Same-Weekday Momentum*

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First Draft: Mar 14, 2024; This Draft: Apr 24, 2024

Abstract

A disproportionately large fraction (70%) of stock momentum reflects return continuation on the same weekday (e.g., Mondays to Mondays), or the same-weekday momentum. Even 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 mis-reaction. 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.
JEL Codes: G12

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*The authors are grateful for advice from Steven Heston, and helpful comments from Robert Battalio, Qinhua Chen, Ian Dew-Becker, Thomas Ernst, Stefano Giglio, Brandon Han, Serhiy Kozak, Pete Kyle, Jonathan Lewellen, Juhani Linnainmaa, Jianan Liu, Mark Loewenstein, Dong Lou, Andreas Neuhierl, Markus Pelger, Shrihari Santosh, David Thesmar, Ruslan Tuneshev, Chenyang Wang, Russ Wermers, Jing Sophia Xue, Rafa Zambrana, Wei Zhou and seminar participants at the Maryland brownbag. All errors are our own.

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1 Introduction

Stocks that outperform (underperform) in the past one year tend to produce higher future returns over the medium term (Jegadeesh and Titman (1993)). Such a 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 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.

If stock momentum is distributed evenly, we would expect the same-weekday

[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).

covariances to 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 the reversal (x) during the holding period to be only partial, about 28% with its 5th and 95th percentiles to be -31.2% and 75.9%, respectively. As a result, the net contribution of same-weekday momentum to the momentum effect, even after accounting for the reversals, is about 47.4%. Such a 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 stock momentum. A large body of momentum theories is based on some forms of investor mis-reaction 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). Ex-ante, however, there is no strong reason why investor mis-reaction should display such a within-week seasonality pattern.

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 experienced significantly larger (absolute) fund flow on a particular weekday than other days of the week in the past one year. Each month, we find 16.4% of mutual funds to experience seasonal flows and their (absolute) flows account for 14.9% of the total fund flows in the past one 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 2008, 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 one year. Each month, We find 25.6% of ANcerno institutions to display within-week seasonality in trading and their trading account for 30.1% of the total ANcerno institutional trading volume in the past one year. Among "seasonal institutions," more than 35.5% of their past trading occur on the same weekday.

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 one year, it's 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 trades more on Mondays in the future. Moreover, 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 inflow (outflow) on Mondays in the future. Consistent with the 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. For each month and each stock, we first identify seasonal ANcerno institutions who have traded the stock in the momentum formation period (months from $t-12$ to $t-2$). While 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 by seasonal institutions. For example, seasonal institutions bought (sold) winners (losers) during the formation period. In other words, seasonal institutional trading could contribute to the past return. Second, we show that a seasonal institution who bought (sold) a winner (loser) on Mondays in the formation period is also more likely to buy (sell) the same stock on Mondays in the holding period. Third, aggregate seasonal trading on a stock in the formation period positively predicts future returns of that stock in the holding period.

Our paper contributes to the momentum literature. Our simple decomposition exercise attributes a significant fraction of stock momentum to the same-weekday momentum, even after accounting for its reversal. This finding suggests that a large group of explanations based on investor mis-reaction, 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 within-week seasonality, seems an important ingredient of momentum effect. Note that the same weekday momentum underestimates the overall contribution of institutional trading to the momentum effect, since it only reflects a special type of persistent institutional trading.

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 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 stock momentum reflects return continuation on the same weekday. Such a same-weekday momentum is both statistically and economically significant.

2.1 Data and sample construction

Our baseline sample covers individual U.S. stocks listed in NYSE, Nasdaq, and Amex from 1963 through 2021. To alleviate the impact of market micro-structure 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, 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:

$$\begin{aligned}\hat{\beta}_t &= \frac{Cov(r_{i,t}, r_{i,t-2,t-12})}{Var(r_{i,t-2,t-12})} \\ &= \underbrace{\sum_{k_1=1}^{5} \frac{Cov(r_{i,t}(k_1), r_{i,t-2,t-12}(k_1))}{Var(r_{i,t-2,t-12})}}_{\text{Same-Weekday (5×1=5 items)}} + \underbrace{\sum_{k_1=1}^{5} \sum_{\substack{k_2=1 \\ k_2 \neq k_1}}^{5} \frac{Cov(r_{i,t}(k_1), r_{i,t-2,t-12}(k_2))}{Var(r_{i,t-2,t-12})}}_{\text{Other-Weekday (5×4=20 items)}},\end{aligned} \tag{3}$$

where k_1 and $k_2 = 1$ to 5, denoting the five weekdays.

Table 1 Panel A reports the decomposition results under different size filters. The first row corresponds to the baseline sample which excludes stocks with market capitalization smaller than the 10th percentile of the NYSE size break point. The average $\hat{\beta}_t$ is 1.17 (t-value = 6.8), confirming a significant momentum effect during the period from 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 $\hat{\beta}_t$.

Table 1 Panel B further reports the decomposition results by each weekday of the formation period. Specifically, we report the average "Same Weekday" and "Other Weekday" components for each $k_2 = 1$ to 5. In other words, we decompose the total momentum coefficient into 10 components. The momentum effect is the strongest on Mondays of the formation period (accounting 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 return continuation from Mondays during the formation period to Mondays during the holding period. The same weekday momentum is also present in 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 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 lower their net contribution to total momentum. As we will 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 past Monday winner is likely to have higher Monday returns during the holding period, reflecting a price pressure. Such a Monday price pressure reverts on other weekdays 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. On the other hand, 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), same weekday price pressure (p), and its reversal ($-xp$). If reversal is incomplete during the holding period ($x < 1$), then the same weekday momentum is a net contributor to the momentum effect.

