Same-Weekday Momentum*

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Abstract

A disproportionately large fraction (70%) of the stock momentum reflects return continuation on the same weekday (e.g., Mondays to Mondays) or the same-weekday momentum. Even after accounting for partial reversals in other weekdays, the same-weekday momentum still contributes to a significant fraction (20% to 60%) of the momentum effect. This pattern is robust to different size filters, weighing schemes, time periods, and sample cuts. The same-weekday momentum is hard to square with traditional momentum theories based on investor misreaction. Instead, we provide direct and novel evidence that links it to within-week seasonality and persistence in institutional trading. Overall, our findings highlight institutional trading as an important driver of the stock momentum.

Key Words: Momentum, Same-Weekday, Return Seasonality.
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1 Introduction

Stocks that outperform (underperform) in the past year tend to produce higher (lower) future returns in the medium term (Jegadeesh and Titman (1993)). This stock momentum is probably the most well-studied asset pricing anomaly.[1] Stock momentum can be illustrated using a standard Fama and MacBeth (1973) cross-sectional regression of (log) return $r_{i,t}$ in month t on the (log) past return $r_{i,t-2,t-12}$ over prior 11 months from $t-12$ to $t-2$, skipping the most recent one month $t-1$:

$$r_{i,t} = \alpha_t + \beta_t r_{i,t-2,t-12} + u_{i,t}, \tag{1}$$

where $\hat{\beta}_t = Cov(r_{i,t}, r_{i,t-2,t-12})/Var(r_{i,t-2,t-12})$. A positive and significant average $\hat{\beta}_t$ confirms the stock momentum.

The term $Cov(r_{i,t}, r_{i,t-2,t-12})$ can be expressed as the sum of the covariance terms between a daily return in the holding period (month t) and a daily return in the formation period (months from $t-12$ to $t-2$). In addition, we can separate covariance terms involving daily returns in the same weekday (Monday to Monday, Tuesday to Tuesday, etc.) from those involving daily returns across different weekdays (Monday to Tuesday, Monday to Wednesday, ..., Tuesday to Monday, Tuesday to Wednesday, etc.):

$$Cov(r_{i,t}, r_{i,t-2,t-12}) = \underbrace{\sum_{k_1=1}^{5} Cov(r_{i,t}(k_1), r_{i,t-2,t-12}(k_1))}_{\text{Same-Weekday } (5\times1=5 \text{ items})} + \underbrace{\sum_{k_1=1}^{5} \sum_{\substack{k_2=1 \\ k_2 \neq k_1}}^{5} Cov(r_{i,t}(k_1), r_{i,t-2,t-12}(k_2))}_{\text{Other-Weekday } (5\times4=20 \text{ items})}, \tag{2}$$

where k_1 and $k_2 = 1$ to 5, denoting the five weekdays. $r(k)$ denotes the sum of all (log) daily returns on weekday k during a particular period.

[1] As of 2024, Jegadeesh and Titman (1993) has received more than 15,000 Google citations. For a comprehensive literature survey, please refer to Jegadeesh and Titman (2011) and Subrahmanyam (2018).

If the stock momentum is evenly distributed, we would expect that the same-weekday covariances account for about 20% of $\hat{\beta}_t$. In reality, almost 70% of $\hat{\beta}_t$ comes from the same-weekday covariances.

To be clear, we are not the first to discover the same-weekday momentum. Keloharju, Linnainmaa, and Nyberg (2016, 2021) have already shown that the average daily return on a particular weekday in the past strongly and positively predicts future returns on the same weekday. Keloharju, Linnainmaa, and Nyberg (2016, 2021) also document a reversal effect associated with the same-weekday momentum. For example, past Monday returns positively predict future Monday returns, but negatively predict future non-Monday returns. If the reversal is complete during the holding period, then the same-weekday momentum does not contribute to the momentum effect at all but simply "redistributes" it from other weekdays to the same weekday.

To estimate the degree of reversal (x), we decompose the total momentum effect ($\hat{\beta}_t$) into three parts: a standard momentum effect (m), the same weekday price pressure (p), and its reversal ($-xp$). We assume that the standard momentum effect (m) does not vary across weekdays but the same weekday price pressure does, and we denote them as $p_1, p_2, ..., p_5$ for the five weekdays. We also assume the reversal to spread evenly across the five weekdays during the holding period.

Under these assumptions, we can estimate the 7 parameters $(m, p_1, p_2, p_3, p_4, p_5, x)$ using the Generalized Method of Moments (GMM). We find that the reversal (x) during the holding period is only partial, about 28%, with its fifth and 95th percentiles -31.2% and 75.9%, respectively. As a result, the net contribution of the same-weekly momentum to the momentum effect, even after accounting for the reversals, is approximately 47.4%. This momentum decomposition pattern is robust to different size filters, weighing schemes, time periods, and sample cuts. The net contribution from the same weekday momentum is always positive and ranges from 18% to 62% of the overall momentum effect.

The decomposition result adds novel insights to our understanding of the stock momentum. A large body of momentum theories is based on some forms of investor misreaction to past information or trading signals. This includes both underreaction (Chan, Jegadeesh, and Lakonishok (1996), Barberis, Shleifer, and Vishny (1998), Hong and Stein (1999), Hong, Lim, and Stein (2000), Grinblatt and Han (2005), Antoniou, Doukas, and Subrahmanyam (2013), Da, Gurun, and Warachka (2014), Luo, Subrahmanyam, and Titman (2021) among others) or continuing overreaction (Daniel, Hirshleifer, and Subrahmanyam (1998), Lou and Polk (2022) among others). However, ex ante, there is no strong reason why investor misreaction should display such a seasonal pattern within the week.[2]

Instead, we provide direct evidence that links within-week seasonality and persistence in institutional trading to the same-weekday momentum. Using Morningstar daily fund flow data from 2008 to 2023 for the sample of active US equity mutual funds, we identify a fund with seasonal flow if it experiences significantly larger (absolute) fund flow on a particular weekday than other days of the week in the past year. Each month, we find 16.4% mutual funds experience seasonal flows and their (absolute) flows account for 14.9% of the total fund flows in the last year. Among these "seasonal" funds, more than 36.6% of their past (absolute) fund flows occur on the same weekday.

Similarly, using institutional trading data from ANcerno from 1999 to 2011, we identify an institution with seasonal trading if it traded significantly larger volume on a particular weekday than other days of the week in the past year. Each month, we find 26.7% of ANcerno institutions to display within-week seasonality in trading and their trading represents 46.4% of the total ANcerno institutional trading volume in the past one year. Among "seasonal institutions", more than 33.6% of their past trading occur on the same weekday.

[2] When we winorize extreme daily returns to alleviate the impact of large information events, we find the same weekday momentum to become even stronger. The evidence again suggests that misreaction to information is unlikely to explain the same-weekday momentum.

Both seasonal flows and seasonal trading are persistent. In other words, if a mutual fund experienced significantly more (absolute) flow on Mondays in the past year, it is more likely to experience more (absolute) flow on Mondays in the next month, as well. Similarly, if an institution traded more on Mondays in the past, it would trade more on Mondays in the future. In addition, the directions of both seasonal flow and seasonal trading are persistent as well. If a fund experienced more inflow (outflow) on Mondays in the past, it is more likely to experience more inflow (outflow) on Mondays in the future. Consistent with flow persistence, if an institution bought (sold) stocks on Mondays in the past, it is also more likely to buy (sell) stocks on Mondays in the future.

Finally, we directly link seasonal trading to the same-weekday momentum.[3] For each month and each stock, we first identify seasonal ANcerno institutions that have traded the stock in the momentum formation period (months from $t-12$ to $t-2$). Although past winners and losers are associated with a similar number of seasonal institutions as other stocks, their past returns are strongly consistent with the trading of seasonal institutions. For example, seasonal institutions bought (sold) winners (losers) during the formation period. In other words, seasonal institutional trading probably contributes to the past return. Second, we show that a seasonal institution who bought (sold) a winner (loser) on Mondays in the formation period will relatively buy (sell) more of the same stock on Mondays in the holding period. Third, aggregate seasonal trading on a stock at one weekday in the formation period positively predicts future same-weekday returns of that stock in the holding period. Fourth, the same-weekday momentum is stronger among stocks that are more exposed to seasonal institutional trading.

Our paper contributes to the momentum literature. Our simple decomposition exercise attributes a significant fraction of stock momentum to the same-weekday

[3] We confirm that the same weekday momentum in our paper is not entirely driven by the cross-sectional variation in mean returns. We do this by controlling for various measures of mean returns in Fama-MacBeth cross-sectional regressions.

momentum, even after accounting for its reversal. This finding suggests that a large group of explanations based on investor misreaction, while relevant, do not offer a complete explanation of the momentum profit. Instead, our evidence is more consistent with momentum theories based on institutional trading (see Grinblatt, Titman, and Wermers (1995), Goetzmann and Massa (2002), Lou (2012), Vayanos and Woolley (2013), Cremers and Pareek (2015), Dong, Kang, and Peress (2023), among others). In particular, persistent institutional trading, combined with its seasonality within the week, appears to be an important ingredient of the momentum effect. Note that the same-weekday momentum underestimates the overall contribution of institutional trading to the momentum effect, as it only reflects a special type of persistent institutional trading.[4]

Our paper also adds to the literature on seasonality in fund flow and institutional trading. For example, Kamstra et al. (2017) study within-year seasonality in fund flows. To our best knowledge, we are the first to examine within-week seasonality.

Finally, our paper also contributes to an emerging literature on seasonality in stock returns. Some examples include Heston and Sadka (2008, 2010), Heston, Korajczyk, and Sadka (2010), Keloharju, Linnainmaa, and Nyberg (2016, 2021), Bogousslavsky (2016, 2021), and Lou, Polk, and Skouras (2019). We provide novel evidence on within-week seasonality and persistence in both mutual fund flow and institutional trading, and we directly link within-week seasonality in trading to within-week seasonality in returns.

The rest of the paper contains two main sections. In Section 2, we present our momentum decomposition results. Section 3 examines within-week seasonality

[4]Many institutional-trading-based explanations of momentum feature a positive feedback mechanism. For example, in Lou (2012), funds holding past winners are likely to receive inflows that are invested by scaling up the current portfolio, pushing the prices of the winners up further, causing the momentum effect. The momentum effect further enhances the fund performance, thus attracting more inflow, etc. Although such a positive feedback mechanism can enhance the same weekday momentum effect, it is not a necessary condition, as the same weekday momentum is also present even among stocks which are neither past winners nor losers and thus do not contribute to the fund's performance.

in mutual flows and institutional trading and links such trading seasonality to the same-weekday momentum. Section 4 concludes.

2 Weekday Momentum Decomposition

In this section, we show that a disproportionately large fraction of the stock momentum reflects the continuation of the return on the same weekday. This same-weekday momentum is both statistically and economically significant.

2.1 Data and sample construction

Our baseline sample covers individual U.S. stocks listed on NYSE, Nasdaq, and Amex from 1963 through 2021. To alleviate the impact of market microstructure noise, we exclude small stocks and penny stocks from our baseline sample. Specifically, at the end of each month, we exclude stocks with a price less than $5. We also exclude stocks whose market capitalization is less than 10th size percentile based on the NYSE breakpoints. We confirm that our results are robust to different definitions of small and penny stocks. We obtain price, return, trading volume, and market value data from CRSP, and book equity data from Compustat.

