Time Series Reversal: An End-of-the-Month Perspective*

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Abstract

This paper documents a new pattern in U.S. aggregate markets: S&P 500 month-end returns negatively predict one-month-ahead returns. Novel in the reversal literature, this pattern is at the aggregate level, persists throughout the following month, clusters on the most liquid U.S. indices, is cyclical, and delivers sizable gains without the need for short selling. Institutional trading data link the novel pattern to pension funds month-end liquidity trading to meet benefit payments. Results are robust across specifications, in- and out-of-sample tests, and extensive controls, pointing to a recurring impact of pension funds' trading on aggregate prices and efficiency.

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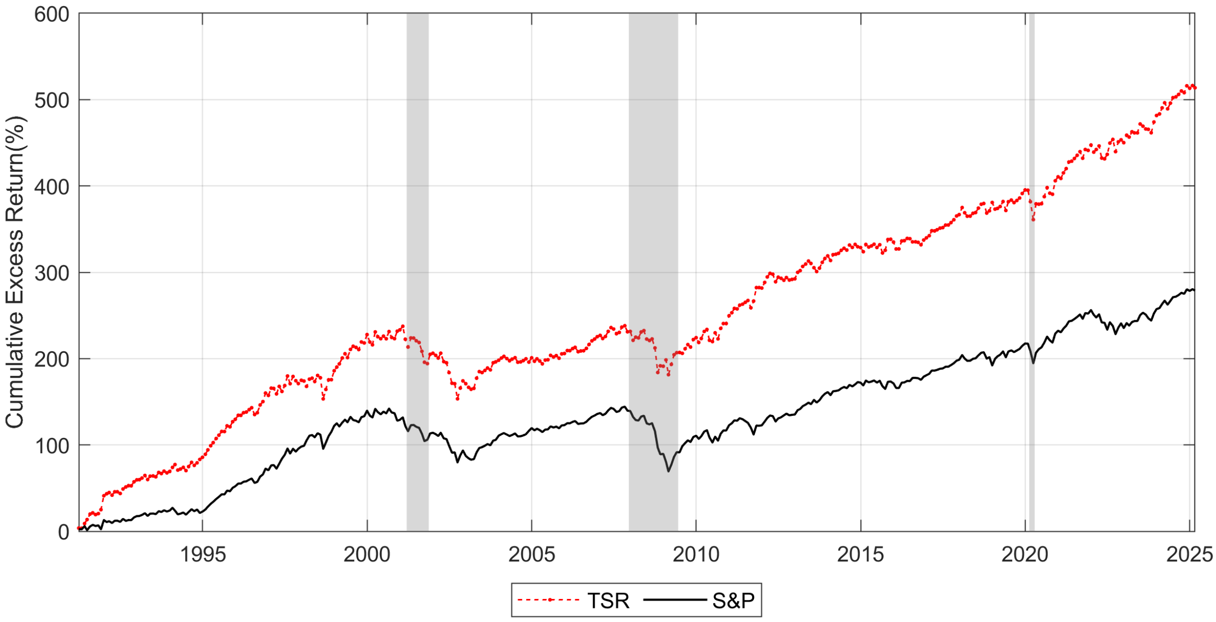
1 Introduction

One of the core questions in asset pricing is whether and how financial markets revert to shocks. At the cross-sectional level, ever since Jegadeesh (1990), the literature has extensively documented a 1-month reversal. In addition, two stylized facts have emerged. First, cross-sectional reversal concentrates on small and illiquid stocks, with its strength increasing during periods of economic downturn (Dai, Medhat, Novy-Marx, and Rizova, 2023). Second, cross-sectional strategies, even though statistically robust, are not economically meaningful due to their high transaction costs and fees (Avramov, Chordia, and Goyal, 2006).

At the aggregate market level, conversely, there is little evidence of reversal. As Hartzmark and Solomon (2022) note: "*[...] much less is known about the speed and extent one should expect entire markets to reverse price pressure.*" This paper addresses this critical gap by studying a novel aggregate reversal pattern. Specifically, I show that *end-of-the-month* returns (i.e., the returns in the last trading week) are negatively correlated with one-month-ahead returns. Figure 1 summarizes the novelty of the empirical pattern by presenting the cumulative returns of a Campbell and Thompson (2008) market-timing strategy using the new reversal predictor. In contrast to cross-sectional findings, the strategy (i) relies only on monthly out-of-sample return forecasts on the S&P 500 (ii) provides large gains over passive investing (iii) is cyclical. In contrast to time-series findings (e.g., Campbell, Lo, MacKinlay, and Whitelaw (1998) and Ariel (1987)), the novel reversal pattern does not fade after a few days but instead persists throughout the entire month ahead.

Taken together, the novel pattern reveals a predictable monthly reversal in aggregate U.S. equity market returns. This challenges standard explanations of short-term reversals, such as investor overreaction or aggregate shocks (e.g., Poterba and Summers (1988), Nagel (2012)), and instead points to a distinct institutional driver. Consistent with

Figure 1: Time Series Reversal (TSR) and S&P 500 Gains



This figure compares the cumulative out-of-sample returns of the time series reversal (TSR - red line) with passive investing on the S&P 500 (black line). The TSR out-of-sample trading strategy follows Campbell and Thompson (2008); for details see Section 2.4. The grey-shaded areas indicate periods of recession according to NBER. The out-of-sample period is from March 1991 to February 2025.

evidence that defined-benefit pension funds finance benefit outflows primarily by selling equities (Andonov, Jansen, and Rauh, 2025), I show that *end-of-month* returns are linked to pension funds' liquidity-driven selling around benefit-payment dates, which cluster at month-end. This mechanism implies that structural month-end liquidity needs in the pension sector generate predictable, cyclical variation in aggregate equity returns.

In the first part of the paper, I document a one-month aggregate market reversal in the S&P 500. First, using a standard predictive regression framework (Table 3), I show that the proposed predictor consistently exhibits a negative and statistically significant coefficient. This result holds regardless of which control variables are included (e.g., past returns, investor attention measures, previously suggested predictors, various factors and anomalies), as well as across different sample periods and sub-samples. Second, following Welch and Goyal (2008), I conduct an out-of-sample predictive exercise (Table 4) and show that the proposed predictor outperforms the historical mean - a notoriously challenging benchmark at the monthly frequency. Notably, I find that aggregate market predictability is concentrated during periods of economic expansion in both in-sample and out-of-sample analyses. This feature markedly improves the predictor's forecasting performance and is novel in both the reversal (Nagel, 2012) and forecasting literature (Huang, Jiang, Tu, and Zhou, 2014).

After establishing a statistical link between the *end-of-the-month* return and the one-month-ahead returns, I assess the implied economic value of this predictor for real-time investors. Following Campbell and Thompson (2008), I devise a dynamic trading strategy based on the out-of-sample forecast (Figure 1 and Table 5). The reversal strategy outperforms the passive benchmark in terms of returns and Sharpe ratio, even after accounting for trading costs and fees. To further support that the reversal strategy effectively times the market, rather than increasing risk exposure, its risk-adjusted α is positive, sizable, and statistically significant. In addition, I show that the reversal pattern is robust by considering futures, index or total returns on the S&P 500 (Table 6), and that it also extends to the Dow Jones index, which consists of 30 of the most highly capitalized and liquid American companies (Table 10). These results suggest that the pattern holds for large, liquid American stocks. In the Appendix, I perform several robustness checks, among which I show that the reversal pattern is robust to (i) the predictor specification, (ii) the choice of the samples and sub-samples, and (iii) transaction costs and fees.

In the second part of the paper, I investigate the economic mechanisms underlying the *end-of-the-month* return predictability. This analysis contributes to a growing body of literature that identifies month-end as a critical period in U.S. financial markets (see Ariel (1987), Etula, Rinne, Suominen, and Vaittinen (2020), Hartzmark and Solomon (2022), Harvey, Mazzoleni, and Melone (2025)). This period frequently coincides with the clustering of significant financial events, such as dividend payments, portfolio rebalancing, and institutional payment cycles, that can generate elevated trading volume and, in turn, contribute to return predictability. I present evidence linking this novel return pattern to the trading activity of defined benefit (DB) pension funds at month-end.

Pension funds disburse benefits precisely at month-end, and are among the most significant institutional investors over the time window considered (1982–2025). The American pension system is based on two approaches: defined benefit pension funds (DB - pension funds) and defined contribution plans (DC - 401k plans). Broadly speaking, in defined benefit plans, companies pay retirees a regular monthly payout. Conversely, in defined contribution plans, companies invest a certain amount in workers' retirement accounts. Although many private firms have shifted from DB to DC plans in recent decades, DB plans still hold more assets than DC plans. Moreover, DB benefit outflows currently exceed DC contribution inflows, implying a net cash outflow for the U.S. pension system (Figure 3).[1] Most importantly, due to their longer history, pre-committed benefit outflows, and increasing population longevity, DB plans face short-term liquidity pressures from chronic underfunding (Merton, 2008).[2]

Given the multi-billion dollar imbalance between DB pension fund assets and liabilities (Novy-Marx and Rauh, 2011) and the decline in U.S. Treasury yields over this period, DB funds have tilted toward riskier, illiquid assets to potentially bridge funding shortfalls (Begenau, Liang, and Siriwardane, 2024). The cash flows from these investments are highly unpredictable, and liquidation costs are significant. Consistent with evidence that DB plans meet cash needs mainly by selling equities (Andonov et al., 2025), I provide market-based evidence that DB equity selling clusters at month-end—when benefits are paid—creating non-informational aggregate market price pressure.

[1]The assets under management (AUM) of defined benefit (DB) pension plans total \$16.1 trillion, whereas defined contribution (DC) plans hold \$11.6 trillion, according to FRED data. Pension fund contribution inflows and benefit outflows are from OECD *Pension Markets in Focus* (2024).

[2]Many industry reports and articles highlight the negative cash flow problem. For example, see Goldman Sachs' report Cash Flow Matching: The Next Phase of Pension Plan Management, and Financial Times "Pension funds must take 'extreme care' with liquidity risks, says OECD" and "US pension funds worth \$1.5tn add risk through leverage" articles.

Access to actual trading data from institutional investors—particularly pension funds—is rare, since most publicly available information is limited to aggregate quarterly or annual disclosures. The only (semi-) public dataset that provides trade-level data at a daily frequency is the ANcerno dataset. This unique dataset includes detailed trade observations from hundreds of public and private institutional investors from 2000 to 2010. To provide initial evidence for the payment-cycle mechanism, Table 1 reports the daily order imbalance—measured as the ratio of signed dollar volume to total dollar volume in S&P 500 constituents, along with the cumulative order imbalance over the last week of the month. The statistics are presented for three groups: all institutional investors (ALL), pension plan sponsors only (PF - including both DB and DC plans), and money managers only (MM - hedge funds, banks, mutual funds, and insurance companies).

Institutional investors as a whole tend to sell at the start of the last week of the month and buy back on the final trading day (Etula et al., 2020). Consistent with the proposed mechanism, Table 1 provides novel evidence that pension plan sponsors drive this pattern. The cumulative order imbalance over the last week is statistically significant *only* for pension plan sponsors, suggesting that institutional selling pressure during the last week is primarily driven by pensions.[3]

In the main body of the text, I formally test the economic channel. *First*, using Commodity Futures Trading Commission (CFTC) data, I show that the reversal is significantly stronger when institutional hedgers are net sellers at month-end (Table 7). *Second*, by cumulating the returns throughout the one month ahead, I show that the reversal pattern peaks in the third week, coinciding with the inflow period when pension funds can buy back, and just before a new potential shock hits the market (Figure 2). Moreover,

[3]Because the available pension-plan identifier does not distinguish between defined benefit (DB) and defined contribution (DC) plans, the reported selling likely understates the true extent of DB-plan sales. DC plans, which have positive cash flows and invest passively around month-end, likely contribute to upward price pressure, partially offsetting DB-related selling. Therefore, the estimates presented should be interpreted as a *lower bound* on DB selling activity. As a robustness check, Appendix B.2 corroborates these findings using futures data from the Commodity Futures Trading Commission (CFTC).

Table 1: Last Week Trading Activity - ANcerno Dataset

	$t-4$	$t-3$	$t-2$	$t-1$	t	Week
ALL	-2.57%	-2.87%	-0.86%	-0.05%	1.98%	-1.14%
	[-3.28]	[-3.65]	[-1.21]	[-0.05]	[1.99]	[-2.10]
PF	-5.49%	-5.37%	-2.53%	-0.58%	0.45%	-3.52%
	[-3.30]	[-3.81]	[-1.80]	[-0.35]	[0.25]	[-2.65]
MM	-2.29%	-2.71%	-0.24%	0.54%	2.38%	-0.65%
	[-3.28]	[-3.34]	[-0.33]	[0.67]	[2.30]	[-1.42]

This table reports order imbalance statistics for all institutional investors (ALL), only pension fund sponsors (PF), and only money managers (MM) active in ANcerno. Specifically, the first five columns report the order imbalance for each day in the last trading week (where t is the last day of the month). The last column reports the total order imbalance for the final week. The daily order imbalance and last week imbalance are defined respectively:

$$\frac{\sum_{i\in I}\$buy_{i,t-d}-\$sell_{i,t-d}}{\sum_{i\in I}\$buy_{i,t-d}+\$sell_{i,t-d}} \qquad \frac{\sum_{d=0}^{4}(\sum_{i\in I}\$buy_{i,t-d}-\$sell_{i,t-d})}{\sum_{d=0}^{4}(\sum_{i\in I}\$buy_{i,t-d}+\$sell_{i,t-d})}$$

where $i \in I$ are the constituents S&P 500 stocks, and the signed position is obtained by multiplying quantity by execution price and sign, all reported by the ANcerno dataset. In brackets are t-statistics testing against a zero order-imbalance null. The sample period goes from January 2000 to December 2010.

I find that end-of-month returns negatively predict hedger institutional order imbalance in the latter half of the month ahead, consistent with the timing of the observed reversal pattern (Table 8). *Third*, I consider whether pension funds turn to other liquidity sources at month-end. The evidence shows the pattern is most pronounced when liquidity is tight – it clusters in months with lower cash reserves and higher month-end borrowing costs (Table 9). Intuitively, the reversal pattern is stronger when pension funds have lower liquidity reserves or a more expensive outside borrowing option. *Fourth*, I examine how the pattern's novel properties align with pension funds' liquidity-driven trading. The cyclical nature of the pattern is consistent with evidence that pension funds reduce precautionary cash reserves during stable periods and that, during recessions, regulatory measures are enacted to ease pension fund liquidity constraints to prevent market panic (e.g., the 2008 Worker, Retiree, and Employer Recovery Act). Additionally, the fact that the reversal pattern is concentrated in American indexes with high-quality stocks is consistent with the preference of institutional investors for minimizing transaction costs and fees while selling for liquidity reasons. It is also consistent with the unique characteristics of U.S. pension funds in terms of assets under management and liquidity imbalance. *Fifth*, I consider competing explanation channels (compensation for standard liquidity factors, behavioral bias, option expiration trading, quarterly activity, information release, and re-balancing) in Appendix B.5, and find no consistent evidence for any of them.

Literature review. I establish a reversal pattern on the aggregate market by departing from the two approaches typically adopted in the literature. The first approach is based on variance ratio tests (Lo and MacKinlay 1988) and it does not reject the null hypothesis of the random walk model at the monthly aggregate level. As a result, the literature has focused on a second approach based on a cross-sectional sorting strategy (see, among others, Fama and MacBeth 1973, De Bondt and Thaler 1985, Medhat and Schmeling 2022 and Dai et al. 2023). The cross-sectional approach suffers two major drawbacks. First, it captures both return auto- and cross-correlation as well as cross-sectional variation in average return. Therefore, the results are possibly driven by cross-sectional differences among stocks rather than reversal properties.[4]

Second, these findings are more pronounced for small and illiquid stocks, raising concerns about whether the predictability is practically meaningful. The gains are generally small and become negligible when costs and fees, which are particularly high for these strategies, are taken into account (Avramov et al., 2006). Finally, the literature offers two opposite explanations of the reversal pattern. The first considers reversal as a consequence of overreaction, market fads, or cognitive biases (Poterba and Summers, 1988).

[4] Lo and MacKinlay (1990) show that positive cross-correlation among portfolio's constituents—rather than negative autocorrelation in each stock—could explain the results. Conrad and Kaul (1993) show that cumulating short-term returns over long periods can generate an upward bias. Zarowin (1990) shows that if loser firms are lower priced than winner firms, returns to the contrarian strategy will have a spurious upward drift.

The second explanation is market-based since it suggests that reversals arise from price pressure due to shifts in the demand and/or supply curve (Nagel, 2012).

