Time Series Reversal: A Payment Cycle Friction*

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Abstract

This paper shows that the aggregate U.S. equity market reverts in one month the non-informational price pressure induced by the end-of-month payment cycle. The pattern survives transaction costs and out-of-sample tests as it is strongest among 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: Asset pricing, anomalies, predictability, time series, market frictions, reversal, turn of the month, liquidity, institutional investors.

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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. Despite many contributions, three major questions are still open. First, there is an ongoing debate whether reversal is an anomaly due to behavioral bias or a compensation factor for liquidity provision - Da, Liu, and Schaumburg (2014). Second, it's unclear whether the reversal pattern is economically meaningful given the large transaction costs and fees the strategy incurs by trading small and illiquid stocks - Avramov, Chordia, and Goyal (2006). Third, little is known at the market level as suggested in Hartzmark and Solomon (2022): "*much less is known about the speed and extent one should expect entire markets to reverse price pressure*". Hence, the questions we aim to answer in this paper are the following: 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**
The figure compares the cumulative Out-of-Sample returns of time series reversal (TSR - red solid line) with the 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.

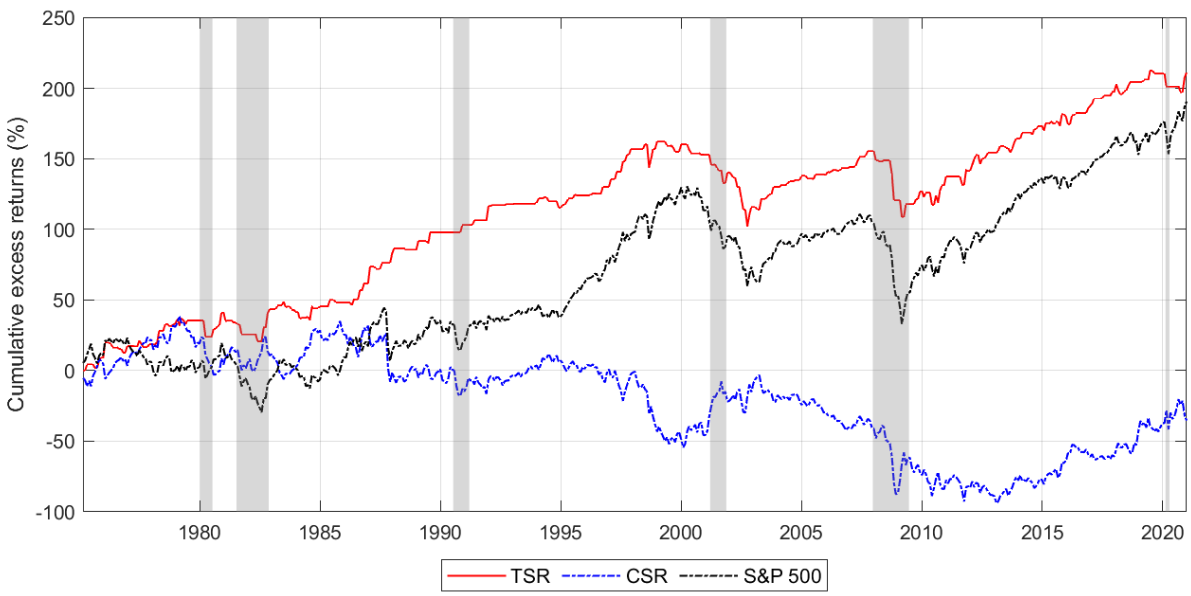


Figure 1 shows the paper's main result: we document a profitable monthly time series reversal in the S&P 500 by establishing a negative predictive channel between the last week's return and the next month's return. Specifically, the reversal trading strategy consists of buying the S&P 500 if the last week of the month has a negative return and holding it for the next month. The strategy is intended to monetize from the predictable, non-informed negative price pressure caused by the end-of-the-month payment cycle as it buys the aggregate market after institutional investors sell stocks in the last week of the month to recoup liquidity. As suggested in the figure and consistently with our explanation, we 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 documented findings, we provide a novel interpretation of the reversal pattern: an anomaly due to liquidity friction.

In the first part of the paper, in light of Vayanos and Gromb (2012), we argue that the last week of the month is an ideal candidate to establish an anomaly. The end-of-the-month payment cycle represents a substantial demand shock for the aggregate economy. Second, and more importantly, institutional investors are at the forefront of this cycle. They engage in trading activities to secure the liquidity needed for paying dividends, salaries, and contributions - Etula, Rinne, Suominen, and Vaittinen (2020). Therefore, the agents typically responsible for correcting market price discrepancies are, in this specific framework, the ones initiating the payment cycle anomaly.

