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

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Abstract

This paper introduces a novel aggregate reversal strategy that exploits monthly calendar effects. Specifically, I show that the end-of-the-month return of the S&P500 negatively correlates with one-month ahead returns. Contrary to the cross-sectional findings, strategies based on the novel aggregate pattern are extremely cost-effective, easy to implement, cyclical, and do not require short-selling. This novel pattern is consistent with pension funds' liquidity trading to meet pension payment obligations.

Keywords: pension funds, liquidity, time series, flows, reversal, predictability.

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1 Introduction

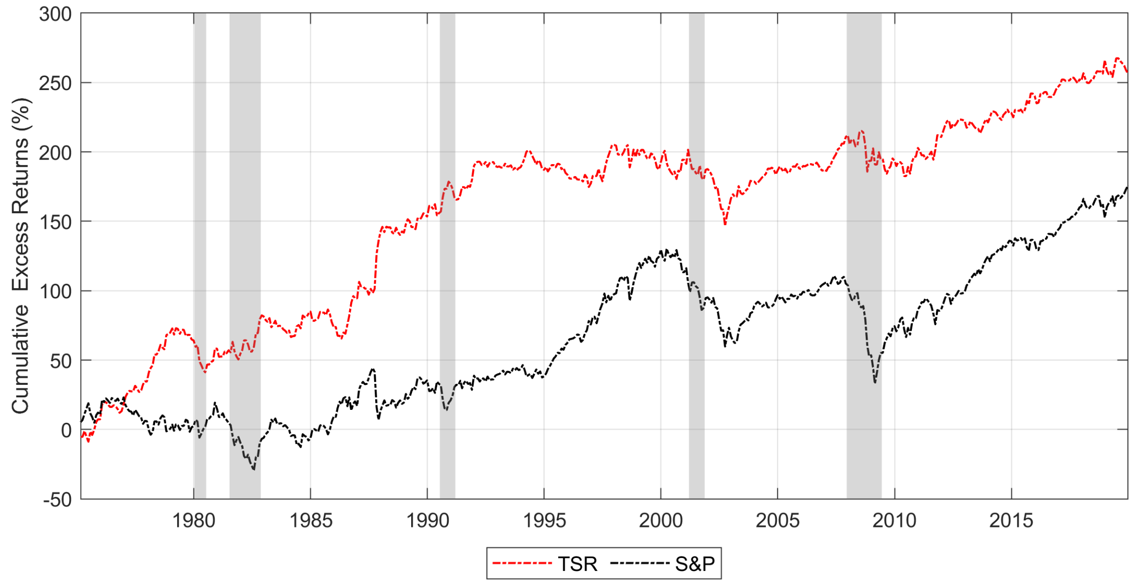
One of the core questions in asset pricing is whether and how financial markets revert to shocks. At the cross-sectional level, ever since Jegadeesh (1990), the literature has extensively documented a 1-month reversal. In addition, two stylized facts have emerged. First, cross-sectional reversal concentrates 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) notes: "*[...] much less is known about the speed and extent one should expect entire markets to reverse price pressure.*" My paper addresses this critical gap by providing a novel strategy that times the market using information concentrated in the last week of the month. In addition, I document that this strategy (i) exhibits significant profitability; (ii) displays novel properties, and (iii) is consistent with pension funds liquidity shocks.

In the first part of the paper, I provide evidence of a 1-month aggregate market reversal in the S&P 500. Specifically, I show that *end-of-the-month* returns (i.e., the returns from the fourth Friday to the last trading day of the month) are negatively correlated with the one-month ahead returns. Figure 1 provides the most straightforward and intuitive evidence of this aggregate pattern. A simple rule of thumb trading strategy, of buying if the *end-of-the-month* return is negative and selling if it is positive, outperforms the buy and hold strategy over a 45-year window. The reversal strategy outperforms the passive benchmark in terms of raw returns, Sharpe ratio, and higher-moment statistics, even considering trading costs and fees. To further support that the reversal strategy effectively times the market, rather than increasing risk exposure, CAPM-adjusted (Jensen's) α are positive, sizable, and statistically significant (Table 2).

After exploring this intuitive estimation-free rule of thumb, I turn my attention to more conventional approaches commonly adopted in the literature. First, I focus on a standard predictive regression framework (Table 4) and show that the proposed predictor has a negative and statistically significant coefficient, regardless of the control variables (including past returns, investor

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 trading strategy buys (sells) the S&P 500 if the *end-of-the-month* return is negative (positive). The grey-shaded areas mark periods of recessions according to the NBER. The sample period is from January 1975 to December 2019.

attention, previously suggested predictors, factors, and anomalies), time window, or sub-sample considered. Second, following Welch and Goyal (2008), I focus on an Out-of-Sample predictive exercise (Table 5), and show that the proposed predictor outperforms the historical mean, that is, 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 of the *end-of-the-month* return significantly enhances its Out-of-Sample forecasting performance and robustness and is a novelty to both the reversal (Nagel, 2012) and forecasting (Huang, Jiang, Tu, and Zhou, 2014) literature.

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 (Table 6). The time-varying strategy significantly outperforms both passive investing and the simple rule-of-thumb reversal strategy, implying that the predictability is statistically significant and, most importantly, economically meaningful. In addition, I show that the reversal pattern also extends to the Dow Jones index, which consists of 30 of the most highly capitalized and liquid American companies. This result suggests that the pattern is not unique to the S&P 500 since it generally extends to highly-priced and liquid American stocks (Table 7). In the Appendix, I perform several robustness checks in order to 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 explore several potential mechanisms that could explain my predictability results. I reject all of them except for one. Specifically, I note that the end of the month is a critical period in the U.S. economy, marked by large financial transfers, including benefits, salaries, and pensions (payment cycle). I argue that pension payments drive the observed empirical evidence, as they are substantial, exclusively paid at the end of the month, and funded by defined benefit pension plans. These plans are notoriously underfunded (Merton, 2008) and hence likely to sell off assets to raise liquidity and pay their obligations (Etula, Rinne, Suominen, and Vaittinen, 2020). Leveraging daily institutional trading data from the ANcerno dataset, I find evidence that pension plan sponsors are net sellers at the end of the month (Table 8). Consequently, the payment cycle may create a temporary selling pressure in the market that causes a negative *end-of-the-month* return and is followed by a rebound in the next month.

I rationalize these empirical results by introducing a stylized three-period model based on Vayanos and Gromb (2012). In the first period, a non-informational liquidity shock affects the equilibrium price, reflecting the price pressure caused by end-of-month liquidity trading. The second period represents the time the market takes to recover from this shock, corresponding to the one-month reversal observed in the data. This model delivers two relevant empirical predictions. First, consistent with Grossman and Miller (1988) and Sentana and Wadhwani (1992), among others, the reversal pattern intensifies with both the size of the supply shock and the stock's riskiness. Intuitively, a larger shock to a riskier asset leads to a greater price impact. This prediction is consistent with my data, as the reversal pattern is more pronounced in months with higher end-of-month volume and volatility (Table 9). Second, the reversal pattern should increase by the time the market absorbs the shock. By cumulating the returns throughout the one month ahead, I show that the reversal pattern peaks a week before the end of the following month (Figure 4). Notably, the coefficients are statistically significant starting from the end of the second week, coinciding with the inflow period when pension funds can buy back. The pattern peaks in the third week, just before a new potential supply shock hits the market, leading to a downward pressure on prices.

In order to provide additional evidence in favour of the payment cycle channel, I run additional tests. I establish that my novel predictability evidence is stronger in months with lower pension funds' inflows and higher end-of-month borrowing costs (Figure 5). Intuitively, the reversal pattern is stronger when pension funds face a large cash flow imbalance or a more expensive outside borrowing option. The cyclical nature of my reversal pattern is consistent with the evidence that pension funds reduce precautionary cash reserves during stable periods. With a smaller liquidity buffer to cover end-of-month needs and facing a rising market, pension funds have a greater incentive to sell off assets to recoup liquidity.

Additionally, the fact that my reversal pattern is concentrated on 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 size, assets under management, and liquidity imbalance. In the Appendix, I consider competing explanation channels (compensation for standard liquidity factors, behavioral bias, option expiration trading, quarterly activity, information release, and pension funds re-balancing) and find no coherent results.

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.[1]

[1] Lo and MacKinlay (1990) show that the positive cross-correlation of the portfolio's constituents and not necessarily the negative auto-correlation of each stock could explain the results of the two cross-sectional approaches. Conrad and Kaul (1993) show that cumulating short-term returns over long periods can generate an upward bias.

Second, these findings are more pronounced for small and illiquid stocks, raising concerns about 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). 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 and novel to the literature, I provide evidence of a monthly reversal pattern at the aggregate level using the *end-of-the-month* return as predictor. Second, contrary to the cross-sectional findings (e.g., Avramov et al. 2006, Nagel 2012, and Dai et al. 2023), the one-month aggregate market reversal concentrates on high-quality stocks forming the most liquid and traded assets (S&P 500) and it spikes in periods of economic expansion. Third, this paper corroborates a market-based explanation of the reversal pattern. Consistent with the Grossman and Miller (1988) model, 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). Importantly, momentum predictors suffer two significant 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)), making (i) their predictability prone to sample bias (Goyal, Welch, and Zafirov, 2021), and (ii) the implied returns net of fees close to zero. Second, the predictors are too persistent and exhibit inferior forecasting power (Ren, Tu, and Yi 2019). My contribution to the forecasting literature

Zarowin (1990) shows that if loser firms are lower priced than winner firms, returns to the contrarian strategy will have a spurious upward drift.

is twofold. First, I propose a novel predictor that avoids both of the abovementioned limitations. Second, my statistical Out-of-Sample predictability translates to significant economic gains thanks to strategies that are easy to implement and based only on the S&P 500.

Finally, this study connects to the broader literature on market flows and their impact on aggregate prices (see, among others, 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 provide evidence that the payment cycle represents a moment of market liquidity distress. In contrast to prior work, I provide evidence that liquidity trading driven by the payment cycle is pervasive enough to generate a monthly aggregate market reversal. As in Hartzmark and Solomon (2022), I use price pressure to establish aggregate market predictability. Importantly, this study provides empirical insights into two key questions raised by Hartzmark and Solomon (2022): first, whether and how aggregate markets revert price pressure, and second, what are the economic sources behind market flows.

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

2 Establishing the pattern

2.1 Data

To determine aggregate market reversal, I collect S&P 500 closing prices from the Global Financial Data (GFD) from January 1975 to December 2019. I focus on data from January 1975 onwards as Vanguard launched its first index fund on the S&P 500 in 1975, marking a key moment in the development of index investing. In the paper, I denote nominal values in capital letters and the respective natural logarithm values in lowercase. Since I use daily, weekly, and monthly time series, I adopt the convention of a composite suffix: I use t to denote a generic month and add w (d) to specify the week (day). For example, p_t is the log closing price in month t, whereas $p_{d=i,t}$ is the i^{th} log closing price in month t.

The novel predictor is the *end-of-the-month* return: the realized return between the 4^{th} Friday

Table 1: Summary Statistics

	Mean(%)	Std. Dev.(%)	Min(%)	Max(%)	Obs.
r_{t+1}	0.326	4.265	-24.992	11.889	540
$r_{w=4,t}$	0.188	1.660	-7.044	9.976	540

This table reports the mean, standard deviation, minimum, maximum, and number of observations for the excess month return (r_{t+1}), and the *end-of-the-month* return ($r_{w=4,t}$). The sample period is from January 1975 to December 2019.

closing price $p_{w=4,t}$ and the monthly closing price p_t. The predicted return is the standard excess monthly return ($r_t = p_t - p_{t-1} - r_t^f$). Table 1 reports the mean, standard deviation, minimum, maximum, and number of observations for both variables. The statistics, in line with Welch and Goyal (2008) and Neely et al. (2014), among others, show that by considering a longer time window, returns tend to display a larger mean and dispersion.

2.2 A Simple Rule of Thumb

My starting point is to provide suggestive evidence of a negative relationship between the *end-of-the-month* return ($r_{w=4,t}$) and the 1-month ahead excess return (r_{t+1}) by considering an estimation-free predictability exercise. Specifically, I assess the monetary value of the following long-short trading strategy:

$$TSR_t = \begin{cases} +r_{t+1} & \text{if } r_{w=4,t} < 0 \\ -r_{t+1} & \text{if } r_{w=4,t} > 0 \end{cases} \tag{1}$$

The strategy in equation (1) takes a market exposure by leveraging on the potential negative correlation between $r_{w=4,t}$ and r_{t+1}. Simply put, the strategy defined in equation (1) involves buying 1 unit of the S&P 500 if the *end-of-the-month* return is negative, and selling if the return is positive. Notably, the strategy is based only on $r_{w=4,t}$ return and, therefore, depends neither on the specific forecasting method nor the chosen training sample. Overall, the exercise can be considered an empirical rule of thumb to intuitively test the reversal pattern between $r_{w=4,t}$ and r_{t+1}.

I compare the reversal strategy against the S&P 500 itself and the 12-Month Momentum:

$$S\&P_t = +r_{t+1} \qquad MOM_t = \begin{cases} +r_{t+1} & \text{if } r_{t-12} > 0 \\ -r_{t+1} & \text{if } r_{t-12} < 0 \end{cases}$$

where $r_{t-12} = p_t - p_{t-12}$. The S&P 500 is the natural benchmark as it captures the gains from passive investing on the index. Given the generally positive trend in a multi-year time window horizon, the index is a challenging benchmark to outperform. While empirical support for time series reversal remains limited, the literature has extensively investigated time-series momentum (Moskowitz et al., 2012). In contrast to the proposed reversal pattern, which is based on a short-term negative correlation, time series momentum captures a positive correlation between the past 1-year return and the one-month-ahead return. Therefore, the 12-month momentum strategy also serves as a natural benchmark.

Table 2 reports the percentage of annual average excess return, Sharpe ratio, standard deviation, kurtosis, skewness, and market adjusted α for all trading strategies. The time series reversal strategy outperforms the two benchmarks in terms of both average realized returns and standard deviation over time. Consequently, its Sharpe ratio improves sizably. Regarding higher-order statistics, the TSR_t is the only strategy with positive skewness, suggesting that the strategy consistently delivers positive returns over time. Finally, in line with log-return properties, all the trading strategies display a kurtosis close to zero, hinting at a bell-shaped return distribution.

The last column in Table 2 reports CAPM-adjusted alphas obtained by the following regression:

$$TS_t = \alpha + \beta \ S\&P_t + \epsilon_t$$

where TS_t is either the time series reversal (TSR_t) or the momentum (MOM_t) strategy. The coefficient β captures the strategy's exposure to a passive investing strategy, whereas the α measures the trading strategy's excess returns on top of the index once adjusted for risks. The TSR_t strategy delivers positive and statistically significant adjusted α. Therefore, considering both higher moments statistics and adjusted alphas, the TSR strategy delivers higher returns due to its ability to better times the market, suggesting investors have an economic incentive

Table 2: Simple Rule of Thumb

	Mean Exc. Ret.(%)	Sharpe Ratio	Std. Dev.	Skewness	Kurtosis	α(%)
TSR	5.702	0.399	0.143	0.066	0.525	5.537**
MOM	3.858	0.261	0.148	−0.124	0.488	2.562
S&P	3.916	0.265	0.148	−0.248	0.499	

This table reports annualized mean excess returns, Sharpe Ratio, Standard Deviation, Skewness, Kurtosis, and CAPM-adjusted alphas (α) for the time series reversal (TSR), momentum (MOM) and passive investing ($S\&P$) strategies. $***$, $**$, 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 January 1975 to December 2019.

to switch from a passive stance to the TSR strategy. Conversely, the momentum strategy does not deliver statistically significant adjusted alphas. Although it is positively correlated with the market, most of its gains occur during periods of economic downturn (Figure 2).

To understand why the short-term reversal strategy delivers sizable and statistically significant adjusted alphas, I decompose the strategy into the long (TSR_t^L) and short (TSR_t^S) leg:

$$TSR_t^L = \begin{cases} +r_{t+1} & \text{if } r_{w=4,t} < 0 \\ 0 & \text{if } r_{w=4,t} \geq 0 \end{cases} \qquad TSR_t^S = \begin{cases} 0 & \text{if } r_{w=4,t} \leq 0 \\ -r_{t+1} & \text{if } r_{w=4,t} > 0 \end{cases}$$

Each strategy buys the risk-free asset in months without a market exposure, hence delivering a zero excess return during those periods. Table 3 reports the annual average excess return, Sharpe ratio, CAPM-adjusted α, market exposure, and activity percentage. The mean excess returns suggest that most of the economic gains of the TSR strategy concentrate on the long leg, whereas the short leg delivers small but still positive economic gains. As expected, the positive leg has a positive market exposure, while the negative leg has a negative market exposure. Both β are close to 0.5 in absolute terms as the TSR strategy almost equally splits between the two sub-strategies (specifically, the TSR buys 44% and sells 56% of the times the index). Consequently, the TSR strategy has zero market exposure since the two legs cancel each other out in the aggregate.