We assume the standard momentum effect does not vary across weekdays. The cross-weekday decomposition results in Table 1 Panel B then suggests the magnitude of price pressure to vary across weekdays. For example, investors may concentrate their trading on certain days of a week. We denote the same-weekday momentum effect from past Monday, Tuesday, ..., and Friday as $p_1, p_2, ..., p_5$ accordingly. Finally, we assume the reversal to spread evenly across the five weekdays.

Under these assumptions, the observed covariance between past Monday and future Monday (scaled by total past return variance) would be $m + p_1 - \frac{1}{5}xp_1$, and the scaled covariance between past Monday and future Tuesday (or Wednesday, Thursday, and Friday) is $m - \frac{1}{5}xp_1$. Similarly, the scaled covariance between past Tuesday and future Tuesday is $m + p_2 - \frac{1}{5}xp_2$, and the scaled covariance between past Tuesday and future non-Tuesday (Monday, Wednesday, ..., and Friday) 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 5th 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.

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 full sample (in red line), or the 5th 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 the net contribution from same-weekday momentum still accounts almost half of total momentum effect in most time of our sample period.

2.4 Momentum decomposition: Robustness

Different size filters The first three 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 the net contribution of the same weekday momentum to the total momentum coefficient is 46%. In the third row, we exclude stocks whose market capitalization are 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 (the second row) that uses the 10% NYSE breakpoints as the size filters.

Equal- vs. value-weighting The baseline results reported in Table 1 weigh each stock equally in the Fama-MacBeth regressions. The fifth row of Table 2 reports the momentum decomposition results when we weigh each stock by its market capitalization. We find the net contribution of the same weekday momentum to be 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 6-8 of Table 2. The pattern is similar across the three groups, with the same-weekday momentum's net contribution ranges from 33% to 58%. In other words, neither small stocks nor a few large-cap stocks are driving our result.

Liquid vs. illiquid stocks In rows 9-11, we sort 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 sub-periods: 1927-1962, 1963-1992, and 1993-2021. The net contribution of the same-weekday momentum is always positive. It was 39% pre-1963, increased to

62% during 1963-1992, and then declined to 18% during the more recent 1993-2021 period.

Past intraday vs. overnight returns A recent paper by Barardehi, Bogousslavsky, and Muravyev (2023) shows that 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.

Implications Keloharju, Linnainmaa, and Nyberg (2016, 2021) have shown that average daily returns in a particular weekday in the past strongly and positively predict future returns in the same weekday. While 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 lights on the driver of stock momentum. A large body of momentum theories is based on some forms of investor mis-reaction to past information or trading signals. Ex-ante, there is no reason why investor mis-reaction should display a strong within-week seasonality pattern. Put differently, why should the stock price on Monday mis-reacts only to information or trading signals in prior 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 trading strategy results are reported in Table 3.

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-factors are higher, but only about one-fourth of those of the same-weekday momentum strategy.

Figure 2 provides a visual illustration of the performance to the three momentum trading strategies. It plots their cumulative returns (in log 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.

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. Column (5) of Table 3 Panel A shows that about 31% of momentum winners and 33% of 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 5).

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. Column (7) of Table 3 Panel A shows that about 66% of momentum winners and 68% of 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 6).

Table 3 Panel B reports the strategy returns by 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 Horserace in cross-sectional regressions

In Table 4, we conduct a horerace among the three momentum effects using Fama-MacBeth cross-sectional regressions. Specfically, 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 $t-2$). The regressions also control for other stock characteristics with return predictive power. The results from the value-weighted regressions (Panel A) and equal-weighted regressions (Panel B) are very similar.

Three 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 stock characteristics does not change the result. Besides, unreported results confirm that controlling for 25 dummy variables for 5×5 size and book-to-market portfolio does change our results, which is suggested by Kamstra (2017) to alleviate the concerns that momentum (or same-weekday momentum) is driven by cross-sectional variation of mean return.

To summarize, in this section, we document a novel empirical pattern: a disproportionately large fraction (70%) of stock momentum reflects return continuation on the same weekday. Even accounting for partial reversals in other weekdays, the same-weekday momentum still contributes to a significant fraction (20% to 60%) of the momentum effect. The same-weekday momentum is 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 mis-reaction. Next, we investigate its potential economic driver.

3 Seasonality and Persistence in Institutional Trading

Many theories of momentum have been proposed in the past. They are not necessarily mutually exclusive and could all contribute to the momentum. But if 70% of stock momentum reflects return continuation on the same weekday, then the primary economic force underlying momentum should also generate such a within-week seasonality pattern. In this section, we provide novel empirical evidence suggesting that seasonality and persistence in institutional trading could be one such force.

3.1 Data

Mutual fund daily fund flow data during 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 compute the daily percentage fund flow. We require an fund to have at least 6-month flows history and at least 20 flow days in the past 11 months. To compare the daily flow at a particular weekday with that at other weekdays for a fund, we first refill the missing daily flow value with 0 to get a balanced number of observations for each of five weekdays.