Consistent with our hypothesis, we provide In-Sample evidence that the return from the last week of the month negatively correlates with one month ahead returns. We 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). Interestingly, the reversal pattern has more predicting power in expansion periods, improving the Out-of-Sample forecasting performance and robustness. This feature, consistent with a market-based explanation, is a novelty as the literature has shown and rationalized why predictability cluster during recession periods - Huang, Jiang, Tu, and Zhou (2014) and Cujean and Hasler (2017). Finally, we 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). We find that the predictor delivers sizable gains, even considering transaction costs and fees.

In the second part of the paper, we investigate the potential economic source behind the reversal pattern. We first provide a direct link between the negative serial correlation and the end-of-month payment cycle. By running a Threshold Autoregressive Regression (TAR), we show that the reversal pattern is stronger in months when salaries, dividends and end of month borrowing costs increase. Secondly, we micro-found the anomaly by providing evidence that institutional (the economic agents paying salaries) and retail investors (the economic agents receiving salaries) foster the documented pattern.

Using the ANcerno dataset and consistently with Etula et al. (2020), we show that institutional investors are net sellers in the S&P 500 stocks in the last week of the month, suggesting liquidity trading of these market participants. In the Campbell, Grossman, and Wang (1993) model, non-informational trading causes price movements that, when absorbed by liquidity suppliers, cause prices to revert. Such non-informed trading is accompanied by high trading volume. Therefore, with high volume, returns should display a negative serial correlation. We analyze the relationship between the reversal pattern and volume to corroborate the non-informational trading of institutional investors as the economic source behind the reversal evidence. We empirically test the Campbell et al. (1993) model prediction in a two-step procedure. We run a TAR and a standard Predictive regression. With the TAR regression, we establish a threshold on volume above which the negative serial correlation is stronger. With the predictive regression analysis, we show that after controlling for volume and its interaction term with the last week's return, the negative serial correlation is significant only when there is high volume in the last week of the previous month.

Using a novel dataset from Nasdaq Data Link ("Retail Trading Activity Tracker"), we 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, we test the prediction of the Sentana and Wadhwani (1992) model. In their model, positive feedback trading - a trading strategy adopted by retail investors (e.g., Merton (1980), Barber, Odean, and Zhu (2008) and Barber and Odean (2013)) - implies a reversal return pattern of the aggregate market, and its strength increases with volatility. Analyzing the relationship between volatility and reversal with the same two-step procedure described above, we 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 accentuates the reversal pattern.

To further establish the end-of-the-month payment cycle as the potential explanation, we document that the reversal evidence is minimally affected by the business cycle and is stronger during periods of economic expansion. This result is consistent with a non-informational trading explanation: during periods of financial distress, price movements are typically driven by informational shocks, and therefore, there should be not any evidence of reversal as changes in prices are permanent or at least perceived as such, Llorente, Michaely, Saar, and Wang (2002). Furthermore, it is consistent with the intuition that institutional investors do not trade in the market to recoup liquidity when it is potentially extremely costly and uncertain. Compatible with the idea that institutional investors try to get liquidity by minimizing transaction costs and price impact, we show, by considering the stocks in the CRSP universe, that the reversal pattern is stronger for high-priced and liquid stocks.

In the final part of the paper, we provide qualitative evidence that pension funds are most likely the institutional investors more exposed to the end-of-the-month payment cycle friction. Pension funds have problems in cash flow budgeting as both inflows and outflows cluster at the end of the month and are highly unpredictable. Therefore, pension funds often incur negative cash flows and likely need to liquidate their position to finance their imbalance. Linking the time serial reversal pattern to the pension funds' cash flow budget helps explain why institutional investors do not anticipate their liquidity trading, why the pattern clusters in the most liquid and capitalized indexes in the U.S., and finally, why the pattern is cyclical.

We perform several robustness checks in the Appendix, among which we show that the reversal pattern is robust to the end of the month return construction, to the turn of the month effect, to previously proposed predictors and factors, previous weekly returns, and the closing price effects. We provide evidence that behavioral bias, option expiration trading, and quarterly trading activity 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 In and Out-of Sample evidence. Section 3 explores the transmission channel behind the reversal pattern. In Section 4, we perform some robustness checks. Section 5 discusses the link between time series reversal and pension funds, and Section 6 concludes.

1.1 Literature Review

We 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, and therefore, the results could possibly be driven by cross-sectional differences among stocks rather than reversal properties.[1] Second, the findings are

[1] Lo and MacKinlay (1990) show that the positive cross-correlation of the portfolio's constituents and not the negative auto-correlation of each stock could explain the results of the two cross-sectional approaches. Conrad and Kaul (1993) shows 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.

more pronounced on small and illiquid stocks, raising concerns about whether the predictability is practically applicable. The cross-sectional reversal may become economically insignificant when transaction costs and fees, which are particularly high for this category of stocks, are taken into account - Avramov et al. (2006).

