta Business School, Emory University, email: chandra.sekhar.mangipudi@emory.edu.

1. Introduction

Many households in the United States access the equity market through equity mutual funds. The market for managed investment products is proliferated with numerous funds scattered among different investment objectives. From the perspective of investors, identifying skilled managers who can consistently outperform the benchmark is a complicated task. Among the many criteria that investors use to identify outperforming funds, past performance of a fund plays a prominent role. Survey evidence from Investment Company Institute indicates that past performance is a very important factor in influencing the investment decisions of investors.[55] Numerous empirical studies starting from Ippolito (1992), Patel, Zeckhauser, and Hendricks (1994) have also established the performance chasing behavior of investors in equity mutual funds. Recent studies by Barber, Huang, and Odean (2016) and Berk and van Binsbergen (2016) use the flow-performance sensitivities to understand the revealed preferences of investors.

In this paper, I study the revealed preference on a different dimension of performance chasing: the length of historical performance information that matters for investors' current investment decisions. Although past performance serves as a noisy proxy for skill, it is not clear ex-ante if investors consider long histories in their current decisions. If all the investors of a fund are continuously attentive to its performance and use this information in their decisions every period in a timely way, then any investment in the current period must be sensitive only to the most recent revisions of the fund's performance. This is specifically true when the unobserved true skill of the manager is constant over time. Therefore, only the most recent performance signal conveys

[55] https://www.ici.org/pdf/per25-08.pdf

additional information about the skill to investors who are continuously invested in the fund and, hence, are already cognizant of all the past information.

The performance information from longer horizons in the past can matter under different plausible alternative scenarios. If investors are inattentive or slow to incorporate information from the recent past, then current investment would be sensitive to past information over long horizons. Additionally, flows from new investors who are influenced by a fund's marketing efforts can be sensitive to information from long past. Funds highlight their past performance in their prospectuses, financial statements, and in their advertisements in the media. Typically, they use performance computed over different horizons such as 1 year, 3 years, 5 years etc. Although funds add a cautionary note that past performance is not indicative of future results, relatively unsophisticated investors who are attention constrained could be swayed by the salience of performance information displayed to them. The usage of performance information from long past can also be consistent with rational expectations. When a fund manager's unobserved skill is time varying and investors act rationally with this belief, then current period flows can be sensitive to performance information from long periods of the past.[56]

I first examine empirically the number of periods of past performance that investors use in their monthly flow decisions as revealed by flow-performance sensitivities over long horizons. Then I address if their choice of horizon is optimal by studying the future investment performance of portfolios formed using long-horizon performance signals. Evidence in recent studies by Barber,

[56] Roussanov, Ruan, and Wei (2018) show this using the following analytical setup. Suppose the unobserved true skill follows an AR(1) process as $\alpha_t = A + \rho\alpha_{t-1} + \epsilon_t$. Recursive substitution yields $\alpha_t = A\left(\sum_{j=0}^{\infty} \rho^j\right) + \epsilon_t + \rho\epsilon_{t-1} + \rho^2\epsilon_{t-2} + \cdots \infty$. Hence, shocks from many periods in the past can matter for current period's abnormal return on the fund. These shocks are unobserved but are part of the fund returns which are observed. Therefore, flows that are rationally directed towards funds with high abnormal returns in the current period (α_t) would also be sensitive to past performance information over longer time periods under this setup.

Huang, and Odean (2016), Phillips, Pukthuanthong, and Rau (2016) indicates that net flows in a month are indeed sensitive to past performance over long horizons. In this paper, I first revisit their evidence on long horizon performance sensitivity in my sample. Importantly, I add to the findings in the above studies by using disaggregated data on purchases and redemptions in addition to net flows used in those studies.

Buying and selling decisions of investors could be driven by different trading motives and can react to performance at different horizons. For example, buying transactions are forward-looking in nature and use past performance to extract skill while selling transactions could be backward-looking and be based on the purchase price of the investor.[57] Keswani and Stolin (2008) use disaggregated purchases and redemptions data for a sample of British funds and show that funds that receive high purchases outperform in future but those with high redemptions do not. In other words, they show that only buying decisions of investors constitute 'smart money' but not the selling decisions. Based on these arguments, I first test the conjecture that length of history that matters for buying and selling decisions would be different.

In my empirical analyses, I use a sample of equity mutual funds that are catered to retail investors. The primary source for most of the variables at the monthly level is the CRSP Mutual Funds database. I use the daily version of this database to compute betas and alphas from different factor models to reduce correlation between the metrics at different lags. This limits the beginning date of the sample I use to 1999. I collect disaggregated data on purchases and redemptions at a

[57] Selling trades could also be forward-looking in the sense that investors who are unhappy with a fund's performance leave the fund to invest elsewhere. But there is an inherent asymmetry between buys and sells because selling can be motivated by additional reasons such as tax-loss harvesting, personal liquidity reasons etc. Ivkovic and Weisbenner (2009) study individual investor trades in mutual funds at a large discount brokerage and document a different kind of asymmetry in buying and selling trades. They report that buying trades are sensitive to relative performance across funds in the cross-section while selling trades are sensitive to absolute performance of a fund based on the purchase price.

monthly level from Morningstar Direct. I match the CRSP Mutual Funds database to Morningstar Direct using a sequence of automated and manual approaches. My sample spans the period 1999 to 2017 with data on purchases and redemptions for 1,955 equity funds.

My first set of results using flow-performance regressions indicate that performance in the distant past does matter for current flow decisions. Buying in the current period is sensitive to over 52 monthly lags of past performance using various proxies of performance. And selling decisions in the current period are sensitive up to 37 monthly lags of performance. In both cases, the magnitudes of the coefficients decrease in an exponential fashion with the highest weight on the most recent performance information. Therefore, investors consider long-horizon information useful when making their buying and selling decisions, with slightly longer look-back for buying. This confirms the asymmetry in the length of performance information that matters for buying and selling trades.

To understand if the horizon choice of investors is optimal, I examine the predictive power of long-horizon past returns and past risk-adjusted returns for one-month returns. This is similar in spirit to Jegadeesh (1990) and Heston and Sadka (2008). Hendricks, Patel, and Zeckhauser (1993) follow the approach used in Jegadeesh (1990) in the context of mutual funds, but they examine past performance only up to eight quarters (i.e. two years). Later studies that examine persistence in past performance use horizons of up to three years. This could be driven by shorter sample periods in the early studies. Using a large time series from 1999 to 2017, I use cross-sectional prediction regressions to forecast the 1-month relative performance of funds using past returns up to 60 months. My results indicate that adding more lags increases in-sample adjusted R^2 with the 60-lag model having the highest value. In addition, I also find an interesting seasonal pattern from these long-horizon predictability regressions. Lags at quarter-ends (such as t-3, t-6, so on) are particularly large and significant in predicting one month ahead net returns.

To assess the economic significance of the increased fit obtained from adding higher lags, I study the performance of portfolios constructed using the predicted values from models with different lags. In this exercise, using one-month lagged return does not involve any estimation issues and is the most easily available option for the investors. I examine if such a simple metric has better ability to detect outperforming funds compared to using a model that incorporates information from all past lags as indicated by the flow-performance results with higher order lags. The results indicate that using the model with higher lags does not lead to identifying outperforming funds when performance is measured using four-factor alpha. In fact, using a simple metric such as prior one-month net-return does a better job comparatively. This indicates that investors' use of long-horizon information in their buying decisions is sub-optimal.

2. Literature

My study is related to three strands of literature. First is the literature on flow-performance relation in equity mutual funds. Early studies by Ippolito (1992), Patel, Zeckhauser, and Hendricks (1994) documented that flows in equity mutual funds chase past performance. Chevalier and Ellison (1997), Sirri and Tufano (1998) show that the flow-performance relation is convex where funds performing well in the cross-section receive proportionately higher net flows compared to funds performing poorly. Cashman et. al. (2012) study the performance sensitivities of inflows and outflows separately and show that they respond strongly to past good performance and bad performance respectively. In contrast to these studies, I study the horizon of past performance that is relevant for inflows and outflows separately.

Phillips, Pukthuanthong, and Rau (2016) also study the long-horizon dependence of net flows on past performance. They show that investors are influenced by performance advertised by funds over a specific horizon which leads to flows reacting positively to most recent performance and negatively to performance that drops out when the horizon moves forward in time. While they study specific horizons that are commonly reported by funds, I ask how long in the past do investors look when investing. Moreover, I study the buying and selling behavior separately and document an asymmetry in how long investors look back in their buying and selling decisions in funds.

The second line of literature my study contributes to is performance persistence. Prior studies on the persistence of past performance in mutual funds use a variety of horizons. Hendricks, Patel, and Zeckhauser (1993) found that past returns up to four quarters are useful in predicting quarter ahead returns. Elton, Gruber, and Blake (1996b) show that risk-adjusted past performance over 1-year and 3-years are useful in predicting alphas in the future up to 3 years. However, Carhart (1997) shows that most of the persistence in previous studies can be explained by expenses and the one-year momentum effect of Jegadeesh and Titman (1993). He shows that using past returns and risk-adjusted returns over longer horizons are not useful in identifying outperforming funds on a risk-adjusted basis. Bollen and Busse (2005) use daily returns data for a sample of 230 funds and find that past performance beyond a quarter is not useful in predicting outperforming funds. I look at the persistence of funds based on their performance over very long horizons such as past 60 months. This is motivated by the use of such long horizon information in the inflow decisions of investors.

Finally, my study is also related to the literature on return seasonalities. Using stock returns, Jegadeesh (1990) and Heston and Sadka (2008) document return continuations over long horizons such as past 3 years to 20 years. In mutual funds, Brown et. al. (2017) study calendar seasonality in aggregate mutual fund returns. They document that mutual funds as a whole underperform the market only in the first month of a calendar quarter. In contrast, I study long horizon persistence in the cross-section of fund returns using the methodology of Jegadeesh (1990) and Heston and Sadka (2008). The seasonality in the cross-section of fund returns at quarterly lags that I document in this paper is not specific to the calendar month and has not been noticed in the literature before.

3. Data and Descriptive Statistics

3.1. Sample Selection

I use monthly returns data from survivorship bias free CRSP Mutual Fund database. The monthly version of this database starts in 1960 and provides net returns, total net assets, expense ratios, style categories, and other share class level characteristics. I use the CRSP comprehensive style code to filter out actively managed US domestic equity funds.[58] I use the CRSP Mutual Funds daily returns database which starts on 2-Sep-1998 to compute alphas and betas from various factor models. I use Morningstar Direct (MS Direct hereafter) to obtain monthly share-class level data on Morningstar rating, share-class type and fund level data on gross purchases and gross redemptions.[59] Mutual funds report monthly purchases and redemptions at the fund level in their semi-annual N-SAR filings for the six months covered by the filing and MS direct provides this data beginning 1999. I merge CRSP and MS Direct following the approach in Pastor, Stambaugh, Taylor (2015) along with some additional manual steps.

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[58] Specifically, I consider records with crsp_obj_cd values in (‘EDC’, ‘EDY’) and then exclude records with crsp_obj_cd values ‘EDYH’ and ‘EDYS’. To drop index funds, ETFs and target date funds, I use the CRSP index fund flag combined with a fund name search for the strings ‘index’, ‘s&p’, ‘idx’, ‘dfa’, ‘program’, ‘etf’, ‘exchange traded’, ‘exchange-traded’, ‘target’, ‘2005’, ‘2010’, ‘2015’, ‘2020’, ‘2025’, ‘2030’, ’2035’, ‘2040’, ‘2045’, ‘2050, ‘2055’.

[59] Morningstar Direct allows collecting data on both surviving and dead funds unlike Morningstar data on disks and the Internet. Therefore, my sample does not suffer from survivorship bias.

Since purchases and redemptions are the fund level, I conduct all my analyses at this level. I aggregate the share class level data from CRSP and Morningstar Direct to fund level using WFICN as the identifier which is obtained from the MFLINKS table. I compute the fund-level returns and expense related metrics as weighted average values of the constituent share classes, with the beginning-of-month TNA as the weight. I compute fund-level TNA as the sum of TNA across share classes, fund-level dividend distributions and capital gains distributions as sum of these values across share classes and fund-level age using the minimum offer date across all share classes and time periods. I consider a fund to be 'no-load' if data on both front-end, back-end loads exists and takes values of zero for all its share classes. I construct fund-level qualitative metrics such as style, management code, fiscal year etc. using the corresponding values from the share class with the largest TNA. Using the comprehensive style code from CRSP, I group funds into four different styles: growth, growth & income, mid-cap and small-cap.[60] I identify funds with 75% or more of their TNA held in share classes that are catered to Institutional investors and Retirement accounts and drop these from my study.[61] I drop records before the fund's first offer date to avoid incubation bias documented in Evans (2010). To avoid survivorship bias documented in Elton, Gruber, Blake (1996a), which is due to reporting conventions in smaller funds, I drop the fund-month observations with TNA less than $15 million.

3.2.Variable Construction

For each fund i in month t, I construct inflows, outflows, and net flows as percentage of TNA as:

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[60] Since micro-cap funds (EDCI) are small in number, I group them with small caps (EDCS). Similarly, I group income funds (EDYI) which are small in number with growth & income funds (EDYB). Mid-cap and growth funds are identified by the CRSP style codes EDCM and EDYG respectively.

[61] I classify share classes I, Y, X, K, Institutional share, Inst, Trust Class, Premier Class, Fiduciary Class, Consultant Class and their variants into institutional channel; share classes R, Investor R, Retirement, R-1, R-2, R-3, R-4, R-5 and their variants into retirement channel.

$$\text{Inflow}_{i,t} = \frac{\text{Purchases}_{i,t} * 100}{\text{TNA}_{i,t\text{-}1}},$$

$$\text{Outflow}_{i,t} = \frac{\text{Redemptions}_{i,t} * 100}{\text{TNA}_{i,t\text{-}1}}, \quad (3.1)$$

$$\text{Net Flow}_{i,t} = \frac{(\text{Purchases}_{i,t}\text{-Redemptions}_{i,t}) * 100}{\text{TNA}_{i,t\text{-}1}}.$$

Since the dollar values of purchases and redemptions would vary to a great extent depending on the size of the fund, scaling by fund size allows easy comparison of the flow metrics across funds. And, to reduce the effect of extreme outliers in the above metrics (due to data coding errors in purchases and redemptions), I winsorize them at the 1% level.

I construct monthly family size as the sum of TNA of all funds within a family in that month after dropping the institutional and retirement funds. Similarly, the number of retail funds in a family each month gives the monthly number of funds in the family. And, I sum the purchases and redemptions across all funds in a family each month and subtract the contribution of the fund itself to get the numerator of family level flow metrics. Dividing these by lagged family TNA gives the family level inflow, outflow, and net flow. To construct style category level flow metrics, I use the sum of purchases, redemptions, and lagged TNA across all funds in a style category each month.

I construct various factor-based performance metrics each month using rolling window time series regressions using data on daily returns. For each fund-month with at least 24 daily return observations on past returns in the prior 3 months, I run time-series OLS regressions of funds' excess net returns on daily common factor returns in equities.[62] I use the betas from each factor model to construct monthly abnormal performance metrics for each fund as the difference between

[62] Data on common factor returns is from Prof. Kenneth French's website. I thank him for making this data easily accessible.

the realized net returns and the predicted return using the factor benchmarks. Finally, I begin my sample in 1999 because purchases and redemptions data in MS Direct and the family identifier in CRSP start in this year.

3.3. Descriptive Statistics

The final sample of actively managed US domestic equity funds used in this study spans the period between Jan-1999 to Dec-2017. After dropping fund-month observations in institutional and retirement categories and the observations with missing purchases and redemptions data, the sample contains 1,955 funds. There are 920, 379, 288 and 438 funds in the style groups growth, growth & income, mid-cap, and small-cap respectively.[63]

Table 27 shows the summary statistics for my final sample with data on purchases and redemptions. The average fund has $1.4 billion in assets and is 13 years old. Fund size is extremely skewed to the right as seen from the difference in mean and median values. Data on loads is missing for many records. Among the funds with available data on loads, a high proportion are classified as load funds, i.e. they have at least one share class with either a front-end load or a back-end load. In unreported analysis, I find that there are 1,147 funds with load and 554 without load in this sample. The average number of share classes per fund is 3 which is consistent with the fact that a lot of funds shifted to a multi-class structure during the 1990s. The average fund in my sample trades 82% of its portfolio over a year as seen from the turnover ratio statistic. In terms of performance after expenses, the average fund in this sample returns the same as the CRSP VW market index with a market excess return of 0.02% per month. After adjusting for exposures to the common factors in the 4-factor model using daily returns, the average 4-factor net alpha per month

[63] The number of funds across style categories do not sum up to the total of 1,955 because some funds switch styles over their life and are counted in all categories they belong to over their life.

is close to zero. All the statistics in my sample correspond well with the statistics in samples of actively managed US domestic equity funds from other studies.

The last three rows of Table 27 report the sample averages of the flow proxies. There is a positive net flow per month on average across all funds. Purchases and redemptions as percentages of TNA (i.e. inflows and outflows) average to 3.13% and 2.90% respectively, while net flow as percentage of TNA averages to 0.20%. The contrast in the magnitudes of net flow vis-à-vis disaggregated inflows, outflows indicates that buying and selling activities are substantially correlated within and across funds in this sample each month. O'Neal (2004) studies inflows, outflows separately and reports similar patterns.

4. Empirical Results

4.1.Flow-performance at long horizons

I first study the revealed preferences of investors in terms of their usage of performance information over long horizons for current investment decisions. I use monthly inflows, outflows, and net flows as the proxies for flow and estimate the following specification with 72 lags of performance.

$$Flow_{i,t} = a + \sum_{k=1}^{72} b_k \hat{\alpha}_{i,t-k} + \boldsymbol{b}.\boldsymbol{X} + \psi_{i,t}. \qquad (3.2)$$

I consider three different metrics of performance $\hat{\alpha}_{i,t}$: market-adjusted return, 1-factor alpha, and 4-factor alpha. I estimate equation (3.2) using Fama-MacBeth approach to adjust for cross-sectional correlation in flows due to correlated demand or supply shocks across funds.[64] In

[64] Using Fama-MacBeth approach yields unbiased coefficient estimates when the unobserved true skill of each manager is constant over time. But if the skill is time-varying, then my estimation still yields unbiased estimates if the unconditional average skill across time of each manager is same in the cross-section. In other words, if skill follows

addition, I use Newey-West correction in standard errors to adjust for autocorrelation in the error term up to 12 lags.

In the set of control variables $\boldsymbol{X}$, I include expense ratio, 12b-1 fees along with a host of other fund characteristics that influence flows. I add the log of fund size to control for non-linear effects of size on flows since bigger funds might grow (in terms of new money) at a different rate than smaller ones. I also control for fund's age and total risk measured by the standard deviation of returns over past 12 months which impact flows as shown in prior literature. To allow for the possibility that fund flows can depend on much longer horizons of performance than captured by the alpha, I use lagged flows from previous month as a control. This variable also captures the persistence of flows for reasons orthogonal to performance such as systematic investment plans. I also include contemporaneous flows into funds of the same objective code to account for style-specific demand shocks. Nanda, Wang, and Zheng (2004) document positive spillover of flows to funds belonging to a family which has a star fund. To control for such spillovers, I use contemporary flows to the family (after excluding the contribution of the fund itself) as an explanatory variable. I include lagged turnover to control for the effect of capital gains distributions on flow. When analyzing purchases and redemptions separately, I use a slightly different set of control variables. In tests involving purchases (redemptions), I use contemporary redemptions (purchases) as a control variable since purchases and redemptions are contemporarily correlated as shown in O'Neil (2004). I also include category level purchases and redemptions, family level purchases and redemptions as controls in this specification.

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an AR(1) process as $\alpha_t = A + \rho\alpha_{t-1} + \epsilon_t$, I assume that A is same across all funds. In this case, the cross-sectional variation in skill is purely due to the shocks ϵ_t.

Table 28 presents the results from estimating (3.2) using market adjusted returns and four-factor alpha. Figures 7A, 7B, 7C and 8A, 8B, 8C depict these results visually by plotting the coefficients on all lags for all three metrics of performance: market-adjusted return, 1-factor alpha, and 4-factor alpha. Across specifications, the results for all flow proxies reveal a long-horizon dependence on past performance. Inflows are significantly positively correlated with past returns for up to 60 months with the magnitude diminishing gradually with lags. The result for outflows shows that past performance up to lags 37 are consistently negative and significant. Thereafter, some additional lags are sporadically significant. These results highlight that investors consider performance over long horizons when making their investment decisions. The weights on past performance decrease with lags with the most recent performance receiving the highest weight. In addition, the extent of look-back is different for buys vs. sells.

4.2.Lag length selection for inflows and outflows

I now statistically examine the asymmetry in the horizon-dependence of performance between buys and sells. Table 29 reports results from an F-test that some lags towards the tail in the estimation of equation (3.2) are jointly zero. Specifically, the results for outflows indicate that lags beyond 38 till 72 are individually indistinguishable from zero. Therefore, I conduct an F-test for whether these lags have significance jointly for the model in equation (3.2). Results in columns (1) and (3) of Table 29 indicate that one cannot reject the null that lags 38-72 are jointly zero. However, the same does not hold for lags 37 to 72. I repeat this analysis for inflows to understand if 37 lags are sufficient to explain the buying behavior. Results in columns (2) and (4) indicate that lags 38 to 72 are jointly significant and are important in explaining inflows. Depending on the performance metric used, lags above 53 or 59 seem to not matter much statistically. Therefore, inflows into a fund have longer lookback on past performance compared to outflows. These results establish that horizon of performance information matters to different extents for buying and selling behavior.

4.3.Performance persistence at long horizons

Based on the results above, I next ask if the long look-back by investors in their flow decisions is optimal. Particularly, if there is valuable information in such long horizon metrics, then this should help in predicting the out of sample relative performance of funds. For example, using such long horizons can increase the precision of the skill estimates. To test this hypothesis, I estimate cross-sectional regressions of monthly four-factor alpha on past performance metrics with different number of lags. I consider net returns and four-factor alphas to measure the past performance. I use a maximum of 60 lags based on the lag length selection in flow-performance tests in the previous section. The specification I estimate using the Fama-MacBeth approach is the following.

$$\hat{\alpha}_{i,t}^{FFC4} = c + \sum_{k=1}^{60} d_k \hat{\alpha}_{i,t-k} + \delta_{i,t}. \quad (3.3)$$

If there is information in higher lags to predict current outperforming funds, then the coefficients d_k should load positively on all the lags in a consistent manner. This is similar to the evidence of return continuations at longer horizons documented by Jegadeesh (1990). I conduct these analyses using both multivariate models as in Jegadeesh (1990) as well as univariate specification considered in Heston and Sadka (2008). I constrain the sample size to be similar for specifications with different lags in order to not induce a systematic bias related to fund age and persistence. For instance, Huij and Verbeek (2007) show that younger funds have stronger persistence patterns compared to older funds. By considering a sample of funds that has information on all 60 lags on monthly net returns, I can compare the performance of different specifications on equal grounds.

I compute monthly four-factor alpha used as the dependent variable in equation (3.3) using beta estimates from a non-overlapping window compared to the beta estimates used in computing monthly alphas that are used as explanatory variables. This is to mitigate the concern that correlation in measurement error in beta estimates impacts the coefficients d_k in equation (3.3). Specifically, I compute forward-looking betas each month using rolling window time series regressions of fund's daily excess net returns on the returns of Fama-French-Carhart four factors. I retain the estimates for fund-months with at least 24 observations on future daily net returns in a 3-month window beginning from the current month. If a fund dies in this window, I replace its return with CRSP VW market return for the remaining period. Using these beta estimates, I compute the monthly four-factor alpha used as the dependent variable as the fund's net return minus expected return from Fama-French-Carhart four factor model.

Table 30 reports the results of these tests and Figures 9A, 9B, 10A, 10B depict the coefficients on different lags of performance from these regressions graphically. The adjusted R^2 values in the last row of Table 30 range from 9.2% to 27.3% depending on the number of lags used. As a comparison, adjusted R^2 from similar regressions for stocks reported in Jegadeesh (1990) range from 8.7% to 17.8%. While the high R^2 values in these cross-sectional regressions in stocks could be due to the momentum effect, the high R^2 values in funds could be due to loading on the momentum factor in the funds' portfolios. Going from columns (1) to (5) in Table 30, adding more lags leads to an increase in the adjusted R^2 as seen in the last row of the table. Although some of the coefficients on higher lags are negative, only a few of these negative coefficients are statistically different from zero. Moreover, the coefficients on the quarterly lags show an interesting pattern. Beyond the first three months, most of the additional lags are significant only at the quarterly intervals. The magnitudes of the coefficients also spike up at the quarterly lags.

This pattern is clearly apparent from Figures 9A and 9B with both performance metrics. The pattern with seasonal spikes in equation (3.3) is different from the pattern of flow-performance in equation (3.2) with declining weights. Therefore, the relation in equation (3.2) is not driven by horizon dependence in alphas with declining weights.