My contribution to the reversal literature is threefold. First, I provide novel evidence of a monthly reversal pattern at the aggregate market level. Second, in contrast to prior cross-sectional findings (e.g., Avramov et al. 2006, Nagel 2012, and Dai et al. 2023), the one-month aggregate market reversal concentrates in high-quality, high-liquid stocks (S&P 500) and spikes during economic expansions. Third, this paper corroborates a market-based explanation of the reversal pattern. Consistent with Grossman and Miller (1988), the payment cycle likely represents a non-informational shock that causes price impact, triggering a return reversal dynamic. Importantly, I consider a liquidity shock that affects only a segment of the market, that is, the pension funds, as opposed to focusing on market-wide liquidity shocks (Nagel 2012).

My work also relates to the forecasting literature which has focused on establishing out-of-sample aggregate monthly predictability by considering past returns that capture the trend, i.e., momentum, of the market (see, among others, Moskowitz, Ooi, and Pedersen 2012 and Neely, Rapach, Tu, and Zhou 2014). However, momentum-based predictors have two major limitations. First, their out-of-sample predictability concentrates on recession periods (e.g., Rapach, Strauss, and Zhou (2010), Dangl and Halling (2012), Huang et al. (2014), Sabbatucci (2024)), which (i) introduces potential sample bias (Goyal, Welch, and Zafirov, 2021), and (ii) leaves net-of-fee returns near zero. Second, momentum predictors are persistent variables, implying a weak forecasting power at the monthly frequency (Ren, Tu, and Yi 2019). My contribution to the forecasting literature is twofold. First, I introduce a novel predictor that avoids both limitations. Second, the statistical out-of-sample predictability translates to significant economic gains via simple trading strategies that rely only on the S&P 500.

Finally, this study connects to the broader literature on pension funds, market flows, and their impact on aggregate prices (see, among others, Franzoni and Marin (2006), Andonov, Bauer, and Cremers (2017), Ben-David, Franzoni, and Moussawi (2018), Etula et al. (2020), Sabbatucci, Tamoni, and Xiao (2023), and Hartzmark and Solomon (2022)). Consistent with Etula et al. (2020), I argue that the payment cycle represents a moment of market liquidity distress. In contrast to prior work, I provide evidence that (i) end of month liquidity trading is sufficiently pervasive to generate a monthly aggregate market reversal (ii) pension funds are likely the main driver of this effect. As in Hartzmark and Solomon (2022), I use price pressure to establish aggregate market predictability. Importantly, this study sheds light on two key questions posed by Hartzmark and Solomon (2022): (i) whether and how aggregate markets revert price pressure, and (ii) what economic forces underlie market flows. This paper relates to and complements Andonov et al. (2025). Using proprietary quarterly holdings, Andonov et al. (2025) document that pension funds' cash management is decoupled from asset allocation and that they meet outflows primarily by selling equities. In turn, I provide evidence on the potential consequences and severity of pension fund underfunding by linking the novel return reversal pattern to pension funds month-end liquidity trading, thereby capturing an initial market-based measure of its price impact. Finally, in independent work, Harvey et al. (2025) study the potential impact of portfolio rebalancing on financial markets. They propose two signals, including an end-of-month calendar measure. My results hold after controlling for their signal, implying fundamentally different sources of return predictability (see Appendix B.5.5).

The rest of this paper is organized as follows: Section 2 provides statistical evidence of the novel pattern; Section 3 explores the transmission channel. Section 4 explores the broader implications of the results, and Section 5 concludes.

2 Establishing the pattern

2.1 Data

To study aggregate market reversal, for the baseline results, I use S&P 500 index futures—one of the most actively traded financial instruments—to test predictability in a realistic market setting.[5] Specifically, I use S&P 500 daily futures prices available in Global Financial Data (GFD) from September 1982 to February 2025. This dataset focuses on the most liquid, near-expiration futures contracts, which minimizes illiquidity and stale-pricing distortions. Upon expiration, the series rolls to the next-nearest contract, yielding a continuous futures price series that begins in September 1982.

Throughout the paper, I denote nominal values using capital letters and their corresponding natural logarithms using lowercase letters. Since the analysis spans daily, weekly, and monthly time series, I adopt a composite time index: t denotes a generic month, with w (week) and d (day) added as needed to specify the frequency.

The novel predictor is the *end-of-the-month* return, defined as the realized return over the final trading week of each month: $r_{\mathrm{EoM},t} = p_t - p_{d=t-4,t}$, where $p_{d=t-4,t}$ denotes the fourth-to-last (log) closing price of the month, and p_t is the final (log) closing price in month t. The predicted variable is the standard monthly return, computed as the difference between the last log futures closing prices of two consecutive months: $r_t = p_t - p_{t-1}$.

Table 2 reports summary statistics—including the mean, standard deviation, minimum, maximum, and number of observations—for both variables. These statistics, consistent with findings in Welch and Goyal (2008) and Neely et al. (2014), show that returns measured over longer time windows tend to exhibit higher average returns and volatility.

[5] Section 2.5 shows that results hold by considering index or total returns.

Table 2: Summary Statistics

	Mean(%)	Std. Dev.(%)	Min(%)	Max(%)	Obs.
r_{t+1}	0.767	4.425	-22.826	12.412	510
$r_{EoM,t}$	0.225	2.286	-13.830	16.342	510

This table reports the mean, standard deviation, minimum, maximum, and number of observations for the month return (r_{t+1}), and the *end-of-the-month* return ($r_{EoM,t}$). The sample period is from September 1982 to February 2025.

2.2 In-Sample Evidence

As standard in the literature, I formally assess the predictability channel between $r_{EoM,t}$ and r_{t+1} via a benchmark predictive regression:

$$r_{t+1} = \alpha + \gamma\ r_{EoM,t} + \beta\ C_t + \epsilon_{t+1} \tag{1}$$

where γ captures the predictability associated with $r_{EoM,t}$, after controlling for previously proposed variables C_t.

Table 3 presents regression results under various specifications of equation (1). In the first column, I report the results without any control variables. In the second column, I control for previous weekly returns ($r_{w=3,t} = p_{d=t-5,t} - p_{d=t-9,t}$, $r_{w=2,t} = p_{d=t-10,t} - p_{d=t-14,t}$, $r_{w=1,t} = p_{d=t-15,t} - p_{d=t-19,t}$, respectively). While empirical support for time series reversal remains limited, the literature has extensively investigated time-series momentum (Moskowitz et al., 2012). Therefore, in the third column, I control for the previous month return and time series momentum ($r_{t-12} = p_t - p_{t-12}$). In the fourth column, I control for the recent predictors in Chen, Tang, Yao, and Zhou (2022). The authors propose three different predictors that aggregate 12 popular individual attention indexes (with partial least square A^{PLS}, principal component A^{PCA}, and scaled principal component approach A^{sPCA}, respectively), establishing a negative predictive channel.[6] In the fifth column, I control for the 3 Fama French factors augmented with

[6] Chen et al. (2022)'s attention measures predict returns negatively via a reversal mechanism: high

Table 3: In-Sample Evidence

α	0.009	α	0.008	α	0.008	α	0.010	α	0.009	α	0.009
	[4.26]		[3.86]		[3.88]		[4.52]		[4.16]		[4.05]
$r_{EoM,t}$	-0.361	$r_{EoM,t}$	-0.374	$r_{EoM,t}$	-0.359	$r_{EoM,t}$	-0.410	$r_{EoM,t}$	-0.375	$r_{EoM,t}$	-0.413
	[-3.81]		[-4.34]		[-3.71]		[-4.47]		[-3.97]		[-5.18]
		$r_{w=3,t}$	-0.135	r_{t-12}	-0.038	IA_t^{PLS}	-0.023	MkT	0.000	$PC1$	0.001
			[-1.31]		[-0.77]		[-2.19]		[0.51]		[2.42]
		$r_{w=2,t}$	0.000	r_{t-1}	0.023	IA_t^{sPCS}	-0.300	SMB	0.000		
			[0.00]		[0.44]		[-0.71]		[0.51]		
		$r_{w=1,t}$	0.016			IA_t^{PCA}	0.001	HML	-0.001		
			[0.14]				[0.52]		[-1.78]		
								MoM	0.000		
									[-0.59]		
								ST_{REV}	-0.001		
									[-0.90]		
N	509		509		496		424		508		424
$Adj.R^2$	0.03		0.03		0.03		0.06		0.03		0.06

This table reports the estimation results for the following predictive regression:

$$r_{t+1} = \alpha + \gamma \; r_{EoM,t} + \beta_i C_{i,t} + \varepsilon_{t+1}$$

where the control variables $C_{i,t}$ considered are previous weekly returns in the second column (from September 1982 to February 2025), monthly and year returns in the third column (from October 1983 to February 2025), Chen et al. (2022)'s investor attention proxies in the fourth column (from September 1982 to December 2017), the three Fama French augmented by Momentum and Short Reversal factors in the fifth column (from September 1982 to December 2024), the first Principal Components (PC) computed from the 100 anomalies portfolio returns in Dong et al. (2022) in the $6th$ column (from September 1982 to December 2017). The predictor variables are downloaded directly from the authors' websites to avoid introducing measurement error. In brackets, I report robust Newey and West (1987) t-statistics.

the cross-sectional momentum and short-term reversal factors. In the sixth column, I control for the first Principal Components (PC) obtained from the 100 anomalies in Dong, Li, Rapach, and Zhou (2022).

The results in Table 3 offer novel insights relative to the extensive literature on return predictability (Goyal et al., 2021). Traditional predictors—such as past monthly or annual returns (columns 2 and 3) and standard risk factors (column 4)—exhibit only limited predictive ability at the monthly frequency. This shortcoming has led researchers to explore more sophisticated predictors, including proxies for market inattention (column

investor attention leads to buying and a temporary price increase, which then reverses once that buying pressure subsides. To avoid measurement error, I download the variables from the authors' website and study the statistical relationship from September 1982 to December 2017.

5) or composite anomaly-based signals (column 6). In contrast, the *end-of-the-month* predictor stands out for its simplicity and robust predictive power, which persists across all specifications. Across all regressions, the coefficient on the proposed predictor is consistently negative, of similar magnitude, and statistically significant. These results confirm a predictive link between $r_{EoM,t}$ and r_{t+1} and suggest that this aggregate reversal reflects a previously undocumented source of return predictability.

Robustness. Appendix A.1 is devoted to the sensitivity analysis. Specifically, Appendix A.1.1 shows that results are robust to proxies of liquidity, volatility, and financial conditions around the end of the month. Appendix A.1.2 shows that the reversal pattern clusters in the last trading week. Appendix A.1.3 shows that the reversal pattern's predictability is robust by excluding the first week's return of the subsequent month. Appendix A.1.4 shows that the results do not depend on a closing price effect. Appendix A.1.5 shows that the reversal pattern disappears in a placebo test centered on the second week of the month. Appendix A.1.6 shows that the reversal's predictive power vanishes after the first month ahead. Finally, A.1.7 shows that the results remain qualitatively unchanged after the introduction of the E-Mini S&P 500 futures.

2.3 Out-of-Sample Evidence

The previous analysis of the reversal pattern is based on the entire in-sample estimation. In this section, I evaluate the out-of-sample (OOS) forecasting power of the *end-of-the-month* return. In line with Goyal et al. (2021), I run predictive regressions recursively

$$r_{t+1|t} = \alpha_t + \gamma_t \, r_{EoM,t} + \epsilon_{t+1} \tag{2}$$

That is, at time t, I use data up to time $t-1$ to obtain OLS estimates of $\hat{\alpha}_t$ and $\hat{\gamma}_t$. The OOS forecast is then generated according to $\hat{r}_{t+1|t} = \hat{\alpha}_t + \hat{\gamma}_t \, r_{EoM,t}$. Hence, the forecast uses information available up to time t to avoid look-ahead bias and to simulate the perspective of a real-time forecaster. The OOS forecast evaluation period goes from March 1991 to February 2025 (80% of the entire sample for a total of 408 OOS point forecasts). Following Moskowitz et al. (2012) among others, I measure the OOS predictability by considering:

$$R^{2,OS} = 1 - \frac{\sum_{t=w}^{T}(r_{t+1} - \hat{r}_{t+1|t})^2}{\sum_{t=w}^{T}(r_{t+1} - \bar{r}_{t+1|t})^2}$$

where $\hat{r}_{t+1|t}$ is the forecasted month $t+1$ return estimated from the proposed predictor, and the benchmark forecast $\bar{r}_{t+1|t}$ is the historical average forecast estimated from the sample mean through period t. When $R^{2,OS} > 0$, the predictive regression forecast outperforms the simple historical average in terms of mean squared forecast error (MSFE) loss. The prevailing historical average forecast – a predictive regression model with $\gamma = 0$ – is a difficult benchmark to outperform at the monthly level (Welch and Goyal, 2008). To assess the OOS forecast performance, I use Clark and West (2007) MSFE-adjusted statistic.[7]

The first column in Table 4 reports $R^{2,OS}$ over the entire out of sample evaluation period. The end-of-month return $r_{EoM,t}$ generates positive, sizable, and statistically significant OOS gains, with an $R^{2,OS}$ of 0.35%. Conversely, the historical mean outperforms the momentum predictor. This finding is consistent with the results in Huang, Li, Wang, and Zhou (2020), which show that past 12-month returns do not have OOS predictability without standardizing for the monthly returns' variance. Since the literature agrees that predictability varies over business cycles, the second and third columns in Table 4 report $R^{2,OS}$ separately for expansion ($R^{2,OS}_{exp}$) and recession periods ($R^{2,OS}_{rec}$). I use the National Bureau of Economic Research (NBER) dates of peaks and troughs to identify recessions

[7] The null hypothesis is that the benchmark historical average forecast delivers lower MSFE than the predictive regression forecast; the alternative hypothesis is that the latter delivers gains compared to the benchmark, corresponding to $H_0 : R^{2,OS} < 0$ against $H_1 : R^{2,OS} > 0$.

Table 4: Out-of-Sample Evidence

	$R^{2,OS}(\%)$	$R^{2,OS}_{exp}(\%)$	$R^{2,OS}_{rec}(\%)$
$r_{EoM,t}$	0.35^{**}	1.92	-4.98
r_{t-12}	-0.13	-0.26	0.32

This table reports the out-of-sample forecasting results compared to the historical mean for the time series reversal ($r_{EoM,t}$) and 12-month return (r_{t-12}). The first column reports the OOS $R^{2,OS}$. The second and third columns report the OOS R^2 for expansions $R^{2,OS}_{exp}$ and recessions $R^{2,OS}_{rec}$, respectively. Statistical significance for $R^{2,OS}$ is assessed using the Clark and West (2007) test. $***$, $**$, and $*$ indicate significance at the 1%, 5%, and 10% levels, respectively. The sample period is from September 1982 to February 2025, and the out-of-sample valuation period starts from March 1991.

and expansions ex-post, i.e., this information is not used in the estimation:

$$R^{2,OS}_{e} = 1 - \frac{\sum_{t=w}^{T} I_t^c (r_{t+1} - \hat{r}_{t+1|t})^2}{\sum_{t=w}^{T} I_t^c (r_{t+1} - \bar{r}_{t+1|t})^2}$$

where I_t^{exp} (I_t^{rec}) is the NBER indicator function that takes a value of 1 when month t is in expansion (recession) and 0 otherwise.

The momentum performance across the business cycle is consistent with the literature. There is significantly stronger evidence of predictability during recessions than during expansions: the $R^{2,OS}$ is positive during recessions but negative in expansions. This feature has been empirically discussed in Huang et al. (2014) and theoretically supported by Cujean and Hasler (2017).[8] Interestingly enough, the end-of-month return $r_{EoM,t}$ behaves very differently. The predictability concentrates during expansion periods, $R^{2,exp}_{OS} = 1.92\%$, but gets lost during recessions, with a large negative $R^{2,exp}_{OS}$ of -4.98%.

Overall, the results in Table 4 strongly corroborate the predictability pattern between $r_{EoM,t}$ and r_{t+1}. From an economic standpoint, the proposed predictor benefits from its cyclical predictability, a feature that is particularly valuable for improving forecasting

[8] In Cujean and Hasler (2017), investors use different forecasting models. As economic conditions worsen, uncertainty rises, and investors' opinions polarize. Disagreement among investors thus spikes in bad times, causing returns to react to past news. This phenomenon creates time-series momentum, which strengthens in bad times. In good times, returns exhibit strong one-month reversal and insignificant momentum thereafter. The reason is that, in their model, news generates little disagreement in good times and returns immediately revert.

accuracy and robustness. Notably, the U.S. economy was in expansion for $\sim 93\%$ of the months from 1991 to 2025. Thus, having a predictor that performs well during expansions offers a significant advantage over relying on the historical mean or other predictors. From a statistical standpoint, the results can be explained by the fact that equation (2) is a balanced predictive regression: $r_{EoM,t}$ matches the persistency of r_{t+1}, substantially improving its forecasting precision (Ren et al., 2019).[9]

Robustness. Appendix A.2 is devoted to the sensitivity analysis. Specifically, Appendix A.2.1 shows the cumulative forecast error over time. Appendix A.2.2 provides in-sample evidence that corroborates the cyclical nature of the aggregate reversal pattern. Finally, Appendix A.2.3 presents an out-of-sample analysis after the introduction of the E-Mini S&P 500 futures.

