Time Series Reversal: A Payment Cycle Friction*

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July 31, 2024

Abstract

This paper shows that the U.S. equity market reverts the liquidity-driven trading induced by the payment cycle within a month. The aggregate reversal is robust to transaction costs and out-of-sample tests as it concentrates on liquid and high-priced stocks and during expansion periods. The findings lead to a novel interpretation of reversal: the pattern measures the liquidity not efficiently provided in the market rather than investors' cognitive bias or compensation for market-making.

Keywords: pension funds, flow, anomalies, time series, market frictions, reversal, liquidity.

*I am very grateful for the advice and support I have received from Pasquale Della Corte, Riccardo Sabbatucci and Max Croce. I would also thank Alireza Aghaee, Yu Bai, Gabriele Confalonieri, Tarun Chordia, Carlo Favero, Christian Skov Jensen, Massimiliano Marcellino, Stefan Nagel, Jose Penalva, Barbara Rindi, Ioanid Rosu, Jakob Ahm Sørensen, Dimitri Vayanos, Fernando Zapatero and Irina Zviadadze for very useful comments and suggestions. An earlier version of the paper has been circulated under the title "Monthly Return Autocorrelation".

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1 Introduction

Since the seminal work of Jegadeesh (1990), the literature has extensively documented cross-sectional 1-month reversal. There is common agreement that the pattern concentrates on small and illiquid stocks, with its strength increasing during periods of economic downturn. The literature still debates whether cross-sectional reversal is implementable in real markets due to its high transaction costs and fees, Avramov, Chordia, and Goyal (2006), and whether the pattern is a consequence of behavioral biases or market-making activity, Da, Liu, and Schaumburg (2014). Conversely, at the aggregate level, there is limited evidence of reversal as pointed out, for example, in Hartzmark and Solomon (2022): "*much less is known about the speed and extent one should expect entire markets to reverse price pressure.*" Therefore, the questions I aim to answer in this paper are: Is there a time series reversal? Can investors profit from it? What are the properties of the pattern, and ultimately, which is its economic source?

Figure 1: **Time Series Reversal (TSR), Cross Sectional Reversal (CSR) and S&P 500 Gains**
This figure compares the cumulative Out-of-Sample returns of the time series reversal (TSR - red solid line) with passive investing on the S&P 500 (black dotted line) and the cross-sectional reversal (CSR - blue dotted line). The TSR trading strategy consists of buying the S&P 500 if the last week of the month has a negative return and holding the asset for the next month. The CRS trading strategy consists of buying the S&P 500 if the Fama French Short-Term Reversal Factor (ST Rev) is negative and selling the index otherwise. The grey-shaded areas mark periods of recessions according to the NBER. The time window is from January 1975 to December 2020.

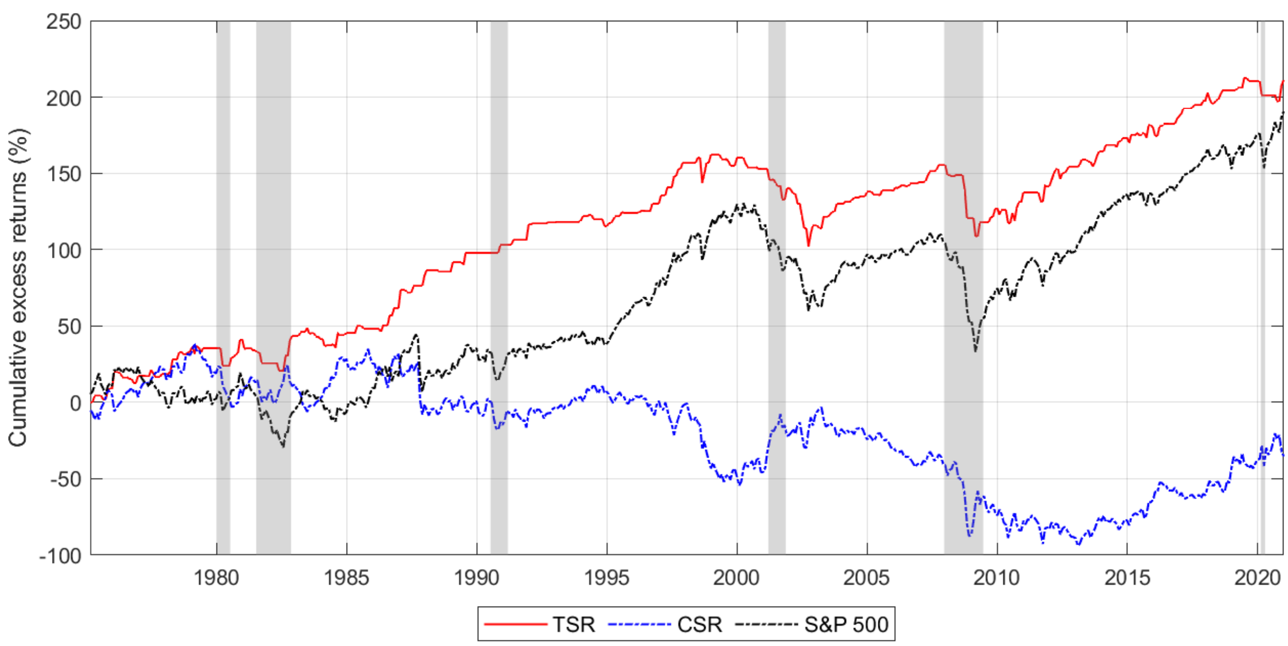


Figure 1 shows the paper's main result: a profitable monthly aggregate reversal in the S&P 500. Specifically, the reversal trading strategy consists of buying the S&P 500 if the last week of the month has a negative return and holding it for the next month. The strategy proxies the predictable negative price pressure induced by the payment cycle as it buys the aggregate market after pension funds potentially sell stocks to recoup liquidity. Consistently with the explanation, I show that the novel time series pattern is cyclical with the economy and stronger for high-priced and liquid stocks, the instruments that compose the S&P 500. Therefore, in light of the opposite findings established in the cross-sectional literature, I offer a novel interpretation of the reversal pattern: an anomaly due to liquidity friction.

In the first part of the paper, following Vayanos and Gromb (2012), I argue that the last week of the month is an ideal candidate to establish an anomaly. Involving around 100 Trillion annually, the payment cycle contemporaneously defines a substantial demand shock and liquidity frictions in the aggregate economy. I argue that American pension funds initiate the economic mechanism by showing that pension plans are equity net sellers at the end of the month. This finding is consistent with the evidence that pension funds may rely on external financing to pay contributions due to their negative cash flows and risky liability-driven investments (LDI). As end-of-month financing costs increase and hedge funds cannot likely finance pension funds' imbalance, pension funds wait to sell stocks for liquidity reasons until the end of the month, when their unpredictable inflows and outflows materialize.

I provide In-Sample evidence that last week's return negatively predicts the one-month ahead returns. The predictability increases over the month and peaks in the third week, before the aggregate market is hit by a new negative price pressure induced by the payment cycle. I then study the reversal pattern in Out-of-Sample exercises to test its robustness and consider the perspective of a real-time investor. The proposed predictor delivers better results than the historical mean, the benchmark in the monthly literature - Welch and Goyal (2008). Notably, the reversal pattern has more predicting power in expansion periods, improving the Out-of-Sample forecasting performance and robustness. This feature is a novelty as the literature has shown and rationalized why predictability clusters during recession periods - Huang, Jiang, Tu, and Zhou (2014) and Cujean and Hasler (2017). Finally, I test the economic value of the reversal pattern in terms of utility, Campbell and Thompson (2008), and monetary gains, Gao, Han, Li, and Zhou (2018). The aggregate reversal delivers sizable gains, even considering transaction costs and fees.

In the second part of the paper, I provide evidence of the payment cycle as the economic channel behind the reversal pattern. I document that the reversal pattern is stronger during periods of economic expansion. The result is consistent with the evidence that pension funds decrease precautionary cash reserves in stable periods. Having less liquidity buffer to cover potential end-of-month liquidity needs and facing a growing market, pension funds have more incentive to sell to recoup liquidity. Furthermore, in line with the idea that institutional investors try to get liquidity by minimizing transaction costs and price impact, I show that the reversal pattern is stronger for high-priced and liquid stocks. I provide a direct link between the negative serial correlation returns and measures linked to the end-of-month payments. By running a Threshold Autoregressive Regression (TAR), I establish that the reversal pattern is stronger in months with lower pension funds' inflows and higher end-of-month borrowing costs. Intuitively, the reversal pattern is stronger when pension funds face a large cash flow imbalance or a more expensive borrowing outside option. Finally, I micro-found the mechanism by providing evidence that both institutional and retail investors foster the documented pattern.

Using the ANcerno dataset and considering pension plan sponsors' order imbalance, I show that these financial investors recoup end-of-month liquidity by substantially selling stocks in the last week of the month. Motivated by the empirical predictions in Campbell, Grossman, and Wang (1993),[1] I analyze the relationship between the reversal pattern and volume to corroborate the non-informational nature of pension plans' trading. I empirically test the Campbell et al. (1993) model prediction in a two-step procedure. With the TAR regression, I establish a threshold on volume above which the negative serial correlation is stronger. With the predictive regression

[1] In their model, non-informational trading causes price movements that eventually revert. Such non-informed trading is accompanied by high trading volume due to a reallocation of risk among market participants.

analysis, I show that, after controlling for volume and its interaction term with the last weeks return, the negative serial correlation is significant only when there is high volume in the last week of the previous month.

Using the "Retail Trading Activity Tracker" from Nasdaq Data Link, I show that retail investors trade more on stocks listed in the S&P 500 at the end of the month. To provide evidence that retail investors' activity fosters the reversal pattern, I test the prediction of Sentana and Wadhwani (1992) model. In their framework, positive feedback trading - a trading strategy adopted by retail investors, Barber, Odean, and Zhu (2008) - drives a reversal aggregate market pattern, and its strength increases with volatility. Analyzing the relationship between volatility and reversal with the same two-step procedure described above, I find statistically significant evidence of reversal only when volatility in the last week of the month is larger. The result supports the hypothesis that retail investors' trading activity might accentuate the reversal pattern.

In the last part of the paper, I provide additional results, among which I show that the pattern extends to the Dow Jones - index formed by the 30 highest capitalized stocks. The result corroborates that the pattern focuses on high-priced and liquid stocks. Moreover, in line with the structural differences between international and American pension funds, I discuss why the pattern concentrates on U.S. indexes. I perform several robustness checks in the Appendix, among which I show that the reversal pattern is robust to the end-of-the-month return construction, to the closing price effect, to previously proposed predictors and factors. I provide evidence that compensation for risk, behavioral bias, option expiration trading, quarterly activity, information release and pension funds rebalancing can not explain the documented empirical findings.

The rest of this paper is organized as follows. Section 2 describes the institutional background and the statistical evidence. Section 3 explores the transmission channel behind the reversal pattern. Section 4 provides some additional results and Section 5 concludes.

1.1 Literature Review

I establish a reversal pattern on the aggregate market by departing from the two approaches typically adopted in the literature. The first methodology, based on variance ratio tests following Lo and MacKinlay (1988), does not reject the null hypothesis of the random walk model at the monthly level due to the test's limited statistical power and the generally low persistence of returns. Consequently, the literature has been mostly investigating reversal with a cross-sectional approach by adopting Fama and MacBeth (1973) regressions and De Bondt and Thaler (1985) losers minus winners portfolios (e.g., Bogousslavsky (2016), Medhat and Schmeling (2022) and Dai, Medhat, Novy-Marx, and Rizova (2023)). The cross-sectional approaches suffer two major drawbacks. First, the results capture both return auto (cross) correlation and cross-sectional variation in average return. Therefore, the results are possibly driven by cross-sectional differences among stocks rather than reversal properties.[2] Second, the findings are more pronounced on small and illiquid stocks, raising concerns whether the predictability is practically meaningful. The gains from the cross-sectional reversal are negligible when costs and fees, which are particularly high for this category of stocks, are taken into account - Avramov et al. (2006).

The proposed methodology is close in spirit to Hartzmark and Solomon (2022) as both papers use predictable price pressures to establish market predictability. Their paper uses the positive, predictable flow after a dividend payment to establish daily aggregate market predictability. Importantly, this paper aims to answer two important questions Hartzmark and Solomon (2022) raise. First, this paper helps to understand whether and how aggregate markets revert price pressure. Second, this work suggests that frictions linked to market conventions and rules can be the economic explanation behind the buying or selling pressure of market participants.

The second contribution to the field lies in arguing that return reversal is a consequence of a

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

specific market convention/friction by micro-founding the empirical pattern. The literature has provided two possible explanations for a negative return autocorrelation. The first explanation is based on overreaction to information, fads, or simply cognitive errors of market participants (e.g., Shiller (1980), Black (1986), Poterba and Summers (1988), and Subrahmanyam (2005)). The alternative explanation, known as market-based, relies on the price pressure that can occur with a shift in the demand and/or supply curve and considers return reversal as a compensation factor for liquidity provision (e.g., Grossman and Miller (1988), Avramov et al. (2006), Nagel (2012), Da et al. (2014), and Dai et al. (2023)). My work connects the reversal pattern to the end-of-the-month payment cycle. Specifically, the trading strategy buys the aggregate market only after the payment cycle and, hence, after institutional investors potentially sell for liquidity reasons. Therefore, I provide a novel interpretation of the aggregate level 1-month reversal: it measures the liquidity demand the financial markets cannot efficiently accommodate. Consequently, the documented reversal pattern can be considered an anomaly due to liquidity frictions.

The third contribution to the field is documenting novel properties of the 1-month reversal pattern. In the cross-sectional literature (e.g., Avramov et al. (2006), Nagel (2012) and Dai et al. (2023)), the pattern concentrates on small and illiquid stocks and generally spikes in periods of uncertainty. The explanations offered from the literature are consistent with the cross-sectional reversal findings. The "behavioral anomaly view" reconciles the findings by arguing that low-priced and illiquid stocks are the financial instruments with the lowest coverage and information and economic downturns are the periods in which generally behavioral biases accentuate. The "liquidity compensation factor view" links lower volume to higher inventory duration costs and higher uncertainty to higher adverse selection risks for the liquidity providers. In contrast to the literature and consistent with a liquidity based explanation, I document that the aggregate reversal is cyclical, as pension funds likely tend to sell equity positions only when it is convenient, and stronger for high-quality stocks, as they try to minimize transaction costs and price impact.

I contribute to the forecasting literature by proposing a new approach to exploring the relationship between past and future returns. Moskowitz, Ooi, and Pedersen (2012), and Neely, Rapach, Tu, and Zhou (2014) try to establish monthly aggregate predictability by considering past returns that capture the trend of the market itself (12-month returns in Moskowitz et al. (2012) and technical indicators based on the last few months performances in Neely et al. (2014)). Instead, I use the last week non-informational price pressure caused by the payment cycle to capture a short-run stock predictability. As a result of the almost opposite approach, the predictor here proposed has polar characteristics in comparison with the ones in Moskowitz et al. (2012), and Neely et al. (2014): I document a negative statistical relationship between the predictor and the aggregate market, and its predictability is during periods of expansion. Predicting the aggregate stock market in good times is a unique feature of the proposed predictor. I finally propose a forecasting exercise in which I mix the aggregate reversal and Momentum. I show that the Out-Sample performance drastically improves, predicting the aggregate market both in expansion and recession times.

I finally contribute to the growing literature studying the financial impact of institutional investors' demand for liquidity. Most studies focus on the swap and government bonds markets (e.g., Klingler and Sundaresan (2019) and Jansen, Klingler, Ranaldo, and Duijm (2024)). This paper builds from Etula, Rinne, Suominen, and Vaittinen (2020), which argues that institutional investors sell equity positions to recoup end-of-month liquidity. However, this work differs from theirs in many dimensions. Importantly, I provide evidence suggesting that pension funds are the institutional investors selling for liquidity reasons. Moreover, Etula et al. (2020) aims to establish the end-of-the-month payment cycle as an event causing general liquidity distress, whereas this paper aims to use the non-informational trading induced by the payment cycle to establish and characterize aggregate market reversal.

2 Evidence of Monthly Time Series Reversal

According to Vayanos and Gromb (2012), a market anomaly likely arises if an economic event imposes simultaneously a demand shock and arbitrage restrictions on the stock market. Does the end-of-month payment cycle trigger both conditions? In the United States, monthly transfers typically occur towards the end of the month and involve a liquidity exchange of around 100 Trillion dollars - five times the annual stock market volume.[3] The substantial liquidity involved, coupled with its clustering at the end of the month, suggests that the payment cycle likely imposes both conditions: market participants may substantially trade for non-informational reasons, and no marginal investor has the resources to correct the inefficiency.

To study the potential liquidity constraints imposed by the payment cycle on institutional investors' trading activity, I explore the ANcerno dataset from 2000 to 2010.[4] In the first row of Table 1, I report the daily dollar imbalance - the ratio between signed dollar volume and dollar volume - and the cumulative average dollar position for the last week of the month. Consistent with Etula et al. (2020), the order imbalance is statistically negative at $T-4$ and $T-3$ (where T is the last trading day), and the average weekly dollar position is negative. The results align with the hypothesis that due to its significant liquidity transfers, the payment cycle imposes liquidity needs on institutional investors.[5]

In the second and third rows of Table 1, I consider the cross-section of institutional investors in the ANcerno dataset. Specifically, the second row displays the results for money managers (mutual funds, hedge funds, banks, and insurance companies). The negative imbalance at $T-4$ and $T-3$ is consistent with the evidence that money managers have large disbursements in the last week - e.g., distributions, salaries, compensations, and insurance claims. Conversely, the positive imbalance in the last three trading days is likely due to mutual funds' passive investing.

The negative order imbalance and dollar position reported in the last row of Table 1 suggest

[3] Pensions and contributions are disbursed on the first day of the month, salaries are paid bi-weekly or at month-end, and dividends are generally distributed on the last day. I proxy the transfers by the total value of cashless payments from IBS, and dollar volume is from the World Bank. I use the 2019 record, the last available year from the World Bank Dataset. The cashless payments in 2019 were around 103 Trillion, whereas the total dollar value traded was around 23 Trillion.

[4] ANcerno (formerly the Abel Noser Corp.) contains trade-level observations for hundreds of public and private institutional investors. For a detailed description of the ANcerno dataset see Appendix A.1.

[5] The average cumulative net position is multiplied by 10 as the dataset, although representative of institutional investors' behavior, maps between 8 to 12% of CRSP volume, Hu, Jo, Wang, and Xie (2018). In Appendix A.2, I use data from Commodity Futures Trading Commission (CFTC) to corroborate the results.

Table 1: Last Week Institutional Investors Trading Activity
This table reports in the first row the daily order imbalance in the last trading week (where T is the last day of the month) and the last week average net dollar position (in Millions) for all institutional investors. In the second and third rows, I consider only money managers and pension plan sponsors respectively. 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

	T-4	T-3	T-2	T-1	T	$ Pos [Mil.]
All	−1.14%	−1.72%	0.17%	1.17%	3.34%	-400
Sample	[-1.77]	[-2.77]	[0.28]	[1.46]	[4.31]	
Money	−1.05%	−1.57%	0.66%	1.66%	3.10%	190
Managers	[-1.69]	[-2.41]	[1.00]	[2.57]	[3.80]	
Pension	−3.46%	−3.69%	−1.98%	1.24%	5.14%	-920
Plan	[-2.43]	[-3.10]	[-1.71]	[0.87]	[3.59]	

that pension plan sponsors drive the overall dynamic. It is important to note that pension plan sponsors include both benefit pension funds (DB - pension funds) and contribution plans (DC - 401k plans).[6] Even though I cannot further distinguish between DB and DC pension plans, the pension plans' negative imbalance is likely due to pension funds: DC plans may aggressively buy at the end of the month as they have positive cash flows, potentially explaining the overall pension plans' buying activity on the last trading day.

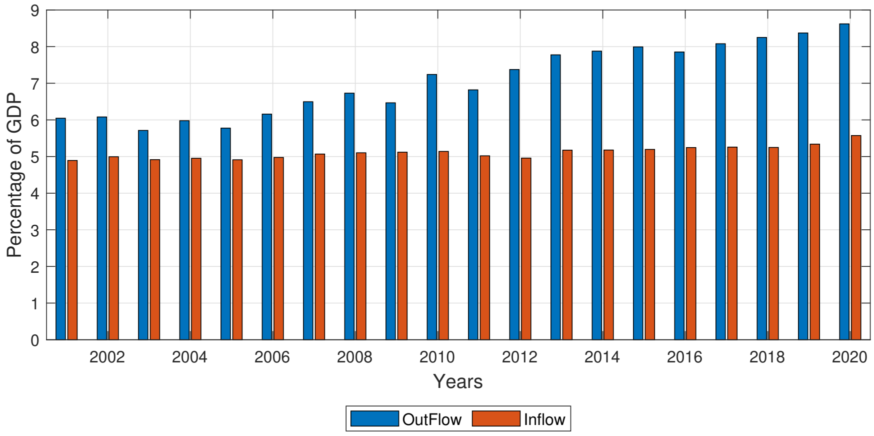
Pension funds, conversely, have negative cash flows, as they distribute more to retirees than collect from active workers - Figure 2. To cover the imbalance, pension funds rely on Liability Driven Investments (LDI) to generate cash-flow from their asset in place. As the imbalance between active workers' and retirees' cash-flow is substantial, pension funds have tilted their investments over riskier and illiquid assets, such as private equity, infrastructure, and real estate.[7] If LDI cashflows do not match the imbalance - as both quantities are highly unpredictable and market-based - pension funds need to resort to external financing to match their leftover liquidity imbalance. Due to an overall dash for cash of market participants, there is a surge in end-of-

[6] In a defined benefit plan (such as pension funds), companies pay retirees a regular monthly payout. Conversely, in defined contribution plans (such as 401k plans), companies do not commit to pay a pre-established amount to retirees but only to invest a certain amount in workers' retirement accounts.