Our methodology is close in spirit to Hartzmark and Solomon (2022) as both papers use predictable price pressures to establish market predictability. In their work, the authors use 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 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 the 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)). Our methodology connects the reversal pattern to the end-of-the-month payment cycle, which acts as a liquidity shock, triggering non-informational trading. Therefore, we provide a novel interpretation of the aggregate level 1-month reversal: it measures the liquidity demands the financial markets cannot efficiently accommodate. Consequently, the documented reversal pattern can be considered an anomaly due to liquidity frictions. Leveraging on the non-informational nature of the last week of the month trading, we use the daily institutional investors' inflows to determine the aggregate market elasticity. The results are in line with the literature, Gabaix and Koijen (2021) but the identification strategy has novel features. It assesses institutional investors' holdings on a daily basis by directly observing their trading activity. Additionally, it employs the frequent liquidity trading caused by the payment cycle friction instead of relying on infrequent events like index inclusions and exclusions.

The third contribution to the field is documenting novel properties of the 1-month reversal pattern. In the literature (e.g., Avramov et al. (2006), Nagel (2012) and Dai et al. (2023)), the pattern is stronger for small and illiquid stocks and generally spikes in periods of uncertainty. Both 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 our liquidity anomaly explanation, we document that the the reversal pattern induced by the liquidity needs of institutional investors is cyclical, as they likely tend to recoup liquidity from the market only when it is not risky, and stronger for high-priced and liquid stocks as institutional investor try to minimize transaction costs and price impact.

We 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, we use the last week temporary inefficiency caused by the end-of-the-month 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): we 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 peculiar feature that distinguishes our predictor. It is instrumental in having a robust and reliable predictability channel, as discussed in Goyal, Welch, and Zafirov (2021). We finally propose a forecasting exercise in which we mix our predictor and the momentum and show that the Out-Sample performance drastically improves, having predictability both in expansion and recession times.

We finally contribute to the turn-of-the-month literature. The literature has shown and investigated the effects of the last month's trading days, mostly focusing on the correlation between the last trading day of the month and the first three days of the month ahead - Lakonishok, Shleifer, Thaler, and Vishny (1991). This paper builds from Etula et al. (2020), which presents several evidence suggesting that institutional investors have liquidity needs due to the end-of-month payment cycle. However, our work differs from theirs in many dimensions: most importantly, Etula et al. (2020) aims to establish the end-of-the-month payment cycle as an event causing systematic patterns in the stock market, whereas this paper aims to use the non-informational trading induced by the payment cycle to provide novel insights on the 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 in the stock market. Does the end-of-month payment cycle trigger both conditions?

Monthly transfers tend to cluster around specific dates. This practice is designed to aid companies in managing their cash budgets and workers in their spending behavior. In the United States, transfers typically occur towards the end of the month. Pensions and contributions are disbursed on the first day of the month, salaries are paid either bi-weekly or at month-end, and dividends are generally distributed on the last day of the month. It's worth noting that the annual amount of dollars exchanged in payments in the American economy is around 100 Trillion dollars per year, 5 times the annual dollar volume exchanged in the stock market.[2]

Institutional investors often engage in stock market trading towards the end of the month to address liquidity requirements due to an increasing end of month financing costs in short-term bonds, equities, and longer-term debt capital markets - Etula et al. (2020). Consequently, the end-of-the-month payment cycle forces a non-fundamental shock due to the liquidity constraint of institutional investors who initiate the demand shock. The trading activity of institutional investors has likely a major impact on the aggregate market price dynamics as they detain more than 75 % of the aggregate market - HBR.

On the other hand, hedge funds do not likely take advantage of the reversal pattern by accommodating the liquidity needs of institutional investors for multiple reasons. First, managing a few trillions per year - statista, hedge funds should likely use most of their capital to accommodate the liquidity needs due to the payment cycle. Second, 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).

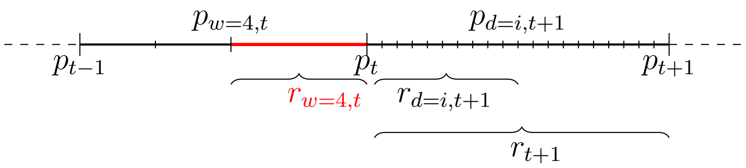
2.1 In Sample Evidence

To study whether the end of the month payment cycle could be effectively used to predict future market returns, we collect closing prices of the S&P 500 from the Global Financial Data (GFD). The sample period is from January 1975 to December 2020. The notation we adopt in the paper is the following. We denote nominal values in capital letters and the respective natural logarithm values in lowercase. As we use daily, weekly, and monthly time series, we adopt the convention of a composite suffix: we 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

[2]We proxy the transfers by the total value of cashless payments from IBS, and dollar amount data exchanged in the stock market is from the World Bank. We use data from 2019, the last available record from the World Bank Dataset. The cashless payments in 2019 were around 103 Trillion, whereas the total dollar value traded was around 23 Trillion.

price in month t, Figure 2.