2.4 Economic Value

The previous sections examined the aggregate market predictability of $r_{EoM,t}$ in statistical terms. Here, I examine the economic value of such predictability. Following the optimal asset allocation approach of Campbell and Thompson (2008), I construct the following trading strategy:[10]

$$TSR_t := \underbrace{\frac{r^{TSR}_{t+1|t}}{\sigma^2_{t+1|t}}}_{w^{TSR}_t} r_{t+1} \tag{3}$$

[9]Using Ren et al. (2019)'s notation:

$$y_t = \mu_y + \beta x_{t-1} + u_t, \quad x_t = \mu_x + \nu_t, \quad \nu_t = \alpha \nu_{t-1} + \epsilon_t$$

where y_t is stock returns and x_t is the main predictor. An unbalanced predictor ($|\alpha|$ close to 1) implies high persistence in y_t. However, excess stock market returns show low autocorrelation, worsening the predictability.

[10]The exercise here proposed directly follows from the dynamic asset allocation of Campbell and Thompson (2008) by setting the risk aversion parameter equal to 1.

Intuitively, the strategy's position w_t^{TSR} determines both the direction and scale of the risky asset investment. The parameter is the ratio between the 1-month ahead OOS forecast ($r_{t+1|t}^{TSR}$) over the return variance in the last quarter $\sigma_{t+1|t}^2 = \sigma^2(\{r_i\}_{i=t}^{t-2})$. Standard in the literature (Neely et al., 2014), I constrain w_t^{TSR} between -1 and 1.5. Hence, the strategy can short-sell at most one unit but can buy on leverage. This constraint is fairly conservative, given that the S&P 500 has many leveraged instruments available (e.g., 5× ETFs, futures and options with double-digit leverage). I compare the reversal strategy against a passive strategy on the S&P 500 futures. Since the index exhibits a generally rising trend over multi-year periods, beating the passive benchmark is a particularly high bar.

Panel A in Table 5 reports annualized average return (%), standard deviation, Sharpe ratio, kurtosis, and skewness for the strategy based on the *end of month* returns (TSR) and the passive investing strategy ($S\&P$). Consistent with Figure 1, the TSR strategy achieves a higher realized return than the passive benchmark. Meanwhile, the TSR and passive strategies exhibit similar standard deviation, skewness, and kurtosis. Thanks to its higher returns (with comparable volatility), the TSR strategy provides a higher Sharpe ratio than passive investing.

Compensation for Risk. One potential concern is that the TSR strategy's high returns might be mechanically driven by leverage or short-selling. To address this concern, Panel B of Table 5 presents annualized percentage risk-adjusted alphas from the following regression:

$$TSR_t = \alpha + \beta\ CS_t + \epsilon_t$$

where CS_t denotes a set of benchmark control strategies. The intercept α in each regression measures the TSR strategy's excess return (alpha) after accounting for its exposure to the control strategies.

Table 5: Time Series Reversal - Economic Value

Panel A: Summary Statistics - Strategies

	Mean Ret.(%)	Std. Dev.	S. Ratio	Skew.	Kurt.
TSR	15.11***	0.21	0.73	−0.23	0.46
S&P	8.20	0.15	0.55	−0.21	0.38

Panel B: Adjusted Alphas TSR Strategy

	S&P	MKT	*FF3*	MR	BAB	ICR
$\alpha(\%)$	5.64**	5.21**	5.16**	5.61**	5.47**	6.72***
$Adj.R^2$	0.69	0.65	0.66	0.65	0.68	0.69

Panel C: TSR Decomposition

	Mean Ret.(%)	S&P	MKT	*FF3*	MR	BAB	ICR
TSR^L	13.88***	3.52**	3.00*	2.87*	3.26*	3.43**	4.31***
TSR^S	1.22***	2.12**	2.22**	2.29**	2.35**	2.04*	2.40**

Panel A reports annualized returns, Standard Deviation, Sharpe Ratio, Skewness, Kurtosis for the time series reversal (TSR) and passive investing ($S\&P$) strategies. **Panel B** reports adjusted alphas controlling for market index ($S\&P$) in column 1, Market factor (MKT) in column 2, Fama-French three-factor model ($FF3$) in column 3. Column 4 (MR) controls for the market, momentum, and short-term reversal factors. Column 5 adds the Betting Against Beta (BAB) factor of Frazzini and Pedersen (2014) to the passive benchmark. Column 6 augments the passive benchmark with the intermediary capital risk (ICR) factor and returns from He, Kelly, and Manela (2017). **Panel C** reports the annualized returns and risk-adjusted alphas for the TSR strategy's long and short sub-strategies, under each set of control factors from Panel B. $***$, $**$, and $*$ indicate significance at the 1%, 5%, and 10% levels, respectively. The statistical significance is based on Newey and West (1987) standard errors. The sample period is from September 1982 to February 2025, and the out-of-sample period starts from March 1991.

In *Column* 1, the control strategy is the passive S&P 500 future position ($S\&P$) benchmark. *Column* 2 uses the Market factor (MKT) as the control. *Column* 3 uses the full Fama-French three-factor model ($FF3$) as controls. *Column* 4 expands the controls to include the market, momentum, and short-term reversal factors together. *Column* 5 adds the Betting Against Beta (BAB) factor (Frazzini and Pedersen, 2014) to the passive benchmark. *Column* 6 augments the passive benchmark with the intermediary capital risk (ICR) factor and returns from He et al. (2017).[11] Even though roughly 70% of the

[11] The BAB factor captures the excess returns of a leveraged portfolio that is long on low-beta stocks and short on high-beta stocks. The factor reflects pricing distortions due to leverage constraints among investors, and it tends to vary over time with shifts in funding conditions and risk appetite. The ICR factor reflects the risk-bearing capacity of financial intermediaries. It proxies the capital of broker-dealers and banks, and it tends to fluctuate with the health of the financial sector.

TSR strategy's total return variation can be explained by these control strategies, the TSR still delivers a statistically significant and economically meaningful alpha (about 5.16% to 6.72% per year across specifications). Crucially, these returns persist even after adjusting for traditional risk exposures.

It is worth noting that most of the control strategies—aside from the passive index and the market factor—are theoretical "on-paper" constructs that are hard to implement in practice. In particular, the short legs of many long–short factor strategies are often infeasible due to high shorting fees, illiquidity, and limited stock borrow. Johansson, Sabbatucci, and Tamoni (2025) document that such frictions can lead to an implementation shortfall of 2–4% per year, with nearly 60% of this gap attributed to trading and shorting costs alone.[12]

Therefore, the TSR strategy's positive alpha is even more notable. It suggests not only that the short-term reversal strategy is exploitable, but also that TSR provides a more practical route to market-timing profits than many classic factor strategies. Crucially, the TSR strategy is implemented using the S&P 500 futures market, one of the most liquid financial instruments in the world. The deep liquidity and low transaction costs of S&P 500 futures make both long and short positions straightforward to execute, in stark contrast to long–short equity factor portfolios where the short leg is often difficult or costly to implement.

Decomposition of TSR strategy. To determine whether the TSR strategy's strong performance comes mainly from its short-selling side, I decompose the strategy into its long (TSR^L) and short (TSR^S) legs. Panel C of Table 5 reports the annualized excess returns for each sub-strategy, along with their risk-adjusted alphas relative to the control strategies. The results show that roughly 92% of the TSR strategy's total gains come

[12]The implementation shortfall stems from both transaction costs and structural challenges in replicating theoretical factor portfolios in live markets. Shorting individual stocks—especially those with low liquidity or high borrowing fees—can be prohibitively expensive.

from the long leg. Both TSR^L and TSR^S exhibit statistically significant alphas across a broad set of controls, confirming that their returns are not simply compensation for standard risk exposures. The short leg, TSR^S, tends to perform well during market downturns, effectively acting as a natural hedge against systematic risk—especially when controlling for market, momentum, and short-term reversal factors. Meanwhile, the long leg, TSR^L, captures the predictive power of end-of-month price reversals, buying into the market when expected returns are most favorable. Crucially, the persistence of high adjusted alphas for TSR^L even after controlling for the Betting Against Beta (BAB) and Intermediary Capital Risk (ICR) factors suggests that the strategy is not merely loading on known funding or intermediary risk premia. Instead, the TSR strategy appears to capture a distinct source of liquidity-related stress, tied to short-term dislocations around month-end.

Robustness. In Appendix A.3, I provide evidence supporting the robustness of the results in Table 5. Specifically, Appendix A.3.1 assesses the impact of trading costs and fees on strategy performance. Appendix A.3.2 presents a simpler trading strategy. Appendix A.3.3 extends the analysis to total returns, allowing for a longer sample period. Appendix A.3.4 confirms that the findings remain valid even after the introduction of E-Mini S&P 500 futures. Finally, Appendix A.3.5 shows that within the final week of the month, predictability and economic value are strongest around the fourth trading day before month-end.

2.5 Which S&P 500?

This section shows that the reversal pattern does not depend on the specific instrument of the S&P 500 examined. I consider three distinct series: futures (traded on the CME), synthetic index (the standard price index reported on websites and newspapers), and total return index (which includes both price changes and dividend payments, compounded continuously). For both index and futures data, the predictor is defined as $r^j_{EoM,t} = p^j_t - p^j_{d=t-4,t}$ where j refers to either the index or futures series. For total returns, the predictor is the sum of daily CRSP value-weighted log returns over the last five trading days of the month ($r^{vw}_{EoM,t} = \sum_{i=0}^{4} r^{vw}_{d=t-i,t}$). Monthly returns for the futures and index series are computed as the log differences of consecutive month-end prices ($p^j_t - p^j_{t-1}$), while monthly total returns are downloaded from Compustat.

Table 6 reports the results for each possible combination of the standard predictive regression

$$r^i_{t+1} = \alpha_j + \gamma_j \, r^j_{EoM,t} + \epsilon^i_{t+1}$$

where each row label defines the main predictor and each column label defines the predicted variable. Overall, the reversal pattern does not depend on the specific S&P 500 instrument used. Both futures and price index end-of-month returns exhibit cross-sectional negative return predictability. In contrast, the total return series yields no significant predictive power. This result is consistent with prior findings that dividend payments — typically concentrated at month end — generate predictable upward price pressure due to reinvestment activity (Hartzmark and Solomon, 2022). A second possible explanation is that total returns may be weaker predictors due to measurement errors in dividend data (Sabbatucci, 2024) and specific assumptions about reinvestment behavior (Schwarz, Walter, and Weiss, 2025).

Since total return indices include dividend payouts and assume immediate reinvesting, the associated mechanical reinvestment inflows counteract price reversals measured in price-only indices. Taken together, the results suggest that the novel predictability pattern in the S&P 500 is driven by trading activity that impacts prices directly, rather than by dividend reinvestment flows. The next section examines this novel mechanism in detail.

Table 6: Reversal Evidence on S&P 500 Futures, Index, and Total Returns

	Futures	Index	Total
Futures	-0.361	-0.316	-0.310
	[-3.80]	[-2.85]	[-3.46]
Index	-0.320	-0.286	-0.279
	[-2.68]	[-2.49]	[-2.45]
Total	-0.210	-0.190	-0.185
	[-1.56]	[-1.46]	[-1.43]

This table reports the estimated γ coefficient for the following regressions:

$$r^i_{t+1} = \alpha_j + \gamma_j \ r^j_{EoM,t} + \ \epsilon^i_{t+1}$$

for each possible combination of futures, index, and total returns. Each row corresponds to a distinct predictor, and each column to a distinct predicted return series. In brackets, I report robust Newey and West (1987) t-statistics. The sample period goes from September 1982 to December 2024. Data for futures and index series is from GFD, while for total value-weighted returns from Compustat.

3 Rationalizing the pattern

3.1 Reversal and End-of-Month Selling Pressure

In this section, I examine whether end-of-month (EoM) return reversal relates to institutional trading flows. I proxy these flows using the Commodity Futures Trading Commission (CFTC) Commitments of Traders (CoT) "Futures" reports, which are publicly available on the CFTC website. The CoT reports aggregate long and short positions separately for *commercial* and *non-commercial* traders. Following prior studies (e.g., Moskowitz et al., 2012), commercial traders are institutional hedgers and non-commercial traders speculators.[13]

The CFTC likely classifies pension funds as commercial traders in S&P 500 futures positions. Indeed, pension sponsors typically use index futures to manage market exposure and cash rather than to speculate. Moreover, many pension sponsors operate under

[13] The CFTC defines "bona fide hedging transactions and positions shall mean transactions or positions in a contract for future delivery on any contract market, or in a commodity option, where such transactions or positions normally represent a substitute for transactions to be made or positions to be taken at a later time in a physical marketing channel, and where they are economically appropriate to the reduction of risks in the conduct and management of a commercial enterprise".

legal or internal policies that restrict speculative derivatives use. To avoid cash drag, pension sponsors "equitize" operating cash (e.g., T-bills) by taking long index-futures positions while posting a portion of cash or Treasuries as collateral, thereby preserving liquidity for benefit payments. They also use short index-futures positions to lock in prices ahead of scheduled equity sales undertaken to fund those payments.[14]

The CFTC sample spans October 1992–December 2024 at a weekly frequency; positions are reported on a Tuesday-to-Tuesday basis. I include all S&P 500 futures, adjusting for different contract notional. Following Kang, Rouwenhorst, and Tang (2020), I define weekly net trading for each class of institutional investor i as

$$Q_t^i \equiv \frac{\Delta\left(\text{Long}_t^i - \text{Short}_t^i\right)}{\text{OI}_{t-1}},$$

i.e., the change in net long positions from week $t-1$ to t, scaled by open interest (the total number of contracts outstanding) in $t-1$. To test whether EoM reversal correlate with institutional flows, I estimate a predictive regression that splits the sample by the sign of institutional net flow:

$$r_{t+1} = \begin{cases} \alpha_-^i + \gamma_-^i \, r_{\text{EoM},t} + \epsilon_{-,t+1}^i, & \text{if } Q_{EoM,t}^i \leq 0, \\ \alpha_+^i + \gamma_+^i \, r_{\text{EoM},t} + \epsilon_{+,t+1}^i, & \text{if } Q_{EoM,t}^i > 0. \end{cases} \tag{4}$$

where $Q_{EoM,t}^i$ denotes the end of month net trading for either hedgers or speculators investors. Because CoT positions are weekly (Tuesday-to-Tuesday), I define the end-of-month net flow window as follows: if the last calendar day of month t falls on a

[14]Several plan documents explicitly describe cash-equitization/overlay programs implemented with index futures. Examples include: Employees' Retirement System of Milwaukee County (MCERS) Investment Policy authorizes a cash overlay to provide synthetic exposure and mandates monthly rebalancing; Pennsylvania Public School Employees' Retirement System (PSERS) board materials recommending a 'Directed Beta Overlay Program' with futures; and San Francisco Employees' Retirement System (SFERS) Parametric guidelines describing 'cash securitization' using index futures.

Table 7: Reversal and End-of-Month Net Trading

		Hedgers		Speculators	
		$Q_{EoM,t} \leq 0$	$Q_{EoM,t} > 0$	$Q_{EoM,t} \leq 0$	$Q_{EoM,t} > 0$
α	0.007	0.006	0.008	0.006	0.010
	[3.10]	[1.98]	[2.49]	[1.79]	[3.02]
γ	-0.254	-0.339	-0.148	-0.147	-0.406
	[-2.53]	[-2.45]	[-0.64]	[-0.75]	[-2.82]
$Adj.R^2$	0.02	0.03	0.01	0.01	0.05
N	387	195	192	212	175

This table reports the estimated coefficients for the baseline predictive regression and for the following split-sample regressions

$$r_{t+1} = \begin{cases} \alpha^i_- + \gamma^i_- \, r_{\mathrm{EoM},t} + \epsilon^i_{-,t+1}, & \text{if } Q^i_{EoM,t} \leq 0, \\ \alpha^i_+ + \gamma^i_+ \, r_{\mathrm{EoM},t} + \epsilon^i_{+,t+1}, & \text{if } Q^i_{EoM,t} > 0. \end{cases}$$

where, following Kang et al. (2020), $Q^i_{EoM,t}$ denotes end-of-month net trading by hedgers or by speculators (as categorized in the CFTC Commitments of Traders reports). The sample period goes from October 1992 to December 2024. In brackets, I report robust Newey and West (1987) t-statistics.

Tuesday, I use that Tuesday's report; otherwise, I use the Tuesday-to-Tuesday window that straddles month-end—i.e., the change from the last Tuesday of month t to the first Tuesday of month t+1.

Table 7 reports estimates by trader class. It shows that the reversal pattern is significantly stronger when hedgers are net sellers at month-end: the coefficient γ^h_- is negative, statistically significant, and similar in magnitude to the baseline (unconditional) coefficient γ. This finding is consistent with a pension-liquidity channel: as benefit payments drain cash reserves, pension plans reduce long positions (previously used to equitize cash) and add short futures positions before month-end equity sales to lock in prices. Furthermore, hedgers' and speculators' flows are almost mirror opposites—when one group is a net buyer, the other is usually a net seller- so the speculator-side coefficients have the opposite sign and significance pattern of the hedger-side.