2.2 Momentum decomposition: Baseline results

Eq.1 measures the standard momentum effect as the slope coefficient from regressing (log) return $r_{i,t}$ in month t on the (log) past return $r_{i,t-2,t-12}$ over prior 11 months from $t-12$ to $t-2$ in a Fama and MacBeth (1973) cross-sectional regression. Following Eq.2, we can decompose such a coefficient in each cross-section into a term reflecting return continuation across the same weekdays and a term reflecting return continuation across different weekdays:

$$
\begin{aligned}
\hat{\beta}_t &= \frac{Cov(r_{i,t}, r_{i,t-2,t-12})}{Var(r_{i,t-2,t-12})} \\
&= \underbrace{\sum_{k_1=1}^{5} \frac{Cov(r_{i,t}(k_1), r_{i,t-2,t-12}(k_1))}{Var(r_{i,t-2,t-12})}}_{\text{Same-Weekday } (5\times1=5 \text{ items})} + \underbrace{\sum_{k_1=1}^{5} \sum_{\substack{k_2=1 \\ k_2 \neq k_1}}^{5} \frac{Cov(r_{i,t}(k_1), r_{i,t-2,t-12}(k_2))}{Var(r_{i,t-2,t-12})}}_{\text{Other-Weekday } (5\times4=20 \text{ items})},
\end{aligned} \tag{3}
$$

where k_1 and $k_2 = 1$ to 5, denoting the five weekdays. $r(k)$ denotes the sum of all (log) daily returns on weekday k during a particular period.

Table 1 Panel A reports the decomposition results under different size filters. The first row shows the baseline result. The average $\hat{\beta}_t$ is 1.17 (t-value = 6.8), confirming a significant momentum effect during the period 1963 to 2021. If the momentum effect spreads evenly across days, we would expect the average "Same Weekday" component to be $20\% \times 1.17 = 0.23$. In reality, it is 0.85, accounting for more than 72% of $\hat{\beta}_t$ on average. This fraction is significantly higher than 20% with a t-value of 13.33. In sharp contrast, the "Other Weekday" component, while accounting for 80% of the covariance terms, is only 28% of $\hat{\beta}_t$.

Insert Table 1 here.

Table 1 Panel B further reports the decomposition results for each weekday of the formation period. Specifically, we report the average "same weekday" and "other weekday" for each $k_2 = 1$ to 5. In other words, we decompose the total momentum coefficient into 10 components. The momentum effect is strongest on Mondays of the formation period (counting for 33% the total momentum coefficient). The same weekday momentum is also strongest on Mondays (accounting for 30% of the total momentum coefficient). Put differently, 30% of the momentum effect reflects the continuation of the return from Monday during the formation period to Monday during the holding period.

The same-weekday momentum is also present on the other four weekdays of the holding period, since the "same weekday" components on these weekdays are also significantly higher than 4%, or the expected fraction of the momentum coefficient. The heterogeneity of the momentum effect across weekdays allows us to estimate the net contribution of the same weekday momentum in the next subsection.

2.3 Net contribution of the same-weekday momentum

There could be a seasonal reversal effect associated with the same-weekday momentum, which offsets the same-weekday momentum and lowers its net contribution to total momentum. As we demonstrate in the next section, the same-weekday momentum could come from persistent seasonal trading. An investor who has bought a stock on Mondays during the momentum formation period is likely to buy the same stock again on Mondays during the momenutm holding period. As a result, a winner on the previous Mondays is likely to have higher Monday returns during the holding period, reflecting persistent price pressure. The price pressure on Mondays reverts on other days of the week during the holding period. In this case, past Monday returns positively predict future Monday returns, but negatively predict future non-Monday returns, as documented by Keloharju, Linnainmaa, and Nyberg (2016, 2021).

If the price pressure reverts completely during the holding period, then the same-weekday momentum does not contribute to the momentum effect at all but simply "redistributes" it from other weekdays to the same weekday. However, if the price pressure only partially reverts during the holding period, then the same-weekday momentum has a net positive contribution to the momentum effect.

To estimate the degree of reversal (x), we decompose the total momentum effect ($\hat{\beta}_t$) into three parts: a standard momentum effect (m), price pressure on the same weekday (p) and its reversal ($-xp$). If the reversal is incomplete during the holding period ($x < 1$), then the same weekday momentum is a net contributor to the momentum effect.

We assume that the standard momentum effect does not vary across weekdays. The results of the cross-weekday decomposition in Table 1 Panel B then suggest that the magnitude of the price pressure differs between weekdays. For example, investors may concentrate their trading on certain days of the week. We denote the same-weekday momentum effect from past Mondays, Tuesdays, ..., and Fridays as $p_1, p_2, ..., p_5$ accordingly. Finally, we assume that the reversal is evenly distributed on the five weekdays.

Under these assumptions, the observed covariance between the past Mondays and the future Mondays (scaled by the total variance of the past return) would be $m + p_1 - \frac{1}{5}xp_1$, and the scaled covariance between the past Mondays and the future Tuesdays (or Wednesdays, Thursdays and Fridays) would be $m - \frac{1}{5}xp_1$. Similarly, the scaled covariance between past Tuesdays and future Tuesdays is $m + p_2 - \frac{1}{5}xp_2$, and the scaled covariance between past Tuesdays and future non-Tuesdays (Mondays, Wednesdays,... and Fridays) is $m - \frac{1}{5}xp_2$. The net contribution of the same weekday momentum is $(p_1 + p_2 + p_4 + p_4 + p_5)(1 - x)$.

We therefore have 7 parameters in total and 25 observed scaled covariances between five past weekdays and five future weekdays. We will estimate these parameters $\theta = \{m, p_1, p_2, p_3, p_4, p_5, x\}$ with 25 moment conditions using the Generalized Method of Moments (GMM). The 25 moment conditions are:

$$\begin{aligned} &E[Cov_{t,k_1,k_1} - (m + p_{k_1} - \frac{1}{5}xp_{k_1})] = 0 \text{ for } k_1 = 1, 2..., 5 \\ &E[Cov_{t,k_1,k_2} - (m - \frac{1}{5}xp_{k_2})] = 0 \text{ for } k_1 = 1, 2..., 5; k_2 = 1, 2..., 5 \text{ and } k_1 \neq k_2 \end{aligned} \tag{4}$$

where $Cov_{t,k_1,k_2} = \frac{Cov(r_{i,t}(k_1), r_{i,t-2,t-12}(k_2))}{Var(r_{i,t-2,t-12})}$ is the covariance between past weekday k_2's return over months $t - 12$ to $t - 2$ and weekday k_1's return at current month t, scaled by past overall return variance. Then the objective function in GMM is:

$$Q(\theta) = (\frac{1}{N}\sum_{t=1}^{N}(g_t(\theta)))'W(\frac{1}{N}\sum_{t=1}^{N}(g_t(\theta))) \tag{5}$$

where $g_t(\theta)$ is the vector of 25 moment conditions for month t, and W is the identify weighting matrix.

In Table 1 Panel C we report the estimates of 7 parameters based on GMM and their 5th and 95th percentiles based on a bootstrap of 1000 samples by resampling with replacement from the full sample of 708 months. The key parameter, x, the reversal effect as a percentage of the same-weekday momentum, is about 28%, and its fifth and 95th percentiles of x based on resampling are -31.2% and 75.9% respectively. As a result, the net contribution of same-weekday momentum after the adjustment of the reversal effect is about 47.4%, with a lower bound (5th percentile) of 15.5%, which is still positive. The evidence confirms that the same weekday momentum is a positive net contributor to the momentum effect, even after accounting for the reversal during the holding period.

Insert Figure 1 here.

In Figure 1 we plot the net contribution of same-weekday momentum in a 10-year rolling sample, that is, $(p_1 + p_2 + p_3 + p_4 + p_5) \times (1 - x)$, given a fixed estimate of $x = 28\%$ based on the full sample (in red line), or the fifth and 95th percentiles of x (in the shaded area) from our bootstrap resamples, which represent the lower bound and upper bound of the net effect, respectively. It shows that the net contribution from the same-weekday momentum still accounts for almost half of the total momentum effect during most of our sample period.

2.4 Momentum decomposition: Robustness

We perform several robustness checks and additional analyses related to the momentum decomposition in this subsection, and the results are reported in Table 2.

Insert Table 2 here.

Different size filters The first two rows of Table 2 report the decomposition results under different size filters. In the first row, we exclude the smallest 10% of all stocks in each month. We find that the net contribution of the same weekday momentum to the total momentum coefficient is 46%. In the second row, we exclude stocks whose market capitalization is smaller than 20th percentile of the NYSE break-point in each month. In this case, the net contribution of the same weekday momentum is 48%. These numbers are very similar to 47%, the net contribution of the same weekday momentum in the baseline case that uses the 10% NYSE breakpoints as size filters.

Equal- vs. value-weighting The baseline results reported in Table 1 weigh each stock equally in the Fama-MacBeth regressions. The third row of Table 2 reports the results of the momentum decomposition when we weigh each stock by its market capitalization. We find that the net contribution of the same weekday momentum is 36%.

Small vs. large stocks We sort stocks in the baseline sample on their market capitalization into "small," "medium" and "large" groups each month and then repeat the decomposition exercise in each group. The results are reported in rows 4-6 of Table 2. The pattern is similar between the three groups, with the net contribution of the same-weekday momentum ranging from 33% to 58%. In other words, neither small stocks nor a few large-cap stocks drive our result.

Liquid vs. illiquid stocks In rows 7-9, we sort the stocks in the baseline sample on their Amihud liquidity measures into "liquid," "medium," and "illiquid" groups each month, and then repeat the decomposition exercise in each group. The net contribution of the same-weekday momentum ranges from 15% to 41%.

Different sub-periods In the last three rows of Table 2, we break our baseline sample period into three subperiods: 1927-1962, 1963-1992, and 1993-2021. The net contribution of the same-weekday momentum is always positive. It was 39% before 1963, increased to 62% during 1963-1992, and then declined to 18% during the more recent period 1993-2021.

Past intraday vs. overnight returns A recent paper by Barardehi, Bogousslavsky, and

Muravyev (2023) shows that the momentum effect is primarily driven by past intraday returns. Unreported results confirm the importance of past intraday returns in our setting as well. Indeed, we find the same weekday momentum to mostly come from past intraday returns.

Decaying in the covariances Figure 2 plots the average covariances between the daily returns during the momentum holding period (month t) and their same weekday counterparts during each of the formation month (month $t-2$, $t-3$, ..., $t-12$). It shows that the same weekday covariances are positive and significant for each of the 11 months, confirming the robustness of the same weekday momentum effect. It also shows a decaying pattern over time, which is consistent with our preferred explanation that persistent seasonal trading is driving the same weekday momentum, and such a persistence decays over time.

Insert Figure 2 here.

Implications Keloharju, Linnainmaa, and Nyberg (2016, 2021) have shown that average daily returns on a particular weekday in the past strongly and positively predict future returns on the same weekday. Although such a same-weekday momentum itself is not new, our contribution is to quantify its net contribution to the standard momentum effect, after accounting for the reversals, via a simple decomposition exercise. We find robust evidence that the same-weekday momentum, in net, drives a significant fraction (20% - 60%) of the standard stock momentum.

The decomposition result sheds new light on the driver of the stock momentum. A large body of momentum theories is based on some forms of investor misreaction to past information or trading signals. Ex-ante, there is no reason why investor misreaction should display a strong within-week seasonality pattern. Put differently, why should the stock price on Monday respond only to information or trading signals in previous Mondays?

2.5 Trading strategies

Before we examine the economic driver of the same-weekday momentum in the next Section, we first evaluate its economic significance using a trading strategy approach. Again, our objective is not to rediscover the within-week return seasonality as a profitable trading strategy, but rather to quantify its economic magnitude relative to that of the standard stock momentum. For this reason, our trading strategies will differ slightly from those considered in Keloharju, Linnainmaa, and Nyberg (2016, 2021).

Specifically, we consider a daily rebalanced trading strategy. Each day during the momentum holding period (month t), we long (short) stocks in our baseline sample whose average daily returns on the same weekday during the momentum formation period (months $t-12$ to $t-2$) are in the top (bottom) decile. For example, on Mondays during month t, we buy (sell) stocks whose average Monday returns during months $t-12$ to $t-2$ are high (low); on Tuesdays during month t, we buy (sell) stocks whose average Tuesday returns during months $t-12$ to $t-2$ are high (low), etc. We label this strategy the "same-weekday momentum strategy."