Figure 2: **Price and Return Notation**
This figure graphically reports the notation adopted for price and returns series in the paper. We use t to denote a generic month and add w (d) to specify the week (day): 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. We 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.



We 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 $(r_{w=4,t} = p_t - p_{w=4,t})$. We start our analysis by testing the predicting power of $r_{w=4,t}$ through the next month cumulative returns $(r_{d=i,t+1} = p_{d=i,t+1} - p_t, \quad i = 1, \cdots, 20)$ that gradually become one month ahead return $(r_{t+1} = p_{t+1} - p_t)$.[3] Figure 3 plots the estimated coefficients and the 95% confidence intervals of the predictive regression for the cumulative returns throughout the month

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

as well as for the standard monthly predictive equation:

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

Consistent with the hypothesis of a non-informational shock and market friction, we establish a statistically significant negative predicting power of the last week's return - indicating a negative market correlation or "time-series reversal" pattern throughout the next monthly returns. Notably, 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 price pressure, consistent with the hypothesis that the market is inelastic - see Section 4.4. In line with the payment cycle as a negative shock for the aggregate market, the largest estimated coefficient, in absolute terms, is registered in the third week $(r_{d=14,t+1})$ before a new negative shock hits the

[3] We report the summary statistics of $r_{w=4,t}$ and r_{t+1} in Appendix A.2.

aggregate market. A possible economic explanation of the pattern displayed in Figure 3 is that institutional investors try to buy back the stocks strategically to avoid positive price pressure in the first few days ahead.

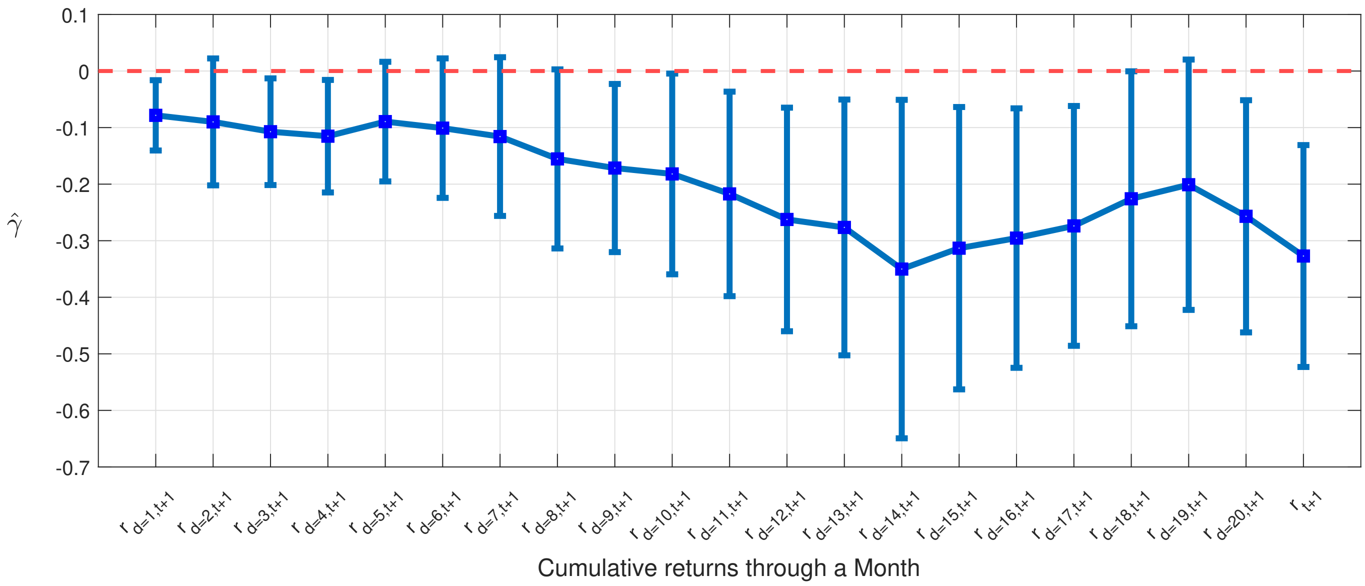
Figure 3: **Time Series Reversal throughout One Month Ahead**
This Figure reports the estimated coefficients and the associated 95% Newey and West (1987) robust confidence intervals of the predictive regression for the cumulative returns throughout the month

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

as well as for the standard monthly predictive equation:

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

where $r_{d=i,t+1} = p_{d=i,t+1} - p_t$, $r_{t+1} = p_{t+1} - p_t$ and $r_{w=4,t} = p_t - p_{w=4,t}$. The sample period goes from January 1975 to December 2020.