3.2 Reversal and One Month ahead Trading Flows

In the previous section, I have shown a contemporaneous relationship between the proposed predictor and institutional flows. In this section, I investigate whether and how end-of-month returns are associated with future flows. First, I consider the predicting power of $r_{EoM,t}$ through the next month cumulative weekly returns ($r_{w=1,t} = p_{d=t-14,t} - p_{t-1}$, $r_{w=2,t} = p_{d=t-9,t} - p_{t-1}$, $r_{w=3,t} = p_{d=t-4,t} - p_{t-1}$ respectively) that gradually become one month return ($r_t = p_t - p_{t-1}$). Figure 2 plots the predictive regression estimated coefficients and 95% confidence intervals on the cumulative returns throughout the month

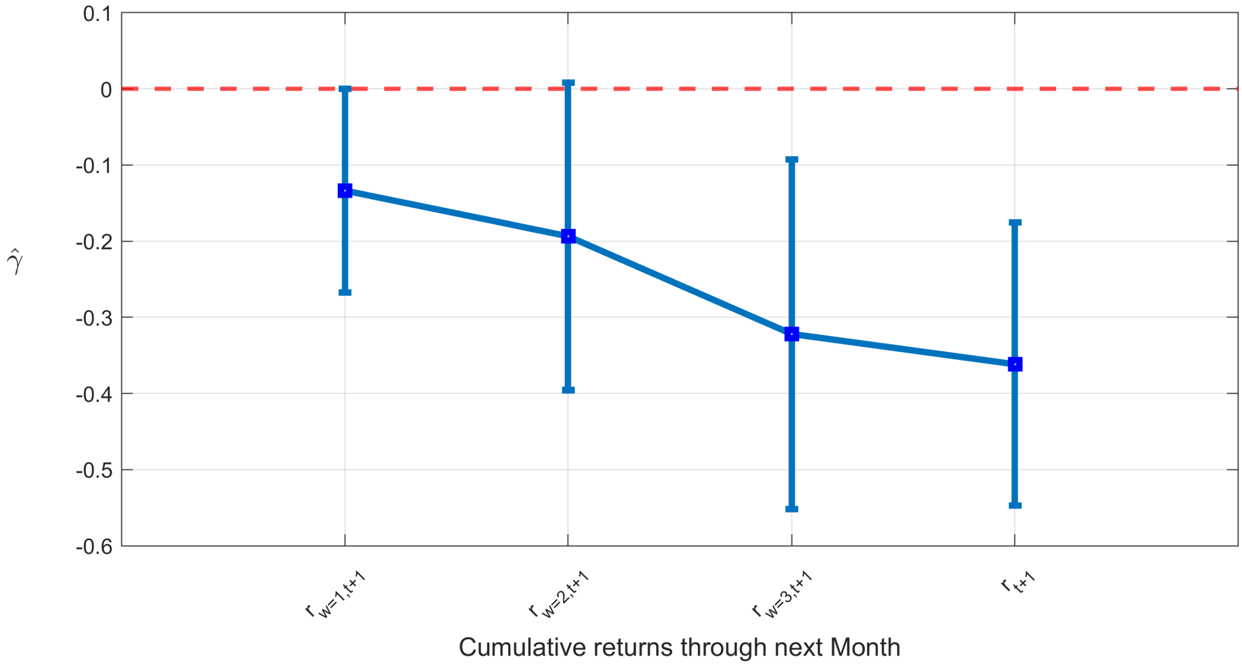
$$r_{w=i,t} = \alpha_i + \gamma_i \; r_{EoM,t-1} + \epsilon_{w=i,t} \tag{5}$$

Figure 2 reveals a clear time-series reversal pattern over the next month: all estimated coefficients are negative and their magnitude grows as the month progresses. In other words, the market does not fully rebound in the immediate days after a month-end shock. This result is novel, as prior studies on end-of-month reversals—such as Ariel (1987) and Harvey et al. (2025)—find that predictability tends to dissipate after the first week of the following month.

Crucially, the timing of this reversal in Figure 2 aligns with the pension-fund liquidity narrative. The estimated coefficients for the *first half* of the month are modest and not significant. Intuitively, pension funds cannot immediately buy back equities because they remain cash-flow negative right after paying out benefits, and it takes time for other investors to absorb the initial selling shock. By contrast, the coefficients in the *second half* of the month increase both in absolute value and significance, coinciding with the period when pension funds receive inflows (they typically get contributions mid-month) and thus can buy back into the equity market or "equitize" the new received cash contributions.

To further examine the relationship between end-of-month returns and institutional

Figure 2: Timing Reversal



This figure plots the estimated regression coefficients with 95% Newey and West (1987) robust confidence intervals for the predictive regression on cumulative weekly returns throughout the next month

$$r_{w=i,t} = \alpha_i + \gamma_i \; r_{EoM,t-1} + \epsilon_{w=i,t}.$$

It also shows the coefficient for the standard monthly predictive regression $r_t = \alpha + \gamma \; r_{EoM,t-1} + \epsilon_t$, where $r_{w=1,t} = p_{d=t-14,t} - p_{t-1}$, $r_{w=2,t} = p_{d=t-9,t} - p_{t-1}$, $r_{w=3,t} = p_{d=t-4,t} - p_{t-1}$ respectively. The sample period goes from September 1982 to February 2025.

trading behavior, I test whether $r_{EoM,t}$ predicts future institutional investors' net weekly trading flows. Specifically, I consider the following regression specification:

$$Q^i_{w=i,t+1} = \alpha^i_w + \gamma^i_w \; r_{EoM,t} + \epsilon^i_{w=i,t+1} \tag{6}$$

Table 8 explores how the previous end-of-month return relates to subsequent net trading by hedgers and speculators. Hedgers (a group likely to include pension funds) do not appear to react immediately to end-of-month returns, but rather adjust their positions with a lag of several days. Interestingly, the coefficients are negative and statistically significant in week 2 and 3, when the reversal pattern significance spikes (Figure 2). Hence, the results in Table 8 suggest that when the previous end-of-month return is

Table 8: **Predicting Institutional Investor Flows (CFTC Dataset)**

	$Q_{w=1,t+1}$	$Q_{w=2,t+1}$	$Q_{w=3,t+1}$	$Q_{w=4,t+1}$
Hedgers	-0.005	-0.115	-0.084	0.064
	[-0.13]	[-3.64]	[-2.17]	[1.12]
Speculators	-0.004	0.043	-0.009	-0.046
	[-0.10]	[1.91]	[-0.33]	[-1.07]

This table reports the estimated γ coefficients from the following regression:

$$Q^i_{w=i,t+1} = \alpha^i_w + \gamma^i_w \; r_{EoM,t} + \epsilon^i_{w=i,t+1}$$

where net trading $Q^i_{w=i,t+1}$ follows from Kang et al. (2020). The results are presented for both hedgers (commercial) and speculators (non-commercial) institutional investors. Weekly net trading data come from the CFTC "Futures" reports, and the time window goes from September 1992 to December 2024. In brackets, I report robust Newey and West (1987) t-statistics.

negative (positive), pension funds tend to be net buyers (sellers) later in the month. The link between the reversal and institutional flows supports the payment-cycle channel: the pattern is stronger when commercial traders sell at the end of the month (Table 7) and predicts hedgers' buy back in the second and third week (Table 8), matching both the cashflow timing of pension funds and the reversal dynamic in Figure 2.[15]

By contrast, end-of-month returns have little predictive power for the next-month flows of speculators. This class of institutional traders likely trades more on market conditions than on predefined trading schedules. The only statistically significant coefficient is positive, which would be more consistent with a momentum rather than with an aggregate market reversal. Appendix B.3 corroborates the results reported in Table 7 and 8 using ANCerno data.

3.3 Other Funding Liquidity Sources

Thus far, the analysis has relied on trading data to provide empirical support for the proposed mechanism. This raises an important question: could pension funds pursue

[15]Mid-month is the mirror image of what happens at month-end: contributions raise pensions' cash balances, so funds add to long index-futures positions used to equitize cash and decrease any temporary short hedges ahead of planned purchases.

alternative strategies to secure liquidity at month-end?

While pension funds may have access to other funding channels, selling equities remains an important and practical means of meeting short-term liquidity needs at month-end. Andonov et al. (2025) estimate that, for each $1 of outflows, pension funds finance at least 50% by selling equities. Moreover, at month-end many market participants simultaneously seek cash (Etula et al., 2020) and Treasury auctions take place (Lou, Yan, and Zhang, 2013). As a result, financing costs tend to rise across both short- and long-term debt markets. Consequently, borrowing becomes more expensive, and selling bonds—including Treasuries—becomes less attractive due to diminished liquidity and increased price impact.[16] In addition, pension funds' participation in the repurchase agreement (repo) market remains limited, particularly compared to the scale of their underfunded liabilities.[17] Finally, Andonov et al. (2025) provide evidence showing that pension funds do not rely on dividends or lines of credit to manage their liquidity needs.

I provide evidence that the reversal pattern is most pronounced in months when market liquidity is relatively scarce, making alternative financing costly or inaccessible. To capture variation in liquidity conditions, I use three proxies: the monthly average federal funds rate, the National Financial Conditions Index (NFCI), and the cash growth rate from Pettenuzzo, Sabbatucci, and Timmermann (2024).[18] For each measure, I split the sample at the median and estimate the following regression separately for high- and low-liquidity periods:

[16]This explanation does not imply a strict pecking order between equities and bonds. Equity positions may simply be sold because stock markets are considerably more liquid and centralized than corporate bond markets, which constitute the primary fixed-income exposure for most pension funds.

[17]For example, according to the Federal Reserve's Flow of Funds latest data, pension funds held approximately $120 billion in repo in contrast to their $4.18 trillion unfunded liabilities.

[18]The cash growth rate in Pettenuzzo et al. (2024) is constructed from U.S. companies' quarterly 10-Q filings. While not specific to pension funds, this measure serves as a proxy for broader cash growth in the economy, capturing aggregate liquidity conditions across firms.

Table 9: Reversal Pattern and Liquidity Proxies

	Fed Funds		NFCI		$\Delta\$$	
	Low	High	Low	High	Low	High
α	0.005	0.012	0.008	0.009	0.009	0.008
	[1.74]	[4.37]	[3.15]	[2.90]	[3.24]	[2.98]
$r_{EoM,t}$	-0.201	-0.520	-0.245	-0.403	-0.459	-0.247
	[-1.11]	[-4.87]	[-0.88]	[-3.65]	[-3.45]	[-1.40]
Obs	255	254	255	254	254	255
$Adj.R^2$	0.01	0.07	0.01	0.05	0.06	0.01

This table reports the estimated coefficients for the following regressions:

$$r_{t+1} = \begin{cases} \alpha_L + \gamma_L \; r_{EoM,t} + \epsilon_{L,t+1} & if \; v_t \leq v_M \\ \alpha_H + \gamma_H \; r_{EoM,t} + \epsilon_{H,t+1} & if \; v_t > v_M \end{cases}$$

where v_M is the median sample value on average monthly fed funds rate, NFCI index from FRED and cash growth rate ($\Delta\$$) from Pettenuzzo et al. (2024). The sample period goes from September 1982 to February 2025. In brackets, I report robust t-statistics.

$$r_{t+1} = \begin{cases} \alpha_L + \gamma_L \; r_{EoM,t} + \epsilon_{L,t+1} & if \; v_t \leq v_M \\ \alpha_H + \gamma_H \; r_{EoM,t} + \epsilon_{H,t+1} & if \; v_t > v_M \end{cases} \tag{7}$$

The results in Table 9 show that the reversal effect is significantly stronger in periods of tight short-term liquidity, when cash growth is low or financing costs are high. These findings are consistent with the proposed mechanism: limited access to external liquidity at month-end amplifies the pressure to sell equity positions, intensifying return reversals. The results are also consistent with the findings in Etula et al. (2020): active money managers—including hedge funds— attempt to provide end-of-month liquidity only when funding liquidity proxies are good.[19]

[19] As discussed in Etula et al. (2020) and consistent with the results in Table 1, on average the hedge fund industry does not appear to accommodate market-wide selling pressure near month-end, due to its relatively small size, its own liquidity needs, and incentives to window-dress for portfolio reporting (Patton and Ramadorai, 2013).

3.4 Reversal Properties

The properties discussed in Section 2 make this novel reversal pattern unique compared to what is typically found in the literature. Unlike previous findings, this pattern is cyclical and is observed in the S&P 500, one of the most liquid assets in the world. In this final section, I discuss how these novel properties align with the proposed pension fund-driven mechanism.

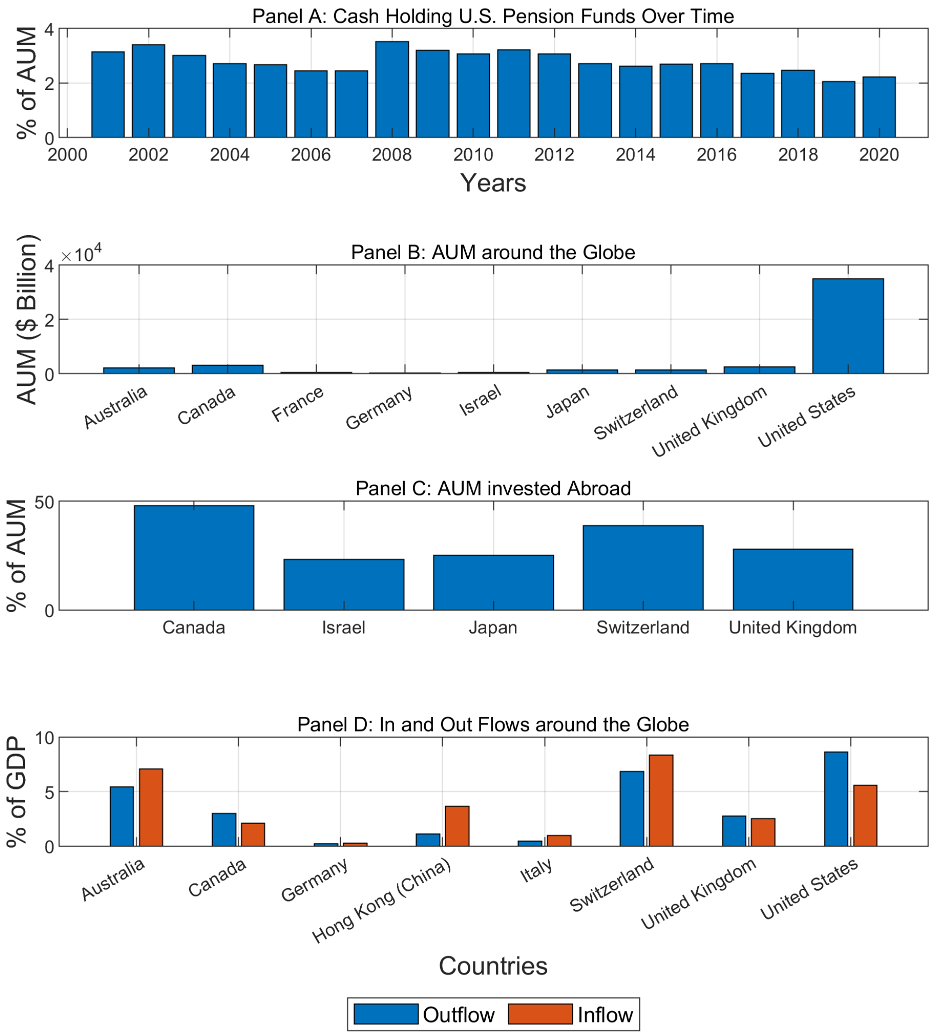
Property 1. *Reversal concentrates on expansion periods*

During periods of economic stability, pension funds reduce their precautionary cash reserves (Figure 3, Panel A). Intuitively, in stable economic conditions, they tend to decrease their liquidity buffers to allocate more capital to riskier assets. As a result, with less cash on hand to manage mismatches, pension funds become more vulnerable to liquidity shortfalls and are more likely to sell at month-end to cover these gaps. Regulation also plays an important role. During recessions, regulators may relax rules and requirements for pension funds to prevent forced selling and the resulting negative market spiral (see, for example, the "Worker, Retiree, and Employer Recovery Act of 2008"). Table 3.B reports pension plans' order imbalances, separately for periods of expansion and recession. The results show that the end-of-month selling pattern in Table 1 is primarily driven by economic expansions.

Property 2. *Reversal concentrates on high-quality stocks*

Consistent with Jansen, Klingler, Ranaldo, and Duijm (2024), among others, when pension funds sell for liquidity reasons, they first sell high-quality positions to minimize price impact and transaction costs. Table 10 reports in the first two columns a predictive regression considering the Dow Jones and Russell 2000. The results for the Dow closely align with those for the S&P 500, while no clear pattern is observed in the Russell. Notably, the aggregate reversal pattern is evident in both the Dow, an index of 30 large-cap

Figure 3: Pension Funds Characteristics Around The World



Panel A reports the percentage of assets under management (AUM) held in cash by American pension funds. Panel B shows total AUM (in $ billions) for selected OECD countries in 2022. Panel C reports the percentage of AUM invested abroad (2022) for selected countries. Panel D compares annual pension benefit outflows to contributions for those countries (2022). Data source: *OECD Pension Markets in Focus* .

stocks, and the S&P 500, but not in the Russell, which tracks the performance of small-cap American firms.[20] Therefore, contrary to cross-sectional studies (e.g., Avramov et al.

