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DOI:
10.1016/j.jbankfin.2017.05.013

Document Version
Accepted author manuscript

Link to publication record in Manchester Research Explorer

Citation for published version (APA):
Brown, S. J., Sotes-Paladino, J., Wang, J., & Yao, C. (2017). Starting on the Wrong Foot: Seasonality in Mutual Fund Performance. *Journal of Banking and Finance*, *82*. https://doi.org/10.1016/j.jbankfin.2017.05.013

Published in:
Journal of Banking and Finance

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Download date:09. Jun. 2022

Starting on the Wrong Foot: Seasonality in Mutual Fund Performance*

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April 2017

Abstract: We document a systematic seasonal component in the aggregate underperformance of active mutual funds. At the aggregate level, active funds underperform the market and other passive benchmarks only in the first month of a quarter. This intra-quarter performance seasonality holds across fund sizes and investment styles. The pattern is consistent with short-term stock return reversal effects along with aggregate window-dressing and, to a lesser extent, NAV-inflation practices around quarter-ends. We find marginal or no evidence of microstructure biases, fund investor flows, or cash distributions as sources of this seasonality. Our findings highlight new features of the active management underperformance puzzle.

JEL classification: G23; G12; G11

Keywords: Mutual funds; performance evaluation; seasonality; benchmark index.

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* We thank Torben Andersen, Tze Chuan Ang (AsianFA discussant), Jonathan Berk, Michael Brennan, John Campbell, Wayne Ferson, Bruce Grundy, Vasso Ioannidou, Narasimhan Jegadeesh, Byoung Uk Kang(FMA discussant), Simi Kedia, Robert Korajczyk, Robert Kosowski, Peter Kyle, Spencer Martin, Federico Nardari, Thomas Ruf (AFBC discussant), Johan Sulaeman (SFM discussant), Russ Wermers, Mungo Wilson, an associate editor, an anonymous referee, and seminar participants at Capital University of Economics and Business, Lund University, Melbourne University, Zhongnan University of Economics and Law, the Asian Finance Association 2016 Annual Meeting, the Financial Management Association 2016 Annual Meeting, the 24th Conference on the Theories and Practices of Securities and Financial Markets, the 29th Australasian Finance and Banking Conference, for their helpful comments. Part of the paper was completed while Jiaguo (George) Wang and Yaqiong Yao were visiting New York University's Stern School of Business in 2012 and 2015. Yaqiong Yao acknowledges financial supports from Lancaster University Management School for visiting NYU Stern in 2015.
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1. Introduction

According to the vast literature on mutual funds, active managers as a group underperform passively managed investment alternatives. Indeed, recent studies have shown that, on average, a dollar-weighted portfolio of active funds yields significantly negative after-fee returns in excess of the market portfolio.[1] In this study, we contribute to this literature by documenting a new seasonal pattern in the returns to active funds, whose aggregate underperformance is largely confined to the first month of each quarter.

We begin by establishing the pervasiveness and economic significance of this seasonality. Between 1967 and 2013, the net-of-fee returns in excess of the market to a value-weighted (VW) portfolio of US active mutual funds average -25 basis points in the first month of a quarter. By contrast, these returns are statistically indistinguishable from zero in the other two months. The beginning-of-quarter effect cumulates to a VW average fund excess return of -105 basis points over January, April, July, and October, exceeding the well-documented underperformance of active funds over the calendar year. This effect remains significant when the VW return to active funds is adjusted by exposure to factor risk. We find no evidence of risk-adjusted under or outperformance in the remaining two months of the quarter.

The performance seasonality of active funds is ubiquitous across fund size quintiles and investment styles. Given that the mutual fund industry is highly concentrated, aggregate patterns in performance could potentially be driven by a few very large funds. By contrast, we find that all but the smallest size quintile exhibit a significant underperformance in the first month of the quarter only. The market-adjusted return to the VW portfolios of active funds across size quintiles typically improves toward the end of the quarter, with smaller funds doing relatively better than their larger peers. Similarly, the benchmark indices that most domestic equity funds outside the large-cap investment style report in their prospectuses (e.g., the Russell 2000 index) differ markedly from a market portfolio. If the benchmark indices associated with the different investment styles exhibit any seasonality with respect to our market proxies, our results could be mechanically driven by these benchmarks. However, we find no evidence that this is the case. The beginning-of-quarter aggregate underperformance holds for VW portfolios of both large- and mid-cap funds before factor risk adjustment and for VW portfolios of funds in all investment styles (large-, mid- and small-cap) after factor risk adjustment. Moreover, none of these portfolios under or outperform their benchmarks in the remaining two months of a quarter at the conventional statistical significance levels.

[1] See, e.g., Fama and French (2010) and Lewellen (2011).

Next, we examine whether the dynamics of funds' trading, investors' money flows, or financial markets can help explain the seasonality in the active fund industry performance. We focus on the seasonal patterns documented in the literature and examine whether these seasonal patterns relate to the aggregate performance of active funds. Specifically, we assess the impact of window-dressing and NAV-inflation practices, market microstructure biases in the computation of stock prices on funds' NAV, and seasonality in fund investor flows and cash distributions on the VW portfolio of all active funds.

Window dressing involves buying stocks with good recent performance ("winners") or dumping stocks with poor recent performance ("losers") near the end of a quarter to improve the appearance of a portfolio that will be presented to clients or shareholders. Agarwal et al. (2014) find that poorly performing and less skilled mutual funds are more likely to engage in window dressing. Consistent with window dressing signaling low managerial skill, they also find that, at the individual-fund level, window dressers suffer lower future returns both in the short (i.e., one quarter ahead) and long (i.e., one to three years ahead) terms.

We contribute to this strand of the literature by showing that *fund-level* window dressing practices (i) can have negative *industry-level* performance implications, and (ii) along with one-month stock return reversal effects, can lead to *intra-quarter seasonality* in aggregate fund performance. It is well known that winner stocks suffer large one-month return reversals (Jegadeesh, 1990; Jegadeesh and Titman, 1993; Grundy and Martin, 2001). Consistent with this effect, we find that funds with high quarter-end loadings on winner stocks systematically suffer the poorest first-month-of-the-quarter performance, as winner stocks experience low returns in the following month. Because this pattern remains significant on a VW basis, it contributes negatively to the excess returns to the dollar-weighted portfolio of all active funds in the first month of a quarter. We find a similar beginning-of-quarter performance pattern when we rank funds directly by their measured levels of window-dressing behavior, which reflects both overweighting of winners and underweighting of loser stocks at quarter ends.

Moreover, we report weak evidence of an aggregate impact of NAV-inflation practices on the performance of active funds at the beginning of a quarter. NAV inflation refers to the practice of marking the close; in other words, it involves inflating the prices of stocks already in a manager's portfolio to boost fund performance at the quarter-end. Carhart et al. (2002) document turn-of-quarter NAV-inflation practices among small-cap funds and show, at the individual-fund level, that these practices can lead to negative fund returns on the first day of a quarter. We find that, as expected from temporary NAV inflation at quarter-ends and the ensuing NAV reversal shortly afterwards, the aggregate excess return to active funds over the first two days of the quarter accounts for nearly one-third of the explained variation in the first month. However, compared to the first day, other days in the first month account for a similar or higher fraction of the explained variation in funds' excess returns in that month.

Other potential sources of seasonality that have been addressed in the literature have limited or no ability to explain the beginning-of-quarter drag on fund returns. In particular, we examine (i) the effect of market microstructure biases in the computation of stock prices on fund NAV and (ii) the impact of seasonality in investor flows and fund cash distributions on active fund performance. We detect marginal evidence of a microstructure bias associated with the turn-of-quarter effect, but this bias still leaves most of the seasonality in aggregate performance unexplained. In turn, fund flows and cash distributions fail to account for the underperformance of active funds in the first month of a quarter.

Finally, we verify that a strategy that switches to passive investment at the turn of the quarter and back to active funds after the first month outperforms a buy-and-hold investment in the VW portfolio of active funds. Glode (2011) and Kosowski (2011) show, theoretically and empirically, that active funds perform abnormally well when the economy is doing poorly. If so, we expect this switching strategy to improve the "insurance" value of active investment by avoiding the unconditionally negative performance of active funds in the first place.

Our work contributes to the long-standing debate regarding the value of active mutual fund management. Fama and French (2010) show that the return to the VW portfolio of active mutual funds is negative by the amount of fund expenses on an after-fee basis, implying that the average mutual fund manager is unskilled. By contrast, Pastor and Stambaugh (2012), Berk and Van Binsbergen (2015), and Pastor et al. (2015) empirically show, appealing to diseconomies of scale in investment, that zero net alphas are still consistent with the average active fund manager being skilled and creating substantial value.

The new features of the active management underperformance puzzle that we highlight can be difficult to rationalize based on the above-mentioned views. Indeed, if this underperformance reflects only lack of skill to deliver alpha, the seasonal pattern we document would imply that the investment ability of active managers is systematically impaired more in the first month of each quarter. Our evidence provides a new prospective, whereby the response of active fund managers to quarter-end tournament-like incentives, along with well-documented stock return effects, can enhance our understanding of the value creation process in this industry.

2. Related Literature

This study is related to the literature on stock market seasonality. Many studies have documented seasonal patterns in both the time series (Penman, 1987) and the cross section of stock returns (Keim, 1989; Grinblatt and Moskowitz, 2004; Heston and Sadka, 2008; Yao, 2012), particularly around the turn of the year. Although US domestic equity mutual funds invest primarily in stocks, few studies have investigated the seasonal patterns of mutual fund returns. To the best of our knowledge, this study is the first to provide comprehensive evidence of intra-quarter seasonality in the aggregate performance of US equity mutual funds.[2]

Our paper is also related to the existing literature on the tournament-like investment behavior of money managers around quarter-ends. Lakonishok et al. (1991), He et al. (2004), and Ng and Wang (2004), among others, report significant window-dressing behavior at the end of the fourth quarter. Agarwal et al. (2011), Ben-David et al. (2013), Hu et al. (2014), and Duong and Meschke (2015) present evidence of quarter-end NAV inflation among mutual funds, hedge funds, and other institutional investors.[3] Overall, we contribute to this strand of literature by examining the significance of either practice as a potential driver of the aggregate active management underperformance puzzle, which has not been currently addressed in the literature.

The evidence in this paper has first-order implications for the literature that infers fund managers' skill from observed returns. Jensen (1968), Carhart (1997), and Wermers (2000), among others, argue that, on average, net returns to active mutual funds are significantly inferior to those of passive benchmarks. In contrast with these results, several studies document superior performance for specific groups of mutual funds (e.g., Kacperczyk et al., 2005, 2008; Kacperczyk and Seru, 2007; Cremers and Petajisto, 2009; Amihud and Goyenko, 2013). In the spirit of Koijen (2014), our evidence highlights the need to account for tournament-like incentives at quarter-ends in the performance evaluation of mutual funds.

3. Hypotheses and Empirical Approach

3.1. A seasonal pattern in the asset allocation of active mutual funds

Using an equilibrium accounting approach, Fama and French (2010) and Lewellen (2011) report that, in the aggregate, institutional investors such as active mutual funds, essentially hold the market portfolio.[4] Their findings reflect average fund holdings over several decades and, as such, describe the long-term aggregate behavior of active funds.[5] To the extent that these findings reflect

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[2] Although not the main focus of their studies, Wermers (2000) and Moskowitz (2000) find evidence of seasonality in mutual fund's gross returns (as implied by funds' disclosed portfolio holdings) around the turn of the year. Gallagher and Pinnuck (2006) study monthly seasonality in the performance of Australian mutual funds.

[3] In the same vein, Gallagher, Gardner, and Swan (2009) use daily institutional trades to provide evidence of quarter-end portfolio pumping and its impact on fund NAV for a sample of Australian active equity funds.

[4] Succinctly, equilibrium accounting implies that, if the excess returns to passive investment are zero, by zero sum logic the excess returns to active investment should also be zero. Since the approach is concerned with performance at an aggregate level, it is measured as the dollar-weighted performance of all investors under examination (e.g., mutual funds).

[5] More precisely, Fama and French (2010) estimate the loadings of active mutual funds on the market portfolio over the period 1984-2006, while Lewellen (2011) analyses average holdings data over 1980-2007.

also the behavior of active funds at higher frequencies, we would expect no systematic deviation in funds' portfolios from the market over shorter-term periods.

Figure 1 shows that this is not the case. Within each calendar quarter, the VW average tracking error volatility (or, simply, tracking error) across active funds relative to the market portfolio systematically peaks at the first month of the quarter.[6] This pattern holds for both the S&P 500 index (Panel A) and the Center for Research in Security Prices (CRSP) VW market index (Panel B) as proxies for the market portfolio, and is statistically significant: the first-month tracking error plots above the 95% confidence interval around the second- and third-month average tracking error in all but the third calendar quarter (Panels C and D). Across either market proxy, the highest yearly tracking error is reached in the beginning of the fourth quarter, while the beginning of the third quarter marks the lowest peak over the year.[7] The outcome is an intra-quarter seasonality whereby mutual funds in the aggregate increase their deviation from the market at the start of a quarter and rebalance their portfolios back toward the market as the end of the quarter approaches.

[Insert Figure 1 here]

The seasonal pattern in funds' deviation from the market portfolio is pervasive across fund size categories and across investment styles. This is illustrated in panels A, B, and C of Figure 2, which plot funds' tracking error relative to the S&P 500 index, the CRSP VW market index, and to funds' prospectus benchmarks, respectively. In panels A and B, the tracking error for each of the five fund size quintiles peaks at the first month of each quarter. In Panel C, the same seasonal behavior is apparent when we account for the differences in investment styles as reflected by each fund's prospectus benchmark index (we expand on these benchmarks in Section 4.3) by computing tracking errors relative to these benchmarks.[8] Across all three panels, the investment pattern is almost identical to the one in Fig. 1, where the highest (lowest) peak in tracking error occurs in the fourth (third) quarter of the year. As a final observation, we note from panels A and B of Figure 2 that in each month of the year the cross-sectional average tracking error falls monotonically with fund size.

[Insert Figure 2 here]

[6] We describe our sample in detail in the next section.

[7] The peak in tracking error in the first month of Q4 coincides with the end of the tax year for mutual funds in the United States, homogenized to take place on October 31 after the 1986 Tax Reform Act (Gibson et al., 2000). Thus, at least part of the high tracking error in October that we observe in Figure 1 could be related to tax-loss selling strategies. We note that tax-motivated trades are unlikely to explain the intra-quarter seasonal pattern that we report for the remaining three quarters of the year.