The findings presented in Figure 3 are consistent with the models in Summers (1986) and Fama and French (1988) as the authors conjecture that returns are negatively correlated given a transitory component in the price dynamic. However, we argue and provide evidence in the next part of the paper that the economic source of the transitory shock is not behavioral but depends on the non-informational price pressure caused by the payment cycle.

Establishing monthly reversal has important implications for real market participants as well as for the asset pricing literature. 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 potentially explains the Shiller (1980) excessive variance stock paradox: the equity market's volatility captures price movements that are not justified by information about their fundamental value.

In Appendix A, we provide several evidence that the results presented in Figure 3 are robust. Specifically, Appendix A.3 shows that the results do not depend on a Friday effect and the reversal pattern is found by considering any end-of-the-month price from $T-4$ to $T-1$, where T is the end of the month. Appendix A.4 shows that the results are not exclusively driven by the ability of $r_{w=4,t}$ to predict the first week of the month's return. Appendix A.5 shows that the reversal pattern is lost by considering a placebo test around the second week of the month. Appendix A.6 shows that the results do not depend on a closing price effect. Appendix A.7 shows that the predicting power of $r_{w=4,t}$ is lost by considering two months ahead returns. Finally, Appendix A.8 shows that the results are qualitatively unchanged by controlling for the previous week's returns, factors, and previously proposed predictors.

In the rest of the paper, we will mainly focus on the reversal pattern between the last week of the month and the one-month ahead returns ($r_{t+1} = \alpha + \gamma \; r_{w=4,t} + \epsilon_{t+1}$) as the literature has established that, opposite to other frequencies, monthly returns have very low predictability and are close to a normal distribution - Appendix A.9. Hence, the monthly frequency is the natural setting to test the reversal pattern against the hypothesis of no return correlation suggested by the efficient markets hypothesis.

2.2 Out of Sample Evidence

Our 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, this 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 has been found to vary over time, Goyal et al. (2021). Thus, In-Sample return autocorrelation does not necessarily imply Out-of-Sample (OOS) predictability.

In this subsection, we evaluate the Out-of-Sample forecasting power of the end-of-the-month return. Basically, we run predictive regression

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

recursively as in the other predictability studies at the monthly frequency. That is, at time t, we 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. We use the initial period of January 1975 to June 1986 (25% of the entire sample); therefore, the Out-of-Sample forecast evaluation period spans from July 1986 to December 2020 (414 OOS forecasts).

Following Campbell and Thompson (2008), Neely et al. (2014) and Moskowitz et al. (2012), among others, we measure the OOS predictability by using

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

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 chosen to be 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 corresponds to a predictive regression model with $\gamma = 0$, which has been found to be a tough benchmark in the literature - Welch and

Goyal (2008). Finally, to assess whether the predictive regression forecast delivers a statistically significant improvement in terms of MSFE, we use Clark and West (2007) MSFE-adjusted statistic to test the null hypothesis that the benchmark historical average forecast delivers lower MSFE than the predictive regression forecast against the alternative hypothesis that the latter delivers gains compared to the benchmark, corresponding to $H_0 : R^{2,OS} < 0$ against $H_1 : R^{2,OS} > 0$.

Table 1: Out of Sample Statistical Evaluation

This Table reports the out-of-sample forecasting results compared to the historical mean using different predictors: our proposed predictor ($r_{w=4,t}$), 12-month return (r_{t-12}) -Huang, Li, Wang, and Zhou (2020)- and two technical indicators ($\mathbb{1}_{MA(1,12)}$ and $\mathbb{1}_{MOM(1,12)}$) -Neely et al. (2014). In the first column, we report the out-of-sample $R^{2,OS}$ (equation 4), in the second and third columns $R^{2,OS}_{exp}$ and $R^{2,OS}_{rec}$ (equation 5). 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. The time window is from January 1975 to December 2020 and the out-sample valuation period goes from July 1986 to December 2020. All the values are reported in percentages.