[20]The Dow criteria are not governed by strict quantitative rules, with the only exception being that companies must be based in the U.S., listed on U.S. exchanges, and not belong to the transportation or utilities sectors. The methodology is far vaguer than the S&P 500: "A stock is typically added only if the company has an excellent reputation, demonstrates sustained growth, and is of interest to a large number of investors." Since the Dow's components are among the largest and most established companies, they are also part of the S&P 500.

Table 10: Reversal Pattern - Other Indices

	DOW	RUSS	E50	TSX	ASX	NIK	FTSE
γ	-0.232**	-0.161	-0.029	-0.019	0.048	-0.068	-0.088

This table reports the γ coefficients from the following predictive regressions:

$$r_{t+1} = \alpha + \gamma\, r_{EoM,t} + \epsilon_{t+1}$$

for the Dow Jones, Russell 2000, Euronext50, Toronto SX, Australian SX, Nikkei and FTSE 100. In brackets, I report robust Newey and West (1987) t-statistics. See Table 5.B for each index's sample period and descriptive statistics.

(2006), Nagel (2012), and Dai et al. (2023)), the aggregate reversal pattern concentrates on high-quality stocks. In Appendix B.4.3, I propose a cross-sectional exercise to corroborate the results in Table 10. Sorting stocks from the CRSP dataset according to stock price and liquidity, I show that the reversal pattern concentrates on high-priced and liquid stocks. Table 4.B reports pension plans' order imbalance, distinguishing between S&P 500 constituent and non-constituent stocks. The results show that there is evidence of an end-of-the-month selling pattern exclusively among the constituents of the S&P 500.

Property 3. *Reversal concentrates on American Indexes*

At the international level, there is limited evidence of an aggregate market reversal (see columns 3-7 of Table 10). International pension funds manage substantially fewer assets (Figure 3, Panel B), invest heavily abroad (Figure 3, Panel C), and typically do not face negative cash flows (Figure 3, Panel D). As a result, international pension funds are unlikely to need to sell assets for liquidity reasons at the end of the month. Even if they must sell, their smaller market size likely prevents them from triggering a broad market shock. Furthermore, in line with Property 2, they may sell U.S. stocks to minimize trading costs and fees.

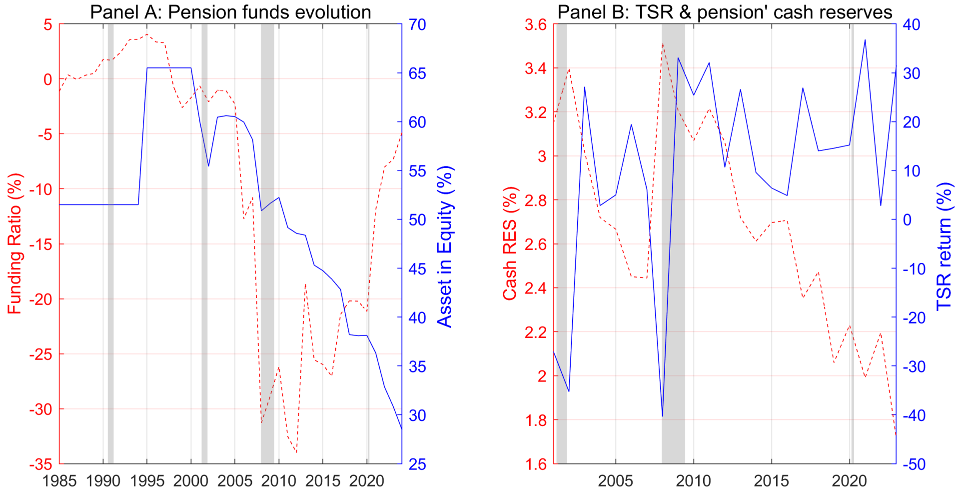
Overall, the evidence presented in this section strongly suggests that the liquidity trading driven by the payment cycle is the most likely explanation for the novel aggregate reversal pattern. While other factors could contribute, Appendix B.5 explores several potential alternative explanations (compensation for standard liquidity risk, behavioral biases, option expiration trading, quarterly activity, information releases, and pension fund re-balancing) and finds no convincing evidence for any of these channels.

4 Discussion

Role of Pension Funds in the Equity Market. Over the last 40 years, pension funds have undergone profound structural and strategic changes (Panel A of Figure 4). In the early part of this period, they were a dominant force in equity markets for two main reasons: (i) they allocated a large share of their portfolios—around 60%—to equities, and (ii) passive investing was still in its early stages, leaving pension funds as key institutional players (Harvard Business Review). Over time, however, their dominance declined due to three major developments: (i) a growing shift from defined benefit (DB) to defined contribution (DC) plans reduced the flow of contributions into traditional pension funds, creating mounting liquidity pressures; (ii) funding imbalances forced many pension funds to reallocate capital from equity and Treasuries toward higher-yielding, illiquid assets such as private equity and REITs; and (iii) the rapid rise of passive investing made mutual funds and ETFs the new leaders in equity market ownership and influence. Although the evolution of pension funds over time raises important questions, the reversal pattern documented in this paper suggests that overall pension fund trading activity is a fundamental force shaping financial market dynamics.

More Granular Data on Pension Funds. To better understand the impact of pension funds on financial markets, more granular and comprehensive data are needed—particularly regarding their holdings and liquidity positions. While some data are available, they are typically limited to aggregate measures and reported only on a quarterly or

Figure 4: Pension Funds Open Questions



Panel A plots the annual average percentage of pension plan assets allocated to equities against the pension funding ratio. The equity-allocation series is measured by the Compustat North America variable "PNATE" (available after 2001, with earlier years from Pensions & Investments data). The funding ratio is calculated as funded status (PCPPAO) divided by plan assets (PPLAO), per Compustat. Panel B plots annual cash reserve levels, from the OECD's Pension Markets in Focus, against the annualized gains from the Time Series Reversal (TSR) strategy.

annual basis. Moreover, the information is fragmented across multiple sources, making it difficult to construct a coherent and timely picture of pension fund behavior. As suggestive evidence of the connection between pension fund liquidity and equity markets, Panel B of Figure 4 plots pension fund cash reserves (sourced from OECD annual data) against the annualized returns of the reversal strategy. Consistent with the interpretation that the reversal reflects pension funds' cash management behavior, TSR gains are negatively correlated with cash reserves. When cash buffers are low, institutions are more likely to rely on equity sales as an additional source of financing to meet payment obligations, thereby amplifying the predictable end-of-month price pressure. However, due to data constraints, this analysis captures only a narrow dimension of what is likely a broader and more complex dynamic. More detailed and better-integrated data are crucial for a comprehensive understanding of the impact of pension fund liquidity management on financial markets, the real economy, and financial stability.

5 Conclusion

This paper documents a novel 1-month aggregate market reversal pattern driven by the previous *end-of-the-month* market return. The empirical evidence is statistically significant both in and out of sample. Importantly, I show that the reversal at the aggregate level has characteristics opposite to those established in the literature: it concentrates on high-priced and liquid stocks, is cyclical with the economy, and persists throughout the following month.

I rationalize the empirical findings via pension funds' end-of-the-month liquidity trading. Leveraging institutional investors' trading flows, I argue that the payment cycle potentially triggers a non-informational trading shock. Consistent with a payment cycle explanation, I show that the reversal pattern increases in absolute terms over the following month, aligning with the timing pension funds receive inflows and with the predicted pension funds order imbalance. Finally, I provide qualitative evidence that the payment-cycle channel can account for the novel pattern's properties.

Overall, the findings show a strong link between pension funds' market pressure and aggregate market reversal. This novel empirical evidence suggests that not only momentum (Lou (2012)) but also reversal can be empirically rationalized through the lens of flow-based asset pricing.

Finally, the findings suggest that pension plans' liquidity shortfalls and underfunding have a direct impact on the aggregate market. Given pension funds' size and importance, further theoretical and empirical research could explore whether their liquidity-driven asset allocation decisions influence the real economy and financial stability.

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Appendices

A Appendix Section 2

A.1 Appendix Section 2.2

A.1.1 Further Control Variables

In this section, I show that the results presented in Table 3 remain robust after controlling for several end-of-month liquidity proxies. Specifically, I consider the following variables:

- End-of-month volume: $VOL_{EoM,t} = \frac{\sum_{i=0}^{4} VOL_{d=t-i,t}}{\sum_{i=0}^{20} VOL_{d=t-i,t}}$
- End-of-month volatility: $vix_{EoM,t} = \ln\left(\frac{\sum_{i=0}^{4} VIX_{d=t-i,t}}{5}\right) - \ln\left(\frac{\sum_{i=6}^{20} VIX_{d=t-i,t}}{15}\right)$
- Monthly volatility: $\Delta vix_t = vix_t - vix_{t-1}$
- End-of-month National Financial Conditions Index:

  $nfci_{EoM,t} = nfci_{w=4,t} - \frac{\sum_{i=1}^{3} nfci_{w=i,t}}{3}$
- End-of-month federal funds rate: $ff_{EoM,t} = \frac{\sum_{i=0}^{4} ff_{d=t-i,t}}{5} - \frac{\sum_{i=6}^{20} ff_{d=t-i,t}}{15}$

- End-of-month growth in cash: $\Delta cash_{EoM,t} = \frac{\sum_{i=0}^{4} \Delta cash_{d=t-i,t}}{5}$

These controls capture various aspects of market liquidity, volatility, and financial conditions around the end of the month. Despite their inclusion, the predictive power of the end-of-month signal remains unaffected.

Table 1.A: In Sample Evidence – Further Control Variables

α	0.007	α	0.007	α	0.007	α	0.008	α	0.007	α	0.009
	[1.30]		[3.34]		[3.38]		[4.38]		[3.73]		[4.31]
$r_{EoM,t}$	-0.396	$r_{EoM,t}$	-0.294	$r_{EoM,t}$	-0.299	$r_{EoM,t}$	-0.387	$r_{EoM,t}$	-0.329	$r_{EoM,t}$	-0.362
	[-4.88]		[-3.41]		[-3.29]		[-4.85]		[-3.65]		[-3.82]
$VOL_{EoM,t}$	0.00	$vix_{EoM,t}$	-0.02	$vix_{EoM,t}$	-0.01	$nfci_{EoM,t}$	-0.14	$ff_{EoM,t}$	0.025	$\Delta cash_{EoM,t}$	-0.001
	[0.18]		[-0.78]		[-0.37]		[-4.08]		[4.34]		[-0.16]
				Δvix_t	-0.008						
					[-0.51]						
N	449		421		421		509		509		509
$Adj.R^2$	0.04		0.02		0.02		0.09		0.05		0.03

This table reports the estimation result of:

$$r_{t+1} = \alpha + \gamma\, r_{EoM,t} + \beta_i C_{i,t} + \varepsilon_{t+1}$$

where the control variables $C_{i,t}$ considered are end of the month volume (September 1982 - February 2020), end of the month volatility (February 1990 - February 2025), monthly volatility (February 1990 - February 2025) National Financial Condition index (September 1982 - February 2025), fed funds (September 1982 - February 2025) and growth in cash (September 1982 - February 2025). In brackets, I report robust Newey and West (1987) t-statistics. Future contract volume (available until February 2020) and VIX (available starting February 1990) data are from GFD, NFCI and fed funds from the FRED website, and daily cash growth from Pettenuzzo et al. (2024).

A.1.2 Previous Weeks Predictability

In this section, I show that previous weekly returns do not have predictive power. Specifically, I consider:

$$r_{t+1} = \alpha_i + \gamma_i\, r_{w=i,t} + \epsilon_{t+1}, \quad 1 \le i \le 3$$

where each weekly predictors are $r_{w=3,t} = p_{d=t-5,t} - p_{d=t-9,t}$, $r_{w=2,t} = p_{d=t-10,t} - p_{d=t-14,t}$, $r_{w=1,t} = p_{d=t-15,t} - p_{d=t-19,t}$ respectively. The results reported in Table 2.A show that no previous weekly return has any predictive power.

Table 2.A: **Previous Weeks Lack of Predictability**

α	0.008	α	0.007	α	0.008
	[3.67]		[3.46]		[3.92]
$r_{w=3,t}$	-0.09	$r_{w=2,t}$	0.07	$r_{w=1,t}$	0.09
	[-0.66]		[0.47]		[0.69]
N	509		509		509
$Adj.R^2$	0.00		0.00		0.00

This table reports the results of the following predictive regressions $r_{t+1} = \alpha_i + \gamma_i\, r_{w=i,t} + \epsilon_{t+1},\ \ 1 \leq i \leq 3$. In brackets, I report the associated Newey and West (1987) t-statistics. The time window is from September 1982 to February 2025.

A.1.3 Predictability after first week of the Month

In this section, I investigate whether the reversal pattern depends solely on the $r_{EoM,t}$'s ability to predict the one-week-ahead return. Therefore, I consider the following predictive regression:

$$r_{AfW,t+1} = \alpha + \gamma\ r_{EoM,t} + \epsilon_{AfW,t+1}$$

where $r_{AfW,t} = p_t - p_{d=t-14,t}$ is the return over the last 15 days of the one-month-ahead period. The estimated coefficient is -0.228, and the Newey and West (1987) t-statistic is -3.97.[21] Therefore, the reversal pattern predictability is distinct from the turn-of-the-month in (Ariel, 1987) and on the end-of-month calendar signal in Harvey et al. (2025) as both patterns cluster in the first week of the month ahead.

A.1.4 Controlling for Closing Price Effect

In this section, I test whether the relationship between last-week returns and the following month's return could be driven by a closing-price effect. As high and low prices are potentially recorded during the regular trading session (lit book phase), I consider high

[21]Running the same regression after the introduction of the E-Mini S&P 500 (September 1997) yields similar results with a coefficient of -0.136 and Newey and West (1987) t-statistics of -2.01.

(low) last week returns:

$$r^H_{EoM,t} = p^H_t - p^H_{d=t-4,t} \qquad (r^L_{EoM,t} = p^L_t - p^L_{d=t-4,t})$$

as the dependent variables of the following distinct regression

$$r^H_{t+1} = \alpha_H + \gamma_H \ r^H_{EoM,t} + \epsilon_{t+1} \qquad (r^L_{t+1} = \alpha_L + \gamma_L \ r^L_{EoM,t} + \epsilon_{t+1})$$

where $r^H_{t+1} = p^H_{t+1} - p^H_t$ and $r^L_{t+1} = p^L_{t+1} - p^L_t$.

The estimated coefficient is -0.306 (-0.236), and the associated Newey and West (1987) t-statistic is -2.26 (-1.71). These results show that the pattern is robust to the closing-price effect. However, consistent with evidence that institutional investors trade more at the market close, the baseline regression exhibits a larger coefficient (in absolute value) and a higher t-statistic.

A.1.5 Placebo Test around mid of the Month

In this section, I conduct a placebo test to verify that the market activity in the last week of the month determines the negative serial correlation. I consider the mid of each month - a second common payment date - as the end of the month ($r^{PT}_{t+1} = p_{M,t+1} - p_{M,t}$ where $p_{M,t}$ is the mid of the month closing price in month t). The predictor is the difference between the closing price in the mid of month t and the fourth-to-middle of the month price ($r^{PT}_{EoM,t} = p_{M,t} - p_{d=M-4,t}$).

The estimated coefficient is -0.034, and the Newey and West (1987) t-statistic is -0.22, suggesting that the combination of a demand shock and liquidity friction at the end of the month drives the reversal pattern documented in the main body of the paper.

A.1.6 Multi - Month Predictability

In this section, I study whether the reversal pattern persists beyond a one-month horizon. I consider a set of predictive regressions that gradually become two-month ahead returns:

$$r'_{w=i,t+2} = \alpha + \gamma\ r_{EoM,t} + \epsilon_{w=i,t+2}$$

where $r'_{w=1,t} = p_{d=t-14,t} - p_{t-1}$, $r'_{w=2,t} = p_{d=t-9,t} - p_{t-1}$, $r'_{w=3,t} = p_{d=t-5,t} - p_{t-1}$ and

$$r_{t+2} = \alpha + \gamma\ r_{EoM,t} + \epsilon_{t+2}$$

The results reported in Table 3.A show that the predictability window is limited to one month.