[8] We obtain funds' prospectus benchmarks from Antti Petajisto's website (http://www.petajisto.net/data.html). For details on the assignment of benchmark indices to mutual funds see Cremer et al., (2012), and Petajisto (2013).

It seems natural to wonder whether the seasonality in the tracking error of active funds with respect to the market or other benchmark indices leads to a similar seasonality in their aggregate excess performance. In principle, this need not be the case. For instance, the attempt by an active fund to trade away from the market portfolio might be met by the trade order, in the opposite direction (i.e., a sell order met by a buy order), of a different active fund. If completed, such trade would deviate the portfolios of both funds from the market and increase the VW average tracking error of the two active funds. By zero-sum logic, these deviations would nevertheless have no impact on the return to the portfolio of the two funds. This is the equilibrium accounting argument used by Fama and French (2010) to contend that, if there are active mutual funds with positive excess returns, they are balanced by active funds with negative excess returns. When applied to the overall active fund industry, this argument implies that a seasonality in the tracking error of active funds should not translate into a similar seasonality in their aggregate performance, and is the basis for our empirical hypothesis.

3.2. Hypothesis

Based on the zero abnormal returns to active funds as a group reported by Fama and French (2010), our starting assumption is that the aggregate performance of mutual funds exhibits no seasonal pattern. In particular, our null hypothesis is that there should be no systematic variation in fund performance within an investment quarter, consistent with the equilibrium accounting view that an active fund's trading profits are the trading losses of a different active fund. Moreover, managerial investment ability is unlikely to change systematically within the quarter. In other words, the relation between ability and performance is likely to be stable (on average) over time. The absence of a seasonal pattern in fund returns would then validate the direct inference of managerial skill from measured returns in the standard performance evaluation literature.

Our alternative hypothesis is based on our findings in Subsection 3.1 that active mutual funds deviate from the market in a predictable way within a quarter. More precisely, we hypothesize that active funds' deviations from the market do not offset one another in the aggregate so that the return to the VW portfolio of active funds in excess of the market exhibits intra-quarter seasonality. We pose our alternative hypothesis in terms of excess returns not only to relate our analysis to the aforementioned studies, but also to capture seasonal patterns beyond well-documented seasonality effects on stock returns (e.g., the January effect).[9, 10]

[9] For an account of seasonal effects on stock returns, see Rozeff and Kinney (1976), Keim (1983), Reinganum (1983), Heston and Sadka (2008), and Kelouharju et al. (2016).
[10] Although for consistency with prior studies we expect the cumulated performance across all four quarters to be negative, we cannot predict any particular intra-quarter performance pattern based on the seasonality in funds' tracking error we report above.

3.3. Data

We obtain mutual fund data from the CRSP Survivorship-Bias-Free U.S. Mutual Fund Database, including net fund returns, total net assets, investment objectives, percentages of stock cash and bond holdings, fees, and other fund characteristics. We use Lipper, Strategic Insight, Weisenberger, and CRSP investment objective codes to identify actively managed domestic equity mutual funds.[11] When fund objective codes are missing or conflict with each other, we check the character strings of fund names for keywords suggesting whether the fund is an index fund, an exchange-traded fund, an international fund, a bond fund, or a balanced fund.[12] We exclude funds with less than 80% or more than 105% of their portfolios invested in equities. For funds with multiple share classes, we compute fund-level variables by aggregating across the different share classes. Our final sample comprises 3,490 distinct funds and an average of 992 funds each month from January 1967 to December 2013.[13] The numbers of funds in the first, middle, and last years of the sample (1967, 1990, and 2013) are, respectively, 91, 463, and 1,866.

We obtain mutual fund holdings data for the period 1980–2013 from Thomson-Reuters Mutual Fund Holdings database. This database contains the holdings of NYSE, AMEX, and NASDAQ stock of all registered mutual funds that report to the U.S. Securities and Exchange Commission (SEC). We obtain the returns to NYSE, AMEX, and NASDAQ stock from the CRSP monthly file. We use all NYSE, AMEX, and NASDAQ common shares to compute VW market returns.

We collect information about funds' prospectus benchmarks from two sources. First, we obtain the identity of funds' prospectus benchmarks from Antti Petajisto's website,[14] whose benchmark assignment process is explained in detail in Cremers et al., (2012), and Petajisto (2013). Second, we obtain benchmark returns (including dividends) at monthly and daily frequencies over the sample period of January 1979 to December 2013 from Morningstar. More precisely, we consider 28 benchmark indices from the three index families (i.e., Standard and Poor's, Frank Russell, and

[11] In line with French (2008), Kacperczyk et al. (2008), and Huang et al. (2011), our sample includes funds with the Lipper class codes AU, CA, CG, CS, EI, FS, G, GI, H, ID, MC, MR, S, SG, SP, TK, TL, and UT or the Lipper objective codes EIEI, G, LCCE, LCVE, MCCE, MCGE, MCVE, MLCE, MLGE, MLVE, SCCE, SCGE, and SCVE. If none of the above objectives is available, our sample also includes all funds whose Strategic Insights objective belongs to the following list: AGG, ENV, FIN, GMC, GRI, GRO, HLT, ING, NTR, SEC, TEC, SCG, UTI, and GLD. If no Lipper or Strategic Insights objectives are available, we use the Wiesenberger objective codes to select funds with the following codes: ENR, FIN, HLT, IEQ, G, GCI, GPM, LTG, MCG, SCG, TCH, and UTL. If none of these objectives is available but the fund's policy is common stocks (CS), then the fund is also included in the sample. Finally, a fund is also included in the sample if its CRSP objective code has *E* as its first character, *D* as its second character, and *C, Y*, or *S* as the third character, without the third and fourth characters being *CL, YH, YS,* or *SR*.

[12] We identify index funds either by the CRSP index fund flag, by their names, or by their stated objective.

[13] To address the potential survivorship bias highlighted by Brown et al. (1992), we do not impose a minimum return history requirement on our sample. Our findings hold if we restrict our sample to mutual funds with at least one or two years of return history.

[14] http://www.petajisto.net/data.html.

Dow Jones Wilshire) commonly followed by practitioners.[15] Within the S&P family, we note that the most common large-cap benchmark is the S&P 500 index, consisting of the 500 largest U.S. stocks, whereas the S&P 400 and S&P 600 are common self-reported benchmarks among funds following, respectively, mid- and small-cap investment styles. Within the Russell family, we consider the Russell 1000 (large-cap), the Russell Midcap, the Russell 2000 (small-cap), and the Russell 3000 (all stock sizes), along with the value and growth component of each.[16] We also include in our analysis the Wilshire indices, such as the Wilshire 4500 and the Wilshire 5000.[17]

3.4. Performance measures

To study seasonal patterns in the aggregate performance of mutual funds, we follow Fama and French (2010) and Lewellen (2011) in examining the return differential between the VW portfolio of actively managed mutual funds and the market portfolio. Following the equilibrium accounting argument in these papers, our first proxy of the market portfolio is the CRSP VW market index. On a practical basis, many small- and micro-cap stocks included in the CRSP VW market index are outside of the set of investable assets of a large fraction of mutual funds.[18] Therefore, our second proxy of the market portfolio is the S&P 500 index (including reinvested dividends), which is the single most popular stock market benchmark for U.S. domestic equity mutual funds (Cremers et al., 2015).

To compute the market-adjusted aggregate performance of mutual funds we proceed as follows. First, we compute the net-of-fees return to fund i in month t, R_{it}, as the relative change in net assets per share ($NAVPS_{i,t}$), including dividend payments (Div_{it}) and capital gain distributions (CAP_{it}):

$$R_{i,t} = \frac{NAVPS_{i,t} + Div_{i,t} + Cap_{i,t} - NAVPS_{i,t-1}}{NAVPS_{i,t-1}}, \tag{1}$$

[15] Specifically, we consider the following indices: S&P Mid-cap 400, S&P Mid-cap Value/Growth 400, S&P 500, S&P 500 Value/Growth, S&P Small-cap 600, S&P 600 Value/Growth, S&P 1000, S&P 1000 Value/Growth, Russell 1000, Russell 1000 Value/Growth, Russell 2000, Russell 2000 Value/Growth, Russell Midcap, Russell Midcap Value/Growth, Russell 3000, Russell 3000 Value/Growth, Wilshire 4500, Wilshire 5000, and Wilshire 5000 Value/Growth. The sample period starts from January 1979, except for the following indices whose return data begin later: S&P 400 (September 1991), S&P 600 (February 1995), S&P 1000 (July 1995), Wilshire 4500 (January 1984), and the Growth and Value components of the Russell Midcap (January 1986), S&P 400 (May 1997), S&P 500 (February 1994) and S&P 600 (May 1997), S&P 1000 (July 1995), and Wilshire 5000 (January 1992).

[16] The Russell 3000 consists of the 3,000 largest stocks in the U.S. The Russell 1000 contains the 1,000 largest stocks; the Russell Midcap index covers the 800 smallest stocks in the Russell 1000; the Russell 2000 covers the 2000 smallest stocks in the Russell 3000.

[17] The Wilshire 5000 contains essentially the entire U.S. equity market. The Wilshire 4500 comprises the stocks included in the Wilshire 5000 but not in the S&P 500.

[18] For instance, Almazan et al. (2004) document that, on average, around 18% of the U.S. domestic equity funds were not allowed to invest in illiquid stocks between 1994 and 2004.

Second, we compute the net returns to the portfolio of actively managed mutual funds in month t, $R_{MF,t}$ as the VW average of the net-of-fee returns $R_{i,t}$ of all available actively managed equity mutual funds:

$$R_{MF,t} = \sum_{i=1}^{m} \frac{TNA_{i,t-1}}{\sum_{i=1}^{m} TNA_{i,t-1}} \mathrm{R}_{i,t}, \tag{2}$$

where $\mathrm{TNA}_{i,t-1}$ is fund i's total net assets under management in the previous month.

Similarly, we compute the return on the market portfolio (with either the S&P 500 or the CRSP VW market indices as market proxies) in month t, $R_{MK,t}$, as the VW average of stock returns $R_{j,t}$:

$$R_{MK,t} = \sum_{j=1}^{n} \frac{ME_{j,t-1}}{\sum_{j=1}^{n} ME_{j,t-1}} \mathrm{R}_{j,t}, \tag{3}$$

where $ME_{j,t-1}$ is stock j's market capitalization in the previous month.

Finally, we define fund market spread as the difference between the net returns to the VW portfolio of mutual funds and the market return:

$$FMS_t = R_{MF,t} - R_{MK,t}, \tag{4}$$

Alternatively, we evaluate the aggregate performance of mutual funds on a risk-adjusted basis following Sharpe's (1964), Lintner's (1965) CAPM, Fama and French's (1996) three-factor model, and Carhart's (1997) four-factor model:

$$R_{MF,t} - R_{f,t} = \alpha + \beta(R_{MK,t} - R_{f,t}) + \varepsilon_t, \tag{5}$$

$$R_{MF,t} - R_{f,t} = \alpha + \beta(R_{MK,t} - R_{f,t}) + sSMB_t + hHML_t + \varepsilon_t, \tag{6}$$

$$R_{MF,t} - R_{f,t} = \alpha + \beta(R_{MK,t} - R_{f,t}) + sSMB_t + hHML_t + mUMD_t + \varepsilon_t, \tag{7}$$

where $R_{f,t}$ is the risk-free rate as approximated by the one-month U.S. Treasury bill rate, $R_{MK,t}$ is the return to the market proxy as represented by the S&P 500 index or the VW market portfolio of NYSE, AMEX, and NASDAQ stocks in month t. The variables SMB_t and HML_t are returns to zero-investment factor-mimicking portfolios for size (small minus big) and book-to-market (high minus low) in month t, and UMD_t is the return to a zero-investment factor-mimicking momentum portfolio that buys prior-year winners and short sells prior-year losers in month t.[19]

In all three specifications (5)–(7) the intercept α ("alpha") is the average return left unexplained by each factor model and is often interpreted as a proxy for fund managers' stock selection skill. We analyze model (5) to address the observation of Barber et al. (2015) that most investors care about market risk when evaluating fund performance but do not treat other factors as compensation for risk. Models (6) and (7) reflect compensation to passive strategies that load on factor risks as

[19] The variables SMB_t and HML_t are constructed following Fama and French (1996).

captured by size, value, and momentum portfolios (Kacperczyk et al., 2005, 2008; Huang et al., 2011).

We test for intra-quarter variation in the aggregate performance of mutual funds by splitting the alpha in models (5)–(7) into the monthly dummies D_1–D_3, (where D_i is one in the i-th month of the quarter and 0 otherwise, for i = 1,2,3) in models (8)–(10) below:

$$R_{MF,t} - R_{f,t} = D_1 + D_2 + D_3 + \beta_1 D_1 (R_{MK,t} - R_{f,t}) + \beta_2 D_2 (R_{MK,t} - R_{f,t}) + \beta_3 D_3 (R_{MK,t} - R_{f,t}) + \varepsilon_t, \quad (8)$$

$$\begin{aligned} R_{MF,t} - R_{f,t} = {} & D_1 + D_2 + D_3 + \beta_1 D_1 (R_{MK,t} - R_{f,t}) + s_1 D_1 SMB_t + h_1 D_1 HML_t + \beta_2 D_2 (R_{MK,t} - R_{f,t}) \\ & + s_2 D_2 SMB_t + h_2 D_2 HML_t + \beta_3 D_3 (R_{MK,t} - R_{f,t}) + s_3 D_3 SMB_t + h_3 D_3 HML_t + \varepsilon_t, \end{aligned} \quad (9)$$

$$\begin{aligned} R_{MF,t} - R_{f,t} = {} & D_1 + D_2 + D_3 + \beta_1 D_1 (R_{MK,t} - R_{f,t}) + s_1 D_1 SMB_t + h_1 D_1 HML_t + m_1 D_1 UMD_t \\ & + \beta_2 D_2 (R_{MK,t} - R_{f,t}) + s_2 D_2 SMB_t + h_2 D_2 HML_t + m_2 D_2 UMD_t \\ & + \beta_3 D_3 (R_{MK,t} - R_{f,t}) + s_3 D_3 SMB_t + h_3 D_3 HML_t + m_3 D_3 UMD_t + \varepsilon_t, \end{aligned} \quad (10)$$

where we allow for intra-quarter variations in funds' exposure to systematic risk factors by interacting D_1–D_3 with the market, size, value, and momentum factors.