[7] Many industry reports corroborate the negative cash-flow problem, see for example Goldman Sachs report Cash Flow Matching: The Next Phase of Pension Plan Management. Pension funds' negative cash-flow problem has recently gained public spotlight in the United States. This issue is, for example, highlighted in 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. Moreover, BlackRock CEO Larry Fink has devoted most of his 2024 Letter to Investors on the U.S. retirement crisis.

month financing costs in short-term bonds and longer-term debt capital markets, Etula et al. (2020), making the usual borrowing channels a more expensive outside option. Consequently, pension funds may sell in the equity market to recoup liquidity.

Figure 2: **American Pension Funds CashFlows**
The 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*.



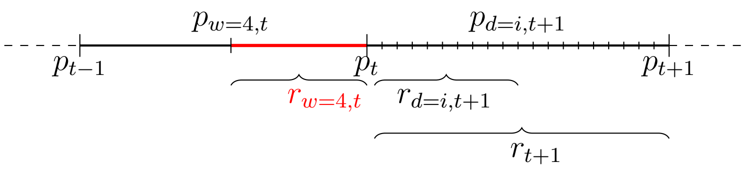
Two questions may arise: first, why do pension funds not anticipate their liquidity needs? Predicting pension funds' inflows and outflows is very hard. Inflows are contingent on market performance, and outflows' amount is uncertain, Davis (2000). Therefore, given that flows materialize towards the end of the month - with contributions paid around the 15th business day and benefits paid on the last business day - pension funds likely wait until the last week of the month to minimize inefficiencies associated to liquidity selling. Second, why do hedge funds not supply further liquidity? Managing a few trillion per year - statista, hedge funds should likely use most of their capital to trade against pension funds. Moreover, hedge funds also have end-of-the-month liquidity needs and are concerned by monthly reports, reducing overall their risk exposure at the end of the month, Patton and Ramadorai (2013).

2.1 In Sample Evidence

To study whether the end-of-the-month payment cycle determines a market anomaly, I collect closing prices of the S&P 500 from the Global Financial Data (GFD) from January 1975 to

December 2020. The notation I adopt in the paper is the following. I denote nominal values in capital letters and the respective natural logarithm values in lowercase. As 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, Figure 3.

Figure 3: **Price and Return Notation**
This figure graphically reports the notation adopted for price and return series. I use t to denote a generic month and add w (d) to specify the week (day). I denote in red the end of the month return by considering the return realized between the 4^{th} Friday closing price $p_{w=4,t}$ and the end of the month closing price p_t.



I capture the end-of-the-month payment cycle effect on the stock price dynamic by considering the realized return from the end of 4^{th} (Friday) weekly closing price to the end of the month ($r_{w=4,t} = p_t - p_{w=4,t}$). I start the analysis by testing 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 ($r_{t+1} = p_{t+1} - p_t - r_t^f$).[8] Figure 4 plots the predictive regression' estimated coefficients and 95% confidence intervals on the cumulative excess returns throughout the month

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

as well as on the standard monthly predictive equation:

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

In Figure 4, I establish a negative predicting power of the last week's return - implying a "time-series reversal" pattern throughout the next monthly returns. The reversal pattern increases in absolute magnitude during the month, suggesting that the aggregate market does not immediately recover from the predictable end-of-the-month negative price pressure. The estimated

[8]The summary statistics of $r_{w=4,t}$ and r_{t+1} are reported in Appendix A.3.

coefficients in the first part of the month are generally not statistically significant. Intuitively, either pension funds do not buy back their equity positions as they are cash flow negative or strategically wait to avoid positive price pressure in the first days of the month ahead. Conversely the estimated coefficients are statistically significant in the second part of the month, aligning with the timing of pension funds' inflows and outflows. Moreover, the largest estimated coefficient in absolute terms is observed in the third week ($r_{d=14,t+1}$), before the new end-of-the-month negative price pressure materializes and around when pension funds receive their inflows.

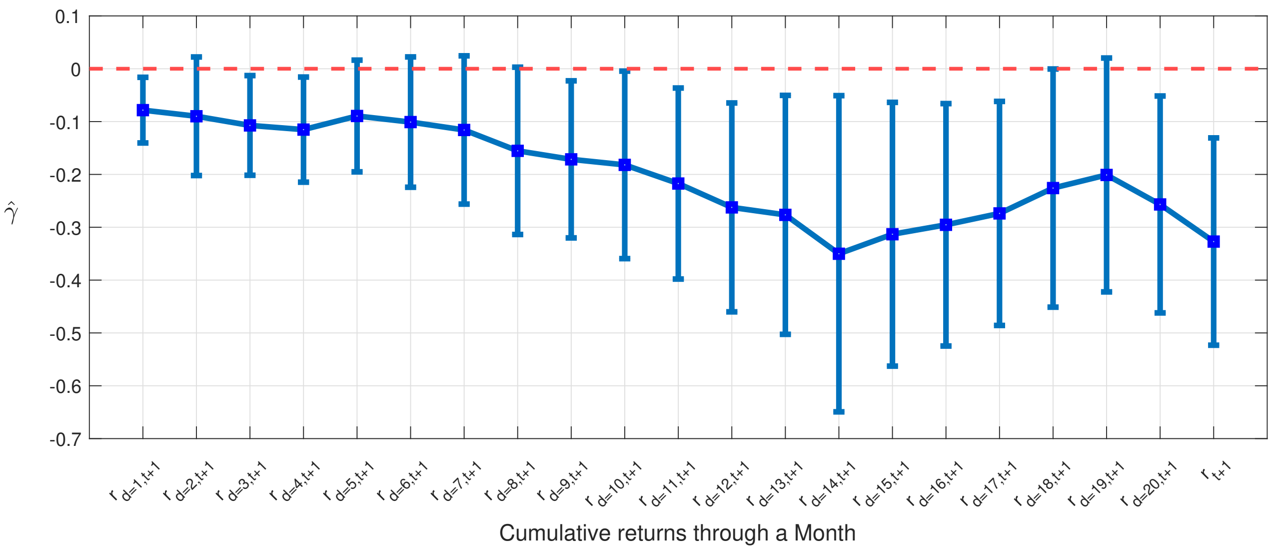
Figure 4: **Time Series Reversal throughout One Month Ahead**
This figure reports the estimated coefficients and the associated 95% Newey and West (1987) robust confidence intervals of the predictive regression on the cumulative returns throughout the month

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

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 2020.



Establishing aggregate monthly reversal has important implications for practitioners. The stock market may be less risky than it appears for long-term investors, Poterba and Summers (1988), as the price dynamic is influenced by temporary shocks that increase the variance but do not depend on the fundamental value. Therefore, the mean-reverting nature of the return dynamic may explain the Shiller (1980) excessive variance stock paradox: the equity market's volatility captures price movements that are not justified by fundamental news.

In Appendix A, I provide several evidence that the results presented in Figure 4 are robust. Specifically, Appendix A.4 shows that the results do not depend on a Friday effect. Appendix A.5 shows that the results do not depend on a closing price effect. Appendix A.6 shows that the reversal pattern is lost by considering a placebo test around the second week of the month. Appendix A.7 shows that the time series reversal' predicting power is lost by considering two months ahead returns. Finally, Appendix A.8 shows that the results are qualitatively unchanged by controlling for previous week's returns, factors, proposed predictors, and anomalies portfolio.

2.2 Out of Sample Evidence

The previous analysis of the reversal pattern is based on the entire sample (In-Sample) estimation. While In-Sample estimation is econometrically more efficient since all available data are used, the approach can be misleading since a real-time investor cannot access all the sample data. In addition, In-Sample estimation may suffer from an instability problem, as predictability varies over time, Goyal, Welch, and Zafirov (2021). Thus, In-Sample return predictability does not necessarily imply Out-of-Sample (OOS) predictability.

In this subsection, I evaluate the Out-of-Sample forecasting power of the end-of-the-month return. In line with the literature, 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 $\hat{\gamma}_t$. Then, Out-of-Sample forecast is 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 simulate the perspective of a real-time forecaster. The Out-of-Sample forecast evaluation period goes from July 1986 to December 2020 (75% of the entire sample for a total of 414 OOS point forecasts). Following Campbell and Thompson (2008), Neely et al. (2014) and Moskowitz et al. (2012), among others, I measure the Out-of-Sample predictability by considering

$$R^{2,OS} = 1 - \frac{\sum_{t=w}^{T}(r_{t+1} - \hat{r}_{t+1|t})^2}{\sum_{t=w}^{T}(r_{t+1} - \bar{r}_{t+1|t})^2}, \quad (4)$$

where $\hat{r}_{t+1|t}$ is the forecasted month t return from the estimated predictive regression through period $t-1$, and the benchmark forecast $\bar{r}_{t+1|t}$ is the historical average forecast estimated from the sample mean through period $t-1$. 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 Out-of-Sample results, I use Clark and West (2007) MSFE-adjusted statistic.[9]

While empirical support for time series reversal remains limited, the literature has extensively investigated time-series momentum - Moskowitz et al. (2012) and Neely et al. (2014). Hence, in Table 2 I include past 12-month return (r_{t-12}) and two technical indicators ($\mathbb{1}_{MA(1,12)}$ and $\mathbb{1}_{MOM(1,12)}$) in the Out-of-Sample analysis.[10] The first column 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 0.699%. The historical mean outperforms all the other predictors - they all have a negative $R^{2,OS}$. This finding is consistent with Huang, Li, Wang, and Zhou (2020) and Goyal et al. (2021), which have shown respectively that past 12-month return and technical indicators do not have a robust Out-Sample-Sample predicting power.[11]

Since the literature agrees that predictability varies over business cycles, the second and third

[9]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 $H_1 : R^{2,OS} > 0$.

[10]Moskowitz et al. (2012) find that the past 12-month excess return r_{t-12} is a positive predictor of future returns. Neely et al. (2014) establish a positive correlation between trend-following technical indicators and future returns. Neely et al. (2014) consider more than 15 specifications. For simplicity, I here analyze the performance of a technical indicator that compares the latest price against the average of the last 12 months' prices ($\mathbb{1}_{MA(1,12)}$) and a momentum strategy that compares the latest price against the past 12-month price ($\mathbb{1}_{MOM(1,12)}$). For details, see Appendix B.1. A comprehensive analysis for all technical indicators can be found in Goyal et al. (2021); results are qualitatively similar to the ones here presented.

[11]Huang et al. (2020) show that past 12-month returns do not have OOS predictability without standardizing for the monthly returns' variance. Goyal et al. (2021) extend the Neely et al. (2014) sample to December 2020 and show that the predictability from technical indicators is lost.

columns in Table 2 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:

$$R_e^{2,OS} = 1 - \frac{\sum_{t=w}^{T} I_t^c (r_{t+1} - \hat{r}_{t+1|t})^2}{\sum_{t=w}^{T} I_t^c (r_{t+1} - \bar{r}_{t+1|t})^2} \tag{5}$$

where I_t^{exp} (I_t^{rec}) is the NBER indicator function that takes a value of 1 when month t is in expansion (recession) and 0 otherwise. The performance from other predictors is consistent with the literature. There is significantly stronger evidence of predictability during recessions than during expansions - it has been empirically discussed in Huang et al. (2014) and theoretically supported by Cujean and Hasler (2017).[12] The $R^{2,OS}$ are positive during recessions but negative in expansions. Interestingly, the end-of-month return $r_{w=4,t}$, behaves very differently. The predictability concentrates during expansion periods, $R_{OS}^{2,exp} = 1.667\%$, but gets lost during recessions, with a large negative $R_{OS}^{2,exp}$ of -2.582%.

Table 2: Out of Sample Statistical Evaluation
This table reports the OOS forecasting results compared to the historical mean for different predictors: time series reversal ($r_{w=4,t}$), 12-month return (r_{t-12}) -Huang et al. (2020)- and two technical indicators ($\mathbb{1}_{MA(1,12)}$ and $\mathbb{1}_{MOM(1,12)}$) -Neely et al. (2014). The first column reports the out-of-sample $R^{2,OS}$ (equation 4), the second and third columns reports respectively $R_{exp}^{2,OS}$ and $R_{rec}^{2,OS}$ (equation 5). 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 time window is from January 1975 to December 2020 and the out-sample valuation period goes from July 1986 to December 2020.

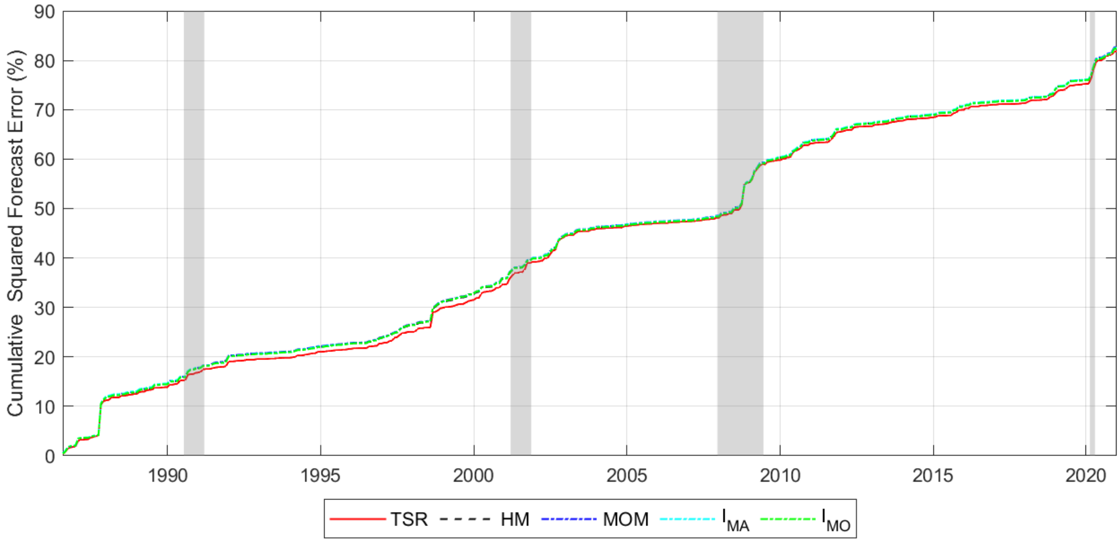
	$R^{2,OS}(\%)$	$R_{exp}^{2,OS}(\%)$	$R_{rec}^{2,OS}(\%)$
$r_{w=4,t}$	0.699⋆⋆	1.667	-2.582
r_{t-12}	-0.349	-0.523	0.242
$\mathbb{1}_{MA(1,12)}$	-0.144	-0.381	0.657
$\mathbb{1}_{MOM(1,12)}$	-0.025	-0.227	0.658

Therefore, I can motivate the Out-of-Sample predictability of the time series reversal based on economic and statistical reasons. From an economic standpoint, the proposed predictor benefits from the predictable and recurring non-informational price pressure due to the end-of-month

[12]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.

payment cycle. This makes it particularly effective during periods of economic expansion, as I will further corroborate in Section 3.1.1. The novel feature is of crucial importance for the Out-of-Sample forecasting performance as the U.S. economy, so far, has been in recession very few times: out of the 414 months forecasted, only 36 months are in recession. 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}, improving the forecasting ability - Ren, Tu, and Yi (2019).[13] Figure 5 shows the cumulative squared error over time for each predictor considered. The cumulative squared error obtained from the time series reversal is never worse than the one from the historical mean. Overall, the results suggest that a few outliers do not drive the analysis reported in Table 2.

Figure 5: **Out of Sample Cumulative Forecast Error**
The figure shows the cumulative OOS squared of the time series reversal (TSR -$r_{w=4,t}$- solid red line), historical mean (HM -$\bar{r}_t$- black dashed line), momentum (MOM -r_{t-12}- blue dash-dot line), and two technical indicators (I_{MA} -$\mathbb{1}_{MA(1,12)}$- magenta dash-dot line and I_{MO} -$\mathbb{1}_{MOM(1,12)}$- green 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 2020 and the Out-of-Sample valuation period goes from July 1986 to December 2020.



It is worth noting the substantial differences between the negative market correlation and the

[13]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.

predictors belonging to the "Momentum approach". The reversal predictability stems from a short horizon return relation ($r_{w=4,t}$ with r_{t+1}), while the previously proposed predictors from a long horizon relation (r_{t-12} with r_{t+1}). The here proposed approach captures a negative return correlation, while Momentum detects a positive correlation. I argue that the economic source behind the reversal pattern is the payment-cycle friction. Conversely, investors' under-reaction is often considered the economic source behind Momentum. Finally, the time series reversal pattern is more robust during expansions, whereas the Momentum predictability peaks during recessions. Given these structural differences, in Section 4.2, I consider whether mixing time series Reversal and Momentum may improve the overall Out-of-Sample forecasting performance.

In Appendix B.2, I consider value-weighted returns instead of index returns to align with many forecasting studies: results do not change qualitatively. Moreover, I consider the time window examined in Neely et al. (2014) (December 1951 to December 2011), obtaining a positive $R^{2,OS}$.

2.3 Utility Gains Evidence

Following Campbell and Thompson (2008), I construct an optimal portfolio for a mean-variance investor who can allocate his wealth between a risky asset, the S&P 500, and the risk-free rate, r^f. The percentage invested in the risky asset is:

$$w_t^i = \frac{1}{\lambda} \frac{\tilde{r^i}_{t+1|t}}{\tilde{\sigma}^2_{t+1|t}} \tag{6}$$

where λ is the relative risk aversion parameter - set to 3 as in Campbell and Thompson (2008), $\tilde{r^i}_{t+1|t}$ is the $t+1$ expected excess return using predictor i to forecast the one month ahead excess return and $\tilde{\sigma}^2_{t+1|t}$ is the forecasted excess return variance - obtained using a 5-year rolling window as in Campbell and Thompson (2008) and Moskowitz et al. (2012). To capture only the negative price pressure due to the payment cycle, the time series reversal portfolio invests on the risky asset only when the last week return of month t ($r_{w=4,t}$) is negative (around 40% of times). For the other predictors, I allow w_t^i to lie between -1 and 1. For each point forecast, the realized portfolio return is:

$$r_{t+1}^{i,p} = w_t^i \times r_{t+1} + r_{t+1}^f \tag{7}$$

Over the Out-of-Sample window, the realized utility is:

$$U_i(p) = \mu_{i,p} - \frac{\lambda}{2}\sigma_{i,p}^2 \tag{8}$$

where $\mu_{i,p}$ and $\sigma_{i,p}^2$ are respectively the mean and variance of the portfolio returns $r^{i,p}$ using predictor i to forecast future excess return. The utility gains delivered by predictor i over the historical mean are measured by the delta certainty equivalent return (CER):

$$\Delta\ CER_i = u_i - u_{HM} \tag{9}$$

where u_i is the utility achieved by considering in equation (6) $\hat{r^i}_{t+1|t}$ as the expected excess return ($\tilde{r}_{t+1|t}$), while u_{HM} is the utility achieved by considering $\bar{r}_{t+1|t}$. Intuitively, $\Delta\ CER_i$ captures the gains for an investor moving from a passive stance on the financial market - the market is efficient, and hence prices follow a martingale process - to exploiting the Out-of-Sample forecasting power of predictor i. In Table 3, I report the annualized Utility (u_i), Sharpe ratio, variance, skewness, and kurtosis for portfolios obtained respectively by the time series reversal ($r_{w=4,t}$), momentum (r_{t-12}), two technical indicators ($\mathbb{1}_{MA(1,12)}$ and $\mathbb{1}_{MOM(1,12)}$) and the historical mean ($\bar{r}_t$); for each proposed predictor I also report the annualized percentage $\Delta\ CER$.