Column (8) of Table 30 also shows the results with each past lag added individually in univariate regressions. The coefficients are plotted in Figures 10A and 10B. In comparison to the multivariate results, most of the coefficients on past return metrics in the univariate specification are not significant predictors of one-month ahead alpha. However, the seasonal patterns in the loadings on quarterly lags are still evident from the univariate specification, albeit with a lesser magnitude. The difference in coefficient patterns across multivariate and univariate specifications highlights the conditional nature of the seasonal patterns. For example, performance 36 months ago matters conditional on the performance in the surrounding months. Phillips, Pukthuanthong, and Rau (2016) argue that advertising fund performance over long horizon windows leads investors to chase funds that get rid of a bad month as the window moves ahead. The pattern I document indicates that similar argument could also be behind the link between higher performance in current month and past quarterly lags at long horizons. Specifically, this could be driven by incentives of managers related to advertising the performance over long horizons.

Most studies on seasonality in stock returns show that the patterns in January are different compared to other calendar months. And studies on mutual funds highlight the importance of calendar-quarter-ends due to funds' quarterly mandatory filing requirements.[65] To understand if

[65] Two such practices widely documented in the literature are portfolio pumping (a.k.a. NAV inflation) and window dressing. Portfolio pumping is the practice of inflating the prices of stocks present in a manager's current portfolio to boost the fund's performance at quarter-end. Window dressing involves buying winner stocks and dumping loser stocks near the end of a quarter to improve the appearance of the portfolio to be disclosed to investors. See Agarwal,

the quarterly seasonal patterns from Table 30 are concentrated only in some calendar months, I estimate equation (3.3) in sub-samples based on calendar months and Table 31 shows these results. Column (1) shows that thee results for only January months are distinct from the patterns for rest of the months. Specifically, the quarterly seasonality is not evident in January months. The results in other columns of Table 31 indicate that quarterly patterns are present but are not that strong in months which form the ends of calendar quarters. It is the other months where the results are heavily concentrated.

4.4.Economic Significance of Long-horizon Predictability

The results from previous section indicate that the model with 60 lags of past performance has the highest adjusted R^2 in sample when predicting four-factor alpha next month. To assess whether the increased fit leads to economically large improvements from an investment perspective, I next study the performance of portfolios formed based on different predictive signals. Using the estimated coefficients from the 60-lag model of equation (3.3), I compute the predicted value of monthly four-factor alpha and use this to form ten portfolios. By repeating this procedure every month, I construct a time-series of value-weighted net returns across funds for each portfolio. By regressing the return series of each portfolio on the Fama-French-Carhart four factors over the entire sample period, I estimate the abnormal return from holding a particularly monthly-rebalanced portfolio. I compare the abnormal performance from using 60-lag model with that of using one-month net return from the previous month. Comparing performance across the two models informs if the use of long-horizon information is optimal as compared to an easier-to-use information set.

Gay, and Ling (2015) and Brown et. al. (2017) for a discussion of literature that studies these issues and their consequences.

Tables 32 and 33 show the results from this exercise. Column (1) of these tables shows the time-series average of monthly value-weighted net returns of each portfolio. Using the predicted value from 60-lag model, the best performing funds which are part of Decile 10 have an average net return of 0.898%. The same number from Table 33 for Decile 10 portfolio based on one-month net return as the signal is 0.885%. On a net-return basis, the long horizon model outperforms the one-month net return signal. However, higher net returns could be driven by passive exposures to factors rather than active skill. Columns (2) to (6) of each table report the four-factor alpha of each decile portfolio and the factor exposures.

The factor loadings for each of the decile portfolio returns in Table 32 indicate that higher net returns in column (1) are driven to a large extent by passive exposure to factors. The four-factor alphas in column (2) are all negative except for Decile 10. Comparing this with columns (2) to (6) of Table 33 leads to a different inference on the relative performance of the two signals. Even with net returns as the signal for portfolio formation, most of the portfolios have negative four-factor alphas. However, the Decile 10 portfolio has a bigger magnitude of four-factor alpha compared to Table 32. Performance comparison using four-factor alphas, therefore, leads to the inference that net returns as the signal is better compared to the 60-lag model. The bottom three rows of Tables 32 and 33 show the performance of spread portfolios from taking a long position in the best performing funds and short position in the bottom most set of funds.[66] The performance of spread portfolios also indicates that one-month net return has better performance both in terms of average net returns and the four-factor alpha.

[66] Mutual funds cannot be shorted like stocks. Therefore, returns on the spread portfolios cannot be directly realized by the investors. However, short position in the worst performing funds can be interpreted as the gains from avoiding investing in such funds which could have led to the non-existence of such funds in the market. It could be interpreted as reversing the opportunity cost for investors in these funds of forgoing investment in the best performing funds.

5. Conclusion

In this paper, I study the revealed preferences of investors in equity mutual funds to identify the performance horizon that matters for investors' current buying and selling decisions separately. Models of investor flows in funds do not have an explicit prediction for the how long do investors look back to extract skill from the performance information. If investors are continuously attentive to their portfolios and use the performance information each period in their flows, then only the most recent performance information should matter when the unobserved skill of the managers is constant over time. Alternatively, fund flows can depend on past performance over longer horizons under a variety of conditions such as: 1) skill is time-varying and investors act with this belief, 2) majority of fund investors add the fund to their attention set only recently, 3) current investors are slow to update or are inattentive to performance, 4) attention-constrained investors are swayed by the long-horizon information salient in fund advertisements. If any of these explanations is true, then flows would be sensitive to past performance over longer horizons.

My empirical analysis confirms the findings of some recent studies that net flows in a fund are sensitive to long horizons of past performance. However, I study buying and selling decisions separately and find that there is an asymmetry in horizon-dependence. Current buying decisions of investors are sensitive to over 52 months of past performance while current selling decisions are sensitive to around 37 months of past performance. I conduct additional analysis to test if this longer horizon performance leads to better predictability in identifying funds with higher out of sample performance. Cross-sectional predictability regressions indicate that model with 60 lags of past performance has the highest adjusted R^2 in predicting one-month ahead four-factor alpha. However, analysis using the performance of portfolios formed using predicted values from the 60-lag model indicates that a simple metric such as prior one-month net returns has better ability to identify outperforming funds. This indicates that investors' dependence on long-horizon performance is sub-optimal.

Figures

Figure 1: Average net flows by calendar month

This figure plots the average value of net flows across funds and years for each calendar month. Net flows at time *t* are computed as $(purchases_t - redemptions_t)*100/TNA_{t-1}$ for each fund and then winsorized at the 1% level to remove the effect of outliers. The sample period is Jan-1994 to Dec-2017.

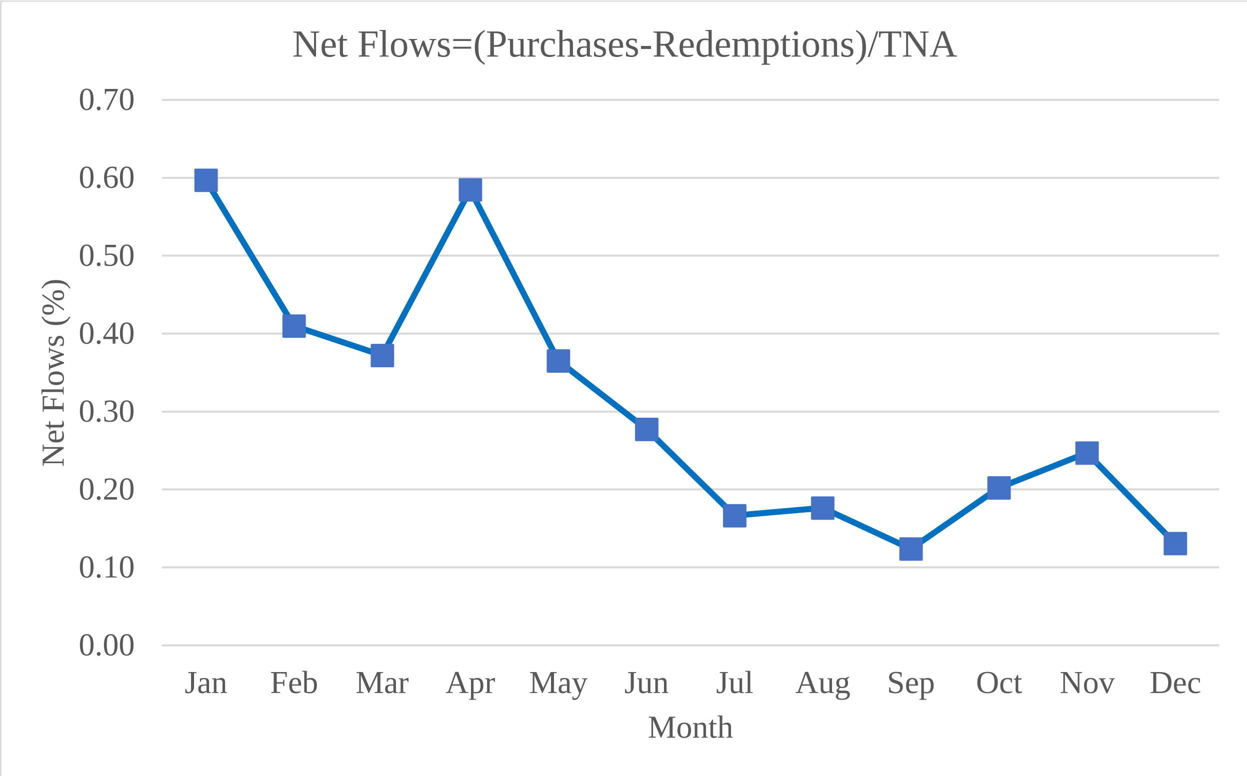


Figure 2: Average outflows by calendar month

This figure plots the average value of outflows across funds and years for each calendar month. Outflows at time *t* are computed as $redemptions_t$*100/TNA_{t-1} for each fund and then winsorized at the 1% level to remove the effect of outliers. The sample period is Jan-1994 to Dec-2017.

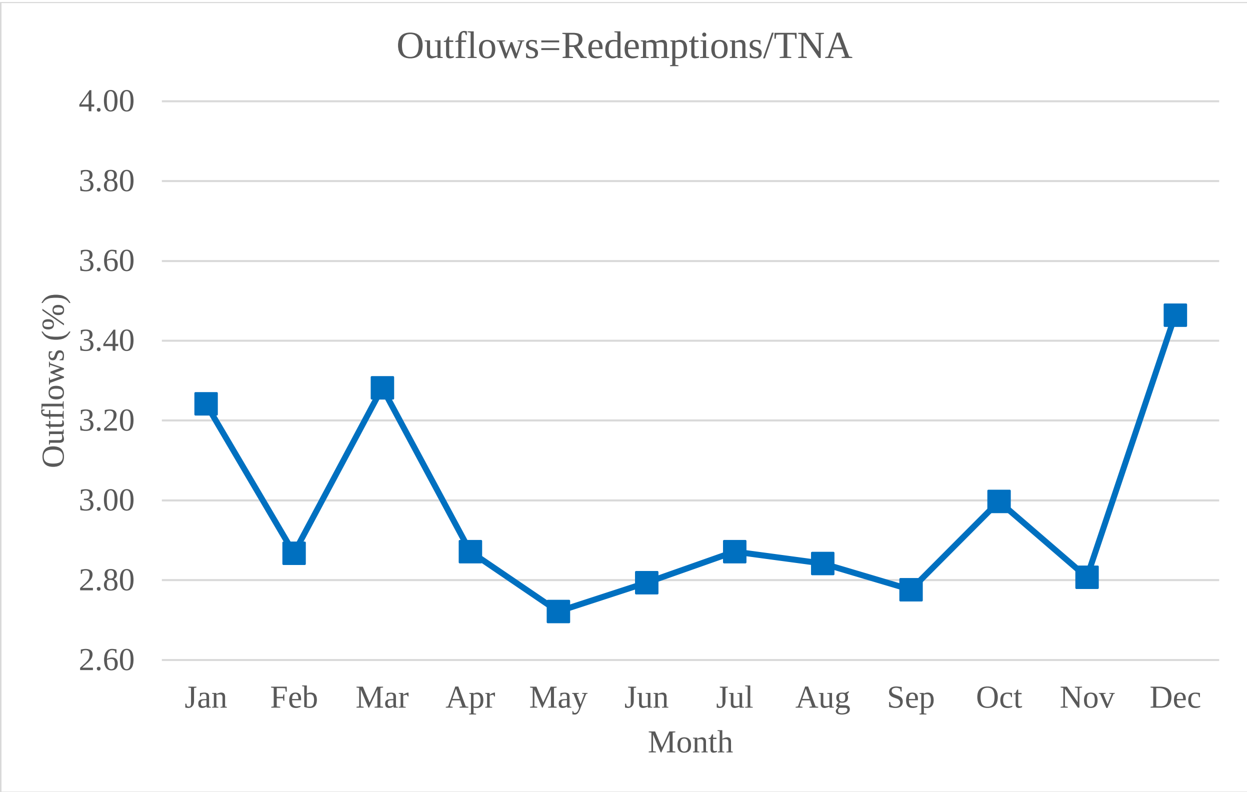


Figure 3: Average inflows by calendar month

This figure plots the average value of inflows across funds and years for each calendar month. Inflows at time *t* are computed as $purchases_t*100/TNA_{t-1}$ for each fund and then winsorized at the 1% level to remove the effect of outliers. The sample period is Jan-1994 to Dec-2017.

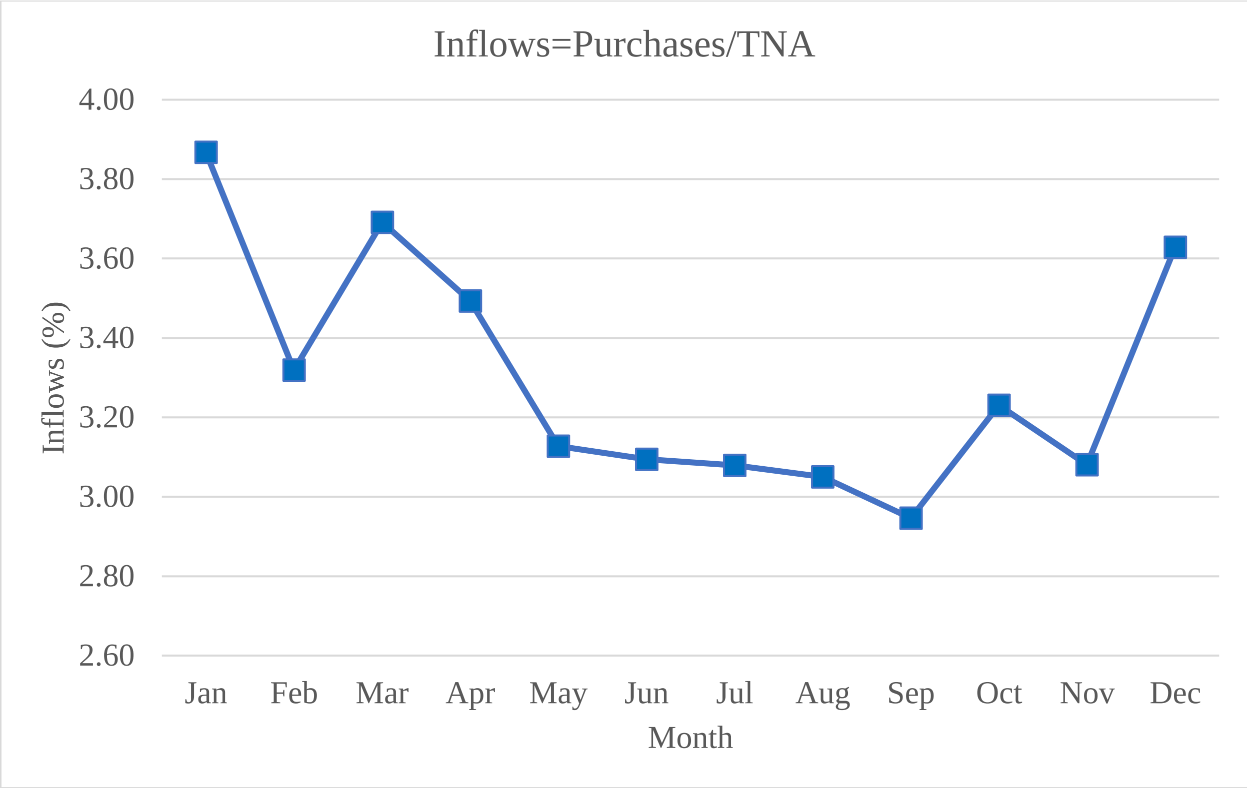


Figure 4: Average inflows & outflows by calendar month and distribution channel

This figure plots the average value of inflows and outflows across funds and years for each calendar month and distribution channel. Panels A and B plot the pattern for inflows and outflows which are computed as $purchases_t*100/TNA_{t-1}$ and $redemptions_t*100/TNA_{t-1}$ respectively for each fund at time *t* and then winsorized at the 1% level to remove the effect of outliers. In each plot, the blue line with square dots represents the pattern for broker-sold funds and red-line with diamond dots represents the pattern for direct-sold funds. There are 936 and 796 funds in the broker-sold and direct-sold channels respectively. The sample period is Jan-1994 to Dec-2017.

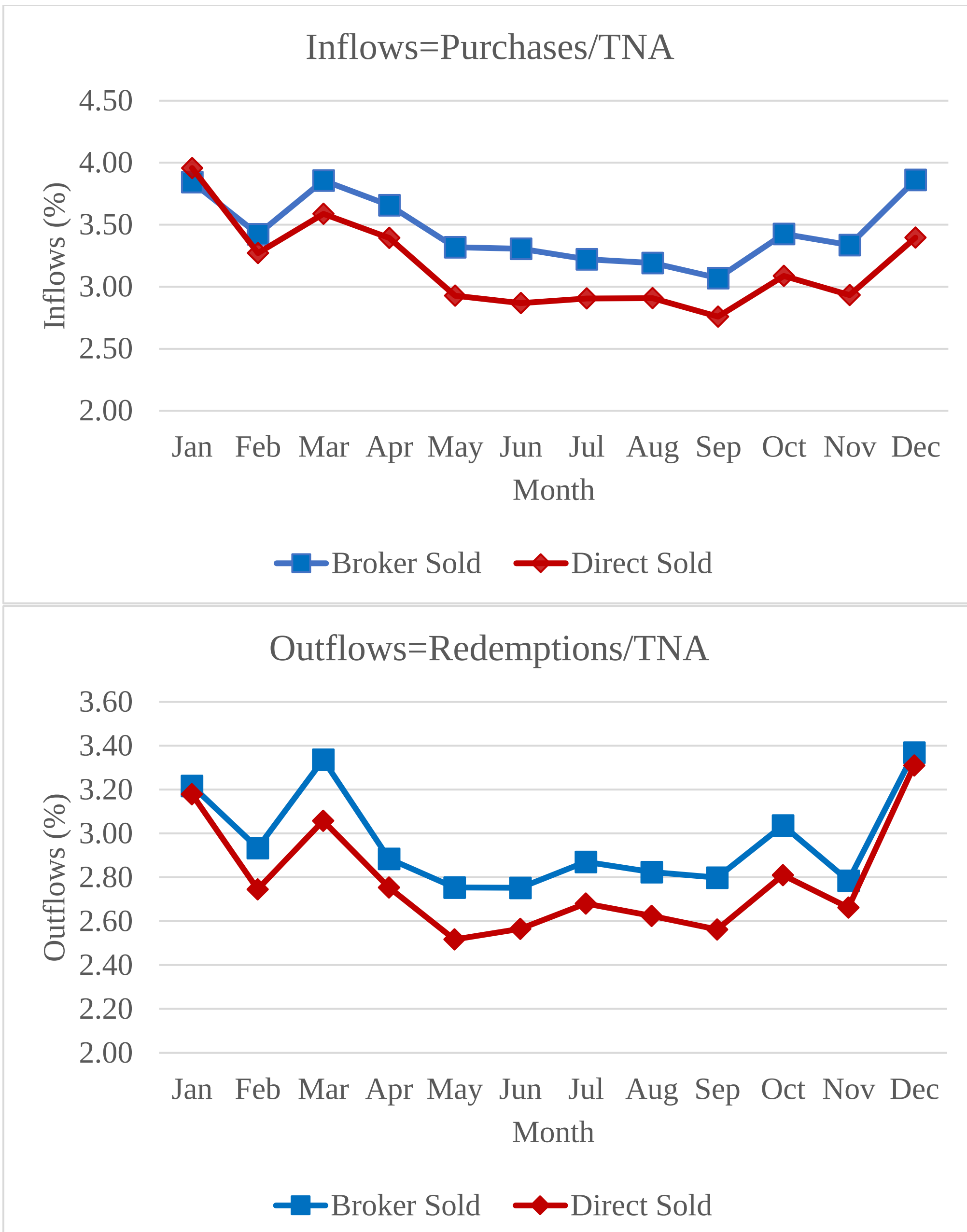
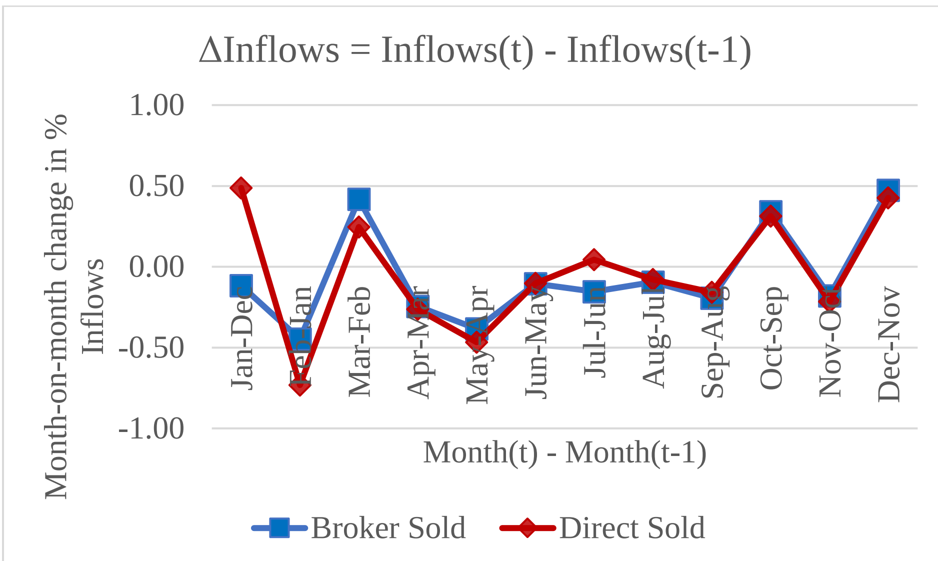


Figure 5: Month-on-month changes in flows by calendar month and distribution channel

This figure plots the average value of **month-on-month changes** in inflows and outflows across funds and years for each calendar month and distribution channel. Panels A and B show the plots for inflows and outflows separately. For each fund at time *t*, inflows and outflows are computed as $purchases_t*100/TNA_{t-1}$ and $redemptions_t*100/TNA_{t-1}$ respectively and then winsorized at the 1% level to remove the effect of outliers. The changes for each month are computed as the difference of a flow proxy for that month from the previous month, i.e. $\Delta Inflows_t=(Inflows_t - Inflows_{t-1})$ and are plotted on the Y-axis. The X-axis shows the two months for which the difference is calculated. In each plot, the blue line with square dots represents the pattern for broker-sold funds and red-line with diamond dots represents the pattern for direct-sold funds. There are 936 and 796 funds in the broker-sold and direct-sold channels respectively. The sample period is Jan-1994 to Dec-2017.



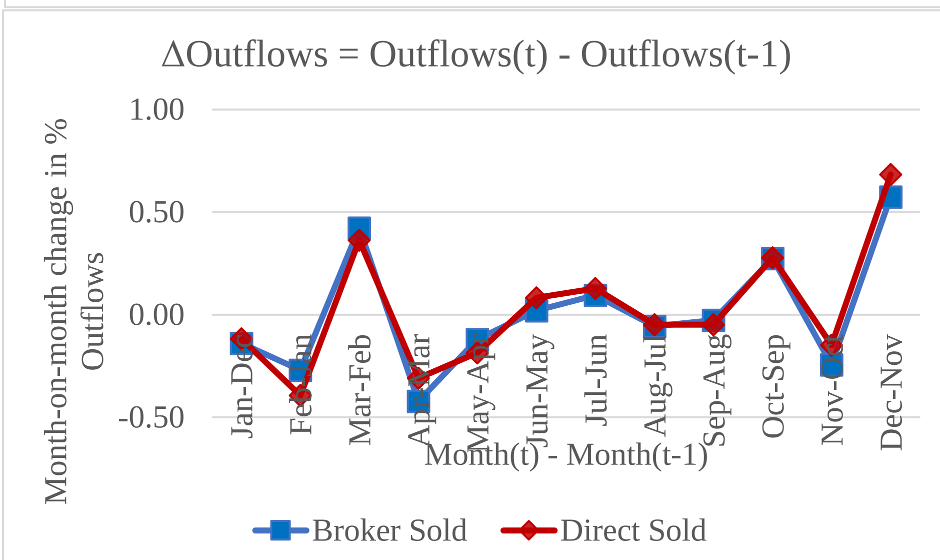


Figure 6: Turn of the year seasonality using Net flows from CRSP MF database

This figure replicates the results in Figures 1 to 5 above using net flows computed from monthly fund size and returns from the CRSP mutual funds database. Net flows at time *t* are computed as $(TNA_t - TNA_{t-1}(1+r_t))*100/TNA_{t-1}$ for each fund and then winsorized at the 1% level to remove the effect of outliers. The sample contains 2541 funds including those from CRSP MF database that do not have a mapping with Morningstar and N-SAR files. Of these, 1174 funds are in the broker-sold channel and 1053 funds are in the direct-sold channel. The left panel in the top row presents average net flows by calendar month and the right panel of the top row presents the calendar seasonal patterns by distribution channel. The bottom panel shows month-on-month changes in net flows which are computed as ΔNet $flows_t$=(Net $flows_t$ – Net $flows_{t-1}$). The X-axis in this panel indicates the two months over which the difference is calculated. The sample period is Jan-1994 to Dec-2017.