4. Seasonality in Mutual Fund Performance

4.1. Aggregate performance

The average monthly FMS from January 1967 to December 2013 reported in Figure 3 suggests that, in the aggregate, mutual fund performance is not evenly distributed over the typical calendar quarter. The first month of each quarter marks the worst performance of the VW portfolio of all funds relative to the S&P 500 index (Panel A) or to the CRSP VW market index (Panel B).[20] This implies that the worst monthly performance over the year coincides with the start of a quarter (Q4 in Panel A and Q1 in Panel B). The generally positive slope of the performance lines in Figure 3 indicates that the average excess performance generally peaks at quarter-end.

[Insert Figure 3 here]

We examine the statistical significance of this pattern in Table 1, which reports the time-series average of the net- and gross-of-fees FMSs computed with respect to the S&P 500 (Panel A) and the CRSP VW market (Panel B). The results are for the first, middle, and last months of a quarter during the same period as illustrated in Figure 3.

[Insert Table 1 here]

Confirming our observations from Figure 3, the monthly FMSs in Table 1 are inconsistent with the null of no seasonality in the excess returns to active mutual funds. The point estimates for

[20] In Panel B, Q2 represents the only exception to this observation.

the average FMS with respect to either market proxy (S&P 500 or CRSP VW market index) drop significantly in the first month of a quarter and (weakly) improve over the following two months. The underperformance of the VW portfolio of active mutual funds at the beginning of the quarter is statistically and economically significant for both net-of-fees and gross-of-fees FMSs, averaging -25 (-18) and -19 (-11) basis points, respectively, when the market proxy is the S&P 500 (CRSP VW market) index.

Table 1 also highlights that the well-documented calendar year underperformance of mutual funds as a group (e.g., Carhart, 1997; Fama and French, 2010) is concentrated in the first month of each quarter only. Indeed, the cumulated after-fee FMS across January, April, July, and October averages -105 (-73) basis points and contributes 111% (68%) of the cumulated annual FMS of 95 (108) basis points over the S&P 500 (CRSP VW market). By contrast, the estimated FMSs for the middle and end months of the quarter are not significant at conventional statistical levels.

Table 2 shows that the seasonal pattern in mutual fund returns remains significant after controlling for fund exposure to systematic risk. Panel A replicates the negative risk-adjusted performance of the VW portfolio of active funds documented by prior literature: on an unconditional basis, the 4-factor alpha of active funds is either -11 or -8 basis points per month (1.32% and 0.96% annually) when the market proxy is either he S&P 500 index or the CRSP VW market index, respectively.

[Insert Table 2 here]

Panel B of Table 2 indicates that the well-documented underperformance of active funds is driven by their negative returns in the first month of a quarter. The average CAPM alpha is -26 (-17) basis points per month when we use the S&P 500 (CRSP VW market) index as a proxy for the market portfolio. The point estimates of the CAPM alpha increase in the second and third months of a quarter, although neither is statistically significant. A similar pattern is evident when we use multifactor risk-adjustment models: the three- and four-factor alphas remain substantially negative in all cases and statistically significant at the 1% level or better. Point estimates for these alphas weakly improve over the second and third months of a quarter. Moreover, the risk-adjusted performance of active funds becomes statistically indistinguishable from zero in the last two months of the quarter. [21]

We note that our finding that active funds' underperformance presents a marked seasonal component does not make active funds more appealing to investors in comparison to, for example,

[21] The similar factor exposure of the VW portfolio of all funds across the three months suggests that differences in excess performance within the quarter stem from managers' active choices in the selection of stocks rather than from their timing of systematic risk factors. In non-tabulated results, we construct a factor-mimicking portfolio for size and value using the tradable benchmark indices proposed by Cremers et al. (2013). In line with our main results, we find that the Fama-French and Carhart alphas are negative only in the first month of the quarter.

passively managed funds. However, unless one can argue for a similar seasonal pattern in the average skill of mutual funds or in their fees, they seem inconsistent with the prevailing view (e.g., Fama and French, 2010) of the underperformance puzzle.

4.2. Analysis by fund size

Given that the mutual fund industry is highly concentrated, aggregate patterns in performance could potentially be driven by a few, very large players. This is not the case for the beginning-of-quarter effect we document. Splitting the intra-quarter performance of active funds by the size of their assets under management, Table 3 shows that all funds but those in the smallest size quintile underperform the market portfolio in the first month of the quarter only. For the top three size quintiles, the net-of-fees FMS relative to both the S&P 500 and the CRSP VW indices is negative at the 1% significance level or better in the first month of each quarter only.

[Insert Table 3 here]

On a risk-unadjusted basis, the VW portfolios of the smallest active funds outperform the market portfolio in the last month of a quarter. Indeed, the net-of-fees FMS for the portfolios of funds in the three smallest size quintiles are positive at the 5% significance level, and of similar magnitude as the first-month underperformance of the VW portfolio of all funds (see Table 1). For the two proxies of the market portfolio we consider, the point estimates of the third-month outperformance fall monotonically with size quintile: from a significantly positive FMS of 33 (27) basis points relative to the S&P 500 index (CRSP VW market index) for the smallest size quintile, to a statistically insignificant FMS of 3 (-3) basis points for the largest size quintile.

However, the third-month outperformance of small funds vanishes after adjusting for the systematic risk exposure of their strategies. Similarly, the first-month drag on fund performance applies to even smaller funds after adjusting their returns by factor risk. Panel B of Table 3 reports the four-factor alphas of the different size quintiles in the three months of a quarter. Identifying the market portfolio with either the S&P 500 index or the CRSP VW market index, the top four size quintiles exhibit statistically significant underperformance only in the first month of the quarter. Moreover, the third-month outperformance of the active funds in the smallest three size quintiles becomes statistically insignificant (or marginally significant) once we control for their exposure to the market, size, value, and momentum factors.

Summing up, the seasonal pattern in the performance of the VW portfolio of active funds is pervasive across fund size quintiles. For all but the smallest size quintile, the pattern shows up as a significant underperformance, both on a market-adjusted and four factor-adjusted bases, in the first month of the quarter only. The market-adjusted return to the VW portfolio of active funds across size quintiles typically turns positive toward the end of the quarter, with smaller funds doing relatively better than their larger peers.

4.3. Analysis by investment style

Most actively managed equity mutual funds report a benchmark index they target to beat. Typically, these benchmarks characterize different "investment styles" such as small-cap or growth stocks. If the returns to these benchmark indices in excess of the market return themselves exhibit intra-quarter seasonality, we would expect the type of seasonal pattern we document above to mechanically arise from funds' tendency to follow their indices closely or "closet index" (see, e.g., Cremers and Petajisto, 2009).

To rule out this possibility, we examine in Table 4 the VW excess returns to active funds with respect to their prospectus benchmarks before (Panel A) and after risk-adjustment (Panel B). To simplify the exposition, we group funds according to their benchmarks into three size-related styles: large-cap, mid-cap and small-cap. We classify a fund as following a large-cap style if it self-reports either of the following indices as its benchmark: S&P 500, S&P 500 Value/Growth, Russell 1000, or Russell 1000 Value/Growth. A fund follows a mid-cap style if it self-reports either of the following indices as its benchmark: S&P 400, S&P 400 Value/Growth, Russell Mid-cap, Russell Mid-cap Value/Growth. Finally, we classify a fund as following a small-cap style if its benchmark is one of the following indices: S&P 600, S&P 600 Value/Growth, Russell 2000, and Russell 2000 Value/Growth.

[Insert Table 4 here]

We show in Panel A of Table 4 that the VW average return to all active funds in excess of their benchmarks exhibits the same seasonal pattern as their market-adjusted return in Table 1. Specifically, active funds underperform their benchmarks in the first month of each quarter only, as shown by their negative excess return of 19 basis points under the column "Overall", statistically significant at better than the 1% level. Active funds as a group do not underperform their benchmarks in the second and third month of the quarter. We observe in the third to fifth columns of Panel A in Table 4 that the beginning-of-quarter underperformance is driven mainly by the large- and mid-cap funds, as the excess performance of the small cap funds is statistically insignificant.

Furthermore, all investment styles show the intra-quarter performance seasonality we report above once excess returns are adjusted by funds' exposure to systematic risk. Indeed, Panel B of Table 4 indicates that active funds as a group underperform their benchmarks in the first month of the quarter only. The average benchmark-adjusted return to the portfolio of all active funds is -16 basis points and is statistically significant at the 5% level in the first month, but statistically insignificant in the second and third months of the quarter.

The same pattern holds at the disaggregated level when we sort funds by investment style. Large-cap, mid-cap, and small-cap active funds underperform their benchmarks by 13, 37 and 25 basis points, respectively, in the beginning of the quarter, at a 5% or better statistical significance. None of the investment-style portfolios of active funds under- or outperform their benchmarks in the remaining two months of a quarter, at the conventional significance levels.

5. Potential Drivers of the Mutual Fund Performance Seasonality

Overall, our market- and risk-adjusted analyses of Section 4 favor the alternative hypothesis of seasonality in the aggregate performance of active mutual funds. This seasonality is consistent with the seasonal pattern in the levels of active management of fund portfolios that we report in Section 3.1. Either empirical regularity seems difficult to rationalize based on a similar seasonality in fund managers' investment skill or in their information (dis)advantage over other market participants. Indeed, such a rationalization would suggest that, at the beginning of each quarter, the average manager becomes less skilled, or trades on worse information, than other market participants. This seasonality in investment skill seems implausible; therefore, in this section we examine to what extent the performance seasonality of active funds is associated with other seasonal patterns documented by the prior literature.

5.1. Tournament-like behavior at the turn of a quarter

Mutual fund managers have strong incentives to look wise in the eyes of investors at quarter-ends. The specialized press and several highly publicized rankings (e.g., Morningstar, U.S. News) often assess fund companies over quarterly horizons. Several authors find that institutional and retail investors pay close attention to these rankings in deciding their allocations across funds, directing disproportionally larger flows to funds that rank higher or that outperform their benchmarks by a larger margin.[22] This competition for investor money is often compared to a tournament in which the winners obtain the lion's share of investors' inflows. Because fund companies collect fees on their assets under management, reporting a strong relative performance by the end of the period secures larger future flows and fees.

[22] See Sirri and Tufano (1998), Chevalier and Ellison (1997), Sapp and Tiwari (2005), and Lou (2012). The prevalent finding in this literature is that mutual funds with high past returns tend to attract disproportionately large new money over the next year. Moreover, flows chasing recent high returns appear to do so in a nonlinear fashion: Funds with high returns induce large subsequent inflows of new money but funds with low returns do not experience withdrawals of a similar magnitude.

Prior literature finds that portfolio managers commonly use two types of quarter-end strategies to mislead investors about their true ability: window dressing and NAV inflation. Window dressing involves buying winner stocks and dumping loser stocks near the end of a quarter to improve the appearance of a portfolio to be presented to clients or shareholders (e.g., Lakonishok et al., 1991; Sias and Starks, 1997; Lynch and Musto, 2003; Agarwal et al., 2014). NAV inflation, or portfolio pumping, refers to the practice of marking the close; that is, of inflating the prices of stocks already in a manager's portfolio to boost the fund's performance at quarter-end (e.g., Zwieg, 1997; Carhart et al., 2002; Bernhardt and Davis, 2005; Agarwal et al., 2011; Bhattacharyya and Nanda, 2012; Zwieg and McGindy, 2012; Ben-David et al., 2013; Hu et al., 2014; Duong and Meshke, 2015).

These quarter-end strategies have been studied extensively at the individual fund level, and associated with specific fund characteristics such as recent past performance. However, their effect on the aggregate behavior and performance of the active fund industry has been largely unexplored. On the one hand, both window dressing and NAV inflation should be negligible at the aggregate level under the above-mentioned equilibrium accounting approach (Fama and French, 2010). Following this line of reasoning, the trading losses of active funds engaging in window dressing or NAV inflation should be the trading profits of their active peers on the opposite side of the window dressing or NAV inflation spectrum. On the other hand, either window dressing or NAV inflation could systematically impact the intra-quarter performance of the VW portfolio of all funds if practiced on a large scale or adopted by the larger funds in the industry. We assess the aggregate performance impact of these quarter-end strategies and their relation to fund return seasonality in the next two subsections.

5.1.1. Window dressing and return reversal

Lakonishok et al. (1991), He et al. (2004), and Ng and Wang (2004), among others, provide empirical evidence of significant window dressing behavior among mutual funds at the end of the fourth quarter. Agarwal et al. (2014) find that poorly performing mutual funds, or those ran by less skilled managers, engage in window dressing on a quarterly basis to obtain higher future flows. They further report that, because window dressing involves costly portfolio churning and signals low managerial skill, funds engaging in this type of behavior suffer lower future returns both in the short (i.e., one quarter ahead) and long (one to three years ahead) terms.

While the low skill level associated with window dressers can explain their documented poor future performance, it seems unlikely to explain why this underperformance is concentrated in the first month of each quarter. We hypothesize that a potential link between window dressing and intra-quarter seasonality in aggregate fund performance is the well-documented short-term stock return reversal (Jegadeesh, 1990; Jegadeesh and Titman, 1993; Grundy and Martin, 2001).[23] According to this empirical effect, the best past performing stocks in the cross section suffer large one-month return reversals.[24] This is precisely the type of stocks that window dressers over-weight in their portfolios. Therefore, window dressers could systematically underperform following the end of a quarter, as the high recent returns on the winner stocks regress in the first month of the following quarter.[25] If prevalent, or if practiced by the larger funds in the cross section, window dressing along with short-term return reversal could contribute to the intra-quarter seasonality in aggregate fund returns of Section 4.

To test this possibility, we first verify that loading on winner stocks at the end of a quarter, along with the return reversal effect of Jegadeesh (1990), leads to significant aggregate underperformance in the first month of the following quarter. Specifically, at the end of each quarter we rank all stocks according to their prior-year performance and assign them into one of three bins: top 30% (winner), middle 40%, or bottom 30% (loser).[26] We add up each fund's end-of-quarter portfolio weights in winner stocks, rank all funds according to this weight, and assign them to one of three terciles from low to high weight in winner stocks. We then compute the FMS of the VW portfolio of active funds in each tercile. If over-weighting winner stocks was related to the aggregate underperformance of active funds in the first month of the following quarter, (i) funds with higher loadings on these stocks should suffer lower performance in the first month of the following quarter; and (ii) the underperformance of these funds should be significant on a VW basis, and of similar magnitude as the beginning-of-quarter underperformance of all active funds.