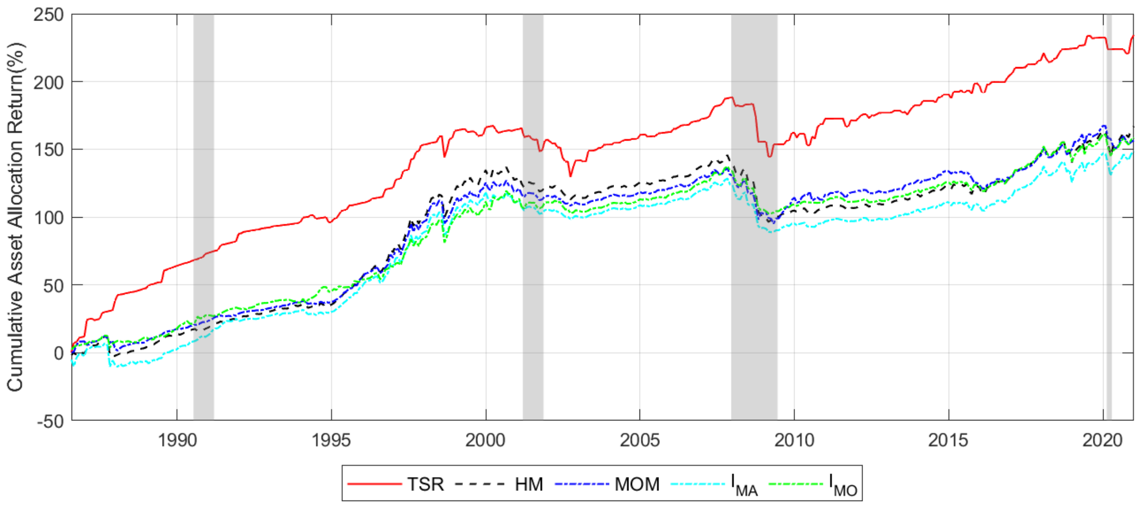
Table 3 shows that the negative market correlation outperforms proposed predictors and historical mean in marginal utility and Sharpe Ratio. Standard deviation, kurtosis, and skewness do not change significantly among the different portfolios. Overall, the utility gains of using the reversal pattern over the historical mean are sizable, being 187 basis points (bps) per year. The Momentum predictors have a marginal utility close to 0, implying that the passive benchmark is better than chasing Momentum not only for forecasting purposes but also for asset allocation decisions. In Figure 6, I plot the cumulative returns of the portfolios. The time series reversal constantly outperforms all the other approaches, while the momentum equals the passive

Table 3: Out of Sample Utility Gains
This table reports annualized percentage Utility $U(p)(\%)$, Sharpe Ratio, Standard Deviation, Skewness, and Kurtosis of an optimal portfolio for a mean variant investor (relative risk aversion set to 3) obtained respectively by our proposed predictor ($r_{w=4,t}$), momentum (r_{t-12}- Huang et al. (2020)), two technical indicators ($\mathbb{1}_{MA(1,12)}$ and $\mathbb{1}_{MOM(1,12)}$ -Neely et al. (2014)) and the historical mean ($\bar{r}_t$); for each proposed predictor I also report the annualized percentage $\Delta\ CER(\%)$ (equation (9)). The time window is from January 1975 to December 2020, and the out-sample valuation period goes from July 1986 to December 2020.

	$r_{w=4,t}$	r_{t-12}	$\mathbb{1}_{MA(1,12)}$	$\mathbb{1}_{MOM(1,12)}$	$\bar{r}_t$
$U(p)(\%)$	5.358	3.439	3.079	3.574	3.487
Sharpe Ratio	0.387	0.178	0.142	0.191	0.192
Std. Deviation	0.098	0.085	0.090	0.082	0.094
Skewness	-0.333	-0.359	-0.489	-0.421	-0.444
Kurtosis	1.152	0.813	0.970	0.892	0.856
$\Delta CER(\%)$	1.871	-0.049	-0.408	0.087	

benchmark only after the great financial crisis.

Figure 6: **Out of Sample Cumulative Asset-Allocation Portfolio Returns**
The figure presents the cumulative Asset-Allocation portfolio return for a risk-averse agent following Campbell and Thompson (2008) for time series reversal (TSR -$r_{4,t}$- solid red line), historical mean (HM -$\bar{r}_t$- black dashed line), momentum (MOM -r_{t-12}- blue dash-dot line), and two technical indicators (I_{MA} -$\mathbb{1}_{MA(1,12)}$- magenta dash-dot line and I_{MO} -$\mathbb{1}_{MOM(1,12)}$- green 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 2020 and the Out-of-Sample valuation period goes from July 1986 to December 2020.



In Appendix B.3, I plot the excess return portfolio obtained from the time series reversal against each considered predictor, graphically showing that on average, the returns obtained from the time series reversal are larger. In Appendix B.4, I report the results by allowing w_t^i to lie between -1 and 1 for the portfolio constructed on the reversal pattern. The portfolio still outperforms the ones obtained from the other predictors; however, its performance decreases consistently with the idea that the reversal pattern is only due to the negative price pressure induced by the payment cycle.

2.4 Monetary Gains Evidence

Following Gao et al. (2018), I assess the monetary value of a trading strategy based on the time series reversal. The trading strategy can be mathematically formalized as:

$$\$r_{w=4,t} = \begin{cases} +r_{t+1} & \text{if } r_{w=4,t} < 0 \\ 0 & \text{if } r_{w=4,t} \geq 0 \end{cases} \tag{10}$$

The strategy in equation (10) captures the potential gains from the perspective of a risk-neutral agent. As for the utility gains exercise, I limit the trading strategy to invest in the market only when the last week of the month has a negative return. Therefore, if the trading strategy is profitable, it is due to the negative correlation between a negative price pressure in the last week of a month and the one-month ahead return, consistent with the economic explanation. It is worth noticing that the strategy defined in equation (10) is based only on the last week's return $r_{w=4,t}$ and therefore depends neither on the specific forecasting method nor the training sample chosen. Overall, the exercise can be considered an empirical rule of thumb to effectively test the reversal pattern between $r_{w=4,t}$ and r_{t+1} and the economic channel behind it.

I compare the reversal strategy against Momentum, the two technical indicators, and passive investing on the S&P 500. The strategies based on the two technical indicators by construction can only buy the index (see Appendix B.1), whereas I allow short selling for the Momentum trading strategy. The S&P 500 passive investing is a very difficult benchmark to beat, given the generally positive trend that distinguishes the index in a multi-year time window horizon. Taking the difference between the mean return obtained from each predictor and passive investing, I obtain a measure of the marginal monetary benefit of each approach:

$$\Delta\$ = \$\bar{r}_i - \$\bar{r}_{S\&P500} \tag{11}$$

where $\$\bar{r}_i$ is the mean return obtained using predictor i and $\bar{r}_{S\&P500}$ is the S&P 500 mean return.

In Table 4, I report the percentage annual average excess return, the annualized variance, kurtosis, and skewness for all the trading strategies; in the last row, I report the annualized percentage $\Delta\$$. The $\Delta\$$ is positive and sizable for the reversal strategy as anticipated in Figure 1, implying that the end-of-the-month negative price pressure could be an effective trading strategy for market participants. Moreover, the portfolio constructed using the time series reversal trading strategy dominates the others also in terms of Sharpe ratio, variance, and kurtosis as it sensibly reduces market exposure, being active only 41% of the time.

Table 4: Out of Sample Monetary Gains

This table reports annualized percentage mean excess returns $\$\bar{r}_i$, annualized Sharpe Ratio, Standard Deviation, Skewness, and Kurtosis for a risk-neutral investor obtained respectively by our proposed predictor ($r_{w=4,t}$), momentum (r_{t-12}- Huang et al. (2020)), two technical indicators ($\mathbb{1}_{MA(1,12)}$ and $\mathbb{1}_{MOM(1,12)}$ -Neely et al. (2014)) and the historical mean ($\bar{r}_{S\&P500}$); for each proposed predictor I also report the annualized percentage Δ $(%) (equation (11)). The time window is from January 1975 to December 2020.

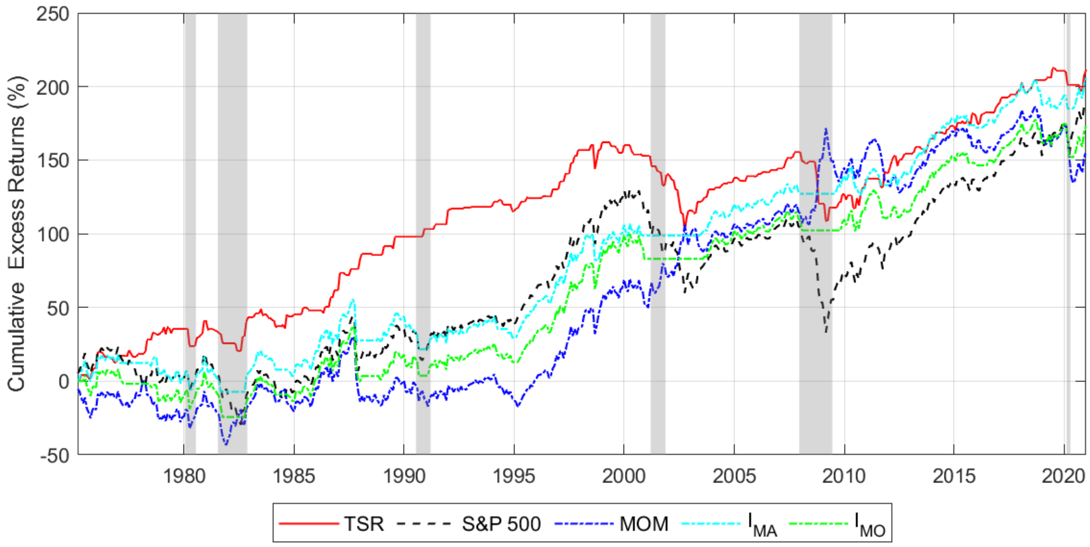
	$r_{w=4,t}$	r_{t-12}	$\mathbb{1}_{MA(1,12)}$	$\mathbb{1}_{MOM(1,12)}$	$\bar{r}_{S\&P500}$
$\$\bar{r}$(%)	4.600	3.816	4.480	3.763	4.146
Sharpe Ratio	0.439	0.224	0.384	0.304	0.275
Std. Deviation	0.105	0.151	0.117	0.124	0.151
Skewness	-0.148	-0.132	-0.318	-0.297	-0.236
Kurtosis	0.866	0.470	0.868	0.750	0.483
$\Delta\$$(%)	0.454	-0.764	0.334	-0.382	

In Figure 7, I show the cumulative excess return of the trading strategies for all the proposed predictors and the benchmark. It is interesting to note that the momentum strategy (MOM) performs particularly during periods of recession, confirming its statistical properties. Second, the reversal strategy outperforms the two technical indicators in their natural environment: these trading tools have been devised by industry practitioners to provide straightforward strategies commonly applied in financial markets.[14] Therefore, based on reported evidence, the reversal

[14]This can explain why technical indicators perform better in a trading exercise than in forecasting. Technical

pattern outperforms the Momentum approach at statistical, utility, and monetary levels.

Figure 7: **Out of Sample Cumulative Monetary Gains**
The figure presents the cumulative excess return obtained from a trading strategy using time series reversal (TSR -$r_{4,t}$- solid red line), S&P 500 (black dashed line), momentum (MOM -r_{t-12}- blue dash-dot line), and two technical indicators (I_{MA} -$\mathbb{1}_{MA(1,12)}$- magenta dash-dot line and I_{MO} -$\mathbb{1}_{MOM(1,12)}$- green 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 2020.



In Section 4.3, I consider trading costs and fees and show that the results do not change qualitatively. In Appendix B.5, I plot the excess return portfolio obtained from the time series reversal against each predictor. In Appendix B.6, I compare the annual Sharpe ratio obtained from the Time Series Reversal and the Buy-and-Hold strategy. The results suggest that the marginal gains of the reversal pattern do not cluster in any specific time period. In Appendix B.7, I show that the results are robust to risk-adjusted measures. In Appendix B.8, I report the results allowing short selling in the reversal strategy. Overall, the performance deteriorates consistently with the end-of-the-month payment cycle channel.

indicators can suffer from collinearity problems as the binary variable can be almost identical to the intercept.

3 Explanation

In this Section, I provide evidence in support of the end-of-the-month payment cycle as the economic channel behind the reversal pattern. In Section 3.1, I show that, consistent with the proposed channel, the pattern is cyclical and concentrates on high-quality stocks. In Section 3.2, I first provide a direct link between the payment cycle and the reversal pattern. Second, leveraging on existing theoretical works, I microfund the economic channel. Appendix C.3.1 and C.3.2 provide evidence that the explanation channels established in the cross-sectional literature, market participants' overconfidence and compensation for liquidity provision, cannot likely be the economic source. Online Appendix 3 provides evidence that option expiration, quarterly trading, information release, and monthly rebalancing could not explain the results.

3.1 Properties of Time Series Reversal

3.1.1 Reversal and Business Cycle

If the payment cycle is the economic mechanism driving the aggregate reversal, the pattern should intensify during periods of economic stability. During such times, institutional investors, particularly pension funds, reduce their precautionary cash reserves, Figure 1.D. Intuitively, in stable economic conditions, pension funds tend to lower their liquidity buffers to allocate more capital towards risky assets. Consequently, with less cash available to manage potential mismatches between end-of-month inflows and outflows and a more liquid and calm market, pension funds are more likely to sell equity positions for liquidity reasons.

I test this hypothesis by studying the relationship between the aggregate market reversal and the business cycle. Specifically, I consider the following regression:

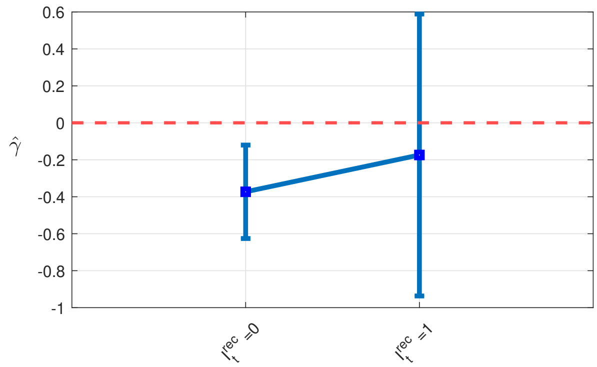
$$r_{t+1} = \alpha + \gamma_1 \, \mathbf{I}_t^{rec} r_{w=4,t} + \gamma_2 \, (1 - \mathbf{I}_t^{rec}) r_{w=4,t} + \epsilon_{t+1} \tag{12}$$

where I_t^{rec} is the NBER indicator function that takes a value of 1 when month t is in recession and 0 otherwise. Consistently with the payment cycle channel, Figure 8 shows that the negative market serial correlation is more robust during expansion periods. To corroborate the results, in Appendix C.1.1, I support the analysis here reported by studying the reversal pattern in relationship with variation in the business cycle (peaks and troughs). Moreover, in Appendix C.1.2, I compare the cumulative TSR excess returns against the implied volatility index VIX.

Figure 8: **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 4^{th} weekly return at month t 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 2020.



3.1.2 Reversal and Stock Characteristics

If the payment cycle is the economic mechanism driving the aggregate reversal, the pattern should concentrate on liquid and high-priced stocks. Intuitively, if institutional investors sell for liquidity reasons, they try selling stocks to minimize price impact and transaction costs. To investigate this hypothesis, I analyze all common stocks traded on NYSE and NASDAQ markets using the daily CRSP file from January 1985 to December 2020. For each stock time series, I calculate the average Amihud illiquidity ratio and average stock price, and I categorize the stocks into quintiles based on these measures. I then construct value-weighted indexes formed on each metric and perform standard predicting equations.[15]

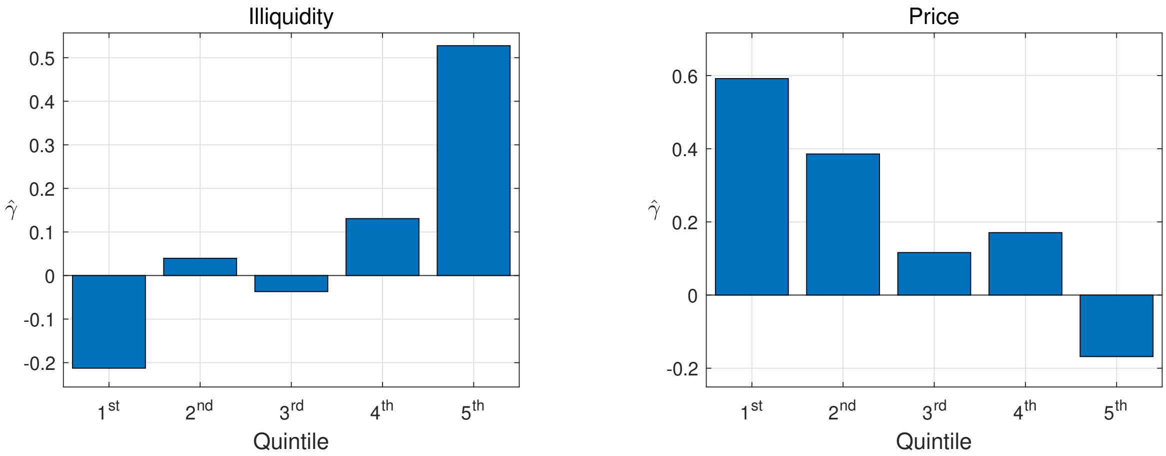
Figure 9 shows a clear trend: a negative correlation characterizes high-priced and liquid stocks

[15]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.

Figure 9: **Stock Characteristics and Serial Correlation**
This figure reports the estimated γ coefficient of the following prediction equations:

$$r_{t+1}^{sc_q} = \alpha + \gamma r_{d=t-3,t}^{sc_q} + \epsilon_{t+1}$$

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 independent variable is the $T-3$ end of month return $r_{d=t-3,t}^{sc_q}$ ($r_{d=t-3,t}^{sc_q} = \frac{1}{N}\sum_{i=1}^{N} p_t^{i\in sc_q} - p_{d=t-3,t}^{i\in sc_q}$). 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). The Data is CRSP: the sample includes 16159 stocks, and the time window goes from January 1985 to December 2020.



consistent with the proposed mechanism, whereas a positive correlation characterizes illiquid and low-priced stocks consistent with stale price theories. Overall, the evidence reported in Figure 9 is opposite to the usual findings in the cross-sectional reversal studies where the results are generally driven by small and illiquid stocks, e.g., Avramov et al. (2006), Nagel (2012), and Dai et al. (2023). A plausible explanation for the striking difference between the time series and cross-sectional approaches is that cross-sectional regression estimates reflect not only return (cross)-autocorrelation but also cross-sectional variation in average return, Bogousslavsky (2016). Therefore, in the latter framework, the results are likely driven by the cross-sectional variation in average return, largely capturing small illiquid stock effects. In Appendix C.1.3, I

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.

compare the time series and cross-sectional approaches to corroborate this conjecture.

The evidence discussed in this Section is consistent with a payment cycle explanation behind the monthly reversal pattern, suggesting a potential novel interpretation of the reversal mechanism. The novel characteristics of the reversal pattern, which differ from the established cross-sectional findings, pose a challenge in interpreting the market reversal as an anomaly due to over-reaction or as a compensation mechanism for liquidity provision. *If* the time series reversal were either a behavioral bias outcome or a compensation factor for liquidity provision, the pattern should not be more pronounced for high-quality stocks and during periods of economic expansion - hence, when investors act more rationally and providing liquidity is less risky.

3.2 Economich Mechanism

3.2.1 Direct Evidence

I provide evidence 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 likely resort more to the equity market to recoup end-of-month liquidity. By using data from the Federal Reserve Economic Data (FRED), I perform a Threshold Autoregressive Regression (TAR) on pension funds' inflows (monthly seasonally adjusted employer contributions for employee pension and insurance funds), $inflow_t$, and last week Fed Fund Rate $ff_{w=4,t}$:

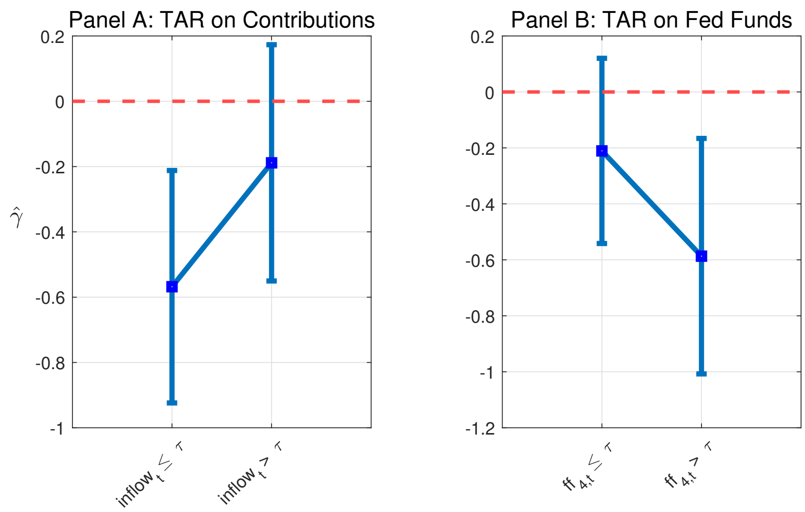
$$r_{t+1} = \begin{cases} \alpha + \gamma_1 \ r_{w=4,t} + \epsilon_{t+1} \quad if \ \ -\infty < inflow_t \ (ff_{w=4,t}) \leq \tau \\ \alpha + \gamma_2 \ r_{w=4,t} + \epsilon_{t+1} \quad if \qquad \tau < inflow_t \ (ff_{w=4,t}) < \infty \end{cases} \tag{13}$$

where τ is the threshold parameter estimated within the TAR algorithm either on monthly pension funds' inflows, $inflow_t$, or on last week Fed funds rate $ff_{w=4,t}$. The coefficients γ_1 and γ_2 capture, respectively, the reversal pattern in periods of smaller and higher cash inflows and end-of-month borrowing costs. Figure 10 reports estimated coefficients and associated 95% robust confidence intervals for both TAR regressions. Results show that when pension funds receive less cash or face higher end-of-month financing costs, the reversal pattern spikes.[16]

Figure 10: **Payment Cycle and Reversal Pattern: Direct Evidence**
The figure reports the estimated coefficients and the robust 95% confidence intervals for the following TAR regressions:

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

where τ is the threshold parameter estimated within the TAR algorithm either on monthly employer contributions for employee pension and insurance funds, $inflow_t$, or on the end of month change in Fed Funds rate, $ff_{w=4,t}$. The estimated threshold for the TAR based on $inflow_t$ is 6.28, and on $ff_{w=4,t}$ is 5.76. The sample period goes from January 1975 to December 2020. Both variables are available on FRED website.