For comparison, we also consider a "other-weekday momentum strategy." Each day during the momentum holding period (month t), we long (short) stocks in our baseline sample whose average daily returns on *other* weekdays during the momentum formation period (months $t-12$ to $t-2$) are in the top (bottom) decile.

Finally, our benchmark is the standard monthly rebalanced momentum strategy. Each month t, we long (short) stocks in our baseline sample whose average returns during the formation period (months $t-12$ to $t-2$) are in the top (bottom) decile. The results of the trading strategy are reported in Table 3.

Insert Table 3 here.

As reported in column (1) of Panel A, in our baseline sample from 1963 to 2021, the standard momentum strategy generates a significant profit of 1.28% per month (t-value = 5.19). Its risk-adjusted returns are also highly significant both statistically and economically. For example, the Fama-French three- and five-factor alphas are 1.65% and 1.53% per month with respective t-values of 7.32 and 6.79.

In column (2), the daily rebalanced same-weekday momentum strategy generates much higher profit. The monthly return, three- and five-factor alphas are 2.05% (t-value = 10.94), 2.18% (t-value = 11.93), and 2.18% (t-value = 11.86), accordingly. In sharp contrast, the other-weekday momentum strategy is much less profitable. In column (3), its monthly return of 0.28% is not even significant. The three- and five-factor alphas are higher, but only about a fourth of those of the same-weekday momentum strategy.

Figure 3 provides a visual illustration of the performance of the three momentum trading strategies. It plots their cumulative returns (on logarithmic scale) since 1963. It is clear that the daily-rebalanced same-weekday momentum performs the best. A dollar invested in this strategy in 1963 will grow to almost 10^6 =1 million dollars in 2021. In sharp contrast, a dollar invested in the other-weekday momentum strategy in 1963 is less than 2 dollars in 2021.

Insert Figure 3 here.

Another way to evaluate the contribution of the same-weekday momentum to the standard momentum return is to exclude the same weekday winners (losers) from the standard momentum winner (loser) portfolio. For example, on Mondays during the holding periods, we exclude stocks in the momentum winner (loser) decile that also belong to the top (bottom) decile of past average Monday returns; on Tuesdays, we exclude stocks in the momentum winner (loser) decile that also belong to the top (bottom) decile of past average Tuesday returns, etc. About 31% of the momentum winners and 33% of the momentum losers are excluded. Excluding these stocks significantly reduces the return to the momentum strategy. For example, its five-factor alpha decreases from 1.53% (column 1) to 1.04% (column 4).

In sharp contrast, excluding other-weekday winners or losers actually improves the profitability of the momentum strategy. Specifically, on Mondays during the holding periods, we exclude stocks in the momentum winner (loser) decile that also belong to the top (bottom) decile of past average *Non-Monday* returns; on Tuesdays, we exclude stocks in the momentum winner (loser) decile that also belong to the top (bottom) decile of past average *Non-Tuesday* returns, etc. About 66% of the momentum winners and 68% of the momentum losers are excluded. Excluding these stocks significantly increases the return to the momentum strategy. For example, its five-factor alpha increases from 1.53% (column 1) to 2.06% (column 5).

To further illustrate the difference between standard momentum and the same-weekday momentum, we zoom in on medium momentum stocks (the middle 40%) which are neither total past return winners nor losers. Column (6) shows that the same weekday momentum remains strong among medium momentum stocks. The five-factor alpha is 1.43%. The flow-based momentum explanation of Lou (2012) involves a positive feedback mechanism. Funds holding past winners are likely to receive inflows that are invested by scaling up the current portfolio, pushing up the prices of the winners further, causing the momentum effect. The momentum effect further enhances the fund performance, thus attracting more inflow, etc. Although this positive feedback mechanism can enhance the same-weekday momentum effect, column 6 suggests that it is not a necessary condition, as the same weekday momentum is also present even when the stock is neither a past winner nor a loser, and thus does not contribute to the fund's relative performance.

The same weekday momentum is hard to explain using misreaction to information. To further rule out the information-based explanation, we winsorize daily returns by replacing the highest and lowest daily return in each month with the second highest and lowest return in that month, respectively. We then implement the same weekday momentum trading strategy using these winsorized daily returns. To the extent that extreme daily returns reflect major information events, winsorizing them alleviates the impact of information. Column 7 shows that the resulting same weekday momentum actually becomes stronger with a five-factor alpha of 2.34%, compared to the baseline alpha of 2.18% (column 2). The larger alpha is more consistent with the notion that the past same-weekday return captures price pressure from persistent seasonal trading. Winsorizing extreme daily returns alleviates the informational effect and results in a more precise price pressure estimate.

Table 3 Panel B reports the strategy returns on weekdays. The same-weekday momentum performs particularly well on Mondays, followed by Fridays. Again, excluding same-weekday winners & losers reduces the momentum profit, while removing other-weekday winners & losers increases it.

2.6 Cross-sectional regressions

In Table 4, we conduct a horserace among the three momentum effects using Fama-MacBeth cross-sectional regressions. Specifically, we regress a daily return in the holding period (month t) on a standard momentum variable (past return during month $t-12$ to $t-2$), a same-weekday momentum variable (past return on the same weekdays during month $t-12$ to $t-2$) and a other-weekday momentum variable (past return on other weekdays during month $t-12$ to $t-2$). Regressions also control for other stock characteristics with predictive power of return. The results of the value-weighted regressions (Panel A) and equal-weighted regressions (Panel B) are very similar.

Insert Table 4 here.

Four patterns emerge from these regressions. First, consistent with the decomposition and trading strategy results, it is the same-weekday rather than other-weekday momentum that reliably predicts future daily returns. Second, when we include the standard momentum variable and the same-weekday momentum variable in the same regression, the predictive power of the standard momentum is reduced significantly. Third, controlling for other characteristics of the stock does not change the result. Fourth, the positive autocorrelation in daily returns on the same weekday goes beyond a mean effect. For example, if returns are consistently higher on Mondays than on Fridays, then daily returns will load positively on their same weekday lags in regressions, as shown in Keloharju, Linnainmaa, and Nyberg (2016). In columns 10 to 13, we control for this mean effect by including the average same weekday return during the second and third years prior to the portfolio formation (or from month $t-36$ to $t-13$. The coefficients on the same weekday return during month $t-12$ to $t-2$ are still positive and significant. Kamstra (2017) suggests using 25 dummy variables for 5×5 size and book-to-market portfolios as an alternative way to alleviate the concern that momentum (or the same-weekday momentum) is driven by cross-sectional variation of the mean return. The unreported results confirm that the use of these dummy variables also does not change our results.

In summary, in this section, we document a novel empirical pattern: a disproportionately large fraction (70%) of the stock momentum reflects the continuation of the return on the same weekday. Even after accounting for partial reversals on other days of the week, the same-weekday momentum still contributes to a significant fraction (20% to 60%) of the momentum effect. The same-weekday momentum is economically significant and robust to different size filters, weighing schemes, time periods, and sample cuts. This within-week seasonality pattern is hard to explain using traditional momentum theories based on investor misreaction. Next, we investigate its potential economic driver.

3 Seasonality and Persistence in Institutional Trading

In this section, we provide novel empirical evidence linking seasonality and persistence in institutional trading to the same-weekday momentum.

3.1 Data

The daily flow data of mutual funds for 2008-2023 is downloaded from Morningstar Direct. We focus on active US equity mutual funds (both dead and currently alive). For each fund, we focus on the oldest share class. The key daily dollar flow variable is named "estimated fund level net flow (comprehensive) (daily)". We divide the daily dollar fund flow by the fund size at the end of the previous day to calculate the daily percentage fund flow. We require a fund to have at least a 6-month flow history and at least 20 flow days in the past year. We use a one-year period to alleviate the effect of within-year seasonality. We fill in the missing daily flow value with 0.

Institutional trading data during 1999-2011 come from ANcerno, which has been widely used in the literature (see the survey by Hu et al. (2018)). We define an institution by aggregating the "clientmgrcode" to "managercode" level based on the manager reference file provided by ANcerno. We have 841 institutions in total during this sample period. We then require an institution to have at least a 6-month trading history and at least 10 trading days in the past year. We merge each trade from an institution in ANcerno with the stock identity in CRSP by matching the items "cusip" and "symbol" from ANcerno with the items "NCUSIP" and "TICKER" from CRSP at the same time. Again, we fill in 0 for the day without trading. The appendix contains details on the matching and cleaning process and summary statistics of institutional trading (Table A.1).

3.2 Seasonal flow and trading

Return continuation across the same weekday can be consistent with concentrated trading on the same weekday. Hence, we first examine the prevalence of such "seasonal" trading by institutions. Such a concentrated trading could in turn arise from concentrated investor fund flow on that weekday. As a result, we also look into "seasonal" flows to mutual funds.

Specifically, for each Morningstar mutual fund in our sample and at each month, we identify a "seasonal" fund if its average (absolute) fund flow on a particular weekday in the past year is significantly higher than the average (absolute) fund flow on other weekdays. For example, if 40% of past one-year (absolute) fund flow occurs on Monday, which is significantly higher than the percentages on the other four days of the week, then the fund is identified as a "seasonal" fund, or more specifically a "Monday seasonal" fund in that month. The corresponding flow concentration ratio is 40%.

Table 5 Panel A reports that on average 304 funds (or 16.4% of the cross section) are classified as the "seasonal" funds each month, during the 2009-2023 Morningstar sample period. Their (absolute) fund flows account for 14.9% of the total (absolute) fund flows in our sample, so seasonable funds are representative in terms of their fund flow size.

Insert Table 5 here.

The average concentration ratio is 36.6% for these "seasonal" funds, meaning that 36.6% of their (absolute) fund flows occur on one particular day of the week. When we break down the results by weekday, we find that "Tuesday seasonal" funds are the most common (32.4%) but their average concentration ratio is the lowest (34%). In contrast, while only 10.1% of the "seasonal" funds are "Monday seasonal" funds, their average concentration ratio of 42.1% is the highest.

Figure 4 Panel A plots the percentage of “seasonal” funds, their (absolute) fund flows as a percentage of total (absolute) fund flows, and their average concentration ratio over time. Although the prevalence of “seasonal” funds has decreased from above 20% of the sample in 2009-2012 to around 10% more recently, their average concentration ratio of just below 40% is fairly stable.

Insert Figure 4 here.

Seasonal flow could lead to seasonal trading. For each ANcerno institution and each month, we identify a “seasonal” institution if its average dollar trading volume on a particular weekday in the past one year is significantly higher than the average dollar trading volume on other weekdays. If that weekday is Monday, then the institution is identified as a ”Monday seasonal” institution in that month.

Table 5 Panel B reports that on average 120 institutions (or 26.7% of the cross section) are classified as the “seasonal” institutions each month during the 1999-2011 ANcerno sample period. Their trading volumes account for 46.4% of the total volume in our sample, so “seasonal” institutions are more active traders.

Their average concentration ratio is 33.6%, meaning that 33.6% of their trading occurs on one particular day of the week. When we break down the results by weekday, we find that “Thursday seasonal” funds are the most common (29.6%) but their average concentration ratio is the lowest (30.3%). In contrast, while only 10.7% and 12.7% of the “seasonal” institutions are ”Monday” and “Friday” seasonal institutions, their average concentration ratios of 35.5% and 36.5% are higher.

Figure 4 Panel B shows the percentage of “seasonal” institutions, their dollar trading volume as a percentage of the total volume in our sample, and their average concentration ratio over time. The prevalence of “seasonal” institutions is quite stable and even increased slightly toward 2011. Their average concentration ratio of around 35% is also fairly stable.

To conclude this subsection, we find a large number of mutual funds experiencing a concentrated flow on a particular weekday and even more institutions that are concentrating their trading on a particular day of the week.

3.3 Persistence in seasonal flow and trading

We then examine whether the within-week seasonality in fund flow and institutional trading is persistent over time.