[Insert Table 5 here]

The test results, presented in Table 5, support this hypothesis. First, point estimates for underperformance in the first month of the quarter increase monotonically—in absolute value—with funds' loading on winner stocks. Second, the aggregate VW underperformance of the two fund terciles with the highest weights on winner stocks is highly statistically significant. Third, the

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[23] We thank the associate editor for suggesting this hypothesis.

[24] We find no evidence of a similar one-month reversion in fund returns. Specifically, in non-tabulated tests each quarter we rank all funds by their prior-year returns and compute their FMS in the first month of the following quarter. Against the hypothesis of fund return reversion, funds in the top performing decile outperform their peers in the bottom decile by 4 basis points (although the FMS is not statistically different from zero in either group).

[25] Indeed, the first-month underperformance of active funds weakens—though does not completely vanish—when controlling for their exposure to a reversal factor. More precisely, we add the reversal factor taken from Ken French's website to the four-factor model (10) and find that (i) point estimates for the first-month risk-adjusted excess returns to active funds fall and, for the CRSP VW market index as the market proxy, even turn insignificant at conventional statistical levels; and (ii) funds' loading on the reversal factor is negative and, in the case of the CRSP VW market index as market proxy, statistically significant at the 1% level.

[26] Specifically, we rank stocks by their cumulative returns over months t-12 to t-1, (i.e., including the prior-month return, as it is well-documented to cause short-term return reversal and is typically skipped in the momentum literature) (e.g., Grundy and Martin, 2001).

magnitude of this VW average underperformance is similar to, or larger than, the corresponding underperformance for the overall industry, as reported in Section 4.[27]

According to these results, an end-of-quarter portfolio that overweighs stocks with high past returns can suffer return reversal in the first month of the following quarter. Such a portfolio is consistent with both window dressing and the skill to pick, ex ante, the best performing stocks. However, for a skilled manager's fund to exhibit this beginning-of-quarter effect as a result of short-term return reversal, the manager must be relatively more successful in picking stocks in the last month of a quarter. Although such intra-quarter systematic variation in investment ability seems unlikely, it needs to be discerned from the tournament-like behavior that we examine in this section.

To this end, our next tests examine the extent of window dressing among active funds and its impact on subsequent performance more directly. Specifically, each quarter we rank all funds by the extent of window dressing they exhibit in the third month and assign them to one of three terciles, ranked from low to high window dressing (WD). Panel A of Table 6 reports the average FMS of the VW portfolio of all funds in each WD tercile in the first month of the following quarter. Once again, we focus on VW returns because, in contrast to the prior literature, our goal is to link WD with the *aggregate* seasonality in active fund performance. To capture window dressing behavior, we adopt the average backward holding return gap (BHRG) measure proposed by Agarwal et al. (2014). The BHRG is defined as the difference between the quarterly return imputed from the reported quarter-end portfolio (assuming the manager held this same portfolio at the beginning of the quarter) and the fund's actual quarterly return. A positive value of BHRG suggests window dressing behavior, and the higher the BHRG, the larger the extent of window dressing. Our goal here is twofold. First, we seek to assess whether window dressing behavior remains significant at the overall industry level, as opposed to manifesting only among a subset of funds with no aggregate impact. Second, we seek to test, similarly to Table 5, whether higher aggregate levels of window dressing along with the return reversal effect can lead to lower average FMS in the first month of a quarter.

[Insert Table 6 here]

The results, tabulated in Panel A of Table 6, suggest significant aggregate window dressing activity at quarter-ends and a subsequent impact on the industry performance in the first month of a quarter. First, the BHRG indicates statistically significant levels of window dressing activity in

[27] In non-tabulated results, we verify that ranking funds by their holdings in the bottom 30% of stocks, which are expected to experience the larger positive impact from the return reversal effect, results in an opposite pattern to that of Table 5 (i.e., funds with the highest loading of loser stocks experience the smallest beginning-of-quarter underperformance).

the third month of a quarter even on a VW basis, particularly for the tercile of high-WD funds. Second, point estimates of the FMS in the first month of the following quarter are lowest for these high-WD funds, consistent with a negative relation between window dressing and beginning-of-quarter aggregate fund performance. These estimates also become more statistically significant with the extent of window dressing. However, the relative impact of window dressing on the beginning-of-quarter underperformance differs depending on the market proxy used. When computing the FMS relative to the CRSP VW market portfolio, only high-WD funds significantly underperform in the first month of a quarter. When compared to the S&P 500 index, even low-WD funds significantly underperform.

Our last test examines the impact of managerial skill on the beginning-of-quarter excess returns to active funds. Agarwal et al. (2014) document a higher prevalence of window dressing behavior and a lower subsequent fund performance among lower-skilled managers. If the first-month underperformance of the VW portfolio of active funds is linked to skill-related window dressing activity, we would thus expect aggregate window dressing activity among low-skill managers to (i) be significant, and (ii) lead to significant aggregate underperformance in the first month of a quarter.

Following Kacperczyk et al. (2008), we identify managerial skill by the fund's *return gap* measure; i.e., the difference between a fund's actual performance and the performance of the fund's prior quarter-end portfolio, assuming this portfolio is held throughout the current quarter. In particular, we are interested in relating managerial skill (return gap) to future beginning-of-quarter fund performance (FMS). Each quarter, we rank all funds by their return gap in the last month of the quarter and assign them to one of three terciles, ranked from low to high managerial skill. We then compute the average FMS of the VW portfolio of all active funds in each tercile in the first month of the following quarter.

The results, presented in Panel B of Table 6, are again consistent with the hypothesis of an aggregate impact of window dressing on fund performance seasonality. First, low-skill managers exhibit statistically significant levels of window dressing activity on a VW basis at quarter-ends. Second, point estimates for the FMS in the first month of the quarter increase monotonically with managerial skill, from negative values for the lowest-skill group to positive values for the highest-skill bin. Third, the beginning-of-quarter drag on active fund performance is significantly negative only among mid- and low-skill managers in the cross section. By contrast, high-skill funds exhibit significantly positive excess returns relative to the CRSP VW market index.[28]

[28] In addition, Panel B Table 6 provides evidence against time-variation in managerial skill as a source of the beginning-of-quarter underperformance. Indeed, if skilled managers exhibited ability only in the last month of the quarter, short-term return reversal should negatively affect their performance in the first month of the following quarter. Table 6 demonstrates this is not the case.

Overall, the evidence in this subsection suggests that mid- to low-skill fund managers tilt the aggregate portfolio of all active funds toward winner stocks at the end of the quarter, likely motivated by window dressing considerations. Since winner stocks suffer the largest return reversal in the following month, window dressing behavior at the aggregate level can contribute to a beginning-of-quarter active funds underperformance, in line with the pattern we document in Section 4.

5.1.2. NAV inflation

Carhart et al. (2002) provide indirect evidence that top-performing mutual funds mark up their NAV at quarter-end by placing last-minute buy orders on stocks already in their portfolios. These orders usually target small, thinly traded stocks for which even a small buy order can have a large price impact. As prices revert to pre-inflation values the following trading day—the first day of the following quarter—so does the performance of portfolio pumpers. Widespread adoption of NAV inflation practices could then lead to an outperformance of the portfolio of active funds in the last day of a quarter, followed by underperformance in the first day of the following quarter.

Although we do not find significant outperformance in the last month of the quarter, we follow two approaches to assess the importance of NAV inflation practices in driving the beginning-of-quarter underperformance. First, we regress the monthly FMS in the first month of each quarter against each trading day of the same month. If the first month performance is systematically related to NAV inflation in the first (two) day(s) of the quarter only, we should expect a positive and significant coefficient on this (these) day(s) but no significant coefficient—consistent with returns being noisy—on most other days of the month. Second, we estimate the contribution of the first-day (first-two-days) performance to the overall performance in the first month of the quarter by performing an analysis of variance (ANOVA) of the above regression. Specifically, we decompose the explained sum of squares of the regression into its day-by-day components. If widespread NAV inflation is the main driver of the active fund performance in the first month of the quarter, we should expect the first (and potentially the second) trading day to explain most of the variation of the monthly FMS. We present the regression results in Figure 4, and the ANOVA results in Figure 5, over the period from September 1998 to December 2013.[29] Across both figures, Panels A and B use the S&P 500 and CRSP VW market indices, respectively, as benchmarks for our FMS measure.[30]

[Insert Figure 4 here]

[29] Our data in this section is limited by the availability of daily return data in the CRSP MF database, which starts in September 1998.

[30] The average FMS relative to the S&P 500 (CRSP VW market) index in the first month of the quarter is -19 (-13) basis points over this more recent period of 1998–2013.

[Insert Figure 5 here]

We find a non-negligible, yet limited, role for NAV inflation to explain the seasonality in active fund performance. First, the first and second day excess returns of active funds are positively and statistically significantly associated with their excess performance in the first month of the quarter. However, most other trading days of the month exhibit a similar positive and, in many cases, even stronger relation to the excess performance of active funds in the same month.

Second, the variation of the FMS in the first trading day of the quarter accounts for around 10% of the explained variation of the FMS in the first month. When the second day is included, this percentage increases to between 30% and 33% of this monthly variation, depending on the market proxy used. However, compared to the first day, other days account for a similar or larger percentage of the explained variation of the FMS in the first month of the quarter. For instance, the 9th trading day accounts for 15% of this variation when the market proxy is the S&P 500 index. Similarly, the 17th trading day accounts for 16% of the first-month-of-the-quarter variation in FMS when the market proxy is the CRSP VW market index. It is unlikely that the FMS in either of these days is driven by NAV inflation practices.

5.2. Microstructure bias

Market microstructure biases can, in principle, introduce additional sources of seasonality on the calculation of returns over the turn of the year. As reviewed below, the literature identifies two channels as affecting these returns through stocks' bid-ask spreads: the "transaction price bias" and the "seasonality in bid-ask spreads." Both channels have been studied as applied to the turn of a calendar year, whereas the seasonality we identify occurs at the turn of the quarter. Thus, we examine the strength of each of these effects on our sample with the understanding that, at most, they can only provide a partial explanation for intra-quarter seasonality in fund performance.[31]

We first examine the presence of a transaction price bias in our sample. In the CRSP database, returns are computed using the last transaction (official closing) price when a stock trades but the bid-ask average instead when the stock does not trade. Keim (1989) documents a systematic tendency for the closing transaction prices of small stocks to occur at bid prices in December and at ask prices in early January. The author shows that this tendency induces a transaction price bias that plays an important role in explaining abnormally high returns for small stocks in January. Jegadeesh and Titman (1993) further note that this bias artificially inflates the returns to small and loser stocks in January. If mutual funds predominantly tilt their portfolios away from small loser

[31] The exact source of these microstructure biases is largely unknown. In principle, it is at least possible that the NAV inflation and window-dressing practices of fund managers contribute to this seasonality in the microstructure of stock markets. If this is the case, the effects we study in this subsection are not independent from the ones we analyse in Subsections 5.1. We thank an anonymous referee for pointing this out.

stocks toward the end of the year, this bias could drive the beginning-of-year (i.e., the beginning of quarter one) underperformance of active funds.

To examine this possibility, we compute stock returns in two ways: (i) using only closing transaction prices ($R_{tr,t}$) and (ii) using only the average of the bid and ask prices ($R_{c,t}$). We measure the bias as the average difference between the bid-ask price returns and the transaction price returns.[32] Finally, we evaluate the impact of the transaction price bias on our results by estimating the following two models:

$$FMS_t = D_1 + D_2 + D_3 + b(R_{tr,t} - R_{c,t}) + \varepsilon_t, \tag{13}$$

$$\begin{aligned} FMS_t = {} & D_1 + D_2 + D_3 + b_{s1}D_1(R^s_{tr,t} - R^s_{c,t}) + b_{s2}D_2(R^s_{tr,t} - R^s_{c,t}) + b_{s3}D_3(R^s_{tr,t} - R^s_{c,t}) \\ & + b_{m1}D_1(R^m_{tr,t} - R^m_{c,t}) + b_{m2}D_2(R^m_{tr,t} - R^m_{c,t}) + b_{m3}D_3(R^m_{tr,t} - R^m_{c,t}) \\ & + b_{l1}D_1(R^l_{tr,t} - R^l_{c,t}) + b_{l2}D_2(R^l_{tr,t} - R^l_{c,t}) + b_{l3}D_3(R^l_{tr,t} - R^l_{c,t}) + \varepsilon_t, \end{aligned} \tag{14}$$

where we use the S&P 500 index as market proxy to capture the impact of the bias not only on the VW portfolio of mutual funds but also on the market portfolio;[33] $R_{tr,t}$ is the hypothetical VW market return to buying all NYSE, AMEX, and NASDAQ stocks on the CRSP monthly file at ask prices in month t -1 and selling at bid prices in month t; and $R_{c,t}$ is the market return computed by using closing transaction prices. The first model measures the overall impact of the transaction price bias on the FMS. The second model measures the impact of the transaction price bias among different stock size groups, identified as small-, medium-, and large-cap companies (with superscripts s, m, and l, respectively) on the FMS.[34]

The second potential bias affecting our FMS measure comes from the transaction costs involved in buying at the ask price and selling at the bid price. Clark et al. (1992) document a seasonal pattern in the bid-ask spreads at the turn of the year whereby the bid-ask spread of NYSE stocks tends to decline from the end of December to the end of January. Along with the well-documented tendency of the bid-ask spread on small stocks to increase in January, the resulting

[32] We follow Subrahmanyam (2005) in computing calendar-month returns using mid-quotes to control for bid-ask bounce.

[33] This bias will not likely affect the S&P 500 index, since it includes only the largest companies in the U.S. stock market.