3.2.2 Volume Channel

Table 1 shows that pension plans have a negative imbalance in the last week of the month, suggesting that they trade for liquidity reasons. To corroborate the non-informational nature of the pension plans' trading activity at the end of the month, I empirically test the Campbell et al. (1993) model. Their model is based on two agents with Constant Absolute Risk Aversion (CARA); the first has a constant risk aversion parameter, while the second has a time-varying risk aversion coefficient. If the second type of investor varies his demand for liquidity - non-informational - reason, I would observe a reallocation of risk from the more risk-averse to the rest of the market through a rise in volume. Returns revert to equilibrium as stock price movements are not linked to fundamental news. Hence, the reversal pattern should be accentuated with a

[16]In Appendix C.2.1, I report the summary statistics of $inflow_t$ and ff_w. Moreover, I show that the pattern is stronger in months with lower (real or nominal) dividends, consistent with pension funds receiving less cash from their equity positions. Considering first differences rather than spot values, I find analogous results for pension funds inflows, fed funds rate, and nominal dividends.

surge of trading volume when investors trade in the market for liquidity reasons. To empirically test the Campbell et al. (1993) model, I collect from GFD weekly S&P 500 volume data from January 1975 to December 2020, and I measure the last week's change in volume through the following metric:

$$\Delta vol_t = \frac{VOL_{w=4,t} - VOL_{w=3,t}}{\sum_{i=1}^{4} VOL_{w=i,t}} \tag{14}$$

where $VOL_{i,t}$ is the i^{th} weekly volume. I empirically test the volume channel as a potential source of the market autocorrelation in a two-step procedure. I first run a TAR to study the relationship between reversal pattern and volume:

$$r_{t+1} = \begin{cases} \alpha + \gamma_1 \; r_{w=4,t} + \epsilon_{t+1} & if \;\; -\infty < \Delta vol_t \leq \tau \\ \alpha + \gamma_2 \; r_{w=4,t} + \epsilon_{t+1} & if \qquad \tau < \Delta vol_t < \infty \end{cases} \tag{15}$$

where τ is the threshold parameter estimated within the TAR algorithm. The results, reported in Table 5, show that the negative autocorrelation between $r_{w=4,t}$ and r_{t+1} is significant only when $\Delta vol_t > \tau$. In Appendix C.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 2.C and Table 2.C). Therefore, the TAR model establishes a change in the regime behavior of return autocorrelation depending on the end-of-the-month volume: an increased market activity in the last week is associated with a stronger reversal pattern.[17] In the second step I control that volume impacts the return dynamic through the return correlation rather than directly. I define the following binary variable based on the estimated threshold τ:

$$\mathbb{1}_{\Delta vol_t} = \begin{cases} 1 & if \;\; \Delta vol_t > \tau \\ 0 & otherwise \end{cases} \tag{16}$$

[17] The estimated threshold τ is negative as $vol_{w=3,t}$ is consistently larger than $vol_{w=4,t}$ (See Panel C Figure 2.C). Alternatively, the results in Table 5 suggest that the reversal pattern disappears when there is a substantial drop in volume ($\Delta vol_t \leq \tau$). In light of Campbell et al. (1993)'s model, a drop in volume characterizes informational trading, and hence returns should not display negative autocorrelation. I divide for the monthly volume to address the concern that the results are driven by specific monthly seasonality. I find consistent results by considering a different volume variable specification in Appendix C.2.3. In the Online Appendix, I show that the impact of volume on reversal is throughout the entire month ahead.

and consider the following Predictive Regression (PR):

$$r_{t+1} = \alpha + \gamma\; r_{w=4,t} + \beta\; \mathbb{1}_{\Delta vol_t} + \psi\; (r_{w=4,t} \times \mathbb{1}_{\Delta vol_t}) + \varepsilon_{t+1} \tag{17}$$

Table 5: Volume Channel

In the first panel of the Table, I report 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 r_{t+1} is the $t+1$ monthly excess return; $r_{w=4,t}$ is the 4^{th} weekly return at month t; τ is the estimated TAR threshold estimated on the volume variable Δvol_t. In the second panel, I report the results of the following Predictive regression:

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

where $\mathbb{1}_{\Delta vol_t}$ is an indicator function based on Δvol_t. In brackets, I report robust Newey and West (1987) t-statics. The sample period goes from January 1975 to December 2020.

TAR regression		Predictive regression			
	r_{t+1}		r_{t+1}	r_{t+1}	r_{t+1}
τ	-0.042	α	0.004	0.004	0.005
			[2.105]	[0.978]	[1.013]
α	0.004	$r_{w=4,t}$	-0.327		-0.051
	[2.150]		[-3.276]		[-0.275]
$r_{w=4,t}$ if $\Delta vol_t \leq \tau$	-0.047	$\mathbb{1}_{\Delta vol_t > \tau}$		-0.001	-0.001
	[-0.150]			[-0.259]	[-0.141]
$r_{w=4,t}$ if $\Delta vol_t > \tau$	-0.438	$r_{w=4,t} \times \mathbb{1}_{\Delta vol_t > \tau}$			-0.386
	[-3.010]				[-1.776]
Obs.	551		551	551	551
R^2	2.07%		1.60%	0.01%	2.07%

The results reported in Table 5 show that $r_{w=4,t}$ has stand-alone predicting power, while $\mathbb{1}_{\Delta vol_t}$ alone does not predict future return. Therefore the results do not support the "pure" ability of the trading volume to forecast stock returns, as reported, for example, by Gervais, Kaniel, and Mingelgrin (2001). If I jointly consider the two variables and their interaction, I can test the hypothesis in Campbell et al. (1993) that a higher trading volume is linked with a negative return serial correlation. The coefficient attached to the interaction term captures the market autocorrelation when there is a higher market activity in the last week of the month. The results in the last column of Table 5 show that the predictability shifts from $r_{w=4,t}$ to the interaction term $r_{w=4,t} \times \mathbb{1}_{\Delta vol_t}$. Therefore, in line with the TAR results, the negative return serial correlation is statistically meaningful only when there is high volume in the last week.[18]

3.2.3 Volatility Channel

I here investigate whether retail investors, the recipient of most of the end-of-the-month liquidity, can potentially impact the reversal pattern. I use a novel dataset from Nasdaq Data Link (Retail Trading Activity Tracker) to study retail investment on the S&P 500. Specifically, for each instrument traded at Nasdaq, I observe the ratio of daily $ traded by retail investors in a given ticker divided by the total $ traded by retail investors across all tickers. Therefore, the measure does not capture the retail dollar volume invested in each instrument but its relative retail importance/investment. I consider the top 150 constituents of the S&P 500 (based on their weight on the index) to measure the intra-monthly relative retail investment on the S&P 500 from January 2016 to January 2023.[19] In Figure 11, I report the average daily retail importance of the S&P 500 in the last and first trading weeks around the turn of the month. The findings suggest that retail investors relatively trade more on stocks included in the S&P 500 around the last week of the month.

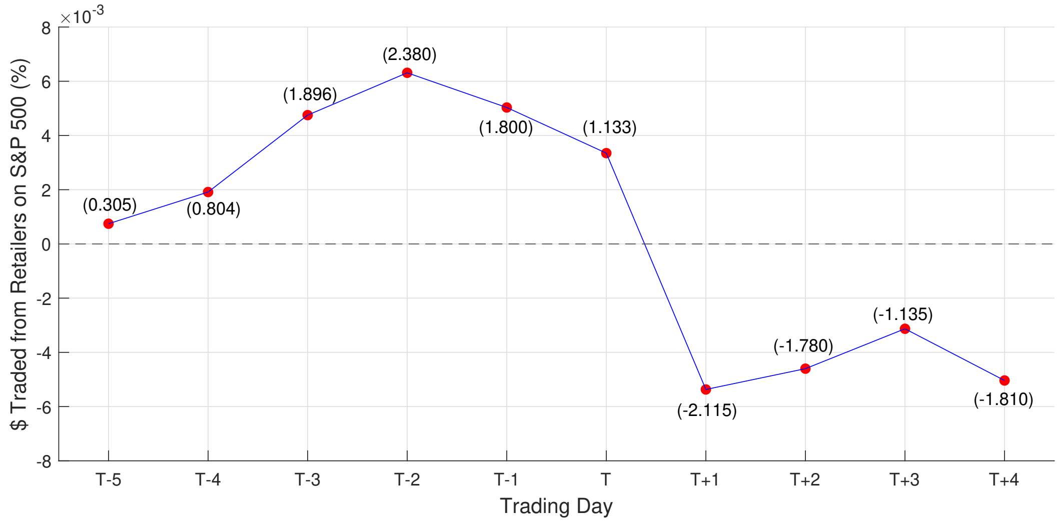
The finance literature has extensively studied the behavior and trading strategies of market participants, and retail investors are likely to be positive feedback traders (buy after prices increase, sell after prices decrease, e.g., Shiller (1987), Barber et al. (2008) and Barber and Odean (2013)).[20] Sentana and Wadhwani (1992) show that the presence of positive feedback traders triggers a return reversal mechanism in the aggregate stock market. The model predicts positive feedback traders significantly influence price dynamics as volatility increases, inducing a greater negative serial correlation of returns.

[18] To address the concern of using an estimated regressor in equation (17), I confirm the significance of the interaction term coefficient through a two-step bootstrapping procedure.

[19] The top 150 costituents accounts for more than 75% of the entire S&P 500. Results do not change qualitatively considering the top 50, 100, and 200 constituents that respectively count for 51%, 67%, and 82% of the S&P 500.

[20] For a more detailed discussion on this topic, see, for example, Economou, Gavriilidis, Gebka, and Kallinterakis (2022). It is important to note that a feedback trading strategy is not necessarily a consequence of behavioral biases but could be a rational strategy if preferences exhibit risk aversion that declines rapidly with wealth -Black (1990)- if there is asymmetric information among market participants -Wang (1993)- and finally, if there is a positive level of payoff uncertainty and /or persistence in liquidity trading -Cespa and Vives (2012).

Figure 11: **S&P 500 Retail Investment over the end-of-the Month**
This figure reports the average percentage \$ retail investment on the S&P 500 around the turn of a month, (where T is the last trading day of the month). For each ticker, the relative importance is measured as the daily retail \$ traded on a specific instrument over the daily \$ retail traded. I consider the top 150 constituents of the S&P 500 (based on their weights on the index) and its major ETFs. Each daily observation is the sum of the individual financial instrument demeaned by the monthly average importance. In parenthesis, I report the associated t-statistic against the null hypothesis of a 0 daily average importance. The Data provider is Nasdaq Data Link, and the sample period goes from January 2016 to January 2023.



To test the Sentana and Wadhwani (1992) model and hence show the potential role of retail investors, I collect, from GFD, VIX data from January 1990 to December 2020 and define the following metric to measure increased volatility in the last week of the month:

$$\Delta vix_t = vix_{w=4,t} - vix_{w=3,t} \tag{18}$$

where $vix_{w=4,t}$ is the i^{th} weekly logarithmic VIX price. I perform the analogous two-step procedure in Section 3.2.2 (defined in equations (15) and (17)) using Δvix_t and $\mathbb{1}_{\Delta vix_t}$.

The results presented in Table 6 are qualitatively equivalent to the ones presented in Table 5: the TAR regression establishes a threshold on volatility above which the reversal pattern is significant. The lack of predictability of $\mathbb{1}_{\Delta vix_t}$ suggests that the end-of-month reversal mechanism does not proxy returns for liquidity provision as in Nagel (2012).[21] The predictive regression

[21] It is worth noticing that Δvix_t is linked with market activity rather than the business cycle. In Figure 3.C, I graphically investigate Δvol_t and Δvix_t over time and find no precise relationship with the NBER recession

analysis establishes that once included volatility 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 volatility in the last week. The empirical results, in line with the theoretical predictions of Sentana and Wadhwani (1992), suggest that feedback trading of retail investors is a potential source of the reversal pattern.

Table 6: Volatility Channel

In the first panel of the Table, I report the results of the following Threshold Autoregressive Regression (TAR):

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

where r_{t+1} is the $t+1$ monthly excess return; $r_{w=4,t}$ is the 4^{th} weekly return at month t; τ is the estimated TAR threshold estimated on the volatility variable Δvix_t. In the second panel, I report the results of the following Predictive regression:

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

where $\mathbb{1}_{\Delta vix_t}$ is an indicator function based on Δvix_t. In brackets, I report robust Newey and West (1987) t-statics. The sample period goes from January 1990 to December 2020.

TAR regression		Predictive regression			
	r_{t+1}		r_{t+1}	r_{t+1}	r_{t+1}
τ	0.083	α	0.005	0.005	0.006
			[2.008]	[2.228]	[2.152]
α	0.005	$r_{w=4,t}$	-0.251		-0.075
	[2.250]		[-2.194]		[-0.483]
$r_{w=4,t}$ if $\Delta vix_t \leq \tau$	-0.072	$\mathbb{1}_{\Delta vix_t > \tau}$		-0.005	-0.002
	[-0.370]			[-0.799]	[-0.312]
$r_{w=4,t}$ if $\Delta vix_t > \tau$	-0.687	$r_{w=4,t} \times \mathbb{1}_{\Delta vix > \tau}$			-0.588
	[-2.880]				[-1.789]
Obs.	371		371	371	371
R^2	2.39%		1.06%	0.26%	2.42%

In terms of magnitude, the values reported in Table 6 are slightly larger than the ones in Table 5 - the coefficient attached to $r_{w=4,t}$ is around -0.6 with high volatility, while -0.4 with high volume. A possible explanation is that the estimated threshold in Table 6 is relatively large compared to the distribution of Δvix_t. Therefore, to be above the threshold, the change in volatility from the 4^{th} to the 3^{rd} week must be pronounced, thus commanding a higher impact (Panel B and D Figure 2.C). The volume (volatility) channel is more (less) likely to be active but has a lower (higher) average impact on the time series reversal. In economic terms, institutional

periods. Therefore, periods with high Δvix_t do not necessarily imply periods of economic downturn.

selling pressure is an event that happens more often, while retail investors' direct activity is less likely to affect reversal, but when it happens, it has a major impact.

Overall, I micro-fund the role of institutional and retail investors in the payment cycle through the volume and volatility channels. At the end of the month, institutional investors trade to pay contributions (volume channel). Retail investors receive contributions and foster the institutional investors' negative trend (volatility channel).

4 Additional Results

4.1 Evidence from other U.S. indexes

In this session, I study whether the aggregate reversal characterizes the other two major American indexes: the Dow Jones Industrial Average (DOW) and the Nasdaq Composite Index (Nasdaq). Table 7 reports the In-Sample predicting regression estimated coefficient, the Out-of-sample R^2, the expansion and recession Out-of-sample R^2_{econ}. The results for the DOW are qualitatively similar to the ones for the S&P 500, while I do not find any pattern in the Nasdaq.

When the In-Sample coefficient is statistically significant (S&P 500 and DOW), the Out-of-Sample predictability is positive and meaningful. The results for the S&P 500 and DOW are very close: an In-Sample coefficient of -0.327 for the S&P 500 and -0.325 for the DoW and very similar Out-of-Sample $R^{2,OS}$. The evidence corroborates that the reversal pattern concentrates on the 30 American most capitalized stocks forming the DOW and included on the S&P 500. At the same time, I do not find statistically significant results for the Nasdaq as the index includes more than 3700 stocks, among which illiquid and small-cap titles. For the DOW, I propose the analysis of the Volume and Volatility channels in Table 1.D: the results are qualitatively equal to the ones for the S&P 500.

To further support the link between the reversal pattern and pension funds, I show little evidence at the international level - Appendix D.3. Internationally, pension funds have a substantially

Table 7: Reversal Pattern on DOW and Nasdaq
This table reports for both the Dow Jones Industrial Average (DOW) and the Nasdaq Composite Index (Nasdaq) indexes the following results. The first column reports the estimated coefficient of the In-Sample predicting equation $r_{t+1} = \alpha + \gamma\ r_{w=4,t} + \epsilon_{t+1}$. The second column reports the Out-Sample $R^{2,OS}$. Statistical significance for the In Sample regression is based on Newey and West (1987) procedure, whereas for the Out-of-Sample $R^{2,OS}$ is based on the Clark and West (2007). $\star\star\star$, $\star\star$, and $\star$ indicate significance at the 1%, 5%, and 10% levels, for both the Newey and West (1987) and Clark and West (2007) tests. The third and fourth columns report the business cycle Out-Sample $R^{2,OS}_{exp}$ and $R^{2,OS}_{rec}$ respectively. The time window is from January 1975 to December 2020, and the out-sample valuation period goes from July 1986 to December 2020.

	$\hat{\gamma}$	$R^{2,OS}$	$R^{2,OS}_{exp}$	$R^{2,OS}_{rec}$
DOW	$-0.325^{\star\star\star}$	$0.719^{\star\star}$	1.926	-3.696
Nasdaq	0.008	$-1.283^{\star}$	-0.968	-2.549

lower amount of assets under management (Figure 2.D Panel A), invest abroad (Figure 2.D Panel B), and generally do not have negative cash flows (Figure 2.D Panel C). Therefore, international pension funds might not have to sell assets at the end of the month due to liquidity concerns. Moreover, if they do, they would probably opt to sell foreign stocks to cover their imbalance.[22]

4.2 Mixing Reversal with Momentum

In Section 2.2, I have discussed the striking difference between the Time Series Reversal and the "Momentum" approach. Given their different peculiarities and characteristics, I analyze in this section whether mixing the two approaches could benefit the Out-of-Sample forecasting power. Specifically, I use the predicting power of $r_{w=4,t}$ in expansion times and the momentum in bad times. I run the Out-Sample-Sample exercise simultaneously for both $r_{w=4,t}$ and r_{t-12}; I use the forecast obtained by the former when $I^{rec}_{t-1} = 0$ and the latter otherwise:

$$\hat{r_1}_{t+1|t} = \hat{\alpha} + \hat{\gamma}\ r_{w=4,t} \qquad \hat{r_2}_{t+1|t} = \hat{\alpha} + \hat{\beta}\ r_{t-12}$$
$$\hat{r_M}_{t+1|t} = \begin{cases} \hat{r_1}_{t+1|t} & if\ I^{rec}_{t-1} = 0 \\ \hat{r_2}_{t+1|t} & if\ I^{rec}_{t-1} = 1 \end{cases} \tag{19}$$

where both $\hat{r_1}_{t+1|t}$ and $\hat{r_2}_{t+1|t}$ are estimated recursively over the Out-of-Sample window and I^{rec}_t is the NBER indicator function that takes a value of 1 when month t is in recession and 0 oth-

[22] I conjecture that international pension funds would opt to sell American stocks to minimize transaction costs and fees. Consistently with the economic mechanism, I partially find evidence of time series reversal in the U.K., where pension funds are similar in cash flow problems and relative equity market importance. Pension funds' cash flow problems have become a significant concern in England after the 2022 gilt crisis.

erwise.[23]

Table 8: Out of Sample Evaluation: Mixing Reversal with Momentum
This table reports the results of out-of-sample forecasting obtained by mixing the predictive power of $r_{w=4,t}$ and r_{t-12}:

$$\hat{r_1}_{t+1|t} = \hat{\alpha} + \hat{\beta} r_{w=4,t} \qquad \hat{r_2}_{t+1|t} = \hat{\alpha} + \hat{\beta} r_{t-12}$$
$$\hat{r_M}_{t+1|t} = \begin{cases} \hat{r_1}_{t+1|t} & if\ I^{rec}_{t-1} = 0 \\ \hat{r_2}_{t+1|t} & if\ I^{rec}_{t-1} = 1 \end{cases}$$

The first column reports the out-of-sample $R^{2,OS}$, the second and third columns $R^{2,OS}_{exp}$ and $R^{2,OS}_{rec}$ respectively. Statistical significance for $R^{2,OS}$ is based on the Clark and West (2007) p-value MSFE-adjusted statistic for testing $H_0 : R^2_{OS} < 0$ against $H_1 : R^2_{OS} > 0$. $\star\star\star$, $\star\star$, and $\star$ indicate significance at the 1%, 5%, and 10% levels, respectively. All the values are reported in percentages. The time window is from January 1975 to December 2020, and the out-sample valuation period goes from July 1986 to December 2020.