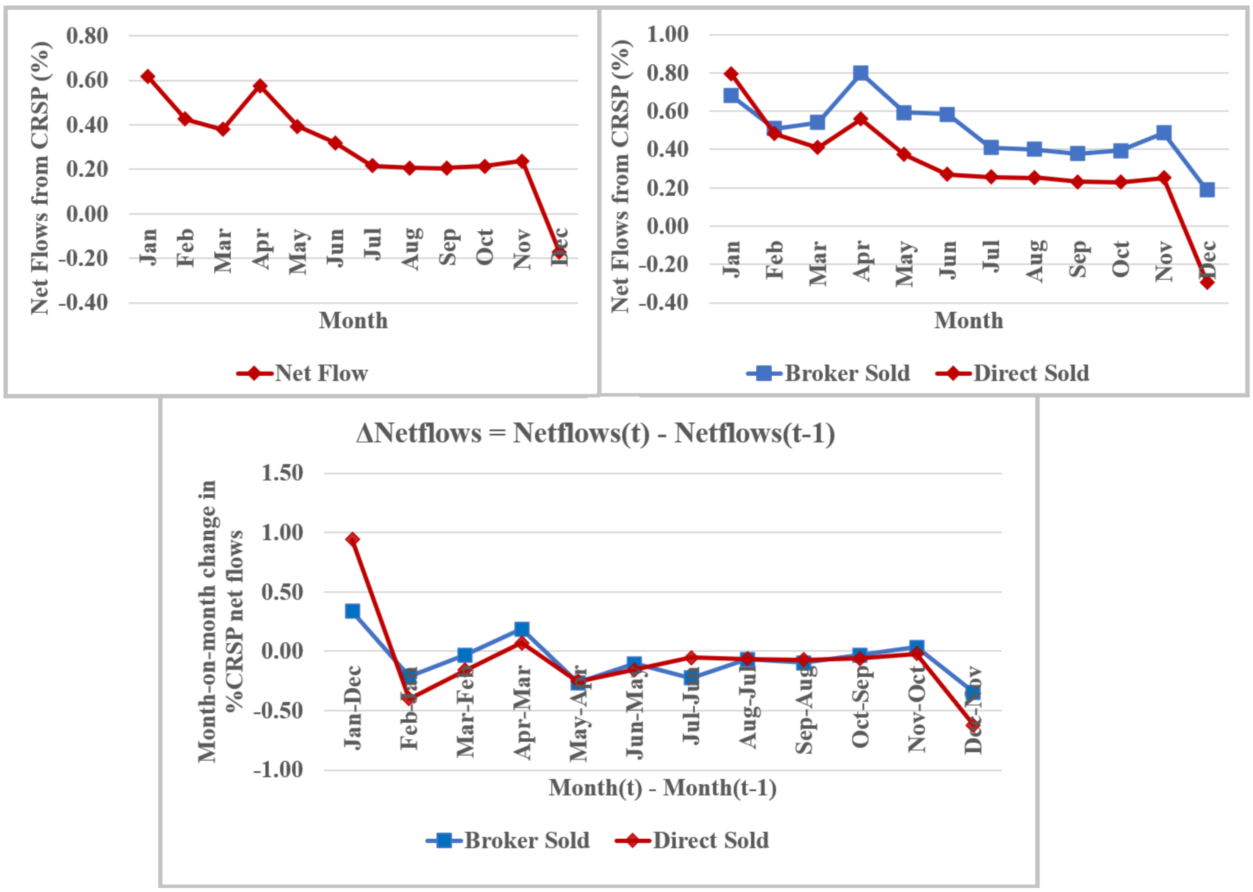
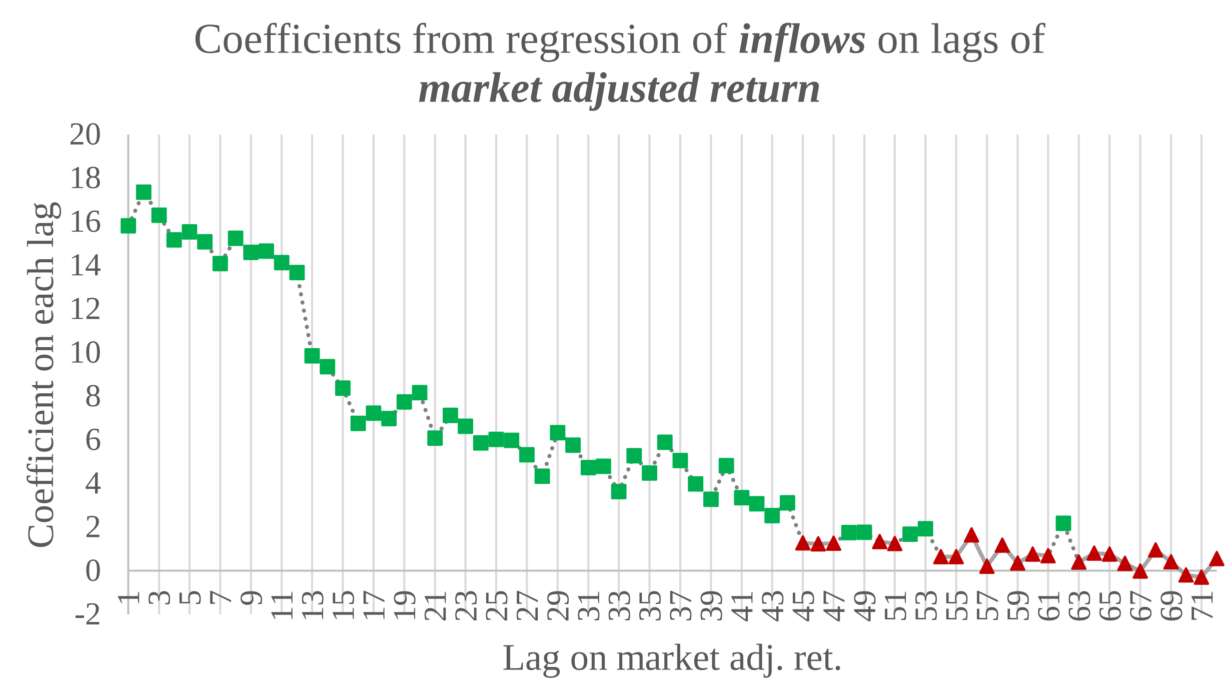


Figure 7A: Long horizon regression coefficients of inflow-performance relation

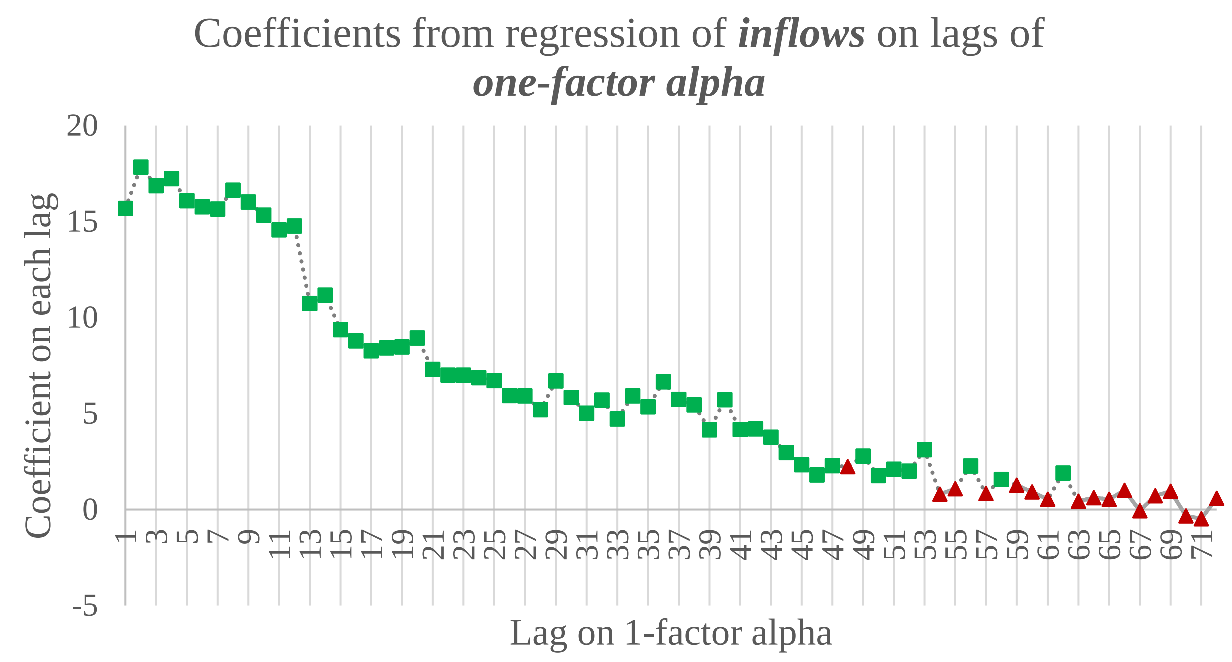
The figure plots the coefficients from Fama-MacBeth regressions of **inflows** on 72 lags of monthly **market adjusted net returns** along with a set of controls. Inflows are defined as purchases*100/TNA_{t-1} and market adjusted return is the fund's net return minus CRSP VW market index. The sample comprises actively managed US domestic equity funds during the period Jan-1999 to Dec-2017 excluding Institutional and Retirement funds. Standard errors are adjusted for autocorrelation up to 12 lags using Newey-West procedure. Coefficients denoted using green squares on the plot are statistically significant at the 10% level or better and coefficients denoted using red triangles are statistically indistinguishable from zero.



Green squares indicate coefficients that are statistically significant at 10% level or better.
Red triangles indicate coefficients that are statistically indistinguishable from zero.

Figure 7B: Long horizon regression coefficients of inflow-performance relation

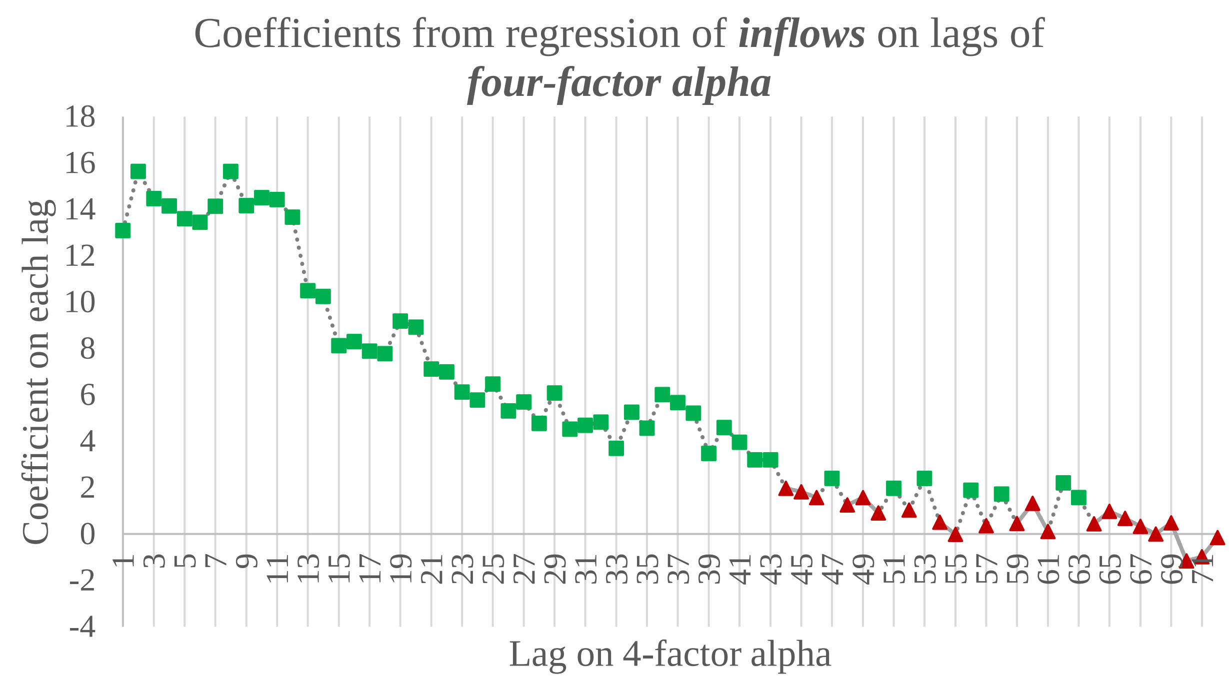
The figure plots the coefficients from Fama-MacBeth regressions of **inflows** on 72 lags of monthly **one-factor alpha** along with a set of controls. Inflows are defined as purchases*100/TNA_{t-1}. Monthly one-factor alpha is computed as the fund's net return minus expected return from CAPM with betas computed using rolling window time series regressions of fund's daily excess net returns on market excess return. These are computed for fund-months with at least 24 observations on past daily net returns in a 3-month window ending prior month. The sample comprises actively managed US domestic equity funds during the period Jan-1999 to Dec-2017 excluding Institutional and Retirement funds. Standard errors are adjusted for autocorrelation up to 12 lags using Newey-West procedure. Coefficients denoted using green squares on the plot are statistically significant at the 10% level or better and coefficients denoted using red triangles are statistically indistinguishable from zero.



Green squares indicate coefficients that are statistically significant at 10% level or better.
Red triangles indicate coefficients that are statistically indistinguishable from zero.

Figure 7C: Long horizon regression coefficients of inflow-performance relation

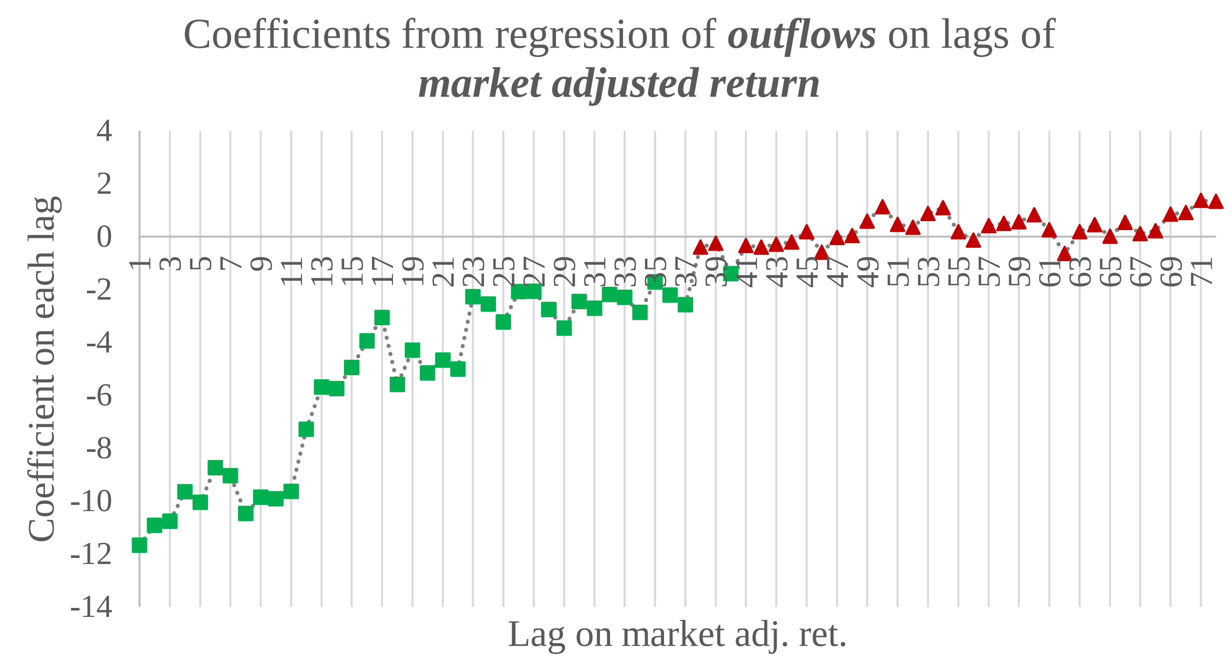
The figure plots the coefficients from Fama-MacBeth regressions of **inflows** on 72 lags of monthly **four-factor alpha** along with a set of controls. Inflows are defined as purchases*100/TNA_{t-1}. Monthly four-factor alpha is computed as the fund's net return minus expected return from Fama-French-Carhart four factor model with betas computed using rolling window time series regressions of fund's daily excess net returns on factor returns. These are computed for fund-months with at least 24 observations on past daily net returns in a 3-month window ending prior month. The sample comprises actively managed US domestic equity funds during the period Jan-1999 to Dec-2017 excluding Institutional and Retirement funds. Standard errors are adjusted for autocorrelation up to 12 lags using Newey-West procedure. Coefficients denoted using green squares on the plot are statistically significant at the 10% level or better and coefficients denoted using red triangles are statistically indistinguishable from zero.



Green squares indicate coefficients that are statistically significant at 10% level or better.
Red triangles indicate coefficients that are statistically indistinguishable from zero.

Figure 8A: Long horizon regression coefficients of outflow-performance relation

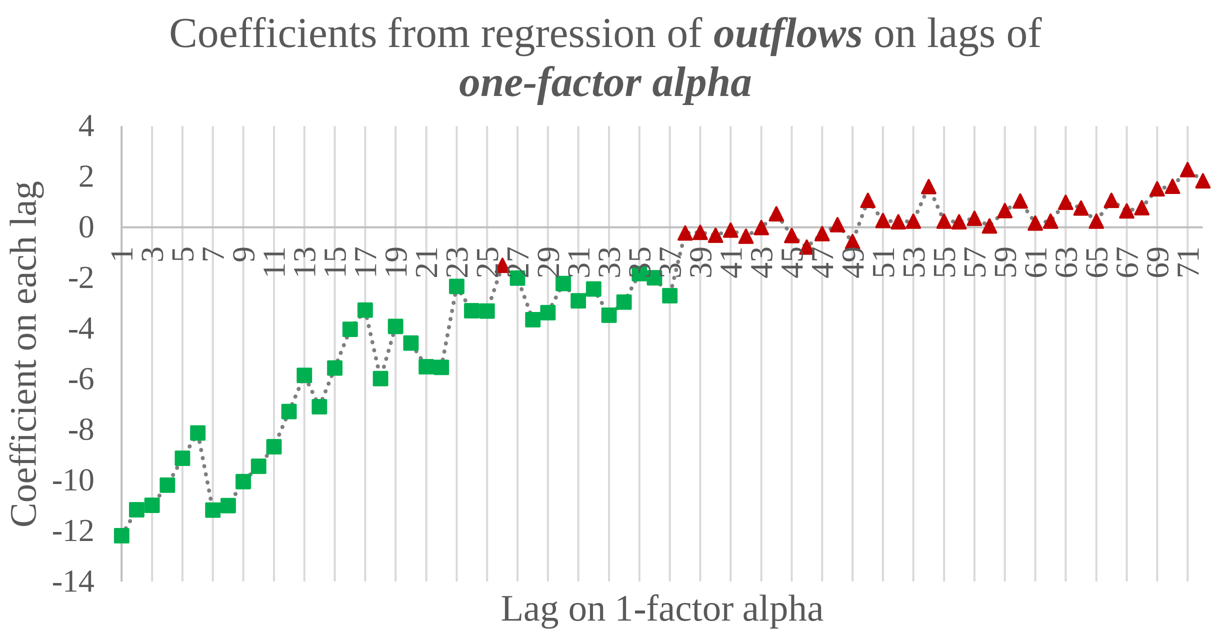
The figure plots the coefficients from Fama-MacBeth regressions of **outflows** on 72 lags of monthly **market adjusted net returns** along with a set of controls. Outflows are defined as redemptions*100/TNA_{t-1} and market adjusted return is the fund's net return minus CRSP VW market index. The sample comprises actively managed US domestic equity funds during the period Jan-1999 to Dec-2017 excluding Institutional and Retirement funds. Standard errors are adjusted for autocorrelation up to 12 lags using Newey-West procedure. Coefficients denoted using green squares on the plot are statistically significant at the 10% level or better and coefficients denoted using red triangles are statistically indistinguishable from zero.



Green squares indicate coefficients that are statistically significant at 10% level or better.
Red triangles indicate coefficients that are statistically indistinguishable from zero.

Figure 8B: Long horizon regression coefficients of outflow-performance relation

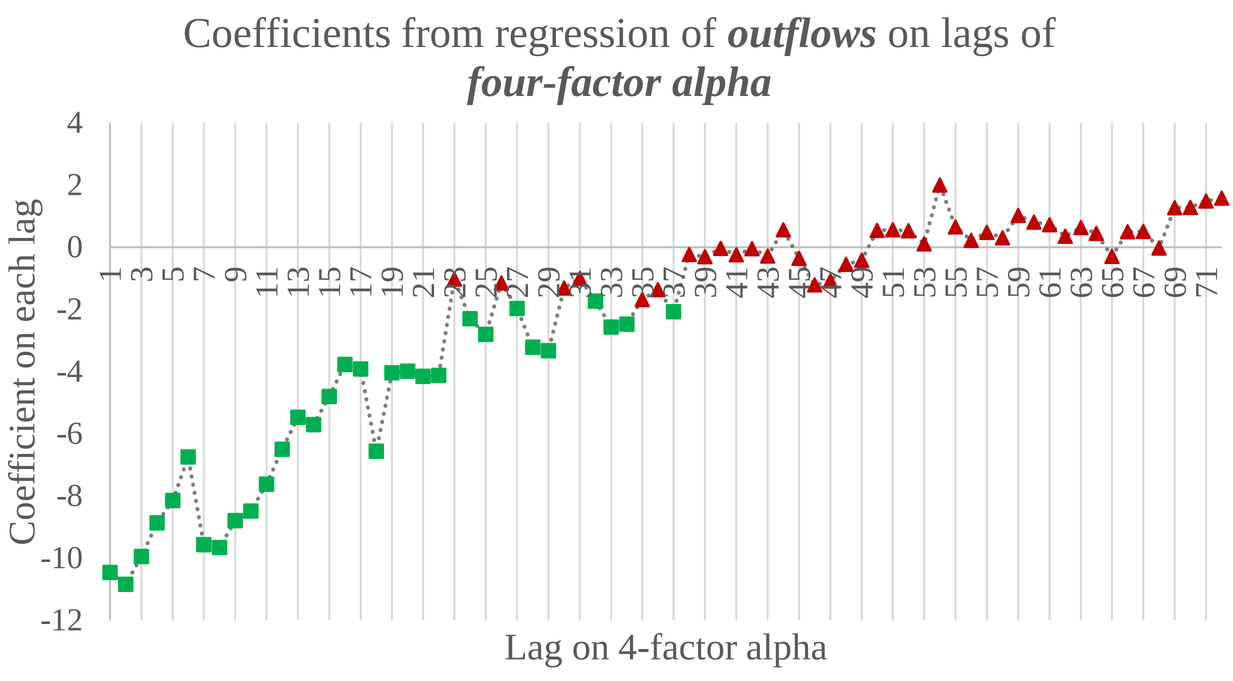
The figure plots the coefficients from Fama-MacBeth regressions of **outflows** on 72 lags of monthly **one-factor alpha** along with a set of controls. Outflows are defined as redemptions*100/TNA_{t-1}. Monthly one-factor alpha is computed as the fund's net return minus expected return from CAPM with betas computed using rolling window time series regressions of fund's daily excess net returns on market excess return. These are computed for fund-months with at least 24 observations on past daily net returns in a 3-month window ending prior month. The sample comprises actively managed US domestic equity funds during the period Jan-1999 to Dec-2017 excluding Institutional and Retirement funds. Standard errors are adjusted for autocorrelation up to 12 lags using Newey-West procedure. Coefficients denoted using green squares on the plot are statistically significant at the 10% level or better and coefficients denoted using red triangles are statistically indistinguishable from zero.



Green squares indicate coefficients that are statistically significant at 10% level or better.
Red triangles indicate coefficients that are statistically indistinguishable from zero.

Figure 8C: Long horizon regression coefficients of outflow-performance relation

The figure plots the coefficients from Fama-MacBeth regressions of **outflows** on 72 lags of monthly **four-factor alpha** along with a set of controls. Outflows are defined as redemptions*100/TNA_{t-1}. Monthly four-factor alpha is computed as the fund's net return minus expected return from Fama-French-Carhart four factor model with betas computed using rolling window time series regressions of fund's daily excess net returns on factor returns. These are computed for fund-months with at least 24 observations on past daily net returns in a 3-month window ending prior month. The sample comprises actively managed US domestic equity funds during the period Jan-1999 to Dec-2017 excluding Institutional and Retirement funds. Standard errors are adjusted for autocorrelation up to 12 lags using Newey-West procedure. Coefficients denoted using green squares on the plot are statistically significant at the 10% level or better and coefficients denoted using red triangles are statistically indistinguishable from zero.



Green squares indicate coefficients that are statistically significant at 10% level or better.
Red triangles indicate coefficients that are statistically indistinguishable from zero.