In Table 6, we examine "seasonal" funds. Each month t, we sort "seasonal" funds into deciles based on their concentration ratio in the prior momentum formation period (months $t-12$ to $t-2$). In Panel A, we report the average concentration ratio for the past 11 months in column (1) and the average concentration ratio on the same weekday during month t in column (2). Importantly, all the concentration ratios in column (2) are above 20%. Take decile 10 for example, the funds in this decile experience 64.07% of (absolute) flow on one particular weekday in the past 11 months. In month t, they continue to experience 24.83% of their (absolute) flow on the same weekday. The number 24.83% is also significantly higher than that of decile 1 (21. 53%), which means that funds with a more concentrated flow in the past continue to have a concentrated flow on the same weekday in the future.

Insert Table 6 here.

In Panel B, we sort "seasonal" funds based on their net daily fund flow of the last 11 months on the concentrated weekday into deciles. Column (1) shows that "seasonal" funds in decile 10 (1) experience an average net daily inflow (outflow) of 1.50% (-0.58%) on the concentrated weekday in the past 11 months. Column (2) reports the average net flow on the same weekday in month t and shows that the direction of the "seasonal" flow is also highly persistent. "Seasonal" funds that experienced inflow (outflow) on the concentrated weekday in the past continue to experience inflow (outflow) on the same weekday in the future.

What economic forces contribute to persistent "seasonal" fund flows? While this is not the focus of our paper, we conjecture that they could in turn reflect regularities in investors' cash injection and / or withdraw behavior. For example, if an investor receives her salary on the last Friday of each month and injects a fixed fraction of it into her existing fund, then the fund will receive an inflow on the last Friday of each month, both in the past and in the future. Consistent with this conjecture, we find that both seasonal inflows and outflows are more concentrated. For example, seasonal inflow (outflow) funds have 46.03% (43.01%) of their inflows (outflow) on the same day of the week.

Persistent "seasonal" fund flows can result in persistent "seasonal" institutional trading, which we confirm in Panels C and D. In Panel C, we sort "seasonal" institutions in each month t into deciles based on their concentration ratios in the momentum formation period (months $t-12$ to $t-2$). We report the average concentration ratio for the last 11 months in column (1) and the average concentration ratio on the same weekday during the month t in column (2). Again, all concentration ratios in column (2) are above 20%. Taking decile 10, for example, the institutions in this decile conduct 66.23% of their trading on a particular weekday in the past 11 months. In month t, they continue to conduct 38.31% of their trading on the same weekday. The number 38.31% is also significantly higher than that of decile 1 (21. 21%), which means that institutions with more concentrated trading in the past continue to have concentrated trading on the same weekday in the future. Compared to the mutual fund results in Panel A, "seasonal" institutional trading seems even more persistent.

In Panel D, we sort "seasonal" institutions based on their net trade imbalance of the last 11 months on the concentrated weekday into deciles. Column (1) shows that "seasonal" institutions in decile 10 bought more stocks than sold on the concentrated weekday in the past 11 months. The opposite is true for "seasonal" institutions in decile

1. Column (2) reports the average net trade imbalance on the same weekday in the month t and shows that the direction of the "seasonal" institutional trading is also highly persistent. "Seasonal" institutions that bought more stocks than sold on the concentrated weekday in the past continue to buy stocks net on the same weekday in the future.

3.4 Momentum and seasonal trading

In this subsection, we link the same-weekday momentum to "seasonal" institutional trading more directly. The basic idea is simple: If an institution has been buying a stock on Mondays during the momentum formation period, it is more likely to buy the same stock on Mondays during the momentum holding period, thus contributing to the persistence in the returns of past Monday winners. We focus on the 1999-2011 sample, where we can use ANcerno data to measure "seasonal" institutional trading.

Each month t, we construct momentum portfolios by sorting stocks in our baseline sample on their formation period (months $t-12$ to $t-2$) returns into terciles. We consider tercile rather than decile-sorts in order to make sure we have a sufficient number of "seasonal" institutions in each portfolio so "seasonal" trading can be measured more precisely. For each stock, we also identify the ANcerno institutions that have traded it during the formation period, and among them those "seasonal" institutions.

Table 7 Panel A reports summary statistics related to institutional trading in these momentum terciles. We do not observe a large difference between the past winners and losers. On average, each stock has been traded by 6 to 7 "seasonal" institutions in the formation period. These "seasonal" institutions represent about 9.02% to 9.18% of all ANcerno institutions that trade the stock. The average concentration ratio is about 31.9% to 32.4% for these "seasonal" institutions. Put differently, the amount of "seasonal" institutional trading does not differ significantly across the momentum terciles.

Insert Table 7 here.

However, when we examine the direction of "seasonal" institutional trading in Panel B, we see a significant difference across the momentum terciles. Column (1) reports the average net trade imbalance by seasonal institutions during the momentum formation period (months $t-12$ to $t-2$). The imbalance is computed for each institution-stock pair first, before being averaged across all institutions who traded that stock. During the formation period, the "seasonal" institutions bought more winners than losers. Their trade imbalances are consistent with past returns. More importantly, when we examine the average net trade imbalance of these seasonal institutions during the month t, or the momentum holding period in column (2), we find that the pattern of imbalance persists. The evidence suggests that "seasonal" institutions bought winners (sold losers) in the past and continue to relatively buy more on winners than losers (actually sell less on winners than losers) on the same weekday in the future.

Columns (3) and (4) repeat columns (1) and (2) but compute trade imbalances by aggregating across different "seasonal" institutions to each stock first. In other words, institutions are weighted by their trading volumes. We find the same pattern: "seasonal" institutions bought winners (sold losers) in the past and continue to relatively buy more (or sell less) of winners than losers on the same weekday in the future. Put differently, persistent "seasonal" institutional trading is consistent with the same-weekday momentum.

In Table 8, we confirm the persistence of "seasonal" institutional trading in a panel regression at the stock-month-weekday level. We use the past trading imbalance of all seasonal institutions on a stock on their concentrated weekday in the past 11 months (months $t-12$ to $t-2$) to predict their future trading imbalance on the same stock at the same weekday in month t. The trading imbalance at the stock-month-weekday level is calculated as the difference between the dollar buy and dollar sell at that stock divided by the sum of the buy and sell of all seasonal institutions. We also refill the missing values of future imbalances if there is no seasonal trading in that stock to avoid potential forward-looking bias. Column (1) presents the baseline results that seasonal institutions are more likely to trade a stock in the same direction as before, with a positively significant coefficient of 0.0163, which means, on average, a seasonal Monday institution will buy 1% more of the same stock on future Mondays if it purchased one standard deviation (64%) of the stock on Mondays of the last 11 months. This result is robust to the size and book-to-market ratio of the stock as controls in column (2).

Insert Table 8 here.

One thing to note is that the persistent trading coefficient remains positively significant even when we control for the last 11-month return of the stock in column (3) of Table 8. In other words, seasonal institutions continue to trade a stock persistently as before, regardless of the past performance of the stock, which implies that the persistence of trading of seasonal institutions is not merely another manifestation of buying winners and selling losers.

We directly link past "seasonal" institutional trading to future stock return using a panel regression at the stock-month-weekday level. In Table 9, we aggregate net trading dollars (buy minus sell) on a stock on a weekday from all seasonal institutions with same concentrated weekday in the past 11 months from $t-12$ to $t-2$ and then scale this aggregated net dollar trading by the market value of that stock at the end of previous month $t-1$, which we label as "past 11-month trading imbalance". In column (1) of Table 9, we use this aggregated stock-weekday level seasonal trading imbalance in the past to predict future same-weekday stock returns in the next month t in a univariate regression, which shows a significantly positive coefficient of about 3. This means that one standard deviation purchase (48%) by seasonal institutions on one weekday in past 11 months will lead to approximately 1.44 bps higher return over the future same weekday in next month. Consistent with the results in the previous table, the stock-weekday regression results are also robust to controlling for size, book-to-market ratio, and the past 11-month return of the stock, as shown in columns (2) and (3).

Insert Table 9 here.

The persistence in the trading of a stock in the past and in the future from various "seasonal" institutions might differ from each other. In columns (4) to (6), we present similar predictive results based on an institution-specific persistence-weighted trading imbalance measure, labeled as "past 11-month trading imbalance weighted by persistence". To construct this measure, we first estimate a trading persistence coefficient for each institution in each month by regressing the next month same-weekday trading imbalance on a stock on its past trading imbalance at concentrated weekday on the same stock across all stocks held by the institution. We sum up all "seasonal" institutions' net trading on a stock with a weight of their estimated average trading persistence coefficient over past 12 months and then scaled it by the stock's total market value. The regression coefficients exhibit a larger magnitude with a similar significance level.

Finally, in order to gauge the economic significance of persistent seasonal trading's impact on momentum, we conduct various double sorts in Table 10. We first sort stocks into terciles each day, based on their aggregate absolute dollar trading by the corresponding seasonal institutions on those weekdays during months $t-12$ to $t-2$ (scaled by the market cap at the end of last month). For example, to construct the terciles for a Monday, we look at Monday seasonal institutions' trading on previous Mondays; to construct the terciles for a Tuesday, we look at Tuesday seasonal institutions' trading on previous Tuesdays; etc. In each tercile, we then sort stocks based on their past same-weekday returns from months $t-12$ to $t-2$.

Insert Table 10 here.

Consistent with the notion that persistent seasonal trading drives the same weekday momentum, we find that the same weekday momentum is much stronger among stocks that are particularly exposed to seasonal trading. For example, column 11 of Panel A reports an average monthly return of 2.28% for stocks in the top seasonal trading tercile, compared to 1.41% for stocks in the bottom seasonal trading tercile. The difference between these two average returns of 0.86% is significant (t-value = 2.13).

To conclude this section, we first find a large fraction of equity funds with seasonal flows and institutions with seasonal trading. Second, we find that both the seasonal flow and the trading are highly persistent. Finally, we directly link persistent seasonal trading to the same-weekday momentum.

4 Conclusion

In this paper, we document a new empirical fact about stock momentum. A significant fraction (47. 4%) of the stock momentum reflects the continuation of the return on the same weekday, even after accounting for the reversals on other weekdays. This pattern is extremely robust to different size filters, weighing schemes, time periods, and sample cuts. The net contribution of the same weekday momentum to the overall stock momentum ranges from about 20% to 60%.

The same-weekday momentum is hard to explain using traditional momentum theories based on investor misreaction. Instead, we find that within-week seasonality and persistence in institutional trading are its driver. A large number of institutions experience disproportionately large flows on a particular day of the week and concentrate their trading on that weekday. Such a seasonal trading tends to be highly persistent, which drives the same-weekday momentum. Overall, our evidence suggests that institutional trading is an important ingredient of the stock momentum effect.

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Figure 1: **The net contribution of the same-weekday momentum over time**

This figure shows the historical monthly average values of the total momentum effect and net contribution of same-weekday momentum with consideration of potential reversal effect in a 10-year rolling window. The dashed green line denotes the average monthly coefficient of total momentum effect, and the red line depicts the net contribution of the same-weekday momentum given a fixed percentage of reversal effect estimated from full sample. We also plot lower bound and upper bound of the net contribution in shaded area given the 5% and 95% percentile of the percentage of reversal effect based on bootstrap. We estimate the raw momentum effect (m), same-weekday momentum (p_1, p_2, p_3, p_4, p_5), and the percentage of reversal effect (x) of the same-weekday momentum by minimizing the 25 weekday-to-weekday covariance moment conditions based on GMM in Eq.5. We estimate the average reversal effect x given the full sample of 708 months, and then estimate the 5% and 95% percentiles of x by resampling with replacement from the original 708-month sample for 1000 times. Then we estimate the net contribution using 6 parameters: $m, p_1, p_2, p_3, p_4, p_5$ (with x given from full-sample estimate or 5% and 95% percentile from resampling) in each of 10-year rolling subsample. The net contribution of same-weekday momentum would be $(p_1 + p_2 + p_3 + p_4 + p_5) \times (1 - x)$ and the total momentum would be $(p_1 + p_2 + p_3 + p_4 + p_5) \times (1 - x) + 25m$. The sample includes all individual stocks listed on NYSE, Amex, and NASDAQ. The penny stocks with price below $5 and small-cap stocks below NYSE 10% breakpoints are excluded each month. The original sample spans period from 1963 through 2021 and the first 10-year rolling average value starts at 1972.