$R^{2,OS}$(%)	$R^{2,OS}_{exp}$(%)	$R^{2,OS}_{rec}$(%)
1.545***	1.840	0.546

I report the Out-Sample Analysis results in Table 8. Mixing $r_{w=4,t}$ with r_{t-12} substantially helps the forecasting power as the $R^{2,OS}$ doubles and its significance increases (from 0.699% to 1.544%). More importantly, the predictability is positive during both expansion and recession periods. Notice that the forecasting exercise proposed here is a first cut on combining Momentum and Reversal approaches to achieve sizable and robust Out-of-Sample predictability.

4.3 Trading Costs

In Sections 2.3 and 2.4, I do not consider the potential transaction costs incurred by the asset allocation portfolio and trading strategy exercises. This choice is motivated by multiple reasons. 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 to trade at the close, as the prices here considered are at the end of the day, almost eliminates the implicit costs attached to the market impact that trading orders

[23] I condition on I^{rec}_{t-1} instead of I^{rec}_t as NBER releases data on expansion and recession with one month lag.

might trigger. Therefore, transaction costs and fees should not significantly impact the results presented in Sections 2.3 and 2.4. Chicago Mercantile Exchange (2016) estimates an execution cost for S&P 500 ETFs of around 1.25 basis points (bps) and management fees between 5.0 and 9.45 bps per year. To take into account higher trading fees before the new millennium, I set a conservative fee of 10 bps per transaction, at least twenty times higher than the actual ones.[24] The Monetary Gains exercise follows the same logic. The trading fees incurred by the negative market correlation are set to 10 bps for each transaction, while the passive strategy incurs only a holding cost- management fee of 3 bps per month.

Table 9: Economic Significance Net of Fees

This table reports the Economic Significance of the time series reversal $r_{w=4,t}$ net of fees. Specifically, the left panel reports the annualized percentage Utility ($U(p)(\%)$) and Sharpe ratio obtained by an optimal portfolio for a mean variant investor (relative risk aversion set to 3) using either the negative market correlation $r_{w=4,t}$ or the historical mean $\bar{r}_t$ to forecast future returns. The right panel reports the annualized percentage expected return ($\bar{r}(\%)$) and Sharpe Ratio for trading strategies based on the the time series reversal $r_{w=4,t}$ and the passive investing $\bar{r}_{S\$P500}$. The fees incurred by monthly trading are set to $10bps$, while the management fees of the passive startegy is set to $3bps$ monthly. The time window is from January 1975 to December 2020, and the out-sample valuation period for the Utility Gains exercise goes from July 1986 to December 2020.

	Utility Gains			Monetary Gains	
	$r_{w=4,t}$	$\bar{r}_t$		$r_{w=4,t}$	$\bar{r}_{S\$P500}$
$U(p)(\%)$	4.816	3.463	$\$\bar{r}(\%)$	4.112	3.786
Sharpe Ratio	0.332	0.190	Sharpe Ratio	0.394	0.251

The net of fees results are reported in Table 9: the left panel reports the Utility Gains, and the right panel reports the Monetary Gains. For both exercises, the values are qualitatively similar to the ones reported in Tables 3 and 4. The time series reversal pattern delivers gains for both risk-averse and risk-neutral agents, even net of fees.

5 Conclusion

This paper answers whether the aggregate American market reverts price pressure by documenting a novel 1-month reversal pattern at the time series level. The empirical evidence is statistically significant both In- and Out-of-Sample. I show that the reversal at the aggregate level has characteristics opposite to those established in the cross-sectional literature: it concen-

[24]By trading each month, the annual transaction fees paid in the exercise are 120 bps, while the average annual expanse for the most common ETFs tracking the S&P 500, SPY, VOO and IVV, is 5 bps.

trates on high-priced and liquid stocks and is cyclical with the economy. Therefore, the novel pattern delivers sizable gains both in utility and monetary terms. I rationalize the empirical findings via the end-of-the-month payment cycle. I first document a direct link between the reversal pattern and quantities linked to the economic mechanism. Secondly, by jointly considering theoretical models and empirical findings, I provide evidence that both institutional and retail investors foster the reversal pattern.

Overall, the findings suggest that the reversal pattern is an anomaly due to liquidity frictions. The proposed predictor likely measures the liquidity not efficiently accommodated in the aggregate market rather than traders over-reaction or compensation for liquidity provision. Therefore, the documented pattern draws regulators' attention to easing liquidity channels when financial markets require the most. As the importance of American pension funds and their negative imbalance will both rise in the future, I conjecture that end-of-month liquidity inefficiency will strengthen without direct regulation.

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Appendices

A Appendix Section 2

A.1 ANcerno Dataset: Institutional Details

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.

A.1.1 ANcerno Dataset: Data Description

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 et al. (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.

A.2 End of Month Institutional Behavior: CFTC data

In this Session, 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 1.A: Institutional Investor behavior at the end of the month (CFTC Dataset)
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.

	Inst. Investors	Dealers	Leveraged Funds	Others
ΔBuy	-38.524	-8937.103	-5912.400	-1045.503
$\Delta Sell$	1516.690	-10508.248	-6115.097	-504.690
$\Delta Buy - \Delta Sell$	-1555.214	1571.145	202.697	-540.814

In Table 1.A, I report the delta between the last two weeks of the month for both net buys and sells across the different investor classes.[25] 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.

A.3 Summary Statistics

In this session, I report mean, standard deviation, minimum, maximum and number of observations for the main predicted variable, the excess monthly return r_{t+1}, and the predictor, the last week return $r_{w=4,t}$. The values are in line with the literature, see for example Welch and Goyal (2008) and Neely et al. (2014).

Table 2.A: Summary Statistics
This table reports mean, standard deviation, minimum, maximum and number of observation for the excess month return, r_{t+1} and the lasr week return, $r_{w=4,t}$. The time window is from January 1975 to December 2020.

	Mean(%)	Std. Dev.(%)	Min(%)	Max(%)	Obs.
r_{t+1}	0.34	4.36	-24.99	11.89	552
$r_{w=4,t}$	0.20	1.68	-7.04	9.98	552

A.4 Controlling for Friday Effect

In this session, I explore whether the reversal pattern is influenced by choosing Friday as the week's closing price. To capture the potential impact of the negative price pressure of the payment cycle on the overall market, I examine the T-3 end-of-month return ($r_{d=t-3,t} = p_t - p_{d=t-3,t}$). This choice is consistent with the findings in Table 1, which shows that the order imbalance on this specific day is negative and statistically significant. I, hence, here perform an analogous analysis discussed in Figure 4 for the $T-3$ return:

[25] CFTC Methodology website: "A traders increase in a net long position or decrease in a net short position can be viewed as net buys. Similarly, a traders 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 weeks daily aggregate net buys and net sells "

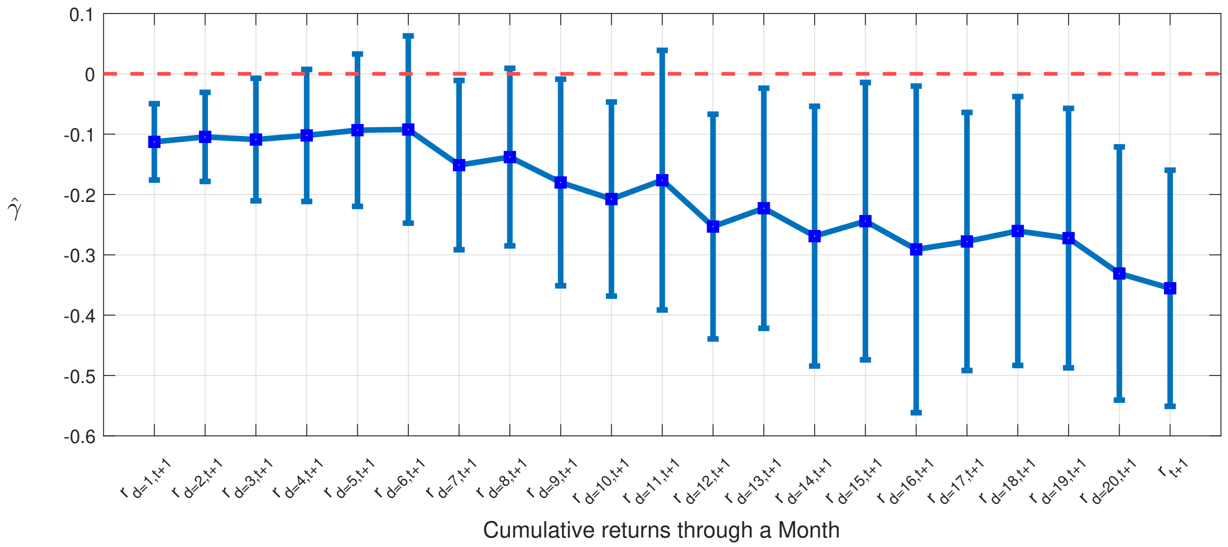
Figure 1.A: **Friday Effect Robustness Check**
This figure reports the estimated coefficients and the associated 95% Newey and West (1987) robust confidence intervals of the predictive regression on the cumulative returns throughout the month

$$r_{d=i,t+1} = \alpha + \gamma_{d=i,t+1}\ r_{d=t-3,t} + \epsilon_{d=i,t+1}$$

as well as on the standard monthly predictive equation:

$$r_{t+1} = \alpha + \gamma\ r_{d=t-3,t} + \epsilon_{t+1}$$

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 $r_{d=t-3,t} = p_t - p_{d=t-3,t}$. The sample period goes from January 1975 to December 2020.



The general pattern in Figure 1.A is qualitatively consistent with the discussion in the main text: the predictor has a negative predictive power, and its market predictability increases over time in absolute terms.

A.5 Controlling for Closing Price Effect

In this session, I consider whether the reversal pattern between the 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[26]

$$r^H_{w=4,t} = p^H_t - p^H_{w=4,t} \qquad (r^L_{w=4,t} = p^L_t - p^L_{w=4,t}) \tag{20}$$

[26]For 21 out of 552 observations, I use closing prices as high and low prices were missing.

as the dependent variables of the following distinct regression

$$r^H_{t+1} = \alpha + \gamma^H \; r^H_{w=4,t} + \epsilon_{t+1} \qquad (r^L_{t+1} = \alpha + \gamma^L \; r^L_{w=4,t} + \epsilon_{t+1}) \tag{21}$$

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 -0.282 (-0.303), and the associated Newey and West (1987) t-statistic is -2.14 (-2.63). 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.6 Placebo Test around 15^{th} of the Month

In this session, 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.[27] 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 0.039, and the Newey and West (1987) t-statistic is 0.168, 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.7 Multi - Month Predictability

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

$$r^{'}_{w=i,t+2} = \alpha + \gamma \; r_{w=4,t} + \epsilon_{w=i,t+2} \tag{22}$$

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

and

$$r_{t+2} = \alpha + \gamma \; r_{w=4,t} + \epsilon_{t+2} \tag{23}$$

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 3.A show that the predictability window is only one month ahead, consistent with the idea that the end-of-the-month payment cycle has a transitory effect on the price dynamic.

Table 3.A: Two Month Ahead Predictability
In this table, I report the estimated coefficient of the following Predictive regressions

$$r^{'}_{w=i,t+2} = \alpha + \gamma \; r_{w=4,t} + \epsilon_{w=i,t+2} \quad 0 < i \leq 4$$

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 $r_{t+2} = p_{t+2} - p_{t+1} - r^{f}_{t+1}$. In brackets, I report robust Newey and West (1987) t-statics. The sample period goes from January 1975 to December 2020.

$r^{'}_{w=1,t+2}$	$r^{'}_{w=2,t+2}$	$r^{'}_{w=3,t+2}$	$r^{'}_{w=4,t+2}$	r_{t+2}
0.005	0.076	0.077	0.027	0.075
	[1.250]	[0.810]	[0.240]	[0.660]

A.8 Controlling For Others Predictors

A.8.1 Controlling for Weekly Returns

In this Session, I study whether the negative serial correlation pattern of $r_{w=4,t}$ is not lost after controlling for the previous *intramonthly* returns:

$$r_{t+1} = \alpha + \gamma \; r_{w=4,t} + \beta_1 \; r_{w=3,t} + \beta_2 \; r_{w=2,t} + \beta_3 \; r_{w=1,t} + \epsilon_{t+1} \tag{24}$$

and standard weekly returns:

$$r_{t+1} = \alpha + \gamma \; r_{w=4,t} + \beta_1 \; r^{''}_{w=4,t} + \beta_2 \; r^{''}_{w=3,t} + \beta_3 \; r^{''}_{w=2,t} + \beta_4 \; r^{''}_{w=1,t} + \epsilon_{t+1} \tag{25}$$

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 4.A show that the predictability channel of $r_{w=4,t}$ is robust to controlling for either *intramonthly* or standard weekly returns.

Table 4.A: Reversal Pattern and Returns within the Month
The left panel of the table (Intramonthly returns) reports the estimated coefficients of the following predicting equation:

$$r_{t+1} = \alpha + \gamma\ r_{w=4,t} + \beta_1\ r_{w=3,t} + \beta_2\ r_{w=2,t} + \beta_3\ r_{w=1,t} + \epsilon_{t+1}$$

where r_{t+1} is one month ahead excess return and $r_{w=i,t} = p_t - p_{w=i,t}$. The right panel of the table (Weekly returns) reports the estimated coefficients of the following predicting equation:

$$r_{t+1} = \alpha + \gamma\ r_{w=4,t} + \beta_1\ r''_{w=4,t} + \beta_2\ r''_{w=3,t} + \beta_3\ r''_{w=2,t} + \beta_4\ r''_{w=1,t} + \epsilon_{t+1}$$

where $r''_{w=i,t} = p_{w=i,t} - p_{w=i-1,t}$, $\forall\ 0 < i \leq 4$. In brackets, I report robust Newey and West (1987) t-statics. The sample period goes from January 1975 to December 2020.

	Intramonthly Returns		Weekly Returns
α	0.004	α	0.004
	[2.100]		[1.880]
$r_{w=4,t}$	-0.464	$r_{w=4,t}$	-0.293
	[-3.400]		[-2.580]
$r_{w=3,t}$	0.147	$r''_{w=4,t}$	0.164
	[-0.840]		[1.160]
$r_{w=2,t}$	0.0459	$r''_{w=3,t}$	0.012
	[0.320]		[0.120]
$r_{w=1,t}$	-0.0348	$r''_{w=2,t}$	-0.0324
	[-0.400]		[-0.370]
		$r''_{w=1,t}$	0.120
			[1.130]
R^2[%]	2.190		2.470
Obs	551		551

A.8.2 Controlling for Economic Variables

In this Session, I control for a set of economic variables commonly used by the forecasting literature, Welch and Goyal (2008). Data is available from Amit Goyals website; in the Online Appendix I briefly describe each variable. The predictive regression is:

$$r_{t+1} = \alpha + \gamma\ r_{w=4,t} + \beta\ EV_t^i + \epsilon_{t+1} \tag{26}$$

where r_{t+1} is the $t+1$ monthly excess return; $r_{w=4,t}$ is the 4^{th} weekly return at month t; EV_t^i are economic variables. The results in Table 5.A show that the economic variables do not affect the magnitude or significance of the time series reversal pattern.

A.8.3 Controlling for Investor Attention Predictor

Most of the proposed predictors in the literature positively correlate with future excess returns; a notable exception is the recently proposed predictors in Chen, Tang, Yao, and Zhou (2022).

Table 5.A: Reversal Pattern and Economic Variables
This table reports the results of the following Predictive regression

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

where r_{t+1} is the $t+1$ monthly excess return; $r_{w=4,t}$ is the 4^{th} weekly return at month t; EV_t^i are standard economic variables used in the forecasting literature, Welch and Goyal (2008). In brackets, I report robust Newey and West (1987) t-statics. The sample period goes from January 1975 to December 2020.

	$\hat{\alpha}$	$\hat{\gamma}$	$\hat{\beta}$
D12	0.002	-0.327	0.000
	[0.537]	-[3.296]	[1.250]
'E12'	0.002	-0.326	0.000
	[0.623]	[-3.269]	[1.260]
BM	0.005	-0.328	-0.002
	[1.246]	[-3.251]	[-0.270]
TBL	0.008	-0.324	-0.082
	[2.492]	[-3.256]	[-1.656]
AAA	0.011	-0.324	-0.095
	[2.354]	[-3.252]	[-1.581]
BAA	0.011	-0.323	-0.080
	[2.259]	[-3.230]	[-1.438]
LTY	0.010	-0.325	-0.088
	[2.380]	[-3.268]	[-1.575]
NTIS	0.004	-0.333	-0.057
	[1.897]	[-3.270]	[-0.415]
RFREE	0.007	-0.324	-0.944
	[2.488]	[-3.255]	[-1.552]
INFL	0.006	-0.333	-0.754
	[2.070]	[-3.307]	[-1.233]
LTR	0.003	-0.343	0.102
	[1.704]	[-3.364]	[2.152]
CORPR	0.003	-0.349	0.203
	[1.291]	[-3.407]	[3.346]
SVAR	0.005	-0.318	-0.170
	[2.063]	[-3.123]	[-0.222]

Therefore, in this session, I examine whether the predictive power of $r_{w=4,t}$ derives from information that is also captured by the predictors in Chen et al. (2022).

Chen et al. (2022) proposes three different predictors (A^{PLS}, A^{PCA} and A^{sPCA}) that aggregate 12 popular individual attention indexes (with partial least square, principal component and scaled principal component approach respectively). To not introduce measurement errors, I directly use the variables available from the authors' website and study the statistical relationship between January 1980 to December 2017. The predictive regression is:

$$r_{t+1} = \alpha + \gamma \; r_{w=4,t} + \beta \; A_t^i + \epsilon_{t+1} \tag{27}$$

where r_{t+1} is the $t+1$ monthly excess return; $r_{w=4,t}$ is the 4^{th} weekly return in month t; AV_t^i is an investor attention variable. The results in Table 6.A show that the economic variables do not affect the magnitude or significance of the proposed predictor $r_{w=4,t}$.

Table 6.A shows that the reversal mechanisms captured by $r_{w=4,t}$ and A^{PLS} are very different. The authors argue that the negative correlation between r_{t+1} and A_t^i is the consequence of an induced reversal pattern. High attention induces investors to buy, resulting in temporary positive price pressure. After the net buying flow slows down, the price dynamic tends to revert. In contrast, I provide evidence of a reversal pattern induced by the negative price pressure of the end-month payment cycle.

Table 6.A: Reversal Pattern and Investors' Attention
This table reports the results of the following Predictive regression

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

where r_{t+1} is the $t+1$ monthly excess return; $r_{w=4,t}$ is the 4^{th} weekly return at month t; A_t^i is a control variable measuring investor attention defined in Chen et al. (2022) (A^{PLS}, A^{PCA} and A^{sPCA} respectively). In brackets, I report robust Newey and West (1987) t-statics. The sample period goes from January 1980 to December 2017 for the third regression.

	r_{t+1}	r_{t+1}	r_{t+1}	r_{t+1}
α	0.004	0.005	0.004	0.004
	[1.823]	[2.637]	[1.780]	[1.754]
$r_{w=4,t}$	-0.348	-0.319	-0.346	-0.326
	[-3.516]	[-3.355]	[-3.509]	[-3.228]
A^{PLS}		-0.024		
		[-2.486]		
A^{PCA}			-0.001	
			[-0.562]	
A^{sPCA}				-0.621
				[-1.978]
Obs.	455	455	455	455
$R^2(\%)$	1.880	3.750	1.930	2.63

A.8.4 Controlling for Cross-Sectional Factors

In this Session, I follow the methodology proposed in Dong, Li, Rapach, and Zhou (2022) to ensure that the negative serial correlation between $r_{w=4,t}$ and r_{t+1} is not spanned by factors previously proposed in the literature. I firstly check that the short serial correlation is not captured by the three Fama French factors augmented by Momentum and Short Reversal available on the

Kenneth R. French website:

$$r_{t+1} = \alpha + \gamma \; r_{w=4,t} + \beta_i F_{i,t} + \varepsilon_{t+1} \tag{28}$$

where $F_{i,t}$ is a factor lagged one month with respect to the excess market return. Secondly, I extract the 10 Principal Components (PC) from the 100 anomalies portfolio returns studied in Dong et al. (2022) and consider the following predicting equation:

$$r_{t+1} = \alpha + \gamma \; r_{w=4,t} + \beta_i PC_{i,t} + \varepsilon_{t+1} \tag{29}$$

In both exercises, the coefficients attached to the last week's return, $r_{w=4,t}$, are negative and statistically significant, suggesting that previously proposed factors do not capture the end-of-the-month market inefficiency.