[34] According to the literature cited above, the transaction price bias is likely to be more evident for small stocks. To measure the impact of this bias across different stock size groups on the FMS, small-, medium-, and large-cap portfolios are constructed according to each stock's lagged market capitalization. We include all NYSE, AMEX, and NASDAQ common shares. The monthly size breakpoints are the 33rd and 67th NYSE percentiles. The returns to the three size portfolios are all value-weighted.

dynamics of the spread at the turn of the year could contribute to the seasonality in the FMS that we document.[35] We implement the following two models to address this concern:[36]

$$FMS_t = D_1 + D_2 + D_3 + b(R_{a,t} - R_{c,t}) + \varepsilon_t, \tag{15}$$

$$\begin{aligned} FMS_t = {} & D_1 + D_2 + D_3 + b_{s1}D_1(R^s_{a,t} - R^s_{c,t}) + b_{s2}D_2(R^s_{a,t} - R^s_{c,t}) + b_{s3}D_3(R^s_{a,t} - R^s_{c,t}) \\ & + b_{m1}D_1(R^m_{a,t} - R^m_{c,t}) + b_{m2}D_2(R^m_{a,t} - R^m_{c,t}) + b_{m3}D_3(R^m_{a,t} - R^m_{c,t}) \\ & + b_{l1}D_1(R^l_{a,t} - R^l_{c,t}) + b_{l2}D_2(R^l_{a,t} - R^l_{c,t}) + b_{l3}D_3(R^l_{a,t} - R^l_{c,t}) + \varepsilon_t, \end{aligned} \tag{16}$$

where the notation follows the same logic as in models (13) and (14) and the subscript a of the return variables represents the VW return computed by using the average bid-ask prices. The first model examines the overall impact of the seasonal bid-ask spreads on the FMS; the second model differentiates this impact by the three stock size groups in models (13) and (14). We report the estimates for models (13) and (14) in Panel A and for the models (15) and (16) in Panel B of Table 7.

[Insert Table 7 here]

The impact of transaction price bias on the seasonal underperformance in the first month of a quarter is limited. After controlling for this bias, the intercepts of -15 basis points and -20 basis points for the first month of a quarter remain negative and significant at the 5% statistical level when stock size is accounted for. Likewise, the average FMSs in the middle and final months of a quarter do not change significantly after this bias is controlled for.

Similarly, the seasonality in the bid-ask spread cannot account for the negative effect of the first month of the quarter on the aggregate performance of active funds. Controlling for the average bid-ask prices, we find that the FMS at the beginning of the quarter remains large (-25 basis points across the two models) and statistically significant at the 1% level or better, whereas the excess performance of mutual funds in the middle and last months of the quarter remains statistically indistinguishable from zero. We conclude that market microstructure biases do not significantly account for the within-quarter seasonal pattern in mutual fund performance that we document.

[35] We note that the market-making behavior of some mutual funds such as Dimensional Fund Advisors could reduce the transaction costs arising from buying at the ask price and selling at the bid price. Such market-making behavior could affect fund returns at the aggregate level, but there is no clear reason to expect it to induce any seasonal pattern within quarters. Thus, we assume that this market-making behavior has a negligible impact on the FMS in the first month of a quarter.

[36] In separate analyses, we also examined whether these microstructure biases could explain the fund underperformance in January only but found no supporting evidence. The results are available upon request.

5.3. Fund flows

A recent study by Kamstra et al. (2013) points to strong seasonality in investors' flows, according to which U.S. mutual funds experience higher flows during the winter and spring months than in the summer and autumn months. Combined with Berk and Green's (2004) argument that large inflows can adversely affect funds' abilities to produce alphas due to diseconomies of scales, seasonality in fund flows could lead to seasonality in fund performance.

To assess the potential impact of fund flows on the performance of the VW portfolio of active mutual funds, we directly regress our FMS measure in each month of the quarter against past fund flows:

$$R_{MF,t} - R_{f,t} = \alpha + \rho_1 flow_{t-1} + \rho_2 flow_{t-2} + \rho_3 flow_{t-3} + \varepsilon_t, \tag{11}$$

where the variable on the left-hand side is our FMS measure and the flow measure *flow* on the right-hand side is constructed as follows. First, as is standard in the literature (e.g., Sirri and Tufano, 1998; Lou, 2012), we measure net flows as the net growth in fund total net assets beyond reinvested dividends:

$$NetFlow_{i,t} = TNA_{i,t} - TNA_{i,t-1}(1 + R_{i,t}) - MGN_{i,t}, \tag{12}$$

where $TNA_{i,t}$ is fund *i*'s total net assets or the dollar value of all shares outstanding in month *t*, $R_{i,t}$ is the fund return in month *t*, and $MGN_{i,t}$ is the increase in total net assets due to fund mergers in month *t*. Next, we divide monthly net flows to funds by total net assets at the end of the prior month and value weight fund flows to compute the flow variable $flow_t$ of the portfolio of domestic actively managed equity mutual funds. Table 8 summarizes the results of regression (11).

[Insert Table 8 here]

Overall, fund flows fail to account for the inter-quarter seasonality in the aggregate performance of active funds. The first-month drag on aggregate fund performance in excess of the market, using either the S&P500 or CRSP VW indices as proxies, remains statistically significant at the 10% level or better after controlling for fund flows in the previous one to three months. Furthermore, the estimated intercepts are of similar magnitude to the FMSs reported in Table 1—despite being computed on a shorter recent sample. We note that past flows affect fund performance negatively, in agreement with the predicted sign of Berk and Green's (2004) diseconomies of scale hypothesis (larger inflows lead to subsequent underperformance), but only with a one-quarter delay. We conclude from these results that flows play no role in explaining the seasonal underperformance of active managers.

5.4. Distributions

Funds implementing tax-efficient investment strategies aim to reduce the burdens of their investors by avoiding stocks with high dividend yields and the realization of capital gains, and by accelerating the realization of capital losses (Sialm and Zhang, 2014). These strategies could lead to seasonality in fund performance if they induced a particular temporal pattern in capital gains and dividend distributions.

We examine the monthly pattern of mutual fund distributions within the quarter in Table 9, where we differentiate between capital gains, income dividends, and total distributions per fund share. No seasonal pattern is evident in either type of distribution. Furthermore, in non-tabulated tests, we find limited correlation between mutual fund performance and their (lagged) distributions. Overall, we find fund distributions to be unrelated to the seasonality in the aggregate performance of active mutual funds.

[Insert Table 9 here]

6. Economic Significance of the Performance Seasonality

The seasonality in fund performance suggests that, in principle, it should be possible to enhance the performance of active management by investing in a VW portfolio of active funds at the end of the first month of a quarter and shifting to an index-tracking mutual fund at quarter-end. Following our findings, this switching strategy should deliver higher returns than a buy-and-hold strategy in the VW portfolio of active funds. We present the raw returns and factor-adjusted alphas of each strategy ("switching" and "buy-and-hold") over our sample period in Table 10, along with the performance of a hypothetical zero-investment strategy that goes short on the buy-and-hold investment and goes long on the switching strategy.

[Insert Table 10 here]

In line with our evidence in Section 4, the hypothetical zero-investment strategy delivers abnormally positive returns that are both economically and statistically significant. Its (annualized) four-factor alpha is 112 basis points when the S&P 500 index is used as the market proxy and 63 basis points relative to the CRSP VW market index. The results confirm that the switching strategy significantly enhances the performance of a buy-and-hold investment in the VW average of active funds.

We note that, by avoiding just the first month of each quarter, the mechanical strategy that switches between active and index funds overcomes the documented underperformance of active management. Indeed, the risk-adjusted net returns to the switching strategy under the CAPM, Fama-French 3-factor and Carhart 4-factor models are not significantly negative. Glode (2011) argues theoretically that investing in active funds expected to perform poorly unconditionally can be rational if these funds perform abnormally well when the economy is doing poorly, a hypothesis for which Kosowski (2011) finds empirical support. If this is the case, our results in this section show that the switching strategy could improve the "insurance" value of active investment even further by avoiding the unconditionally negative performance of active funds in the first place.[37]

7. Conclusions

We document a strong seasonal component in the aggregate performance of US active domestic equity mutual funds in excess of the market and other benchmark indices. Each calendar quarter, active funds as a group underperform in the first month but not in the remaining two months. The intra-quarter seasonality in funds' aggregate performance is pervasive across fund size quintiles, investment styles, risk-adjustment methods, or benchmarks employed to compute excess returns. Moreover, the first-month underperformance of all active funds compares in magnitude to the year-round negative excess return documented in the literature. This performance seasonality coincides with a similar intra-quarter pattern at the level of active management of mutual fund portfolios, whereby fund portfolios deviate the most from passive benchmarks at the beginning of each quarter.

We find evidence of a negative impact on the performance seasonality of short-term stock return reversal effects along with quarter-end, industry-wide window-dressing behavior and, to a lesser extent, NAV-inflation practices. By contrast, we report limited or no evidence of microstructure biases, money flows, and fund cash distribution as sources of intra-quarter performance seasonality.

Our findings have important implications. First, they draw attention to a relatively overlooked link between money managers' quarter-end trading behavior at the individual fund level and the overall industry performance within a quarter. Second, our findings challenge existing and potential rationalizations of the active management underperformance puzzle by documenting a new stylized fact—intra-quarter performance seasonality, which such rationalizations should aim to explain. Finally, these findings highlight novel commonalities in the dynamic patterns of stock returns and the aggregate mutual fund behavior and performance. We believe our findings will stimulate further

[37] Given that it is outside the scope of this paper, we do not explore the insurance value of the switching strategy further. Such examination should account for the potential individual tax implications of buying and selling fund shares every quarter. Individual investors are required to pay long- or short-term capital gain taxes on any profits they make on the sales of their fund shares. Capital gains are considered short term if they are realized over a period shorter than one year and pay an average tax rate substantially higher than those realized over a period longer than one year. Any individual investor attempting to profit from a strategy designed to exploit the monthly seasonality that we report within the quarter must then bear the tax burden that results from the short-term capital gains taxes on any realized profits. Additional transaction costs that investors would need to incur to implement the switching strategy include the price impact cost documented by Coval and Stafford (2007), who find that individual investors forcing funds to quickly sell assets in their portfolios incur potentially large liquidity premiums, resulting in transaction prices considerably below fundamental values.

research on such commonalities and their importance for the performance evaluation of active managers.

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Figure 1. Aggregate fund-market tracking errors

Each month, we compute the volatilities of the daily FMSs (i.e., tracking error) for each actively managed domestic mutual fund. The FMS refers to the difference between fund net returns and the returns to the S&P 500 portfolio in Panel A (C) and between fund net returns and the returns to the CRSP VW market portfolio in Panel B (D). The figure presents the VW tracking error of active mutual funds, represented as the solid line in Panel A to D. In Panel C and D, the broken line represents the average of tracking errors all months except for the first months of a quarter; the dot line represents the corresponding 95% confidence intervals. All numbers are in percentages. The sample period is September 1, 1998 to December 31, 2013.

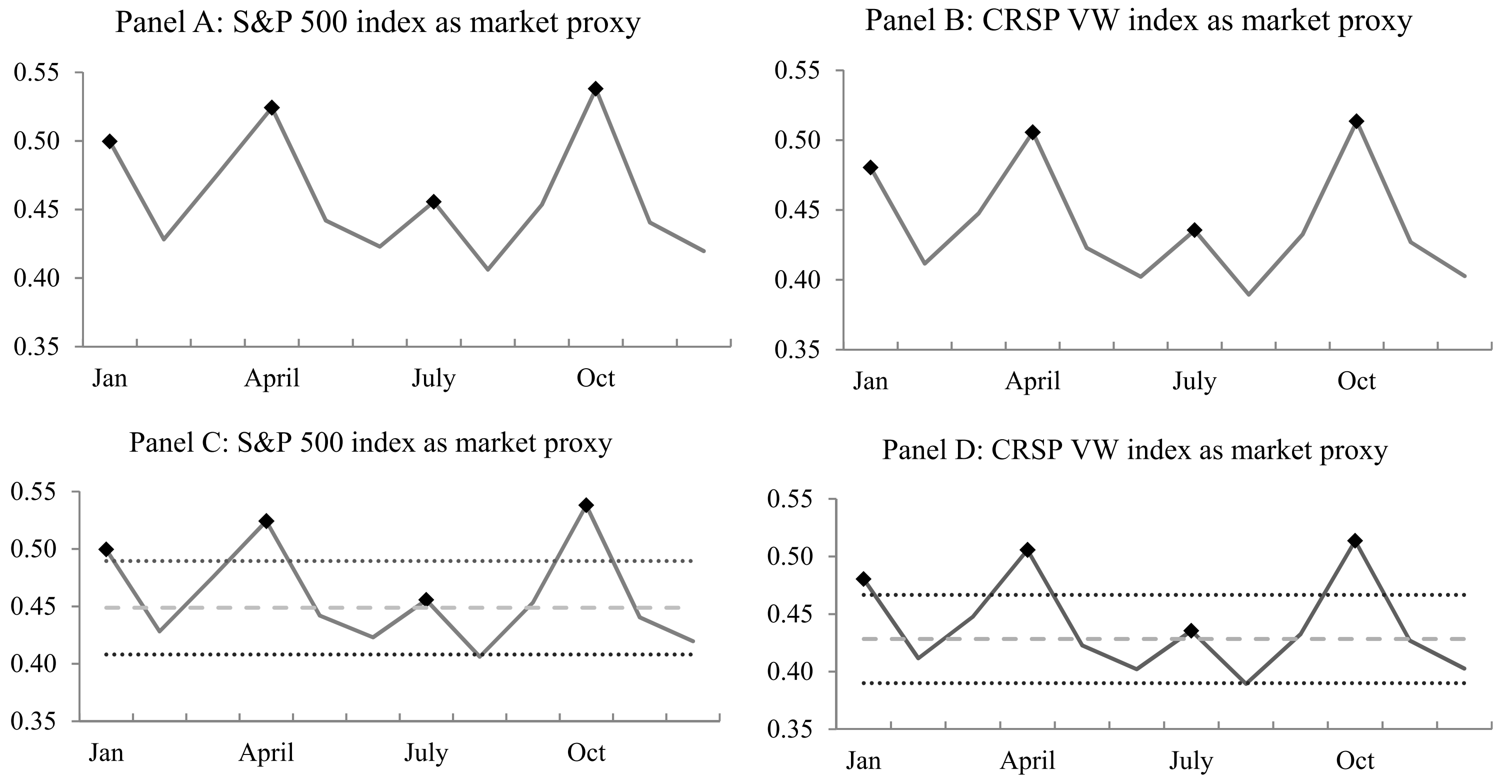
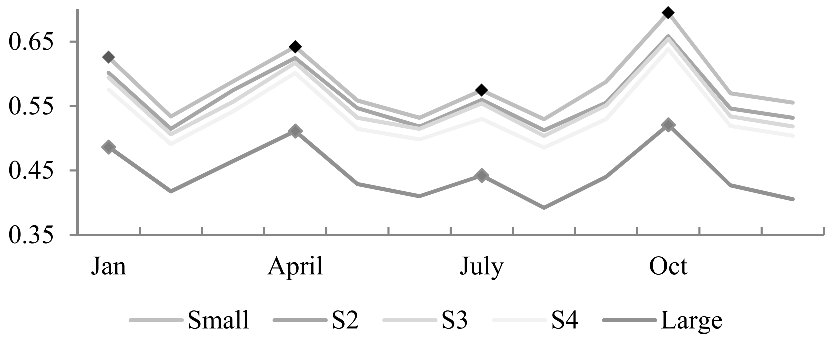