Both sub-strategies deliver positive and significantly adjusted alphas. Intuitively, the positive leg achieves higher raw returns than the index, being exposed to the market almost half the time. The negative leg, on the other hand, pays off in periods of market downturn (Figure 2), defining a natural hedge over the benchmark. Consequently, the TSR strategy benefits from

Table 3: Decomposition TSR strategy

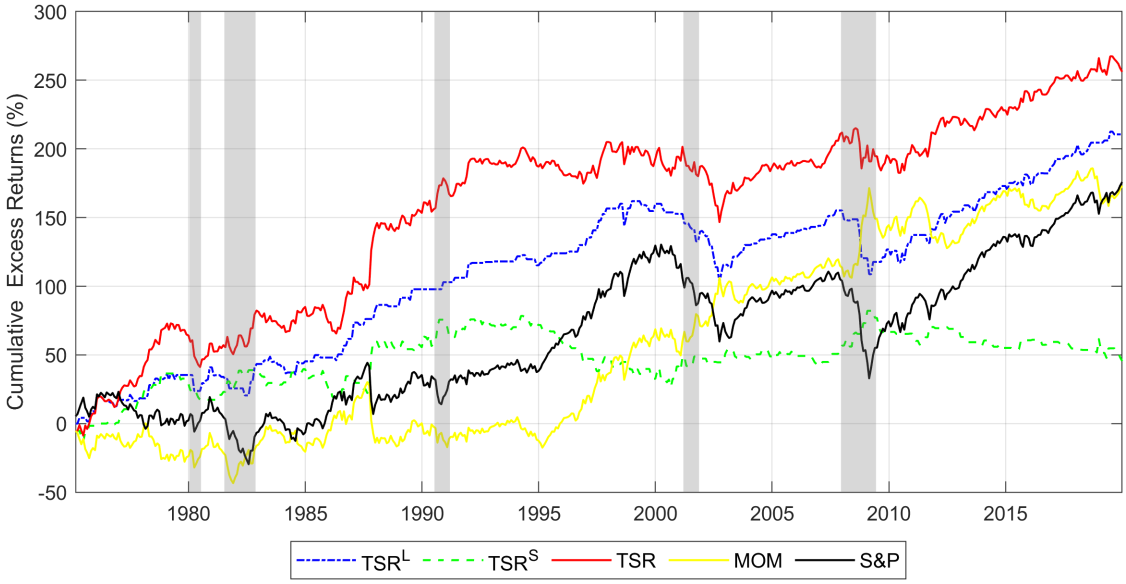
	Mean Exc. Ret. (%)	Sharpe Ratio	α(%)	β	Activity (%)
TSR^L	4.689	0.453	2.763**	0.492***	0.44
TSR^S	1.014	0.103	2.774**	−0.450***	0.56
TSR	5.702	0.399	5.537**	0.042	

This table reports annualized mean excess returns, Sharpe Ratio, CAPM-adjusted alphas (α), market exposure (β), and Activity for the long, short, and long-short leg of the time series reversal strategy. $***$, $**$, 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 January 1975 to December 2019.

both sub-components. Notably, the decomposition of the TSR strategy hints that many market participants can use the short-run negative market predictability. Retail investors may choose to employ only the long leg to avoid the risks and costs associated with short-selling, thereby obtaining a remuneration over passive investing. Meanwhile, more sophisticated traders are incentivized to employ the full strategy, as the TSR improves performance by reducing market exposure, thereby increasing overall portfolio diversification.

Robustness. Overall, this intuitive exercise provides suggestive evidence of a negative correlation between $r_{w=4,t}$ and r_{t+1}. Appendix A.1 is devoted to the sensitivity analysis. Specifically, Appendix A.1.1 reports adjusted alphas considering various benchmarks. Appendix A.1.2 reports the results by extending the time window from 1950 to 2023. Appendix A.1.3 examines the potential impact of trading costs and fees. Appendix A.1.4 shows that the results are robust to the *end-of-the-month* return specification. Appendix A.1.5 reports the annual Sharpe Ratio through the years. Finally, Appendix A.1.6 shows the scatter plot TSR returns against the benchmarks. In the next section, I conduct standard tests in the literature to corroborate the negative short-term predictability channel.

Figure 2: Cumulative Monetary Gains Over Time



This figure presents the cumulative excess return obtained from a trading strategy using time series reversal (TSR - solid red line), momentum (MOM - solid yellow line), and S&P 500 (*S&P* - solid black line). Moreover, the plot reports the decomposition of the TSR strategy between the positive (TSR^L - blue dash line) and the short (TSR^S - green dash line) leg. The grey shaded areas mark periods of recessions according to the NBER indicator function. The sample period is from January 1975 to December 2019.

2.3 Evidence of Negative Market Predictability

2.3.1 In-Sample Evidence

As standard in the literature, I formally assess the predictability channel between $r_{w=4,t}$ and r_{t+1} via a benchmark predictive regression:

$$r_{t+1} = \alpha + \gamma \; r_{w=4,t} + \beta \; C_t + \epsilon_{t+1} \tag{2}$$

where γ captures the predictability associated with $r_{w=4,t}$, after accounting for the potential predictability explained by previously proposed control variables in the literature, C_t.

Table 4 reports the results for different specifications of equation (2). In the first column, I report the results without any control variable. In the second column, I control for previous *end-of-the-month* returns. In the third column, I control for the previous month return and time series momentum. 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.[2] In the fifth column, I control for the 3 Fama French augmented with the cross-sectional momentum and short-term reversal factors. From the sixth column, I control for the 5 Principal Components (PC) obtained from the 100 anomalies in Dong, Li, Rapach, and Zhou (2022).

The estimated coefficients attached to the *end-of-the-month* return are negative, qualitatively similar, and statistically significant across all the proposed specifications. The results corroborate the predictive relationship between $r_{w=4,t}$ and r_{t+1} and hint that the aggregate market reversal captures a new source of predictability.

Robustness. In Appendix A.2, I provide evidence that the results reported in Table 4 are robust. Specifically, Appendix A.2.1 shows that the results are qualitatively unchanged, considering different sub-samples. Appendix A.2.2 shows that the results are not exclusively driven by the ability of the reversal pattern to predict the first week of the month's return. Appendix A.2.3 shows that the results do not depend on a closing price effect. Appendix A.2.4 shows that the reversal pattern is lost by considering a placebo test around the second week of the month. Finally, Appendix A.2.5 shows that the time series reversal's predicting power vanishes after the first month.

[2] The authors argue that the negative correlation between r_{t+1} and A_t^i results from a reversal pattern. High attention induces investors to buy, resulting in temporary positive price pressure. The price dynamic tends to revert after the net buying flow slows down. To not introduce measurement errors, I use the variables from the authors' website and study the statistical relationship between January 1980 and December 2017.

Table 4: In Sample Evidence

α	0.004	α	0.004	α	0.004	α	0.005	α	0.004	α	0.004	0.004	0.004	0.004	0.004
	[2.00]		[1.94]		[1.42]		[0.56]		[1.96]		[2.03]	[2.04]	[2.09]	[2.10]	[2.10]
$r_{w=4,t}$	-0.353	$r_{w=4,t}$	-0.391	$r_{w=4,t}$	-0.367	$r_{w=4,t}$	-0.310	$r_{w=4,t}$	-0.361	$r_{w=4,t}$	-0.355	-0.354	-0.364	-0.364	-0.364
	[-3.78]		[-2.88]		[-3.67]		[-3.14]		[-3.75]		[-3.69]	[-3.69]	[-3.71]	[-3.72]	[-3.66]
		$r_{w=3,t}$	-0.005	r_t	0.048	A^{PCA}	0.001	MKT	0.000	PC1	0.001	0.001	0.001	0.001	0.001
			[-0.03]		[0.83]		[-2.05]		[0.64]		[2.56]	[2.59]	[2.50]	[2.44]	[2.44]
		$r_{w=2,t}$	0.069	r_{t-12}	-0.002	A^{PLS}	-0.021	SMB	0.001	PC2		0.000	0.000	0.000	0.000
			[0.47]		[-0.10]		[-0.99]		[0.91]			[-0.55]	[-0.55]	[-0.55]	[-0.55]
		$r_{w=1,t}$	-0.012			A^{sPCA}	-0.465	HML	-0.001	PC3			0.001	0.001	0.001
			[-0.13]				[2.51]		[-1.31]				[1.29]	[1.27]	[1.27]
								MOM	0.000	PC4				-0.001	-0.001
									[-0.95]					[-1.43]	[-1.42]
								REV	0.000	PC5					0.000
									[-0.40]						[0.02]
$R^2(\%)$	1.9		2.03		2.1		3.97		2.79		3.13	3.17	3.85	4.11	4.11
Obs	539		539		539		455		539		516	516	516	516	516

This table reports the estimation result of:

$$r_{t+1} = \alpha + \gamma\ r_{w=4,t} + \beta_i C_{i,t} + \varepsilon_{t+1}$$

where the control variables $C_{i,t}$ considered are previous *end-of-month* returns in the second column, monthly and year returns in the third column, Chen et al. (2022)'s investor attention proxies in the fourth column, the three Fama French augmented by Momentum and Short Reversal factors in the fifth column, the i^{th} Principal Components (PC) computed from the 100 anomalies portfolio returns in Dong et al. (2022) from the $6th$ column. In brackets, I report robust Newey and West (1987) t-statics. The sample period considered in the first, second, third, and fifth columns is from January 1975 to December 2019. The sample period in the fourth column is from January 1980 to December 2017, and in the sixth column onwards from January 1975 to December 2018. To avoid introducing measurement errors, I directly download the variables from the respective authors' websites.

2.3.2 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

$$r_{t+1|t} = \alpha_t + \gamma_t \; r_{w=4,t} + \epsilon_{t+1} \tag{3}$$

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 $\hat{r}_{t+1|t} = \hat{\alpha}_t + \hat{\gamma}_t \; r_{w=4,t}$. 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 April 1986 to December 2019 (75% of the entire sample for a total of 405 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 statistically compare the OOS results, I use Clark and West (2007) MSFE-adjusted statistic.[3]

The first column in Table 5 reports $R^{2,OS}$ over the entire evaluation period. The end-of-month return $r_{w=4,t}$ generates positive, sizable, and statistically significant OOS gains, with $R^{2,OS}$ of 1.307%. Conversely, the historical mean outperforms momentum: this finding is consistent with Huang, Li, Wang, and Zhou (2020), which shows that past 12-month returns do not have OOS

[3]The null hypothesis is that the benchmark historical average forecast delivers lower MSFE than the predictive regression forecast; the alternative hypothesis 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 5: Out of Sample Evidence

	$R^{2,OS}(\%)$	$R^{2,OS}_{exp}(\%)$	$R^{2,OS}_{rec}(\%)$
$r_{w=4,t}$	1.307**	2.142	-1.958
r_{t-12}	-0.088	-0.261	0.592

This table reports the Out-of-sample forecasting results compared to the historical mean for the time series reversal ($r_{w=4,t}$) 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 January 1975 to December 2019, and the out-sample valuation period starts from April 1986.

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 5 report $R^{2,OS}$ separately for expansion and recession periods. I use the National Bureau of Economic Research (NBER) dates of peaks and troughs to identify recessions and expansions ex-post, i.e., this information is not used in the estimation:

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

where I^{exp}_{t} (I^{rec}_{t}) 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).[4] Interestingly enough, the end-of-month return $r_{w=4,t}$ behaves very differently. The predictability concentrates during expansion periods, $R^{2,exp}_{OS} = 2.142\%$, but gets lost during recessions, with a large negative $R^{2,exp}_{OS}$ of -1.958%.

Overall, the results in Table 5 strongly corroborate the predictability pattern between $r_{w=4,t}$ and r_{t+1}. From an economic standpoint, the proposed predictor benefits from its cyclical pre-

[4]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.

dictability, a feature that is particularly valuable for improving forecasting accuracy and robustness. Given that the U.S. economy was in expansion for approximately 92% of the months between 1969 and 2019, making predictions during such periods provides a significant hedge over the historical mean and other proposed predictors. From a statistical standpoint, the results can be explained by the fact that equation (3) is a balanced predictive regression: $r_{w=4,t}$ matches the persistency of r_{t+1}, substantially improving its forecasting precision (Ren et al., 2019).[5]

Robustness. Appendix A.3 is devoted to the sensitivity analysis. Specifically, Appendix A.3.1 shows the cumulative forecast error over time. Appendix A.3.2 considers a longer Out-of-Sample time window. Finally, Appendix A.3.3 provides in-sample evidence that corroborates the cyclical nature of the aggregate reversal predictability.

2.4 Dynamic Reversal Trading Strategy

The previous sections formally assessed the aggregate market predictability of $r_{w=4,t}$. It is, therefore, worth investigating the economic value of such predictability. In the spirit of the optimal asset allocation approach in Campbell and Thompson (2008), I consider the returns of the following trading strategy:[6]

$$TSR - TV_t := \underbrace{\frac{r^{TSR}_{t+1|t}}{\sigma^2_{t+1|t}}}_{w^{TSR}_t} r_{t+1} \tag{4}$$

Intuitively, the direction and the amount invested on the risky asset depend on w^{TSR}_t. The parameter is the ratio between the 1-month ahead OOS forecast ($r^{TSR}_{t+1|t}$) over the return variance in the last quarter $\sigma^2_{t+1|t} = \sigma^2(\{r_i\}^{t-2}_{i=t})$. Unlike the rule-of-thumb strategy discussed in Section 2.2, the $TSR - TV$ strategy presented here dynamically adjusts both the investment direction

[5]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.

[6]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.

and the amount based on the OOS TSR forecast.

I impose two restrictions on the trading strategy. First, I allow the weight w_t^{TSR} to lie between -1 and 2. Hence, the strategy can short-sell at a maximum of 1 index unit but can buy on leverage. The assumption is rather conservative as the S&P 500 is among the financial instruments with the most available leveraged instruments, ranging from 5× ETFs to futures and options with double-digit leverage. Second, I restrict the trading strategy to have a market exposure ($w_t^{TSR} \neq 0$) only if $I_{t-1}^{NBER} = 0$. Intuitively, due to its cyclical predictability, the strategy aims to invest in the market only during expansion periods. Since the NBER indicator is released with a one-month lag, the strategy uses the previous month's value as the best proxy for the current economic state.

Table 6 reports the results for the rule of thumb strategy (TSR), time-varying strategy ($TSR - TV$), and the passive investing strategy ($S\&P$). These results highlight the marginal benefit for a real-time investor of using OOS predictability over a simple rule-of-thumb approach. The TSR preserves its main properties and results discussed in Section 2.2: the simple strategy has a market exposure close to zero and delivers positive and statistically significant adjusted alpha. Notably, the gains of the $TSR - TV$ increase substantially: the excess returns are statistically different from the ones delivered by the $S\&P$ strategy. The result does not mechanically depend on leverage, as the adjusted alphas are also positive and statistically significant, implying that increased precision drives the results. The side effect of timing the market rather than following a predefined rule is that the $TSR - TV$ strategy increases the number of times the strategy buys (from 40% to 64%), and henceforth its market exposure (from 0.025 to 0.810). Overall, the increased precision of the trading strategy dominates the higher market exposure, suggesting that real-time investors have an incentive to employ the short-term aggregate predictability.

Robustness. In Appendix A.4, I provide evidence supporting the robustness of the results in Table 6. Specifically, Appendix A.4.2 presents a sensitivity analysis of the trading strategy restrictions, while Appendix A.4.3 examines the potential effects of trading costs and fees. Appendix A.4.4 offers a sub-sample analysis, and Appendix A.4.5 shifts the focus to total returns rather than index returns.

Table 6: Dynamic Reversal Trading Strategy

	Mean Exc. Ret.	Sharpe Ratio	$\alpha(\%)$	β	% Buy
TSR-TV	12.355**	0.588	8.618***	0.810***	0.64
TSR	5.588	0.384	5.475**	0.025	0.40
S&P	4.617	0.308			

This table reports the annualized mean excess returns, Sharpe Ratio, CAPM-adjusted alphas (α), market exposure (β), and number of times the strategy buys for the time series reversal time-varying ($TSR - TV$), time series reversal (TSR) and passive investing ($S\&P$) strategies. $***$, $**$, 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 April 1986 to December 2019.

2.5 Evidence from other American Indexes

In this section, I investigate whether the negative correlation between $r_{w=4,t}$ and r_{t+1} is specific to the S&P 500 by extending the analysis to the two other major U.S. indices: the Dow Jones Industrial Average (DOW) and the Russell 2000 (RUSS). Table 7 presents the key statistics discussed in the previous sections for the two indexes. Specifically, the first column reports the adjusted alphas for the TSR strategy. The second and third columns display the estimated coefficient from the In-Sample predictive regression and the OOS $R^{2,OS}$, respectively. The final column reports the adjusted alphas for the $TSR - TV$ strategy.