B Appendix Section 2.2

B.1 Technical Indicators

I here report the definition of the Neely et al. (2014)'s technical indicators $\mathbb{1}_{MA(1,12)}$ and $\mathbb{1}_{MOM(1,12)}$. The first technical indicator is based on a moving average approach:

$$\mathbb{1}_{MA(1,12),t} = \begin{cases} 1 & if \; p_t \geq \frac{1}{12}\sum_{i=0}^{11} p_{t-i} \\ 0 & if p_t < \frac{1}{12}\sum_{i=0}^{11} p_{t-i} \end{cases} \tag{30}$$

The second technical indicator is based on momentum:

$$\mathbb{1}_{MOM(1,12),t} = \begin{cases} 1 & if \; p_t \geq p_{t-i12} \\ 0 & if p_t < p_{t-12} \end{cases} \tag{31}$$

Table 7.A: Reversal Pattern and Factor Anomalies
This table reports in the first column the estimation result of:

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

where the factors $F_{i,t}$ considered are the three Fama French factors augmented by Momentum and Short Reversal. From the second column, I report the estimation results of the following:

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

where $PC_{i,t}$ is the i^{th} Principal Components (PC) extracted from the 100 anomalies portfolio returns in Dong et al. (2022). In brackets, I report robust Newey and West (1987) t-statics. The time window considered in the first regression is from January 1975 to December 2020 and the factors are downloaded from Kenneth R. French website. The time window from the second row is from January 1975 to December 2018, and the 100 anomalies portfolio returns are available from Zhou's personal website.

α	0.004	α	0.004	0.004	0.004	0.004	0.004	0.004	0.004	0.004	0.004	0.004
	[2.070]		[2.030]	[2.040]	[2.090]	[2.100]	[2.100]	[2.110]	[2.120]	[2.120]	[2.130]	[2.140]
$r_{w=4,t}$	-0.342	$r_{w=4,t}$	-0.355	-0.354	-0.364	-0.364	-0.364	-0.365	-0.357	-0.358	-0.370	-0.370
	[-3.410]		[-3.690]	[-3.690]	[-3.710]	[-3.720]	[-3.660]	[-3.710]	[-3.700]	[-3.690]	[-3.770]	[-3.720]
MKT	0.000	PC1	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
	[0.780]		[2.560]	[2.590]	[2.500]	[2.440]	[2.440]	[2.410]	[2.380]	[2.400]	[2.420]	[2.410]
SMB	0.001	PC2		0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	[1.030]			[-0.550]	[-0.550]	[-0.550]	[-0.550]	[-0.550]	[-0.560]	[-0.540]	[-0.570]	[-0.570]
HML	-0.001	PC3			0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
	[-1.410]				[1.290]	[1.270]	[1.270]	[1.280]	[1.290]	[1.270]	[1.360]	[1.360]
MOM	0.000	PC4				-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001
	[-1.040]					[-1.430]	[-1.420]	[-1.420]	[-1.390]	[-1.380]	[-1.380]	[-1.370]
REV	0.000	PC5					0.000	0.000	0.000	0.000	0.000	0.000
	[-0.670]						[0.020]	[0.020]	[0.030]	[0.030]	[0.010]	[0.010]
		PC6						0.001	0.001	0.001	0.001	0.001
								[0.940]	[0.940]	[0.930]	[0.990]	[0.990]
		PC7							-0.001	-0.001	-0.001	-0.001
									[-1.320]	[-1.330]	[-1.340]	[-1.340]
		PC8								-0.001	-0.001	-0.001
										[-0.450]	[-0.460]	[-0.460]
		PC9									-0.002	-0.002
											[-1.080]	[-1.080]
		PC10										0.000
												[0.000]
R^2[%]	2.630		3.130	3.170	3.850	4.110	4.110	4.250	4.500	4.530	4.860	4.860
Obs	551		516	516	516	516	516	516	516	516	516	516

B.2 Value Weighted Return Analysis

In the main body of the text, I have considered excess index returns ($r_{t+1} = p_{t+1} - p_t - r_t^f$) as the monthly reference returns to study its correlation with $r_{w=4,t} = p_t - p_{4,t}$. In this session, I consider excess value-weighted returns as the dependent variable. Studying the relationship between $r_{w=4,t}$ and excess value-weighted returns allows comparing the proposed predictor with many empirical and forecasting asset pricing studies. However, it should be noticed that the statistical relationship between $r_{w=4,t}$ and excess value-weighted returns does not define a proper serial correlation, as the two return time series are different due to dividends and earnings considered in the latter. In Table 1.B, I report the results of the standard In-Sample predictive regression equation:

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

and the Out-of Sample $R^{2,OS}$, $R^{2,OS}_{exp}$, and $R^{2,OS}_{rec}$. The results do not change qualitatively considering value-weighted returns instead of index returns.

As excess value-weighted returns are often the forecasting objective in the empirical finance literature, I can test the negative market correlation in different samples. I test the predicting power of $r_{w=4,t}$ in the time window considered in Neely et al. (2014) (from Dec 1951 to Dec 2011). Overall, the monthly reversal is robust to different time windows in In and Out-of Sample exercises, confirming the forecasting power of $r_{w=4,t}$ and alleviating data-mining concern, Schwert (2003). For the Out-of-Sample exercise, I run the experiment on the same window considered in Neely et al. (2014): the $R^{2,OS}$ is small but still positive, and the predictability comes from periods of expansion. The Out-of-Sample window in Table 1.B Panel B is characterized by many recession periods (from January 1966 to December 2011, 83 out of the 550 predicted months are in recession). Hence, the predictability is positive but shrinks consistently with the findings in the main body of the paper.

Table 1.B: Evidence on Value Weigheted Returns
In this table, I consider value-weighted returns as r_{t+1}. In each Panel, in the first column, I report the coefficient attached to $r_{w=4,t}$ in the In-Sample regression:

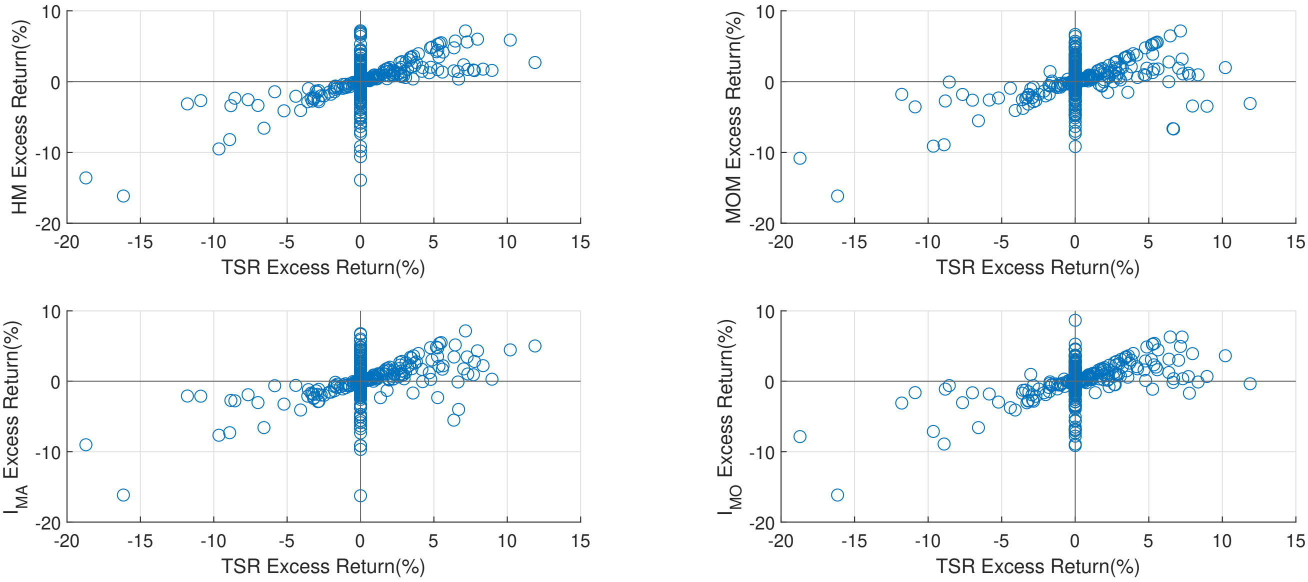
$$r_{t+1} = \alpha + \gamma\, r_{w=4,t} + \epsilon_{t+1}$$

In parenthesis, I report robust Newey and West (1987) t-statistics. In the second column, I report the Out-Sample $R^{2,OS}$. Statistical significance for $R^{2,OS}$ is based on the Clark and West (2007) p-value MSFE-adjusted statistic for testing $H_0 : R^2_{OS} < 0$ against $H_1 : R^2_{OS} > 0$. $\star\star\star$, $\star\star$, and $\star$ indicate significance at the 1%, 5%, and 10% levels, respectively. In the third and fourth columns, I report the business cycle Out-Sample $R^{2,OS}_{exp}$ and $R^{2,OS}_{rec}$ respectively. In Panel A, the out-sample valuation period goes from July 1986 to Dec 2020, while in Panel B from January 1966 to December 2011.

Panel A: January 1975 - December 2020				Panel B: December 1951 - December 2011			
$\hat{\gamma}$	$R^{2,OS}$	$R^{2,OS}_{exp}$	$R^{2,OS}_{rec}$	$\hat{\gamma}$	$R^{2,OS}$	$R^{2,OS}_{exp}$	$R^{2,OS}_{rec}$
$-0.325^{\star\star\star}$	$0.659^{\star\star}$	1.548	-2.367	$-0.190^{\star}$	0.010	0.526	-1.170

B.3 Scatter Plot Utility Gains

Figure 1.B: **Out-Sample-Sample Evidence: Asset-Allocation Portfolio**
This figure presents the portfolio return for a risk-averse agent following Campbell and Thompson (2008) for time series reversal (TSR -$r_{w=4,t}$- solid red line) respectively against the ones from historical mean (HM -$\bar{r}_t$), momentum (MOM -r_{t-12}), and two technical indicators (I_{MA} -$\mathbb{1}_{MA(1,12)}$ and I_{MO} -$\mathbb{1}_{MOM(1,12)}$). The time window is from January 1975 to December 2020 and the Out-of-Sample valuation period goes from July 1986 to December 2020.

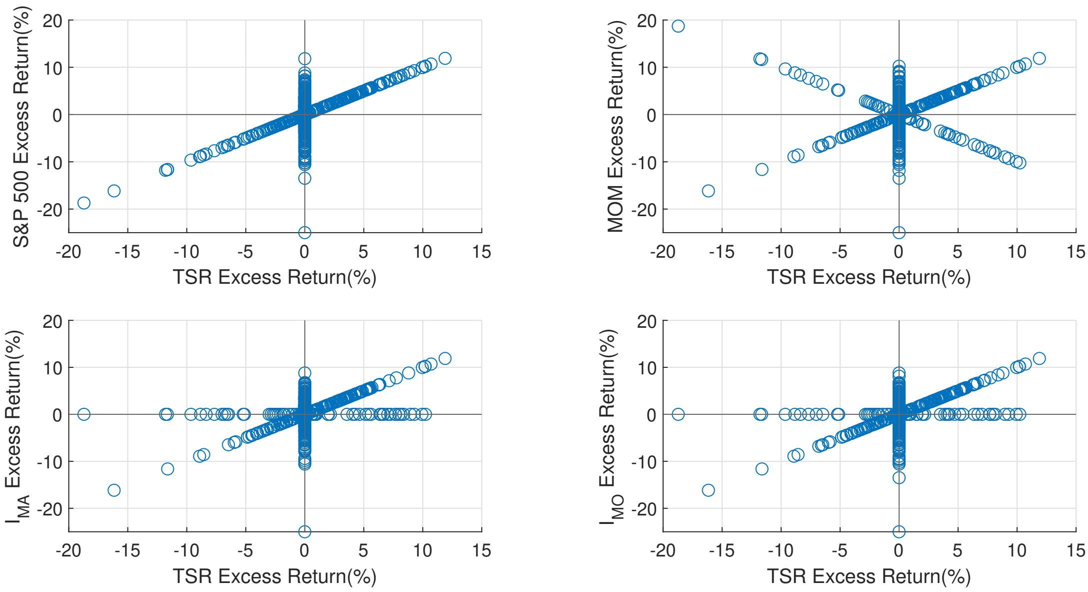


B.4 Short Selling TSR - Utility Gains

In this Session, I study the asset allocation exercise constructed on the short-term reversal by allowing w_t^i to lie between -1 and 1. Consistently with predictability due to the negative end-of-the-month price pressure, short selling qualitatively worsens the results. The annualized average percentage return goes from 5.358 to 5.028, and the variance increases from 0.098 to 0.124. Consequently, both the Sharpe ratio and ΔCER decrease to 0.350 and 1.541 respectively. Finally, Skewness and Kurtosis move to -0.173 and 0.578. However, it has to be noticed that even after allowing w_t^i to lie between -1 and 1, the utility gains from the reversal predictor outperform the other predictors and the benchmark.

B.5 Scatter Plot Monetary Gains

Figure 2.B: **Out-Sample-Sample Evidence: Asset-Allocation Portfolio**
This figure presents the excess returns for time series reversal (TSR -$r_{w=4,t}$- solid red line) respectively against the ones from the S&P 500, momentum (MOM -r_{t-12}), and two technical indicators (I_{MA} -$\mathbb{1}_{MA(1,12)}$ and I_{MO} -$\mathbb{1}_{MOM(1,12)}$). The time window is from January 1975 to December 2020.



B.6 Annual Sharpe Ratio

In this Session, I report the rolling annualized Sharpe ratio for both the Time series reversal (TSR) and the Buy and Hold (BH) strategy. Specifically, I compute the Sharpe ratio for each year of the evaluation window. The results in table 2.B suggest that the TSR does not cluster its gains in a specific time window, strengthening the results discussed in Section 2.4. Out of 46 years considered, the TSR strategy has a higher annual Sharpe ratio 26 times.

Table 2.B: Annual Sharpe Ratio
This table reports the number of times the TSR strategy outperforms the benchmark in terms of annual Sharpe Ratio. The time window is from January 1975 to December 2020.

	1975-1989	1990-1999	2000-2009	2010-2020
# SR >	10	5	7	5

B.7 Risk Adjusted Alphas

In Table 2.B, I report a comparative analysis of the performance of the Time Series Reversal (TSR) strategy against the Buy and Hold strategy, taking into account various risk-adjusted measures. Each column reports annualized risk and alphas

1. Benchmark: this column provides the results reported in the main text.
2. SML: compares the TSR strategy against closest point in the Security Market Line.
3. CAPM: compares the TSR strategy against Market portfolio
4. MM: risk-adjusted returns and alphas based on the Modigliani & Modigliani framework.
5. GH1: performance of TSR strategy against the S&P 500 by matching the two volatilities.
6. GH2: volatility matched by leveraging or deleveraging the TSR using Tbills.

Table 2.B: Montery Gains: Risk Adjusted Alphas
This table reports monetary risk-adjusted α and returns for the Time Series Reversal (TSR) strategy. Specifically, in the first column, I report the benchmark (not risk-adjusted) results. In the second column, results are adjsuted for the Security Market Line; in the third column, for the Capital Asset Pricing Model; in the fourth column, for the Modigliani & Modigliani Measure; in the fifth column, for the Graham-Harvey Measure 1 and finally, in the sixth column, for the Graham-Harvey Measure 2. The time window goes from January 1975 to December 2020.

	Benchmark	SML	CAPM	MM	GH1	GH2
Risk Adj. α (%)	0.454	1.723	2.601	2.484	1.723	2..484
Risk Adj. Ret (%)	4.600	2.876	1.999	6.630	2.876	6.630

B.8 Short Selling TSR - Monetary Gains

In this Session, I study the effect of short selling on the time series reversal trading strategy:

$$\$r_{w=4,t} = \begin{cases} +r_{t+1} & \text{if } r_{w=4,t} < 0 \\ 0 & \text{if } r_{w=4,t} \geq 0 \end{cases} \quad \$r^{s}_{w=4,t} = \begin{cases} 0 & \text{if } r_{w=4,t} < 0 \\ -r_{t+1} & \text{if } r_{w=4,t} \geq 0 \end{cases} \quad \$r^{ls}_{w=4,t} = \begin{cases} +r_{t+1} & \text{if } r_{w=4,t} < 0 \\ -r_{t+1} & \text{if } r_{w=4,t} \geq 0 \end{cases}$$

where $\$r_{w=4,t}$ is the benchmark trading strategy, $\$r^{s}_{w=4,t}$ is the orthogonal strategy operating in the market only when the last week return is non-negative and $\$r^{ls}_{w=4,t}$ combines the two.

Table 3.B: Monetary Gains

This table reports the annualized percentage expected return, the annualized percentage average excess return, annualized Sharpe Ratio, Variance, Skewness, and Kurtosis for $\$r_{w=4,t}$, $\$r^{s}_{w=4,t}$ and $\$r^{ls}_{w=4,t}$. The time window is from January 1975 to December 2020.

	$\bar{r}(\%)$	Sharpe Ratio	Variance	Skewness	Kurtosis
$\$r_{w=4,t}$	4.600	0.439	0.105	-0.148	0.866
$\$r^{s}_{w=4,t}$	0.453	0.042	0.109	0.404	0.992
$\$r^{ls}_{w=4,t}$	5.053	0.335	0.151	0.058	0.456

Figure 4.B: **Monetary Gains over Time**

This figure presents the cumulative excess return obtained from a trading strategy using $\$r_{w=4,t}$, $\$r^{s}_{w=4,t}$ and $\$r^{ls}_{w=4,t}$. The grey shaded areas mark periods of recessions according to the NBER indicator function. The time window is from January 1975 to December 2020.

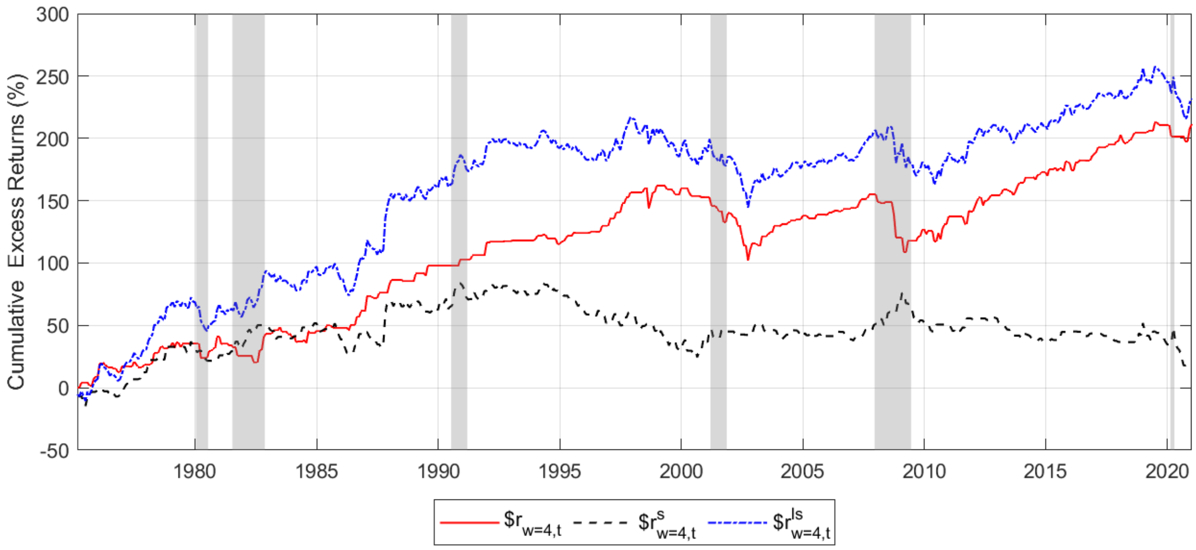


Table 3.B shows that allowing short selling minimally improves average returns but substantially increases variance. Hence, the Sharper ratio drastically deteriorates from 0.439 to 0.335. Figure 4.B shows that the small short-selling gains focus on recession periods, reconcilable with a compensation for liquidity provision.