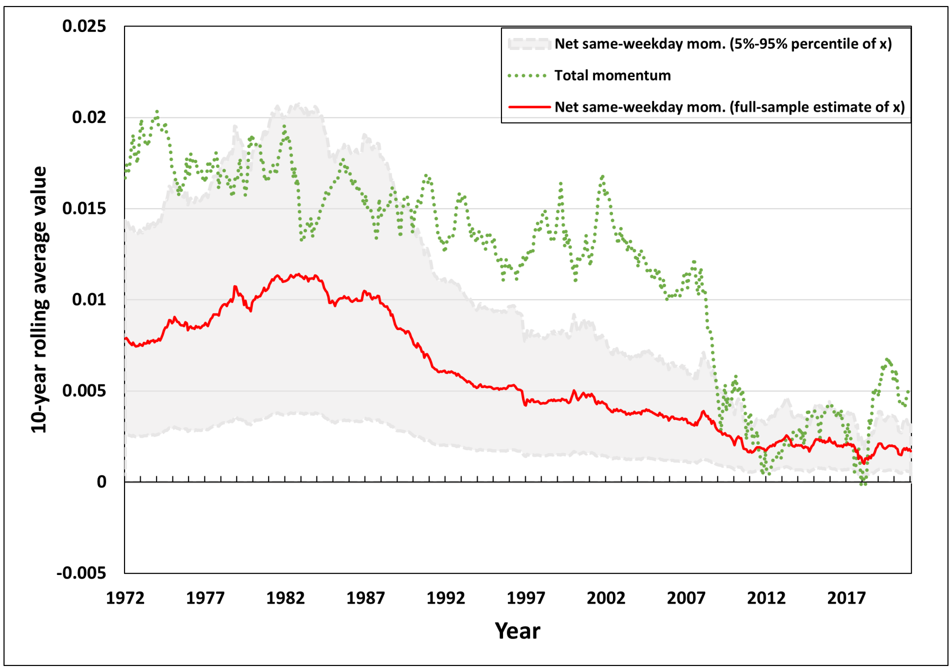


Figure 2: **Same-Weekday covariances with monthly lags**

This figure plots the average monthly same-weekday covariance between weekday return in current month and the same-weekday return in each of past 11 months ($t-2$ to $t-12$) over prior 1 year (skipping most recent one month), respectively. The covariance is scaled by the past 11-month total return variance as the first component in Eq.3 shows (the difference between this figure and Eq.3 is that we only include one month of past 11 months each time) and then multiplied by 100. The blue line presents the average covariance for each monthly lag and the red bar depicts the 90% confidence interval for each average value. The sample spans from 1963 to 2021 and includes all individual stock listed in NYSE, Nasdaq, and Amex, except for penny stocks with price below $5 and small stocks below NYSE 10% breakpoints.

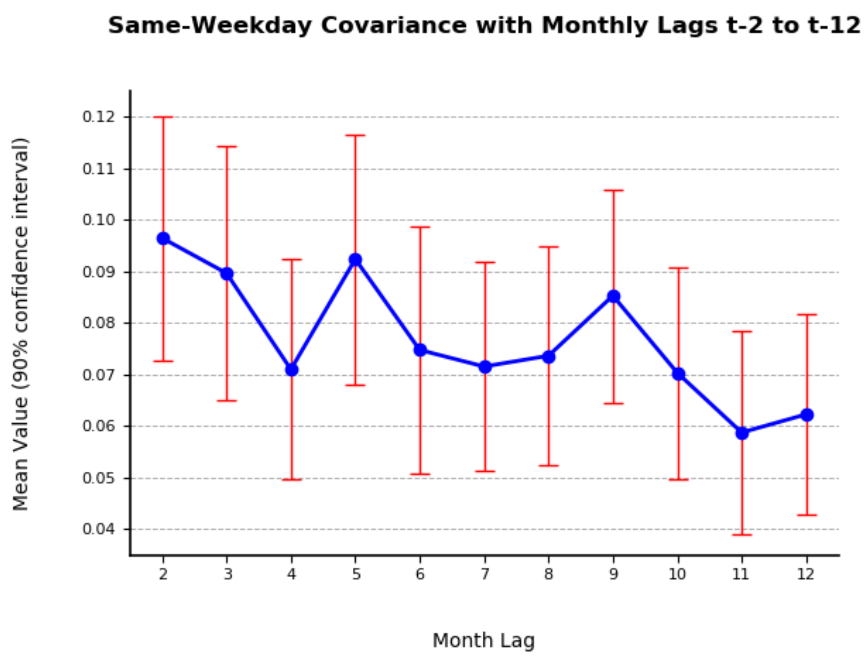


Figure 3: **Cumulative returns of three momentum trading strategies**

This figure presents the cumulative return (in log scale) of investing $1 since 1963 in long-short portfolios of three strategies—momentum, same-weekday, and other-weekday—by sorting individual stocks equally into 10 decile portfolios based on past 11-month (skipping recent one month) overall return, same-weekday return and other-weekday return respectively. The decile portfolios are value-weighted. The sample includes all individual stocks listed on NYSE, Amex, and NASDAQ. The penny stocks with price below $5 and small-cap stocks below NYSE 10% breakpoints are excluded each month. The sample covers years 1963 through 2021.

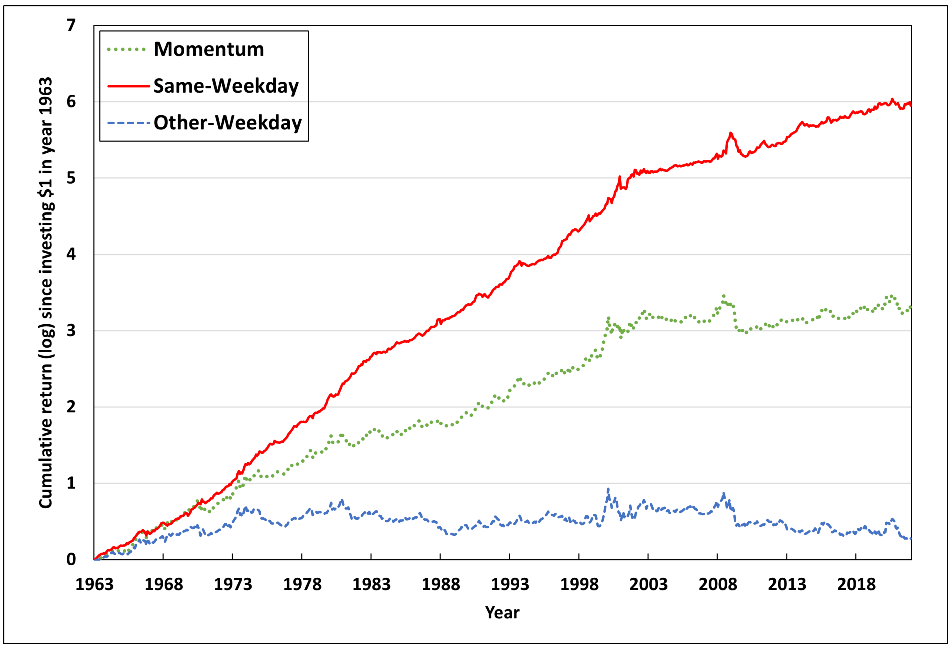
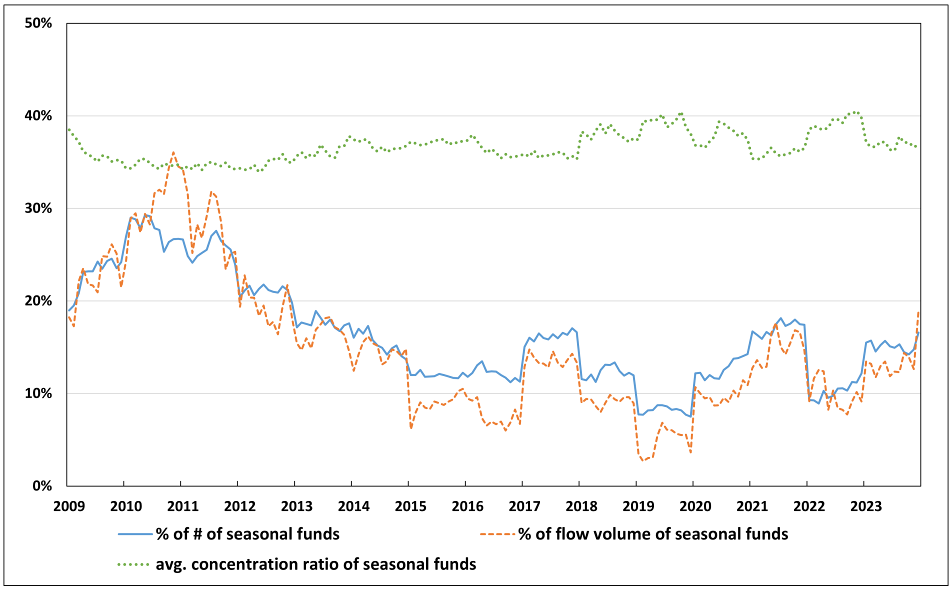


Figure 4: **Seasonal funds and seasonal institutions**

This figure plots the percentage of seasonal fund flow and institutional trading out of all fund flow and institutional trading every month. The blue line and orange line denote the number of and the flow (or trading volume) of seasonal funds (or institutions) as a percentage of all funds (or institutions). The green line plots the average concentration ratio of the seasonal funds (or institutions) at their concentrated weekday to all five weekdays. Every month, we define a seasonal fund (or institution) at a specific weekday by comparing its daily absolute flows (or dollar trading volume) on that particular weekday and on other four weekdays in the past year based on T-test at 10% significance level. Panel A covers all equity funds from 2009 to 2023 from Morningstar and Panel B all institutions from 1999 to 2011 from ANcerno.

Panel A: Seasonal fund flow



Panel B: Seasonal institutional trading

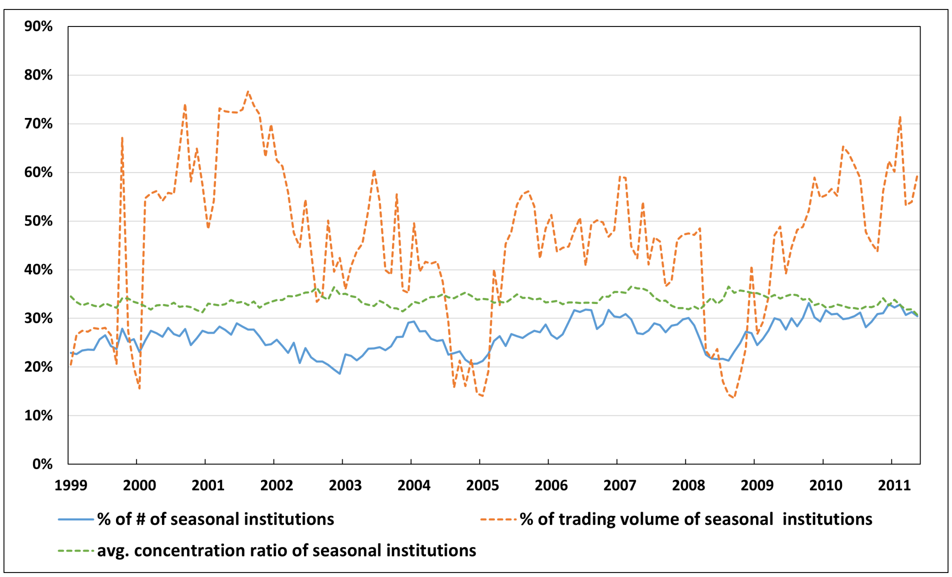


Table 1: **Weekday Momentum Decomposition**

This table reports the decomposition of Fama-Macbeth regression coefficient into 5 same-weekday items and 20 other-weekday items:

$$\hat{\beta}_{t,l} = \frac{Cov(r_{i,t}, r_{i,t-2,t-12})}{Var(r_{i,t-2,t-12})} = \underbrace{\sum_{k_1=1}^{5} \frac{Cov(r_{i,t}(k_1), r_{i,t-2,t-12}(k_1))}{Var(r_{i,t-2,t-12})}}_{\text{Same-Weekday (5×1=5 items)}} + \underbrace{\sum_{k_1=1}^{5} \sum_{\substack{k_2=1 \\ k_2 \neq k_1}}^{5} \frac{Cov(r_{i,t}(k_1), r_{i,t-2,t-12}(k_2))}{Var(r_{i,t-2,t-12})}}_{\text{Other-Weekday (5×4=20 items)}}$$

where $r_{i,t}$ and $r_{i,t}(k)$ are the log monthly return and the log weekday k's return at month t. And $r_{i,t-2,t-12}$ and $r_{i,t-1,t-12}(k)$ are the log past 11-month return and its log weekday k's return. Panel A columns (1), (2), and (3) present the average value of total momentum, the same-weekday, and the other-weekday respectively. The t-stat in below parentheses of columns (2) and (3) are based on the test of whether the same-weekday (and other-weekday) component contributes more than 20% (and 80%) to total effect. Columns (4) and (5) present the contribution of same-weekday and other-weekday in percentage out of the total momentum. Panel B reports the monthly average value of total momentum, the same-weekday and the other-weekday by five weekdays in formation period, and their contribution to total momentum in percentage. The t-stat in below parentheses of columns (2) and (3) refers to the test of whether the same-weekday (and other-weekday) component contributes more than 4% (and 16%) to total momentum effect. In panel C, columns (1) through (7) report the estimates of 7 parameters: total raw momentum effect ($25 \times m$), same-weekday momentum (p_1, p_2, p_3, p_4, p_5), and the percentage of reversal effect (x) of the same-weekday momentum by minimizing the 25 weekday-to-weekday covariance moment conditions based on GMM in Eq.5. Columns (8) and (9) report the net contribution of the same-weekday momentum ($(p_1 + p_2 + p_3 + p_4 + p_5) \times (1 - x)$) and its contribution to total momentum in percentage. In below brackets we report the 5% and 95% percentiles of these parameters respectively based on 1000 samples resampled with replacement from original sample of 708 months. Our data covers sample period from 1963 to 2021, and includes all individual stock listed in NYSE, Nasdaq, and Amex, except for penny stocks with price below $5 and small stocks below NYSE 10% breakpoints. All scaled covariance values are multiplied by 100.

Panel A: Decomposition of monthly covariance

	(1)	(2)	(3)	(4)	(5)
	Total momentum	Same-Weekday	Other-Weekday	% of same-weekday	% of other-weekday
mean	1.17	0.85	0.32	72%	28%
	(6.80)	(13.33)	(-13.33)		
# of items per month	25	5	20	20%	80%
# of month	708	708	708		

Panel B: Decomposition of monthly covariance by five weekdays in formation period

	(1)	(2)	(3)	(4)	(5)	(6)
Weekday	Total momentum	Same-Weekday	Other-Weekday	% of total momentum	% of same-weekday	% of other-weekday
Monday	0.39	0.35	0.03	33%	30%	3%
		(10.20)	(-10.20)			
Tuesday	0.32	0.14	0.17	27%	12%	15%
		(5.01)	(-5.01)			
Wednesday	0.18	0.12	0.06	15%	10%	5%
		(3.94)	(-3.94)			
Thursday	0.16	0.07	0.09	14%	6%	8%
		(2.06)	(-2.06)			
Friday	0.12	0.16	-0.04	10%	14%	-4%
		(7.62)	(-7.62)			
# of items per month	5	1	4	20%	4%	16%
# of month	708	708	708			

Panel C: Estimation of parameters based on GMM

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	m (total)	$p1$	$p2$	$p3$	$p4$	$p5$	x	Net contribution	% of net contribution
full sample estimate	0.61	0.35	0.12	0.10	0.05	0.15	28.0%	0.55	47.4%
[5% percentile, 95% percentile]	[0.03, 1.10]	[0.29, 0.40]	[0.08, 0.16]	[0.05, 0.14]	[0.01, 0.09]	[0.11, 0.19]	[-31.2%, 75.9%]	[0.19, 1.01]	[15.5%, 97.2%]

Table 2: **Robustness check**

This table reports the decomposition results of momentum Fama-Macbeth regression coefficient into same-weekday and other-weekday components in cross-section with different filter of small stocks, based on equal- (reported in previous table) or value-weight, within three market-cap (size) or Amihud liquidity subgroups, and by three subperiods, respectively. Columns (1), (2), and (3) report the average monthly value of total momentum, same-weekday and other-weekday respectively. The t-stats are provided in parentheses below (for columns (2) and (3)) based on a test of whether the same-weekday (and other-weekday) component contributes more than 20% (and 80%) to total effect. Columns (4) through (6) report the total raw momentum effect ($25 \times m$), total same-weekday momentum ($p_1 + p_2 + p_3 + p_4 + p_5$) and reversal effect ($x$) as a percentage of same-weekday momentum based on an estimation of these 7 parameters by minimizing the 25 weekday-to-weekday covariance moment conditions in Eq.5. Columns (7) and (8) are the net contribution of the same-weekday momentum ($(p_1 + p_2 + p_3 + p_4 + p_5) \times (1 - x)$) and its contribution of percentage to total momentum effect. The sample includes all individual stocks listed in NYSE, Nasdaq, and Amex from 1963 to 2021 (except for sub-period 1: 1927 to 1962), excluding penny stocks with price below $5 and small stocks below NYSE 10% breakpoints. All covariance values are multiplied by 100.

Different weight, size, liquidity, and subperiods

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Category		Total momentum	Same-Weekday	Other-Weekday	m (total)	p (total)	x	Net contribution	% of net contribution
Size filter	10% all-sample	1.33	0.88	0.45	0.72	0.77	20.8%	0.61	46%
			(15.26)	(-15.26)					
	20% NYSE	1.13	0.81	0.32	0.59	0.73	26.2%	0.54	48%
			(11.75)	(-11.75)					
Weight	value	1.09	0.96	0.13	0.70	0.93	57.5%	0.39	36%
			(10.41)	(-10.41)					
Size	small	1.18	0.86	0.32	0.50	0.78	12.5%	0.68	58%
			(12.48)	(-12.48)					
	medium	1.14	0.79	0.35	0.77	0.71	46.2%	0.38	33%
			(10.67)	(-10.67)					
	large	1.05	0.74	0.31	0.54	0.66	23.7%	0.51	48%
			(8.35)	(-8.35)					
Amihud liquidity	liquid	1.38	0.81	0.57	0.81	0.66	14.2%	0.57	41%
			(8.11)	(-8.11)					
	medium	1.36	0.81	0.55	1.00	0.67	47.3%	0.36	26%
			(10.58)	(-10.58)					
	illiquid	0.91	0.77	0.14	0.77	0.74	80.9%	0.14	15%
			(12.15)	(-12.15)					
Subperiods	period 1: 1927-1962	1.71	1.69	0.02	1.22	1.34	41.3%	0.79	39%
			(10.08)	(-10.08)					
	period 2: 1963-1992	1.67	1.27	0.40	0.64	1.17	11.2%	1.04	62%
			(13.16)	(-13.16)					
	period 3: 1993-2021	0.70	0.43	0.27	0.57	0.36	65.2%	0.13	18%
			(5.26)	(-5.26)					

Table 3: **Various momentum trading strategies**

This table reports the average value-weighted monthly return (in percent, computed from daily return series) of decile portfolios constructed based on past 12-month overall, same-weekday, and other-weekday returns, skipping the most recent one-month, as shown in columns (1), (2), and (3), respectively. Portfolios are daily rebalanced since stocks are equally sorted based on different past return information every day for same-weekday and other-weekday strategies. In columns (4) and (5), we exclude the top 10% of same-weekday or other-weekday winners for momentum decile 10, and the bottom 10% of same-weekday or other-weekday losers from momentum decile 1, with the percent of stocks excluded in the parentheses. In column (6) we sort a subgroup of stocks in the middle 40% momentum stocks by the past same-weekday returns into 10 deciles. Column (7) presents the portfolios returns by past 11-month same-weekday returns based on winsorized daily returns (replace the highest and lowest daily return in each month with the second highest and lowest respectively and then calculate same-weekday returns). The last three rows in panel A present the long-short spread along with the Fama-French three- and five- factor adjusted returns. Panel B reports the long-short average monthly returns on five weekdays for these five strategies respectively. The sample includes individual stocks listed in NYSE, Nasdaq, and Amex from 1963 to 2021, excluding penny stocks with price below $5 and small stocks below NYSE 10% breakpoints. T-statistics are provided in parentheses below.

Panel A: Average monthly return of three strategies

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Deciles	Momentum	Same-weekday	Other-weekday	Mom. excl. same-weekday (% excluded)	Mom. excl. other-weekday (% excluded)	Same-weekday (within Mom. middile 40%)	Same-weekday (winsorize extreme daily ret)
1	0.04	-0.33	0.62	0.32 (31%)	-0.35 (66%)	-0.02	-0.41
2	0.46	0.10	0.77			0.27	0.05
3	0.60	0.25	0.79			0.32	0.28
4	0.57	0.45	0.62			0.48	0.43
5	0.58	0.59	0.57			0.56	0.57
6	0.60	0.64	0.63			0.66	0.61
7	0.70	0.73	0.65			0.57	0.73
8	0.79	1.03	0.61			0.86	1.00
9	0.92	1.26	0.59			1.05	1.28
10	1.32	1.72	0.90	1.13 (33%)	1.46 (68%)	1.40	1.80
Long-short	1.28	2.05	0.28	0.81	1.81	1.43	2.21
	(5.19)	(10.94)	(1.22)	(3.24)	(6.99)	(8.70)	(11.42)
FF3	1.65	2.18	0.55	1.14	2.13	1.46	2.36
	(7.32)	(11.93)	(2.58)	(4.99)	(8.71)	(8.86)	(12.49)
FF5	1.53	2.18	0.49	1.04	2.06	1.43	2.34
	(6.79)	(11.86)	(2.28)	(4.52)	(8.41)	(8.65)	(12.31)

Panel B: The average holding return on five weekdays respectively

	(1)	(2)	(3)	(4)	(5)
Weekdays	Momentum	Same-weekday	Other-weekday	Mom. excl. same-weekday	Mom. excl. other-weekday
Monday	1.03	4.04	-1.39	-0.11	2.67
	(1.64)	(8.12)	(-2.54)	(-0.18)	(3.83)
Tuesday	1.69	1.36	1.17	1.46	1.78
	(3.07)	(3.58)	(2.22)	(2.59)	(3.23)
Wednesday	1.59	1.52	1.38	1.56	1.27
	(2.78)	(3.48)	(2.66)	(2.73)	(2.12)
Thursday	0.56	1.00	0.12	0.21	0.88
	(1.03)	(2.55)	(0.23)	(0.38)	(1.62)
Friday	1.53	2.45	0.00	0.83	2.51
	(3.25)	(6.40)	(-0.01)	(1.71)	(5.06)

Table 4: **Fama-Macbeth cross-sectional regressions**

This table reports the Fama-Macbeth regression of different past return components in predicting the daily return in next month. ”Ret all”, ”Ret same-weekday”, and ”Ret other-weekday” refer to the overall return, same-weekday return, and other-weekday return in the past 11 months (skipping recent one month) respectively. Control variables include Size (market value by the end of last month, B/M (book value divided by market value by the end of last month), ”Ret same-weekday 2y-3y” (same-weekday cumulative return over prior years t-2 to t-3), Amihud (absolute daily return divided by daily dollar volume and then averaged over previous 11 months), Turnover (daily turnover ratio and then averaged over previous 11 months), Amihud same-weekday (absolute daily return divided by daily dollar volume and then averaged over same weekdays in previous 11 months), Turnover same-weekday (daily turnover ratio and then averaged over same weekdays in previous 11 months). Panel A and B report the regression results based on value or equal weight for each individual stock observation in the cross-section respectively. The sample includes individual stocks listed in NYSE, Nasdaq, and Amex from 1963 to 2021, excluding penny stocks with price below \$5 and small stocks below NYSE 10% breakpoints. All coefficients are multiplied by 10000. T-statistics are provided in parentheses below.