Institutional trading data during 1999-2008 is from ANcerno database. We define an institution at the client-manager level by at looking at the items “clientcode” and “clientmgrcode” in the dataset. We require an institution to have at least 6-month trading history and at least 10 trading days in the past 11 months. 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 items “NCUSIP” and “TICKER” from CRSP at the same time. Again, to compare the daily trading at one day of the week with other days, we refill 0 for the day without any trading for the sake of a balanced daily trading subsample of five weekdays.

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 and each month, we identify a “seasonal” fund if its average (absolute) fund flow on a particular weekday in the past one 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.

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 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 3 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. While the prevalence of “seasonal” funds has declined 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.

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 291 institutions (or 25.6% of the cross-section) are classified as the “seasonal” institutions each month during the 1999-2008 ANcerno sample period. Their trading volumes account for 30.1% of the total volume in our sample, so “seasonal” institutions are more active traders.

Their average concentration ratio is 35.5%, meaning that 35.5% 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 most common (28.5%) but their average concentration ratio is the lowest (32.3%). In contrast, while only 12.9% and 13.7% of the “seasonal” institutions are ”Monday” and “Friday seasonal” institutions, their average concentration ratios of 38.4% and 37.6% are higher.

Figure 3 Panel B plots the percentage of “seasonal” institutions, their dollar trading volume as a percentage of total volume in our sample, and their average concentration ratio over time. The prevalence of "seasonal" institutions is quite stable and even increased a bit towards 2008. Their average concentration ratio of just below 40% is also fairly stable.

To conclude this subsection, we find a large number of mutual funds to experience concentrated flow on a particular weekday and even more institutions to concentrate 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 past 11-month average concentration ratio 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 for decile 1 (21.53%), meaning that funds with more concentrated flow in the past continue to have concentrated flow on the same weekday in the future. Columns (3) to (7) break down the "seasonal" funds by weekdays in each decile. The pattern is similar to those reported in Table 5 Panel A that Monday and Friday see more funds with highly concentrated flows than other three weekdays.

In Panel B, we sort "seasonal" funds based on their past 11-month net daily fund flow 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 daily net flow on the same weekday in month t and it shows that the direction of the "seasonal" flow is also highly persistent. "Seasonal" funds experiencing inflow (outflow) on the concentrated weekday in the past continue to experience inflow (outflow) on the same weekday in the future. Columns (3) to (7) again break down the "seasonal" funds by weekdays in each decile. It shows that Monday and Friday see more funds with extreme (inflow and outflow) flows than other three weekdays as well.

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 past 11-month average concentration ratio in column (1) and the average concentration ratio on the same weekday during month t in column (2). Again, all the concentration ratios in column (2) are above 20%. Take decile 10 for example, the institutions in this decile conduct 72.89% of their trading on one particular weekday in the past 11 months. In month t, they continue to conduct 34.77% of their trading on the same weekday. The number 34.77% is also significantly higher than that for decile 1 (20.70%), meaning 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. Columns (3) to (7) break down the "seasonal" institutions by weekdays in each decile. The pattern is also similar to those reported in Table 5 Panel B in that Monday and Friday see more institutions with highly concentrated trading than Tuesday, Wednesday, and Friday.

In Panel D, we sort "seasonal" institutions based on their past 11-month net trade imbalance 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 month t and it shows that the direction of the "seasonal" institutional trading is also highly persistent. "Seasonal" institutions who bought more stocks than sold on the concentrated weekday in the past continue to buy stocks in net on the same weekday in the future. Columns (3) to (7) again break down the "seasonal" institutions by weekdays in each decile. Similar to the fund flow results in Panel B, Monday and Friday also see more institutions with extreme (buy and sell) trading than other three weekdays. These breakdown results on five weekdays for fund flow and institutional trading are all consistent with our decomposition results by weekday in Tables 1 and 3 that Monday and Friday contribute more to same-weekday momentum than other weekdays.

3.4 Momentum and seasonal trading

In this subsection, we link momentum to "seasonal" institutional trading more directly. We focus on the 1999-2008 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 ANcerno institutions who have traded it during the formation period, and among them those "seasonal" institutions.

Table 7 Panel A reports summary statistics related to institutional trading on these momentum terciles. We do not observe a large difference between past winners and losers. On average, each stock has been traded by 5 to 6 "seasonal" institutions in the formation period. These "seasonal" institutions represent about 5.35% to 5.47% of all ANcerno institutions trading the stock. The average concentration ratio is about 35% to 36% for these "seasonal" institutions. Put differently, the amount of "seasonal" institutional trading does not differ significantly across the momentum terciles.

When we examine the direction of "seasonal" institutional trading in Panel B, however, we see a significant difference across the momentum terciles. Column (1) reports the average net trade imbalance by the 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, "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 by these seasonal institutions during month t, or the momentum holding period in column (2), we find the imbalance pattern to persist. The evidence suggests that "seasonal" institutions bought winners (sold losers) in the past and continue to buy winners (sell 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 buy winners (sell 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 stock-institution-month level. We use the past net trading imbalance from a seasonal institution on a stock in the past 11 months (months $t-12$ to $t-2$) to predict its net trading imbalance of the same stock on the same concentrated weekday in month t. The net trading imbalance of an institution on a stock is calculated as the difference between the dollar buy and dollar sell at that stock divided by the sum of the buy and sell. Column (1) presents the baseline results that seasonal institutions are more likely to trade a stock in same direction as before, with a positively significant coefficient of 0.0217, which means, on average, a Monday seasonal institution will buy (or sell) 2.17% more of the same stock on future Mondays if it traded the stock with purely 100% buy (or sell) on the past Mondays. This result is robust to the size and book-to-market ratio of the stock as controls in column (2).