C Appendix Section 3

C.1 Properties of Time Series Reversal

C.1.1 Market Correlation over Peaks and Troughs

In this session, I study the reversal pattern in relationship with peaks and troughs in the U.S. economy. Using the NBER binary function, I classify month t as a peak (trough) month if it is in expansion (recession) and the subsequent month is in recession (expansion). Following Neely et al. (2014), I consider the following specification:

$$r_t = \alpha + \sum_{l=2}^{-1} \beta^P_{t-l}\ I^P_{t-l} + \sum_{l=2}^{-1} \beta^T_{t-l}\ I^T_{t-l} + \epsilon_t \tag{32a}$$

$$\hat{r}_t = \alpha + \sum_{l=2}^{-1} \beta^P_{t-l}\ I^P_{t-l} + \sum_{l=2}^{-1} \beta^T_{t-l}\ I^T_{t-l} + \epsilon_t \tag{32b}$$

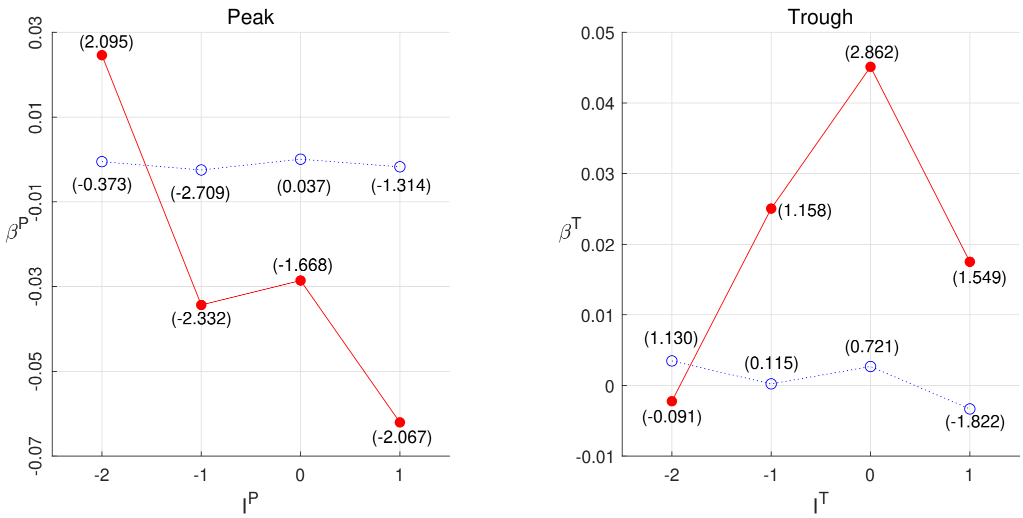
where r_t is the actual excess return at month t; $\hat{r}_t$ is the in-sample equity risk premium estimated with $r_{w=4,t}$; I^P (I^T) is an indicator variable equal to 1 when month t is a peak (trough) and 0 otherwise. Each β^P_{t-l} (β^P_{t-l}) coefficient captures the average change in the actual equity risk premium (in equation (32a)) and in the estimated equity risk premium (in equation (32b)) from a cyclical peak (trough). As the equity market is forward-looking, I consider an asymmetric window that includes 2 months before a peak (trough) and 1 month after.

In Figure 4.C, I report the estimated coefficients of I^P (left Panel) and I^T (right Panel); the coefficients obtained from (32a) are in a solid red line, while the coefficients of (32b) are in a blue dotted line. The results show that the forecast returns, $\hat{r}_t$, do not detect the behavior of the equity risk premium around variation in the business cycle. The coefficients estimated from equation (32b) are, on average, 1 magnitude smaller than the corresponding ones estimated from (32a) and, most of the time, are not significant. Consistently with the hypothesis, the coefficients from the regression equation (32b) are significant in months in which the economy is in expansion, e.g., a month before the peak and a month after the trough.

Figure 4.C: **Equity Risk Premium over Peaks and Troughs**
This figure reports the coefficients attached of I^P (Peak-left Panel) and I^T (Troughs-right Panel) of the following regressions:

$$r_t = \alpha + \sum_{l=2}^{-1} \beta^P_{t-l}\, I^P_{t-l} + \sum_{l=2}^{-1} \beta^T_{t-l}\, I^T_{t-l} + \epsilon_t \qquad \hat{r}_t = \alpha + \sum_{l=2}^{-1} \beta^P_{t-l}\, I^P_{t-l} + \sum_{l=2}^{-1} \beta^T_{t-l}\, I^T_{t-l} + \epsilon_t$$

where r_t is the excess actual return and $\hat{r}_t$ is the in-sample equity risk premium forecast with $r_{w=4,t}$; I^P (I^T) is an indicator variable equal to 1 when month t is a peak (trough) and 0 otherwise. The coefficients of (32a) are in a solid red line, while the coefficients of (32b) are in a blue dotted line. For each coefficient estimated marked with a dot, I report robust Newey and West (1987) t-statics in parenthesis. The sample period goes from January 1975 to December 2020.



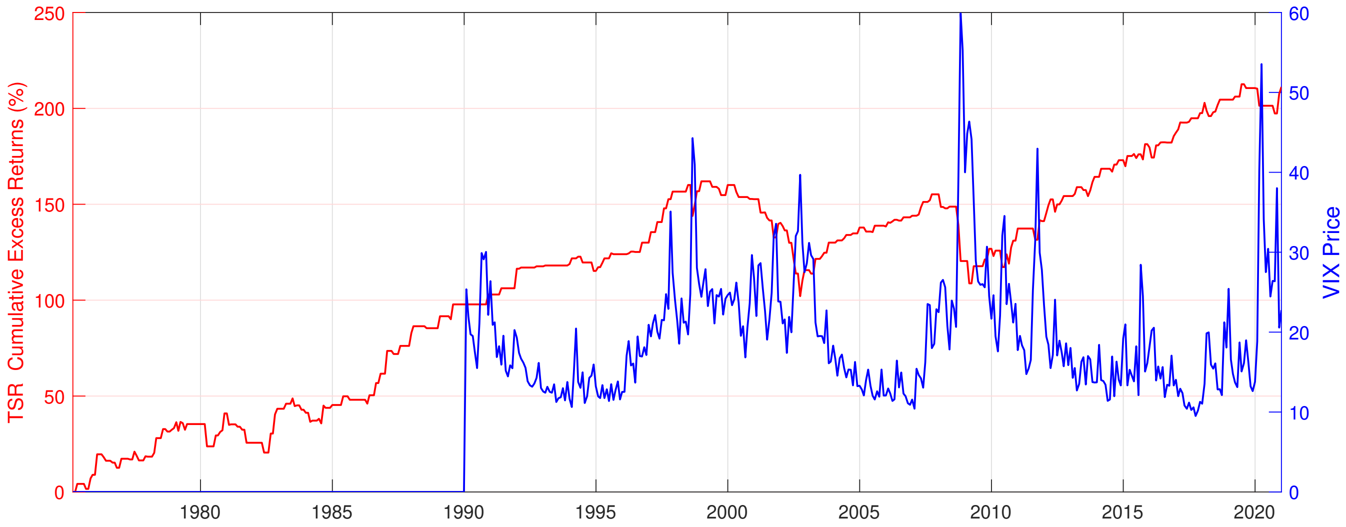
C.1.2 TSR performance and VIX

In light of Nagel (2012), I jointly report the cumulative excess returns obtained from the TSR strategy and the implied volatility index VIX. Figure 5.C shows that the TSR reversal strategy return is not positively correlated to the monthly VIX index. Differently from the cross-sectional approach in Nagel (2012), the TSR strategy does not proxy a compensation factor for liquidity provision.

C.1.3 Time Series and Cross-Sectional Approach

In this Section, I evaluate how the relationship between reversal and stock characteristics changes using either a time series or a cross-sectional approach. In each month I sort the common stocks traded either at NASDAQ or NYSE of the CRSP Dataset according to either price or illiquidity.

Figure 5.C: **TSR performance and VIX**
The left y-axis reports the cumulative excess return obtained from the time serial reversal strategy (TSR - red line), whereas the right y-axis reports the price of the implied volatility index (VIX - blue line). The time window considered for the TSR strategy goes from January 1975 to December 2020, for data availability the VIX series starts from January 1990.



At time series level, I define an equal-weighted portfolio based on each stock characteristic as the average return of the individual stocks belonging to the group ($r_t^{sc_q} = \frac{1}{N}\sum_{i=1}^{N} r_t^{i\in sc_q}$). I compute the time series predicting equation:

$$r_{t+1}^{sc_q} = \alpha + \gamma r_{d=t-3,t}^{sc_q} + \epsilon_{t+1} \tag{33}$$

where $r_{t+1}^{sc_q}$ is one month ahead return of the equally value-weighted return of a portfolio based on stock characteristic sc quantile q and $r_{d=t-3,t}^{sc_q}$ is the average $T-3$ end of month return of a portfolio based on stock characteristic sc quantile q. The time series coefficient reflects two components: return autocorrelation and return cross-autocorrelation, Lo and MacKinlay (1990). The cross-sectional estimation is obtained by the Fama and MacBeth (1973) procedure. For each month, I regress cross-sectionally:

$$r_{t+1}^{i\in sc_q} = \alpha + \gamma^{CS} r_{d=t-3,t}^{i\in sc_q} + \epsilon_{t+1} \tag{34}$$

and then average over time the cross-sectional coefficient β^{CS}. The average cross-sectional coefficient reflects return autocorrelation, return cross-autocorrelation, and cross-sectional variation in average returns, Bogousslavsky (2016).

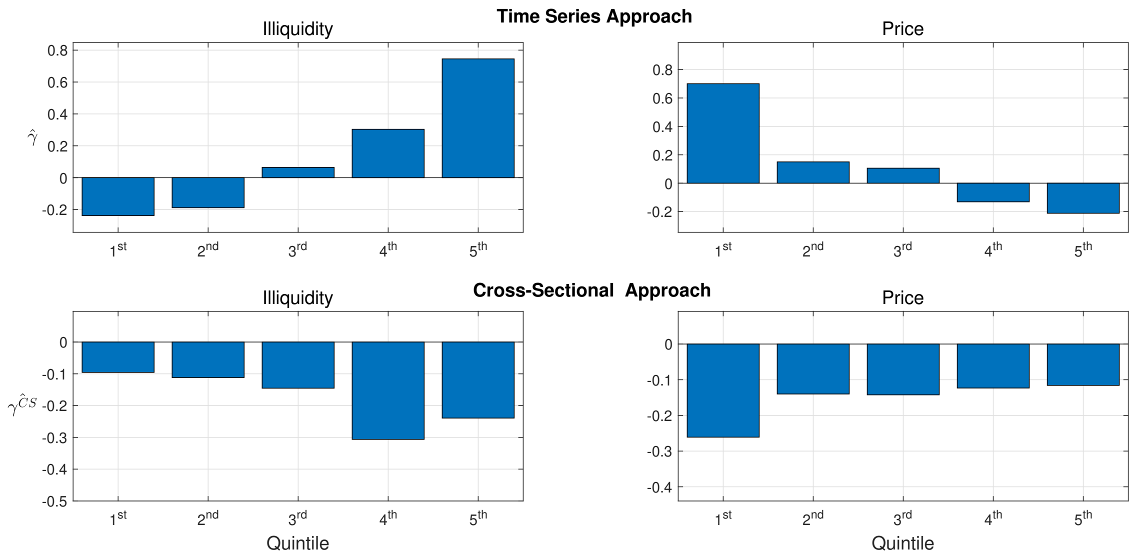
Figure 6.C: **Time Series and Cross-Sectional Approach**
This figure reports on the top panel the β coefficient of the following prediction equations:

$$r_{t+1}^{sc_q} = \alpha + \gamma r_{d=t-3,t}^{sc_q} + \epsilon_{t+1}$$

where $r_{t+1}^{sc_q}$ ($r_{t+1}^{sc_q} = \frac{1}{N}\sum_{i=1}^{N} r_{t+1}^{i \in sc_q}$) is one month ahead return of the equally value-weighted return of a portfolio sorted into quintile q on stock characteristic sc and $r_{d=t-3,t}^{sc_q}$ is the average return at $T-3$ of a portfolio based on stock characteristic sc quantile q. The bottom panel reports the average coefficient over time of the following cross-sectional estimation:

$$r_{t+1}^{i \in sc_q} = \alpha + \gamma^{CS} r_{d=t-3,t}^{i \in sc_q} + \epsilon_{t+1}$$

where $r_{t+1}^{i \in sc_q}$ is one month ahead return of an individual stock i belonging to quintile q according to stock characteristic sc and $r_{d=t-3,t}^{i \in sc_q}$ is the corresponding $T-3$ end of month return. The stock characteristics considered are the Amihud illiquidity measure (the fifth being the most illiquid portfolio) and stock price (the fifth being the most high-priced portfolio). The Amihud illiquidity ratio is calculated as a rolling 6-month average, while the average price is calculated at a 1-month frequency. The Data is CRSP, and the sample period goes from January 1985 to December 2020.



In Figure 6.C, I report the time series and cross-sectional results. It is possible to notice how the results drastically change from the time series to the cross-sectional results for both price and liquidity metrics. The discrepancy between the two approaches can be motivated by the cross-sectional variation in average returns only captured in the cross-sectional procedure. Finally, it is worth noticing that the coefficients reported at the time series level corroborate the analysis reported in Section 3.1.2, suggesting that the results do not depend on whether the sorting is a time series (sorting based on the metrics' time series average) or at cross-sectional level (sorting based on the monthly metrics values).

C.2 Appendix Economic Mechanism

C.2.1 Direct Evidence between Reversal Pattern and Payment Cycle

Table 1.C 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 $ff_{w=4,t}$, nominal dividends, $Nom.\ div_t$, and real dividends, $Real\ div_t$.

Table 1.C: Descriptive Statistics Payment Cycle Variable
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 $ff_{w=4,t}$, nominal dividends, $Nom.\ div_t$, and real dividends $Real\ div_t$. In the remaining columns, I report statistics conditional to the TAR threshold: number of observations, sample mean (arithmetic), volatility (standard deviation), Skewness, and Kurtosis. The sample period goes from January 1975 to December 2020.

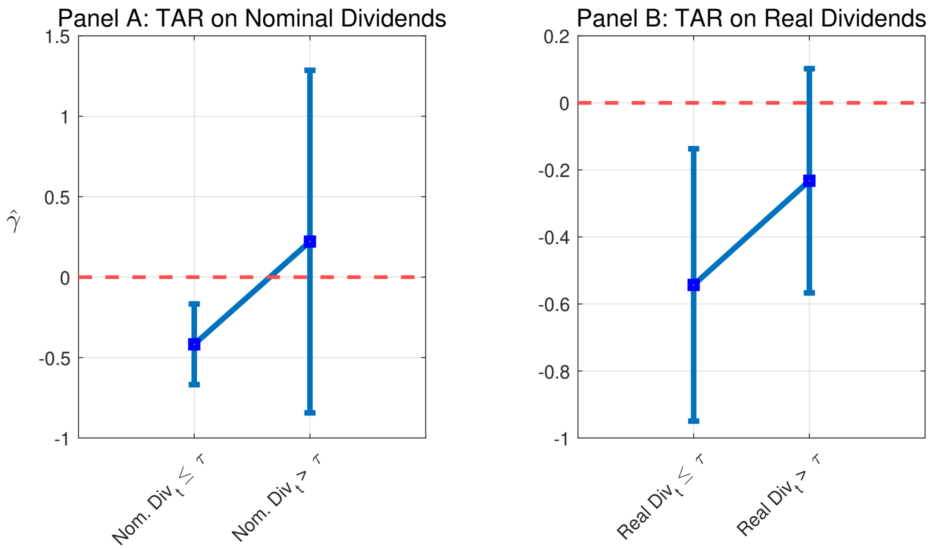
	τ	Obs.	Mean	Std.Dev.	Skewness	Kurtosis
$inflow_t$ if $inflow_t > \tau$	6.28	284	6.903	0.284	-0.539	2.294
$inflow_t$ if $inflow_t \leq \tau$		267	5.533	0.576	-0.346	1.909
$ff_{4,t}$ if $ff_{4,t} > \tau$	5.76	190	9.046	3.111	1.519	4.924
$ff_{4,t}$ if $ff_{4,t} \leq \tau$		361	2.586	2.097	0.161	1.420
$Nom.\ div_t$ if $Nom.\ div_t > \tau$	3.358	104	3.781	0.216	-0.323	2.062
$Nom.\ div_t$ if $Nom.\ div_t \leq \tau$		447	2.445	0.568	-0.324	2.127
$Real\ div_t$ if $Real\ div_t > \tau$	3.135	333	6.787	0.384	-0.560	2.152
$Real\ div_t$ if $Real\ div_t \leq \tau$		218	5.401	0.559	-0.002	2.070

The nominal dividends are obtained from the Shiller website, whereas real dividends are nominal dividends multiplied by the ratio between the December 2020 Consumer Price Index (CPI) and month t CPI level. Figure 1.C shows that, independently from inflation, the reversal pattern is more robust in months when dividends are below the estimated thresholds. Intuitively, when pension funds receive fewer proceedings from their equity positions, they likely increase their end-of-month liquidity selling.

Figure 1.C: **Payment Cycle and Reversal Pattern: Direct Evidence**
This figure reports the estimated coefficients and the robust 95% confidence intervals for the following TAR regressions:

$$r_{t+1} = \begin{cases} \alpha + \gamma_1 \, r_{w=4,t} + \epsilon_{t+1} & if \quad -\infty < Nom.Div_t \ (RealDiv_t) \leq \tau \\ \alpha + \gamma_2 \, r_{w=4,t} + \epsilon_{t+1} & if \qquad \tau < Nom.Div_t \ (RealDiv_t) < \infty \end{cases}$$

where τ is the threshold parameter estimated within the TAR algorithm either on nominal dividends, $Nom.Div_t$, or on real dividends, $RealDiv_t$. The estimated threshold for the TAR based on $Nom.Div_t$ is 3.358, and on $RealDiv_t$ is 3.135. The sample period goes from January 1975 to December 2020.



C.2.2 Volume and Volatility Variables

This Appendix reports the statistical properties of the two variables introduced in Section 3: Δvol_t and Δvix_t. In Panel A (B) of Figure 2.C, 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. In Panel A, I can observe that 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. In Panel B, the cumulative distribution function of $vix_{4,t}$ conditional on $\Delta vix_t > \tau$ pointwise stochastically dominates.

The statistical analysis reported in Table 2.C corroborates the visual inspection in Figure 2.C. In Panel C (D), I report the estimated density function of Δvol_t (Δvix_t).

Figure 2.C: **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 estimated in Section 3 (red vertical bar). The sample period for Panel A and C goes from January 1975 to December 2020, while for Panel B and D goes from January 1990 to December 2020.

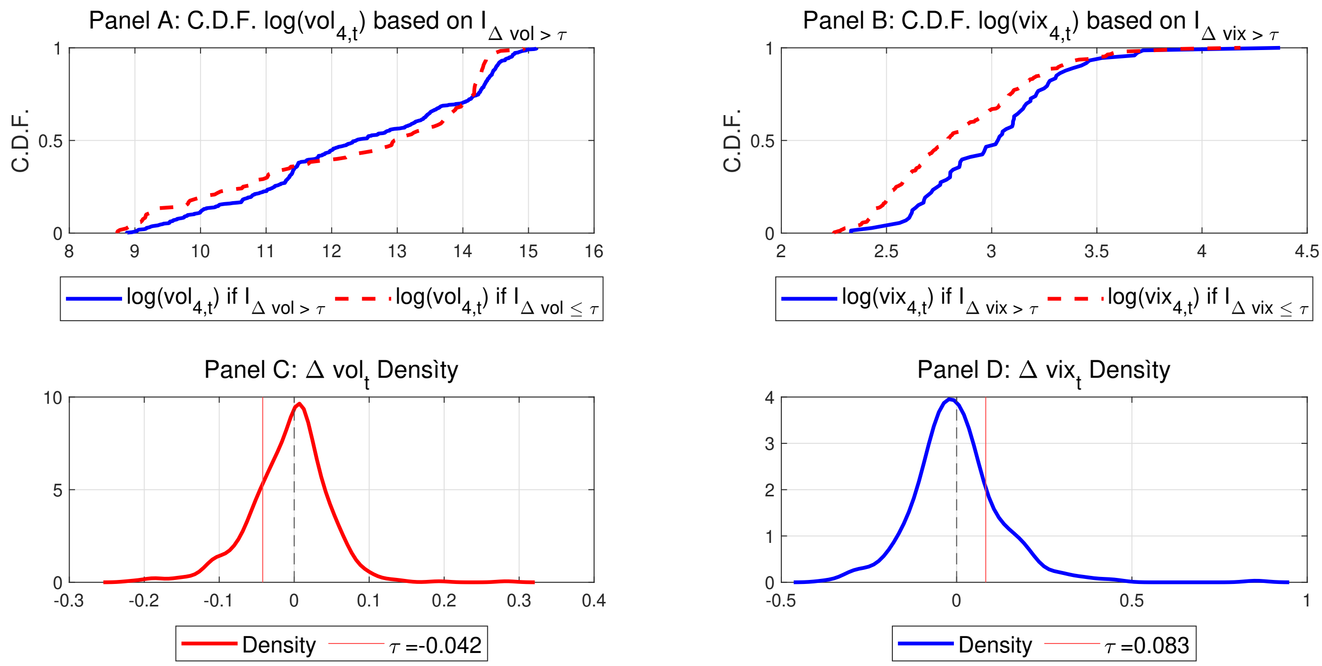


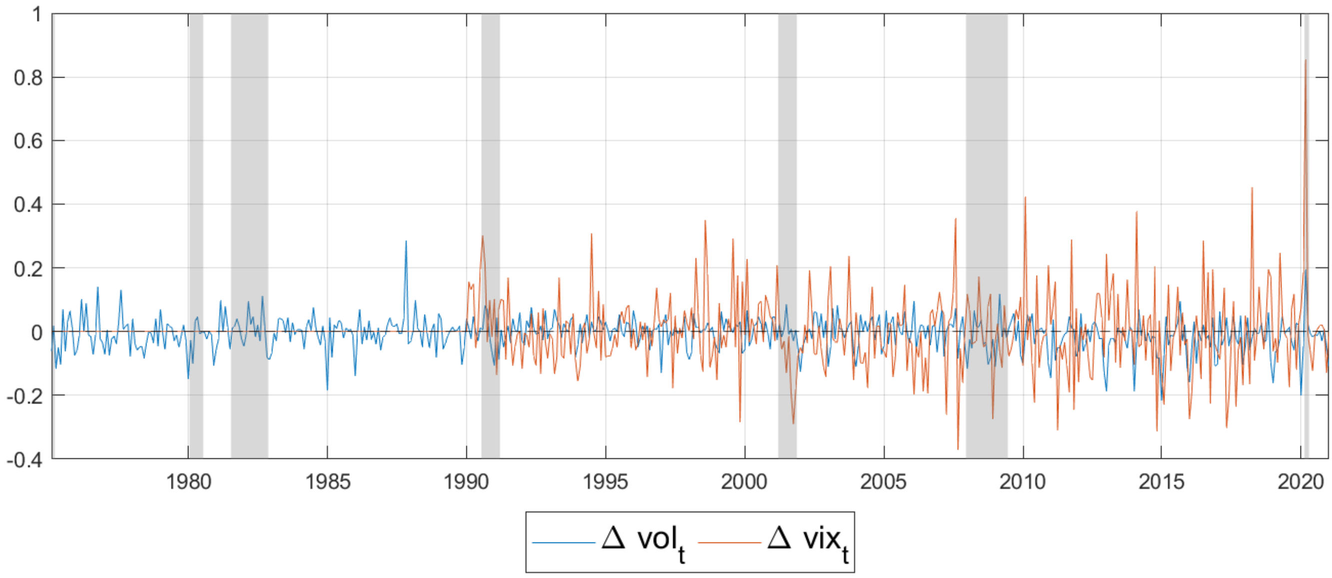
Table 2.C: Statistical Properties of Volume and Volatility Variables
This table reports the number of observations, sample mean (arithmetic), volatility (standard deviation), minimum, maximum, Skewness, and kurtosis for the subgroups of last week's volume $vol_{4,t}$ (volatility $vix_{4,t}$) defined according to the criterium $\Delta vol_t > \tau$ ($\Delta vix_t > \tau$). In the last column, I report the p-value of the two side Kolmogorov-Smirnov test for equality of distribution functions: the null hypothesis is that the two subgroups have the same distribution. The sample period for $vol_{4,t}$ goes from January 1975 to December 2020, while for $vix_{4,t}$ goes from January 1990 to December 2020. All the values are in log.