Panel A: Value weight

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Ret all	3.38			1.06	11.99		3.37				1.57	1.90	1.85
	(3.86)			(1.23)	(10.54)		(3.73)				(1.73)	(2.20)	(2.15)
Ret same-weekday		17.30		15.48		16.90		13.88		13.14	11.34	10.46	10.47
		(11.98)		(12.26)		(11.91)		(9.68)		(9.33)	(9.04)	(8.99)	(8.99)
Ret other-weekday			0.91		-11.30	1.36			1.42				
			(1.00)		(-10.62)	(1.50)			(1.52)				
Size							-0.19	-0.21	-0.22	-0.23	-0.23	-0.30	-0.29
							(-1.50)	(-1.59)	(-1.69)	(-1.80)	(-1.87)	(-2.34)	(-2.25)
B/M							-0.14	-0.13	-0.17	-0.17	-0.15	-0.17	-0.17
							(-1.37)	(-1.29)	(-1.71)	(-1.43)	(-1.39)	(-1.71)	(-1.71)
Ret same-weekday 2y-3y										4.35	4.37	4.13	4.18
										(5.91)	(6.28)	(6.38)	(6.45)
Amihud												-5.79	
												(-1.53)	
Turnover												-2.23	
												(-1.48)	
Amihud same-weekday													-5.14
													(-1.14)
Turnover same-weekday													-2.03
													(-1.32)
R2	2.14%	1.27%	1.86%	2.94%	2.84%	3.01%	4.57%	3.70%	4.30%	4.56%	6.12%	7.65%	7.62%

Panel B: Equal weight

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Ret all	3.09			1.27	9.49		3.22				1.57	1.84	1.81
	(4.95)			(2.09)	(12.14)		(4.91)				(2.41)	(2.98)	(2.93)
Ret same-weekday		13.89		12.19		13.73		12.08		11.40	9.85	8.70	8.87
		(14.52)		(15.35)		(14.16)		(12.90)		(12.24)	(12.72)	(12.81)	(12.96)
Ret other-weekday			1.05		-8.18	1.57			1.24				
			(1.68)		(-12.75)	(2.47)			(1.92)				
Size							-0.34	-0.33	-0.34	-0.36	-0.37	-0.46	-0.45
							(-2.38)	(-2.28)	(-2.38)	(-2.77)	(-2.64)	(-3.34)	(-3.28)
B/M							0.12	0.11	0.11	0.06	0.07	-0.01	0.00
							(2.00)	(1.89)	(2.00)	(0.98)	(1.12)	(-0.23)	(0.03)
Ret same-weekday 2y-3y										3.52	3.48	3.08	3.13
										(7.78)	(7.99)	(7.77)	(7.87)
Amihud												-4.53	
												(-2.55)	
Turnover												-3.25	
												(-2.22)	
Amihud same-weekday													-5.79
													(-2.84)
Turnover same-weekday													-2.69
													(-1.86)
R2	0.94%	0.48%	0.80%	1.23%	1.20%	1.26%	1.84%	1.33%	1.69%	1.64%	2.41%	3.65%	3.61%

Table 5: **Seasonal fund flow and seasonal institutional trading by weekday**

This table reports the number of seasonal funds and seasonal institutions (in total and by the day of the week), respectively. To define a seasonal fund-weekday, at the end of each month, we look at the daily flows (absolute flow value scaled by the total net asset by the end of previous day, refilled with 0 if missing) of a fund in the past year to test whether the daily flows on a specific weekday is significantly larger than that on other four weekdays based on a T-test of the mean of these two samples. For example, in January, to test whether a fund is a seasonal fund on Monday, we compare the mean of its Monday daily flows and the mean of Tuesday, Wednesday, Wednesday, Thursday, and Friday daily flows in last year using the T-statistics ($T = \frac{\mu_1 - \mu_2}{\sqrt{\sigma_1^2/n_1 + \sigma_2^2/n_2}}$, where μ_1, σ_1^2 and μ_2, σ_2^2 are the mean and variance of daily flows on Monday and on other four weekdays, respectively) at 10% significance level. We only take one weekday with largest daily flow for a fund at a given month if there are multiple weekdays with significantly larger flows in past year. The seasonal institution-weekday is defined in a similar way but using the daily absolute trading volume in dollars (refilled with 0 if missing). Panel A covers all equity funds from Morningstar from 2009 to 2023 and Panel B all institutions from ANcerno from 1999 to 2011. Columns (1) and (2) present the average number of all funds (or institutions) and seasonal funds (or institutions) across months; Columns (3) and (4) present the average percentage of the number and of the flow volume (or trading volume) in past year of seasonal funds (or institutions) out of all funds (or institutions). And column (5) reports the average concentration ratio of the weekday with significantly larger daily flows out of all five weekdays among all defined seasonal funds (or institutions) across months. We also breakdown the seasonal funds (or institutions) by their concentrated weekday in five rows Mon, Tue, Wed, Thu, and Fri, respectively.

Panel A: Seasonal fund flow

	(1)	(2)	(3)	(4)	(5)
	# of funds	# of seasonal funds	% of seasonal funds	% of flow volume of seasonal funds	avg. concentration ratio of seasonal funds
% of all	1824.1	303.7	16.4%	14.9%	36.6%
by weekday (% of all seasonal)	Mon	29.8	10.1%	15.1%	42.1%
	Tue	103.1	32.4%	27.6%	34.0%
	Wed	72.4	24.0%	23.0%	35.7%
	Thu	51.5	18.0%	17.5%	38.1%
	Fri	46.2	15.6%	16.8%	38.6%

Panel B: Seasonal institutional trading

	(1)	(2)	(3)	(4)	(5)
	# of institutions	# of seasonal institutions	% of seasonal institutions	% of trading volume of seasonal institutions	avg. concentration ratio of seasonal institutions
% of all	453.0	120.3	26.7%	46.4%	33.6%
by weekday	Mon	13.7	10.7%	6.8%	35.5%
	Tue	24.5	19.0%	12.0%	33.7%
	Wed	36.5	28.0%	32.6%	33.5%
	Thu	38.6	29.6%	40.5%	30.3%
	Fri	16.5	12.7%	7.9%	36.5%

Table 6: **Persistence in seasonal fund flow and seasonal institutional trading**

This table presents the monthly sorting results to test the persistence of the concentration and of the direction at the same weekday in the past and in the future for seasonal fund flow (Panels A and B) and seasonal institutional trading (Panels C and D), respectively. In Panel A, at each month, we sort all defined seasonal funds equally into ten deciles based on their concentration ratio of the daily absolute flow at the weekday with significantly larger flow out of all five weekdays in past 11 months (skipping most recent month), as shown in column (1), and report the next-month concentration ratio of the absolute daily flow at the same weekday out of all five weekdays in column (2). The rows in "decile" from 1 to 10 report the average values over institutions in same decile and across months. And the row "10-1" calculates the difference between decile 10 and 1 and the below row presents the t-value accordingly. In Panel B, we sort seasonal funds equally into ten deciles based on their past average net daily flow at the weekday with significantly larger absolute daily flow in past 11 months as shown in column (1) and report the next-month average daily flow at the same weekday in column (2). Again, deciles 1 to 10 report the average values over institutions and across months and row "10-1" the difference between decile 10 and 1 with t-stat in below parenthesis. Panels A and B cover all defined seasonal equity funds from Morningstar from 2009 to 2023.

Panel A: Persistence of seasonal fund flow concentration

	(1)	(2)
decile	sorting past 11-month concentration ratio	next-month concentration ratio
1	23.95%	21.53%
2	26.33%	21.71%
3	28.26%	21.81%
4	30.23%	22.39%
5	32.43%	22.08%
6	35.01%	22.39%
7	38.08%	22.69%
8	42.12%	22.60%
9	48.59%	23.00%
10	64.07%	24.83%
10-1	40.12%	3.30%
t-stat		(6.67)

Panel B: Persistence of seasonal fund flow direction

	(1)	(2)
decile	sorting past 11-month net flow	next-month net flow
1	-0.58%	-0.27%
2	-0.19%	-0.11%
3	-0.11%	-0.08%
4	-0.07%	-0.05%
5	-0.04%	-0.03%
6	0.00%	0.00%
7	0.04%	0.01%
8	0.12%	0.03%
9	0.26%	0.09%
10	1.50%	0.23%
10-1	2.08%	0.51%
t-stat		(10.84)

Table 6: **Persistence in seasonal fund flow and seasonal institutional trading (continued)**

In Panel C, we sort all defined seasonal institutions every month equally into ten deciles based on their concentration ratio of the daily trading volume in dollars at the weekday with significantly larger trading volume out of all five weekdays in past 11 months (skipping most recent month), as shown in column (1), and report the next-month concentration ratio of the daily trading volume at the same weekday out of all five weekdays in column (2). The rows in "decile" from 1 to 10 report the average values across months. And the row "10-1" calculates the difference between decile 10 and 1 and the below row presents the t-value accordingly. In Panel D, we sort seasonal institutions equally into ten deciles based on their trading imbalance (the difference between buy and sell in dollars scaled by the sum of buy and sell) at the weekday with significantly larger trading volume in past 11 months as shown in column (1) and report the next-month trading imbalance at the same weekday in column (2). Again, deciles 1 to 10 report the average values across months and row "10-1" the difference between decile 10 and 1 with t-stat in below parenthesis. Panel C and D cover all defined seasonal institutions from ANcerno from 2000 to 2011.

Panel C: Persistence of seasonal institutional trading concentration

	(1)	(2)
decile	sorting past 11-month concentration ratio	next-month concentration ratio
1	22.41%	21.21%
2	23.92%	21.42%
3	25.07%	22.03%
4	26.40%	21.99%
5	28.01%	22.94%
6	30.03%	23.08%
7	32.97%	23.92%
8	37.27%	25.27%
9	44.72%	26.76%
10	66.23%	38.31%
10-1	43.82%	17.10%
t-stat		(18.22)

Panel D: Persistence of seasonal institutional trading direction

	(1)	(2)
decile	sorting past 11-month trading imbalance	next-month trading imbalance
1	-47.25%	-2.29%
2	-19.19%	1.01%
3	-10.60%	-1.39%
4	-5.87%	-1.10%
5	-2.36%	-0.13%
6	0.35%	1.28%
7	3.15%	-0.58%
8	7.49%	3.76%
9	16.67%	3.50%
10	46.33%	15.11%
10-1	93.57%	17.41%
t-stat		(6.60)

Table 7: **Seasonal institutional trading and stock momentum**

This table presents the persistence of seasonal institutional trading in momentum tercile portfolios. We first equally sort individuals stocks into three terciles every month based on their past 11-month return (skipping recent one month). Then we look at how many (seasonal) institutions trading on these stocks at each of five weekdays in the past 11 months. Panel A column (1) reports the total number of month-weekday in the sample. Panel A columns (2) and (3) report the average number of institutions who traded the stocks on a weekday of past 11 month and the average number of seasonal institutions who traded the stocks on their concentrated weekday of past 11 month. Columns (4) and (5) present the percentage of seasonal institutions out of all institutions and the average trading concentration ratio of seasonal institutions at their concentrated weekday. Panel B reports the equal-weighted trading imbalance (the difference between buy and sell divided by the sum of buy and sell) on a stock across seasonal institutions who traded the stock at its own concentrated weekday in past 11 months in column (1) and the next-month average trading imbalance among these seasonal institutions on the stock at future same weekday in column (2). We then average the equal-weighted trading imbalance over stocks within same tercile, and finally over five weekdays of months. Panel B columns (3) and (4) reports the dollar value-weighted trading imbalance (the difference between total buy and total sell in dollars on a stock from all seasonal institutions at a concentrated weekday divided by the sum of the total buy and total sell) in the past 11 months and in the next one month respectively. We then average the value-weighted trading imbalance over stocks within same tercile and finally average over five weekdays of months. The row "3-1" indicates the difference between tercile 3 and 1, and with the t-stat in below parentheses for next-month trading imbalance. The sample includes individual stocks listed in NYSE, Nasdaq, and Amex, excluding penny stocks with price below $5 and small stocks with size below NYSE 10% breakpoints, and covers all defined seasonal institutions with specific concentrated weekday at each month from ANcerno during 2000 to 2011. We require that each stock has at least 50 institutions who traded it on each of five weekdays in past 11 months.