The results for the DOW closely align with those for the S&P 500, while no clear pattern is observed in the Russell. When the in-sample coefficient is statistically significant, out-of-sample predictability is positive and meaningful, and a reversal-based trading strategy yields substantial gains. Notably, the aggregate reversal pattern is evident in both the Dow, an index of 30 large-cap stocks, and the S&P 500, but not in the Russell, which tracks the performance of small-cap American firms.[7] Therefore, contrary to cross-sectional studies (e.g., Avramov et al. (2006), Nagel (2012) and Dai et al. (2023)), the aggregate reversal pattern concentrates on high-quality stocks.

Robustness. In Appendix A.5.1, I propose a cross-sectional exercise to corroborate the results in Table 7. Sorting stocks from the CRSP dataset according to stock price and liquidity, I show

[7] 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 7: Reversal Pattern on DOW and Russell 2000

	TSR $\alpha(\%)$	γ	$R^{2,OS}(\%)$	TSR-TV $\alpha(\%)$
DOW	5.310**	−0.329***	1.027**	9.433***
RUSS	0.882	−0.190	−0.712	2.026

This table reports in the first column the annualized CAPM-adjusted alphas (α) for the full sample rule of thumb strategy (TSR) against respective index. The second column reports the In Sample predicting coefficient attached to $r_{w=4,t}$. The third column reports the OOS $R^{2,OS}$. Finally, the fourth column reports the CAPM-adjusted alphas (α) for the time-varying reversal strategy ($TSR - TV$) against respective index. $***$, $**$, 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 OOS $R^{2,OS}$.

that the reversal pattern concentrates on high-quality stocks. Moreover, in Appendix A.5.2, I consider the most popular indexes at the international level and find little evidence of aggregate market reversal. The results suggest that the pattern characterizes only American listed stocks. In the next section, I aim to rationalize the new source of predictability and its novel properties.

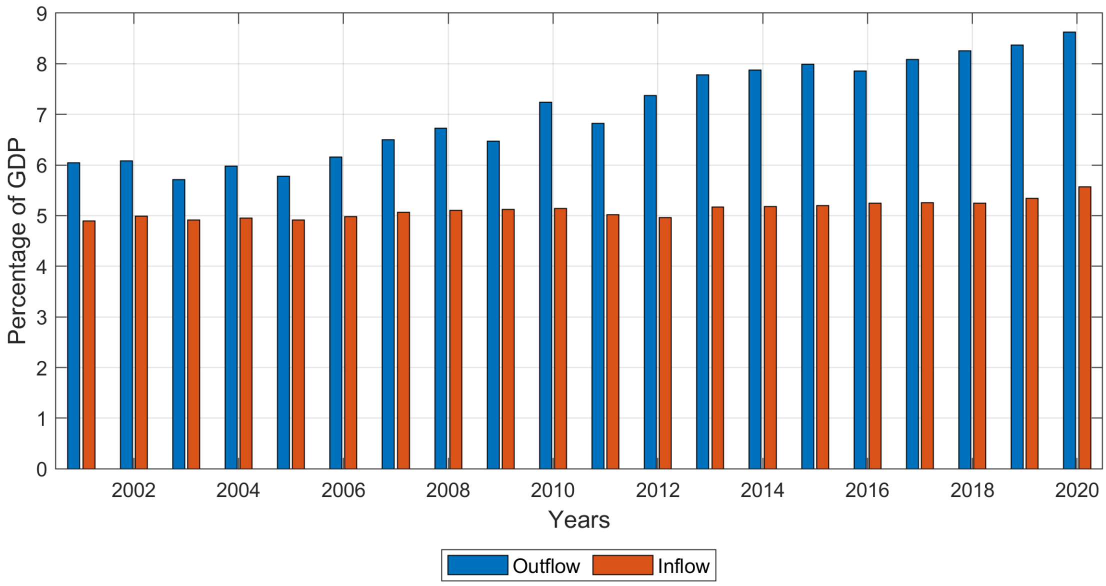
3 Rationalizing the pattern

3.1 What happens at the end of the month?

In the United States, a considerable amount of liquidity is transferred at the end of each month, driven largely by salary, contributions, and pension payments. Pensions, in particular, require special attention as they are exclusively disbursed at the end of the month and constitute a substantial portion of these financial flows. The American pension system is based on two approaches: defined benefit pension funds (DB - pension funds) and defined contribution plans (DC - 401k plans). On a high level, in defined benefit plans, companies pay retirees a regular monthly payout. Conversely, in defined contribution plans, companies do not commit to paying a pre-established amount to retirees. Instead, these plans invest a certain amount in workers' retirement accounts. Although many companies are transitioning from DB to DC plans to shift investment and longevity risks to employees, DB plans still hold more assets ($ 16.5 trillion) compared to DC plans ($ 11.3 trillion).

DB funds are severely underfunded as famously pointed out in Merton (2008): *"I have no magic solution if you are underfunded by 1 billion. [...]. And just to be clear, when I say*

Figure 3: American Pension Funds CashFlows Mismatch



This figure compares the annual pension benefit flows (blue bars - benefits paid from occupational plans and IRAs as a percentage of GDP) against the contributions into pension plans (red bars - contributions paid into occupational plans and IRAs as a percentage of GDP). The Data Source is OECD *Pension Markets in Focus.*

"underfunded," I mean that the current marked-to-market value of the pension assets is less than the current marked-to-market value of the pension liabilities. " To cover the imbalance, pension funds rely on Liability Driven Investments (LDI) to generate cashflows from their assets in place. As the imbalance between active workers' and retirees' flows is substantial (Figure 3), pension funds have tilted their investments over riskier and illiquid assets, such as private equity, infrastructure, and real estate.[8] The cash flows generated by these strategies are highly unpredictable, potentially exposing DB pension funds to short-fall liquidity problems. Therefore, given that flows materialize towards the end of the month - with contributions received around the 15th business day and benefits paid on the last business day - pension funds are likely to realize their potential liquidity needs only at the end of the month.

Securing liquidity at month-end is challenging. As market participants rush for cash, financing costs rise sharply in both short-term bonds and long-term debt markets (Etula et al., 2020), making the usual borrowing channels a more expensive outside option. Furthermore, other

[8]Many industries' reports corroborate the negative cash flow problem, See for example, Figure 1 of Goldman Sachs report Cash Flow Matching: The Next Phase of Pension Plan Management. The pension funds' negative cash flow problem has recently become a concern in the United States, see for example these recent 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.

market participants typically reduce their trading activity due to their own end-of-month liquidity requirements and concerns over monthly reporting. As a result, they generally reduce their overall risk exposure during this period (Patton and Ramadorai, 2013).

A potential strategy that pension funds use to address end-of-month liquidity shortfalls is selling equity positions to raise needed funds.[9] To test this hypothesis, I analyze the ANcerno dataset (formerly Abel Noser Corp.) from 2000 to 2010, focusing on the trading activity of pension plan sponsors in the last week of each month.[10] Table 8 reports the daily order imbalance, measured as the ratio of signed dollar volume to total dollar volume, for pension plans trading on S&P 500 constituents, along with the overall last week order imbalance. The observed negative imbalance supports the hypothesis that pension funds sell during the last week to meet liquidity needs. The selling activity clusters between $t-4$ and $t-2$, aligning with the timing necessary to secure sufficient cash for pension payouts on the last business day t. Conversely, the positive pressure observed at t is consistent with the behavior of DC plans, which likely buy at month-end due to positive cash flows as passive investors. However, the selling pressure in the first few days of the final week outweighs the buying pressure on the last trading day, as shown in the last column of Table 8. The results suggest that the liquidity trading induced by the pension payment cycle may create a non-informational positive supply shock in the aggregate market.

In the next section, I evaluate the potential impact of a supply shock using a 3-Period model à la Vayanos and Gromb (2012). Appendix B.1.3 corroborates the results by considering the Commodity Futures Trading Commission (CFTC) dataset. Appendix B.1.2 reports analogous statistics discussed in Table 8 for money managers.

[9] Bonds also experience an end-of-month price pressure, driven by institutional investors (Etula et al., 2020) and by bond auctions (Lou, Yan, and Zhang, 2013). Consequently, selling bonds—including Treasuries—becomes more costly at this stage. The stock market is considerably more liquid, faster, and centralized than the corporate bond market, which represents the primary bond instruments in which pension funds invest. Finally, if pension funds face liquidity shortfalls at the end of the month, they cannot likely engage in overnight repurchase agreements (repo) because their earliest cash inflows, such as worker contributions, arrive only after two weeks. Hence, they would likely need to undersign long-term repos, which are far less liquid and common.

[10] ANcerno contains trade-level observations for hundreds of public and private institutional investors. Pension plan sponsors include defined benefit (DB) pension funds and contribution (DC) plans. For a more detailed description of the ANcerno Dataset and the historical constituents of the S&P 500, see Appendix B.1.1.

Table 8: Last Week Pension Plan Sponsor Trading Activity

$t-4$	$t-3$	$t-2$	$t-1$	t	Weekly
-5.492%	-5.369%	-2.534%	-0.581%	0.453%	-3.522%
[-3.299]	[-3.813]	[-1.796]	[-0.350]	[0.247]	[-2.655]

This table reports in the first five columns the order imbalance 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. 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, 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.

3.2 Effect of a Supply Shock

The proposed 3-Period model aims to capture the explanation channel in a stylized way. At time t_1, the market experiences a positive supply shock, reflecting the end-of-month liquidity trading driven by the payment cycle. Between t_1 and t_2, enough market participants enter the market and absorb the shock, representing the trading activity within the one month ahead. The final period serves as a terminal condition for assessing final wealth.

In the economy, a risky asset that pays its claim at time t_3 follows a random walk with volatility clustering:

$$\begin{aligned} d_t &= d_{t-1} + \epsilon_t \\ \epsilon_t &= \nu_t \sqrt{a_0 + a_1 \epsilon_{t-1}^2} \qquad \nu_t \sim N(0,1) \end{aligned}$$

The asset dynamics intuitively reflect key characteristics of financial assets: while returns are notoriously difficult to predict, volatility tends to fluctuate between high and low periods. In each period, two types of traders are active: outside investors and arbitrageurs. Outside investors' supply is inelastic, while arbitrageurs, who are competitive and exhibit exponential utility, aim to maximize their expected final wealth.

As is standard in the literature, I set the asset supply equal to zero. Therefore, the supply shock u can be interpreted as net supply. It follows that, absent a supply shock u, the equilibrium price of the risky asset at time t_2 is equal to:

$$p_2 = d_2 = E[\bar{d}_3 | t_2]$$

Intuitively, the asset's price is not determined by supply and demand, but rather by the underlying risky asset dynamic. At time t_1, the positive supply shock u, capturing the situation outside investors wish to sell the asset, implies that the equilibrium price of the risky asset is equal to:

$$p_1 = d_1 - u(a_0 + a_1 \epsilon_1^2)$$

The quantity $u(a_0 + a_1\epsilon_1^2)$ is the discount arbitrageurs require to buy from outside investors, or, alternatively, the immediate price impact induced by the supply shock. Intuitively, the larger the shock, u, arbitrageurs absorb, and the riskier the asset, $(a_0 + a_1\epsilon_1^2)$, the more significant the price impact and hence the potential profit for arbitrageurs. Following Grossman and Miller (1988), I study the impact of the supply shock on return correlation by considering:

$$\rho = \frac{cov(r_1, r_2)}{\sqrt{var(r_1)var(r_2)}}$$

where $r_1 = p_1 - E[p_1|t_0]$ and $r_2 = p_2 - p_1$. Consistent with the empirical evidence discussed in the first part of the paper, the correlation between successive price changes is negative:

$$0 > \rho = -\frac{2(a_1 u)^2}{1 + a_1^2(-3 + 2u^2)} > -1$$

Intuitively, returns exhibit a negative correlation because a positive supply shock lowers the price at t_1, while at t_2, the price reverts as enough traders offload the arbitrageurs' risky positions. Furthermore, as shown in Appendix B.2.1, the magnitude of the reversal pattern increases in absolute terms with both supply shock u and volatility clustering a_1.

3.2.1 Testing the Empirical Predictions

The first empirical prediction directly follows from the reversal specification:

Empirical Prediction 1. *Reversal increases in u (supply shock) and a_1 (volatility clustering)*

To test the first empirical prediction, I proxy a supply shock with

$$\Delta vol_t = \frac{VOL_{w=4,t} - VOL_{w=3,t}}{\sum_{i=1}^{4} VOL_{w=i,t}}$$

where $VOL_{i,t}$ is the i^{th} weekly volume from GFD weekly S&P 500 volume data from January 1975 to December 2019. Intuitively, a supply shock mechanically implies that market participants are willing to sell more units. Hence, by acquiring these extra positions, the arbitrageurs cause a surge in trading in the last week. I proxy the volatility clustering with

$$\Delta vix_t = vix_{w=4,t} - vix_{w=3,t}$$

where $vix_{w=4,t}$ is the i^{th} weekly logarithmic VIX price from GFD VIX weekly data from January 1990 to December 2019. The rationale is that a_1 represents how much of the current period's volatility influences the expected period's conditional volatility. A higher a_1 suggests that large past shocks result in high expected future volatility. Empirically, positive values of Δvix_t imply that market participants expect a period of sustained high volatility. Conversely, negative Δvix_t values suggest a return to more stable market conditions.

I test Empirical Prediction 1 in a two-step procedure. I first run a Threshold Autoregression (TAR) to study the relationship between the reversal pattern and the two proxies:

$$r_{t+1} = \begin{cases} \alpha + \gamma_1 \; r_{w=4,t} + \epsilon_{t+1} & if \;\; -\infty < \Delta v_t \leq \tau \\ \alpha + \gamma_2 \; r_{w=4,t} + \epsilon_{t+1} & if \;\;\;\;\; \tau < \Delta v_t < \infty \end{cases} \tag{5}$$

where τ is the threshold parameter estimated within the TAR algorithm on each proxy ($\Delta v_t = \Delta vol_t$ and $\Delta v_t = \Delta vix_t$). The coefficients γ_1 and γ_2 capture, respectively, the reversal pattern in periods of smaller and higher values of end-of-the-month volume or volatility. The results, reported in Table 9, suggest that the negative autocorrelation between $r_{w=4,t}$ and r_{t+1} is significant only when $\Delta v_t > \tau$.

Therefore, the TAR model establishes a change in the regime behavior of return autocorrelation depending on the end-of-the-month proxies: consistent with the first Empirical Prediction, increased market activity and increased volatility at the end of the month are associated with a stronger reversal pattern.[11]

In the second step, I control that the two proxies do not directly impact the return dynamic. For each proxy, I define the following binary variable based on the estimated threshold τ:

$$\mathbb{1}_{\Delta v_t > \tau} = \begin{cases} 1 & if \quad \Delta v_t > \tau \\ 0 & otherwise \end{cases} \tag{6}$$

and consider the following Predictive Regression (PR):

$$r_{t+1} = \alpha + \gamma \; r_{w=4,t} + \beta \; \mathbb{1}_{\Delta v_t > \tau} + \psi \; (r_{w=4,t} \times \mathbb{1}_{\Delta v_t > \tau}) + \varepsilon_{t+1} \tag{7}$$

The results reported in Table 9 show that $r_{w=4,t}$ has stand-alone predicting power, while each $\mathbb{1}_{\Delta v_t > \tau}$ alone does not predict future return. Therefore, the results do not support the "pure" ability of volume and volatility variables to predict stock returns, as discussed, for example, in Gervais, Kaniel, and Mingelgrin (2001) and Nagel (2012). Finally, for each proxy, I report in the last column of each Panel a predictive regression considering the *end-of-the-month* return, $\mathbb{1}_{\Delta v_t > \tau}$ and their interaction term $r_{w=4,t} \times \mathbb{1}_{\Delta v_t > \tau}$. Consistent with the TAR estimates, the results suggest that once included $\mathbb{1}_{\Delta v_t > \tau}$ and its interaction term with the last week's return $r_{w=4,t}$, the negative correlation between r_{t+1} and $r_{w=4,t}$ is robust and significant only when there is high end of the month volume or volatility.[12]

[11] In Appendix B.2.2, I show that the threshold condition $\Delta vol_t > \tau$ likely indicates a month with a high trading activity in the last week of the month (Panel A Figure 1.B and Table 3.B). The estimated threshold τ is negative as $vol_{w=3,t}$ is consistently larger than $vol_{w=4,t}$ (See Panel C Figure 1.B). I divide by the monthly volume to de-trend the series from monthly seasonality. I find consistent results by considering different proxy specifications, see Appendix B.2.3.

[12] To address the concern of using an estimated regressor in equation (7), I confirm the significance of the interaction term coefficient through a two-step bootstrapping procedure.