Table 3.A: Two Month Ahead Predictability

	$r'_{w=1,t+2}$	$r'_{w=2,t+2}$	$r'_{w=3,t+2}$	r_{t+2}
α	0.003	0.006	0.005	0.008
	[2.47]	[3.06]	[2.12]	[3.89]
$r_{EoM,t}$	0.000	0.013	-0.009	-0.036
	[0.00]	[0.13]	[-0.07]	[-0.30]
N	508	508	508	508
$Adj.R^2$	0.00	0.00	0.00	0.00

This table reports the estimated coefficients of $r'_{w=i,t+2} = \alpha + \gamma\ r_{EoM,t} + \epsilon_{w=i,t+2}\quad 1 \le i \le 3$ and $r_{t+2} = \alpha + \gamma\ r_{EoM,t} + \epsilon_{t+2}$ where $r'_{w=i,t+2}$ are weekly 2-ahead month cumulative returns that become two-month-ahead returns $r_{t+2} = p_{t+2} - p_{t+1}$. In brackets, I report robust Newey and West (1987) t-statistics. The sample period goes from September 1982 to February 2025.

A.1.7 Sub-Sample Analysis

In this section, I examine the negative correlation between $r_{EoM,t}$ and r_{t+1} in the period following the introduction of the E-Mini S&P 500 futures contract in September 1997. The launch of the E-mini marked a pivotal development in U.S. equity index trading:

with a notional value equal to one-fifth of the standard S&P 500 futures contract, it dramatically lowered the capital required to take positions in the index. This innovation broadened access to a wider spectrum of market participants, particularly retail and smaller institutional traders, and significantly contributed to the financialization and liquidity of index trading.

Table 4.A replicates the predictive regressions from Table 3 for the subsample spanning September 1997 to February 2025. The results confirm that the reversal pattern between $r_{EoM,t}$ and r_{t+1} persists in the post-E-Mini era, suggesting that the predictive relationship is robust to structural changes in index trading. However, consistent with increased liquidity and broader participation, particularly from retail investors, the magnitude of the estimated coefficient declines in absolute terms.

A.2 Appendix Section 2.3

A.2.1 Forecast Errors Over Time

A.2.2 Reversal and Business Cycle

In this section, I provide In-Sample evidence corroborating the cyclical nature of the aggregate market reversal. Specifically, I consider the following regression:

$$r_{t+1} = \alpha + \gamma_1 \mathbf{I}_t^{rec} \times r_{EoM,t} + \gamma_2 (1 - \mathbf{I}_t^{rec}) \times r_{EoM,t} + \epsilon_{t+1}$$

where I_t^{rec} is the NBER indicator function that takes a value of 1 when month t is in recession and 0 otherwise. Table 5.A shows that the negative market serial correlation is statistically significant only during expansion periods.

Table 4.A: In Sample Evidence - After Introduction E-Mini

α	0.006	α	0.006	α	0.006	α	0.006	α	0.006	α	0.005
	[2.30]		[2.09]		[2.29]		[2.06]		[2.29]		[1.76]
$r_{EoM,t}$	-0.235	$r_{EoM,t}$	-0.224	$r_{EoM,t}$	-0.238	$r_{EoM,t}$	-0.272	$r_{EoM,t}$	-0.260	$r_{EoM,t}$	-0.279
	[-2.17]		[-2.38]		[-2.17]		[-2.95]		[-2.24]		[-3.16]
		$r_{w=3,t}$	-0.106	r_{t-12}	-0.052	IA_t^{PLS}	-0.030	MkT	0.000	$PC1$	0.001
			[-0.83]		[-0.96]		[-2.37]		[0.39]		[1.97]
		$r_{w=2,t}$	0.030	r_{t-1}	0.027	IA_t^{sPCS}	-0.265	SMB	0.000		
			[0.18]		[0.38]		[-0.58]		[-0.05]		
		$r_{w=1,t}$	-0.004			IA_t^{PCA}	0.001	HML	-0.001		
			[-0.03]				[0.35]		[-1.66]		
								MoM	0.000		
									[-0.79]		
								ST_{REV}	-0.001		
									[-0.96]		
N	329		329		329		244		328		244
$Adj.R^2$	0.01		0.01		0.01		0.05		0.01		0.03

This table reports the estimation result of:

$$r_{t+1} = \alpha + \gamma \; r_{EoM,t} + \beta_i C_{i,t} + \varepsilon_{t+1}$$

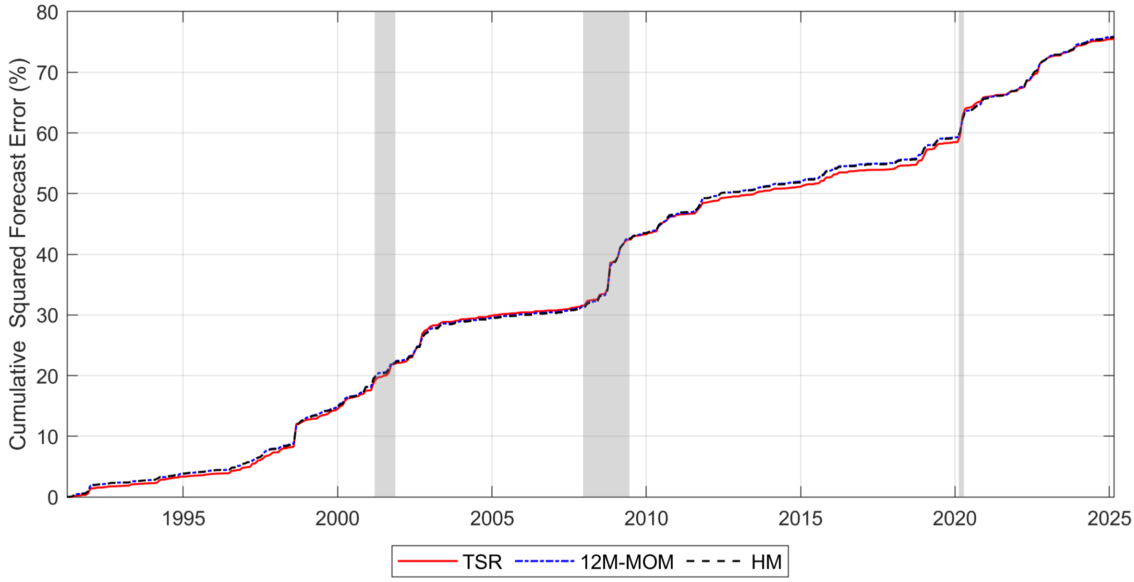
where the control variables $C_{i,t}$ considered are previous weekly returns in the second column (from September 1997 to February 2025), monthly and year returns in the third column (from September 1997 to February 2025), Chen et al. (2022)'s investor attention proxies in the fourth column (from September 1997 to December 2017), the three Fama French augmented by Momentum and Short Reversal factors in the fifth column (from September 1997 to December 2024), the first Principal Components (PC) computed from the 100 anomalies portfolio returns in Dong et al. (2022) in the $6th$ column (from September 1997 to December 2017). In brackets, I report robust Newey and West (1987) t-statistics. I directly download the variables from the respective authors' websites to avoid introducing measurement errors.

Table 5.A: Reversal and Business Cycle - In Sample Evidence

α	0.008	0.008	0.008
	[4.15]	[3.99]	[4.23]
$(1 - \mathbf{I}^{rec}) \times r_{EoM,t}$	-0.363		-0.364
	[-2.81]		[-2.81]
$\mathbf{I}^{rec} \times r_{EoM,t}$		-0.348	-0.351
		[-1.69]	[-1.70]
N	509	509	509
$Adj.R^2$	0.03	0.01	0.03

This table reports the estimated coefficients of $r_{t+1} = \alpha + \gamma_1 \mathbf{I}_t^{rec} \times r_{EoM,t} + \gamma_2 (1 - \mathbf{I}_t^{rec}) \times r_{EoM,t} + \epsilon_{t+1}$ where I_t^{rec} is the NBER indicator function that takes a value of 1 when month t is in recession and 0 otherwise. In brackets, I report robust Newey and West (1987) t-statistics. The sample period goes from September 1982 to February 2025.

Figure 1.A: Out of Sample Cumulative Forecast Error



This figure shows the cumulative OOS squared of the time series reversal (TSR- solid red line), historical mean (HM - black dashed line), and momentum (12M-MOM - blue dash-dot line). The grey shaded areas mark periods of recessions according to the NBER indicator function. The time window is from September 1982 to February 2025 and the out-of-sample valuation period goes from March 1991 to February 2025.

A.2.3 Sub Sample Analysis

In this section, I present an out-of-sample analysis starting with the introduction of the E-Mini S&P 500 futures in September 1997 and extending through February 2025. Following the approach in Section 2.3, the evaluation period covers 80% of the full sample (from March 2003 to February 2025 for a total of 264 observations).

As shown in Table 6.A, the proposed predictor continues to outperform the historical mean even when focusing exclusively on the post E-Mini period. Moreover, its predictive accuracy exhibits a cyclical pattern, consistent with the main findings of the paper.

Table 6.A: out of Sample Evidence - After Introduction E-Mini

	$R^{2,OS}(\%)$	$R^{2,OS}_{exp}(\%)$	$R^{2,OS}_{rec}(\%)$
TSR	0.91	2.27	-2.37
12M-MOM	-1.16	-1.94	0.70

This table reports the Out-of-sample forecasting results compared to the historical mean for the time series reversal ($r_{EoM,t}$) and 12-month return (r_{t-12}). The first column reports the OOS $R^{2,OS}$, the second and third columns report respectively $R^{2,OS}_{exp}$ and $R^{2,OS}_{rec}$. The $R^{2,OS}$ statistical significance is based on the Clark and West (2007) test. $***$, $**$, and $*$ indicate significance at the 1%, 5%, and 10% levels, respectively. The sample period is from September 1997 to February 2025, and the out-of-sample valuation period starts from March 2003.

A.3 Appendix Section 2.4

A.3.1 Trading Costs and Fees

In this section, I argue that transaction costs and fees are unlikely to materially affect the results. Execution costs in financial markets—particularly for S&P 500 futures—have declined substantially over the past two decades due to increased competition and decimalization. S&P 500 futures now have among the lowest trading costs in global markets. Additionally, the TSR strategy relies on public end-of-day prices, requiring minimal infrastructure and virtually no implementation cost. Because trades are assumed to occur at the close, implicit trading frictions are also largely avoided.

To illustrate, a back-of-the-envelope calculation shows that the TSR strategy would need to incur transaction costs of at least 57.6 basis points per transaction to match the gross return of a passive S&P 500 strategy without any fees incurred (in a real-world setting, passive investing with futures would actually incur a rolling fee). This break-even cost is well above typical transaction costs for futures trading, according to estimates from the CME Group (CME Report: Futures vs. ETFs).

A.3.2 Simpler Trading Strategy Sensitivity Analysis

In this section, I provide evidence that the time-varying TSR strategy is robust to the model specification. I report the results for a simple trading strategy that buys (sells) 1 unit if the out-of-sample forecast is positive (negative). Table 7.A reports mean realized returns and adjusted alphas for the $STSR$ strategy. Consistent with the findings in the main paper, the simple strategy outperforms a passive investing strategy (8.20% annualized returns) and delivers positive and statistically significant adjusted alphas.

Table 7.A: Simple Time Series Reversal Strategy - Economic Value

	Mean Ret.(%)	S&P	MKT	*FF3*	MR	BAB	ICR
$STSR$	10.31	4.11**	3.85**	3.87**	4.24**	3.90*	4.79**

This table reports in column 1 annualized returns for the simple time series reversal strategy ($STSR$); from the second column reports adjusted alphas. Specifically, I control for market index ($S\&P$) in column 1, Market factor (MKT) in column 2, Fama-French three-factor model ($FF3$) in column 3. Column 4 includes the market, momentum, and short-term reversal factors. Column 5 adds the Betting Against Beta (BAB) factor from Frazzini and Pedersen (2014) to the passive benchmark, and Column 6 augments the passive benchmark with the intermediary capital risk (ICR) factor and returns from He et al. (2017). $***$, $**$, and $*$ indicate significance at the 1%, 5%, and 10% levels, respectively. The statistical significance is based on Newey and West (1987) standard errors. The sample period is from September 1982 to February 2025, and the out-of-sample $STSR$ strategy is from March 1991.

A.3.3 Total Return Analysis

In this section, I show that the results are robust when using total returns—specifically, the $CRSP\ SPvw$ index—as the dependent variable instead of price-based futures returns ($r_{t+1} = p_{t+1} - p_t$). The $CRSP\ SPvw$ is the S&P 500 total return index, which assumes all dividends paid by constituent stocks are reinvested into the index. Focusing on total returns allows for a longer historical window. I use data from January 1975—shortly before the launch of the first investable S&P 500 ETF—through December 2024.

Table 8.A summarizes the results. The first column reports the in-sample coefficient, while columns two through four present out-of-sample R^2 values under the full sample, expansion, and recession subsamples. The final column shows the TSR strategy's adjusted

alpha relative to passive investing in total return.

Table 8.A: Reversal Pattern & Total Returns

γ	$R^{2,OS}$	$R^{2,OS}_{exp}$	$R^{2,OS}_{rec}$	TSR $\alpha(\%)$
-0.263^{**}	1.20^{**}	2.85	-5.54	4.43^{**}

This table reports in the first column the In Sample predicting coefficient of the following regression:

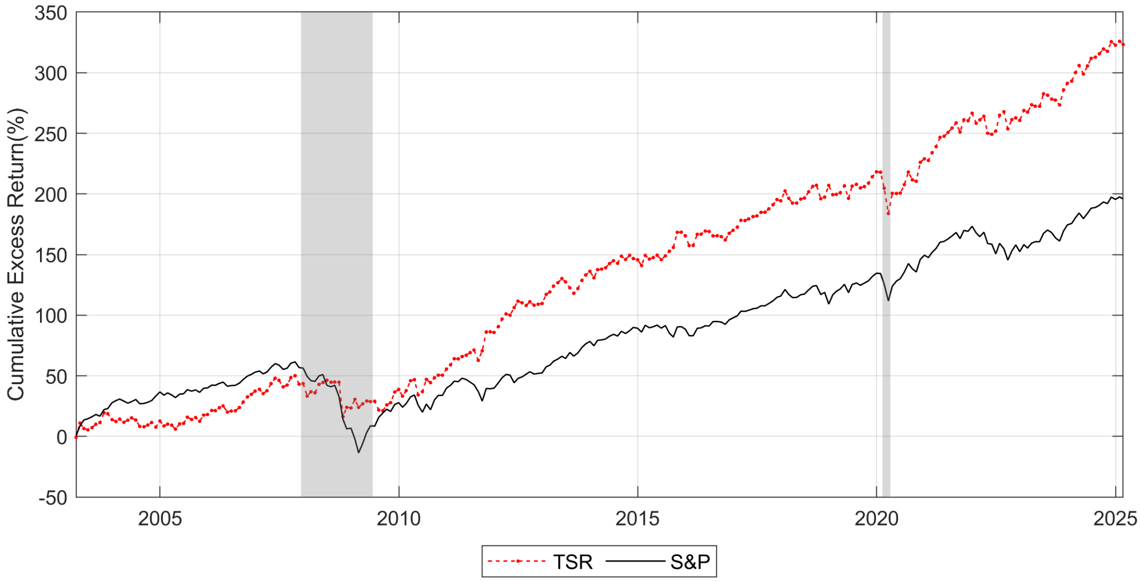
$$r^{vw}_{t+1} = \alpha + \gamma\, r_{EoM,t} + \varepsilon_{t+1}$$

where r^{vw}_{t+1} is the value weighted total return index and $r_{EoM,t}$ in the end of the month return using the S&P 500 price index. The second column reports the Out-of-Sample $R^{2,OS}$, whereas the third and fourth columns report the expansion and recession Out-of-Sample $R^{2,OS}$. The fifth column reports the annualized adjusted Jensen alphas (α) for the TSR strategy against the total return as benchmark. $***$, $**$, and $*$ indicate significance at the 1%, 5%, and 10% levels, respectively. The statistical significance is based on Newey and West (1987) standard errors for In-Sample regressions and Clark and West (2007) for Out-of-Sample $R^{2,OS}$. The time period goes from January 1975 to December 2024.

A.3.4 Sub-Sample Analysis

In this section, I present the economic analysis starting with the introduction of the E-Mini S&P 500 futures in September 1997 and extending through February 2025. Figure 2.A graphically shows that the TSR strategy outperforms passive investing, while Table 9.A reports the adjusted alphas for the different control strategies

Figure 2.A: Economic Value - After Introduction E-Mini



This figure compares the cumulative out-of-sample returns of the time series reversal (TSR - red line) with passive investing on the S&P 500 (black line). The grey-shaded areas mark periods of recessions according to the NBER. The time window is from September 1997 to February 2025 and the out-of-sample valuation period goes from March 2003 to February 2025.

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Table 9.A: Adjusted Alphas -After Introduction E-Mini

	S&P	MKT	3FF	MR	BAB	ICR
$\alpha(\%)$	4.11**	3.85**	3.87**	4.24**	3.90*	4.79**
$Adj.R^2$	0.58	0.55	0.56	0.55	0.58	0.58

This table reports adjusted alphas controlling for market index ($S\&P$) in column 1, Market factor (MKT) in column 2, Fama-French three-factor model ($FF3$) in column 3. Column 4 includes the market, momentum, and short-term reversal factors. Column 5 adds the Betting Against Beta (BAB) factor from Frazzini and Pedersen (2014) to the passive benchmark, and Column 6 augments the passive benchmark with the intermediary capital risk (ICR) factor and returns from He et al. (2017). $***$, $**$, and $*$ indicate significance at the 1%, 5%, and 10% levels, respectively. The statistical significance is based on Newey and West (1987) standard errors. The sample period is from September 1997 to February 2025, and the out-of-sample valuation period starts from March 2003.