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

Finally, we directly link past "seasonal" institutional trading to future stock return using a panel regression at stock-month level. In Table 9, we aggregate the net (buy minus sell) trading dollars on a stock from all seasonal institutions who traded that stock at their own concentrated weekday in 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 seasonal trading imbalance". In column (1) of Table 9, we use this stock-level aggregate seasonal trading imbalance in the past to predict monthly stock return at t in a univariate regression, which shows a significantly positive coefficient of 0.00119. This means that if all seasonal institutions together traded a stock with net positive 100% volume of the total market value over the past 11 months, it will lead to 0.119% return next month. Consistent with the results in previous table, the stock-month 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).

Notably, in column (3), the coefficient for past seasonal trading imbalance represents roughly a quarter of the coefficient for the past 11-month return, signifying its substantial explanatory power on future returns. This significance is noteworthy given the fact that ANcerno institutions only account for about 10% of all institutions in the market.

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

4 Conclusion

In this paper, we document a new empirical fact about the stock momentum. A significant fraction (47.4%) of stock momentum reflects return continuation on the same weekday, even after accounting for reversals in 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 mis-reaction. Instead, we find within-week seasonality and persistence in institutional trading to be 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: **Historical decomposition of momentum covariance**

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 first estimate the percentage of 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 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.

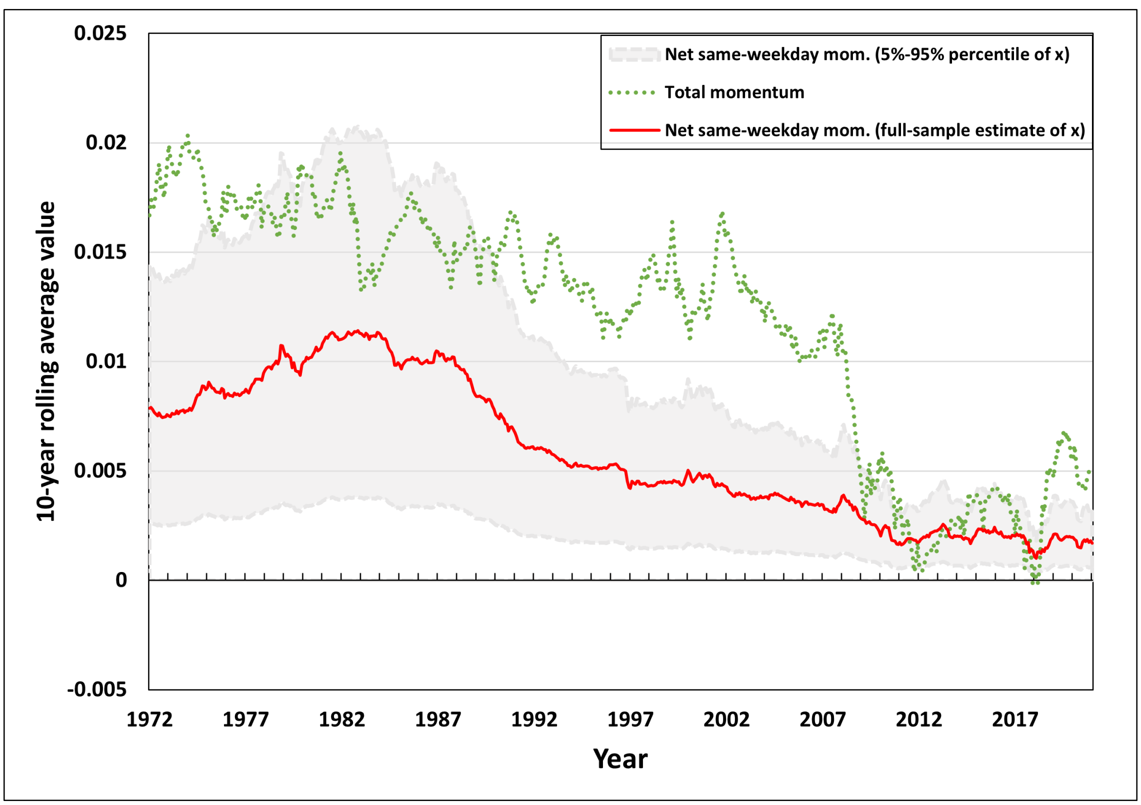


Figure 2: **Historical cumulative return of three trading strategies**

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.