Table 9: Testing Empirical Prediction 1

Panel A: Proxy Supply Shock						Panel B: Proxy Volatility Clustering					
TAR regression		Predictive regression				TAR regression		Predictive regression			
τ	-0.042	α	0.004	0.005	0.005	τ	0.083	α	0.005	0.004	0.004
			[2.00]	[1.10]	[1.17]				[1.89]	[1.90]	[1.83]
α	0.004	$r_{w=4,t}$	-0.353		-0.100	α	0.005	$r_{w=4,t}$	-0.282		-0.071
	[2.07]		[-3.78]		[-0.57]		[2.25]		[-2.72]		[-0.46]
$r_{w=4,t}$ if $\Delta_{vol} \leq \tau$	-0.088	$\mathbb{1}_{t,\ \Delta vol>\tau}$		-0.002	-0.002	$r_{w=4,t}$ if $\Delta_{vol} \leq \tau$	-0.072	$\mathbb{1}_{t,\ \Delta vol>\tau}$		-0.001	0.003
	[-0.29]			[-0.46]	[-0.39]		[-0.36]			[-0.21]	[0.45]
$r_{w=4,t}$ if $\Delta_{vol} > \tau$	-0.463	$r_{w=4,t} \times \mathbb{1}_{t,\ \Delta vol>\tau}$			-0.360	$r_{w=4,t}$ if $\Delta_{vol} > \tau$	-0.756	$r_{w=4,t} \times \mathbb{1}_{t,\ \Delta vol>\tau}$			-0.708
	[-3.17]				[-1.65]		[-3.34]				[-2.15]
Obs.	539		539	539	539		359		359	359	359
$R^2(\%)$	1.98		1.90	0.05	2.36		1.94		1.38	0.01	3.18

In Panel A, I report in the first column the results of the following Threshold Autoregressive Regression (TAR):

$$r_{t+1} = \begin{cases} \alpha + \gamma_1 \ r_{w=4,t} + \epsilon_{t+1} & if \ \ -\infty < \Delta vol_t \leq \tau \\ \alpha + \gamma_2 \ r_{w=4,t} + \epsilon_{t+1} & if \qquad \tau < \Delta vol_t < \infty \end{cases}$$

where τ is the estimated TAR threshold estimated on $\Delta vol_t = \frac{VOL_{w=4,t} - VOL_{w=3,t}}{\sum_{i=1}^{4} VOL_{w=i,t}}$. From the third column, I report the results of the following Predictive regression:

$$r_{t+1} = \alpha + \gamma \ r_{w=4,t} + \beta \ \mathbb{1}_{\Delta vol_t} + \psi \ (r_{w=4,t} \times \mathbb{1}_{\Delta vol_t > \tau}) + \varepsilon_{t+1}$$

where $\mathbb{1}_{\Delta vol_t > \tau}$ is an indicator function based on $\Delta vol_t > \tau$. In brackets, I report robust Newey and West (1987) t-statics. In Panel B, I report analogous results obtained for $\Delta vix_t = vix_{w=4,t} - vix_{w=3,t}$. The sample period goes from January 1975 to December 2019 in Panel A and from January 1990 to December 2019 in Panel B.

In terms of magnitude, the values reported in Panel B (volatility clustering) are slightly larger than the ones in Panel A (supply shock): the coefficient attached to $r_{w=4,t}$ is around -0.7 with high volatility, while around -0.4 with high volume. A possible explanation is that the estimated threshold in Panel B is relatively large compared to the distribution of Δvix_t. Therefore, to be above the threshold, the change in volatility expectations from the 4^{th} to the 3^{rd} week must be pronounced, thus commanding a higher impact (Panel B and D Figure 1.B). In economic terms, the supply (volatility clustering) effect is more (less) likely to be active but has a lower (higher) average impact on the time series reversal.

The second empirical implication follows from the fact that between t_1 and t_2, enough market participants come to market and fully counterbalance the effect of the supply shock. Empirical evidence shows the reversal pattern is absorbed after one month. Therefore, within that month, the reversal pattern should remain consistent and not decrease over time. Intuitively, as the end of the following month approaches, an increasing number of market participants will have traded against the arbitrageurs, gradually unwinding their excess positions and thereby offsetting the effect of the supply shock on price dynamics.

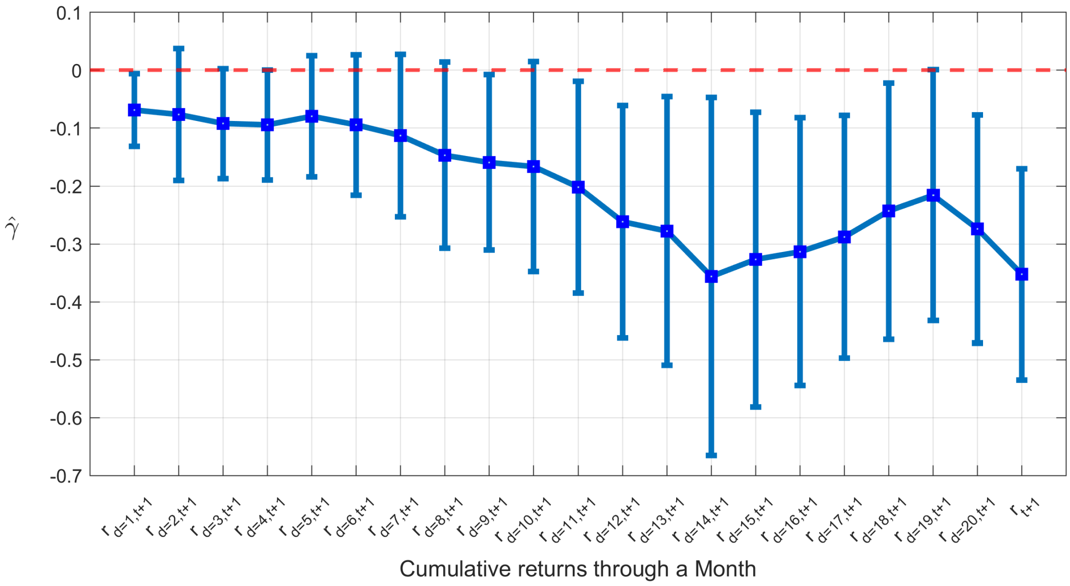
Empirical Prediction 2. *Reversal increases within the one month ahead*

I test the second empirical prediction by considering the predicting power of $r_{w=4,t}$ through the next month cumulative excess returns ($r_{d=i,t+1} = p_{d=i,t+1} - p_t - r_t^f, \quad i = 1, \cdots, 20$) that gradually become one month ahead excess return ($r_{t+1} = p_{t+1} - p_t - r_t^f$). Figure 4 plots the predictive regression' estimated coefficients and 95% confidence intervals on the cumulative excess returns throughout the month

$$r_{d=i,t+1} = \alpha + \gamma_{d=i,t+1}\ r_{w=4,t} + \epsilon_{d=i,t+1} \tag{8}$$

Figure 4 establishes a general time-series reversal pattern throughout the next monthly returns as all the estimated coefficients are negative. Consistent with Empirical Prediction 2, the reversal pattern increases in absolute magnitude during the month, suggesting that the aggregate market does not immediately recover from the end-of-the-month negative price pressure.

Figure 4: Testing Empirical Prediction 2



This figure reports the estimated coefficients and the associated 95% Newey and West (1987) robust confidence intervals of the predictive regression on the cumulative returns throughout the month

$$r_{d=i,t+1} = \alpha + \gamma_{d=i,t+1}\ r_{w=4,t} + \epsilon_{d=i,t+1}$$

as well as on the standard monthly predictive equation $r_{t+1} = \alpha + \gamma\ r_{w=4,t} + \epsilon_{t+1}$ where $r_{d=i,t+1} = p_{d=i,t+1} - p_t - r_t^f$, $r_{t+1} = p_{t+1} - p_t - r_t^f$ and $r_{w=4,t} = p_t - p_{w=4,t}$. The sample period goes from January 1975 to December 2019.

Importantly, the reversal pattern in Figure 4 aligns with the payment cycle explanation channel. The estimated coefficients in the first part of the month are generally not statistically significant. Intuitively, pension funds do not immediately buy back their equity positions as they are cash flow negative, and other market participants need time to absorb the shock from one of the largest active players in the market. Conversely, the estimated coefficients in the second part of the month are statistically significant, matching the timing at which pension funds receive their inflows and, hence, can buy back in the equity market. Moreover, the largest estimated coefficient in absolute terms is observed in the third week ($r_{d=14,t+1}$), before a new end-of-the-month negative price pressure potentially materializes.

3.3 Further Evidence Linking Reversal and Payment Cycle

In this section, I present additional evidence connecting the reversal pattern to end-of-month liquidity trading by pension funds. Specifically, I show that the reversal pattern is stronger in months with lower pension funds' inflows and higher end-of-month borrowing costs. Consistent with the end-of-the-month payment cycle explanation, when pension funds face a larger cashflow imbalance or worse financing conditions, they are more likely to resort to the equity market to recoup end-of-month liquidity. I perform a Threshold Autoregressive Regression (TAR) on pension funds' inflows, $inflow_t$, last week Fed Fund Rate (FF), $ff_{w=4,t}$, and last week National Financial Conditions Index (NFCI) $nfci_{w=4,t}$:

$$r_{t+1} = \begin{cases} \alpha + \gamma_1 \, r_{w=4,t} + \epsilon_{t+1} & if \quad -\infty < v_t \leq \tau \\ \alpha + \gamma_2 \, r_{w=4,t} + \epsilon_{t+1} & if \qquad \tau < v_t \; < \infty \end{cases} \tag{9}$$

Figure 5 reports estimated coefficients and associated 95% robust confidence intervals for all TAR regressions. Results show that when pension funds receive less cash or face tighter end-of-month financing costs, the reversal pattern spikes.[13]

3.4 Reversal Properties and Payment Cycle

In this last section, I qualitatively discuss how the liquidity trading induced by the payment cycle potentially rationalizes the properties discussed in Section 2.

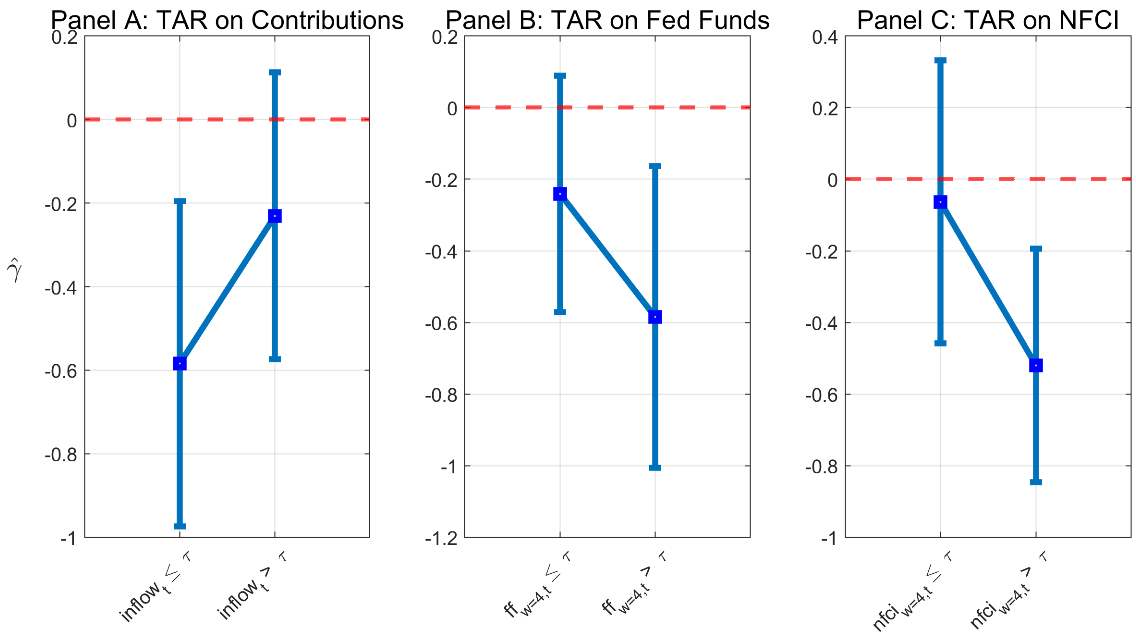
Property 1. *Reversal concentrates on expansion periods*

During periods of economic stability, pension funds reduce their precautionary cash reserves (Figure 6, Panel A). Intuitively, in stable economic conditions, pension funds tend to decrease their liquidity buffers to allocate more capital to riskier assets. As a result, with less cash on hand to manage potential mismatches, they become more vulnerable to liquidity shortfalls and are more likely to sell at the end of the month to cover potential liquidity gaps. Table 6.B reports pension plans' order imbalance, distinguishing between expansion and recession periods. The results show that the overall end-of-the-month selling pattern is driven by expansion periods.

Property 2. *Reversal concentrates on high quality stocks*

[13] In Appendix B.3.1, I report the summary statistics of $inflow_t$, ff_w and $nfci_{w=4,t}$. Pension funds' inflows series and weekly fed funds are from FRED, whereas NCFI from the Federal Reserve Bank of Chicago. I find analogous results considering first differences rather than spot values.

Figure 5: Payment Cycle and Reversal Pattern: Direct Evidence



This figure reports the estimated coefficients and the robust 95% confidence intervals for the following TAR regressions:

$$r_{t+1} = \begin{cases} \alpha + \gamma_1 \, r_{w=4,t} + \epsilon_{t+1} & if \; -\infty < v_t \leq \tau \\ \alpha + \gamma_2 \, r_{w=4,t} + \epsilon_{t+1} & if \quad \tau < v_t \; < \infty \end{cases}$$

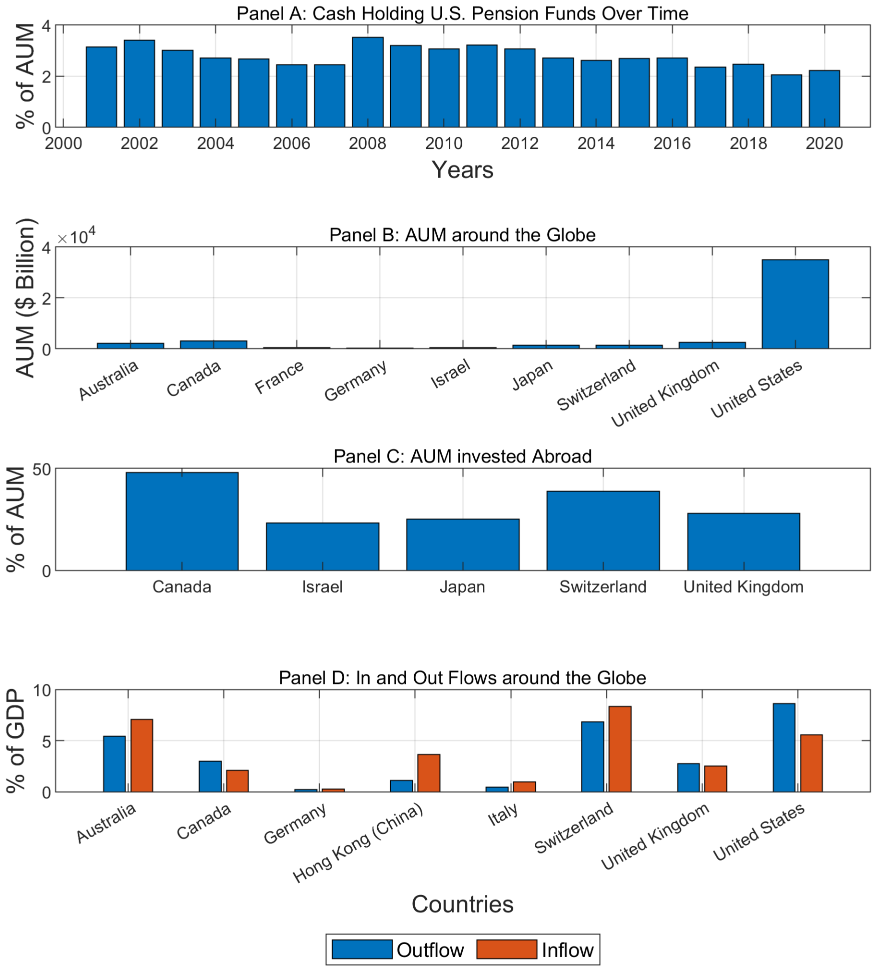
where τ is the threshold parameter estimated within the TAR algorithm either on monthly employer contributions for employee pension and insurance funds, $inflow_t$, on the end of month change in Fed Funds rate, $ff_{w=4,t}$, or on last week National Financial Conditions Index (NFCI). The sample period goes from January 1975 to December 2019.

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 7.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. This is consistent with the proposed economic mechanism: international pension funds manage substantially fewer assets (Figure 6, Panel B), heavily invest abroad (Figure 6, Panel C), and typically do not face negative cash flows (Figure 6, Panel D). As a result, international pension funds do not likely need to sell assets for liquidity reasons at the end of the month. Even if they do need to sell, their smaller market size likely prevents them from triggering a broad market shock, and,

Figure 6: Pension Funds Characteristics Around The World



Panel A reports the percentage of Asset Under Management (AUM) on Cash Holding for American Pension Funds. Panel B reports the Asset under Management (AUM) in $ Billion for some OECD representative countries in 2022. Panel C reports the percentage of AUM invested abroad in 2022 for some representative countries. Panel D compares the annual pension benefit outflows against the contributions into pension plans for some representative countries in 2022. The Data Source is OECD *Pension Markets in Focus*.