	$R^{2,OS}(\%)$	$R^{2,OS}_{exp}(\%)$	$R^{2,OS}_{rec}(\%)$
$r_{w=4,t}$	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

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 1 we include past 12-month return (r_{t-12}) and two technical indicators ($\mathbb{1}_{MA(1,12)}$ and $\mathbb{1}_{MOM(1,12)}$) in our Out-of-Sample analysis.[4] 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 benchmark outperforms all the other predictors - they all have a negative $R^{2,OS}$. This finding is consistent with Huang et al. (2020) and Goyal et al. (2021), which have shown respectively that past 12-month return and technical

[4]More specifically, 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, we 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 on the two technical indicators, see Appendix B.1. An extensive analysis of the performance of all technical indicators can be found in Goyal et al. (2021); the results are qualitatively similar to ours.

indicators do not have a robust Out-Sample-Sample predicting power.[5]

Since the literature agrees that predictability varies over business cycles, the second and third columns in Table 1 report $R^{2,OS}$ separately for expansion and recession periods. We 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 of predictive regressions:

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

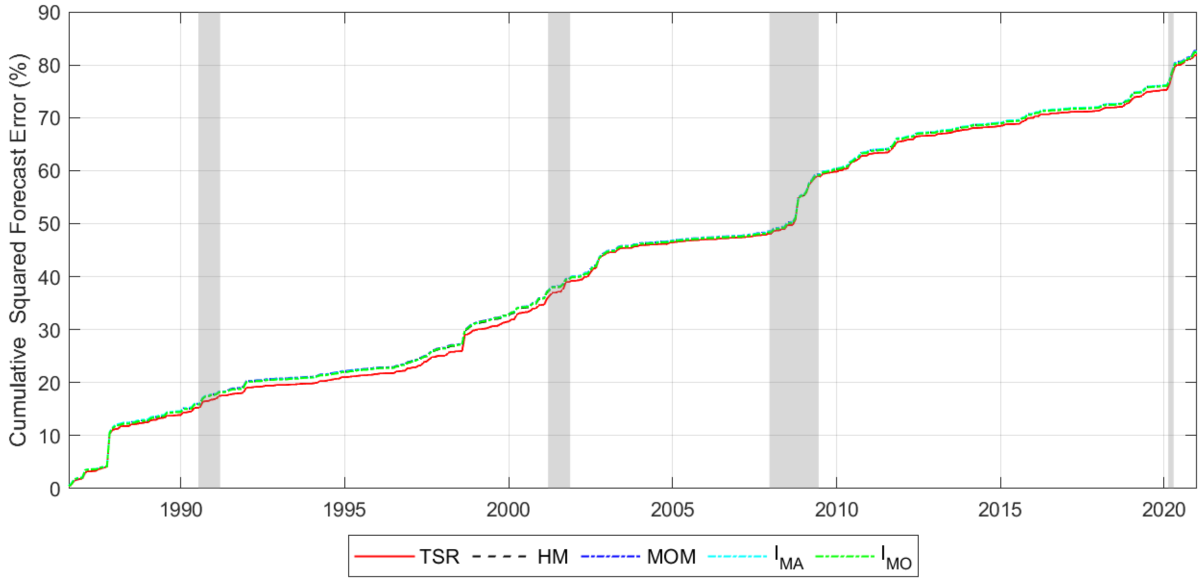
where I_t^{exp} (I_t^{rec}) is the NBER indicator function that takes a value of 1 when month t is in expansion (recession) and 0 otherwise. The performance from other predictors is consistent with the literature. There is significantly stronger evidence for predictability during recessions than during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

Therefore, we can motivate the Out-of-Sample predictability of $r_{w=4,t}$ based on economic and statistical reasons. From an economic standpoint, our proposed predictor benefits from the predictable and recurring non-informational price pressure due to the end-of-month payment cycle. This makes it particularly effective during periods of economic expansion, as we will further corroborate in Section 3.4.1. 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: $r_{w=4,t}$

[5]Specifically, 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.

matches the persistency of r_{t+1}, improving the forecasting ability - Ren, Tu, and Yi (2019).[6] Figure 4 shows the cumulative squared error over time for each predictor considered. The squared error of $r_{w=4,t}$ is never worse than the one of the historical mean, suggesting that few outliers do not drive the results reported in Table 1 and the reversal pattern systematically out-performs the historical mean.

Figure 4: **Out of Sample Cumulative Forecast Error**
The figure presents the cumulative Out-of-Sample squared errors obtained by 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 predictors belonging to the "Momentum approach". Our 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

[6]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.

relation (r_{t-i} with r_{t+1}). Our approach captures a negative return correlation, while Momentum detects a positive correlation. The economic source behind the predictability studied here is friction-based, linked to the payment cycle. On the other hand, investors' under-reaction has often been argued to be the economic source behind Momentum. Finally, the correlation between $r_{w=4,t}$ with r_{t+1} does not capture business cycle variations, and its predictability is more robust during expansion periods. On the other hand, the Momentum approach better proxies the business cycle variations, and its predictability is stronger during recession periods. Given the structural differences between the two approaches, in Section 4.2, we consider whether mixing $r_{w=4,t}$ with r_{t-12} could improve the Out-of-Sample forecasting performance.