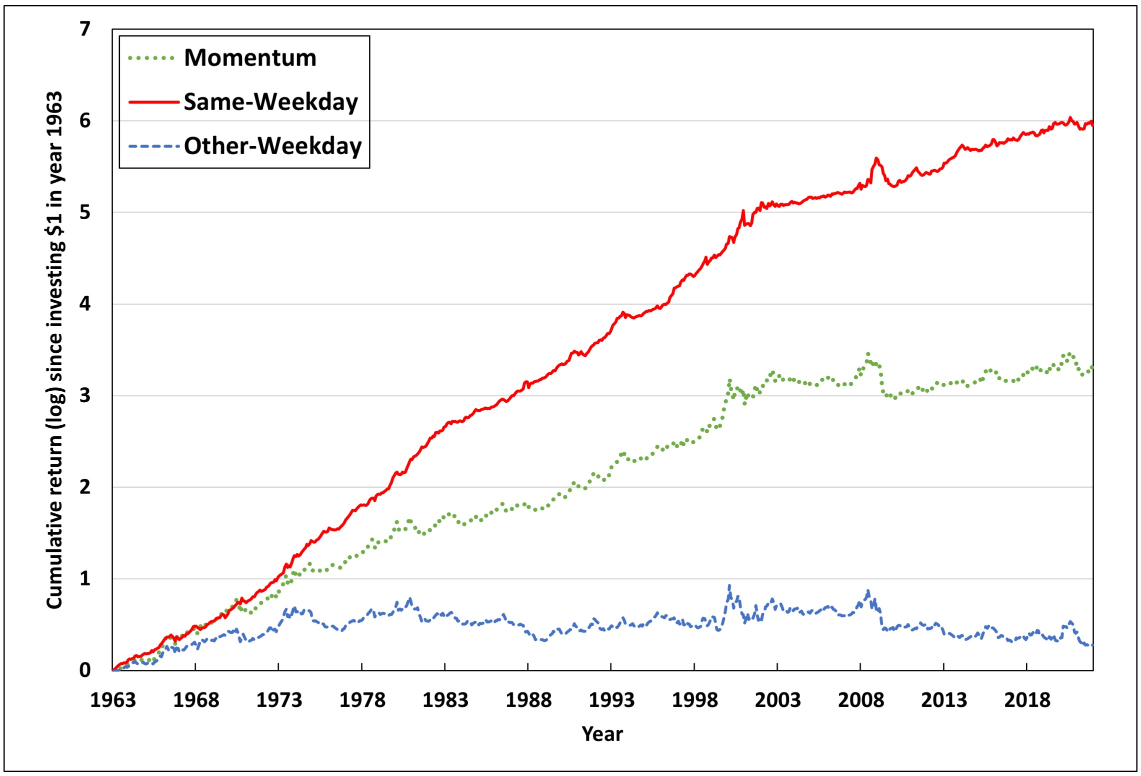
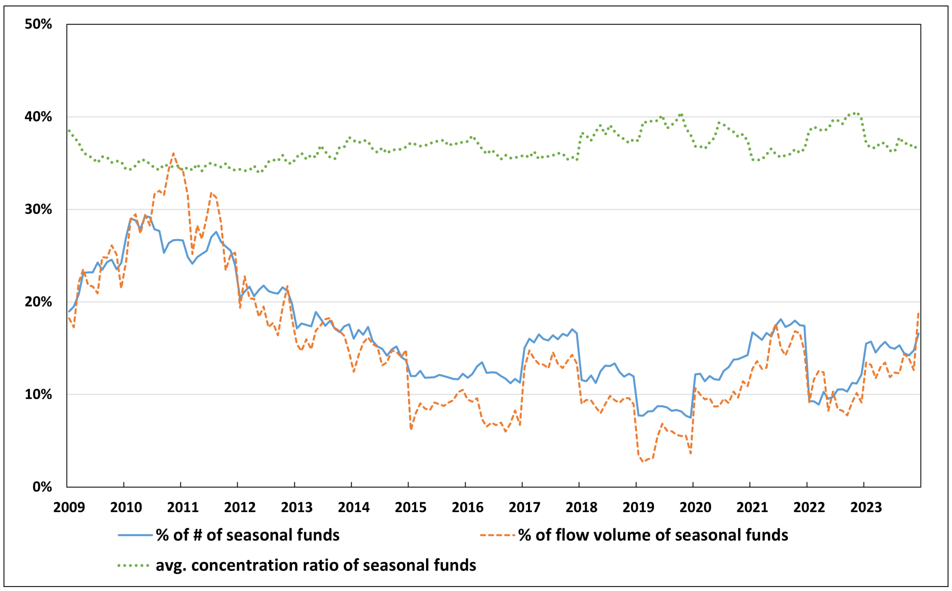


Figure 3: **Seasonal fund flow and seasonal institutional trading**

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 2008 from ANcerno.