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 acknowledging the possibility of other contributing factors, Appendix B.4 explores alternative explanations of the novel empirical pattern — compensation for standard liquidity risk, behavioral biases, option expiration trading, quarterly activity, information releases, and pension fund re-balancing — but finds no comprehensive result for each competing channel.

4 Conclusion

This paper documents a novel 1-month aggregate market reversal pattern. This pattern is driven by the previous *end-of-the-moth* 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 cross-sectional literature: it concentrates on high-priced and liquid stocks and is cyclical with the economy. Consequently, a simple rule of thumb and more sophisticated strategies deliver sizable economic gains.

I rationalize the empirical findings via pension funds' end-of-the-month liquidity trading. Leveraging on recent findings and on direct evidence from daily pension funds trading activity, 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 *within* the one month ahead, aligning with the time pension funds receive inflows. Finally, I provide qualitative evidence on how a payment cycle channel rationalizes the properties of my novel reversal pattern.

Overall, my findings show a strong link between pension funds' market pressure and my reversal pattern. 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. Importantly and in line with both Grossman and Miller (1988) and Hartzmark and Solomon (2022), this paper hints that liquidity supply in financial markets is not fixed and static but varies and adapts as typically discussed in market microstructure. Finally, this study suggests that pension plans' liquidity shortfalls and underfunding directly impact the aggregate market. Given pension funds' growing size and importance, further theoretical and empirical research could explore whether their liquidity-driven asset allocation potentially influences real economy and financial stability.

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Appendices

A Appendix Section 2

A.1 Appendix Section 2.2

A.1.1 Adjusted Alphas Benchmarks

In this section, I show that the TSR strategy delivers sizable and statistically significant adjusted alphas considering different market benchmarks. In Table 1.A, I report the results of the following regression:

$$TSR_t = \alpha + \beta \; B_{i,t} + \epsilon_t$$

where $B_{i,t}$ is the i benchmark market strategy. The benchmarks considered are the $CRSP$ Market Factor, the 3 Fama-French factors, the short-term cross-sectional factor, the Momentum Factor, and the first 10 Principal Components (PCA) formed on the 100 anomalies portfolios.

The results do not qualitatively change from the ones reported in the main body of the text, hinting that, independently from the benchmark chosen, investors have the incentive to switch

Table 1.A: Robustness Check: Adjusted Alphas

	MKT	3FF	REV	MOM	100 Anomalies
$\alpha(\%)$	5.309	5.075	5.702	5.636	5.842
	[2.15]	[2.06]	[2.77]	[2.81]	[2.83]

This table reports the estimated intercept and attached robust Newey and West (1987) t-statics in brackets from the following equation:

$$TSR_t = \alpha + \beta \; B_{i,t} + \varepsilon_t$$

where the control benchmark returns $B_{i,t}$ considered are the CRSP market factor, the three Fama French, the Momentum, Short Reversal factors, and the first 10 Principal Components from the 100 anomalies portfolio returns in Dong et al. (2022) respectively. The time window in the first four columns is from January 1975 to December 2019. The time window for the last specification is from January 1975 to December 2018. Each control variable considered is directly downloaded from the respective authors' websites.

to a short-term reversal market strategy. All the returns from the cross-sectional strategies represent an upper bound as they do not consider fees, re-balancing, and trading costs that can be exceptionally severe when trading individual stocks. For example, the $CRSP$ market factor (returns buying more than 3,500 constituents across mega, mid, small, and micro-listed American stocks) is synthetically traded only since April 2011.

A.1.2 Longer Time Window

In this section, I provide evidence that the TSR results and properties do not change by considering a long time series. Specifically, Table 2.A reports analogous statistics discussed in Table 3 for the time period December 1950-December 2023:

Table 2.A: Robustness Check: Long Time Window

	Mean Exc. Ret.	Sharpe Ratio	Risk Adj. $\alpha(\%)$	β	Activity(%)
TSR^L	3.735	0.372	2.095^{**}	0.466^{***}	0.44
TSR^S	0.056	0.006	1.685^{*}	-0.463^{***}	0.56
TSR	3.791	0.267	3.780^{**}	0.003	
S&P 500	3.519	0.239			

This table reports annualized mean excess returns ($\bar{\$}$), Sharpe Ratio, CAPM-adjusted alphas (α), market exposure (β), and Activity for the long, short, and long-short leg of the time series reversal and of the passive investing strategies, respectively. $***$, $**$, and $*$ indicate significance at the 1%, 5%, and 10% levels, respectively. The statistical significance is based on Newey and West (1987) standard errors. The time window is from December 1950 to December 2023.

A.1.3 Trading Costs and Fees

In this section, I show that transaction costs and fees should not significantly impact the results. Trading fees have constantly declined in the last twenty years thanks to higher financial market competition and decimalization. This is particularly true for the financial instruments considered, indexes, for which execution and management fees are the lowest in the market. Moreover, the proposed predictor is obtained by observing available public prices at the end of the trading days. Therefore, the technology required to implement the trading strategy is minimal and virtually free. Finally, the possibility of trading at the close, as the prices here are considered at the end of the day, almost eliminates the implicit costs that trading orders might trigger.

To support this hypothesis, I provide a simple back-of-the-envelope exercise. I compute the necessary trading costs and fees incurred by the short-term reversal strategy to equate to the passive market $S\&P$ strategy (with no attached trading costs or fees). The TSR strategy should trigger around $16.24bps$ per transaction (while for TSR^L around $15.84bps$) to guarantee the same gross gains of passive investing. The values are extremely above the trading costs usually attached to index trading as nowadays the usual cost range between 3 to 9 bps per year (SPY, VOO and IVV) and in the early 1980-1990 around 20 bps per year.

A.1.4 Friday Effect Robustness Check

In this section, I show that the results are robust on the main predictor specification. First, I show that previous *end-of-the-month* returns as well as weekly returns do not have predictive power. Specifically, I consider

$$r_{t+1} = \alpha + \gamma \; r_{w=i,t} + \epsilon_{t+1}$$

and standard weekly returns:

$$r_{t+1} = \alpha + \gamma \; r''_{w=4,t} + \epsilon_{t+1}$$

where $r_{w=i,t} = p_t - p_{w=i,t}$ and $r''_{w=i,t} = p_{w=i,t} - p_{w=i-1,t}$. The results reported in Table 3.A show that, focusing on weekly returns, only the main predictor ($r_{w=4,t}$) has actual predictive power.

Importantly, if I focus on daily returns ($r_{d=t-i,t} = p_t - p_{d=t-i,t}$), only returns *within* the last

Table 3.A: Predictability of Previous Weekly Returns

α	0.004	α	0.003	α	0.003	α	0.003
	[2.00]		[1.69]		[1.64]		[1.57]
$r_{w=4,t}$	-0.353	$r_{w=3,t}$	-0.100	$r_{w=2,t}$	-0.019	$r_{w=1,t}$	0.003
	[-3.78]		[-1.06]		[-0.26]		[0.05]
$R^2(\%)$	1.90		0.32		0.00		0.00
Obs.	539		539		539		539
α	0.003	α	0.003	α	0.003	α	0.003
	[1.76]		[1.64]		[1.68]		[1.51]
$r''_{w=4,t}$	0.094	$r''_{w=3,t}$	0.078	$r''_{w=2,t}$	0.042	$r''_{w=1,t}$	0.151
	[0.78]		[0.74]		[0.45]		[1.42]
$R^2(\%)$	0.20		0.17		0.02		0.44
Obs.	539		539		539		539

This table reports the results of the following predictive regressions $r_{t+1} = \alpha + \gamma\ r_{w=i,t}(r''_{w=i,t}) + \epsilon_{t+1}$ where $r_{w=i,t} = p_t - p_{w=i,t}$ and $r''_{w=i,t} = p_{w=i,t} - p_{w=i-1,t}$ with $1 \leq i \leq 4$. In brackets, I report the associated Newey and West (1987) t-statistics. The time window is from January 1975 to December 2019.

week of the month have predictive power (specifically from $r_{d=t-4,t}$ to $r_{d=t-1,t}$). As an example, I report in the first Panel of Table 4.A analogous statistics discussed in Table 3 for the t-3 end-of-month return ($r_{d=t-3,t}$). For completeness, the second and third panels report analogous statistics discussed in Sections 2.3 and 2.4, respectively. Results and main properties do not qualitatively change compared to the $r_{w=4,t}$ return and across the daily returns within the last week. Therefore, in the main body of the paper, I focus on $r_{w=4,t}$ to capture a generalized negative predictability within the end of the month and to avoid arbitrarily choosing a specific daily return between $t-4$ and $t-1$.

A.1.5 Annual Sharpe Ratio

In this section, I report the number of times the rolling annualized Sharpe ratio of the TSR and its sub-strategies outperform the passive ($S\&P$) strategy. The results in Table 5.A suggest that the TSR does not cluster its gains in a specific time window, strengthening the results discussed in the main body of the text.

Table 4.A: Reversal pattern with $r_{d=t-3,t}$

	Mean Exc. Ret.	Sharpe Ratio	Adj. α(%)	β	Activity(%)
TSR^L	4.746	0.458	2.815***	0.493***	0.43
TSR^S	0.830	0.079	2.815***	−0.507***	0.57
TSR	5.577	0.378	5.630***	−0.014	
	γ	$R^{2,OS}$	$R^{2,OS}_{exp}$	$R^{2,OS}_{rec}$	
	−0.398***	2.660***	3.776	−1.705	
	Mean Exc. Ret.	Sharpe Ratio	Adj. α(%)	β	Buy (%)
$TSR-TV$	12.173**	0.584	8.521***	0.800***	0.70
TSR	5.588	0.384	5.475***	0.025	0.40

The first panel reports annualized mean excess returns, Sharpe Ratio, CAPM-adjusted alphas (α), market exposure (β), and Activity for the long, short, and long-short leg of the time series reversal strategies, respectively. The second panel reports the In-sample estimated coefficient, the $R^{2,OOS}$, and the $R^{2,OOS}$ in expansion and recession, respectively. The third panel reports annualized mean excess returns, Sharpe Ratio, adjusted Jensen alphas (α), market exposure (β), and percentage buy for time-varying and simple rule of thumb time series reversal strategies, respectively. $***$, $**$, 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 exercises. The time window is from January 1975 to December 2019 for the first panel and the In sample coefficient (γ), from April 1986 t to December 2019 for the remaining statistics.

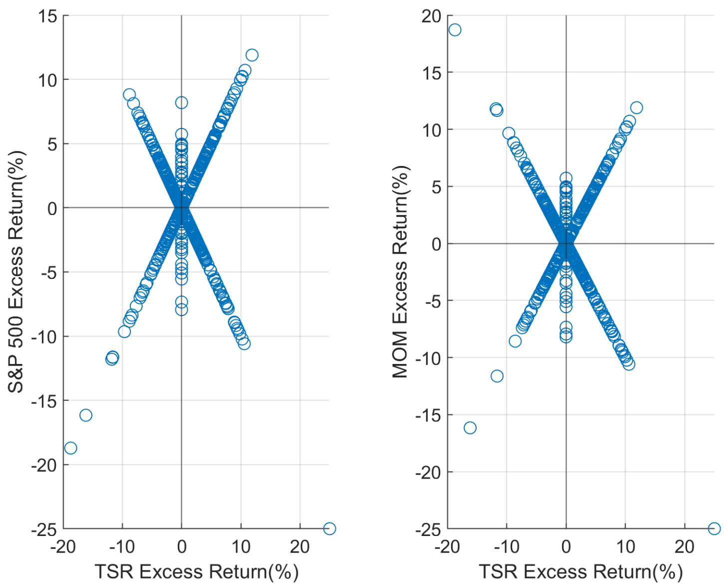
Table 5.A: Annual Sharpe Ratio

$\# > S\&P$	1975-1989	1990-1999	2000-2009	2010-2019	Full Sample
TSR	7	3	7	3	20
TSR^L	10	5	7	5	27
TSR^S	7	2	6	3	18

This table reports the number of times the rolling annualized Sharpe ratio of the TSR and its sub-strategies outperform the passive (S&P) strategy. The time window is from January 1975 to December 2019.

A.1.6 Scatter Plot

Figure 1.A: Scatter Plot - Rule of Thumb TSR



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 trading strategy buys (sells) the S&P 500 if the *end-of-the-month* return is negative (positive). The grey-shaded areas mark periods of recessions according to the NBER. The time window is from January 1975 to December 2019.

A.2 Appendix Section 2.3.1

A.2.1 Sub Sample Analysis

In this section, I study the negative correlation between $r_{w=4,t}$ and r_{t+1} over time. In the first column of Table 6.A, I report the coefficient for the period before the launch of the first S&P 500 index (1950-1975). In the second column, I report the coefficient for the time between the first index fund and the first S&P ETF (1975-1993). In the third column, I report the estimated coefficient for the time window after the launch of the first S&P ETF (1993-2019). The results hint that the negative correlation is statistically robust over time: only immediately after the post-war period, the estimated γ is not negative and statistically significant.

Table 6.A: In Sample Predictability Sub Sample Analysis

	1950-1975	1975-1993	1993-2019
γ	0.185	-0.567^{***}	-0.239^{**}

This table reports the estimated coefficient attached to the *end of the month* return $r_{w=4,t}$ on the following regression:

$$r_{t+1} = \alpha + \gamma \; r_{w=4,t} + \varepsilon_{t+1}$$

$***$, $**$, and $*$ indicate significance at the 1%, 5%, and 10% levels, respectively. The statistical significance is based on Newey and West (1987) standard errors.

A.2.2 Predictability after First Week of the Month

In this section, I investigate whether the time serial reversal pattern exclusively depends on the ability of $r_{w=4,t}$ to predict the one ahead week return. Therefore, I consider the following predicting equation:

$$r_{w=1,t+1} = \alpha + \gamma \; r_{w=4,t} + \epsilon_{t+1}$$

where $r_{w=1,t+1} = p_{t+1} - p_{w=1,t+1}$. The estimated coefficient is -0.272, and the Newey and West (1987) t-statistic is -3.16. Therefore, the result suggests that the reversal pattern does not depend solely on a turn-of-the-month effect studied in the literature.

A.2.3 Controlling for Closing Price Effect

In this section, I consider whether the reversal pattern between last week's return and the one month ahead depends on a closing price effect. As high and low prices are potentially recorded during the lit book phase, I consider high (low) last week returns:[14]

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

as the dependent variables of the following distinct regression

$$r^H_{t+1} = \alpha + \gamma^H \; r^H_{w=4,t} + \epsilon_{t+1} \qquad (r^L_{t+1} = \alpha + \gamma^L \; r^L_{w=4,t} + \epsilon_{t+1})$$

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 -0.295 (-0.316), and the associated Newey and West (1987)

[14] For 21 out of 540 observations, I use closing prices as high and low prices were missing.

t-statistic is -2.23 (-2.86). The results show that the pattern survives the closing price effect. However, consistent with institutional investors trading more during the market on close, the baseline regression is stronger in absolute terms and the t-statistic.

A.2.4 Placebo Test around 15^{th} 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 15^{th} of each month - a second common payment date - as the end of the month.[15] I consider as the predictor the difference between the closing price in the 15^{th} day in month t and the closing price of the second week.

The estimated coefficient is 0.205, and the Newey and West (1987) t-statistic is 1.062, 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.2.5 Multi - Month Predictability

In this section, I study whether the reversal pattern persists after one month ahead. I consider a set of predictive regression that gradually becomes a two-month ahead returns:

$$r'_{w=i,t+2} = \alpha + \gamma\ r_{w=4,t} + \epsilon_{w=i,t+2}$$

and

$$r_{t+2} = \alpha + \gamma\ r_{w=4,t} + \epsilon_{t+2}$$

where $r'_{w=i,t+2} = p_{w=i,t+2} - p_{t+1} - r^f_{t+1}$ and $r_{t+2} = p_{t+2} - p_{t+1} - r^f_{t+1}$. The results reported in Table 7.A show that the predictability window is only one month ahead.

[15]When in the 15^{th} markets are closed, I sequentially use $p_{d=14,t}$, $p_{d=16,t}$ or $p_{d=17,t}$.