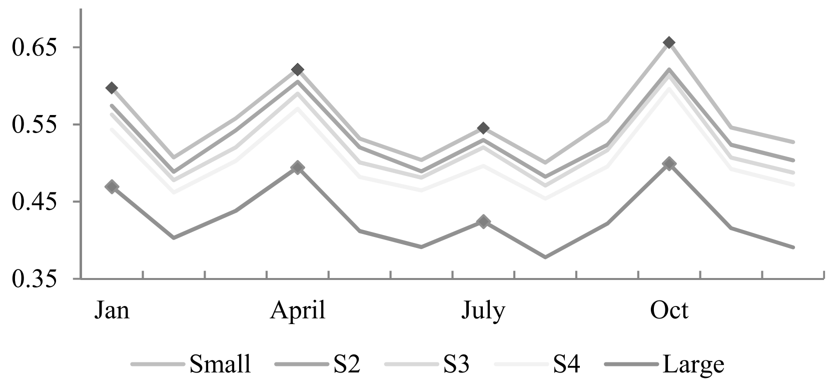
Figure 2. Fund-market tracking errors by fund size and investment style

Panel A and B reports the tracking errors for five fund size groups across different calendar months. At each month, we rank all the funds based on the prior-month total net assets into five fund-size portfolios, compute the volatility of daily FMS (i.e., tracking errors) of each fund within the portfolios and then value weight the volatilities of all active mutual funds in the corresponding group. FMS is defined as the difference between fund net returns and the returns to the S&P 500 portfolio in Panel A; FMS is defined as the difference between fund net returns and the returns to the CRSP VW market portfolio in Panel B. Panel C reports the tracking errors of mutual funds relative to their respective prospectus benchmark indices. All numbers are in percentages. The sample period is September 1, 1998 to December 31, 2013.

Panel A: the S&P 500 index



Panel B: the CRSP VW index



Panel C: Self-reported index as benchmark

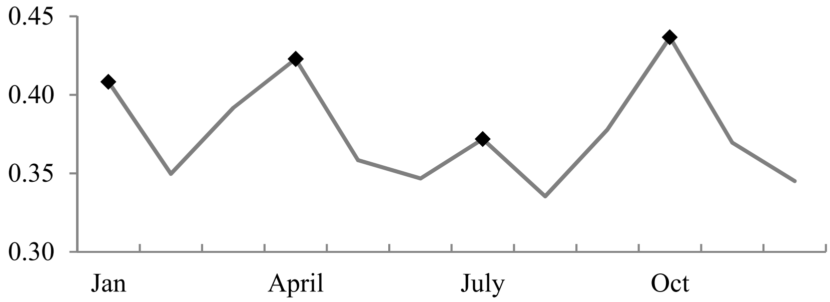
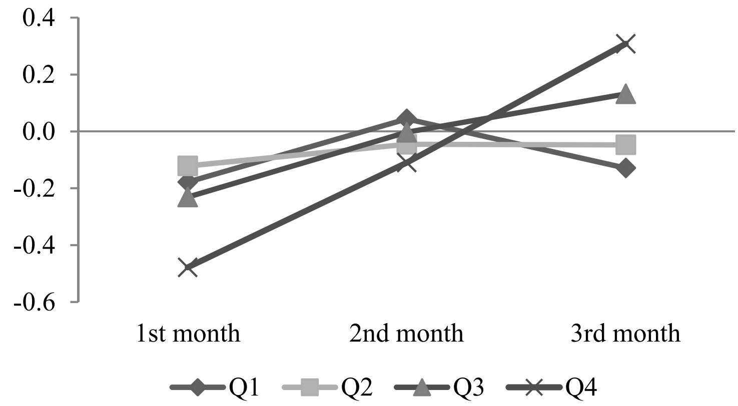


Figure 3. Average monthly FMS

This figure depicts, within each calendar quarter Q1 to Q4, the monthly return spread or FMS (%) between aggregate U.S. domestic active equity mutual funds and the S&P 500 portfolio in Panel A and between aggregate U.S. domestic active equity mutual funds and the CRSP VW market portfolio in Panel B. Aggregate (net) mutual fund returns are computed as the VW average net returns (after fees) over all available U.S. active domestic equity mutual funds. The weights in the portfolio of mutual funds are constructed using the lagged total net assets of the previous month. The CRSP market index denotes the VW average return (including dividends reinvested) of all NYSE, AMEX, and NASDAQ common shares. The S&P 500 index denotes the VW returns (including reinvested dividends) of all S&P 500 companies. All numbers are in percentages. The sample period is from January 1967 to December 2013.

Panel A: S&P 500 index as market proxy



Panel B: CRSP VW market index as market proxy

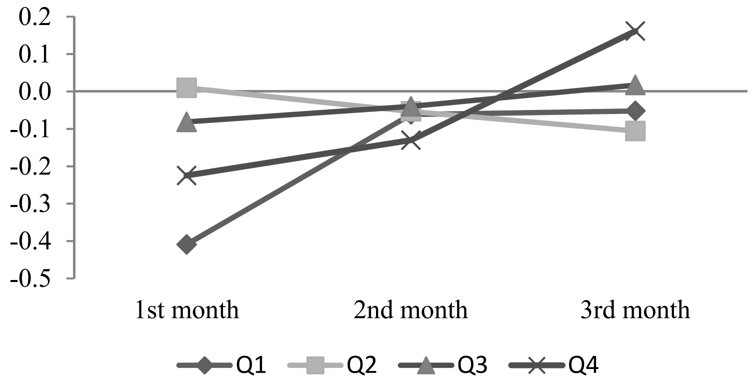
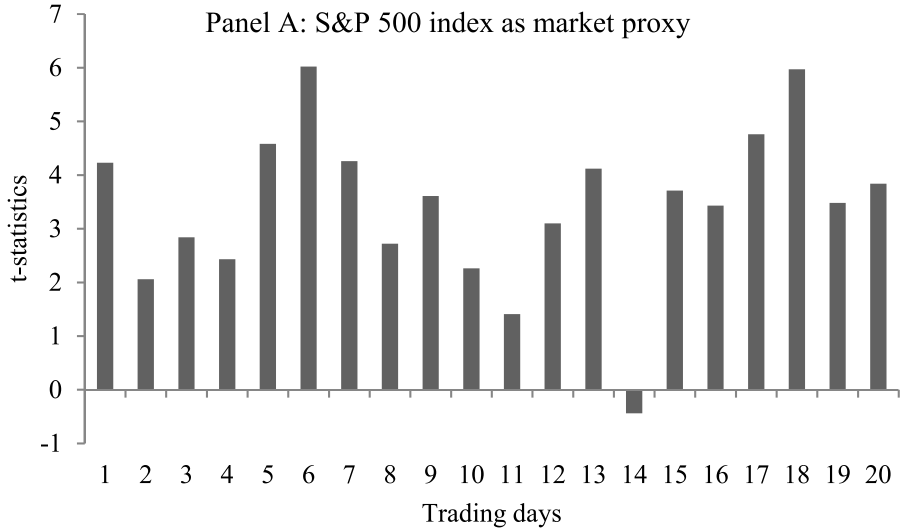


Figure 4. Relation between daily and monthly FMS in the first month of a quarter

This figure reports the *t*-statistics of regressing the monthly FMS at the first month of a quarter on the first, second, . . . , and 20th daily FMS in the same month. The CRSP market index denotes the VW average return (including reinvested dividends) of all NYSE, AMEX, and NASDAQ common shares. The S&P 500 index denotes the VW returns (including reinvested dividends) of all S&P 500 companies. FMS is defined as the difference between fund net returns and the returns to the S&P 500 portfolio in Panel A; FMS is defined as the difference between fund net returns and the returns to the CRSP VW market portfolio in Panel B. The sample period is September 1, 1998 to December 31, 2013.



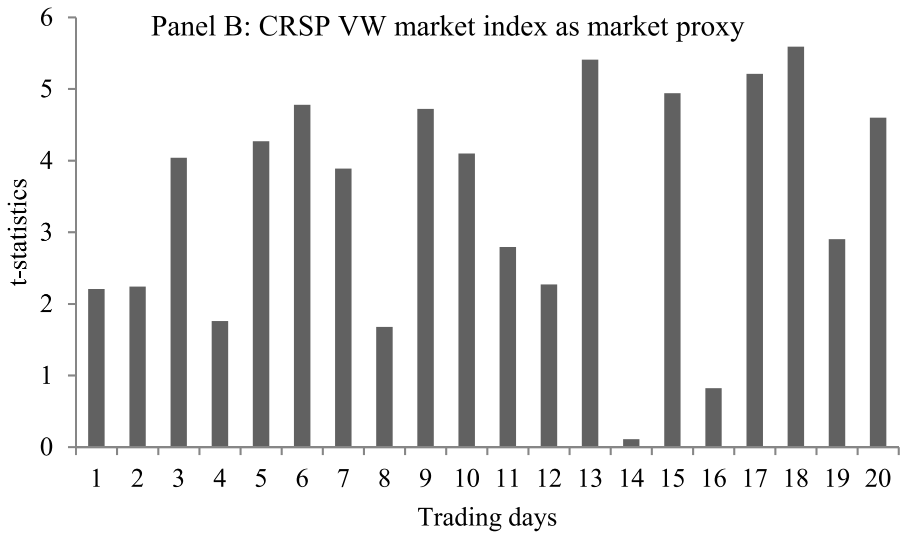
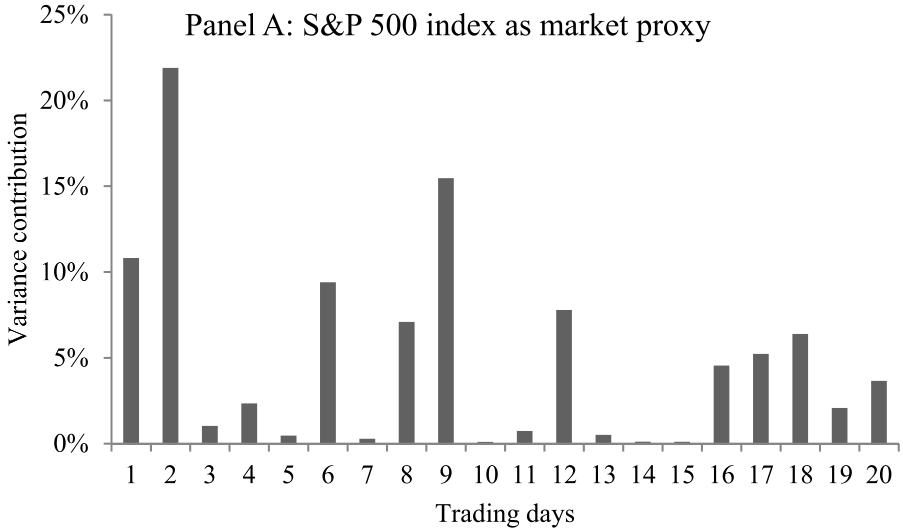


Figure 5. Contribution of each trading day to the FMS in the first month of a quarter

This figure reports the percentage contributions to the variance of the monthly FMS in the first month of a quarter, of the variance of the first, second, . . . , and 20th daily FMS in the same month. The contributions are calculated from an analysis of variance (ANOVA) of the regression underlying Fig. 4, as the fraction of the explained sum of squares contributed by each trading day. The CRSP market index denotes the VW average return (including reinvested dividends) of all NYSE, AMEX, and NASDAQ common shares. The S&P 500 index denotes the VW returns (including reinvested dividends) of all S&P 500 companies. FMS is defined as the difference between fund net returns and the returns to the S&P 500 portfolio in Panel A; FMS is defined as the difference between fund net returns and the returns to the CRSP VW market portfolio in Panel B. The sample period is September 1, 1998 to December 31, 2013.



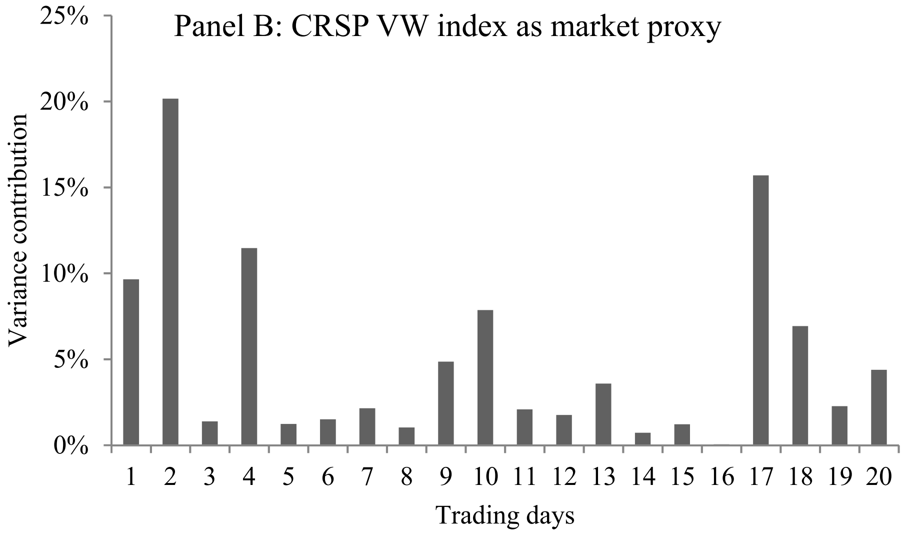


Table 1. Fund-Market Spread (FMS)

The variable R_{MF} is the net return to a value-weighted (VW) portfolio of actively managed U.S. equity mutual funds. The lagged total net assets of the previous month are used as the weight to compute the VW returns to the aggregate mutual fund portfolio. Net returns are those received by investors after all management expenses and 12-b fees. Gross returns are computed by adding back 1/12 of the respective funds' expense ratio. The variable R_{SP} is the VW return (including dividends reinvested) of all S&P 500 companies and R_{MK} is the VW return (including dividends reinvested) of NYSE, AMEX and NASDAQ stocks on the CRSP monthly file (including dividends reinvested). Panel A reports the difference in the VW monthly returns between the mutual fund portfolio and the S&P 500 portfolio across the year and in the first, second, and third months of a quarter, respectively. Panel B presents the difference in monthly returns between the VW portfolio of mutual funds and the CRSP VW market portfolio, R_{MF}-R_{MKT}, across the year and in the first, second, and third months of a quarter, respectively. All the net and gross differences are in percentages. Associated *t*-statistics are reported in parentheses. The table also presents cumulative differences across the year and in the first/middle/last month of a quarter, as well as the ratios of cumulative differences of the first/second/third month of a quarter over the annual cumulative differences. The sample period is January 1967 through December 2013. Statistical significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *, respectively.