In Appendix B.2, we consider value-weighted returns instead of index returns to align with the forecasting literature, and the results do not change qualitatively. Moreover, we test our predictor in 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), we 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).

Importantly, we restrict w_t^i to lie between 0 and 1 for the time series reversal portfolio so that the representative investor invests in the risky asset only when the last week's return is negative, capturing only the negative price pressure due to the payment cycle. For the other predictors, we allow w_t^i to lie between -1 and 1. For each point forecast, the realized portfolio return is:

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

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.

Table 2: 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 we also report the annualized percentage Δ $CER(\%)$ (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.

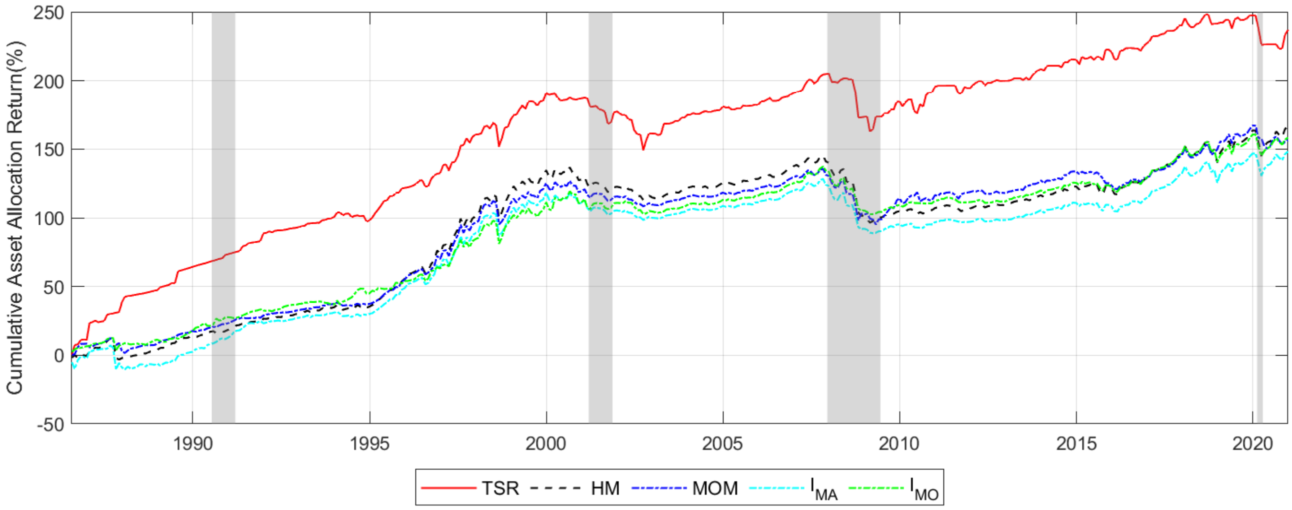
	$r_{w=4,t}$	r_{t-12}	$\mathbb{1}_{MA(1,12)}$	$\mathbb{1}_{MOM(1,12)}$	$\bar{r}_t$
$U(p)(\%)$	5.184	3.439	3.079	3.573	3.487
Sharpe Ratio	0.365	0.178	0.142	0.191	0.192
Std. Deviation	0.106	0.085	0.090	0.082	0.094
Skewness	-0.338	-0.359	-0.489	-0.421	-0.444
Kurtosis	0.932	0.813	0.970	0.892	0.856
$\Delta CER(\%)$	1.700	-0.049	-0.408	0.087	

In Table 2, we 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 we also report the annualized percentage Δ CER.

Table 2 shows that the negative market correlation outperforms proposed predictors and historical mean in portfolio 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 170 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 5, we plot the cumulative returns of the portfolios. The proposed predictor constantly outperforms all the other predictors, while the momentum approach equals the passive benchmark only after the great financial crisis.

In Appendix B.3, we plot the excess return portfolio obtained from the time series reversal against each considered predictor, graphically showing that on average, the returns obtained from $r_{w=4,t}$

Figure 5: **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.



are larger. In Appendix B.4, we report the results by allowing w_t^i to lie between -1 and 1 for the portfolio constructed on the reversal pattern. The time series reversal is still outperforming the other predictors; however, its performance decreases consistently with the idea that the reversal pattern is due to the negative price pressure induced by the payment cycle.