A.3.5 Daily returns around End of Month

In this section, I examine whether the predictive power of the TSR strategy varies depending on the specific daily return used within the final week of the month. Specifically, I define daily returns as $r_{d=t-i,t} = p_t - p_{d=t-i,t}$ for $1 \leq i \leq 6$, where i indexes the number of days prior to month-end.

Table 10.A reports the in-sample coefficients, out-of-sample R^2, and adjusted alphas for each return definition within the final week of the month. Predictive power and economic value are most robust when using the return from the fourth-to-last trading day $(t-4)$. The main predictor retains statistical significance after controlling for multiple comparisons using the Holm–Bonferroni procedure. Results for $t-3$ return are similar, consistent with an end-of-month liquidity trading by institutions.

By contrast, the second-to-last day return $(t-1)$ shows a larger in-sample coefficient. However, this predictor is less statistically robust both in and out of sample, and delivers statistically insignificant alpha. This is largely due to its predictive strength being concentrated in a few extreme observations, particularly during the 2008 financial crisis.

Table 10.A: Daily returns around End of Month

	$r_{d=t-6,t}$	$r_{d=t-5,t}$	$r_{d=t-4,t}$	$r_{d=t-3,t}$	$r_{d=t-2,t}$	$r_{d=t-1,t}$
γ	-0.201 [-1.49]	-0.243 [-1.90]	-0.361 [-3.81]	-0.405 [-3.47]	-0.352 [-1.82]	-0.689 [-3.52]
$R^{2,OS}$	-1.00	-1.075	0.35^{**}	0.56^{**}	-1.73	0.68^{*}
$\alpha(\%)$	1.90	3.13^{*}	5.64^{**}	3.18^{*}	1.19	3.25

This table reports in the first row the In Sample predicting coefficient of the following regression:

$$r_{d=t-i,t} = p_t - p_{d=t-i,t}$$

for each $1 \leq i \leq 6$. The second row reports the Out-of-Sample $R^{2,OS}$. The third column reports the annualized adjusted Jensen alphas (α) for the TSR strategy against the S&P strategy. $***$, $**$, and $*$ indicate significance at the 1%, 5%, and 10% levels, respectively. The statistical significance is based on Newey and West (1987) standard errors for In-Sample regressions and Clark and West (2007) for Out-of-Sample $R^{2,OS}$. The sample period is from September 1982 to February 2025.

B Appendix Section 3

B.1 ANcerno Dataset

Abel Noser is a brokerage firm that provides transaction cost analysis to institutional investors. Historically friendly to the academic world, the firm shared a publicly available dataset (ANcerno) until 2017. The dataset samples the trading activity of institutional investors and is considered to be highly representative of overall institutional market activity. It covers approximately 10% of CRSP volume, and the institutions sampled do not differ from SEC 13F filings regarding return characteristics, stock holdings, and trades. The main advantage of the ANcerno dataset over 13F SEC filings and CRSP Thomson Reuters is its high-frequency granularity compared to the quarterly frequency of the latter two datasets. I obtained the daily ANcerno dataset from 1997 to 2010 included. As the first three years have very few observations, I consider only data from 2000 onwards - a common practice in the literature Hu, Jo, Wang, and Xie (2018). The variables in the dataset are:

- *clientcode*: Ancerno defined Client identifier. Each client gets a unique code. It is impossible to reverse engineering Client names.
- *clienttypecode*: ANcerno furnishes a reference file containing an institution type identifier for each client, with "1" denoting pension plan sponsors and "2" indicating money managers.
- *tradedate*: The trade day execution.
- *side*: Binary variable equal to $+1$ if the trade is a buy, -1 if the trade is a sell.
- *price*: Price per share as reported by the client.
- *volume*: Volume traded as reported by the client.

- *ncusip*: 8 digit CUSIP identifier.

B.2 End of Month Institutional Behavior: CFTC data

In this section, I use data from Commodity Futures Trading Commission (CFTC) to corroborate the results established with the ANcerno dataset. I use the "Large Trader Net Position Changes" data set publicly available on the CFTC website. The data reports the average weekly net buys and sells on futures linked to the S&P 500 for Institutional Investors, dealers, and Leveraged funds from January 2009 to May 2011. More precisely, the futures are the S&P 500 (ticker: SP) and the E-Mini S&P 500 futures (ticker: ES). To jointly consider both, I multiply the number of SP contracts by 5 as the nominal value of the SP future is 5 times larger than the ES.

Table 1.B: Institutional Investor behavior at the end of the month (CFTC Dataset)

Inst. Investors	Dealers	Leveraged Funds	Others
-3.44%**	1.35%	1.20%	-0.42%

This table reports the last week order imbalance on futures linked to the S&P 500 for Institutional, Investors, dealers, and Leveraged funds from January 2009 to May 2011 according to the "Large Trader Net Position Changes" CFTC Dataset. $***$, $**$, and $*$ indicate significance at the 1%, 5%, and 10% levels, respectively.

In Table 1.B, I report the *order imbalance for the last week of the month*, calculated as $\frac{\Delta \text{Buy}_t - \Delta \text{Sell}_t}{\Delta \text{Pos}_t}$, where t refers to the *last week of the month.*[22] Consistent with the findings in the main body of the paper, institutional investors -among which pension funds are predominant- reduce their exposure to S&P 500 futures instruments during the last week of the month.

[22] As the data is released weekly on Tuesdays, the “last week” refers to the one for which at least one observation falls within the final calendar week of the month. See the CFTC methodology: CFTC Methodology. According to the CFTC, “A trader’s increase in a net long position or decrease in a net short position can be viewed as net ‘buys.’ Similarly, a trader’s decrease in a net long position or increase in a net short position can be viewed as net ‘sells.’ For each reporting week, the values reported are the simple average of that week’s daily aggregate net ‘buys’ and net ‘sells.”’

B.3 Reversal and Institutional Flows: ANcerno data

In this section, I propose a similar analysis of Tables 7 and 8 leveraging the ANcerno dataset. Specifically, Panel A of Table 2.B presents the results for the following regression:

$$r_{t+1} = \begin{cases} \alpha_-^i + \gamma_-^i \, r_{\text{EoM},t} + \epsilon_{-,t+1}^i, & \text{if } OI_{EoM,t}^i \leq 0, \\ \alpha_+^i + \gamma_+^i \, r_{\text{EoM},t} + \epsilon_{+,t+1}^i, & \text{if } OI_{EoM,t}^i > 0. \end{cases}$$

where $OI_{EoM,t}^i$ is the overall last week's demeaned order imbalance for either pension funds (PF) or money managers (MM).

Panel B of Table 2.B tests whether $r_{EoM,t}$ predicts the order imbalance of pension funds and money managers. Leveraging the daily frequency of the ANcerno dataset, I compute daily order imbalance separately for each sub-group. I then estimate predictive regressions of order imbalance on lagged end-of-month returns, pooling observations by week within the one month ahead. The regression specification is:

$$OI_{d=t-d,t}^{w=i} = \alpha_i + \gamma_i \, r_{EoM,t-1} + \epsilon_{w=i,t}$$

where $OI_{d=t-d,t}^{w=i}$ denotes the daily order imbalance from day $t-d$ to t, for week $w = i$. Specifically, week $w = 1$ corresponds to days $t - d \in [15, 19]$, week $w = 2$ to $[10, 14]$, week $w = 3$ to $[5, 9]$, and week $w = 4$ to $[0, 4]$, with t defined as the last trading day of the month.

Pension fund predicted flows exhibit a clear directional pattern: the estimated coefficients are positive in the first part of the month, but turn negative in the second half. Their trading activity closely mirrors the return reversal pattern shown in Figure 2, where the reversal effect becomes pronounced only in the last two weeks of the month. By contrast, money managers display the opposite pattern. Their coefficients are negative early in the month and then flip to positive in the later weeks, implying that they initially

Table 2.B: Reversal and ANCerno Flows

Panel A

	γ_{-}^{PF}	γ_{+}^{PF}	γ_{-}^{MM}	γ_{+}^{MM}
	-0.109	-0.331	0.053	-0.370
	[-0.41]	[-1.62]	[0.19]	[-1.81]

Panel B

	$OI_{d=t-d,t}^{w=1}$	$OI_{d=t-d,t}^{w=2}$	$OI_{d=t-d,t}^{w=3}$	$OI_{d=t-d,t}^{w=4}$
PF	0.524	0.239	-0.272	-0.555
	[1.90]	[0.94]	[-1.04]	[-1.96]
MM	-0.468	-0.090	0.006	0.304
	[-3.46]	[-0.71]	[0.05]	[2.06]

Panel A reports the results for the following regression:

$$r_{t+1} = \begin{cases} \alpha_{-}^{i} + \gamma_{-}^{i}\, r_{\text{EoM},t} + \epsilon_{-,t+1}^{i}, & \text{if } OI_{EoM,t}^{i} \leq 0, \\ \alpha_{+}^{i} + \gamma_{+}^{i}\, r_{\text{EoM},t} + \epsilon_{+,t+1}^{i}, & \text{if } OI_{EoM,t}^{i} > 0. \end{cases}$$

where $OI_{EoM,t}^{i}$ is the overall demeaned end of month (between $4 \leq t-d \leq 0$ and t is the last trading day) order imbalance for either pension funds (PF) or money managers (MM). **Panel B** reports the estimated coefficients of the predictive regression on the Order Imbalance throughout the month ahead

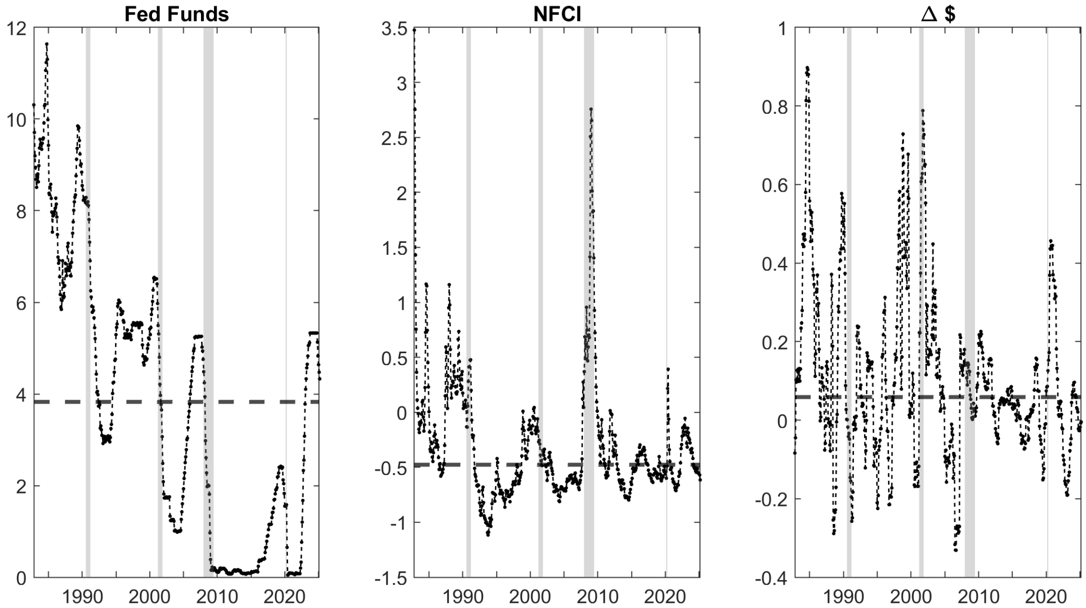
$$OI_{d=t-d,t}^{w=i} = \alpha_i + \gamma_i\; r_{EoM,t-1} + \epsilon_{w=i,t}$$

where for $w = 1$ I consider the order imbalance in the days between $19 \leq t-d \leq 15$, for $w = 2$ the days between $14 \leq t-d \leq 10$, for $w = 3$ the days between $9 \leq t-d \leq 5$, and for $w = 4$ the days between $4 \leq t-d \leq 0$ and t is the last trading day. In brackets, I report t-statistics. The data for the daily order imbalance is from ANcerno; the sample period goes from January 2000 to December 2010.

trade against the previous end-of-month return, likely to rebalance their previous week positions, but later move in the same direction as the proposed predictor.

Overall, the results based on ANcerno data—more granular in trader classification and frequency but covering a much shorter sample—are consistent with the findings reported in the main text.

Figure 1.B: Economic Variables Evolution over Time



This figure shows the evolution over time of average monthly fed funds, NFCI, and cash growth rate. For each plot, the horizontal line represents the sample median value. The time window goes from September 1982 to February 2025.

B.4 Economic Evidence Appendix

B.4.1 Order Imbalance across Business Cycle

Table 3.B reports pension funds' order imbalance for each trading day in the last week, splitting the sample between expansion (106 obs.) and recession (26 obs.) periods. The exercise hints that the results presented in the main body of the paper do not depend on outliers during the great financial crisis. During recession periods, most of the selling activity clusters on the last trading, and no clear pattern emerges between $t-4$ and $t-1$.

B.4.2 Order Imbalance across Stocks

Table 4.B reports the order imbalance for each trading day in the last week for S&P 500 constituents and remaining stocks. The results are consistent with the fact that institutional investors concentrate their selling on liquid stock to minimize trading cost and fees.

Table 3.B: Last Week Pension Plan Sponsor Trading Activity Across Business Cycle

	$t-4$	$t-3$	$t-2$	$t-1$	t	Weekly
EXP	-5.808%	-5.079%	-4.422%	0.788%	2.663%	-2.352%
	[-3.260]	[-3.183]	[-2.940]	[0.496]	[1.410]	[-1.763]
REC	-4.204%	-6.547%	5.162%	-6.160%	-8.556%	-8.295%
	[-0.956]	[-2.176]	[1.538]	[-1.151]	[-1.736]	[-2.125]

This table reports in the first five columns the order imbalance on S&P 500 constituents stocks for each day in the last trading week (where t is the last day of the month), differentiating between expansion and recession periods. In the last column, I report the overall imbalance in last week's order. In brackets, I report the associated t-statistic against the null hypothesis of a zero-order imbalance. The Data is ANcerno, and the sample period goes from January 2000 to December 2010.

Table 4.B: Last Week Pension Plan Sponsor Trading Activity Across Stocks

	$t-4$	$t-3$	$t-2$	$t-1$	t	Weekly
ALL	-3.461%	-3.691%	-1.978%	1.239%	5.139%	-0.706%
	[-2.432]	[-3.097]	[-1.709]	[0.873]	[3.587]	[-0.644]
S&P 500	-5.492%	-5.369%	-2.534%	-0.581%	0.453%	-3.522%
	[-3.299]	[-3.813]	[-1.796]	[-0.350]	[0.247]	[-2.655]
NO S&P 500	-2.039%	-2.207%	-1.416%	3.235%	8.870%	1.867%
	[-1.318]	[-1.613]	[-1.084]	[2.218]	[5.842]	[1.690]

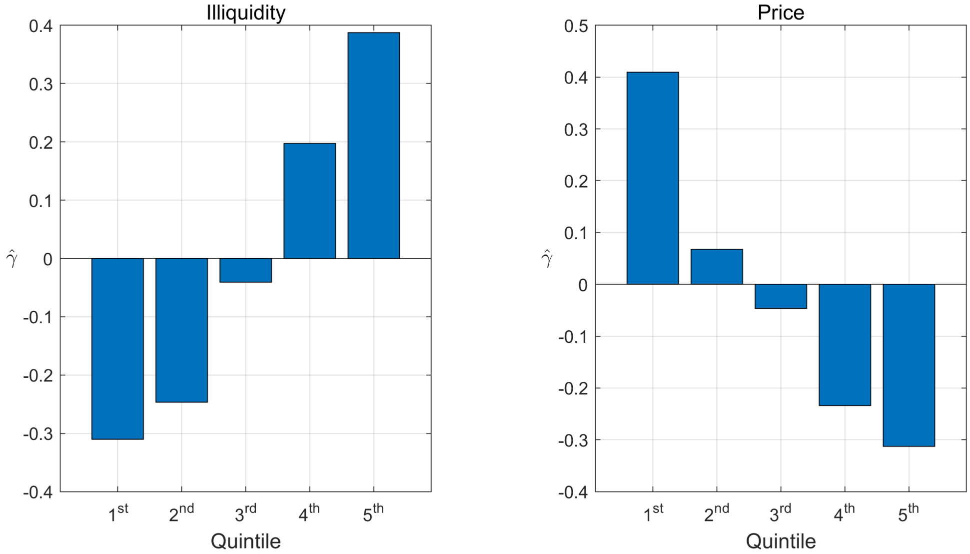
This table reports in the first five columns the order imbalance on all the ANcerno dataset, S&P 500 constituents and non-constituents stocks for each day in the last trading week (where t is the last day of the month). In the last column, I report the overall imbalance in last week's order. In brackets, I report the associated t-statistic against the null hypothesis of a zero-order imbalance. The Data is ANcerno, and the sample period goes from January 2000 to December 2010.