Panel A: Seasonal fund flow



Panel B: Seasonal institutional trading

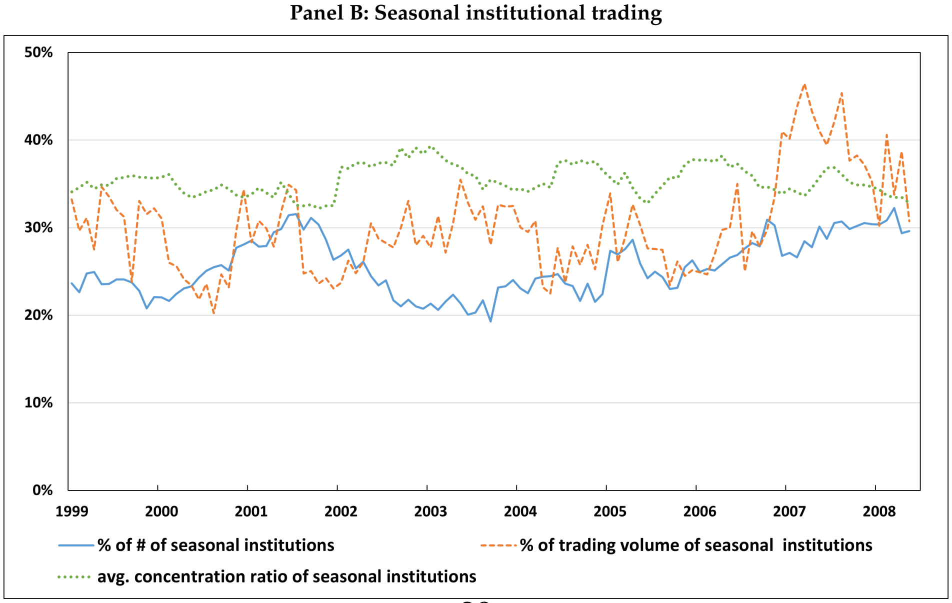


Table 1: **Weekday Momentum Decomposition**

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

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

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 moenntum 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- 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), exluding 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)					
	10% NYSE	1.17	0.85	0.32	0.61	0.77	28.0%	0.55	47%
			- (13.33)	-(13.33)					
	20% NYSE	1.13	0.81	0.32	0.59	0.73	26.2%	0.54	48%
			- (11.75)	-(11.75)					
Weight	equal	1.17	0.85	0.32	0.61	0.77	28.0%	0.55	47%
			(13.33)	- (13.33)					
	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: **Decile portfolios performance of momentum, same-weekday and other-weekday trading strategies**

This table reports the average value-weighted monthly return (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) or (6), 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. The columns (5) and (7) indicate the percentage of stocks excluded from the original momentum decile portfolios in columns (4) and (6) respectively. Panel A presents the average monthly returns for ten deciles and long-short portfolios for five strategies respectively. The last three rows present the long-short average return, along with the Fama-French three- and five-factor adjusted alphas. 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, exluding 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	% of stocks excluded	Mom. excl. other-weekday	% of stocks excluded
1	0.04	-0.33	0.62	0.32	31%	-0.35	66%
2	0.46	0.10	0.77				
3	0.60	0.25	0.79				
4	0.57	0.45	0.62				
5	0.58	0.59	0.57				
6	0.60	0.64	0.63				
7	0.70	0.73	0.65				
8	0.79	1.03	0.61				
9	0.92	1.26	0.59				
10	1.32	1.72	0.90	1.13	33%	1.46	68%
Long-short	1.28	2.05	0.28	0.81		1.81	
	(5.19)	(10.94)	(1.22)	(3.24)		(6.99)	
FF3	1.65	2.18	0.55	1.14		2.13	
	(7.32)	(11.93)	(2.58)	(4.99)		(8.71)	
FF5	1.53	2.18	0.49	1.04		2.06	
	(6.79)	(11.86)	(2.28)	(4.52)		(8.41)	

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 regression**

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” are 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), 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 of each stock respectively. The sample includes individual stocks listed in NYSE, Nasdaq, and Amex from 1963 to 2021, exluding penny stocks with price below $5 and small stocks below NYSE 10% breakpoints. All coefficients are multiplied by 1000. T-statistics are provided in parentheses below.

Panel A: Value weight

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Ret all	3.38			1.06	11.99		3.37			1.56	1.87	1.83
	(3.86)			(1.23)	(10.54)		(3.73)			(1.73)	(2.17)	(2.14)
Ret same-weekday		17.30		15.48		16.90		13.88		12.00	11.09	11.10
		(11.98)		(12.26)		(11.91)		(9.68)		(9.48)	(9.49)	(9.48)
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	-0.21	-0.28	-0.26
							-(1.50)	-(1.59)	-(1.69)	-(1.69)	-(2.17)	-(2.09)
B/M							-0.14	-0.13	-0.17	-0.13	-0.18	-0.19
							-(1.37)	-(1.29)	-(1.71)	-(1.38)	-(2.02)	-(2.12)
Amihud											-4.43	
											-(1.44)	
Turnover											-2.36	
											-(1.48)	
Amihud same-weekday												-3.23
												-(0.95)
Turnover same-weekday												-2.17
												-(1.35)
R2	2.14%	1.27%	1.86%	2.94%	2.84%	3.01%	4.57%	3.70%	4.30%	5.32%	6.86%	6.82%

Panel B: Equal weight

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Ret all	3.09			1.27	9.49		3.22			1.66	1.98	1.98
	(4.95)			(2.09)	(12.14)		(4.91)			(2.56)	(3.24)	(3.22)
Ret same-weekday		13.89		12.19		13.73		12.08		10.31	9.16	9.28
		(14.52)		(15.35)		(14.16)		(12.90)		(13.30)	(13.58)	(13.67)
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	-0.34	-0.43	-0.42
							-(2.38)	-(2.28)	-(2.38)	-(2.41)	-(2.96)	-(2.89)
B/M							0.12	0.11	0.11	0.11	0.04	0.03
							(2.00)	(1.89)	(2.00)	(1.93)	(0.96)	(0.67)
Amihud											-3.88	
											-(2.43)	
Turnover											-4.25	
											-(2.82)	
Amihud same-weekday												-4.08
												-(2.37)
Turnover same-weekday												-3.73
												-(2.54)
R2	0.94%	0.48%	0.80%	1.23%	1.20%	1.26%	1.84%	1.33%	1.69%	2.10%	3.32%	3.28%