Table 7.A: Two Month Ahead Predictability

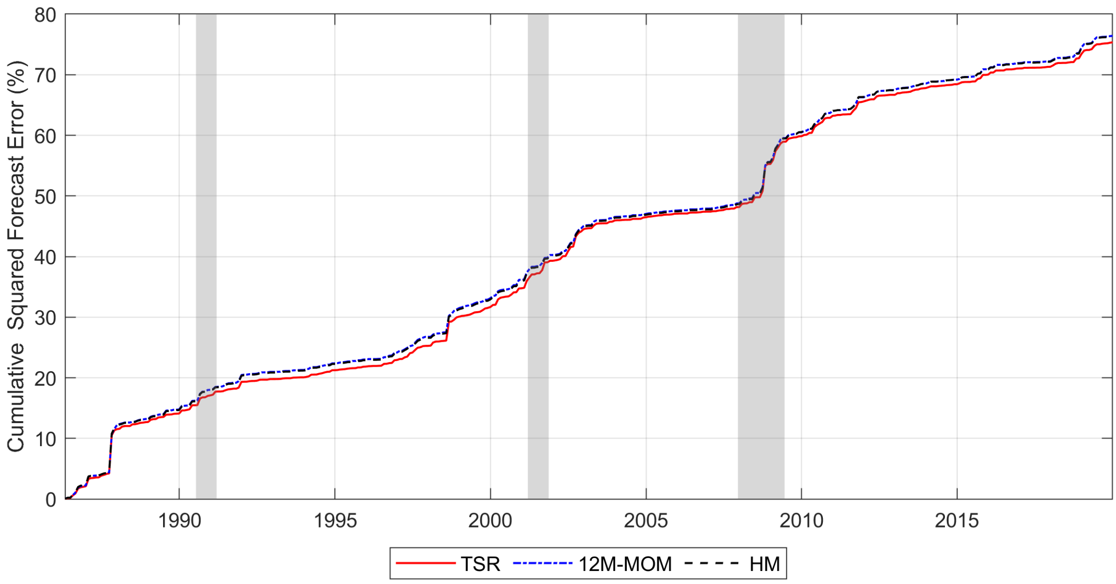
$r'_{w=1,t+2}$	$r'_{w=2,t+2}$	$r'_{w=3,t+2}$	$r'_{w=4,t+2}$	r_{t+2}
0.000	0.059	0.038	-0.011	0.033
[−0.02]	[0.98]	[0.42]	[−0.09]	[0.29]

This table reports the estimated γ of $r'_{w=i,t+2} = \alpha + \gamma\, r_{w=4,t} + \epsilon_{w=i,t+2}$ $\quad 0 < i \leq 4 \quad$ $r_{t+2} = \alpha + \gamma\, r_{w=4,t} + \epsilon_{t+2}$ where $r'_{w=i,t+2} = p_{w=i,t+2} - p_{t+1} - r^f_{t+1}$ and $r_{t+2} = p_{t+2} - p_{t+1} - r^f_{t+1}$. In brackets, I report robust Newey and West (1987) t-statics. The sample period goes from January 1975 to December 2019.

A.3 Appendix Section 2.3.2

A.3.1 Forecast Errors Over Time

Figure 2.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 January 1975 to December 2019 and the Out-of-Sample valuation period goes from April 1986 to December 2019.

A.3.2 Longer Time Window

In this section, I provide evidence that the Out-of-Sample results do not change by considering a longer time series (December 1950-December 2023). Specifically, I consider an Out-of-Sample forecast evaluation period from January 1975 to December 2023. The $R^{2,OS}(\%)$ is 1.643** with its predictability clustered in expansion periods ($R^{2,OS}_{exp}(\%)$ is 2.232, whereas $R^{2,OS}_{rec}(\%)$ is -0.300).

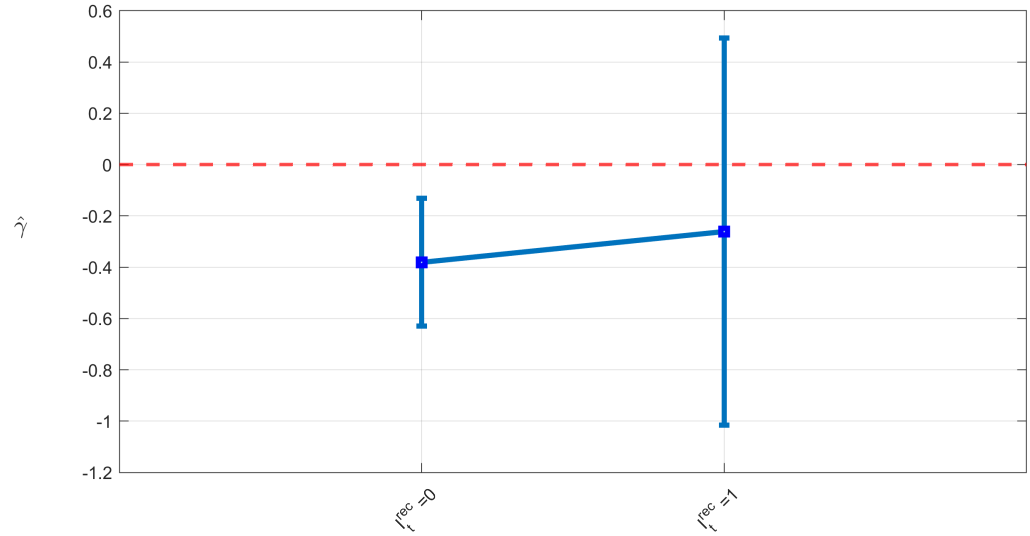
A.3.3 Reversal and Business Cycle

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

$$r_{t+1} = \alpha + \gamma_1 \, \mathbf{I}_t^{rec} r_{w=4,t} + \gamma_2 \, (1 - \mathbf{I}_t^{rec}) r_{w=4,t} + \epsilon_{t+1}$$

where I_t^{rec} is the NBER indicator function that takes a value of 1 when month t is in recession and 0 otherwise. Figure 3.A shows that the negative market serial correlation is statistically significant only during expansion periods.

Figure 3.A: Reversal Pattern and Business Cycle



This figure reports the estimated coefficients and the 95% robust confidence intervals of the following regression: $r_{t+1} = \alpha + \gamma_1 \, \mathbf{I}_t^{rec} r_{w=4,t} + \gamma_2 \, (1 - \mathbf{I}_t^{rec}) r_{w=4,t} + \epsilon_{t+1}$ where r_{t+1} is the $t+1$ monthly excess return; $r_{w=4,t}$ is the *end-of-the-month* return and I_t^{rec} is the NBER indicator function that takes a value of 1 when month t is in recession and 0 otherwise. The sample period goes from January 1975 to December 2019.

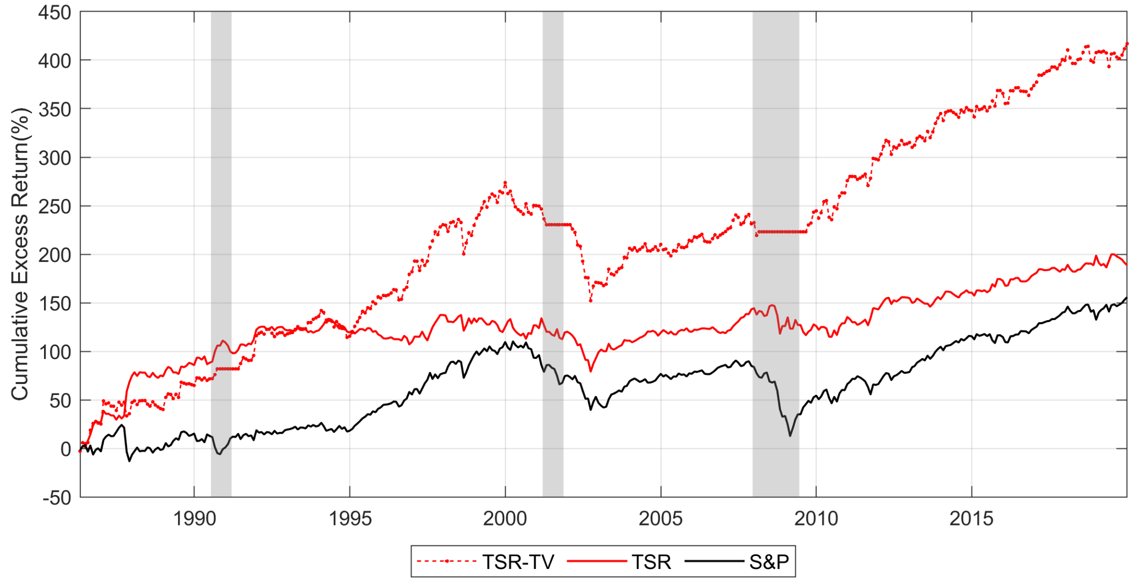
A.4 Appendix Section 2.4

A.4.1 Plots Section 2.4

A.4.2 Trading Strategy Sensitivity Analysis

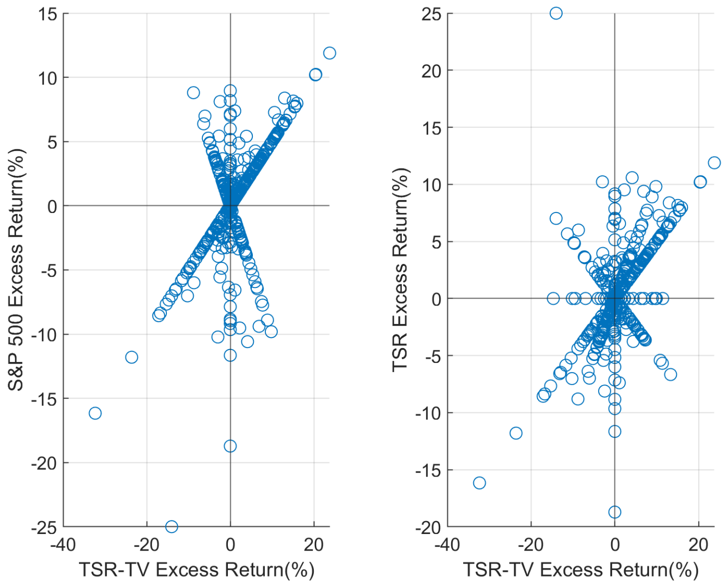
In this section, I provide evidence that the time-varying TSR strategy is robust to the model specification. I report the results without the NBER trading restriction in the first row of Table

Figure 4.A: Out of Sample Cumulative Excess Returns



This figure presents the cumulative excess return for the time varying time series reversal (TSR TV- dashed red line), time series reversal (TSR- red solid line), and passive investing (S&P - black solid line) strategies. The grey shaded areas mark periods of recessions according to the NBER indicator function. The time window is from April 1986 to December 2019.

Figure 5.A: Scatter Plot - Rule of Thumb TSR TV



This figure presents the excess returns for the time-varying time series reversal (TSR- TV) respectively against the returns from the S&P 500 and time series reversal (TSR). The time window is from April 1986 to December 2019.

8.A. The results partially deteriorate, consistent with the cyclicality of the negative market predictability. However, the strategy still outperforms the market as alphas and adjusted alphas are still positive and statistically significant. In the second row, I report the results without

Table 8.A: Sensitivity Analysis Time Varying Trading Strategy

	$\bar{\$}(\%)$	Sharpe Ratio	Adj. $\alpha(\%)$	β	Buy (%)
$w_t^{TSR} \neq 0 \vert I_{t-1}^{NBER} = 1$	11.064**	0.475	6.443**	1.000***	0.70
$-1 \leq w_t^{TSR} \leq 1$	6.034	0.495	4.338**	0.367***	0.64
$0 \leq w_t^{TSR} \leq 1$	6.040	0.567	3.557**	0.538***	0.64
$\sigma^2_{t+1\vert t} = \sigma^2(\{r_i\}_{i=t}^{t-5})$	11.845**	0.565	8.118***	0.807***	0.64
$\sigma^2_{t+1\vert t} = \sigma^2(\{r_i\}_{i=t}^{t-11})$	12.256**	0.589	8.633***	0.785***	0.64
$\sigma^2_{t+1\vert t} = \sigma^2(\{r_i\}_{i=t}^{t-59})$	11.698**	0.583	8.246***	0.748***	0.64
$\sigma^2_{t+1\vert t} = \sigma^2(\{r_i\}_{i=t}^{t-119})$	11.582**	0.563	8.012***	0.773***	0.64

This table reports annualized mean excess returns ($\bar{\$}$), Sharpe Ratio, CAPM-adjusted alphas (α), market exposure (β), and number of times the strategy buys for the time series reversal time-varying ($TSR - TV$) without the NBER restriction (first row), without leverage (second row), without leverage and short selling (third row), and for different variance forecast horizons (from fourth row), respectively. $***$, $**$, and $*$ indicate significance at the 1%, 5%, and 10% levels, respectively. The statistical significance is based on Newey and West (1987) standard errors. The time window is from April 1986 to December 2019.

leverage. The raw returns mechanically decrease. However, the adjusted alphas are positive and statistically significant. In the third row, I present the results without leverage and short selling: while raw returns improve compared to the previous specification, adjusted alphas (still positive and statistically significant) decrease due to the loss of the hedging component from the short leg.

From the third row, I report the results for different specifications of the variance forecast, ranging from a 6-month to a 10-year time window. Independently from the variance forecast specification, the strategy delivers sizable and statistically significant alphas.

A.4.3 Trading Costs and Fees

In this section, I show that transaction costs and fees do not significantly impact the results. Following Appendix A.1.3, I compute the necessary trading costs and fees incurred by the time-varying short-term reversal strategy (TSR-TV) to equate to the passive market S&P strategy (with no attached trading costs or fees). The TSR-TV strategy should trigger an exorbitant 70.40bps per transaction to deliver the same gross gains of passive investing.

A.4.4 Sub-Sample Analysis

In this section, I provide evidence that the $TSR-TV$ strategy outperforms the passive strategy on several sub-samples. I here consider three sub-samples: after the introduction of the first S&P 500 ETF (January 1993), after financialization (January 2005) and after the great financial crisis (August 2009).

Table 9.A: Sub Sample Analysis $TSR-TV$ strategy

	Mean Exc. Ret.	Sharpe Ratio	$\alpha(\%)$	β	% Buy
1993-2019	11.070*	0.515	6.211*	0.963***	0.7
2005-2019	13.791**	0.714	9.430**	0.828***	0.7
2009-2019	18.608*	0.872	4.864	1.261***	0.8

This table reports annualized mean excess returns ($\bar{\$}$), Sharpe Ratio, CAPM-adjusted alphas (α), market exposure (β), and number of times the strategy buys for the time series reversal time-varying ($TSR-TV$) for different sub-samples. $***$, $**$, and $*$ indicate significance at the 1%, 5%, and 10% levels, respectively. The statistical significance is based on Newey and West (1987) standard errors.

A.4.5 Total Return Analysis

In this section, I show that results do not change by considering total returns ($CRSPSPvw$) instead of index returns ($r_{t+1} = p_{t+1} - p_t - r_t^f$) as dependent variable. The $CRSPSPvw$ is the S&P total returns: the variable assumes that all dividends payed by the constituent stocks are immediately reinvested in the index itself. It must be noticed that total returns represent an upper-bound as they do not consider transaction, management, re-balancing costs and taxes on dividends (CRSP data description). Table 10.A shows that results are qualitatively unaffected.

Table 10.A: Reversal Pattern & Total Returns

γ	$R^{2,OS}$	$R^{2,OS}_{exp}$	$R^{2,OS}_{rec}$	TSR Adj $\alpha(\%)$	TV-TSR Adj $\alpha(\%)$
−0.350***	1.265**	2.022	-1.705	5.419**	6.691**

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

$$r^{vw}_{t+1} = \alpha + \gamma \, r_{w=4,t} + \varepsilon_{t+1}$$

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 full sample rule of thumb strategy (TSR) against the total return as benchmark. Finally, the sixth column reports the annualized adjusted Jensen alphas (α) for the time-varying reversal strategy ($TSR-TV$) 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 $R^{2,OS}$.

In the main body of the text, I focus on index returns rather than total returns for multiple reasons. First, the S&P 500 is an index return so dividends are not included in the calculations and most ETFs are tracking the index itself.[16] Second, consistently with Moskowitz et al. (2012), I focus on index returns to capture only capital gains (and not dividends gains) predictability, hence assessing a more precise return reversal driven only by price movements.[17] Finally, $CRSPSPvw$ returns can be quite far from actual returns real market traders realize. It is still debated which dividends are measured and how they are re-invested, compounded, and taxed.

A.5 Appendix Section 2.5

A.5.1 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 predicting equations.[18]

The differences in estimated coefficients for top-bottom quintiles are significant at 1% significance level: Figure 6.A shows a clear trend: a negative correlation characterizes high-priced and liquid stocks consistent with the results proposed in Table 7. In contrast, a positive correlation

[16] See for example FRED:" Since this is a price index and not a total return index, the S&P 500 index here does not contain dividends."