	Obs	Mean	Std.Dev.	Min	Max	Skewness	Kurtosis	KS-Test
$vol_{4,t}$ if $\Delta vol_t > \tau$	433	12.412	1.748	8.877	15.129	-0.221	1.812	0.077
$vol_{4,t}$ if $\Delta vol_t \leq \tau$	119	12.361	1.948	8.732	14.934	-0.524	1.770	
$vix_{4,t}$ if $\Delta vix_t > \tau$	73	3.020	0.346	2.331	4.371	0.851	4.833	0.002
$vix_{4,t}$ if $\Delta vix_t \leq \tau$	299	2.846	0.358	2.249	4.183	0.697	3.204	

Figure 3.C plots Δvol_t and Δvix_t over time. The two series are positively correlated and unrelated to the business cycle. During periods of recession (grey shaded area in the plot), Δvol_t is mostly positive (therefore $vol_{4,t} \geq vol_{3,t}$) while Δvix_t is mostly negative (therefore $vix_{4,t} \leq vix_{3,t}$). Therefore, in recessions, I do not observe in the last week a dramatic drop in

volume or a rise in volatility (only during the coronavirus 2020 recession, Δvix_t significantly spikes). Intuitively, the two measures, being at weekly frequency, most likely capture market movements instead of business-cycle variations.

Figure 3.C: 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 2020, while for Δvix_t goes from January 1990 to December 2020.



C.2.3 Different Metrics of Volume and Variance

In this session, I present evidence that the results presented in Sections 3.2.2 and 3.2.3 are robust to different volume and volatility variables specifications. Here, I consider the following:

$$\Delta vol_t = vol_{w=4,t} - vol_{w=3,t} \qquad \Delta vix_t = vix_{w=4,t} - vix_t \tag{35}$$

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 3.C: Volume Channel: Robustness Check

In the first panel of the Table, I report 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 r_{t+1} is the $t+1$ monthly excess return; $r_{w=4,t}$ is the 4^{th} weekly return at month t; τ is the estimated TAR threshold estimated on the volume variable $\Delta vol_t = vol_{w=4,t} - vol_{w=3,t}$. In the second panel, I report the results of the following Predictive regression:

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

where $\mathbb{1}_{\Delta vol_t}$ is an indicator function based on Δvol_t. In brackets, I report robust Newey and West (1987) t-statics. The sample period goes from January 1975 to December 2020.

TAR regression		Predictive regression			
	r_{t+1}		r_{t+1}	r_{t+1}	r_{t+1}
τ	-0.135	α	0.004	0.004	0.005
			[2.105]	[0.993]	[1.032]
α	0.004	$r_{w=4,t}$	-0.327		-0.093
	[2.160]		[-3.276]		[-0.536]
$r_{w=4,t}$ if $\Delta vol_t \leq \tau$	-0.090	$\mathbb{1}_{\Delta vol_t > \tau}$		-0.001	-0.001
	[-0.320]			[-0.247]	[-0.132]
$r_{w=4,t}$ if $\Delta vol_t > \tau$	-0.436	$r_{w=4,t} \times \mathbb{1}_{\Delta vol_t > \tau}$			-0.342
	[-2.900]				[-1.589]
Obs.			551	551	551
R^2	1.98%		1.60%	0.02%	1.99%

Table 4.C: Volatility Channel: Robustness Check

In the first panel of the Table, I report the results of the following Threshold Autoregressive Regression (TAR):

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

where r_{t+1} is the $t+1$ monthly excess return; $r_{w=4,t}$ is the 4^{th} weekly return at month t; τ is the estimated TAR threshold estimated on the volatility variable $\Delta vix_t = vix_{w=4,t} - vix_t$. In the second panel, I report the results of the following Predictive regression:

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

where $\mathbb{1}_{\Delta vix_t}$ is an indicator function based on Δvix_t. In brackets, I report robust Newey and West (1987) t-statics. The sample period goes from January 1990 to December 2020.

TAR regression		Predictive regression			
	r_{t+1}		r_{t+1}	r_{t+1}	r_{t+1}
τ	0.075	α	0.005	0.005	0.005
			[2.008]	[2.312]	[2.354]
α	0.006	$r_{w=4,t}$	-0.251		-0.080
	[2.710]		[-2.194]		[-0.426]
$r_{w=4,t}$ if $\Delta vix_t \leq \tau$	-0.076	$\mathbb{1}_{\Delta vix_t > \tau}$		-0.005	0.020
	[-0.360]			[-0.592]	[1.950]
$r_{w=4,t}$ if $\Delta vix_t > \tau$	-0.561	$r_{w=4,t} \times \mathbb{1}_{\Delta vix_t > \tau}$			-0.944
	[-2.620]				[-2.918]
Obs.	371		371	371	371
R^2	1.94%		1.06%	0.14%	2.93%

C.3 Potential Other Explanation of Reversal Pattern

C.3.1 Over-Confidence Channel

Based on the theoretical models and the empirical findings, I argue that the end-of-month payment cycle is the economic source of the negative market correlation. However, Odean (1998)'s model could suggest an alternative explanation based on potential biases in decision-making and, in general, the irrationality of market participants. Odean (1998) proposes a model in which overconfident traders increase market volume and volatility. Moreover, returns are negatively correlated if overconfident traders overweight information. 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).[28] The variables' objective is to capture "a belief about future cash-flows and investment risks that is not justified by the facts at hand", Baker and Wurgler (2007).

I run a TAR regression

$$r_{t+1} = \begin{cases} \alpha + \gamma_1 \; r_{w=4,t} + \epsilon_{t+1} & if \quad -\infty < BF_t^i \leq \tau \\ \alpha + \gamma_2 \; r_{w=4,t} + \epsilon_{t+1} & if \qquad \tau < BF_t^i < \infty \end{cases} \tag{36}$$

where BF^i is either $SENT$ or $SENT^{\perp}$. Table 5.C 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

[28] 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.

serial correlation is statistically stronger when the BF^i values are below the estimated threshold.

Table 5.C: Over-Confidence Channel
This table reports the results of the following Threshold Autoregressive Regression [TAR]:

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

where r_{t+1} is the $t+1$ monthly excess return; $r_{w=4,t}$ is the 4^{th} weekly return at month t; τ is the estimated TAR threshold estimated on the sentiment index BF_t^i variable, Baker and Wurgler (2006). In the first column, the BF^i variable considered is $SENT$, in the second column is $SENT^{\perp}$. In brackets, I report robust t-statics. The sample period goes from January 1975 to December 2020.

	r_{t+1}		r_{t+1}
τ	-0.349	τ	-0.213
α	0.004	α	0.004
	[2.145]		[2.169]
$r_{w=4,t}$ if $SENT_t \leq \tau$	-0.558	$r_{w=4,t}$ if $SENT_t^{\perp} \leq \tau$	-0.519
	[−1.895]		[−2.499]
$r_{w=4,t}$ if $SENT_t > \tau$	-0.273	$r_{w=4,t}$ if $SENT_t^{\perp} > \tau$	-0.248
	[−1.822]		[−1.525]
Obs.	551	Obs.	551
R^2	1.78%	R^2	1.82%

To corroborate the results, I perform the standard predictive regression $r_{t+1} = \alpha + \gamma \; r_{w=4,t} + \beta BF_t^i + \epsilon_{t+1}$. I show that controlling for each BF^i, the magnitude and significance of γ do not change. Table 6.C shows that $r_{w=4,t}$ predicts the stock market through a channel not captured by the control variables, as the coefficient attached to $r_{w=4,t}$ does not change in terms of magnitude and significance.

Table 6.C: Over-Confidence Channel: Predictive Regression
This table reports the results of the following Predictive regression

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

where r_{t+1} is the $t+1$ monthly excess return; $r_{w=4,t}$ is the 4^{th} weekly return at month t; BF_t^i are control variables measuring market sentiment defined in Baker and Wurgler (2006). In brackets, I report robust Newey and West (1987) t-statics. The sample period goes from January 1975 to December 2020.

	r_{t+1}	r_{t+1}	r_{t+1}	r_{t+1}
α	0.004	0.004	0.004	0.004
	[2.105]	[2.147]	[2.184]	[1.997]
$r_{w=4,t}$	-0.327	-0.333	-0.329	-0.337
	[-3.276]	[-3.414]	[-3.356]	[-3.505]
$SENT_t$		-0.003		-0.009
		[-1.364]		[-0.993]
$SENT_t^{\perp}$			-0.003	0.006
			[-1.147]	[0.617]
Obs.	551	551	551	551
R^2	1.60%	1.99%	2.05%	2.05%

C.3.2 Compensation for Liquidity Provision

To assess whether the time series reversal captures a compensation for liquidity, I consider whether the returns generated from the strategy in equation (10) can be predicted by previously proposed factors and portfolio anomalies.

First, similar to the exercise proposed in Table 7.A, I consider whether the reversal returns can be predicted by factors and other portfolios. Consistent with the results in Section A.8.4, forecasting the reversal returns with proposed predictors generates positive and statistically significant alphas (results reported in the Online Appendix). Second, I study whether portfolios and factors have a contemporaneous predictability over the reversal returns ($\$r_{w=4,t} = \alpha + \beta_i F_{i,t} + \varepsilon_t$). Table 7.C shows that anomalies portfolios and factors linked to liquidity provision do not explain the aggregate market reversal returns.

Table 7.C: Reversal Pattern, Factors and Portfolio Anomalies
This table reports in the first row the estimation result of:

$$\$r_{w=4,t} = \alpha + \beta_i F_{i,t} + \varepsilon_t$$

where the factors $F_{i,t}$ considered are Buy and Hold on S&P 500, Time Series Momentum, Size (SML), Book to Market (HML), Momentum and Short Cross Sectional Reversal. The second row reports the estimation results of the following:

$$\$r_{w=4,t} = \alpha + \beta_i PC_{i,t} + \varepsilon_t$$

where $PC_{i,t}$ is the i^{th} Principal Components (PC) extracted from the 100 anomalies portfolio returns in Dong et al. (2022). In brackets, I report robust Newey and West (1987) t-statics. The time window considered in the first regression is from January 1975 to December 2020. The SML, HML, Cross Sectional Momentum and Short term Reversal factors are downloaded from Kenneth R. French website. The time window from the second row is from January 1975 to December 2018, and the 100 anomalies portfolio returns are available from Zhou's personal website.

α	BH	12M-MOM	SMB	HML	MOM	REV				
0.002	0.533	-0.102	-0.000	0.000	-0.000	0.000				
[2.352]	[21.250]	[−4.110]	[−0.407]	[0.804]	[1.524]	[−0.823]				
α	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	PC9	PC10
0.004	0.002	0.000	0.001	0.001	-0.004	-0.004	0.000	-0.005	0.002	-0.003
[3.079]	[7.070]	[−0.330]	[1.190]	[1.300]	[−5.300]	[−5.090]	[−0.310]	[−5.480]	[1.330]	[−3.030]

D Appendix Section 4

D.1 OECD Plots

Figure 1.D: **American Pension Funds Cash Holding**
The figure shows the percentage of Asset Under Management (AUM) on Cash Holding for American Pension Funds. The Data Source is OECD *Pension Markets in Focus*.

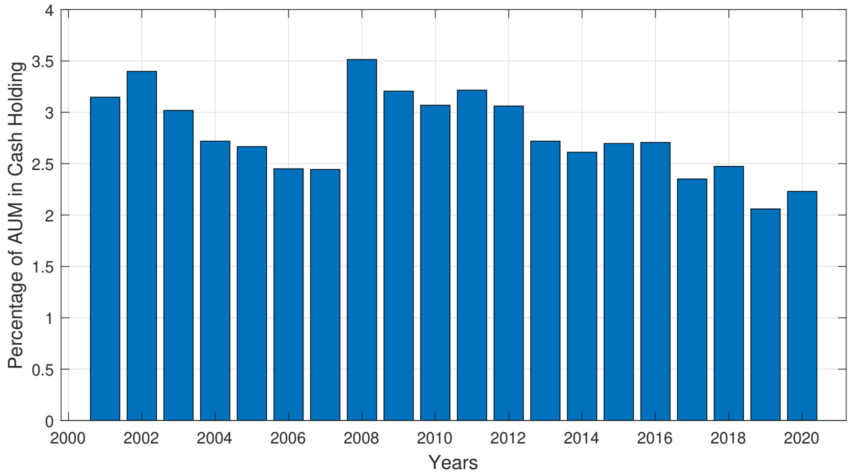
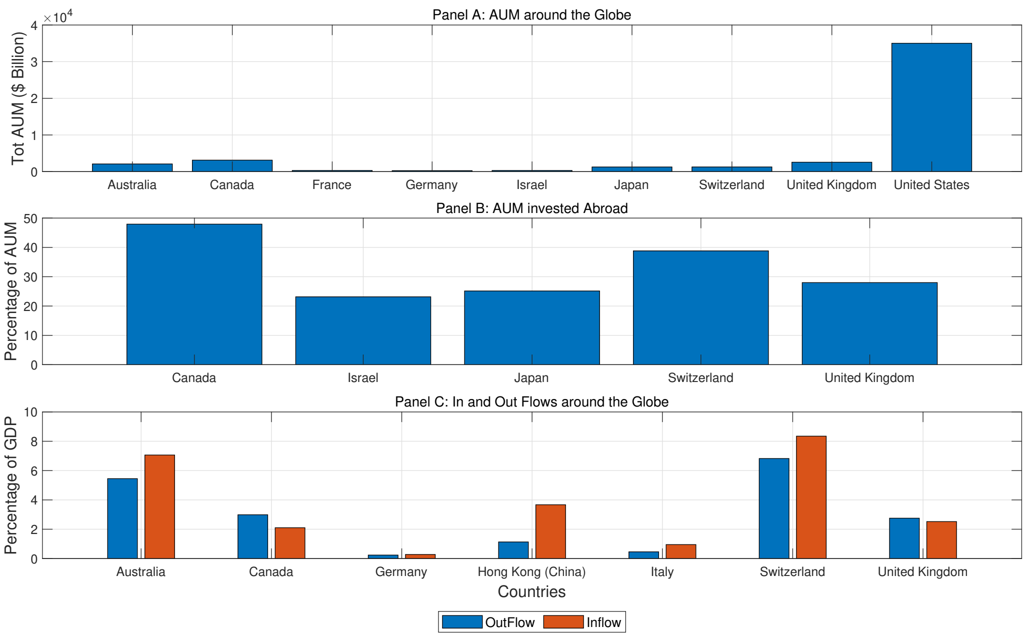


Figure 2.D: **Pension Funds Characteristics**
Panel A reports the Asset under Management (AUM) in $ Billion for some OECD representative countries in 2022. Panel B reports the percentage of AUM invested abroad in 20222 for some representative countries. Panel C compares the annual pension benefit outflows against the contributions into pension plans for some representative countries in 2022. The Data Source is OECD *Pension Markets in Focus*.



D.2 Volume and Volatility Channels DoW Jones

Table 1.D: Volume and Volatility Channel on DOW
This table reports the volume and volatility channels on the Dow Jones Industrial Average (DOW). In Panel A, I report 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 r_{t+1} is the $t+1$ monthly excess return; $r_{w=4,t}$ is the 4^{th} weekly return at month t; τ is the estimated TAR threshold estimated on the volume variable $\Delta vol_t = \frac{VOL_{w=4,t} - VOL_{w=3,t}}{\sum_{i=1}^{4} VOL_{w=i,t}}$. In the second panel, I report the results of the following Predictive regression:

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

where $\mathbb{1}_{\Delta vol_t}$ is an indicator function based on Δvol_t. In brackets, I report robust Newey and West (1987) t-statics. In Panel B, I report the analogous regression results obtained for $\Delta vix_t = vix_{w=4,t} - vix_t$. The sample period goes from January 1975 to December 2020 in Panel A and from January 1990 to December 2020 in Panel B.

Panel A: Volume Channel						Panel B: Volatility Channel					
TAR regression		Predictive regression				TAR regression		Predictive regression			
	r_{t+1}		r_{t+1}	r_{t+1}	r_{t+1}		r_{t+1}		r_{t+1}	r_{t+1}	r_{t+1}
τ	0.019	α	0.004	0.005	0.005	τ	-0.023	α	0.005	0.009	0.008
			[1.996]	[2.464]	[2.579]				[1.689]	[2.048]	[2.002]
α	0.004	$r_{w=4,t}$	-0.325		-0.226	α	0.005	$r_{w=4,t}$	-0.309		0.010
	[1.980]		[-3.232]		[-1.954]		[1.730]		[-1.899]		[0.594]
$r_{w=4,t}$ if $\Delta vol_t \leq \tau$	-0.215	$\mathbb{1}_{\Delta vol_t > \tau}$		-0.009	-0.008	$r_{w=4,t}$ if $\Delta vix_t \leq \tau$	0.136	$\mathbb{1}_{\Delta vix_t > \tau}$		-0.006	-0.005
	[-1.450]			[-1.569]	[-1.580]		[0.560]			[-0.717]	[-0.632]
$r_{w=4,t}$ if $\Delta vol_t > \tau$	-0.779	$r_{w=4,t} \times \mathbb{1}_{\Delta vol_t > \tau}$			-0.524	$r_{w=4,t}$ if $\Delta vix_t > \tau$	-0.515	$r_{w=4,t} \times \mathbb{1}_{\Delta vix_t > \tau}$			-0.591
	[-3.210]				[-2.115]		[-2.050]				[-1.916]
Obs.	551		551	551	551		188		188	188	188
R^2	0.80%		1.56%	0.65%	2.87%		1.67%		1.68%	0.53%	3.50%

D.3 Evidence on International Indexes

In this Session, I study whether the negative serial correlation between the last week return, $r_{w=4,t}$, and the one month ahead return, r_{t+1}, holds internationally. The international indices considered are reported in Table 2.D.

Table 2.D: Indices around the World: Descriptive Statistics
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.

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

The results show a negative relationship even though not statically significant:

Table 3.D: Last week predictability around the World
This table reports in the first row the coefficient attached to last week return 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 4^{th} weekly return at month t. In the last two rows, I report the cross-countries' lead-lag analysis:

$$r_{t+1} = \alpha + \gamma_{US} \; r^{US}_{w=4,t} + \varepsilon_{t+1}$$

where $r^{US}_{w=4,t}$ is he S&P 500 last week return. In brackets, I report robust Newey and West (1987) t-statics.

	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]
$\hat{\gamma_{US}}$	0.003	-0.133	0.01	0.181	-0.153	-0.074	-0.223
	[0.150]	[0.940]	[0.060]	[1.040]	[1.070]	[0.320]	[1.030]