Figure 9A: Multivariate performance predictability regression coefficients

The figure plots the coefficients from Fama-MacBeth regressions of monthly four-factor alpha on 60 lags of monthly net returns. Monthly four-factor alpha used as the dependent variable is computed as the fund's net return minus expected return from Fama-French-Carhart four factor model with betas computed in a forward-looking window using rolling window time series regressions of fund's daily excess net returns on factor returns. These are computed for fund-months with at least 24 observations on future daily net returns in a 3-month window beginning from the current month. If a fund dies in this window, I replace its return with CRSP VW market return for the remaining period. The sample comprises actively managed US domestic equity funds during the period Jan-1999 to Dec-2017 excluding Institutional and Retirement funds. Coefficients denoted using green squares on the plot are statistically significant at the 10% level or better and coefficients denoted using red triangles are statistically indistinguishable from zero.

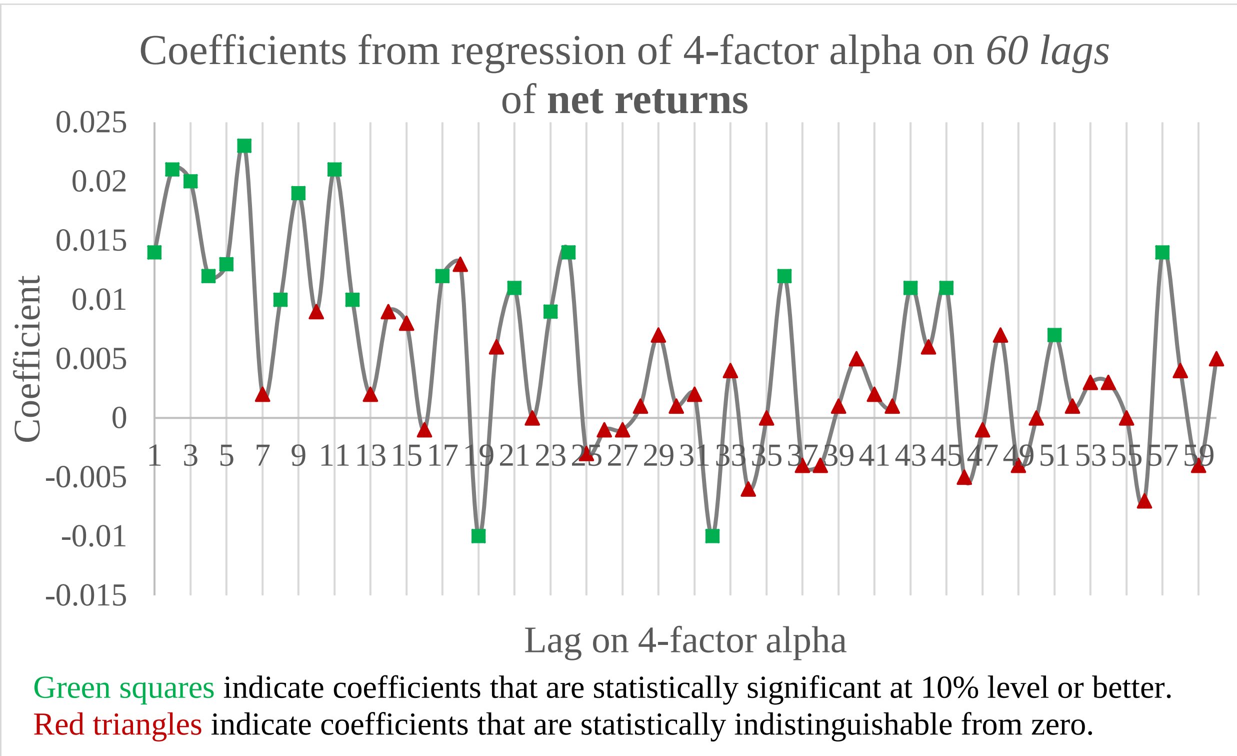


Figure 9B: Multivariate performance predictability regression coefficients

The figure plots the coefficients from Fama-MacBeth regressions of monthly four-factor alpha on 60 lags of monthly four-factor alpha. Monthly four-factor alpha used as the dependent variable is computed as the fund's net return minus expected return from Fama-French-Carhart four factor model with betas computed in a forward-looking window using rolling window time series regressions of fund's daily excess net returns on factor returns. These are computed for fund-months with at least 24 observations on future daily net returns in a 3-month window beginning from the current month. If a fund dies in this window, I replace its return with CRSP VW market return for the remaining period. Monthly four-factor alpha used as the explanatory variable is computed as the fund's net return minus expected return from Fama-French-Carhart four factor model with betas computed in backward-looking window using rolling window time series regressions of fund's daily excess net returns on factor returns. These are computed for fund-months with at least 24 observations on past daily net returns in a 3-month window ending prior month. The sample comprises actively managed US domestic equity funds during the period Jan-1999 to Dec-2017 excluding Institutional and Retirement funds. Coefficients denoted using green squares on the plot are statistically significant at the 10% level or better and coefficients denoted using red triangles are statistically indistinguishable from zero.

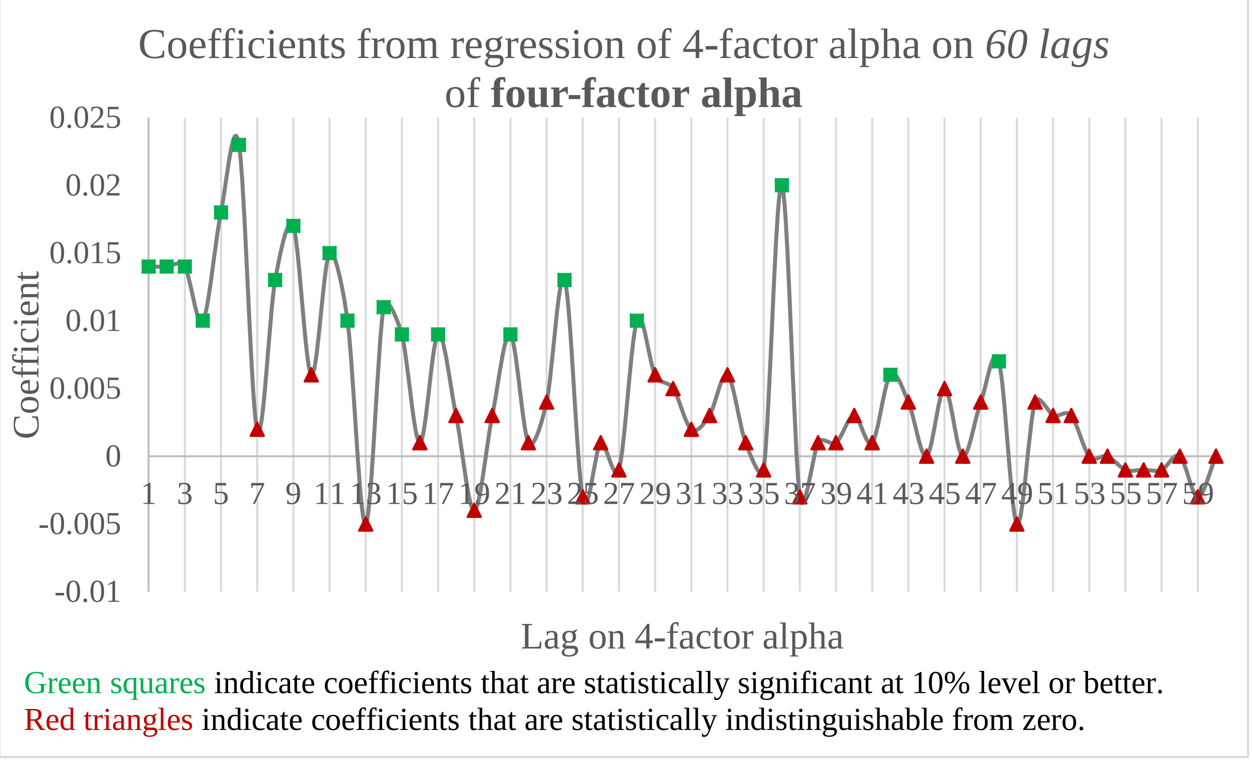
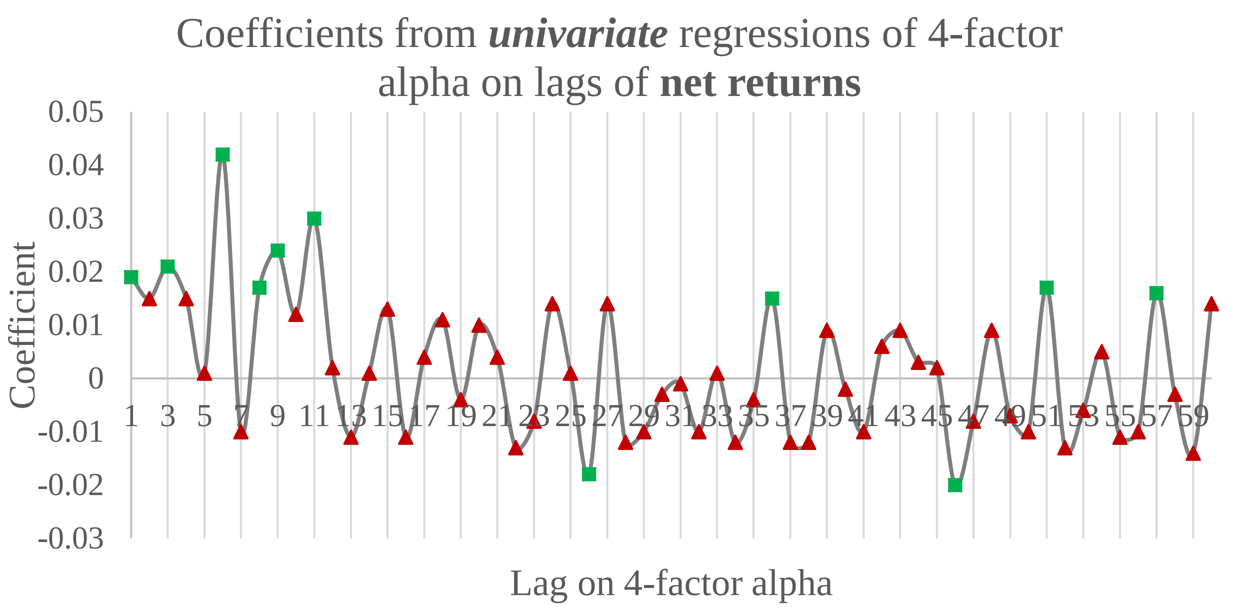


Figure 10A: Univariate performance predictability regression coefficients

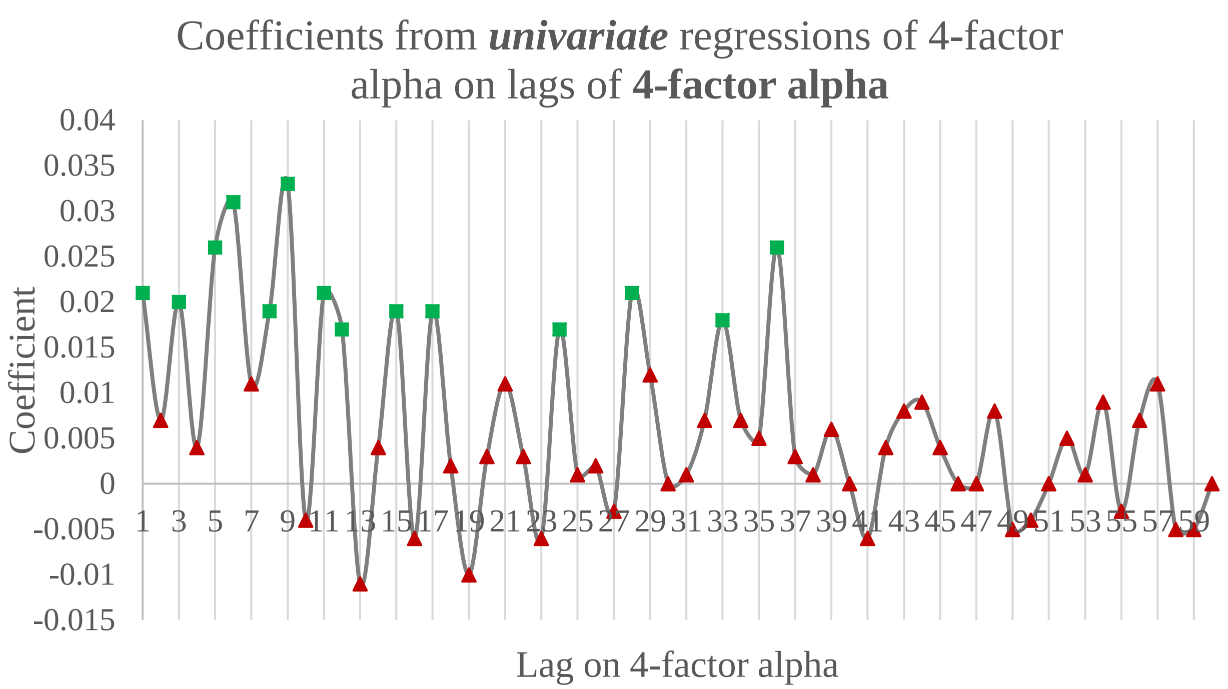
The figure plots the coefficients from separate Fama-MacBeth regressions of monthly four-factor alpha on each of the 60 lags of monthly net returns. The sample used in all regressions is uniform with data available on all the 60 lags. Monthly four-factor alpha used as the explanatory variable is computed as the fund's net return minus expected return from Fama-French-Carhart four factor model with betas computed in backward-looking window using rolling window time series regressions of fund's daily excess net returns on factor returns. These are computed for fund-months with at least 24 observations on past daily net returns in a 3-month window ending prior month. The sample comprises actively managed US domestic equity funds during the period Jan-1999 to Dec-2017 excluding Institutional and Retirement funds. Coefficients denoted using green squares on the plot are statistically significant at the 10% level or better and coefficients denoted using red triangles are statistically indistinguishable from zero.



Green squares indicate coefficients that are statistically significant at 10% level or better.
Red triangles indicate coefficients that are statistically indistinguishable from zero.

Figure 10B: Univariate performance predictability regression coefficients

The figure plots the coefficients from separate Fama-MacBeth regressions of monthly four-factor alpha on each of the 60 lags of monthly four-factor alpha. The sample used in all regressions is uniform with data available on all the 60 lags. Monthly four-factor alpha used as the dependent variable is computed as the fund's net return minus expected return from Fama-French-Carhart four factor model with betas computed in a forward-looking window using rolling window time series regressions of fund's daily excess net returns on factor returns. These are computed for fund-months with at least 24 observations on future daily net returns in a 3-month window beginning from the current month. If a fund dies in this window, I replace its return with CRSP VW market return for the remaining period. Monthly four-factor alpha used as the explanatory variable is computed as the fund's net return minus expected return from Fama-French-Carhart four factor model with betas computed in backward-looking window using rolling window time series regressions of fund's daily excess net returns on factor returns. These are computed for fund-months with at least 24 observations on past daily net returns in a 3-month window ending prior month. The sample comprises actively managed US domestic equity funds during the period Jan-1999 to Dec-2017 excluding Institutional and Retirement funds. Coefficients denoted using green squares on the plot are statistically significant at the 10% level or better and coefficients denoted using red triangles are statistically indistinguishable from zero.



Green squares indicate coefficients that are statistically significant at 10% level or better.
Red triangles indicate coefficients that are statistically indistinguishable from zero.

Tables

Table 1: Explanatory variables used to estimate abnormal flows

This table presents the list of explanatory variables used in the estimation of abnormal flows with each of the flow proxies: net flows, inflows, and outflows which are defined as (purchases-redemptions)*100/TNA_{t-1}, purchases*100/TNA_{t-1} and redemptions*100/TNA_{t-1} respectively. The following panel regression is first estimated for each flow proxy on a set of explanatory variables $\boldsymbol{X}$, which depend on the flow proxy used, and month fixed effects μ_t: $\text{Flow}_{i,t} = \alpha + \boldsymbol{\beta}.\boldsymbol{X} + \mu_t + \epsilon_{i,t}$. Abnormal flow proxies for each month are then computed as the sum of the month fixed effect estimate and the residual from the above regression. Columns I, II, III in the table below list the set of explanatory variables used in the regression for net flows, inflows, and outflows respectively. The explanatory variable related to a performance metric (such as net returns, 1-factor alpha etc.) is first converted to percentiles within style groups each month and then decomposed into three variables LOW, MID, and HIGH. These are defined as: LOW=min(Rank, 20), MID=min(60, Rank-LOW), HIGH=Rank-LOW-MID, where Rank is the percentile rank ranging from 1 to 100. These variables are then used in the above regression to estimate a piece-wise linear specification.

<table>
<tr><th>I. Flow proxy is Net flows$_t$</th><th>II. Flow proxy is Inflows$_t$</th><th>III. Flow proxy is Outflows$_t$</th></tr>
<tr>
<td>Explanatory Variables ($\boldsymbol{X}$) are:
• LOW_t, MID_t, $HIGH_t$
• Expense $ratio_{t-1}$
• 12B-1 $ratio_{t-1}$
• Net $flows_{t-1}$
• Aggregate net flows in style $category_t$
• Aggregate net flows in the fund $family_t$
• $\log(TNA_{t-1})$
• $\log(Age_{t-1})$
• Return Std. Devn. (t-12 t-1)
• Turnover $Ratio_{t-1}$
• Capital gains $distribution_t$
• Dividend $distribution_t$</td>
<td>Explanatory Variables ($\boldsymbol{X}$) are:
• LOW_t, MID_t, $HIGH_t$
• Expense $ratio_{t-1}$
• 12B-1 $ratio_{t-1}$
• $Outflows_t$
• $Inflows_{t-1}$
• $Outflows_{t-1}$
• Aggregate Inflows in style $category_t$
• Aggregate Outflows in style $category_t$
• Aggregate Inflows in the fund $family_t$
• Aggregate Outflows in the fund $family_t$
• $\log(TNA_{t-1})$
• $\log(Age_{t-1})$
• Return Std. Devn. (t-12 t-1)
• Turnover $Ratio_{t-1}$
• Capital gains $distribution_t$
• Dividend $distribution_t$</td>
<td>Explanatory Variables ($\boldsymbol{X}$) are:
• LOW_t, MID_t, $HIGH_t$
• Expense $ratio_{t-1}$
• 12B-1 $ratio_{t-1}$
• $Inflows_t$
• $Inflows_{t-1}$
• $Outflows_{t-1}$
• Aggregate Inflows in style $category_t$
• Aggregate Outflows in style $category_t$
• Aggregate Inflows in the fund $family_t$
• Aggregate Outflows in the fund $family_t$
• $\log(TNA_{t-1})$
• $\log(Age_{t-1})$
• Return Std. Devn. (t-12 t-1)
• Turnover $Ratio_{t-1}$
• Capital gains $distribution_t$
• Dividend $distribution_t$</td>
</tr>
</table>

Table 2: Mapping statistics between CRSP and monthly purchases & redemptions

This table shows the mapping statistics between the CRSP Mutual Funds sample and the monthly purchases and redemptions data from N-SAR filings (from 1994 to 1998), Morningstar Direct (from 1999 to 2017). Panel A shows the number of funds with data available on purchases and redemptions by year and panel B compares the characteristics of funds with and without a mapping. Column (1) of panel A shows the number of equity funds in the CRSP MF database that remain after applying the standard selection filters and column (2) shows the number of these funds that have a mapping with the purchases and redemptions data.

Panel A: Number of funds with available mapping to purchases and redemptions data by year

Year	No. of funds	No. of funds with mapping	%	Year	No. of funds	No. of funds with mapping	%
	(1)	(2)	(3)		(1)	(2)	(3)
1994	538	208	38.7	2006	1555	1331	85.6
1995	619	292	47.2	2007	1578	1352	85.7
1996	720	352	48.9	2008	1658	1318	79.5
1997	863	451	52.3	2009	1568	1227	78.3
1998	994	581	58.5	2010	1466	1149	78.4
1999	1138	827	72.7	2011	1427	1103	77.3
2000	1298	987	76	2012	1342	1041	77.6
2001	1362	1119	82.2	2013	1286	1008	78.4
2002	1404	1228	87.5	2014	1227	971	79.1
2003	1443	1251	86.7	2015	1191	821	68.9
2004	1468	1278	87.1	2016	1167	901	77.2
2005	1546	1323	85.6	2017	1108	867	78.2

Panel B: Characteristics comparison between full sample and sample with available mapping

	Full sample from CRSP	Sample with available mapping to monthly purchases and redemptions
Number of actively managed domestic equity funds	2541	2026 (79.7%)
TNA ($ mn)	1295.7	1467.6
Age (months)	153.7	160.5
Number of share-classes	3.1	3.2
Monthly Net Returns	0.70%	0.66%
1-factor alpha	-0.04%	-0.01%
4-factor alpha	-0.08%	-0.07%
Morningstar Rating	3.12	3.11
Expense Ratio (per annum)	1.27%	1.28%
12b-1 Fees (per annum)	0.23%	0.23%
Annual Turnover	85.4%	82.6%

Table 3: Distribution of fiscal months

This table shows the frequency distribution of different fiscal months in my sample of actively managed domestic equity funds during Jan-1994 to Dec-2017 with data available on monthly purchases and redemptions. Column (1) shows the tabulation for number of observations and column (3) shows the tabulation of number of funds. Funds can change fiscal year end and can appear in multiple groups for counting.

Fiscal Month	Obs. Count	% of Obs.	Fund Count
	(1)	(2)	(3)
Jan	2,011	0.93	23
Feb	4,002	1.86	48
Mar	18,204	8.45	197
Apr	5,393	2.5	76
May	7,016	3.26	99
Jun	17,821	8.27	207
Jul	13,529	6.28	144
Aug	14,999	6.96	151
Sep	28,878	13.41	294
Oct	47,295	21.96	539
Nov	12,843	5.96	116
Dec	43,403	20.15	467
Missing	2,011	0.93	1200
Total	215,394	100	

Table 4: Descriptive statistics

This table shows the means of the variables for a sample of actively managed US domestic equity funds with data on purchases and redemptions during 1994 to 2017. The sample excludes Institutional and Retirement funds. There are 2,026 funds in this sample which are classified into four broad style groups: growth (1011 funds), growth & income (414 funds), mid-cap (299 funds) and small-cap (458 funds). Funds are categorized into a distribution channel at the monthly level and the number of funds in observations categorized as broker-sold, direct-market, and other categories are 936, 796, and 988 respectively. Funds with 75% of TNA in one distribution channel across all its share-classes are assigned to that channel for the month. Funds with less than 75% assets in any particular channel or with 75% TNA in share-classes that could not be classified into any channel are categorized as 'Other'. Fund level returns, expenses, 12B-1 fees, turnover are computed from share class level variables using lagged TNA as weights. Fund age is computed as the age of the oldest share class. No-Load dummy takes a value of one if all share classes in a fund have zero front-end and back-end loads. Fund level Morningstar rating is the maximum rating across all share classes in a month. Market excess return is the fund's return in excess of CRSP VW market index. One-, three- and four-factor alphas are intercepts from monthly rolling window time series regressions of fund's excess net returns on market excess return, Fama French three factors, Fama French Carhart four factors respectively. These are computed for fund-months with at least 24 observations on past net returns in a 36-month window ending prior month. Net flow is computed as (purchases-redemptions)/TNA_{t-1}.

Sample comprises:	Broker-Sold funds	Direct-Sold funds	Other funds	All Funds
	(1)	(2)	(3)	(4)
TNA ($ mn)	1028.9	1509.1	2017.9	1467.6
Age (months)	156.1	161.9	164.7	160.5
Number of share-classes	4.0	1.6	4.4	3.2
Number of funds in family	11.0	9.7	12.0	10.8
Family TNA ($ bn)	20.1	34.6	22.7	26.2
Monthly Net Returns	0.56%	0.70%	0.73%	0.66%
Net Ret – Market Ret	-0.01%	0.01%	-0.05%	-0.01%
Monthly Gross Returns	0.68%	0.79%	0.82%	0.76%
Gross Ret – Market Ret	0.11%	0.10%	0.04%	0.09%
1-factor alpha	-0.01%	0.01%	-0.03%	-0.01%
3-factor alpha	-0.08%	-0.03%	-0.06%	-0.06%
4-factor alpha	-0.09%	-0.04%	-0.07%	-0.07%
Morningstar Rating	3.1	3.0	3.3	3.1
Expense Ratio (per annum)	1.52%	1.14%	1.13%	1.28%
12b-1 Fees (per annum)	0.42%	0.06%	0.16%	0.23%
Annual Turnover	88.6%	81.0%	76.8%	82.6%
No-Load Dummy	0.30	0.03	0.28	0.21
Return SD (t-12, t-1)	4.89%	4.76%	4.50%	4.74%
Adj. R^2 from 4-factor model	0.90	0.89	0.92	0.90
Net Flow (% of TNA)	0.43	0.33	0.09	0.30
Inflow (% of TNA)	3.48	3.23	3.14	3.30
Outflow (% of TNA)	2.98	2.88	3.04	2.96

Table 5: Fund flows at the turn of the year vis-à-vis other months

This table reports results from regressions of various flow proxies on dummy variables for January and December months. Net flows, inflows, and outflows are defined as (purchases-redemptions)*100/TNA_{t-1}, purchases*100/TNA_{t-1} and redemptions*100/TNA_{t-1} respectively. Columns (4) and (5) report the results in sub-samples where net flows are positive and negative respectively. The sample comprises actively managed US domestic equity funds with data available on monthly purchases and redemptions during the period Jan-1994 to Dec-2017 excluding Institutional and Retirement funds. Panel A shows the results using all funds in this sample while panel B shows results within the sample that omits funds with fiscal years ending in December, January or missing. Standard errors double-clustered by fund and month are reported in the parentheses. ***, **, * indicate statistical significance at the 1%, 5%, 10% levels respectively.