B.4.3 Aggregate Reversal and Stock Characteristics

In this section, I analyze all common stocks traded on NYSE and NASDAQ markets using the daily CRSP file from January 1985 to December 2019. For each stock time series, I calculate the average Amihud illiquidity ratio and average stock price, and I sort the stocks into quintiles based on these measures. I then construct equally-weighted indexes formed on each metric and perform standard predictive equations.[23]

[23]From CRSP, I select only traded stocks with exchange variable *EXCHG* equal to either 11, 12, or 14. Due to data availability, of the 1.8 Millions observations, the independent variable is the $t-4$ end of month return ($r_{d=t-4,t}$) 56% of the time; otherwise, I consider $r_{d=t-3,t}$ (23%). Finally, if both returns are not available, the independent variable is the difference between the monthly closing price and the

Figure 2.B: Stock Characteristics and Reversal Pattern



This figure reports the estimated γ coefficient of the following prediction equations:

$$r_{t+1}^{sc_q} = \alpha_{sc} + \gamma_{sc} r_{EOM,t}^{sc_q} + \epsilon_{t+1}$$

where $r_{t+1}^{sc_q}$ ($r_{t+1}^{sc_q} = \frac{1}{N}\sum_{i=1}^{N} r_{t+1}^{i \in sc_q} = \frac{1}{N}\sum_{i=1}^{N} p_{t+1}^{i \in sc_q} - p_t^{i \in sc_q}$) is one month ahead return of the equally value-weighted return of a portfolio sorted into quintiles q on stock characteristic sc. The stock characteristics considered are the Amihud illiquidity measure (the fifth being the most illiquid portfolio) and stock price (the fifth being the most highly priced portfolio). Stocks are sorted into quintiles each month. The Data is CRSP: the sample includes 15701 stocks, and the time window goes from January 1985 to December 2019.

The differences in estimated coefficients for top-bottom quintiles are significant at 1% level: Figure 2.B shows a clear trend: a negative correlation characterizes high-priced and liquid stocks. In contrast, a positive correlation characterizes illiquid and low-priced stocks, consistent with stale price theories.

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average price in the last 5 days. The Amihud illiquidity ratio for each stock is calculated at a monthly frequency:

$$AH_t = \frac{1}{D}\sum_{i=1}^{D} \frac{|r_{d=i,t}|}{\$VOL_{d=i,t}}$$

where D is the number of daily trading records in month t (for each month, I require at least 12 daily observations), $|r_{d=i,d}|$ is the absolute daily return and $\$VOL_{d=i,d}$ is the daily dollar volume. Daily returns are measured as the difference between two consecutive log prices. I then consider normal returns to construct the portfolios. I sort the stocks in quintile each month, results do not change qualitatively by sorting stocks on the entire time series.

B.4.4 Evidence on other Indices

Table 5.B provides institutional information as well as the time window for each index considered in Table 10.

Table 5.B: Other Indices: Descriptive Information

Index	Region/Country	Initial Date	End Date
DoW Jones 30	U.S.A.	30/09/1982	28/02/2025
Russell 2000	U.S.A.	30/09/1982	28/02/2025
EUSTOXX 50	Europe Union (EU)	30/01/1987	28/02/2025
S&P/TSX	Canada (CAN)	30/10/1984	28/02/2025
S&P/ASX 200	Australia (AUS)	30/06/1992	28/02/2025
NIKKEI 225	Japan (JAP)	31/01/1990	28/02/2025
FTSE 100	England (ENG)	31/01/1986	28/02/2025

This table reports the list of indices considered in Table 10. For each index, I report the region-country of the index constituents and the time window considered. Data is from the "Wall Street Journal", except for the Russell 2000 index, which is obtained from Eikon.

B.5 Potential Other Explanation of Reversal Pattern

B.5.1 Compensation for Standard Liquidity Risk Factors

The proposed predictor can not be regarded as a standard liquidity factor as, intuitively, the aggregate reversal predictability is cyclical and tends to cluster around high-quality stocks. Therefore, as standard in the literature, gains from liquidity provision should decrease following lower risk. To provide further evidence, Table 6.B reports the percentage annualized adjusted alphas of the TSR strategy against four anomalies in Dong et al. (2022) pricing liquidity: RETVOL, DOLVOL, IDIOVOL,and ILLIQ.[24]

[24] *RETVOL* sorts stocks into deciles based on return volatility for the previous month. *DOLVOL* sorts stocks based on dollar trading volume of the last 2 months. *IDIOVOL* sorts stocks based on idiosyncratic return volatility. *ILLIQ* sorts stocks based on yearly Amihud ratio.

Table 6.B: Compensation for Standard Liquidity Compensation

	RETVOL	DOLVOL	IDIOVOL	ILLIQ	ALL
$\alpha(\%)$	15.982	16.923	14.705	15.987	17.694
	[5.01]	[4.96]	[4.49]	[4.49]	[5.55]

This table reports the estimated annualized $\alpha(\%)$ of the following regression:

$$TSR_t = \alpha + \beta\, CS_t + \epsilon_t$$

where TSR_t is the reversal trading strategy presented in Section 2.4 and the control strategies are the liquidity factors in Dong et al. (2022) pricing liquidity (RETVOL, DOLVOL, IDIOVOL,and ILLIQ). The time window goes from March 1991 to December 2017. In brackets, I report robust Newey and West (1987) t-statistics.

B.5.2 Over-Confidence Channel

A standard explanation of reversal is due to market over-reaction. Among many examples, Odean (1998) proposes a model in which overconfident traders increase market volume and volatility and, by over-weighting information, cause market reversal. Therefore, I study whether the overconfidence of market participants could be the economic source behind the results.

To measure overconfidence in the stock market, I consider the standard Baker and Wurgler (2006) 's investor sentiment indexes: $SENT$ (based on the first principal component of five sentiment proxies), and $SENT^{\perp}$ (based on the first principal component of five sentiment proxies where each of the proxies has first been orthogonalized to a set of six macroeconomic indicators).[25] The variables' objective is to capture "a belief about future cash-flows and investment risks that is not justified by the facts at hand", Baker and Wurgler (2007). I perform the standard predictive regression

$$r_{t+1} = \alpha + \gamma\, r_{EoM,t} + \beta BF_t^i + \epsilon_{t+1}$$

[25]To not introduce measurement errors, I use sentiment indexes directly provided by their authors (monthly values). The monthly dimension is a valid frequency as Baker and Wurgler (2006) show that investors still react to month-old sentiment measures. I work with sentiment values ($SENT_t$) and not with the first difference ($\Delta SENT_t = SENT_t - SENT_{t-1}$) as the authors recommend not to consider lag versions of the sentiment variables as changes in sentiment.

Table 7.B shows that $r_{w=4,t}$ predicts the stock market through a channel not captured by the control variables, as the coefficient attached to $r_{w=4,t}$ does not change in terms of magnitude and significance.

Table 7.B: Market Over-Confidence

α	0.008	α	0.009	α	0.010	α	0.009
	[3.93]		[4.38]		[4.37]		[4.00]
$r_{EoM,t}$	-0.354	$r_{EoM,t}$	-0.367	$r_{EoM,t}$	-0.365	$r_{EoM,t}$	-0.367
	[-3.14]		[-3.25]		[-3.24]		[-3.23]
		$SENT_t$	-0.005	$SENT_t^{\perp}$	-0.006	$SENT_t$	-0.005
			[-1.75]		[-1.66]		[-0.42]
						$SENT_t^{\perp}$	-0.001
							[-0.05]
N	491		491		491		491
$Adj.R^2$	0.03		0.04		0.04		0.04

This table reports the results of the following Predictive regression:

$$r_{t+1} = \alpha + \gamma\ r_{EoM,t} + \beta\ SENT_t^i + \epsilon_{t+1}$$

In brackets, I report robust Newey and West (1987) t-statistics. The sample period goes from September 1982 to December 2023.

B.5.3 Option Expiration Effect

In this section, I provide evidence that the results are not driven by the S&P 500 option expiration on the third Friday of the month. Specifically, Cao, Chordia, and Zhan (2021) argues that the expiration triggers a selling pressure due to re-balancing activities, and the magnitude increases with volatility. The intuition is that investors are more likely to liquidate the option-exercise-created positions in the more risky and volatile stocks.

In Table 8.B, I show that the reversal pattern discussed in the main body of the paper does not depend on increased volatility in the third week of the month. I measure a spike in volatility around option expiration through $\Delta vix_{OE,t} = vix_{w=3,t} - vix_{w=1,t}$.

Table 8.B: Option Expiration Channel

				Low Δvix_{OE}	High Δvix_{OE}
α	0.007	α	0.007	0.006	0.008
	[3.03]		[3.05]	[1.82]	[2.51]
$r_{EoM,t}$	-0.286	$r_{EoM,t}$	-0.297	-0.395	-0.255
	[-2.73]		[-2.86]	[-1.68]	[-1.67]
		Δvix_{OE}	0.010		
			[0.67]		
N	391		391	196	195
$Adj.R^2$	0.02		0.02	0.02	0.03

This table reports in the first two columns the results of the following Predictive regression:

$$r_{t+1} = \alpha + \gamma\, r_{EoM,t} + \beta\, \Delta vix_{OE,t} + \epsilon_{t+1}$$

In the third and fourth columns, I split the sample according to the median value Δvix_{OE} and run a predictive regression for both regimes. In brackets, I report robust t-statistics. The sample period goes from January 1990 to July 2022.

B.5.4 Quarterly Robustness Check

In this section, I investigate whether the reversal pattern between $r_{EoM,t}$ and r_{t+1} is a consequence of quarterly rebalancing and reports. Hence, I split the full sample (September 1982 - February 2025) between end-of- and non-end-of-quarter months. The results presented in Table 9.B show that for both subsamples, the serial correlation is negative and statistically significant, therefore the pattern documented in the main body of the paper could not be rationalized only due to a "quarter effect". However, at the end of quarter months, the reversal pattern is stronger. Intuitively, when institutional investors face stronger liquidity constraints due to legal requirements, they increase the non-informational selling.

B.5.5 Pension Funds Rebalancing

Pension funds are unlikely to sell at the end of the month due to legal constraints. U.S. pension funds do not typically face specific asset allocation restrictions related to portfolio

Table 9.B: Quarterly Rebalancing Effect

α	0.008	0.008	0.008
	[4.12]	[3.87]	[4.08]
$(1-\mathbf{I}_t^Q) \times r_{EoM,t}$	-0.273		-0.272
	[-2.14]		[-2.13]
$\mathbf{I}_t^Q \times r_{EoM,t}$		-0.769	-0.768
		[-2.85]	[-2.85]
N	509	509	509
$Adj.R^2$	0.02	0.03	0.04

This table reports the correlation coefficient of $r_{t+1} = \alpha + \gamma_1(1-\mathbf{I}_t^Q) \times r_{EoM,t} + \gamma_2\mathbf{I}_t^Q \times r_{EoM,t} + \varepsilon_{t+1}$ where $\mathbf{I}^Q$ is an indicator function equal to 1 when month t is an end of quarter month. In brackets, I report robust Newey and West (1987) t-statistics. The sample period goes from September 1982 to February 2025.

weights (see Survey of Investment regulation of pension funds, OECD Secretariat). The only notable limitation applies to self-managed defined benefit (DB) plans, such as, for example, Boeing's pension fund, which cannot hold more than 10% of shares in their parent company to reduce idiosyncratic risk. However, this restriction is unlikely to be significant for most pension funds, as they generally operate as independent trustees managing portfolios for multiple clients. Additionally, many of the largest pension funds serve state employees, and this limitation does not apply to them.

A potential concern is that pension funds might rebalance their portfolios at the end of the month purely as a matter of convention. However, the trading behavior of pension plan sponsors in the ANcerno dataset reveals that even though each pension plan sponsor sells (buys) on average 79 (71) S&P 500 stocks at the end of each month, the top two stocks sold (bought) from each institution account for around 60% of the total average signed flow.[26]

Harvey et al. (2025) propose a calendar-based signal to capture institutional investors' rebalancing activity. Consistent with liquidity-driven trading at month-end, they show

[26] If we consider the entire ANcerno dataset, each pension plan sponsor sells (buys) around 274 (257) stocks at month end, but the top 2 stocks define 40% (42%) total order flow respectively.

that the predictive power of their calendar signal peaks during the final week of the month ($Calendar \times Week4$). Interestingly, the end-of-month return and their calendar predictor are (i) negatively correlated (-0.153), (ii) capture a different horizon predictability, and (iii) features different business cycle properties, suggesting they capture different underlying mechanisms. Supporting this interpretation, Table 10.B examines the daily specification from Harvey et al. (2025), controlling for $r_{EoM,t}$. Even when forecasting daily returns one month ahead and controlling for contemporaneous intra-month returns through the calendar-based signal, the predictability of the previous end-of-month return remains statistically significant. Notably, both main predictors—r_{EoM} and $Calendar \times Week4$—keep their significance and magnitude across specifications, reinforcing the idea that they reflect distinct predictability channels. These differences are consistent with Andonov et al. (2025), who document that rebalancing and liquidity trading are disconnected in pension-plan decision-making.[27]

B.5.6 Information Release

In this section, I examine whether the results could be caused by informational trading. I construct a time series on the most important U.S. economic announcements (announcements on GDP, CPI, WPI, PPI, Fed Interest, and Unemployment) by web-scraping Investing. Figure 3.B shows that very few announcements are released in the last week, around 13% of entire series.[28] Considering the time series before 2005, the percentage halves.

[27]Appendix A.1.3 supports this interpretation by showing that the reversal pattern is robust by excluding the first part of the month ahead— the period the calendar signal exhibits its predictability. Running the same daily regression proposed in Table 10.B from the launch of the E-Mini S&P 500 futures (September 1997) yields a negative coefficient attached to r_{EoM} but only almost statistically significant.

[28]The announcements in the last week are mostly quarter-on-quarter GDP (72%) and Fed Interest announcements (22%).

Table 10.B: End Of Month Rebalancing

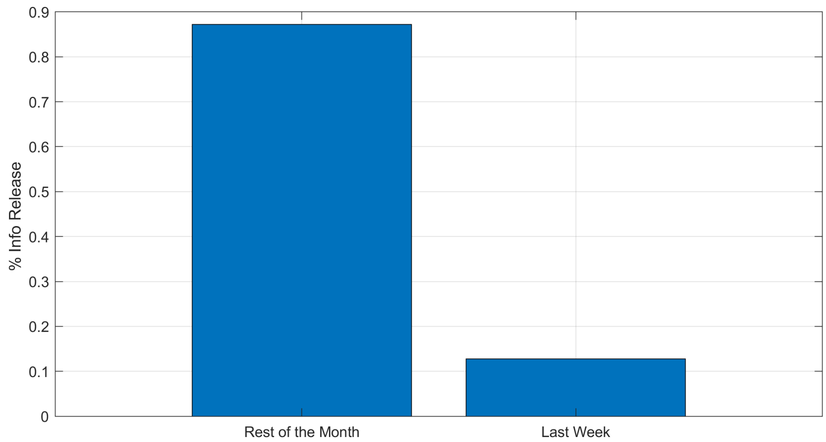
α	0.000	0.000	0.000
	[3.88]	[1.61]	[1.94]
$r_{EoM,t-1}$	-0.017		-0.022
	[-2.59]		[-2.96]
$Cal_{d=i,t}$		-0.036	-0.044
		[-1.36]	[-1.68]
$Week4_{d=i,t}$		0.001	0.001
		[3.18]	[3.24]
$Cal_{d=i,t} \times Week4_{d=i,t}$		-0.184	-0.183
		[-2.99]	[-3.00]
N	10784	10784	10784
$Adj.R^2$	0.00	0.01	0.01

This table reports the estimated coefficients of

$$r^{S\&P}_{d=i+1,t} = \alpha + \gamma r_{EoM,t-1} + \beta_1 Cal_{d=i,t} + \beta_2 Week4_{d=i,t} + \beta_3 Cal_{d=i,t} \times Week4_{d=i,t} + \varepsilon_{d=i+1,t}$$

where $r^{S\&P}_{d=i+1,t}$ are daily log returns in the S&P 500, Cal is the calendar signal defined in Harvey et al. (2025) and $Week4$ is a binary variable equal to 1 in the last 5 trading days. In brackets, I report robust Newey and West (1987) t-statistics. The sample period goes from September 1982 to February 2025.

Figure 3.B: Economic Announcements during the Month



This figure reports the percentage frequency of economic announcements in the last week of the month. The time series is constructed by web-scraping Investing and focusing on announcements on GDP, CPI, WPI, PPI, Fed Interest, and Unemployment). The sample period goes from January 2005 to December 2019.