Panel A: % seasonal traders for momentum portfolios

	(1)	(2)	(3)	(4)	(5)
Tercile by momentum	# of month-weekday	avg. # of institutions	avg. # of seasonal institutions	% of seasonal institutions	avg. concentration ratio of seasonal institutions
1	715	72.7	6.5	9.02%	32.1%
2	715	73.4	6.6	9.09%	32.4%
3	715	69.5	6.4	9.18%	31.9%

Panel B: Imbalance persistence for winners and losers

	(1)	(2)	(3)	(4)
Tercile by momentum	past 11-month trading imbalance (equal-weight)	next-month trading imbalance (equal-weight)	past 11-month trading imbalance (value-weight)	next-month trading imbalance (value-weight)
1	-6.02%	-5.86%	-4.65%	-4.47%
2	-2.11%	-4.42%	-0.86%	-3.42%
3	3.67%	-3.08%	4.76%	-2.63%
3-1	9.69%	2.90%	9.41%	1.96%
t-stat		(3.99)		(2.65)

Table 8: **Persistence in seasonal institutional trading of individual stocks**

This table presents the regression results of the persistence of trading for seasonal institutions at stock-month-weekday level. The regression model is: $TradeImb_{i,t,k} = TradeImb_{i,t-12,t-2,k} + Controls + \epsilon_{i,t,k}$, where i refers to any stocks in our baseline sample at month t, and the independent variable $TradeImb_{i,t-12,t-2,k}$ is the trading imbalance calculated as the difference between buy and sell in dollars divided by the sum of buy and sell from all seasonal institution who traded stock i at their concentrated weekday k in past months $t-12$ to $t-2$. The dependent variable $TradeImb_{i,t,k}$ is the next-month trading imbalance defined as the difference between buy and sell divided by the sum of buy and sell from all seasonal institutions who traded stock i before at their concentrated weekday k and trade it again at weekday k of month t. We refill this future imbalance measure with 0 if there is no seasonal trading on stock i from those who traded it before to avoid forward-looking bias. The control variables include the log market value and book to market ratio at the end of last month, and the past 11-month returns respectively in columns (2), and (3). We impose institution-, month-, and stock-level fixed effects in each regression and cluster the standard errors at institution level. The clustered standard errors are attached in below parentheses. The institution sample covers all defined seasonal institutions with specific concentrated weekday at each month from ANcerno during 2000 to 2011. The stock sample includes all individual stocks listed in NYSE, Nasdaq, and Amex over the same period, excluding penny stocks with price below $5 and small stocks with size below NYSE 10% breakpoints. We denote the 10%, 5%, and 1% significance levels with *, **, and *** respectively.

	(1)	(2)	(3)
Dep. Var.	next-month same-weekday trading imbalance	next-month same-weekday trading imbalance	next-month same-weekday trading imbalance
Indep. Var.			
past 11-month trading imbalance	0.0163***	0.0161***	0.0160***
	(0.000953)	(0.000967)	(0.000970)
log(ME)		-0.00796***	-0.00875***
		(0.00170)	(0.00180)
B/M		0.00274**	0.00235*
		(0.00127)	(0.00129)
past 11-month return			0.00230
			(0.00157)
Constant	-0.0152***	0.0969***	0.108***
	(2.97e-05)	(0.0246)	(0.0259)
# of Obs	1,373,534	1,338,588	1,338,588
R-squared	0.014	0.014	0.014
Month FE	YES	YES	YES
Stk FE	YES	YES	YES
Clu. Std	Stk	Stk	Stk

Table 9: **Past seasonal institutional trading imbalance and future stock returns**

This table presents the results of predicting next-month same-weekday stock returns using past aggregate seasonal institutional trading at their concentrated weekday in a regression: $R_{i,t,k} = TradeImb_{i,t-12,t-2,k} + Controls + \epsilon_{i,t,k}$, where the independent variable, $TradeImb_{i,t-12,t-2,k}$, labeled as "past 11-month trading imbalance", is the sum of net trading of all seasonal institutions who traded the stock i at their concentrated weekday k in past 11 months from $t-12$ to $t-2$, scaled by the market value of the stock by the end of the previous month $t-1$, and the dependent variable $R_{i,t,k}$ is the stock i's same-weekday k return in month t. The control variables include the log market value and book to market ratio at the end of last month, and the past 11-month return of the stock respectively in columns (2) and (3). In columns (4) to (6), we use an alternative measure labeled by "past 11-month trading imbalance weighted by persistence". We first estimate a trading persistence coefficient for each institution at each month by regressing the next-month same-weekday trading imbalance of a stock on its past trading imbalance of the same stock at concentrated weekday in past 11 months over all stocks held by the institution. We sum up all "seasonal" institutions' net trading on a stock with a weight of their estimated average trading persistence coefficients over past 12 months and then scaled it by the stock's total market value. We impose month-, and stock-level fixed effects in each regression and cluster the standard errors at stock level. The clustered standard errors are attached in below parentheses. The stock sample includes all individual stocks listed in NYSE, Nasdaq, and Amex, excluding penny stocks with price below $5 and small stocks with size below NYSE 10% breakpoints. The institution sample covers all defined seasonal institutions with specific concentrated weekday at each month from ANcerno, from 2000 to 2011. The dependent variable stock returns are in basis points. We denote the 10%, 5%, and 1% significance levels with *, **, and *** respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.	next-month same-weekday return	next-month same-weekday return	next-month same-weekday return	next-month same-weekday return	next-month same-weekday return	next-month same-weekday return
Indep. Var.						
past 11-month trading imbalance	2.979**	3.360**	2.841**			
	(1.407)	(1.427)	(1.427)			
past 11-month trading imbalance weighted by persistence				20.45**	20.94**	21.42**
				(9.707)	(9.871)	(9.879)
log(ME)		-70.13***	-75.07***		-70.06***	-75.02***
		(2.023)	(2.197)		(2.021)	(2.195)
B/M		3.100***	0.666		3.086***	0.640
		(1.079)	(1.096)		(1.079)	(1.096)
past 11-month return			14.32***			14.37***
			(1.561)			(1.559)
Constant	17.63***	1,022***	1,091***	17.66***	1,021***	1,091***
	(0.0338)	(29.10)	(31.53)	(0.0402)	(29.07)	(31.50)
# of Obs	1,373,534	1,338,588	1,338,588	1,370,193	1,335,399	1,335,399
R-squared	0.045	0.047	0.047	0.045	0.047	0.047
Month FE	YES	YES	YES	YES	YES	YES
Stk FE	YES	YES	YES	YES	YES	YES
Clu. Std	Stk	Stk	Stk	Stk	Stk	Stk

Table 10: **Double sort on same-weekday seasonal trading and momentum**

This table reports the average monthly returns (in percent) of a 3×10 double sort. Individual stock returns within each portfolio are value weighted. It shows the average weekday returns at each month (transformed into average monthly returns by multiplying 5) for portfolios sorted first by the absolute dollar trading volume from seasonal institutions on their same concentrated weekdays (scaled by the market cap at the end of last month) during months $t-12$ to $t-2$, and then by the same-weekday returns in that period. Columns (11) and (12) report the return difference between winner and loser deciles and its t-stat within each of three seasonal trading subgroups. In last two rows we also report the return difference between the winner-loser spreads in high and low seasonal trading groups, with t-stat in below parentheses. The seasonal institution with specific concentrated weekday is identified every month based on their daily trading volume in each weekday of past 1 year during 2000 to 2011 based on ANcerno in the way same as Table 5. The stock sample includes all individual stocks listed in NYSE, Nasdaq, and Amex, excluding penny stocks with price below $5 and small stocks with size below NYSE 10% breakpoints.

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
		sort by past 11-month same-weekday return											
		1=loser	2	3	4	5	6	7	8	9	10=winner	diff 10-1	t-stat
sort by same-weekday seasonal trading	1=low trading	-0.44	0.06	-0.12	0.78	0.05	0.38	0.93	0.51	0.61	0.98	1.41	(2.45)
	2	-0.61	0.01	-0.06	0.29	0.18	0.45	-0.10	0.53	0.74	1.12	1.73	(2.58)
	3=high trading	-0.62	0.30	0.05	0.21	0.25	0.24	0.76	0.26	0.84	1.66	2.28	(2.95)
	diff 3-1											0.86	
	t-stat											(2.13)	

Appendix

ANcerno dataset cleaning and matching

ANcerno institution identity: ANcerno provides an extra reference file linking the ″clientmgrcode″ in the main database to a more general institution identity: ″manager-code″, even with the real name of the institution attached. We then merge all trades from different ″clientmgrcode″s to identical institution with the same ″clientmgrcode″.

ANcerno Symbol to CRSP Permno: We match ANcerno daily stock observation with CRSP stock info (a file called ″msenames″ with main items: Permno, Ticker, ncusip, namedt, and nameendt) through ″symbol″ and ″cusip″ (only keep the first 8 digits) in ANcerno paired with ″Ticker″ and ″ncusip″ in CRSP msenames file, requiring the stock day in ANcerno within the date range from ″namedt″ to ″nameendt″ in CRSP msenames.

We end up with a total of 841 institutions (actually 764 institutions after requiring a 6-month trading history and 10 trading days) with their daily trading summary statistics as follows:

Table A.1: **ANcerno institution trading statistics**

This table reports the summary statistics of 764 institutions from ANcerno during 1999 to 2011. We present the statistics for a list of variables: total trading history in days (″num_total_day″), the number of actual trading days (″num_trd_day″), the percent of trading days out of all existing days (″pct_trd_day_of_total″), the average daily dollar trading volume (″dollar_abs_daily_mean″), the total absolute dollar trading volume (″dollar_abs_sum″), the total net dollar trading volume (″dollar_sum″), the total positive (buying) trading volume (″dollar_pos″), and the total negative (selling) trading volume (″dollar_neg″). We require each institution to have more than 120 trading days history and 10 actual trading days in our sample.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Variable	N	Mean	Median	StdDev	25th	75th	10th	90th	Min	Max
num_total_day	764	1957	1867	1019	1111	3057	536	3241	120	3242
num_trd_day	764	1074	726	979	264	1686	98	2767	10	3239
pct_trd_day_of_total	764	51.9%	52.4%	32.3%	21.6%	83.0%	9.2%	96.5%	0.6%	100.0%
dollar_abs_daily_mean ($ thousands)	764	18963.5	997.1	98431.6	233.2	5063.5	61.4	29146.1	0.7	1405927.2
dollar_abs_sum ($ mils)	764	50021.2	1608.9	306471.9	321.9	10043.3	62.9	62119.8	1.5	4558016.0
dollar_sum ($ mils)	764	175.8	-14.8	15928.0	-227.3	31.2	-1005.0	257.3	-66402.7	423858.5
dollar_pos ($ mils)	764	25098.5	792.5	155507.2	164.2	4935.7	28.4	29652.6	0.0	2288065.7
dollar_neg ($ mils)	764	24922.7	819.5	151350.1	177.6	5211.7	32.1	29217.0	0.4	2269950.3