Panel A: Full Sample					
Dependent variable is:	Net Flows	Inflows	Outflows	Net $Flows^+$	Net $Flows^-$
	(1)	(2)	(3)	(4)	(5)
January Dummy	0.306	0.658**	0.360**	0.522***	-0.221**
	(0.215)	(0.292)	(0.156)	(0.201)	(0.092)
December Dummy	-0.160	0.419	0.581***	0.433**	-0.456***
	(0.193)	(0.274)	(0.150)	(0.187)	(0.066)
Constant	0.291***	3.209***	2.882***	3.291***	-1.816***
	(0.060)	(0.087)	(0.055)	(0.068)	(0.031)
Observations	239,478	239,478	239,478	99,311	140,167
Adj. R^2	0.000	0.002	0.003	0.001	0.003

Panel B: Sample excluding funds with fiscal months in January, December or missing					
Dependent variable is:	Net Flows	Inflows	Outflows	Net $Flows^+$	Net $Flows^-$
	(1)	(2)	(3)	(4)	(5)
January Dummy	0.266	0.609**	0.349**	0.503**	-0.222**
	(0.206)	(0.279)	(0.167)	(0.209)	(0.100)
December Dummy	-0.138	0.471*	0.613***	0.498***	-0.478***
	(0.183)	(0.263)	(0.157)	(0.182)	(0.074)
Constant	0.062	2.938***	2.854***	3.128***	-1.836***
	(0.058)	(0.083)	(0.056)	(0.070)	(0.032)
Observations	169,980	169,980	169,980	65,429	104,551
Adj. R^2	0.000	0.002	0.003	0.002	0.003

Table 6: Abnormal flows at the turn of the year vis-à-vis other months

This table reports results from regressions of various **abnormal** flow proxies on dummy variables for January and December months. The explanatory variables used to estimate expected flows and the construction of abnormal flow proxies are discussed in Table 1. The performance metric used is the 1-factor alpha which is the intercept from time series regression of net excess returns on market excess returns over past 36 months ending in (t-1) with at least 24 observations. Columns (1), (2), and (3) show the results with abnormal flows computed from net flows, inflows, and outflows as which are defined as (purchases-redemptions)*100/TNA_{t-1}, purchases*100/TNA_{t-1} and redemptions*100/TNA_{t-1} respectively. The sample comprises actively managed US domestic equity funds with data available on monthly purchases and redemptions during the period Jan-1994 to Dec-2017 excluding Institutional and Retirement funds. Panel A shows the results using all funds in this sample while panel B shows results within the sample that omits funds with fiscal years ending in December, January or missing. Standard errors double-clustered by fund and month are reported in the parentheses. ***, **, * indicate statistical significance at the 1%, 5%, 10% levels respectively.

Panel A: Full Sample

Dependent variable is:	Abnormal Net Flows	Abnormal Inflows	Abnormal Outflows
	(1)	(2)	(3)
January Dummy	0.225***	0.134*	-0.023
	(0.076)	(0.079)	(0.101)
December Dummy	-0.089	0.208***	0.381***
	(0.060)	(0.062)	(0.057)
Constant	-0.011	-0.028	-0.030
	(0.023)	(0.021)	(0.026)
Observations	184,778	184,778	184,778
Adj. R^2	0.000	0.000	0.002

Panel B: Sample excluding funds with fiscal months in January, December or missing

Dependent variable is:	Abnormal Net Flows	Abnormal Inflows	Abnormal Outflows
	(1)	(2)	(3)
January Dummy	0.179**	0.080	-0.016
	(0.075)	(0.079)	(0.107)
December Dummy	-0.076	0.216***	0.379***
	(0.066)	(0.063)	(0.062)
Constant	-0.022	-0.046**	-0.038
	(0.024)	(0.021)	(0.027)
Observations	136,579	136,579	136,579
Adj. R^2	0.000	0.000	0.002

Table 7: Month-on-month *changes* in flows by distribution channel

This table shows a regression of **month-on-month changes** in various flow proxies on a dummy for the month of January. Columns (1), (2), and (3) show results with net flows, inflows, and outflows as the relevant flow proxies which are defined as (purchases-redemptions)*100/TNA_{t-1}, purchases*100/TNA_{t-1} and redemptions*100/TNA_{t-1} respectively. The changes for each month are computed as the difference of a flow proxy for that month from the previous month, i.e. ΔNet $Flows_t$=(Net $Flows_t$ – Net $Flows_{t-1}$). Panel A shows the results for funds with direct-market distribution channel and panel B shows results for funds with broker-sold distribution channel. The sample comprises actively managed US domestic equity funds with data available on monthly purchases and redemptions during the period Jan-1994 to Dec-2017 excluding Institutional and Retirement funds. Standard errors double-clustered by fund and month are reported in the parentheses. ***, **, * indicate statistical significance at the 1%, 5%, 10% levels respectively.

Panel A: Direct-sold funds

Dependent variable is:	ΔNet Flows	ΔInflows	ΔOutflows
	(1)	(2)	(3)
January Dummy	0.755***	0.576***	-0.155
	(0.130)	(0.146)	(0.156)
Constant	-0.120***	-0.088**	0.038
	(0.037)	(0.040)	(0.032)
Observations	87,055	87,055	87,055
Adj. R^2	0.003	0.002	0.000

Panel B: Broker-sold funds

Dependent variable is:	ΔNet Flows	ΔInflows	ΔOutflows
	(1)	(2)	(3)
January Dummy	0.108	-0.065	-0.163
	(0.128)	(0.143)	(0.132)
Constant	-0.070*	-0.050	0.024
	(0.039)	(0.041)	(0.037)
Observations	85,397	85,397	85,397
Adj. R^2	0.000	0.000	0.000

Table 8: Month-on-month changes in *abnormal flows* by distribution channel

This table shows a regression of **month-on-month changes** in various **abnormal** flow proxies on a dummy for the month of January. The explanatory variables used to estimate expected flows and the construction of abnormal flow proxies are discussed in Table 1. The performance metric used is the 1-factor alpha which is the intercept from time series regression of net excess returns on market excess returns over past 36 months ending in (t-1) with at least 24 observations. Columns (1), (2), and (3) show results with abnormal flows computed from net flows, inflows, and outflows which are defined as (purchases-redemptions)*100/TNA_{t-1}, purchases*100/TNA_{t-1} and redemptions*100/TNA_{t-1} respectively. The changes for each month are computed as the difference of an abnormal flow proxy for that month from the previous month, i.e. ΔAbnormal Net $Flows_t$=(Abnormal Net $Flows_t$ – Abnormal Net $Flows_{t-1}$). Panel A shows the results for funds with direct-market distribution channel and panel B shows results for funds with broker-sold distribution channel. The sample comprises actively managed US domestic equity funds with data available on monthly purchases and redemptions during the period Jan-1994 to Dec-2017 excluding Institutional and Retirement funds. Standard errors double-clustered by fund and month are reported in the parentheses. ***, **, * indicate statistical significance at the 1%, 5%, 10% levels respectively.

Panel A: Direct-sold funds

Dependent variable is:	ΔAbnormal Net Flows	ΔAbnormal Inflows	ΔAbnormal Outflows
	(1)	(2)	(3)
January Dummy	0.615***	0.280***	-0.429***
	(0.118)	(0.102)	(0.114)
Constant	-0.056*	-0.022	0.050*
	(0.034)	(0.033)	(0.029)
Observations	60,690	60,690	60,690
Adj. R^2	0.001	0.000	0.001

Panel B: Broker-sold funds

Dependent variable is:	ΔAbnormal Net Flows	ΔAbnormal Inflows	ΔAbnormal Outflows
	(1)	(2)	(3)
January Dummy	0.015	-0.316***	-0.223**
	(0.102)	(0.109)	(0.112)
Constant	0.005	0.045*	0.022
	(0.029)	(0.025)	(0.031)
Observations	69,904	69,904	69,904
Adj. R^2	0.000	0.000	0.000

Table 9: Difference-in-difference estimation for changes in flow proxies

This table shows results from a difference-in-difference estimation which compares the dependent variables at the turn of the year with other months in broker-sold funds vs. direct-sold funds. The dependent variables in Panel A are month-on-month changes in various flow proxies while in panel B they are month-on-month changes in various **abnormal** flow proxies. The explanatory variables used to estimate expected flows and the construction of abnormal flow proxies are discussed in Table 1. The performance metric used is the 1-factor alpha which is the intercept from time series regression of net excess returns on market excess returns over past 36 months ending in (t-1) with at least 24 observations. Columns (1)-(2), (3)-(4), and (5)-(6) of the table below report results with dependent variables computed from the flow proxies net flows, inflows, and outflows which are defined as (purchases-redemptions)*100/TNA_{t-1}, purchases*100/TNA_{t-1} and redemptions*100/TNA_{t-1} respectively. The changes for each month are computed as the difference of a flow proxy for that month from the previous month, i.e. ΔNet $Flows_t$=(Net $Flows_t$ – Net $Flows_{t-1}$), ΔAbnormal Net $Flows_t$=(Abnormal Net $Flows_t$ – Abnormal Net $Flows_{t-1}$). Columns (1), (3), (5) report results without using any fixed effects in the estimation while columns (2), (4), (6) report results by including fund and month fixed effects. The sample comprises actively managed US domestic equity funds with data available on monthly purchases and redemptions during the period Jan-1994 to Dec-2017 excluding Institutional and Retirement funds. Standard errors double-clustered by fund and month are reported in the parentheses. ***, **, * indicate statistical significance at the 1%, 5%, 10% levels respectively.

Panel A: Month-on-month changes in flow proxies						
Dependent variable is:	ΔNet Flows		ΔInflows		ΔOutflows	
	(1)	(2)	(3)	(4)	(5)	(6)
Broker_sold dummy	0.051***	0.024	0.038**	-0.023	-0.014	-0.059
	(0.015)	(0.066)	(0.018)	(0.093)	(0.018)	(0.075)
January dummy	0.755***		0.576***		-0.155	
	(0.130)		(0.146)		(0.156)	
Broker_sold*January dummy	-0.647***	-0.625***	-0.641***	-0.638***	-0.008	-0.027
	(0.119)	(0.122)	(0.126)	(0.125)	(0.068)	(0.073)
Constant	-0.120***	-0.047	-0.088**	-0.012	0.038	0.049
	(0.037)	(0.031)	(0.040)	(0.046)	(0.032)	(0.036)
Fund and Month FE	No	Yes	No	Yes	No	Yes
Observations	172,452	172,435	172,452	172,435	172,452	172,435
Adj. R^2	0.001	0.025	0.001	0.030	0.000	0.035

Panel B: Month-on-month changes in **abnormal** flow proxies

Dependent variable is:	ΔAbnormal Net Flows		ΔAbnormal Inflows		ΔAbnormal Outflows	
	(1)	(2)	(3)	(4)	(5)	(6)
Broker_sold dummy	0.062***	-0.002	0.067***	-0.020	-0.029**	-0.016
	(0.013)	(0.069)	(0.016)	(0.090)	(0.013)	(0.049)
January dummy	0.615***		0.280***		-0.429***	
	(0.118)		(0.102)		(0.114)	
Broker_sold*January dummy	-0.600***	-0.577***	-0.595***	-0.575***	0.206***	0.191**
	(0.129)	(0.125)	(0.116)	(0.111)	(0.077)	(0.078)
Constant	-0.056*	0.027	-0.022	0.046	0.050*	0.009
	(0.034)	(0.035)	(0.033)	(0.047)	(0.029)	(0.024)
Fund and Month FE	No	Yes	No	Yes	No	Yes
Observations	130,594	130,585	130,594	130,585	130,594	130,585
Adj. R^2	0.001	0.015	0.000	0.014	0.001	0.022

Table 10: Flow-performance sensitivity at the turn of the year vis-à-vis other months

This table reports results from a comparison of flow-performance sensitivity in January, December with other months. Panel A, B, and C report results using net flows, inflows, and outflows as the dependent variables respectively which are defined as (purchases-redemptions)*100/TNA_{t-1}, purchases*100/TNA_{t-1}, redemptions*100/TNA_{t-1}. The performance metric used is the 1-factor alpha which is the intercept from time series regression of net excess returns on market excess returns over past 36 months ending in (t-1) with at least 24 observations. This is converted to percentiles within style groups each month and then decomposed into three variables LOW, MID and HIGH to estimate a piece-wise linear specification. These are defined as: LOW=min(Rank, 20), MID=min(60, Rank-LOW), HIGH=Rank-LOW-MID, where Rank is the percentile rank ranging from 1 to 100. The sample comprises actively managed US domestic equity funds with data available on monthly purchases and redemptions during the period Jan-1994 to Dec-2017 excluding Institutional and Retirement funds. The sample comprises actively managed US domestic equity funds with data available on monthly purchases and redemptions during the period Jan-1994 to Dec-2017 excluding Institutional and Retirement funds. Standard errors clustered by fund are reported in the parentheses. ***, **, * indicate statistical significance at the 1%, 5%, 10% levels respectively.

Performance metric is:	1-factor alpha					
Dependent variable is:	Panel A: Net Flow		Panel B: Inflow		Panel C: Outflow	
	All Months	Interactions	All Months	Interactions	All Months	Interactions
	(1)	(2)	(3)	(4)	(5)	(6)
LOW Perf	0.062***	0.059***	0.000	0.001	-0.060***	-0.057***
	(0.005)	(0.005)	(0.008)	(0.008)	(0.008)	(0.008)
MID Perf	0.023***	0.023***	0.015***	0.015***	-0.009***	-0.009***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
HIGH Perf	0.113***	0.109***	0.134***	0.130***	0.018***	0.018***
	(0.007)	(0.007)	(0.009)	(0.009)	(0.005)	(0.005)
LOW Perf*December dummy		0.036***		0.001		-0.034***
		(0.005)		(0.008)		(0.005)
MID Perf*December dummy		0.004		0.002		-0.002
		(0.002)		(0.002)		(0.002)
HIGH Perf*December dummy		0.011		0.005		-0.007
		(0.013)		(0.014)		(0.008)
LOW Perf*January dummy		0.004		-0.007		-0.005
		(0.008)		(0.010)		(0.009)
MID Perf*January dummy		0.007***		0.007***		-0.001
		(0.002)		(0.002)		(0.002)

HIGH Perf*January dummy		0.039**		0.043**		0.006
		(0.018)		(0.018)		(0.009)
December dummy		-1.010***		0.280		1.284***
		(0.161)		(0.294)		(0.228)
January dummy		-0.138		0.397		0.472*
		(0.217)		(0.337)		(0.271)
Controls	No	No	No	No	No	No
Observations	211,170	211,170	211,170	211,170	211,170	211,170
Adj. R^2	0.090	0.092	0.047	0.050	0.014	0.018

Table 11: Flow sensitivity to fund characteristics at the turn of the year

This table reports results from a comparison of flow sensitivity to various fund characteristics such as performance, expenses, 12b-1 fees etc. in January, December with other months through interaction terms. Panel A, B, and C report results using net flows, inflows, and outflows as the dependent variables respectively which are defined as (purchases-redemptions)*100/TNA_{t-1}, purchases*100/TNA_{t-1}, redemptions*100/TNA_{t-1}. The performance metric used is the 1-factor alpha which is the intercept from time series regression of net excess returns on market excess returns over past 36 months ending in (t-1) with at least 24 observations. This is converted to percentiles within style groups each month and then decomposed into three variables LOW, MID and HIGH to estimate a piece-wise linear specification. These are defined as: LOW=min(Rank, 20), MID=min(60, Rank-LOW), HIGH=Rank-LOW-MID, where Rank is the percentile rank ranging from 1 to 100. The sample comprises actively managed US domestic equity funds with data available on monthly purchases and redemptions during the period Jan-1994 to Dec-2017 excluding Institutional and Retirement funds. The control variables used on panels A, B, and C depend on the flow proxy used as the dependent variable and are listed in Table 1. Standard errors clustered by fund are reported in the parentheses. ***, **, * indicate statistical significance at the 1%, 5%, 10% levels respectively.

Performance metric is:	1-factor alpha					
Dependent variable is:	Panel A: Net Flow		Panel B: Inflow		Panel C: Outflow	
	All Months	Interactions	All Months	Interactions	All Months	Interactions
	(1)	(2)	(3)	(4)	(5)	(6)
LOW Perf	0.029***	0.026***	0.016***	0.004	-0.028***	-0.025***
	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)
MID Perf	0.013***	0.013***	0.011***	0.008***	-0.008***	-0.006***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
HIGH Perf	0.058***	0.056***	0.057***	0.051***	-0.021***	-0.006***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.002)	(0.002)
Expense Ratio (t-1)	-13.531**	-15.122***	-11.907**	-9.216	9.503*	8.697
	(5.510)	(5.431)	(5.802)	(6.455)	(4.942)	(5.569)
12b-1 Fees (t-1)	14.264*	16.974**	5.644	2.140	-23.630***	-21.419**
	(8.110)	(7.830)	(8.954)	(10.629)	(8.280)	(10.078)
LOW Perf*December dummy		0.037***		0.012		-0.028***
		(0.004)		(0.008)		(0.007)
MID Perf*December dummy		0.003		0.001		-0.002*
		(0.002)		(0.002)		(0.001)
HIGH Perf*December dummy		0.006		0.003		-0.006
		(0.009)		(0.009)		(0.004)

Expense Ratio (t-1)*December dummy		7.092		-20.201		-26.238**
		(15.351)		(15.496)		(11.877)
12b-1 Fees (t-1)*December dummy		49.953***		24.904		-27.482*
		(13.691)		(20.246)		(15.856)
LOW Perf*January dummy		-0.004		-0.006		-0.001
		(0.008)		(0.007)		(0.007)
MID Perf*January dummy		0.004***		0.004**		-0.001
		(0.001)		(0.002)		(0.001)
HIGH Perf*January dummy		0.029***		0.029***		0.003
		(0.011)		(0.010)		(0.006)
Expense Ratio (t-1)*January dummy		10.849		24.756		7.440
		(15.746)		(19.452)		(12.737)
12b-1 Fees (t-1)*January dummy		-81.920***		-106.694***		-17.364
		(21.018)		(23.561)		(19.107)
December dummy		-1.280**		0.365		1.804***
		(0.589)		(0.529)		(0.397)
January dummy		0.330		0.726		0.371
		(0.412)		(0.579)		(0.557)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Controls*December dummy	No	Yes	No	Yes	No	Yes
Controls*January dummy	No	Yes	No	Yes	No	Yes
Observations	211,170	211,170	211,170	211,170	211,170	211,170
Adj. R^2	0.090	0.092	0.047	0.050	0.014	0.018

Table 12: Flow performance sensitivity at the turn of the year by market state

This table reports results from a comparison of flows at the turn of the year in *up-market* vs. *down-market years* through interaction terms. If the compounded return on CRSP value-weighted market portfolio from January to December of a calendar year is negative, then the months Feb-Dec of that calendar year and the month of January in the following calendar year are coded with a value one for the 'down-market dummy' and zero otherwise. The 10 calendar years with negative market returns in my sample are 1994, 2000, 2001, 2002, 2005, 2007, 2008, 2011, 2014, 2015. Panel A shows the results with normal flow proxies while panel B reports results with various **abnormal** flow proxies. The explanatory variables used to estimate expected flows and the construction of abnormal flow proxies are discussed in Table 1. The performance metric used is the 1-factor alpha which is the intercept from time series regression of net excess returns on market excess returns over past 36 months ending in (t-1) with at least 24 observations. Columns (1), (2), and (3) of the table below report results with dependent variables computed from the flow proxies net flows, inflows, and outflows which are defined as (purchases-redemptions)*100/TNA_{t-1}, purchases*100/TNA_{t-1} and redemptions*100/TNA_{t-1} respectively. The sample comprises actively managed US domestic equity funds with data available on monthly purchases and redemptions during the period Jan-1994 to Dec-2017 excluding Institutional and Retirement funds. Standard errors double-clustered by fund and month are reported in the parentheses. ***, **, * indicate statistical significance at the 1%, 5%, 10% levels respectively.

Panel A: Normal Flow metrics

	Net Flows	Inflows	Outflows
	(1)	(2)	(3)
January dummy	0.531**	0.800**	0.270
	(0.240)	(0.394)	(0.215)
December dummy	-0.113	0.352	0.479**
	(0.241)	(0.360)	(0.196)
Down market dummy	-0.006	0.122	0.106
	(0.116)	(0.160)	(0.090)
January Dummy*Down market dummy	-0.490	-0.309	0.194
	(0.436)	(0.590)	(0.294)
December Dummy*Down market dummy	-0.105	0.151	0.226
	(0.394)	(0.545)	(0.284)
Constant	0.294***	3.154***	2.834***
	(0.078)	(0.103)	(0.058)
Observations	239,478	239,478	239,478
Adj. R^2	0.001	0.002	0.003

Panel B: Abnormal flow metrics

	Abnormal Net Flows	Abnormal Inflows	Abnormal Outflows
	(1)	(2)	(3)
January dummy	0.254***	0.227***	0.011
	(0.096)	(0.079)	(0.116)
December dummy	-0.082	0.187***	0.374***
	(0.068)	(0.062)	(0.075)
Down market dummy	0.019	0.025	0.009
	(0.044)	(0.037)	(0.048)
January Dummy*Down market dummy	-0.064	-0.203	-0.073
	(0.152)	(0.158)	(0.206)
December Dummy*Down market dummy	-0.017	0.044	0.017
	(0.123)	(0.127)	(0.114)
Constant	-0.019	-0.040*	-0.034
	(0.026)	(0.024)	(0.034)
Observations	184,778	184,778	184,778
Adj. R^2	0.001	0.001	0.002

Table 13: Turn-of-the-year seasonality in *first half* of the sample

This table replicates the main results of my paper in the **first half sub-sample, i.e. 1994 to 2005**. Columns (1), (2), and (3) of panel A replicate the result in Table 5 on turn-of-the-year seasonality using net flows, inflows, and outflows as dependent variables which are defined as (purchases-redemptions)*100/TNA_{t-1}, purchases*100/TNA_{t-1} and redemptions*100/TNA_{t-1} respectively. Columns (4)-(6) of panel A replicate the result in Table 6 using various *abnormal* flow proxies as the dependent variables. The explanatory variables used to estimate expected flows and the construction of abnormal flow proxies are discussed in Table 1. The performance metric used is the 1-factor alpha which is the intercept from time series regression of net excess returns on market excess returns over past 36 months ending in (t-1) with at least 24 observations.

Panel B replicates the results in Table 9 for test of timing gaming with *month-on-month changes* in various flow proxies as the dependent variables. Columns (1)-(3) of panel B use *changes* in flow proxies and columns (4)-(6) use *changes in abnormal* flow proxies as the dependent variables. The changes for each month are computed as the difference of a flow proxy for that month from the previous month, i.e. ΔNet $Flows_t$=(Net $Flows_t$ – Net $Flows_{t-1}$), ΔAbnormal Net $Flows_t$=(Abnormal Net $Flows_t$ – Abnormal Net $Flows_{t-1}$). The sample comprises actively managed US domestic equity funds with data available on monthly purchases and redemptions during the period Jan-1994 to Dec-2005 excluding Institutional and Retirement funds. Standard errors double-clustered by fund and month are reported in the parentheses. ***, **, * indicate statistical significance at the 1%, 5%, 10% levels respectively.