Table 5: **Seasonal fund flow and seasonal institutional trading by day of the week**

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 2008. 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	1144.3	291.2	25.6%	30.1%	35.5%
by weekday (% of all seasonal)	Mon	37.8	12.9%	9.1%	38.4%
	Tue	59.6	19.6%	18.7%	35.6%
	Wed	78.9	25.3%	28.4%	34.9%
	Thu	91.2	28.5%	32.4%	32.3%
	Fri	42.7	13.7%	11.4%	37.6%

Table 6: **Persistence of 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. Columns (3) to (7) report the percentage of seasonal funds at each of five weekdays out of all seasonal funds within a given decile group, respectively. 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. Columns (3) through (7) present the percentage of seasonal funds at five weekdays respectively within each decile group. 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)	(3)	(4)	(5)	(6)	(7)
decile	sorting past 11-month concentration ratio	next-month concentration ratio	Mon	Tue	Wed	Thu	Fri
1	23.95%	21.53%	3.2%	43.2%	27.1%	14.5%	12.0%
2	26.33%	21.71%	4.3%	42.1%	25.4%	14.7%	13.5%
3	28.26%	21.81%	6.1%	39.3%	24.8%	16.0%	13.8%
4	30.23%	22.39%	8.0%	36.3%	25.2%	15.6%	14.9%
5	32.43%	22.08%	8.7%	34.2%	22.8%	18.3%	15.9%
6	35.01%	22.39%	11.5%	31.3%	23.7%	17.7%	15.8%
7	38.08%	22.69%	13.5%	26.8%	23.0%	20.5%	16.2%
8	42.12%	22.60%	14.9%	26.6%	21.5%	19.4%	17.6%
9	48.59%	23.00%	14.5%	23.4%	20.7%	23.6%	17.8%
10	64.07%	24.83%	18.5%	20.8%	22.5%	19.9%	18.2%
10-1	40.12%	3.30%					
t-stat		(6.67)					

Panel B: Persistence of seasonal fund flow direction

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
decile	sorting past 11-month daily flow	next-month daily flow	Mon	Tue	Wed	Thu	Fri
1	-0.58%	-0.27%	13.9%	22.6%	24.3%	20.9%	18.3%
2	-0.19%	-0.11%	10.4%	32.7%	22.7%	20.7%	13.5%
3	-0.11%	-0.08%	7.1%	36.5%	24.0%	19.4%	12.9%
4	-0.07%	-0.05%	5.7%	41.1%	24.3%	14.1%	14.9%
5	-0.04%	-0.03%	7.0%	38.4%	26.0%	14.7%	13.9%
6	0.00%	0.00%	10.6%	34.1%	25.7%	16.5%	13.2%
7	0.04%	0.01%	11.3%	31.9%	22.5%	18.1%	16.2%
8	0.12%	0.03%	13.0%	32.3%	22.3%	16.6%	15.9%
9	0.26%	0.09%	12.0%	29.5%	22.8%	18.4%	17.3%
10	1.50%	0.23%	11.6%	25.6%	21.5%	21.4%	19.9%
10-1	2.08%	0.51%					
t-stat		(10.84)					

Table 6: **Persistence of 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. Columns (3) to (7) report the percentage of seasonal institutions at each of five weekdays out of all seasonal institutions within a given decile group, respectively. 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. Columns (3) through (7) presents the percentage of seasonal institutions at five weekdays respectively within each decile group. Panel C and D cover all defined seasonal institutions from ANcerno from 2000 to 2008.

Panel C: Persistence of seasonal institutional trading concentration

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
decile	sorting past 11-month concentration ratio	next-month concentration ratio	Mon	Tue	Wed	Thu	Fri
1	22.98%	20.70%	20.4%	12.8%	19.6%	37.9%	9.3%
2	24.61%	21.25%	10.5%	16.7%	24.0%	38.3%	10.4%
3	25.87%	21.67%	8.6%	17.1%	27.7%	34.4%	12.2%
4	27.21%	21.86%	9.0%	18.8%	28.1%	30.6%	13.4%
5	28.86%	22.43%	10.6%	20.3%	26.7%	29.4%	13.0%
6	31.07%	22.12%	10.7%	22.7%	26.7%	27.0%	12.9%
7	34.17%	22.50%	11.9%	23.8%	24.9%	25.4%	14.1%
8	38.99%	24.94%	13.8%	23.4%	23.7%	22.8%	16.2%
9	48.00%	24.44%	16.1%	20.8%	21.4%	22.5%	19.1%
10	72.89%	34.77%	18.2%	20.8%	25.0%	17.7%	18.3%
10-1	49.91%	14.08%					
t-stat		(12.72)					