Panel A: R_{MF}-R_{SP}				
	Net (monthly)	*t*-Statistic	Gross (monthly)	*t*-Statistic
Overall	-0.07	(-1.60)	-0.01	(-0.14)
1st month	-0.25***	(-3.27)	-0.19**	(-2.43)
2nd month	-0.03	(-0.35)	0.04	(0.45)
3rd month	0.07	(0.91)	0.13*	(1.82)
	Net (cumulative)	Percentage		
Overall	-0.95			
1st month	-1.05	111		
2nd month	-0.11	12		
3rd month	0.27	-29		
Panel B: R_{MF}-R_{MKT}				
	Net (monthly)	*t*-Statistic	Gross (monthly)	*t*-Statistic
Overall	-0.08***	(-3.12)	-0.02	(-0.59)
1st month	-0.18***	(-3.46)	-0.11**	(-2.17)
2nd month	-0.07*	(-1.73)	-0.01	(-0.14)
3rd month	0.01	(0.13)	0.07*	(1.72)
	Net (cumulative)	Percentage		
Overall	-1.08			
1st month	-0.73	68		
2nd month	-0.30	27		
3rd month	0.02	-2		

Table 2. Mutual fund risk-adjusted performance seasonality

This table presents the CAPM, Fama-French three-factor, and Carhart four-factor net alphas on the aggregate portfolios of actively managed equity mutual funds. The variable R_{SP} is the return to the S&P 500 portfolio including dividends reinvested; R_{MK} is the return to a VW market portfolio of NYSE, AMEX, and NASDAQ stocks on the CRSP monthly file; R_f is the one-month Treasury bill rate. The construction of SMB, HML, and MOM follows Fama and French (1996). At the end of June of each year k, the NYSE, AMEX, and NASDAQ stocks are sorted into two size groups, where small/big includes stocks with June market capitalization below/above the NYSE medium. All stocks are also sorted into three book-to-market equity (B/M) groups: Growth includes the bottom 30% of the NYSE B/M; neutral includes the middle 40% of the NYSE B/M; value includes the top 30% of the NYSE B/M. The book equity is for the fiscal year ending in calendar year $k-1$ and the market value in B/M is for the end of December of calendar year $k-1$. The intersection of the size and B/M sorts generates six VW portfolios, refreshed yearly. The size return, SMB, is the average of returns in month t to the three small stock portfolios minus the average of returns to the three big stock portfolios. The value growth return, HML, is the average of the returns to the two value portfolios minus the average of returns to the two growth portfolios. The momentum return, MOM, is defined similarly as for HML, except that stocks are sorted by prior one-year returns rather than by B/M and the momentum factor is constructed monthly rather than annually. At the end of each month $t-1$, all the NYSE, AMEX, and NASDAQ stocks are sorted by the 30th and 70th NYSE breakpoints—which are determined according to the returns from month $t-12$ to month $t-2$—into low-, medium-, and high-momentum groups. There is a one-month skip to avoid the microstructure bias. The intersection of the size and momentum sorts generates six VW portfolios, refreshed monthly. The momentum return, MOM, is the average of returns to the two high-momentum portfolios minus the average of returns to the two low-momentum portfolios. α is the intercept (in percentage). D_i is a dummy variable that equals 1 in the i-th month of the quarter and 0 otherwise, for i = 1, 2, 3. The t-statistics, shown in parentheses, are computed based on standard errors clustered by year using the approach described by Petersen (2009) under the null that the coefficient estimates are equal to zero (except for the market slope, which tests whether beta is different from one). The sample period is January 1967 through December 2013. Statistical significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *, respectively.

	S&P 500 index			CRSP VW index		
	CAPM	FF3	Carhart	CAPM	FF3	Carhart
Panel A: Annual performance						
α	-0.07*	-0.09***	-0.11***	-0.07**	-0.06**	-0.08**
	(-1.65)	(-2.71)	(-3.02)	(-2.50)	(-2.21)	(-2.43)
MKT	1.00	0.96***	0.96***	0.99	0.96***	0.97***
	(0.22)	(-3.56)	(-2.73)	(-1.49)	(-3.56)	(-3.01)
SMB		0.24***	0.25***		0.06***	0.06***
		(15.76)	(17.64)		(5.49)	(5.67)
HML		-0.07***	-0.06***		-0.04***	-0.04***
		(-5.04)	(-4.83)		(-3.16)	(-2.88)
MOM			0.03			0.02
			(1.88)			(1.44)
Adj-R^2	94.60%	97.73%	97.79%	98.21%	98.49%	98.51%
Panel B: Monthly intra-quarter performance						
D_1	-0.26***	-0.19***	-0.18***	-0.17***	-0.12**	-0.12**
	(-3.61)	(-3.32)	(-3.39)	(-3.39)	(-2.48)	(-2.47)
D_2	-0.03	-0.04	-0.06	-0.06	-0.06	-0.07
	(-0.37)	(-0.97)	(-1.38)	(-1.53)	(-1.60)	(-1.84)
D_3	0.07	-0.05	-0.08	0.01	-0.01	-0.02

	(1.04)	(-1.01)	(-1.42)	(0.27)	(-0.34)	(-0.31)
$D_1 \times$MKT	1.01	0.96*	0.97*	0.99	0.97**	0.97*
	(0.78)	(-1.94)	(-1.74)	(-0.92)	(-1.96)	(-1.84)
$D_1 \times$SMB		0.21***	0.23***		0.04*	0.05**
		(7.87)	(9.66)		(1.72)	(2.23)
$D_1 \times$HML		-0.08***	-0.08***		-0.06**	-0.06**
		(-3.02)	(-3.04)		(-2.27)	(-2.25)
$D_1 \times$MOM			0.03			0.02
			(1.23)			(1.06)
$D_2 \times$MKT	0.99	0.95***	0.96**	0.98	0.96***	0.96***
	(-0.27)	(-4.50)	(-2.99)	(-1.47)	(-5.14)	(-4.10)
$D_2 \times$SMB		0.28***	0.27***		0.09***	0.09***
		(20.18)	(19.68)		(7.74)	(8.16)
$D_2 \times$HML		-0.05**	-0.04**		-0.02**	-0.02
		(-2.40)	(-2.12)		(-2.12)	(-1.60)
$D_2 \times$MOM			0.03			0.02
			(1.50)			(1.15)
$D_3 \times$MKT	1.00	0.97**	0.97**	0.99	0.97**	0.97**
	(-0.04)	(-2.49)	(-2.04)	(-0.99)	(-2.36)	(-2.16)
$D_3 \times$SMB		0.25***	0.25***		0.07***	0.07***
		(15.33)	(16.67)		(6.10)	(6.18)
$D_3 \times$HML		-0.02	-0.02		-0.02	-0.02
		(-0.73)	(-0.51)		(-0.78)	(-0.72)
$D_3 \times$MOM			0.02			0.00
			(1.15)			(0.06)
Adj-R^2	94.49%	97.79%	97.83%	98.24%	98.52%	98.53%

Table 3. Mutual fund performance seasonality by fund-size group

This table presents the FMS (Panel A) and the Carhart four-factor adjusted returns (Panel B) on the aggregate portfolios of actively managed equity mutual funds for each of three months of a quarter within five fund size groups. At each month, we assign all funds into five quintiles (Small, S2, S3, S4, and Large) by their total net assets in the prior month. D_i is a dummy variable that equals 1 in the *i*-th month of the quarter and 0 otherwise, for *i*=1, 2, 3. The *t*-statistics, shown in parentheses, are computed based on standard errors clustered by year using the approach described by Petersen (2009) under the null that the coefficient estimates are equal to zero. The sample period is January 1967 to December 2013. Statistical significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *, respectively.

	S&P 500 index					CRSP VW index				
	Small funds	S2	S3	S4	Large funds	Small funds	S2	S3	S4	Large funds
Panel A: Fund market spread										
1st month	-0.11	-0.20*	-0.30***	-0.32***	-0.24***	-0.03	-0.12	-0.23***	-0.25***	-0.17***
	(-0.83)	(-1.69)	(-2.71)	(-3.15)	(-3.39)	(-0.35)	(-1.51)	(-2.99)	(-3.50)	(-3.26)
2nd month	0.10	0.13	0.04	0.02	-0.05	0.05	0.08	0.00	-0.02	-0.09**
	(0.75)	(1.09)	(0.35)	(0.19)	(-0.60)	(0.62)	(1.11)	(-0.03)	(-0.32)	(-2.31)
3rd month	0.33**	0.27**	0.24**	0.17*	0.03	0.27**	0.21***	0.18***	0.11*	-0.03
	(2.17)	(2.55)	(2.32)	(1.79)	(0.49)	(2.08)	(2.83)	(2.60)	(1.81)	(-0.71)
Panel B: Risk-adjusted performance regression										
D_1	-0.07	-0.15***	-0.25***	-0.25***	-0.18***	-0.01	-0.09*	-0.19***	-0.19***	-0.11**
	(-0.88)	(-2.66)	(-3.58)	(-3.66)	(-3.25)	(-0.13)	(-1.67)	(-2.92)	(-2.96)	(-2.26)
D_2	0.05	0.05	-0.03	-0.03	-0.07	0.04	0.04	-0.04	-0.04	-0.08**
	(0.79)	(0.93)	(-0.55)	(-0.58)	(-1.60)	(0.63)	(0.79)	(-0.77)	(-0.80)	(-2.12)
D_3	0.21	0.02	-0.01	-0.06	-0.09	0.27*	0.09	0.05	0.00	-0.03
	(1.32)	(0.29)	(-0.12)	(-0.78)	(-1.57)	(1.75)	(1.18)	(0.85)	(0.06)	(-0.50)
4-factor adj.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj-R^2	93.50%	96.78%	96.76%	96.99%	97.78%	94.21%	97.27%	97.53%	97.72%	98.46%

Table 4. Mutual fund performance seasonality by investment style

This table presents the FMS (Panel A) and the Carhart 4-factor adjusted returns (Panel B) on the aggregate portfolios for three major investment styles (i.e., small-, medium-, and large-cap). Funds are classified as large-cap styles if they self-report the following indices as benchmarks: S&P 500, S&P 500 Value/Growth, Russell 1000, or Russell 1000 Value/Growth; funds are classified as mid-cap styles if they self-report the following indices as benchmarks: S&P 400, S&P 400 Value/Growth, Russell Midcap, Russell Midcap Value/Growth; funds are classified as small-cap styles if they self-report the following indices as benchmarks: S&P 600, S&P 600 Value/Growth, Russell 2000, Russell 2000 Value/Growth. The sample period is January 1979 to December 2013, except for the following indices whose return data begin later: S&P 400 (September 1991), S&P 600 (February 1995), and the Growth and Value components of the Russell Midcap (January 1986), S&P 400 (May 1997), S&P 500 (February 1994), S&P 600 (May 1997), and S&P 1000 (July 1995). For each investment style, we compute value-weighted portfolio of the corresponding active mutual funds. The lagged total net assets of the previous month are used as the weight to compute the VW returns to the aggregate mutual fund portfolio. Fund market spread is defined as the value-weighted net returns to those funds following large-, medium-, and small-cap style minus the corresponding self-declared benchmark index. Net returns are those received by investors. Statistical significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *, respectively.

	Overall	Large-cap	Mid-cap	Small-cap
Panel A: Fund market spread				
1st month	-0.19***	-0.21***	-0.22***	0.06
	(-3.43)	(-3.51)	(-2.66)	(0.52)
2nd month	0.00	0.01	-0.14*	-0.12
	(0.04)	(0.21)	(-1.66)	(-1.32)
3rd month	0.02	0.02	0.03	0.00
	(0.30)	(0.32)	(0.34)	(-0.05)
Panel B: Risk-adjusted performance regression				
D_1	-0.16**	-0.13**	-0.37***	-0.25**
	(-2.41)	(-2.09)	(-3.21)	(-2.42)
D_2	-0.06	-0.07	0.09	-0.08
	(-1.26)	(-1.43)	(1.05)	(-1.31)
D_3	-0.06	-0.07	-0.06	-0.04
	(-0.88)	(-1.21)	(-0.45)	(-0.53)
4-factor adj.	Yes	Yes	Yes	Yes
Adj-R^2	98.15%	98.39%	94.75%	96.31%

Table 5: Winning stocks holdings and FMS

This table analyzes the relation between mutual funds' winning stock holdings in the third month of a quarter and their performance in the subsequent month. We rank all stocks at the end of each quarter according to their prior-year performance and assign them into one of three bins: top 30% (winner), middle 40% or bottom 30% (loser). We then add up each fund's end-of-quarter portfolio weights in winner stocks, rank all funds by their weights in winners, and assign them into three terciles from low to high weights in winners. Within each tercile, we compute the FMS of the VW portfolio of all active funds. The sample period starts from 1980 to 2013. Statistical significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *, respectively.