Panel A: Test of turn of the year seasonality						
	Flow proxies			Abnormal flow proxies		
Dependent variable is:	Net Flows	Inflows	Outflows	Abn. Net Flows	Abn. Inflows	Abn. Outflows
	(1)	(2)	(3)	(4)	(5)	(6)
January Dummy	0.442	0.953**	0.527**	0.274**	0.258**	0.043
	(0.271)	(0.412)	(0.256)	(0.120)	(0.120)	(0.080)
December Dummy	-0.064	0.412	0.479*	-0.160	0.159	0.391***
	(0.209)	(0.384)	(0.257)	(0.105)	(0.113)	(0.075)
Constant	1.011***	4.310***	3.212***	0.058	0.024	-0.051
	(0.090)	(0.142)	(0.102)	(0.043)	(0.041)	(0.040)
Observations	100,488	100,488	100,488	74,884	74,884	74,884
Adj. R^2	0.001	0.002	0.002	0.001	0.001	0.002

Panel B: Test of timing gaming using month-on-month changes

	Flow proxies			Abnormal flow proxies		
Dependent variable is:	ΔNet Flows	ΔInflows	ΔOutflows	ΔAbn. Net Flows	ΔAbn. Inflows	ΔAbn. Outflows
	(1)	(2)	(3)	(4)	(5)	(6)
Broker_sold dummy	0.047*	0.047	0.002	0.070***	0.081***	-0.026
	(0.028)	(0.029)	(0.026)	(0.023)	(0.030)	(0.022)
January dummy	0.966***	0.866***	-0.074	0.862***	0.524***	-0.476***
	(0.210)	(0.201)	(0.103)	(0.163)	(0.161)	(0.092)
Broker_sold*January dummy	-0.922***	-0.987***	-0.063	-0.799***	-0.820***	0.239**
	(0.188)	(0.212)	(0.086)	(0.176)	(0.176)	(0.114)
Constant	-0.157**	-0.143*	0.022	-0.080	-0.049	0.055
	(0.071)	(0.076)	(0.050)	(0.064)	(0.064)	(0.043)
Observations	85,066	85,066	85,066	63,944	63,944	63,944
Adj. R^2	0.002	0.002	0.000	0.001	0.001	0.001

Table 14: Turn-of-the-year seasonality in *second half* of the sample

This table replicates the main results of my paper in the **second half sub-sample, i.e. 2006 to 2017**. Columns (1), (2), and (3) of panel A replicate the result in Table 5 on turn-of-the-year seasonality using net flows, inflows, and outflows as dependent variables which are defined as (purchases-redemptions)*100/TNA_{t-1}, purchases*100/TNA_{t-1} and redemptions*100/TNA_{t-1} respectively. Columns (4)-(6) of panel A replicate the result in Table 6 using various *abnormal* flow proxies as the dependent variables. The explanatory variables used to estimate expected flows and the construction of abnormal flow proxies are discussed in Table 1. The performance metric used is the 1-factor alpha which is the intercept from time series regression of net excess returns on market excess returns over past 36 months ending in (t-1) with at least 24 observations.
Panel B replicates the results in Table 9 for test of timing gaming with *month-on-month changes* in various flow proxies as the dependent variables. Columns (1)-(3) of panel B use *changes* in flow proxies and columns (4)-(6) use *changes in abnormal* flow proxies as the dependent variables. The changes for each month are computed as the difference of a flow proxy for that month from the previous month, i.e. ΔNet $Flows_t$=(Net $Flows_t$ – Net $Flows_{t-1}$), ΔAbnormal Net $Flows_t$=(Abnormal Net $Flows_t$ – Abnormal Net $Flows_{t-1}$). The sample comprises actively managed US domestic equity funds with data available on monthly purchases and redemptions during the period Jan-2006 to Dec-2017 excluding Institutional and Retirement funds. Standard errors double-clustered by fund and month are reported in the parentheses. ***, **, * indicate statistical significance at the 1%, 5%, 10% levels respectively.

Panel A: Test of turn of the year seasonality						
	Flow proxies			Abnormal flow proxies		
Dependent variable is:	Net Flows	Inflows	Outflows	Abn. Net Flows	Abn. Inflows	Abn. Outflows
	(1)	(2)	(3)	(4)	(5)	(6)
January Dummy	0.262	0.535***	0.271*	0.199**	0.060	-0.065
	(0.207)	(0.167)	(0.152)	(0.096)	(0.100)	(0.156)
December Dummy	-0.308**	0.320*	0.634***	-0.041	0.240***	0.376***
	(0.137)	(0.163)	(0.165)	(0.070)	(0.066)	(0.083)
Constant	-0.228***	2.416***	2.645***	-0.057**	-0.064***	-0.016
	(0.057)	(0.059)	(0.049)	(0.025)	(0.020)	(0.034)
Observations	138,990	138,990	138,990	109,894	109,894	109,894
Adj. R^2	0.001	0.002	0.003	0.000	0.001	0.002

Panel B: Test of timing gaming using month-on-month changes

	Flow proxies			Abnormal flow proxies		
Dependent variable is:	ΔNet Flows	ΔInflows	ΔOutflows	ΔAbn. Net Flows	ΔAbn. Inflows	ΔAbn. Outflows
	(1)	(2)	(3)	(4)	(5)	(6)
Broker_sold dummy	0.067***	0.045**	-0.027	0.056***	0.054***	-0.031**
	(0.014)	(0.020)	(0.020)	(0.015)	(0.015)	(0.015)
January dummy	0.595***	0.355*	-0.217	0.409***	0.074	-0.389**
	(0.155)	(0.197)	(0.262)	(0.146)	(0.105)	(0.193)
Broker_sold*January dummy	-0.428***	-0.371***	0.029	-0.437**	-0.409***	0.179*
	(0.132)	(0.088)	(0.093)	(0.172)	(0.133)	(0.102)
Constant	-0.090***	-0.042	0.051	-0.034	0.003	0.047
	(0.032)	(0.036)	(0.042)	(0.029)	(0.023)	(0.038)
Observations	87,386	87,386	87,386	66,650	66,650	66,650
Adj. R^2	0.001	0.000	0.000	0.000	0.000	0.001

Table 15: Turn-of-the-year seasonality using net flows from CRSP MF database

This table replicates the main results of my paper using net flows computed from monthly fund size and returns from the CRSP mutual funds database. Net flows at time *t* are computed as $(TNA_t - TNA_{t-1}(1+r_t))*100/TNA_{t-1}$ for each fund and then winsorized at the 1% level to remove the effect of outliers. Panel A replicates results in Tables 5 and 6 on turn-of-the-year seasonality using net flows and *abnormal* net flows. The explanatory variables used to estimate expected flows and the construction of abnormal flow proxies are discussed in Table 1. The performance metric used is the 1-factor alpha which is the intercept from time series regression of net excess returns on market excess returns over past 36 months ending in (t-1) with at least 24 observations.
Panel B replicates the results in Table 9 for test of timing gaming with *month-on-month changes* in net flows and *changes in abnormal net flows* as the dependent variables. The changes for each month are computed as the difference of a flow proxy for that month from the previous month, i.e. ΔNet $Flows_t$=(Net $Flows_t$ – Net $Flows_{t-1}$), ΔAbnormal Net $Flows_t$=(Abnormal Net $Flows_t$ – Abnormal Net $Flows_{t-1}$). The sample contains 2541 funds including those from CRSP MF database that do not have a mapping with Morningstar and N-SAR files excluding Institutional and Retirement funds. Of these, 1174 funds are in the broker-sold channel and 1053 funds are in the direct-sold channel. In both panels A and B, the sample period is 1994-2017 for results in columns (1), (2), 1994-2005 for columns (3), (4), and 2006-2017 for columns (5), (6). Standard errors double-clustered by fund and month are reported in the parentheses. ***, **, * indicate statistical significance at the 1%, 5%, 10% levels respectively.

Panel A: Test of turn of the year seasonality						
	Full Sample		First-half sub-sample		Second-half sub-sample	
Dependent variable is:	Net Flows	Abn. Net Flows	Net Flow	Abn. Net Flows	Net Flow	Abn. Net Flows
	(1)	(2)	(3)	(4)	(5)	(6)
January Dummy	0.302	0.082	0.475*	0.080	0.203	0.082
	(0.218)	(0.068)	(0.244)	(0.099)	(0.201)	(0.092)
December Dummy	-0.489***	-0.176**	-0.486***	-0.220	-0.519***	-0.139**
	(0.180)	(0.070)	(0.145)	(0.133)	(0.159)	(0.065)
Constant	0.317***	0.008	1.066***	-0.029	-0.265***	0.036
	(0.059)	(0.023)	(0.076)	(0.037)	(0.054)	(0.030)
Observations	328,036	242,264	143,406	104,670	184,630	137,594
Adj. R^2	0.001	0.000	0.001	0.000	0.002	0.000

Panel B: Test of timing gaming using month-on-month changes

	Full sample		First-half sub-sample		Second-half sub-sample	
Dependent variable is:	ΔNet Flows	ΔAbn. Net Flows	ΔNet Flows	ΔAbn. Net Flows	ΔNet Flows	ΔAbn. Net Flows
	(1)	(2)	(3)	(4)	(5)	(6)
Broker_sold dummy	0.058***	0.071***	0.059*	0.074***	0.076***	0.068***
	(0.020)	(0.017)	(0.033)	(0.028)	(0.023)	(0.018)
January dummy	1.104***	0.585***	1.500***	0.779***	0.758***	0.392***
	(0.152)	(0.091)	(0.249)	(0.135)	(0.148)	(0.102)
Broker_sold*January dummy	-0.662***	-0.597***	-0.986***	-0.811***	-0.404***	-0.386***
	(0.128)	(0.107)	(0.182)	(0.164)	(0.136)	(0.106)
Constant	-0.163***	-0.052***	-0.224***	-0.072***	-0.104***	-0.031
	(0.034)	(0.017)	(0.061)	(0.026)	(0.033)	(0.020)
Observations	239,297	175,253	124,696	91,771	114,601	83,482
Adj. R^2	0.003	0.001	0.004	0.001	0.002	0.000

Table 16: Flow sensitivity at the turn of the year by market state with alternative classification of down-market periods

This table replicates results from Table 12 which compares flows at the turn of the year in up-market vs. down-market years using an alternative classification scheme for down-market periods. The sample of 24 years from 1994 to 2017 are divided into terciles based on the compounded return on CRSP value-weighted market portfolio from January to December. The bottom-most 8 and the top-most 8 years are classified as down-market and up-market years respectively and only these sixteen years are included in the regressions. When assigning these dummies, the months Feb-Dec of a calendar year and the January of the following calendar year are assigned a value based on the market return from Jan to Dec of the current calendar year. In my sample, the bottom 8 years are 1994, 2000, 2001, 2002, 2007, 2008, 2011, 2015 while the top 8 are 1995, 1996, 1997, 1998, 1999, 2003, 2009, 2013. Panel A shows the results with normal flow proxies while panel B reports results with various **abnormal** flow proxies. The explanatory variables used to estimate expected flows and the construction of abnormal flow proxies are discussed in Table 1. The performance metric used is the 1-factor alpha which is the intercept from time series regression of net excess returns on market excess returns over past 36 months ending in (t-1) with at least 24 observations. Columns (1), (2), and (3) of the table below report results with dependent variables computed from the flow proxies net flows, inflows, and outflows which are defined as (purchases-redemptions)*100/TNA_{t-1}, purchases*100/TNA_{t-1} and redemptions*100/TNA_{t-1} respectively. The sample comprises actively managed US domestic equity funds with data available on monthly purchases and redemptions and the sample period includes sixteen years during Jan-1994 to Dec-2017 with extreme market returns. The sample excludes Institutional and Retirement funds. Standard errors double-clustered by fund and month are reported in the parentheses. ***, **, * indicate statistical significance at the 1%, 5%, 10% levels respectively.

Panel A: Normal Flow metrics			
	Net Flows	Inflows	Outflows
	(1)	(2)	(3)
January dummy	0.260	0.563	0.336
	(0.274)	(0.569)	(0.322)
December dummy	-0.172	0.257	0.472
	(0.333)	(0.636)	(0.356)
Down market dummy	-0.487***	-0.473**	0.021
	(0.157)	(0.223)	(0.125)
January Dummy*Down market dummy	-0.079	0.174	0.237
	(0.588)	(0.842)	(0.410)
December Dummy*Down market dummy	-0.090	0.245	0.272
	(0.498)	(0.803)	(0.403)
Constant	0.803***	3.938***	3.074***
	(0.117)	(0.170)	(0.101)
Observations	146,690	146,690	146,690
Adj. R^2	0.003	0.003	0.003

Panel B: Abnormal flow metrics

	Abnormal Net Flows	Abnormal Inflows	Abnormal Outflows
	(1)	(2)	(3)
January dummy	0.217	0.296***	0.185
	(0.153)	(0.112)	(0.170)
December dummy	-0.221***	0.122	0.476***
	(0.057)	(0.094)	(0.118)
Down market dummy	-0.105*	-0.081	0.087
	(0.059)	(0.053)	(0.068)
January Dummy*Down market dummy	0.025	-0.304	-0.309
	(0.238)	(0.235)	(0.314)
December Dummy*Down market dummy	0.143	0.146	-0.089
	(0.139)	(0.162)	(0.155)
Constant	0.112***	0.046	-0.128**
	(0.039)	(0.040)	(0.053)
Observations	111,740	111,740	111,740
Adj. R^2	0.001	0.001	0.003

Table 17: Summary statistics

This table presents the summary statistics for the sample of actively managed domestic equity funds used in this study. The number of fund-month observations is 404,042. We compute the respective statistics across funds each month and report the averages over the entire sample period. The sample period is from January, 1990 to June, 2017.

	Mean	Std. Dev.	Median
Number of funds each month	1224		
Flow (%)	0.25	10.8	-0.42
TNA ($ mn)	1120.4	4507.4	223.6
Age (months)	376.8	306.6	299.2
Expense Ratio (%)	1.22	0.45	1.19
Load Dummy	0.49	0.50	0
Return Volatility (t-1,t-12)	4.7	2.3	4.2

Table 18: Factor model R^2

This table fits the following regression:

$$(r_{p,\tau} - r_{f,\tau}) = \alpha_{p,\eta,\tau} + \sum_{k=1}^{\eta} \beta_{k,p} F_{k,\tau} + e_{p,\eta,\tau},$$

where $r_{p,\tau}, r_{f,\tau}$ and $F_{k,\tau}$ are fund return, risk-free rate and realization of factor k in month τ, respectively. For each fund p and month t, the regression is fitted for various η-factor models from $\tau = t - 60$ to $t - 1$ using OLS. With these estimates, we compute the abnormal return for fund p in month t under each η-factor model as $\hat{\alpha}_{p,\eta,t} = r_{p,t} - \sum_{k=1}^{\eta} \hat{\beta}_{k,p} F_{k,t}$. Column (1) reports the cross-sectional averages of time-series means of adjusted R^2 from the OLS regressions. Column (2) reports the cross-sectional averages of time-series means of monthly adjusted R^2 computed using the formula $1 - [Var(\hat{\alpha}_{p,\eta}) \times (T_p - 1)/Var(r_p) \times (T_p - \eta - 1)]$ where T_p is the number of months the fund is in the sample. The sample period is January, 1990 to June, 2017.

	Adj. R^2	
	From OLS	$1 - \left(Var(\hat{\alpha}_{p,\eta}) \times (T-1) \big/ Var(r_p) \times (T - \eta - 1)\right)$
	(1)	(2)
Estimated factor model (η):		
Market Adj. Return		0.761
Market Model	0.820	0.829
FF3	0.892	0.883
FFC4	0.901	0.883
FFC4 + 3 IND	0.910	0.884

Table 19: Measurement Errors in betas

This table reports the slope coefficients from the following cross-sectional regressions:

$$\hat{\beta}_{p,k,t}^{future} = a_t + b_t \times \hat{\beta}_{p,k,t}^{past} + e_{p,t},$$

where for each fund p, $\hat{\beta}_{p,k,t}^{future}$ and $\hat{\beta}_{p,k,t}^{past}$ are estimated using time-series regressions with data from t to $t+11$ and $t-1$ to $t-60$, respectively. Backward-looking and forward-looking betas are estimated monthly using multiple regressions of fund returns on the seven factors. The above regression is then fitted each month for betas with respect to each factor and the table reports time-series averages of the slope coefficients. Standard errors from the second stage of Fama-MacBeth regressions are adjusted for serial correlation using Newey-West correction with lag length of 11 months. Sample period for these regressions is Jan-1990 to Jul-2016. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels respectively.

Betas	Average b_t	Std. Err.
Market	0.656***	0.06
SMB	0.894***	0.02
HML	0.720***	0.05
UMD	0.523***	0.06
IND1	0.403***	0.07
IND2	0.315***	0.05
IND3	0.270***	0.04

Table 20: Variance of empiricist alpha estimates

This table reports variance of empiricist's alpha estimates from different η-factor models. We use $\hat{\beta}$ estimates from the time series regression (2.19) to compute $\hat{\alpha}_{\eta}^{E}$ each month and its cross-sectional variance. We average the monthly estimates over time and report the value multiplied by 10^6. The sample period is January, 1990 to June, 2017.

	$\sigma^2_{\hat{\alpha}_{\eta}^{E}}$
Alpha Estimated Using (η):	
Mkt adj. ret.	650.5
Market model	544.4
FF3	370.9
FFC4	357.7
FFC4+3 IND	363.2

Table 21: Summary Statistics on Factors and Factor Betas

Panel A of this table reports the sample mean and standard deviations of Market, SMB, HML and UMD factors. Panel B presents the covariance matrix of "true" factor betas. We estimate the true beta covariance matrix from OLS beta covariance matrix using Eq. (2.25). IND1, IND2 and IND3 are industry factors that are the first three principal components of regression residuals of Fama-French 17 equal weighted industry portfolios regressed on FFC4 factors. The table reports the average of monthly estimates. The sample period is January, 1990 to June, 2017.

Panel A: Factor Statistics

Factor	Mean (%)	Std Dev (%)
$mktrf$	0.64	4.26
SMB	0.15	3.22
HML	0.21	3.01
UMD	0.51	4.82

Panel B: Covariance matrix of true betas

	β_{mktrf}	β_{smb}	β_{hml}	β_{umd}	β_{ind1}	β_{ind2}	β_{ind3}
β_{mktrf}	0.023						
β_{smb}	0.016	0.114					
β_{hml}	-0.018	-0.003	0.080				
β_{umd}	0.006	0.008	-0.020	0.017			
β_{ind1}	0.001	0.001	-0.002	0.001	0.002		
β_{ind2}	0.000	0.001	0.003	0.000	0.000	0.002	
β_{ind3}	-0.001	0.000	0.000	0.000	0.000	0.000	0.003

Table 22: Components of alpha estimation error in the mutual fund sample

This table presents the components of cross-sectional variance of multifactor model alpha estimates, decomposed as in Eq. (2.24) for various combinations of hypothesized true asset pricing models (K=0, 1, 3, 4) and multifactor models. Alphas are estimated as: Mkt adj. return is fund return minus market returns and the other alphas are estimated using the indicated models. The hypothesized true asset pricing models are No-beta risk premium model (NBRP) where none of the common factors are priced factors, CAPM, FF3 and FFC4. The column $\sigma^2_{\hat{\alpha}_J}$ presents the cross-sectional variance of alphas estimated under the assumption that the true asset pricing model and true betas are known. The other columns present the variance due to the following: (i) APM misspecification: unpriced factors used to compute alphas; (ii) "Omitted factors": common factors excluded from the computation of alphas, (iii) "Covariance": Covariance of betas on excluded unpriced factors and betas of included priced factors and (iv) "Beta measurement error": factor beta estimation errors. The sample includes actively managed equity funds in the Jan-1990 to Jun-2017 sample period.

		$\sigma^2_{\hat{\alpha}_J}$	APM Misspecification Error Variance	Omitted Factors Variance	Covariance	Beta measurement error Variance	Variance in addition to $\sigma^2_{\hat{\alpha}_J}$	
		(1)	(2)	(3)	(4)	(5)	(6)	(7)
True asset pricing Model (K):	Alpha Estimated Using (η):						(2)+(3)+(4)	(5)+(6)
NBRP	Mkt adj. ret.	309.7	0	340.9	0	0	340.9	340.9
	Market model	309.7	1.94	222.5	-0.76	11.0	223.7	234.7
	FF3	309.7	1.44	38.4	0.00	21.4	39.9	61.2
	FFC4	309.7	1.85	15.7	0.07	30.4	17.6	48.0
	FFC4+3 IND	309.7	1.94	0	0	51.6	1.9	53.6
CAPM	Mkt adj. ret.	310.8	1.94	340.9	-3.12	0	339.7	339.7
	Market model	310.8	0	222.5	0	11.0	222.5	233.6
	FF3	310.8	0.64	38.4	-0.38	21.4	38.7	60.1
	FFC4	310.8	0.77	15.7	-0.03	30.4	16.4	46.8
	FFC4+3 IND	310.8	0.76	0	0	51.6	0.8	52.4
FF3	Mkt adj. ret.	311.1	1.44	340.9	-2.87	0	339.4	339.4
	Market model	311.1	0.64	222.5	-0.90	11.0	222.3	233.3
	FF3	311.1	0	38.4	0	21.4	38.4	59.8
	FFC4	311.1	0.44	15.7	0.04	30.4	16.2	46.6

	FFC4+3 IND	311.1	0.50	0	0	51.6	0.5	52.1
	Mkt adj. ret.	311.6	1.85	340.9	-3.77	0	338.9	338.9
	Market model	311.6	0.77	222.5	-1.50	11.0	221.8	232.8
FFC4	FF3	311.6	0.44	38.4	-0.92	21.4	38.0	59.3
	FFC4	311.6	0	15.7	0	30.4	15.7	46.1
	FFC4+3 IND	311.6	0.02	0	0	51.6	0.0	51.7

Table 23: Simulation Parameters

We generate net returns each month using the following seven-factor model:

$$r_{p,t} = \Phi_p - c_{t-1}(q_{t-1}) + E^{model}(r_{p,t}) + \beta_{p,m}(\widetilde{mkt - rf})_t + \beta_{p,smb}\widetilde{SMB}_t + \beta_{p,hml}\widetilde{HML}_t + \beta_{p,umd}\widetilde{UMD}_t + \beta_{p,ind1}\widetilde{IND1}_t + \beta_{p,ind2}\widetilde{IND2}_t + \beta_{p,ind3}\widetilde{IND3}_t + \epsilon_{p,t}$$

where Φ_p is the fund manager skill and $c_{t-1}(q_{t-1})$ is the cost per unit size. The variables under $tilde$ are demeaned realizations of the seven common factors and βs are the corresponding factor sensitivities. We use the factor realizations in the data over January 1990 to June 2017 sample period in our simulations. We draw seven factor betas for each fund from a multivariate Normal distribution as $\beta_{7\times1} \sim MVN([1,0,0,0,0,0,0]', \Omega)$ with covariance matrix Ω reported in panel B of Table 21. We generate monthly flow according to Eq. (2.12). We draw all random variables from normal distributions with means and variances shown below.

Random Variable	Mean	Variance
Φ_p	ϕ_0 =0.15%	$1/\nu$ = (0.2%)^2
ϵ	0	$1/\vartheta_{\hat{\alpha},J}$ = (1.75%)^2

Table 24: Components of alpha estimation error in the simulated sample

This table presents the components of cross-sectional variance of multifactor model alpha estimates, decomposed as in Eq. (2.24) for various combinations of hypothesized true asset pricing models (K=0, 1, 3, 4) and multifactor models in the simulated sample. Alphas are estimated as: Mkt adj. return is fund return minus market returns and the other alphas are estimated using the indicated models. The hypothesized true asset pricing models are a model with no beta risk premium for any factors (NBRP), CAPM, FF3 and FFC4. The column $\sigma^2_{\hat{\alpha}_J}$ presents the cross-sectional variance of alphas estimated under the assumption that the true asset pricing model and true betas are known. The other columns present the variance due to the following: (i) APM misspecification: unpriced factors used to compute alphas; (ii) "Omitted factors": common factors excluded from the computation of alphas, (iii) "Covariance": Covariance of betas on excluded unpriced factors and betas of included priced factors and (iv) "Beta measurement error": factor beta estimation errors. The results are based on 500 simulations.

		$\sigma^2_{\hat{\alpha}_J}$	APM Misspecification Error Variance	Omitted Factors Variance	Covariance	Beta measurement error Variance	Variance in addition to $\sigma^2_{\hat{\alpha}_J}$	
		(1)	(2)	(3)	(4)	(5)	(6)	(7)
True asset pricing Model (K):	Alpha Estimated Using (η):						(2)+(3)+(4)	(5)+(6)
NBRP	Mkt adj. ret.	307.8	0	0	324.1	0	324.1	324.1
	Market model	307.8	0.931	-0.032	234.3	32.4	235.2	267.7
	FF3	307.8	1.334	-0.018	50.4	33.5	51.7	85.2
	FFC4	307.8	1.842	-0.010	18.2	36.8	20.0	56.8
	FFC4+3 IND	307.8	1.945	0	0	56.7	1.94	58.6
CAPM	Mkt adj. ret.	307.8	0.931	0.008	324.1	0	325.1	325.1
	Market model	307.8	0	0	234.3	32.4	234.3	266.8
	FF3	307.8	0.579	0.193	50.4	33.5	51.2	84.7
	FFC4	307.8	0.715	-0.001	18.2	36.8	18.9	55.7
	FFC4+3 IND	307.8	0.761	0	0	56.7	0.76	57.4
FF3	Mkt adj. ret.	307.8	1.334	0.014	324.1	0	325.5	325.5
	Market model	307.8	0.579	-0.383	234.3	32.4	234.5	267.0
	FF3	307.8	0	0	50.4	33.5	50.4	83.9
	FFC4	307.8	0.435	0.009	18.2	36.8	18.6	55.4

	FFC4+3 IND	307.8	0.504	0	0	56.7	0.50	57.2
	Mkt adj. ret.	307.8	1.842	0.008	324.1	0	326.0	326.0
	Market model	307.8	0.715	-0.033	234.3	32.4	235.0	267.5
FFC4	FF3	307.8	0.435	0.449	50.4	33.5	51.3	84.8
	FFC4	307.8	0	0	18.2	36.8	18.2	55.0
	FFC4+3 IND	307.8	0.024	0	0	56.7	0.02	56.7

Table 25: Flow-Performance relation in simulated sample

This table presents the estimates of the slope coefficients of flow-alpha regression (2.14) in simulations with returns generated under the following models for expected returns: a model with no beta risk premium for any factors (NBRP), CAPM, FF3 and FFC4 models. The column headings identify the expected returns model. Alphas are computed with respect to the models indicated in the first column. Monthly flow is determined by the model as specified by Eq. (2.12). Panel A presents the results using true betas to compute alphas and panel B presents the results with factor betas estimated from the data. The table reports average coefficients across 500 repetitions of the simulations.