Panel D: Persistence of seasonal institutional trading direction

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
decile	sorting past 11-month trading imbalance	next-month trading imbalance	Mon	Tue	Wed	Thu	Fri
1	-0.57	-0.10	15.8%	23.7%	21.8%	22.8%	15.8%
2	-0.22	-0.03	11.4%	19.6%	24.9%	31.4%	12.6%
3	-0.12	-0.04	11.1%	16.4%	28.3%	31.9%	12.3%
4	-0.06	0.00	11.9%	17.0%	26.5%	33.7%	10.9%
5	-0.02	-0.01	12.2%	20.9%	25.5%	30.9%	10.5%
6	0.01	-0.01	13.8%	22.2%	26.4%	25.3%	12.3%
7	0.05	0.01	13.0%	20.9%	25.1%	28.2%	12.8%
8	0.11	0.02	12.2%	18.4%	23.5%	31.1%	14.8%
9	0.22	0.05	13.2%	17.4%	22.9%	29.6%	16.9%
10	0.57	0.20	15.3%	20.7%	23.0%	21.3%	19.8%
10-1	1.13	0.30					
t-stat		(10.76)					

Table 7: **Seasonal trading of 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 average institution-level 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 institution-level trading imbalance among these seasonal institutions on the stock at future same weekday in column (2). We then average the averaged institution-level trading imbalance of each stock across stocks within same tercile, and finally average across five weekdays of months. Panel B columns (3) and (4) reports the trading imbalance of seasonal institutions aggregated at stock level (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 stock-level trading imbalance across stocks within same tercile and finally average across 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, from 2000 to 2008. We require that each stock has at least 50 institutions who traded it in one weekday of 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	535	117.5	6.1	5.35%	35.1%
2	535	118.6	6.2	5.39%	36.0%
3	535	103.4	5.7	5.47%	35.0%

Panel B: Imbalance persistence for winners and losers

	(1)	(2)	(3)	(4)
Tercile by momentum	past 11-month trading imbalance (institution-level)	next-month trading imbalance (institution-level)	past 11-month trading imbalance (stock-level)	next-month trading imbalance (stock-level)
1	0.99%	-2.65%	2.14%	-3.00%
2	3.95%	0.04%	5.03%	-0.37%
3	10.74%	0.98%	10.49%	0.24%
3-1	9.74%	3.64%	8.35%	3.24%
t-stat		(4.38)		(3.78)

Table 8: **Regression: Persistence in seasonal trading at individual stock**

This table presents the regression results of the persistence of trading for seasonal institutions at stock-institution-month level. The regression model is: $TradeImb_{i,j,t} = TradeImb_{i,j,t-12,t-2} + Controls + \epsilon_{i,j,t}$, where i refers to any stocks in our baseline sample at month t, j is the defined seasonal institution at month t who also traded stock i in past 11 months and the independent variable $TradeImb_{i,j,t-12,t-2}$ is therefore the trading imbalance (the difference between buy and sell in dollars divided by the sum of buy and sell) of seasonal institution j on stock i in months $t-12$ to $t-2$. The dependent variable $TradeImb_{i,j,t}$ is the next-month trading imbalance of seasonal institution j on stock i at 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). 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 from 2000 to 2008. 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)
Indep. Var.	next-month trading imbalance	next-month trading imbalance	next-month trading imbalance
Dep. Var.			
past 11-month trading imbalance	0.0217***	0.0208***	0.0206***
	(0.00713)	(0.00711)	(0.00714)
log(ME)		0.0114**	0.00582
		(0.00545)	(0.00526)
B/M		0.000275	-0.000536
		(0.00148)	(0.00133)
past 11-month return			0.0126***
			(0.00457)
Constant	-0.0245***	-0.204**	-0.118
	(0.00203)	(0.0856)	(0.0826)
# of Obs	1,203,735	1,181,005	1,181,005
R-squared	0.177	0.177	0.177
Institution FE.	YES	YES	YES
Month FE.	YES	YES	YES
Stock FE.	YES	YES	YES
Clu. Std.	Institution	Institution	Institution

Table 9: **Regression: Past seasonal trading imbalance and future stock return**

This table presents the regression results of predicting next-month individual stock returns using past aggregate seasonal institutional trading in a regression: $R_{i,t} = TradeImb_{i,t-12,t-2} + Controls + \epsilon_{i,t}$, where the independent variable, the past 11-month seasonal trading imbalance $TradeImb_{i,t-12,t-2}$, is the sum of trading imbalance of all seasonal institutions who traded the stock i at their concentrated weekday in the past 11 months from $t - 12$ to $t - 2$ (the difference between total buy and total sell in dollars from all seasonal institutions at their concentrated weekday in past 11 months) scaled by the market value of the stock by the end of the previous month $t-1$, and the dependent variable $R_{i,t}$ is the next-month return of stock i at 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). 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 2008. We denote the 10%, 5%, and 1% significance levels with *, **, and *** respectively.

	(1)	(2)	(3)
Indep. Var.	next-month return	next-month return	next-month return
Dep. Var.			
past 11-month seasonal trading imbalance	0.00119***	0.00107**	0.00105**
	(0.000410)	(0.000421)	(0.000419)
log(ME)		-0.0410***	-0.0434***
		(0.00121)	(0.00128)
B/M		1.07e-05	-0.000150
		(0.000163)	(0.000144)
past 11-month return			0.00451***
			(0.000666)
Constant	0.00373***	0.585***	0.618***
	(2.32e-05)	(0.0171)	(0.0182)
# of Obs	238,502	231,940	231,940
R-squared	0.189	0.203	0.203
Month FE.	YES	YES	YES
Stock FE.	YES	YES	YES
Clu. Std.	Stock	Stock	Stock