	S&P 500 index		CRSP VW market index	
Holding positions in winning stocks	3rd month of a quarter	1st month of next quarter	3rd month of a quarter	1st month of next quarter
Low	-0.34***	-0.15	-0.39***	-0.02
	(-3.49)	(-1.43)	(-3.78)	(-0.25)
Mid	0.12	-0.30***	0.07	-0.17***
	(1.44)	(-3.50)	(1.30)	(-3.27)
High	0.53***	-0.43**	0.48***	-0.31**
	(2.72)	(-2.43)	(3.20)	(-2.14)

Table 6: Sort by window dressing and managerial skill

Panel A analyzes the relation between mutual funds' window dressing (WD) behavior (backward holding return gap, BHRG) and fund performance seasonality. BHRG is defined following Agarwal et al. (2014) as the differences between the return to a hypothetical portfolio invested in the fund's most recent quarter-end holdings (i.e., assuming that the manager held the same portfolio at the beginning of the quarter) and the reported quarterly return. Panel B analyzes the relation between return gaps (RG) and fund performance seasonality. RG is defined following Kacperczyk, Sialm and Zheng (2008) as the differences between the actual fund return and the return to a hypothetical portfolio invested in the fund's most-recent prior quarter's reported holdings (i.e., assuming that the portfolio is held throughout the current quarter). The next-month FMS refers to the fund-market-spread of each group in the month following a quarter-end. The *t*-statistics are presented in parentheses. In each panel, averages are calculated by value-weighting all funds in each rank bin. All figures are reported in percentages. The sample period is 1980–2013. Statistical significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *, respectively.

	Panel A: Sort by backward holding return gap		
BHRG Rank	BHRG 3rd month of a quarter	Fund market spread 1st month of next quarter	
		S&P 500 index	CRSP VW market index
Low WD	-0.68***	-0.20**	-0.08
	(-27.02)	(-2.03)	(-1.11)
Mid WD	0.04***	-0.16**	-0.04
	(3.81)	(-2.17)	(-0.77)
High WD	0.99***	-0.36***	-0.23**
	(22.57)	(-2.81)	(-2.49)
	Panel B: Sort by return gap		
RG/Skill Rank	RG 3rd month of a quarter	Fund market spread 1st month of next quarter	
		S&P 500 index	CRSP VW market index
High	0.73***	0.06	0.19***
	(29.06)	(0.52)	(2.68)
Mid	0.02**	-0.26***	-0.13**
	(2.09)	(-3.37)	(-2.36)
Low	-0.69***	-0.60***	-0.46***
	(-19.58)	(-5.62)	(-6.55)

Table 7. Microstructure bias and fund performance seasonality

This table estimates the relation between the FMS and either the transaction price bias or the seasonal bid-ask spread. The transaction price bias refers to the difference between the VW hypothetical trading return from buying at the ask price in month $t-1$ and selling at the bid price in month t for NYSE, AMEX, and NASDAQ stocks and the VW market return computed by using closing transaction prices. The seasonal bid-ask spread bias refers to the differences between the VW market return computed by using the average bid-ask prices of NYSE, AMEX, and NASDAQ stocks and the VW market return computed by using closing transaction prices. The table also reports estimates of the impact of the transaction price bias and the seasonal bid-ask spread on the FMS of small, medium, and large groups. Each month, the small, medium, and big portfolios are constructed according to the 33% and 67% NYSE breakpoints. Accordingly, NYSE, AMEX, and NASDAQ common shares are assigned to three size groups and the VW portfolio returns are calculated. *t*-statistics, based on standard errors clustered by year using the approach described by Petersen (2009), are reported in parentheses. The regression equations are:

$$FMS_t = D_1 + D_2 + D_3 + b(R_{tr,t} - R_{c,t}) + \varepsilon_t,$$

$$\begin{aligned} FMS_t = {} & D_1 + D_2 + D_3 + b_{s1}D_1(R^s_{tr,t} - R^s_{c,t}) + b_{s2}D_2(R^s_{tr,t} - R^s_{c,t}) + b_{s3}D_3(R^s_{tr,t} - R^s_{c,t}) \\ & + b_{m1}D_1(R^m_{tr,t} - R^m_{c,t}) + b_{m2}D_2(R^m_{tr,t} - R^m_{c,t}) + b_{m3}D_3(R^m_{tr,t} - R^m_{c,t}) \\ & + b_{l1}D_1(R^l_{tr,t} - R^l_{c,t}) + b_{l2}D_2(R^l_{tr,t} - R^l_{c,t}) + b_{l3}D_3(R^l_{tr,t} - R^l_{c,t}) + \varepsilon_t, \end{aligned}$$

where FMS_t is the difference between the mutual fund net return and the S&P 500 return in month *t*; $R_{tr,t}$ is the hypothetical VW market return to buying all NYSE, AMEX, and NASDAQ stocks on the CRSP monthly file at the ask prices in month $t-1$ and selling at the bid prices in month *t*; $R_{c,t}$ is the market return computed by using closing transaction prices; $R^s_{tr,t}$ is the hypothetical VW return to the bottom 33% caps of NYSE, AMEX and NASDAQ stocks computed by buying at the ask prices in month $t-1$ and selling at the bid prices in month *t*; and $R^s_{c,t}$ is the VW returns to the bottom 33% caps of NYSE, AMEX, and NASDAQ stocks computed by using closing transaction prices. The dummy variables are defined as in Table 2. $R^m_{c,t}$ and $R^l_{c,t}$ are constructed in an analogous way. The regression equations are:

$$FMS_t = D_1 + D_2 + D_3 + b(R_{a,t} - R_{c,t}) + \varepsilon_t,$$

$$\begin{aligned} FMS_t = {} & D_1 + D_2 + D_3 + b_{s1}D_1(R^s_{a,t} - R^s_{c,t}) + b_{s2}D_2(R^s_{a,t} - R^s_{c,t}) + b_{s3}D_3(R^s_{a,t} - R^s_{c,t}) \\ & + b_{m1}D_1(R^m_{a,t} - R^m_{c,t}) + b_{m2}D_2(R^m_{a,t} - R^m_{c,t}) + b_{m3}D_3(R^m_{a,t} - R^m_{c,t}) \\ & + b_{l1}D_1(R^l_{a,t} - R^l_{c,t}) + b_{l2}D_2(R^l_{a,t} - R^l_{c,t}) + b_{l3}D_3(R^l_{a,t} - R^l_{c,t}) + \varepsilon_t, \end{aligned}$$

where the notation follows the same logic as in two models above, except for the subscript *a*, which denotes VW returns computed by using the average bid-ask prices. Statistical significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *, respectively.

Panel A: Transaction price bias			Panel B: Seasonal bid-ask bias		
D_1	-0.15*	-0.20**	D_1	-0.25***	-0.25***
	(-1.79)	(2.13)		(-3.39)	(-3.52)
D_2	0.03	-0.05	D_2	-0.03	-0.03
	(0.38)	(-0.46)		(-0.48)	(-0.46)
D_3	0.05	0.00	D_3	0.07	0.06
	(0.71)	(0.56)		(1.08)	(0.94)
$D_1 \times (R_{tr} - R_c)$	0.38*		$D_1 \times (R_{tr} - R_c)$	-0.08	
	(1.91)			(-0.03)	
$D_1 \times (R^s_{tr} - R^s_c)$		-0.17**	$D_1 \times (R^s_{tr} - R^s_c)$		-0.20
		(-2.00)			(-0.69)
$D_1 \times (R^m_{tr} - R^m_c)$		0.27*	$D_1 \times (R^m_{tr} - R^m_c)$		-0.21
		(1.75)			(-0.24)
$D_1 \times (R^l_{tr} - R^l_c)$		0.68**	$D_1 \times (R^l_{tr} - R^l_c)$		-0.01
		(2.28)			(-0.00)
$D_2 \times (R_{tr} - R_c)$	0.23*		$D_2 \times (R_{tr} - R_c)$	2.43	
	(1.70)			(1.58)	
$D_2 \times (R^s_{tr} - R^s_c)$		-0.11	$D_2 \times (R^s_{tr} - R^s_c)$		-0.07
		(-1.53)			(-0.12)
$D_2 \times (R^m_{tr} - R^m_c)$		0.05	$D_2 \times (R^m_{tr} - R^m_c)$		-0.36
		(0.46)			(-0.44)
$D_2 \times (R^l_{tr} - R^l_c)$		0.82	$D_2 \times (R^l_{tr} - R^l_c)$		2.67
		(2.64)			(1.51)
$D_3 \times (R_{tr} - R_c)$	-0.05		$D_3 \times (R_{tr} - R_c)$	0.47	
	(-0.25)			(0.15)	
$D_3 \times (R^s_{tr} - R^s_c)$		-0.05	$D_3 \times (R^s_{tr} - R^s_c)$		0.10
		(-0.74)			(0.24)
$D_3 \times (R^m_{tr} - R^m_c)$		0.09	$D_3 \times (R^m_{tr} - R^m_c)$		-0.50
		(0.97)			(-1.04)
$D_3 \times (R^l_{tr} - R^l_c)$		-0.06	$D_3 \times (R^l_{tr} - R^l_c)$		1.08
		(-0.16)			(0.33)
Adj-R^2	1.83%	2.16%	Adj-R^2	1.25%	0.59%

Table 8. Fund flows and intra-quarter performance seasonality

This table reports estimates of the response of the FMS to fund flows during the sample period 1990–2013. The dependent variable is the FMS in month *t*, which refers to the differences in returns between the VW portfolio of active equity mutual funds and the S&P 500 portfolio in Panel A (the CRSP VW market portfolio in Panel B). The independent variable is the flow ratio in months $t-1$, $t-2$, and $t-3$ and the dummy variables as well as their interactive items. The dummy variables are defined as in Table 2. The flow ratio refers to the aggregate net flows divided by aggregate total net assets. Net flows are measured as the net growth in fund total net assets beyond reinvested dividends, calculated as

$$\text{NetFlow}_{i,t} = TNA_{i,t} - TNA_{i,t-1}(1+R_{i,t}) - MGN_{i,t},$$

Where $TNA_{i,t}$ is fund *i*'s total net assets in month *t,* $R_{i,t}$ is the fund return in month *t*, and $MGN_{i,t}$ is the increase in total net assets due to fund mergers in month *t*. The *t*-statistics, shown in parentheses, are computed based on standard errors clustered by year using the approach described by Petersen (2009). Statistical significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *, respectively.

	S&P 500 index			CRSP VW index		
	(1)	(2)	(3)	(4)	(5)	(6)
D_1	-0.27**	-0.22**	-0.21*	-0.15**	-0.15**	-0.15*
	(-2.43)	(-2.14)	(-1.94)	(-1.99)	(-2.05)	(-1.95)
D_2	-0.00	0.01	0.05	-0.07	-0.06	-0.04
	(-0.04)	(0.10)	(0.53)	(-1.26)	(-1.12)	(-0.81)
D_3	0.17	0.13	0.13	0.01	-0.02	-0.01
	(1.52)	(1.22)	(1.23)	(0.19)	(-0.21)	(-0.18)
D_1 ×Flow ratio_1	0.00	0.08	0.11	0.02	0.03	0.01
	(0.02)	(0.42)	(0.56)	(0.23)	(0.25)	(0.13)
D_1 × Flow ratio_2		-0.19	-0.18		-0.01	-0.01
		(-1.54)	(-1.25)		(-0.08)	(-0.16)
D_1 × Flow ratio_3			-0.05			0.02
			(-0.24)			(0.21)
D_2 ×Flow ratio_1	0.02	0.09	0.21	0.01	0.05	0.09
	(0.25)	(0.63)	(1.17)	(0.20)	(0.57)	(0.88)
D_2 × Flow ratio_2		-0.16	-0.15		-0.08	-0.08
		(-0.89)	(-0.82)		(-0.83)	(-0.80)
D_2 × Flow ratio_3			-0.22**			-0.08
			(-2.16)			(-1.23)
D_3 ×Flow ratio_1	-0.25**	-0.33**	-0.39**	-0.12*	-0.18**	-0.20**
	(-1.99)	(-2.35)	(-1.97)	(-1.82)	(-2.39)	(-2.26)
D_3 × Flow ratio_2		0.18	0.13		0.14*	0.12*
		(1.51)	(1.17)		(1.88)	(1.85)
D_3 × Flow ratio_3			0.18			0.05
			(0.74)			(0.47)
Adj-R^2	1.33%	1.81%	1.86%	1.82%	2.33%	1.75%

Table 9. Intra-quarter capital gains and dividend distributions to investors

This table presents the capital and dividend distributions of U.S. domestic actively managed equity mutual funds during 1967−2013. Capital gains refer to the amount of capital gains distribution per share divided by the reinvestment price; dividend income refers to the amount of income dividend distribution per share divided by the reinvestment price; total distribution refers to the total amount of capital gains plus dividend incomes divided by the reinvestment price. All numbers are reported in percentages.

	Dividend income	Capital gains	Total distribution
1st month	0.81	3.61	1.64
2nd month	0.73	4.25	1.93
3rd month	0.82	3.85	1.86

Table 10. Hypothetical strategy

This table reports the raw returns and the CAPM, Fama-French (FF) and Carhart alphas on a hypothetical switching strategy that buys the VW portfolio of active funds at the end of the first month of a quarter and shifts to a market index-tracking mutual fund at quarter-end. The table also presents the return and alphas on a buy-and-hold portfolio that invests in the VW portfolio of active funds. A hypothetical zero-investment strategy of going short on the buy-and-hold portfolio and going long on the switching strategy (i.e., the performance difference between the switching and buy-and-hold strategy) is shown in the last column. All numbers are in percentages and the associated *t*-statistics are reported in parentheses. The sample period is January 1967 to December 2013. Statistical significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *, respectively.

	Switching strategy	Buy-and-hold strategy	Difference
	Panel A: S&P 500 index as market proxy		
Raw return	0.93***	0.85***	0.08***
	(4.93)	(4.43)	(3.22)
CAPM alpha	0.01	-0.07*	0.09***
	(0.39)	(-1.67)	(3.57)
FF alpha	0.01	-0.09***	0.09***
	(0.27)	(-2.71)	(3.95)
Carhart alpha	-0.02	-0.11***	0.09***
	(-0.68)	(-3.02)	(3.34)
	Panel B: CRSP VW index as market proxy		
Raw return	0.91***	0.85***	0.06***
	(4.72)	(4.43)	(3.39)
CAPM alpha	-0.02	-0.07**	0.06***
	(-0.88)	(-2.50)	(3.37)
FF alpha	-0.02	-0.06**	0.05***
	(-0.81)	(-2.21)	(2.82)
Carhart alpha	-0.02	-0.08**	0.05***
	(-1.29)	(-2.43)	(2.70)