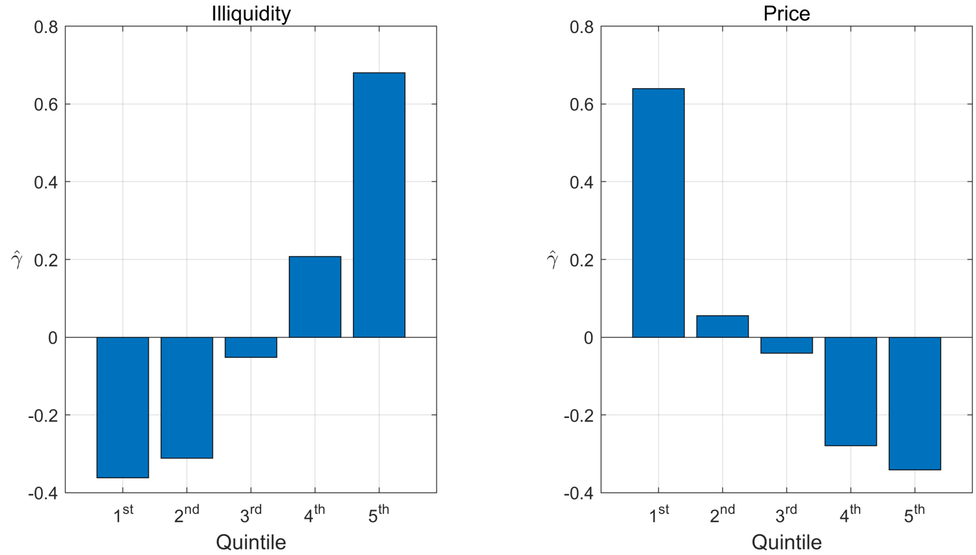
[17] "For the equity indexes, our return series are almost perfectly correlated with the corresponding returns of the underlying cash indexes in excess of the Treasury bill rate.", Moskowitz et al. (2012).

[18] 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 $t-3$ end of month return ($r_{d=t-3,t}$) 63% of the time; otherwise, I consider $r_{d=t-4,t}$ (16%). Finally, if both returns are not available, the independent variable is the difference between the monthly closing price and the 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.

Figure 6.A: Stock Characteristics and Reversal Pattern



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

$$r_{t+1}^{sc_q} = \alpha + \gamma r_{4,t}^{sc_q} + \epsilon_{t+1}$$

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 Amihud illiquidity measure (the fifth being the most illiquid portfolio) and stock price (the fifth being the most high-priced portfolio). Stocks are sorted in quintiles each month. The Data is CRSP: the sample includes 16159 stocks, and the time window goes from January 1985 to December 2019.

Table 11.A: Indices around the World

Index	Region/Country	Initial Date	End Date
EUSTOXX 50	Europe Union (EU)	26/02/1999	31/12/2020
S&P/TSX	Canada (CAN)	31/01/1977	31/12/2020
S&P/ASX 200	Australia (AUS)	30/06/1992	31/12/2020
NIKKEI 225	Japan (JAP)	31/01/1975	31/12/2020
FTSI 100	England (ENG)	30/05/1986	31/12/2020
DAX 40	Germany (GER)	26/02/1999	31/12/2020
CAC 40	France (FRA)	26/02/1999	31/12/2020

This table reports the list of international indices. For each index, I report the region-country of the index constituents and the time window considered. The data provider is Bloomberg.

characterizes illiquid and low-priced stocks consistent with stale price theories.

A.5.2 Evidence Around the World

In this section, I study whether the negative serial correlation between $r_{w=4,t}$ and the one-month ahead return, r_{t+1}, holds internationally. The international indices considered are reported in Table 11.A and the estimation results in Table 12.A

Table 12.A: Reversal Pattern Around the World

	EU	CAN	AUS	JAP	ENG	GER	FRA
$\hat{\gamma}$	-0.125	-0.152	0.043	-0.05184	-0.205	-0.141	-0.136
	[0.720]	[0.990]	[0.240]	[0.360]	[1.572]	[0.880]	[0.790]

This table reports in the first row the coefficient attached to $r_{w=4,t}$ of the following predictive regression:

$$r_{t+1} = \alpha + \gamma \, r_{w=4,t} + \epsilon_{t+1}$$

where r_{t+1} is the $t+1$ monthly excess return; $r_{w=4,t}$ is the *end-of-the-month* return. In brackets, I report robust Newey and West (1987) t-statics.

B Appendix Section 3

B.1 Appendix Section 3.1

B.1.1 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 limited 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.1.2 Analysis for Money Managers

In this section, I report analogous statistics reported in Table 8 for Money Managers (mutual funds, hedge funds, banks, and insurance companies). Consistent with the rise of passive investing, money managers do not necessarily sell at the end of the month. Additionally, trades made on behalf of pension plans may be recorded under money managers if only the latter are ANcerno clients.

Table 1.B: Last Week Money Manager Trading Activity

$t-4$	$t-3$	$t-2$	$t-1$	t	Weekly
−2.291%	−2.713%	−0.240%	0.539%	2.381%	−0.645%
[-3.282]	[-3.345]	[-0.325]	[0.666]	[2.300]	[-1.423]

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). 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.1.3 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 set 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 the two different futures, I divide the number of ES contracts by 5 as the nominal value of the SP future is 5 times larger than the ES.

Table 2.B: Institutional Investor behavior at the end of the month (CFTC Dataset)

	Inst. Investors	Dealers	Leveraged Funds	Others
ΔBuy	-39	-8937	-5912	-1046
$\Delta Sell$	1517	-10508	-6115	-505
$\Delta Buy - \Delta Sell$	-1555	1571	203	-541

This table reports the average difference between the last two weeks of the month of 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.

In Table 2.B, I report the delta between the last two weeks of the month for both net buys and sells across the different investor classes.[19] Consistently with the results in the main body of the text, institutional investors decrease their exposure on S&P 500 futures instruments as, on average, ΔBuy is negative and $\Delta Sell$ is positive and $\Delta Buy - \Delta Sell$ is negative. Interestingly, dealers and leveraged buy as $\Delta Buy - \Delta Sell$ is positive, whereas others (among which retail investors) sell consistently with the positive feedback trader hypothesis.

B.2 Appendix Section 3.2

B.2.1 Model Derivation

By the dynamic of the risky asset immediately follows that, given information H_{t-h}, $d_t \sim N(d_{t-h}, \sqrt{a_0 + a_1\epsilon^2_{t-h}})$. Standard in the literature, let's assume the price p_t on the risky asset follows the same dynamic. The solution of the stylized model proceeds by backward induction. Without loss of generality, assume that the arbitrageur starts with an initial wealth W_0 and denote by x_t his asset holding position after the trading round $\{t_i\}_{i=1}^2$. It follows that after the second trading round, t_2, the final wealth can be written as:

$$W_3 = W_2 + (\bar{d}_3 - p_2)x_2$$

Intuitively, the final wealth is given by the sum of trading gains between t_1 and t_2 (W_2) and the change in value of the quantity held at maturity. Hence, at time t_2, the expected final wealth

[19] CFTC Methodology website: "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" "

of the arbitrageur is $E[W_3|H_2] = E[W_2 + x_2(\bar{d_3} - p_2)|H_2]$. As $\bar{p_3}|H_2 \sim N(d_2, \sqrt{a_0 + a_1\epsilon_2^2})$. The arbitrageur maximizes $E[-e^{W_2+x_2(\bar{d_3}-p_2)}|H_2]$. In virtue of the Normal distribution properties, $W_2 + x_2(\bar{p_3} - p_2) \sim N(W_2 + x_2(d_2 - p_2), x_2\sqrt{a_0 + a_1\epsilon_2^2})$ and :

$$E[-e^{-(W_2+x_2(p_3-p_2))}|H2] = e^{\frac{1}{2}x_2^2(a_0+a_1\epsilon_2^2)-(W_2+x_2(d_2-p_2))}$$

Therefore the optimal quantity held at t_2 is $x_2 = \frac{d_2-p_2}{a(a_0+a_1\epsilon_2^2)}$. At the time t_2, the supply shock has been absorbed. Hence zero supply equals demand, imposing $p_2 = d_2 = E[\bar{d_3}|H_2]$.

At time t_1 the expected wealth of the arbitrageur is $E[W_0 + (p_2 - p_1)x_1|H_1]$. Intuitively, the arbitrageur liquidates at time t_2 the entire position acquired at time t_1 due to the positive supply shock; hence, he is out of the game at the end of the second trading round. With the same line of reasoning as the previous calculations, the optimal quantity held after the first trading round is:

$$x_1 = \frac{d_1 - p_1}{(a_0 + a_1\epsilon_1^2)}$$

In this case the equilibrium price is determined by $\frac{d_1-p_1}{(a_0+a_1\epsilon_1^2)} = u$, hence the price at time t_1 is $p_1 = d_1 - u(a_0 + a_1\epsilon_1^2)$

Finally, let's derive the correlation coefficient. Recall that $\rho = \frac{cov(r_1,r_2)}{\sqrt{var(r_1)var(r_2)}}$ where $r_1 = p_1 - E[p_1|H_0] = (d_1 - d_0) - ua(a_0 + a_1\epsilon_1^2) = \epsilon_1 - ua(a_0 + a_1\epsilon_1^2)$ and $r_2 = p_2 - p_1 = (d_2 - d_1) + ua(a_0 + a_1\epsilon_1^2) = \epsilon_2 + ua(a_0 + a_1\epsilon_1^2)$. To ease the derivation, impose $a_0 = 1 - a_1$. First, consider the numerator:

$cov(\epsilon_1 - u(a_0 + a_1\epsilon_1^2), \epsilon_2 + u(a_0 + a_1\epsilon_1^2)) =$

$cov(\epsilon_1, \epsilon_2) + cov(\epsilon_1, +u(a_0 + a_1\epsilon_1^2)) - cov(u(a_0 + a_1\epsilon_1^2), \epsilon_2) - var(u(a_0 + a_1\epsilon_1^2))$

By ARCH(1) properties:

- $cov(\epsilon_1, \epsilon_2) = 0$
- $cov(\epsilon_1, +u(a_0 + a_1\epsilon_1^2)) = 0 + E[ua_1\nu_3^3] \times E[(\sqrt{a_0 + a_1e_0^2})^3] - E[\epsilon_1]E[ua_1\epsilon_1^2] = 0$
- $-cov(u(a_0 + a_1\epsilon_1^2), \epsilon_2) = 0 - E[\nu_2]E[ua_1\nu_1^2(a_0 + a_1\epsilon_0^2)\sqrt{a_0 + a_1e_1^2}] + 0 = 0$
- $-var(u(a_0 + a_1\epsilon_1^2)) = -var(ua_1\epsilon_1^2) = -(ua_1)^2\{E[(\epsilon_1^2)^2] - E[\epsilon_1^2]^2\}$.

The term $E[(\epsilon_1^2)^2] = E[(\nu_1^2(a_0 + a_1\epsilon_0^2))^2] = E[\nu_1^4]E[(a_0^2 + a_1^2\epsilon_0^4 + 2a_0a_1\epsilon^2] =$ $3(a_0^2 + a_1^2E[\epsilon_0^4] + 2a_0a_1E[\epsilon^2])$. The term $E[\epsilon_1^2] = 1$ follows from the ARCH(1) property $E[\epsilon_t^2] = \frac{a_0}{1-a_1}$. Therefore $E[\epsilon^4] = 3(a_0^2 + a_1^2E[\epsilon^4] + 2a_0a_1) \rightarrow E[\epsilon^4] = \frac{3(a_0^2+2a_0a_1)}{1-3a_1^2}$. To ensure that the fourth moment is positive, it follows that $a_1 < \frac{1}{\sqrt{3}}$.[20]

Hence, $-var(u(a_0 + a_1\epsilon_1^2)) = -(ua_1)^2\left\{\frac{3(a_0^2+2a_0a_1)}{1-3a_1^2} - 1\right\} = -\frac{2(ua_1)^2}{1-3a_1^2}$

The denominator follows the same line of reasoning:

- $var(r_1) = var(\epsilon_1 - u(a_0 + a_1\epsilon_1^2)) = var(\epsilon_1) + var(u(a_0 + a_1\epsilon_1^2)) - 2cov(\epsilon_1, (a_0 + a_1\epsilon_1^2))$
  Hence $1 + \frac{2(ua_1)^2}{1-3a_1^2}$
- $var(r_2) = var(\epsilon_2 + u(a_0 + a_1\epsilon_1^2)) = var(r_1)$

Hence the correlation is:

$$\rho = -\frac{\frac{2(ua_1)^2}{1-3a_1^2}}{1 + \frac{2(ua_1)^2}{1-3a_1^2}} = -\frac{2(a_1u)^2}{1 + a_1^2(-3 + 2u^2)}$$

Given $0 < \alpha_1 < \frac{1}{\sqrt{3}}$, the correlation is always negative. Moreover, the first derivative of the correlation expression w.r.t. a_1 and u are respectively:

- $-\frac{4u^2a_1}{\left((2u^2-3)a_1^2+1\right)^2}$
- $-\frac{4a_1^2\left(1-3a_1^2\right)u}{\left(a_1^2(2u^2-3)+1\right)^2}$

Both expressions have quadratic denominators, so it is sufficient to focus on the numerator to evaluate whether the correlation is decreasing on the two parameters. Considering the first expression, $4u^2a_1$ is always positive for $a_1 > 0$, hence the correlation is decreasing w.r.t. a_1. Similarly for the second expression, as $4a_1^2\left(1 - 3a_1^2\right)$ is always positive for $0 < a_1 < \frac{1}{\sqrt{3}}$, the correlation is decreasing w.r.t. u.

[20] This is similar to the condition $\alpha_1 < 1$ imposed to ensure that the unconditional variance is positive: $E[\epsilon_t^2] = \frac{a_0}{1-a_1}$.

Table 3.B: Statistical Properties of Volume and Volatility Variables

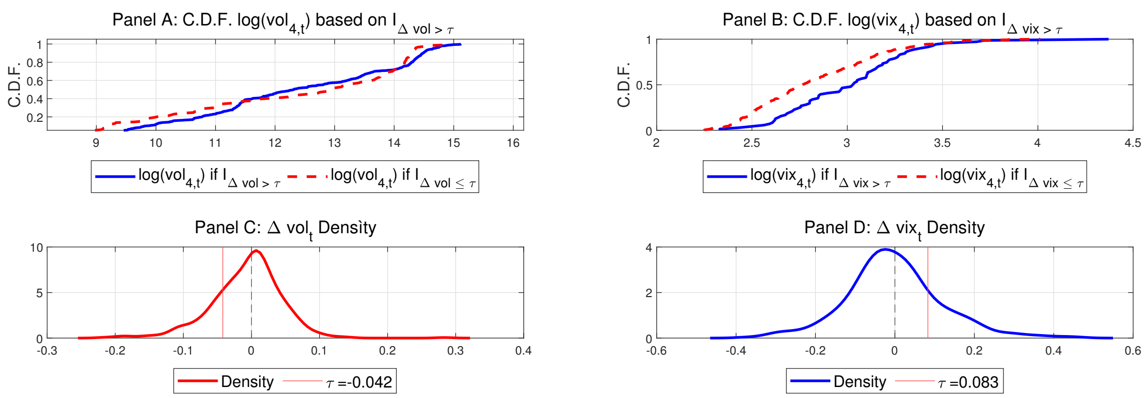
	Obs	Mean	Std.Dev.	Min	Max	Skewness	Kurtosis
$vol_{4,t}$ if $\Delta vol_t > \tau$	424	12.363	1.733	8.877	15.125	-0.199	1.817
$vol_{4,t}$ if $\Delta vol_t \leq \tau$	116	12.310	1.947	8.732	14.934	-0.487	1.737
$vix_{4,t}$ if $\Delta vix_t > \tau$	71	3.015	0.399	2.331	4.371	0.874	5.198
$vix_{4,t}$ if $\Delta vix_t \leq \tau$	289	2.828	0.346	2.249	4.012	0.665	3.008

This table reports the number of observations, mean, standard deviation, minimum, maximum, Skewness, and kurtosis for the subgroups of last week's volume $vol_{4,t}$ (volatility $vix_{4,t}$) defined according to the estimated threshold. The sample period for $vol_{4,t}$ goes from January 1975 to December 2019, while for $vix_{4,t}$ goes from January 1990 to December 2019.

B.2.2 Volume and Volatility Variables

This Appendix reports the statistical properties of the two proxies: Δvol_t and Δvix_t. In Panel A (B) of Figure 1.B, I show the cumulative distribution function (C.D.F.) of $vol_{4,t}$ ($vix_{4,t}$) conditional on the estimated threshold. For both variables, the estimated threshold likely implies a high volume (volatility) value in the last week of the month. The cumulative distribution function of $vol_{4,t}$, conditional on $\Delta vol_t > \tau$, stochastic dominates the opposite case (its cumulative distribution is lower) most of the time (Panel A). The cumulative distribution function of $vix_{4,t}$ conditional on $\Delta vix_t > \tau$ pointwise stochastically dominates (Panel B). The statistical analysis reported in Table 3.B corroborates the visual inspection in Figure 1.B. In Panel C (D), I report the estimated density function of Δvol_t (Δvix_t).