	Panel A: True betas used to estimate alphas				Panel B: 60 month rolling window $\hat{\beta}$s used to estimate alphas			
True asset pricing model (K):	NBRP	CAPM	FF3	FFC4	NBRP	CAPM	FF3	FFC4
Alpha Estimated Using (η):								
Market Adjusted Ret	2.21	2.19	2.19	2.19	2.21	2.19	2.19	2.19
Market model	2.36	2.36	2.36	2.36	2.34	2.35	2.35	2.34
FF3	3.07	3.07	3.08	3.07	2.92	2.92	2.93	2.92
FFC4	3.27	3.28	3.29	3.29	3.04	3.05	3.05	3.05
FFC4+3 IND	3.48	3.50	3.50	3.51	3.01	3.02	3.02	3.02

Table 26: Flow-Performance relation with sign-regressions in simulated sample

This table presents the estimates of the slope coefficients of flow-alpha regression (2.32) in simulations with returns generated under the following models for expected returns: a model with no beta risk premium for any factors (NBRP), CAPM, FF3 and FFC4 models. The column headings identify the expected returns model. Alphas are computed with respect to the models indicated in the first column. Monthly flow is determined by the model as specified by Eq. (2.12). Flow and alpha are assigned values of +1 when positive and -1 when negative. Panel A presents the results using true betas to compute alphas and panel B presents the results with factor betas estimated from the data. The table reports average coefficients across 500 repetitions of the simulations.

	Panel A: True betas used to estimate alphas				Panel B: 60 month rolling window $\hat{\beta}$s used to estimate alphas			
True asset pricing model (K):	NBRP	CAPM	FF3	FFC4	NBRP	CAPM	FF3	FFC4
Alpha Estimated Using (η):								
Market Adjusted Ret	0.594	0.591	0.592	0.591	0.594	0.591	0.592	0.591
Market model	0.626	0.626	0.627	0.626	0.620	0.621	0.621	0.620
FF3	0.789	0.792	0.794	0.792	0.744	0.745	0.747	0.745
FFC4	0.846	0.851	0.853	0.855	0.774	0.777	0.778	0.779
FFC4+3 IND	0.950	0.968	0.974	0.994	0.768	0.772	0.773	0.774

Table 27: Descriptive Statistics

This table shows the descriptive statistics of the variables in the sample of actively managed US domestic equity funds with data on purchases and redemptions. The sample excludes Institutional and Retirement funds. There are 1,955 funds in this sample which are classified into four broad style groups: growth (920 funds), growth & income (379 funds), mid-cap (288 funds) and small-cap (438 funds). Fund level returns, expenses, 12B-1, turnover are aggregated from share class level using lagged TNA as weights. Fund age is computed as the age of the oldest share class. No-Load dummy takes a value of one if all share classes in a fund have zero front-end and back-end loads. Fund level Morningstar rating is the maximum rating across all share classes in a month. Market excess return is the fund's return in excess of CRSP VW market index. One-, three- and four-factor alphas are intercepts from rolling window time series regressions of fund's daily excess net returns on market excess return, Fama French three factors, Fama French Carhart four factors respectively. These are computed for fund-months with at least 24 observations on past daily net returns in a 3-month window ending prior month. Inflow, Outflow, Net flow are computed as purchases*100/TNA_{t-1}, redemptions*100/TNA_{t-1}, and (purchases-redemptions)*100/TNA_{t-1} respectively. The sample period is Jan-1994 to Dec-2017.

	Obs	Median	Mean	Std. Dev.
TNA ($ mn)	222177	289	1488.0	5641.7
Age (months)	222180	133	162.5	127.5
Number of share-classes	222180	3	3.3	2.2
Number of funds in family	222180	8	11.1	11.6
Family TNA ($ bn)	222177	4.6	27.2	69.3
Monthly Net Returns	222093	1.02%	0.59%	5.29%
Monthly Gross Returns	222093	1.12%	0.69%	5.29%
Net Ret. – Market Ret.	222093	-0.05%	0.02%	2.62%
Monthly 1-factor alpha	221601	0.00%	0.00%	0.10%
Monthly 3-factor alpha	221601	0.00%	0.00%	0.08%
Monthly 4-factor alpha	221601	0.00%	0.00%	0.08%
Morningstar Rating	143130	3	3.1	1.0
Expense Ratio (per annum)	215869	1.24%	1.27%	0.40%
12B-1 Fees (per annum)	190800	0.21%	0.23%	0.23%
Annual Turnover	216300	62.8%	82.3%	81.8%
No-Load Dummy	172732	0	0.22	0.42
Return SD (t-12, t-1)	210219	4.30%	4.78%	2.30%
Net Flow (% of TNA)	222180	-0.36	0.20	4.35
Inflow (% of TNA)	222180	1.58	3.13	4.83
Outflow (% of TNA)	222180	2.03	2.90	3.37

Table 28: Flow Reaction to Performance over Long Horizons

This table shows results from Fama-MacBeth regressions of different flow proxies on monthly performance metrics from lags 1 to 72 along with a set of controls. The performance metric in columns (1)-(3) is market adjusted return and in columns (4)-(6) is the 4-factor alpha. Market adjusted return is the fund's net return minus CRSP VW market index. Monthly four-factor alpha is computed as the fund's net return minus expected return from Fama-French-Carhart four factor model with betas computed in backward-looking window using rolling window time series regressions of fund's daily excess net returns on factor returns. These are computed for fund-months with at least 24 observations on past daily net returns in a 3-month window ending prior month. Net flows, inflows, and outflows are defined as (purchases-redemptions)*100/TNA_{t-1}, purchases*100/TNA_{t-1}, and redemptions*100/TNA_{t-1} respectively. The sample comprises actively managed US domestic equity funds during the period Jan-1999 to Dec-2017 excluding Institutional and Retirement funds. Standard errors are adjusted for autocorrelation up to 12 lags using Newey-West procedure and are reported in the parentheses. ***, **, * indicate statistical significance at the 1%, 5%, 10% levels respectively.

Performance metric is:	Market adj. ret.			4-factor alpha		
Dependent variable is:	Net Flow(%)	Inflow(%)	Outflow(%)	Net Flow(%)	Inflow(%)	Outflow(%)
	(1)	(2)	(3)	(4)	(5)	(6)
Perf (t-1)	19.055***	15.140***	-11.031***	17.318***	13.776***	-9.913***
	(1.563)	(1.485)	(0.922)	(1.434)	(1.375)	(0.912)
Perf (t-2)	20.313***	16.864***	-10.476***	17.875***	14.653***	-9.007***
	(1.834)	(1.549)	(1.163)	(1.675)	(1.425)	(1.038)
Perf (t-3)	18.861***	15.533***	-9.747***	17.495***	14.213***	-9.024***
	(1.762)	(1.384)	(1.157)	(1.529)	(1.322)	(1.022)
Perf (t-4)	17.857***	14.979***	-9.328***	15.842***	13.736***	-8.337***
	(1.837)	(1.719)	(1.298)	(1.816)	(1.541)	(1.158)
Perf (t-5)	17.998***	15.264***	-9.583***	16.087***	13.687***	-8.571***
	(1.639)	(1.450)	(0.996)	(1.661)	(1.407)	(0.977)
Perf (t-6)	16.833***	14.473***	-7.929***	15.767***	13.357***	-7.516***
	(1.761)	(1.505)	(0.984)	(1.868)	(1.650)	(1.059)
Perf (t-7)	17.019***	14.027***	-8.239***	15.699***	13.064***	-6.902***
	(1.828)	(1.621)	(1.017)	(1.687)	(1.713)	(0.769)
Perf (t-8)	17.408***	14.917***	-9.923***	16.274***	13.662***	-8.819***
	(1.866)	(1.504)	(1.284)	(1.885)	(1.698)	(1.083)
Perf (t-9)	16.348***	13.614***	-8.936***	14.506***	12.460***	-6.727***
	(1.758)	(1.609)	(0.974)	(1.629)	(1.537)	(0.876)
Perf (t-10)	16.866***	14.407***	-9.330***	15.958***	13.745***	-8.242***
	(1.838)	(1.437)	(0.961)	(1.553)	(1.367)	(0.964)
Perf (t-11)	17.198***	13.962***	-9.634***	14.846***	12.802***	-7.227***
	(1.348)	(1.292)	(0.920)	(1.062)	(1.197)	(0.679)
Perf (t-12)	14.177***	12.776***	-6.775***	12.790***	11.612***	-5.625***
	(1.512)	(1.407)	(0.899)	(1.251)	(1.381)	(0.762)
Perf (t-13)	10.926***	9.161***	-4.994***	10.357***	9.212***	-4.392***
	(1.127)	(0.947)	(0.600)	(1.118)	(1.023)	(0.626)
Perf (t-14)	10.530***	8.615***	-5.155***	9.331***	8.058***	-4.432***
	(1.411)	(1.211)	(0.990)	(1.164)	(1.040)	(0.920)
Perf (t-15)	9.850***	7.669***	-4.988***	8.649***	6.695***	-4.199***
	(1.208)	(0.948)	(0.968)	(1.105)	(0.999)	(0.911)

Perf (t-16)	7.526***	6.686***	-3.858***	6.642***	5.991***	-3.268***
	(0.960)	(1.004)	(0.721)	(1.071)	(1.172)	(0.841)
Perf (t-17)	6.965***	6.573***	-2.705***	5.883***	6.294***	-2.310***
	(0.826)	(0.854)	(0.545)	(0.679)	(0.807)	(0.770)
Perf (t-18)	8.890***	6.814***	-5.373***	7.718***	6.170***	-5.144***
	(0.977)	(0.826)	(0.916)	(0.928)	(0.761)	(0.755)
Perf (t-19)	8.610***	7.009***	-3.665***	7.064***	6.313***	-3.172***
	(1.046)	(0.932)	(0.717)	(1.128)	(1.083)	(0.845)
Perf (t-20)	8.526***	7.468***	-4.382***	8.197***	7.509***	-3.898***
	(1.084)	(1.112)	(0.775)	(1.145)	(1.169)	(0.782)
Perf (t-21)	7.781***	6.000***	-4.338***	6.390***	4.970***	-4.090***
	(1.124)	(1.063)	(0.720)	(0.945)	(1.083)	(1.014)
Perf (t-22)	7.968***	6.588***	-4.676***	6.212***	5.075***	-3.609***
	(0.945)	(0.695)	(0.876)	(0.904)	(0.789)	(0.862)
Perf (t-23)	7.347***	6.740***	-2.705***	6.371***	6.135***	-2.161***
	(0.917)	(0.721)	(0.679)	(0.858)	(0.781)	(0.816)
Perf (t-24)	6.711***	5.568***	-2.338***	5.705***	4.794***	-2.550***
	(0.845)	(1.011)	(0.665)	(0.839)	(0.823)	(0.694)
Perf (t-25)	6.521***	5.672***	-3.427***	5.609***	4.731***	-2.933***
	(0.817)	(0.640)	(0.806)	(0.910)	(0.858)	(0.896)
Perf (t-26)	5.990***	5.514***	-1.829***	4.496***	4.127***	-1.092
	(0.999)	(0.755)	(0.655)	(1.147)	(0.904)	(0.717)
Perf (t-27)	5.445***	5.163***	-1.718***	4.370***	4.103***	-1.469**
	(0.784)	(0.742)	(0.599)	(0.971)	(0.900)	(0.670)
Perf (t-28)	5.499***	4.295***	-2.741***	5.282***	4.624***	-3.227***
	(0.738)	(0.817)	(0.569)	(0.915)	(0.995)	(0.740)
Perf (t-29)	6.524***	5.901***	-3.191***	5.802***	5.786***	-2.557**
	(0.900)	(0.766)	(0.805)	(1.208)	(0.913)	(1.062)
Perf (t-30)	5.987***	5.512***	-2.360***	4.657***	4.081***	-1.206*
	(0.982)	(0.858)	(0.640)	(1.061)	(0.929)	(0.645)
Perf (t-31)	5.203***	4.528***	-2.276***	5.370***	4.992***	-1.541***
	(0.981)	(0.916)	(0.602)	(0.843)	(0.867)	(0.561)
Perf (t-32)	4.928***	4.510***	-1.592*	4.298***	4.332***	-0.688
	(1.155)	(0.919)	(0.913)	(1.066)	(0.865)	(0.792)
Perf (t-33)	4.208***	3.815***	-2.159***	4.571***	4.127***	-1.826**
	(1.045)	(0.788)	(0.695)	(0.905)	(0.870)	(0.754)
Perf (t-34)	5.586***	5.259***	-3.047***	6.104***	5.139***	-2.621***
	(1.165)	(0.907)	(0.891)	(0.967)	(0.943)	(0.756)
Perf (t-35)	3.914***	4.311***	-1.682**	3.559***	3.407***	-0.962
	(1.041)	(0.968)	(0.663)	(1.259)	(1.165)	(0.982)
Perf (t-36)	6.190***	5.875***	-2.636***	5.914***	5.430***	-2.350***
	(1.024)	(0.938)	(0.719)	(1.058)	(1.028)	(0.878)
Perf (t-37)	4.795***	4.789***	-2.476***	4.108***	3.693***	-2.180***
	(0.751)	(0.738)	(0.621)	(1.025)	(1.034)	(0.807)
Perf (t-38)	3.517***	4.433***	-0.980	2.759***	3.166***	-1.164*
	(0.707)	(0.746)	(0.614)	(0.913)	(1.016)	(0.608)
Perf (t-39)	3.307***	3.643***	-0.745	3.258***	3.478***	-0.602
	(0.803)	(0.769)	(0.714)	(1.007)	(0.864)	(0.968)
Perf (t-40)	3.694***	4.622***	-1.587**	2.352**	2.922***	-0.282
	(0.645)	(0.727)	(0.671)	(1.114)	(1.086)	(0.777)

Perf (t-41)	2.974***	3.312***	-0.240	2.350***	3.010***	-0.202
	(0.685)	(0.802)	(0.607)	(0.850)	(0.894)	(0.769)
Perf (t-42)	2.137***	3.426***	-0.546	1.329	2.308**	-0.283
	(0.740)	(0.844)	(0.784)	(1.079)	(1.072)	(0.726)
Perf (t-43)	1.992**	2.664***	-0.316	2.643**	3.308***	-1.706***
	(0.950)	(1.024)	(0.706)	(1.034)	(0.982)	(0.655)
Perf (t-44)	2.736***	3.129***	-0.469	2.892***	3.036***	-1.499*
	(0.900)	(0.926)	(0.794)	(1.064)	(1.044)	(0.818)
Perf (t-45)	1.509	1.200	0.167	1.506	1.793*	-0.272
	(0.962)	(0.831)	(0.768)	(1.161)	(0.958)	(0.858)
Perf (t-46)	1.490*	1.175	-0.494	0.837	0.696	-1.010
	(0.811)	(0.833)	(0.682)	(0.952)	(0.951)	(0.840)
Perf (t-47)	1.249	1.391	-0.206	-0.279	0.029	0.459
	(0.851)	(0.851)	(0.600)	(1.095)	(0.989)	(1.010)
Perf (t-48)	1.416*	2.394***	-0.161	1.455	2.580**	-1.154
	(0.735)	(0.873)	(0.563)	(0.993)	(1.022)	(0.749)
Perf (t-49)	1.606**	2.392***	0.059	1.034	1.700**	-0.118
	(0.808)	(0.786)	(0.745)	(0.962)	(0.847)	(0.873)
Perf (t-50)	0.835	1.653**	0.471	0.743	1.347	0.427
	(0.679)	(0.766)	(0.545)	(0.954)	(0.918)	(0.598)
Perf (t-51)	1.645**	1.557**	-0.121	0.911	1.034	0.356
	(0.634)	(0.627)	(0.517)	(0.936)	(0.658)	(0.867)
Perf (t-52)	1.785**	1.885**	-0.075	1.147	1.410**	0.548
	(0.689)	(0.735)	(0.624)	(0.852)	(0.701)	(0.919)
Perf (t-53)	0.634	1.596*	0.794	1.418**	2.044***	0.299
	(0.735)	(0.821)	(0.618)	(0.587)	(0.553)	(0.643)
Perf (t-54)	0.037	0.567	0.879	0.121	0.407	0.716
	(0.685)	(0.658)	(0.714)	(0.957)	(0.956)	(0.745)
Perf (t-55)	0.115	0.462	0.162	0.711	1.991**	0.405
	(0.635)	(0.602)	(0.699)	(0.862)	(0.790)	(0.795)
Perf (t-56)	1.120*	1.692**	-0.239	1.857**	3.272***	0.181
	(0.615)	(0.833)	(0.629)	(0.806)	(0.977)	(0.419)
Perf (t-57)	-0.034	0.097	0.375	0.652	0.951	0.344
	(0.713)	(0.827)	(0.534)	(0.710)	(0.796)	(0.647)
Perf (t-58)	1.330	1.326**	0.225	1.057	1.550**	0.546
	(0.842)	(0.627)	(0.671)	(0.693)	(0.666)	(0.736)
Perf (t-59)	0.661	1.164**	0.035	0.625	1.259	0.191
	(0.638)	(0.582)	(0.556)	(0.759)	(0.803)	(0.661)
Perf (t-60)	0.169	0.876	1.003	0.181	1.240*	1.048
	(0.917)	(0.700)	(0.717)	(0.779)	(0.714)	(0.674)
Perf (t-61)	0.133	0.689	0.353	-0.171	0.773	0.727
	(0.654)	(0.540)	(0.497)	(0.796)	(0.830)	(0.895)
Perf (t-62)	1.747***	2.449***	-0.512	1.326	1.871*	0.642
	(0.672)	(0.709)	(0.614)	(0.858)	(1.015)	(0.612)
Perf (t-63)	0.303	0.691	0.405	0.126	0.666	0.984*
	(0.758)	(0.654)	(0.733)	(0.687)	(0.894)	(0.595)
Perf (t-64)	0.477	0.819	0.326	1.059	1.087	0.078
	(0.759)	(0.707)	(0.593)	(0.775)	(0.888)	(0.613)
Perf (t-65)	-0.426	-0.163	0.713	-0.239	0.273	0.323
	(0.722)	(0.837)	(0.578)	(0.932)	(0.909)	(0.661)

Perf (t-66)	-0.431	0.003	0.379	-1.647**	-0.835	1.369**
	(0.581)	(0.701)	(0.497)	(0.698)	(0.803)	(0.569)
Perf (t-67)	-0.497	-0.198	0.201	-1.247	-0.454	0.522
	(0.778)	(0.822)	(0.638)	(0.771)	(0.827)	(0.632)
Perf (t-68)	-0.185	0.650	0.613	-0.101	0.759	-0.348
	(0.867)	(0.838)	(0.541)	(1.117)	(0.924)	(1.084)
Perf (t-69)	-0.915*	0.038	1.250**	-1.633**	-0.974	1.290**
	(0.530)	(0.692)	(0.510)	(0.692)	(0.856)	(0.565)
Perf (t-70)	-1.337*	-0.569	1.350**	-2.012**	-1.259	1.780**
	(0.742)	(0.753)	(0.672)	(0.913)	(0.874)	(0.748)
Perf (t-71)	-1.713***	-0.962	1.529***	-2.183***	-1.862**	0.979
	(0.534)	(0.684)	(0.483)	(0.778)	(0.764)	(0.664)
Perf (t-72)	-0.854	0.182	1.538***	-0.387	0.194	0.052
	(0.724)	(0.713)	(0.512)	(0.900)	(0.886)	(1.230)
Expense Ratio (t-1)	-0.749	14.018**	8.704*	-5.065	11.685*	16.921***
	(7.213)	(7.114)	(4.570)	(5.594)	(6.067)	(3.442)
Cat. Flow/TNA (t)	0.562			0.262**		
	(0.353)			(0.122)		
Fam. Flow/TNA (t)	0.294***			0.198***		
	(0.081)			(0.026)		
Purchases/TNA (t)			0.343***			0.337***
			(0.044)			(0.048)
Redemptions/TNA (t)		0.465***			0.461***	
		(0.060)			(0.062)	
Cat. Purchases/TNA (t)		0.012	0.176		0.228	-0.110
		(0.152)	(0.260)		(0.162)	(0.090)
Cat. Redemptions/TNA (t)		-0.533**	-0.069		-0.696***	0.282**
		(0.206)	(0.300)		(0.177)	(0.132)
Fam. Purchases/TNA (t)		0.224***	-0.074		0.202***	0.029
		(0.024)	(0.082)		(0.038)	(0.027)
Fam. Redemptions/TNA (t)		0.005	0.313***		0.027	0.268***
		(0.024)	(0.027)		(0.043)	(0.047)
Log(TNA) (t-1)	-0.036	-0.013	0.053***	-0.014	0.044**	0.070***
	(0.024)	(0.040)	(0.013)	(0.021)	(0.020)	(0.013)
Log(Fam. TNA) (t-1)	0.040	0.024	-0.078***	0.001	-0.016	-0.085***
	(0.026)	(0.041)	(0.020)	(0.021)	(0.013)	(0.016)
Log(Age) (t-1)	-0.319**	-0.363***	-0.161***	-0.113***	-0.328***	-0.235***
	(0.127)	(0.045)	(0.042)	(0.032)	(0.061)	(0.040)
Return SD (t-12,t-1)	21.020	62.318***	44.489***	6.632	22.875***	19.573***
	(17.462)	(22.672)	(9.250)	(6.745)	(8.411)	(2.973)
Constant	0.264	0.511	0.019	0.471	2.184***	1.389***
	(0.955)	(1.055)	(0.500)	(0.347)	(0.625)	(0.316)
Observations	132,386	132,386	132,386	112,234	112,234	112,234
R-squared	0.330	0.453	0.419	0.350	0.469	0.446
Number of groups	228	228	228	228	228	228

Table 29: Lag Length Selection for Buys vs. Sells

This table reports the p-Values from an F-test that some lags are jointly zero in the regressions in Table 28 of inflows and outflows on 72 lags of different performance metrics. Market-adjusted return is the performance metric used in the results of columns (1) and (2) below and 1-factor alpha is the metric used in columns (3) and (4). The main regression model is estimated with standard errors adjusted for cross-sectional and time-series correlation in error term for 12 months and these are used in the F-test as well. The sample used is equivalent to the estimation sample from Table 28.

Model:	Regression on lags of market-adjusted return		Regression on lags of 1-factor alpha	
Dependent Variable:	Outflows	Inflows	Outflows	Inflows
	(1)	(2)	(3)	(4)
Statistical Test:				
F-test that lags **t-38 to t-72** are jointly zero	0.524	0.000	0.125	0.000
F-test that lags **t-37 to t-72** are jointly zero	0.069		0.018	
F-test that lags **t-53 to t-72** are jointly zero		0.115		
F-test that lags **t-52 to t-72** are jointly zero		0.006		
F-test that lags **t-59 to t-72** are jointly zero				0.177
F-test that lags **t-58 to t-72** are jointly zero				0.093

Table 30: Performance Predictability using Long Horizon Past Returns

This table reports results from Fama-MacBeth regressions of one-month four-factor alpha on past monthly four-factor alphas at different lags. Columns (1) to (7) show the results using multivariate models with all lags included simultaneously and column (8) shows the coefficients on the lags in univariate regression models. The number of lags included increases from columns (1) to (5). Column (6) reports results using lagged one month four-factor alpha and just the quarterly lags and column (7) shows the results with just quarterly lags. Monthly four-factor alpha used as the dependent variable is computed as the fund's net return minus expected return from Fama-French-Carhart four factor model with betas computed in a forward-looking window using rolling window time series regressions of fund's daily excess net returns on factor returns. These are computed for fund-months with at least 24 observations on future daily net returns in a 3-month window beginning from the current month. If a fund dies in this window, I replace its return with CRSP VW market return for the remaining period. Monthly four-factor alpha used as the explanatory variable is computed as the fund's net return minus expected return from Fama-French-Carhart four factor model with betas computed in backward-looking window using rolling window time series regressions of fund's daily excess net returns on factor returns. These are computed for fund-months with at least 24 observations on past daily net returns in a 3-month window ending prior month. The sample comprises actively managed US domestic equity funds during the period Jan-1999 to Dec-2017 excluding Institutional and Retirement funds. Standard errors are reported in the parentheses. ***, **, * indicate statistical significance at the 1%, 5%, 10% levels respectively.

Dependent variable is: one-month four-factor alpha								
	Multivariate Models							Univariate
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Four-factor alpha [t-1]	0.017*	0.018**	0.014**	0.014**	0.014**	0.014*		0.021**
	(0.010)	(0.009)	(0.007)	(0.007)	(0.007)	(0.008)		(0.011)
Four-factor alpha [t-2]	0.010	0.012	0.011	0.013**	0.014**			0.007
	(0.009)	(0.008)	(0.007)	(0.006)	(0.006)			(0.010)
Four-factor alpha [t-3]	0.018*	0.019**	0.016**	0.015**	0.014**	0.017**	0.017**	0.020*
	(0.009)	(0.009)	(0.007)	(0.007)	(0.006)	(0.008)	(0.008)	(0.011)
Four-factor alpha [t-4]	0.000	0.004	0.009	0.009*	0.010*			0.004
	(0.008)	(0.007)	(0.006)	(0.005)	(0.005)			(0.010)
Four-factor alpha [t-5]	0.022***	0.019**	0.018***	0.018***	0.018***			0.026***
	(0.008)	(0.007)	(0.006)	(0.006)	(0.006)			(0.010)
Four-factor alpha [t-6]	0.026***	0.027***	0.024***	0.023***	0.023***	0.025***	0.026***	0.031***
	(0.008)	(0.007)	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)	(0.009)
Four-factor alpha [t-7]		0.005	0.004	0.003	0.002			0.011
		(0.008)	(0.006)	(0.006)	(0.006)			(0.010)

Four-factor alpha [t-8]	0.015**	0.016***	0.014**	0.013**			0.019*
	(0.007)	(0.006)	(0.005)	(0.005)			(0.010)
Four-factor alpha [t-9]	0.025***	0.019***	0.018***	0.017***	0.023***	0.023***	0.033***
	(0.007)	(0.005)	(0.005)	(0.005)	(0.006)	(0.007)	(0.009)
Four-factor alpha [t-10]	-0.003	0.004	0.005	0.006			-0.004
	(0.007)	(0.006)	(0.006)	(0.005)			(0.009)
Four-factor alpha [t-11]	0.020***	0.016***	0.015***	0.015***			0.021**
	(0.007)	(0.005)	(0.005)	(0.005)			(0.009)
Four-factor alpha [t-12]	0.016**	0.013**	0.011**	0.010**	0.014**	0.015**	0.017*
	(0.007)	(0.006)	(0.005)	(0.005)	(0.007)	(0.007)	(0.010)
Four-factor alpha [t-13]		-0.007	-0.006	-0.005			-0.011
		(0.005)	(0.005)	(0.005)			(0.009)
Four-factor alpha [t-14]		0.010	0.010*	0.011**			0.004
		(0.006)	(0.006)	(0.006)			(0.012)
Four-factor alpha [t-15]		0.011*	0.010*	0.009*	0.014**	0.015**	0.019*
		(0.006)	(0.006)	(0.005)	(0.007)	(0.007)	(0.010)
Four-factor alpha [t-16]		0.000	0.001	0.001			-0.006
		(0.005)	(0.005)	(0.005)			(0.010)
Four-factor alpha [t-17]		0.008	0.009	0.009*			0.019*
		(0.006)	(0.005)	(0.005)			(0.010)
Four-factor alpha [t-18]		0.007	0.004	0.003	0.004	0.004	0.002
		(0.006)	(0.005)	(0.005)	(0.007)	(0.007)	(0.010)
Four-factor alpha [t-19]		-0.006	-0.006	-0.004			-0.010
		(0.005)	(0.005)	(0.004)			(0.009)
Four-factor alpha [t-20]		0.002	0.003	0.003			0.003
		(0.006)	(0.005)	(0.005)			(0.010)
Four-factor alpha [t-21]		0.010**	0.009**	0.009**	0.007	0.007	0.011
		(0.005)	(0.005)	(0.004)	(0.005)	(0.005)	(0.008)
Four-factor alpha [t-22]		0.003	0.002	0.001			0.003
		(0.005)	(0.004)	(0.004)			(0.009)

Four-factor alpha [t-23]	0.000	0.003	0.004			-0.006
	(0.005)	(0.005)	(0.005)			(0.009)
Four-factor alpha [t-24]	0.015***	0.014***	0.013***	0.012**	0.013**	0.017**
	(0.005)	(0.004)	(0.004)	(0.006)	(0.006)	(0.008)
Four-factor alpha [t-25]	-0.005	-0.004	-0.003			0.001
	(0.005)	(0.005)	(0.005)			(0.009)
Four-factor alpha [t-26]	0.001	0.001	0.001			0.002
	(0.005)	(0.004)	(0.004)			(0.009)
Four-factor alpha [t-27]	0.001	-0.001	-0.001	-0.002	-0.001	-0.003
	(0.005)	(0.004)	(0.004)	(0.006)	(0.006)	(0.009)
Four-factor alpha [t-28]	0.014***	0.012***	0.010**			0.021**
	(0.004)	(0.004)	(0.004)			(0.009)
Four-factor alpha [t-29]	0.005	0.005	0.006			0.012
	(0.005)	(0.005)	(0.004)			(0.009)
Four-factor alpha [t-30]	0.004	0.004	0.005	0.004	0.005	-0.000
	(0.004)	(0.004)	(0.004)	(0.005)	(0.006)	(0.008)
Four-factor alpha [t-31]	0.005	0.003	0.002			0.001
	(0.004)	(0.004)	(0.004)			(0.008)
Four-factor alpha [t-32]	0.004	0.002	0.003			0.007
	(0.004)	(0.004)	(0.004)			(0.008)
Four-factor alpha [t-33]	0.009**	0.007	0.006	0.011**	0.010*	0.018**
	(0.005)	(0.004)	(0.004)	(0.006)	(0.006)	(0.009)
Four-factor alpha [t-34]	-0.001	0.001	0.001			0.007
	(0.004)	(0.004)	(0.004)			(0.008)
Four-factor alpha [t-35]	0.000	0.000	-0.001			0.005
	(0.004)	(0.004)	(0.004)			(0.008)
Four-factor alpha [t-36]	0.022***	0.021***	0.020***	0.019***	0.020***	0.026***
	(0.005)	(0.004)	(0.004)	(0.005)	(0.005)	(0.008)
Four-factor alpha [t-37]		-0.003	-0.003			0.003
		(0.004)	(0.004)			(0.008)

Four-factor alpha [t-38]	0.002	0.001			0.001
	(0.004)	(0.004)			(0.008)
Four-factor alpha [t-39]	0.003	0.001	0.003	0.002	0.006
	(0.004)	(0.004)	(0.005)	(0.005)	(0.007)
Four-factor alpha [t-40]	0.004	0.003			0.000
	(0.004)	(0.004)			(0.008)
Four-factor alpha [t-41]	0.000	0.001			-0.006
	(0.004)	(0.004)			(0.009)
Four-factor alpha [t-42]	0.007*	0.006*	0.004	0.004	0.004
	(0.004)	(0.004)	(0.004)	(0.005)	(0.007)
Four-factor alpha [t-43]	0.005	0.004			0.008
	(0.004)	(0.004)			(0.007)
Four-factor alpha [t-44]	0.000	-0.000			0.009
	(0.004)	(0.003)			(0.007)
Four-factor alpha [t-45]	0.005	0.005	0.006	0.005	0.004
	(0.003)	(0.003)	(0.005)	(0.005)	(0.008)
Four-factor alpha [t-46]	-0.002	-0.000			0.000
	(0.004)	(0.004)			(0.008)
Four-factor alpha [t-47]	0.003	0.004			0.000
	(0.004)	(0.004)			(0.008)
Four-factor alpha [t-48]	0.007*	0.007*	0.007	0.007	0.008
	(0.004)	(0.004)	(0.005)	(0.005)	(0.008)
Four-factor alpha [t-49]		-0.005			-0.005
		(0.004)			(0.008)
Four-factor alpha [t-50]		0.004			-0.004
		(0.004)			(0.007)
Four-factor alpha [t-51]		0.003	0.001	0.001	0.000
		(0.004)	(0.005)	(0.005)	(0.007)
Four-factor alpha [t-52]		0.003			0.005
		(0.004)			(0.008)

Four-factor alpha [t-53]					-0.000			0.001
					(0.004)			(0.008)
Four-factor alpha [t-54]					-0.000	0.005	0.004	0.009
					(0.004)	(0.005)	(0.005)	(0.008)
Four-factor alpha [t-55]					-0.001			-0.003
					(0.004)			(0.007)
Four-factor alpha [t-56]					-0.001			0.007
					(0.003)			(0.007)
Four-factor alpha [t-57]					-0.001	0.000	0.000	0.011
					(0.003)	(0.005)	(0.005)	(0.007)
Four-factor alpha [t-58]					-0.000			-0.005
					(0.003)			(0.008)
Four-factor alpha [t-59]					-0.003			-0.005
					(0.004)			(0.008)
Four-factor alpha [t-60]					0.000	0.000	0.001	0.000
					(0.003)	(0.004)	(0.004)	(0.007)
Intercept	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	
Adj. R^2	0.092	0.146	0.237	0.257	0.273	0.164	0.155	
Obs	207479	207479	207479	207479	207479	207479	207479	207479

Table 31: Performance Predictability using Long Horizon Past Returns by Calendar Month Sub-Samples

This table reports results from Fama-MacBeth regressions of one-month four-factor alpha on 60 lags of past monthly four-factor alphas. Columns (1) to (4) show the results in different sub-samples formed based on the calendar month. Column (1) uses sample with only January months; (2) uses sample with all non-January months; (3) uses sample with only the quarter-beginning months Jan, Apr, Jul, Oct; (4) uses sample with only the quarter-end months Mar, Jun, Sep, Dec; and (5) uses sample with only non-quarter-end months. In the regressions, monthly four-factor alpha used as the dependent variable is computed as the fund's net return minus expected return from Fama-French-Carhart four factor model with betas computed in a forward-looking window using rolling window time series regressions of fund's daily excess net returns on factor returns. These are computed for fund-months with at least 24 observations on future daily net returns in a 3-month window beginning from the current month. If a fund dies in this window, I replace its return with CRSP VW market return for the remaining period. Monthly four-factor alpha used as the explanatory variable is computed as the fund's net return minus expected return from Fama-French-Carhart four factor model with betas computed in backward-looking window using rolling window time series regressions of fund's daily excess net returns on factor returns. These are computed for fund-months with at least 24 observations on past daily net returns in a 3-month window ending prior month. The sample comprises actively managed US domestic equity funds during the period Jan-1999 to Dec-2017 excluding Institutional and Retirement funds. Standard errors are reported in the parentheses. ***, **, * indicate statistical significance at the 1%, 5%, 10% levels respectively.

	Dependent variable is: one-month four-factor alpha				
Sample contains:	Only January months	Only Non-Jan months	Only Quarter-beginning months	Only Quarter-end months	Only Non-quarter-end months
	(1)	(2)	(3)	(4)	(5)
Four-factor alpha [t-1]	-0.014	0.016**	0.010	0.018	0.012
	(0.018)	(0.007)	(0.014)	(0.012)	(0.008)
Four-factor alpha [t-2]	-0.017	0.017***	0.002	0.016	0.013*
	(0.020)	(0.006)	(0.010)	(0.010)	(0.008)
Four-factor alpha [t-3]	0.022	0.013*	0.002	0.017	0.012
	(0.023)	(0.007)	(0.011)	(0.012)	(0.008)
Four-factor alpha [t-4]	0.022	0.009	0.011	0.020**	0.004
	(0.019)	(0.005)	(0.010)	(0.008)	(0.006)
Four-factor alpha [t-5]	0.012	0.019***	0.018	0.011*	0.022***
	(0.021)	(0.006)	(0.011)	(0.006)	(0.008)
Four-factor alpha [t-6]	0.050**	0.020***	0.021**	0.013	0.027***
	(0.017)	(0.006)	(0.009)	(0.009)	(0.007)
Four-factor alpha [t-7]	0.031*	-0.000	0.004	0.008	-0.001
	(0.016)	(0.006)	(0.010)	(0.011)	(0.006)
Four-factor alpha [t-8]	0.011	0.014**	0.023**	0.005	0.017**
	(0.023)	(0.006)	(0.011)	(0.008)	(0.007)
Four-factor alpha [t-9]	-0.005	0.019***	0.021**	0.021***	0.015**
	(0.022)	(0.005)	(0.010)	(0.008)	(0.007)

Four-factor alpha [t-10]	-0.012	0.008	0.003	0.012	0.003
	(0.014)	(0.006)	(0.010)	(0.009)	(0.007)
Four-factor alpha [t-11]	0.006	0.016***	0.011	0.014*	0.015**
	(0.014)	(0.005)	(0.009)	(0.008)	(0.006)
Four-factor alpha [t-12]	0.016	0.010*	0.002	0.010	0.010*
	(0.022)	(0.005)	(0.009)	(0.010)	(0.006)
Four-factor alpha [t-13]	0.006	-0.007	0.002	-0.006	-0.005
	(0.021)	(0.005)	(0.009)	(0.008)	(0.006)
Four-factor alpha [t-14]	0.002	0.012**	0.011	0.010	0.012
	(0.014)	(0.006)	(0.011)	(0.009)	(0.007)
Four-factor alpha [t-15]	0.012	0.009*	0.026**	-0.004	0.016**
	(0.017)	(0.006)	(0.010)	(0.009)	(0.007)
Four-factor alpha [t-16]	0.041*	-0.002	0.006	-0.008	0.006
	(0.021)	(0.005)	(0.010)	(0.009)	(0.006)
Four-factor alpha [t-17]	-0.004	0.011**	0.010	0.015**	0.007
	(0.013)	(0.005)	(0.011)	(0.006)	(0.007)
Four-factor alpha [t-18]	0.019	0.002	0.002	-0.004	0.007
	(0.021)	(0.005)	(0.009)	(0.009)	(0.006)
Four-factor alpha [t-19]	-0.014	-0.003	-0.000	0.006	-0.009
	(0.014)	(0.005)	(0.009)	(0.007)	(0.006)
Four-factor alpha [t-20]	0.006	0.003	-0.004	-0.003	0.007
	(0.021)	(0.005)	(0.010)	(0.007)	(0.007)
Four-factor alpha [t-21]	-0.014	0.011**	-0.007	0.015*	0.006
	(0.014)	(0.005)	(0.006)	(0.008)	(0.005)
Four-factor alpha [t-22]	0.026	-0.001	0.007	-0.007	0.006
	(0.020)	(0.004)	(0.008)	(0.008)	(0.005)
Four-factor alpha [t-23]	0.008	0.004	0.005	-0.001	0.007
	(0.024)	(0.005)	(0.009)	(0.007)	(0.006)
Four-factor alpha [t-24]	0.008	0.013***	0.018**	0.008	0.015***
	(0.014)	(0.004)	(0.008)	(0.008)	(0.005)
Four-factor alpha [t-25]	0.022	-0.005	0.002	-0.006	-0.001
	(0.015)	(0.005)	(0.008)	(0.009)	(0.006)
Four-factor alpha [t-26]	0.016	-0.001	-0.004	-0.004	0.003
	(0.013)	(0.004)	(0.007)	(0.006)	(0.006)
Four-factor alpha [t-27]	0.001	-0.001	-0.001	0.003	-0.003
	(0.009)	(0.004)	(0.007)	(0.007)	(0.005)
Four-factor alpha [t-28]	-0.011	0.012***	0.013*	0.014*	0.008*
	(0.017)	(0.004)	(0.007)	(0.008)	(0.005)
Four-factor alpha [t-29]	0.014	0.005	0.003	0.013**	0.003
	(0.012)	(0.004)	(0.008)	(0.005)	(0.006)
Four-factor alpha [t-30]	-0.010	0.006	0.002	0.005	0.004
	(0.014)	(0.004)	(0.006)	(0.007)	(0.005)

Four-factor alpha [t-31]	-0.009	0.003	0.003	-0.000	0.004
	(0.011)	(0.004)	(0.007)	(0.005)	(0.005)
Four-factor alpha [t-32]	0.007	0.003	-0.002	0.010	-0.000
	(0.012)	(0.004)	(0.006)	(0.006)	(0.005)
Four-factor alpha [t-33]	-0.004	0.007	0.000	0.001	0.008
	(0.012)	(0.005)	(0.007)	(0.008)	(0.005)
Four-factor alpha [t-34]	-0.020*	0.003	-0.002	-0.002	0.003
	(0.010)	(0.004)	(0.008)	(0.006)	(0.005)
Four-factor alpha [t-35]	-0.001	-0.001	0.007	-0.002	-0.000
	(0.013)	(0.004)	(0.007)	(0.006)	(0.005)
Four-factor alpha [t-36]	0.015	0.021***	0.024***	0.020**	0.021***
	(0.011)	(0.004)	(0.006)	(0.009)	(0.004)
Four-factor alpha [t-37]	-0.014	-0.002	-0.010	0.002	-0.006
	(0.014)	(0.004)	(0.007)	(0.006)	(0.005)
Four-factor alpha [t-38]	-0.024	0.003	-0.004	-0.001	0.002
	(0.018)	(0.004)	(0.007)	(0.007)	(0.005)
Four-factor alpha [t-39]	0.023	-0.001	-0.002	0.012	-0.004
	(0.016)	(0.004)	(0.008)	(0.008)	(0.005)
Four-factor alpha [t-40]	-0.001	0.003	0.009	0.001	0.004
	(0.010)	(0.005)	(0.008)	(0.008)	(0.005)
Four-factor alpha [t-41]	0.014**	-0.000	0.001	0.002	0.001
	(0.006)	(0.005)	(0.009)	(0.006)	(0.006)
Four-factor alpha [t-42]	0.026	0.004	0.013**	0.001	0.009*
	(0.015)	(0.004)	(0.007)	(0.005)	(0.005)
Four-factor alpha [t-43]	0.015	0.003	0.011	0.006	0.004
	(0.008)	(0.004)	(0.007)	(0.008)	(0.005)
Four-factor alpha [t-44]	0.005	-0.000	0.006	-0.007	0.003
	(0.011)	(0.004)	(0.007)	(0.005)	(0.004)
Four-factor alpha [t-45]	0.008	0.005	0.005	0.007	0.004
	(0.013)	(0.003)	(0.006)	(0.005)	(0.004)
Four-factor alpha [t-46]	0.008	-0.001	0.010	-0.007	0.003
	(0.010)	(0.004)	(0.006)	(0.006)	(0.005)
Four-factor alpha [t-47]	0.000	0.004	0.007	0.005	0.004
	(0.019)	(0.004)	(0.007)	(0.006)	(0.005)
Four-factor alpha [t-48]	0.011	0.006	0.010*	0.016***	0.002
	(0.010)	(0.004)	(0.006)	(0.006)	(0.005)
Four-factor alpha [t-49]	-0.007	-0.005	-0.007	-0.007	-0.004
	(0.016)	(0.004)	(0.007)	(0.007)	(0.005)
Four-factor alpha [t-50]	0.020*	0.002	0.005	0.003	0.004
	(0.011)	(0.004)	(0.006)	(0.005)	(0.005)
Four-factor alpha [t-51]	-0.013	0.004	-0.003	0.004	0.002
	(0.014)	(0.004)	(0.006)	(0.007)	(0.004)

Four-factor alpha [t-52]	0.005	0.003	0.008	0.000	0.004
	(0.017)	(0.004)	(0.007)	(0.006)	(0.005)
Four-factor alpha [t-53]	0.003	-0.001	0.001	0.001	-0.001
	(0.017)	(0.004)	(0.008)	(0.005)	(0.005)
Four-factor alpha [t-54]	-0.012	0.001	-0.006	-0.009	0.005
	(0.009)	(0.004)	(0.006)	(0.006)	(0.005)
Four-factor alpha [t-55]	-0.018*	0.001	-0.007	0.001	-0.002
	(0.010)	(0.004)	(0.007)	(0.007)	(0.004)
Four-factor alpha [t-56]	0.013	-0.002	0.009	-0.009	0.004
	(0.010)	(0.004)	(0.006)	(0.006)	(0.004)
Four-factor alpha [t-57]	0.005	-0.001	-0.003	0.001	-0.002
	(0.008)	(0.003)	(0.005)	(0.006)	(0.004)
Four-factor alpha [t-58]	0.006	-0.001	-0.005	0.006	-0.003
	(0.012)	(0.004)	(0.005)	(0.007)	(0.004)
Four-factor alpha [t-59]	-0.009	-0.002	-0.005	0.005	-0.006
	(0.014)	(0.004)	(0.007)	(0.005)	(0.005)
Four-factor alpha [t-60]	-0.004	0.001	0.001	0.000	0.000
	(0.009)	(0.003)	(0.004)	(0.006)	(0.003)
Intercept	-0.001	-0.001***	-0.001***	-0.000	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Adj. R^2	0.266	0.274	0.265	0.277	0.271
Obs	17389	190090	68448	69554	137925

Table 32: Economic Significance of Predictability with the 60-lag model

This table shows the monthly value-weighted net returns and four-factor alphas on portfolios formed using the predicted value from regression model of four-factor alpha on 60 lags of monthly four-factor alphas. Each month, funds are assigned to ten portfolios based on this predicted value and the performance of each portfolio is tracked for one month, with the process repeating every month. Column (1) reports the net returns of each portfolio averaged across all funds in the portfolio using prior month TNA as weights. Columns (2) to (6) report the four-factor alpha and betas from regressing the VW-weighted net returns time series of each portfolio in the full sample on the Fama-French-Carhart four factors. Decile 1A is the bottom third sub-division of decile 1 which has funds performing poorly on the metric used to form portfolios. Decile 10C is the upper third sub-division of decile 10 which has the best-performing funds on the metric used to form portfolios. Last three rows of the table report performance of spread portfolios formed from the other portfolios. The sample comprises actively managed US domestic equity funds during the period Jan-1999 to Dec-2017 excluding Institutional and Retirement funds. Statistical significance is assessed using standard errors that are robust to heteroscedasticity. ***, **, * indicate statistical significance at the 1%, 5%, 10% levels respectively.

Performance at (t) of portfolios sorted on predicted value from the model with 60 lags of FFC4 alphas						
	Net Return	α_{FFC4}	β_{mkt}	β_{SMB}	β_{HML}	β_{UMD}
Portfolio	(1)	(2)	(3)	(4)	(5)	(6)
Bottom 10 funds	0.404	-0.629***	1.173***	0.485***	-0.147**	-0.068
Decile 1A	0.633*	-0.328***	1.099***	0.403***	-0.109**	-0.124***
Decile 1 (Bottom)	0.655*	-0.285***	1.072***	0.368***	-0.124***	-0.095***
Decile 2	0.690**	-0.194***	1.009***	0.240***	-0.111***	-0.039***
Decile 3	0.737**	-0.162***	1.032***	0.209***	-0.099***	-0.028**
Decile 4	0.728**	-0.170***	1.039***	0.150***	-0.159***	-0.032**
Decile 5	0.780**	-0.094**	1.012***	0.116***	-0.091***	-0.011
Decile 6	0.759**	-0.108**	1.006***	0.100***	-0.100***	-0.023
Decile 7	0.816***	-0.055	1.008***	0.094***	-0.092***	0.007
Decile 8	0.856***	-0.019	1.012***	0.093***	-0.072***	0.013
Decile 9	0.815***	-0.066	1.018***	0.100***	-0.085***	0.029**
Decile 10 (Top)	0.898***	0.021	1.004***	0.140***	-0.127***	0.038*
Decile 10C	0.894***	0.011	1.007***	0.186***	-0.150**	0.017
Top 10 funds	0.912***	0.041	0.966***	0.322***	-0.178***	0.043
10-1 Spread	0.243**	0.306***	-0.068**	-0.228***	-0.003	0.133***
10C-1A Spread	0.261*	0.339**	-0.092*	-0.218***	-0.041	0.141***
Top 10-Bottom 10 Spread	0.508**	0.670***	-0.207***	-0.163*	-0.031	0.111

Table 33: Economic Significance of Predictability with One-month Net Returns

This table shows the monthly value-weighted net returns and four-factor alphas on portfolios formed using one-month net returns in the prior period. Each month, funds are assigned to ten portfolios based on their net returns in the prior month and the performance of each portfolio is tracked for one month, with the process repeating every month. Column (1) reports the net returns of each portfolio averaged across all funds in the portfolio using prior month TNA as weights. Columns (2) to (6) report the four-factor alpha and betas from regressing the VW-weighted net returns time series of each portfolio in the full sample on the Fama-French-Carhart four factors. Decile 1A is the bottom third sub-division of decile 1 which has funds performing poorly on prior 1-month net return. Decile 10C is the upper third sub-division of decile 10 which has the best-performing funds on prior 1-month net return. Last three rows of the table report performance of spread portfolios formed from the other portfolios. The sample comprises actively managed US domestic equity funds during the period Jan-1999 to Dec-2017 excluding Institutional and Retirement funds. Statistical significance is assessed using standard errors that are robust to heteroscedasticity. ***, **, * indicate statistical significance at the 1%, 5%, 10% levels respectively.

Performance at (t) of portfolios sorted on 1-month net return at (t-1)						
	Net Return	α_{FFC4}	β_{mkt}	β_{SMB}	β_{HML}	β_{UMD}
Portfolio	(1)	(2)	(3)	(4)	(5)	(6)
Bottom 10 funds	0.026	-0.823***	1.224***	0.237*	-0.192	0.057
Decile 1A	0.302	-0.528***	1.216***	0.194*	-0.122	0.026
Decile 1 (Bottom)	0.407	-0.374***	1.169***	0.126	-0.062	-0.003
Decile 2	0.494	-0.252***	1.114***	0.076	-0.031	0.015
Decile 3	0.558*	-0.147**	1.064***	0.044	-0.043	0.006
Decile 4	0.591**	-0.096*	1.045***	0.018	-0.035	0.006
Decile 5	0.629**	-0.052	1.012***	0.058	-0.022	-0.008
Decile 6	0.624**	-0.052	0.995***	0.031*	0.011	0.021
Decile 7	0.651**	-0.027	0.972***	0.096***	-0.018	0.008
Decile 8	0.717**	0.008	0.968***	0.181**	-0.032	0.027
Decile 9	0.777***	0.079	0.931***	0.208***	-0.021	0.017
Decile 10 (Top)	0.885***	0.166	0.899***	0.342***	-0.076	0.020
Decile 10C	0.891**	0.186	0.853***	0.420***	-0.127	-0.013
Top 10 funds	0.828**	0.193	0.719***	0.476***	-0.194	-0.045
10-1 Spread	0.478*	0.539**	-0.270**	0.215	-0.014	0.024
10C-1A Spread	0.589	0.714**	-0.363***	0.226	-0.005	-0.039
Top 10-Bottom 10 Spread	0.802*	1.016**	-0.505***	0.239	-0.002	-0.102

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