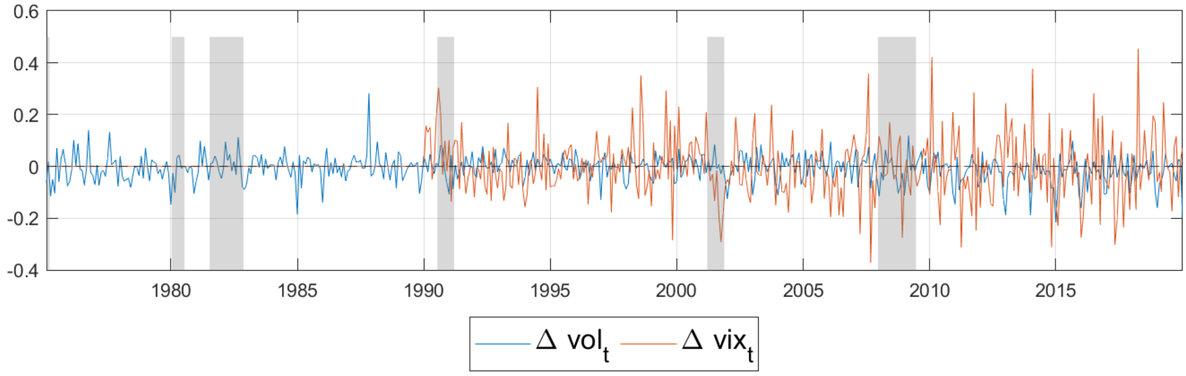
Figure 1.B: Statistical Properties of Δvol_t and Δvix_t



Panel A (B) reports the C.D.F. of $vol_{4,t}$ ($vix_{4,t}$) conditional on the estimated threshold τ: in solid blue line if $\Delta vol_t > \tau$ ($\Delta vix_t > \tau$) and in dashed red line if $\Delta vol_t \leq \tau$ ($\Delta vix_t \leq \tau$). Panel C (D) reports the estimated kernel density function of Δvol_t (Δvix_t) and the threshold parameter τ. The sample period for Panel A and C goes from January 1975 to December 2019, while for Panel B and D goes from January 1990 to December 2019.

Figure 2.B plots Δvol_t and Δvix_t over time. The two series are positively correlated and unre-

Figure 2.B: Δvol_t and Δvix_t over Time



This figure reports Δvol_t and Δvix_t over time. The grey shaded areas mark periods of recessions according to the NBER indicator function. The sample period for Δvol_t goes from January 1975 to December 2019, while for Δvix_t goes from January 1990 to December 2019.

lated to the business cycle. During periods of recession, Δvol_t is mostly positive, while Δvix_t is mostly negative. Intuitively, the two measures, being at weekly frequency, most likely capture market movements instead of business-cycle variations.

B.2.3 Different Metrics of Volume and Variance

In this section, I present evidence that the results presented in the main body of the paper are robust to different proxies specifications. Here, I consider the following:

$$\Delta vol_t = vol_{w=4,t} - vol_{w=3,t} \qquad \Delta vix_t = vix_{w=4,t} - vix_t$$

where $vol_{w=i,t}$ and $vix_{w=i,t}$ are the i^{th} weekly volume and VIX values and vix_t is the end of the month VIX closing price.

Table 4.B: Testing Empirical Prediction 1: Different Proxies

Panel A: Proxy Supply Shock						Panel B: Proxy Volatility Clustering					
TAR regression		Predictive regression				TAR regression		Predictive regression			
τ	-0.186	α	0.004	0.004	0.005	τ	0.075	α	0.005	0.005	0.005
			[2.00]	[0.84]	[1.17]				[1.89]	[2.40]	[2.46]
α	0.004	$r_{w=4,t}$	-0.353		-0.099	α	0.006	$r_{w=4,t}$	-0.282		-0.059
	[2.07]		[-3.78]		[-0.56]		[2.75]		[-2.72]		[-0.31]
$r_{w=4,t}$ if $\Delta_{vol} \leq \tau$	-0.089	$\mathbb{1}_{t,\ \Delta vol>\tau}$		-0.001	-0.001	$r_{w=4,t}$ if $\Delta_{vol} \leq \tau$	-0.056	$\mathbb{1}_{t,\ \Delta vol>\tau}$		-0.010	0.015
	[-0.29]			[-0.26]	[-0.19]		[-0.26]			[-1.26]	[1.55]
$r_{w=4,t}$ if $\Delta_{vol} > \tau$	-0.459	$r_{w=4,t} \times \mathbb{1}_{t,\ \Delta vol>\tau}$			-0.358	$r_{w=4,t}$ if $\Delta_{vol} > \tau$	-0.656	$r_{w=4,t} \times \mathbb{1}_{t,\ \Delta vol>\tau}$			-0.929
	[-3.17]				[-1.62]		[-3.16]				[-2.90]
Obs.	539		539	539	539		359		359	359	359
$R^2(\%)$	1.98		1.90	0.02	2.31		1.94		1.38	0.55	3.37

In Panel A, I report in the first column the results of the following Threshold Autoregressive Regression (TAR):

$$r_{t+1} = \begin{cases} \alpha + \gamma_1\ r_{w=4,t} + \epsilon_{t+1} & if\ \ -\infty < \Delta vol_t \leq \tau \\ \alpha + \gamma_2\ r_{w=4,t} + \epsilon_{t+1} & if\ \ \ \ \tau < \Delta vol_t < \infty \end{cases}$$

where τ is the estimated TAR threshold estimated on the volume variable $\Delta vol_t = vol_{w=4,t} - vol_{w=3,t}$. From the third column, I report the results of the following Predictive regression:

$$r_{t+1} = \alpha + \gamma\ r_{w=4,t} + \beta\ \mathbb{1}_{\Delta vol_t} + \psi\ (r_{w=4,t} \times \mathbb{1}_{\Delta vol_t > \tau}) + \varepsilon_{t+1}$$

where $\mathbb{1}_{\Delta vol_t > \tau}$ is an indicator function based on $\Delta vol_t > \tau$. In brackets, I report robust Newey and West (1987) t-statics. In Panel B, I report analogous results obtained for $\Delta vix_t = vix_{w=4,t} - vix_t$. The sample period goes from January 1975 to December 2019 in Panel A and from January 1990 to December 2019 in Panel B.

B.3 Appendix Economic Mechanism

B.3.1 Direct Evidence between Reversal Pattern and Payment Cycle

Table 5.B reports summary statics conditional on the TAR threshold estimated on pension funds' inflows (monthly seasonally adjusted employer contributions for employee pension and insurance funds), $inflow_t$, last week Fed Fund Rate $ff_{w=4,t}$ and last week National Financial Conditions Index (NFCI), $nfti_{w=4,t}$.

Table 5.B: Descriptive Statistics Payment Cycle Variable

	τ	Obs.	Mean	Std.Dev.	Min	Max	Skewness	Kurtosis
$inflow_t$ if $inflow_t > \tau$	6.237	309	6.81	0.33	6.24	7.30	-0.41	1.88
$inflow_t$ if $inflow_t \leq \tau$		230	5.42	0.54	4.37	6.24	-0.23	1.93
$ff_{w=4,t}$ if $ff_{w=4,t} > \tau$	5.76	190	9.05	3.11	5.79	19.44	1.52	4.92
$ff_{w=4,t}$ if $ff_{w=4,t} \leq \tau$		349	2.66	2.09	0.06	5.76	0.11	1.41
$nfti_{w=4,t}$ if $nfti_{w=4,t} > \tau$	-.409	263	0.50	1.01	-0.41	3.91	1.52	4.92
$nfti_{w=4,t}$ if $nfti_{w=4,t} \leq \tau$		276	-0.65	0.15	-1.12	-0.41	-0.78	3.53

This table reports in the first column the estimated TAR threshold considering pension funds' inflows (monthly seasonally adjusted employer contributions for employee pension and insurance funds), $inflow_t$, last week Fed Fund Rate $ff_{w=4,t}$, and last week National Financial Conditions Index (NFCI), $nfti_{w=4,t}$. In the remaining columns, I report statistics conditional to the TAR threshold: number of observations, mean, standard deviation, min, max, Skewness, and Kurtosis. The sample period goes from January 1975 to December 2019.

B.3.2 Order Imbalance across Business Cycle

Table 6.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.3.3 Order Imbalance across Stocks

Table 7.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 6.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 7.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 Potential Other Explanation of Reversal Pattern

B.4.1 Compensation for Standard Liquidity Risk

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, I here report the adjusted alphas of the rule of thumb TSR strategy against four anomalies in Dong et al. (2022) pricing liquidity: IDIOVOL, RETVOL, DOLVOL, and ILLIQ.[21] Moreover I report a standard predictive regression controlling for the

[21] $RETVOL$ 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

Table 8.B: Time Series Reversal and Standard Liquidity Factor

	Panel A: Adjusted Alphas							Panel B: Predictive Regression			
	STR CS	RETVOL	DOLVOL	IDIOVOL	ILLIQ	ALL		Base	Econ Var	Anom.	ALL
	5.636	6.193	6.108	5.947	5.985	6.521		-0.353	-0.297	-0.356	-0.302
α	[2.81]	[3.13]	[2.99]	[2.95]	[2.82]	[3.17]	γ	[-3.78]	[-2.78]	[-3.31]	[-2.68]

Panel A reports the results of the following regression: $TSR_t = \alpha + \beta LF_t + \epsilon_t$ where LF_t is either the short-term cross-sectional factor, RETVOL, DOLVOL, IDIOVOL, ILLIQ or all the liquidity-based anomalies. Panel B reports the attached coefficient to the main predictor of the following regression $r_{t+1} = \alpha + \gamma\, r_{w=4,t} + \beta C_t + \epsilon_{t+1}$ where C_t is a set of economic variables (svar, last week fed funds, and NFCI) in the second column, liquidity-based anomalies in the third column, and all the previous variables in the fourth column. The baseline time window is from January 1975 to December 2019, whereas when I control for anomalies return, the time window is from January 1975 to December 2018.

four anomalies, stock variance (svar), short-term cross-sectional reversal factor, and fourth week NFCI and Fed funds. The results reported in Panel A Table 8.B show that the adjusted alphas are positive and statistically significant, Panel B shows that the attached coefficient to the proposed predictor is negative and statistically significant. Even though the findings show that standard factors do not span the proposed predictor, it is worth exploring in future research whether infrequent factors capturing pension funds liquidity problems span the novel predictor.

B.4.2 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).[22] 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).

volatility. $ILLIQ$ sorts stocks based on yearly Amihud ratio.

[22]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.

I control that Sentiment measures do not impact the reversal pattern by first running a TAR regression

$$r_{t+1} = \begin{cases} \alpha + \gamma_1 \ r_{w=4,t} + \epsilon_{t+1} & if \ -\infty < BF^i_t \leq \tau \\ \alpha + \gamma_2 \ r_{w=4,t} + \epsilon_{t+1} & if \qquad \tau < BF^i_t < \infty \end{cases}$$

where BF^i is either $SENT$ or $SENT^{\perp}$. Second, I perform the standard predictive regression

$$r_{t+1} = \alpha + \gamma \ r_{w=4,t} + \beta BF^i_t + \epsilon_{t+1}$$

Panel A Table 9.B shows that the negative correlation does not depend on market sentiment as the reversal pattern does not change according to the monthly sentiment level. Moreover, by considering a higher sentiment as a measure of overconfidence, the behavioral channel proposed in Odean (1998) is less likely to explain the findings as the negative serial correlation is statistically more robust when the BF^i values are below the estimated threshold. Consistently with the previous analysis, Panel 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.

B.4.3 Option Expiration Effect

In this section, I provide evidence that the results can not be 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 10.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. Specifically, I show both with a TAR regression and with a linear predicting equation that an increase in the third-week volatility ($\Delta vix_{w=3,t} = vix_{w=3,t} - vix_{w=2,t}$) has no impact on the reversal pattern.

Table 9.B: Over-Confidence Channel

Panel A: TAR				Panel B: Predictive Regression				
τ	-0.349	τ	-0.213	α	0.004	0.004	0.004	0.004
					[2.00]	[2.05]	[2.08]	[1.94]
α	0.004	α	0.004	$r_{w=4,t}$	-0.353	-0.358	-0.355	-0.36
	[2.08]		[2.11]		[-3.78]	[-3.96]	[-3.90]	[-4.00]
$r_{w=4,t}$ if $SENT_t \leq \tau$	-0.557	$r_{w=4,t}$ if $SENT_t^{\perp} \leq \tau$	-0.517	SENT		-0.003		0-006
	[-1.89]		[-2.49]			[-1.36]		[-0.76]
$r_{w=4,t}$ if $SENT > \tau$	-0.302	$r_{w=4,t}$ if $SENT^{\perp} > \tau$	-0.280	$SENT_t^{\perp}$			-0.003	0.003
	[-2.02]		[-1.71]				[-1.19]	[0.37]
Obs.	539		539		539	539	539	539
$R^2(\%)$	1.78		1.82		1.9	2.29	2.23	2.31

Panel A reports the results of the following Threshold Autoregressive Regression (TAR):

$$r_{t+1} = \begin{cases} \alpha + \gamma_1 \; r_{w=4,t} + \epsilon_{t+1} & if \quad -\infty < SENT_t^i \leq \tau \\ \alpha + \gamma_2 \; r_{w=4,t} + \epsilon_{t+1} & if \qquad \tau < BF_t^i < \infty \end{cases}$$

where τ is the estimated TAR threshold estimated on the Baker and Wurgler (2006)'s sentiment index $SENT$ (first column) $SENT^{\perp}$ (second column). Panel B reports the results of the following Predictive regression:

$$r_{t+1} = \alpha + \gamma \; r_{w=4,t} + \beta \; SENT_t^i + \epsilon_{t+1}$$

In brackets, I report robust Newey and West (1987) t-statics. The sample period goes from January 1975 to December 2019.

Table 10.B: Volatility Channel: Option Expiration Effect

τ	0.099		
α	0.005	α	0.005
	[2.17]		[1.87]
$r_{w=4,t}$ if $\Delta vix_{w=3,t} \leq \tau$	-0.500	$r_{w=4,t}$	-0.282
	[-3.34]		[-2.72]
$r_{w=4,t}$ if $\Delta vix_{w=3,t} > \tau$	0.525	$\Delta vix_{w=3,t}$	-0.001
	[1.17]		[-0.05]
Obs	359		359

This table reports in the first column the results of the following Threshold Autoregressive Regression (TAR):

$$r_{t+1} = \begin{cases} \alpha + \gamma_1 \; r_{w=4,t} + \epsilon_{t+1} & if \quad -\infty < \Delta vix_{w=3,t} \leq \tau \\ \alpha + \gamma_2 \; r_{w=4,t} + \epsilon_{t+1} & if \qquad \tau < \Delta vix_{w=3,t} < \infty \end{cases}$$

The second column reports the results of the following regression: $r_{t+1} = \alpha + \gamma \; r_{w=4,t} + \beta \; \Delta vix_{w=3,t} + \varepsilon_{t+1}$. In brackets, I report Newey and West (1987) t-statics. The sample period is from January 1990 to December 2019.

Table 11.B: Reversal Pattern and End of Quarter Effect

α	0.004	0.003	0.004
	[1.95]	[1.75]	[1.99]
$r^{NOQ}_{w=4,t}$	-0.266		-0.268
	[-2.43]		[-2.44]
$r^{Q}_{w=4,t}$		-0.679	-0.681
		[-2.14]	[-2.15]
$R^2(\%)$	0.86	1.44	2.31
Obs.	539	539	539

This table reports the correlation coefficient of $r_{t+1} = \alpha + \gamma_1(1 - \mathbf{I}^Q_t) \times r_{w=4,t} + \gamma_2 \mathbf{I}^Q_t \times r_{w=4,t} + \varepsilon_{t+1}$ 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-statics. The sample period goes from January 1975 to December 2019.

B.4.4 Quarterly Robustness Check

In this section, I investigate whether the reversal pattern between $r_{w=4,t}$ and r_{t+1} is a consequence of quarterly rebalancing and reports. Hence, I split the full sample (January 1975 - December 2019) between end-of- and non-end-of-quarter months. The results presented in Table 11.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.

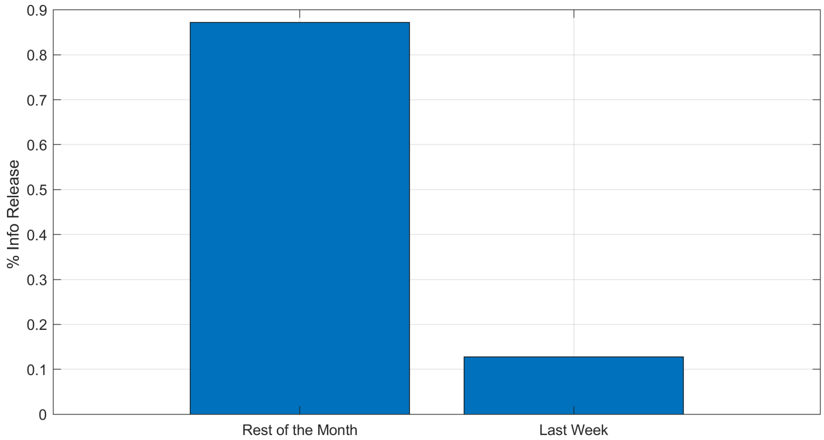
B.4.5 Information Release

I examine whether the results can potentially 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.[23] Considering

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

the time series before 2005, the percentage halves.

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.

B.4.6 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 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 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.