2.4 Monetary Gains Evidence

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

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

The strategy in equation (10) captures the potential gains from the perspective of a risk-neutral agent. As for the utility gains exercise, we limit our 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 our economic explanation. It is worth noticing that the strategies defined in equation (10) are based only on the last week's return $r_{w=4,t}$ and therefore depend neither on the specific forecasting method nor the training sample chosen. Overall, the trading strategy 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.

We compare the strategy outcome against the monetary gains analogously defined on 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 we allow short selling for the momentum trading strategy.[7] 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 the mean return of passive investing, we obtain a measure of the marginal monetary benefit of the predictors:

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

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

[7] By the definition of $\mathbb{1}_{MOM(1,12)}$, this strategy captures the results from r_{t-12} by disallowing short selling. As the historical mean is always positive when considering long time windows, the strategy defined on $\bar{r}_t$ measures the gains from passively buying the S&P 500.

Table 3: 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 we also report the annualized percentage Δ \$(%) (equation (11)). The time window is from January 1975 to December 2020.

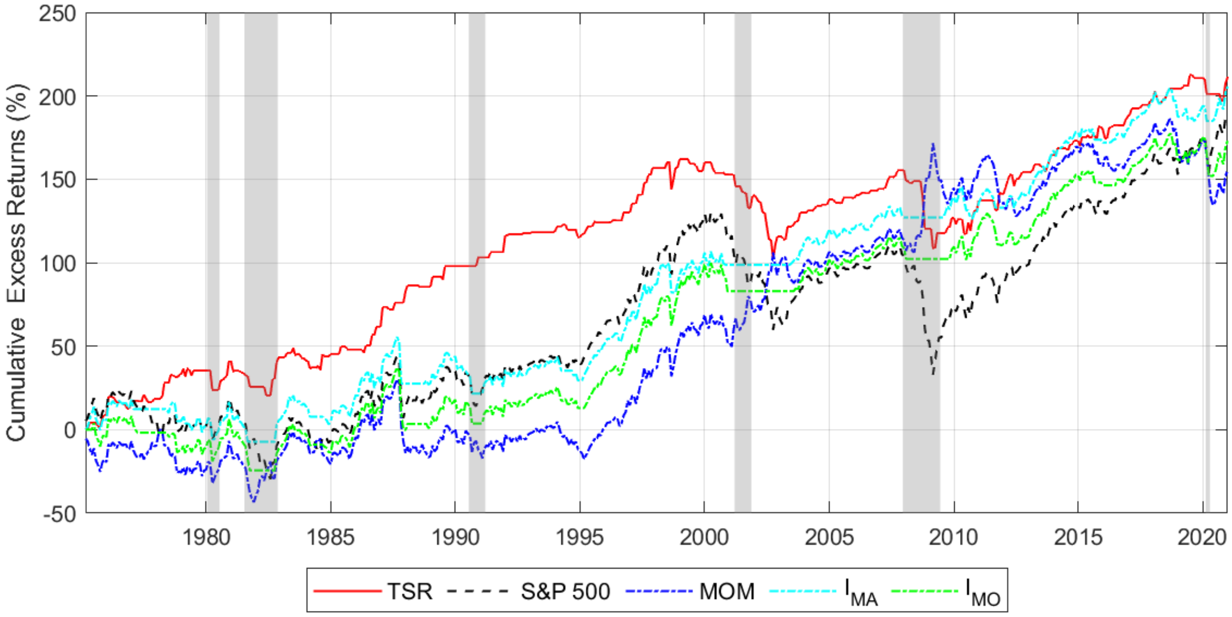
	$r_{w=4,t}$	r_{t-12}	$\mathbb{1}_{MA(1,12)}$	$\mathbb{1}_{MOM(1,12)}$	$\bar{r}_{S\&P500}$
$\$\bar{r}$(%)	4.600	3.816	4.480	3.763	4.146
Sharpe Ratio	0.439	0.224	0.384	0.304	0.275
Std. Deviation	0.105	0.151	0.117	0.124	0.151
Skewness	-0.148	-0.132	-0.318	-0.297	-0.236
Kurtosis	0.866	0.470	0.868	0.750	0.483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

In Table 3, we report the percentage annual average excess return, the annualized variance, kurtosis, and skewness for all the trading strategies; we report the annualized percentage Δ\$ for the trading strategies obtained from proposed predictors in the last row. The Δ\$ 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 on the time series reversal trading strategy dominates the others also in terms of Sharpe ratio, variance, and kurtosis.

In Figure 6 we 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.[8] Therefore, based on reported evidence, the reversal pattern outperforms the Momentum approach at statistical, utility, and monetary levels.

[8] This can explain why technical indicators perform better in a trading exercise than in forecasting. Technical indicators can suffer from collinearity problems as the binary variable can be almost identical to the intercept.

Figure 6: **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.

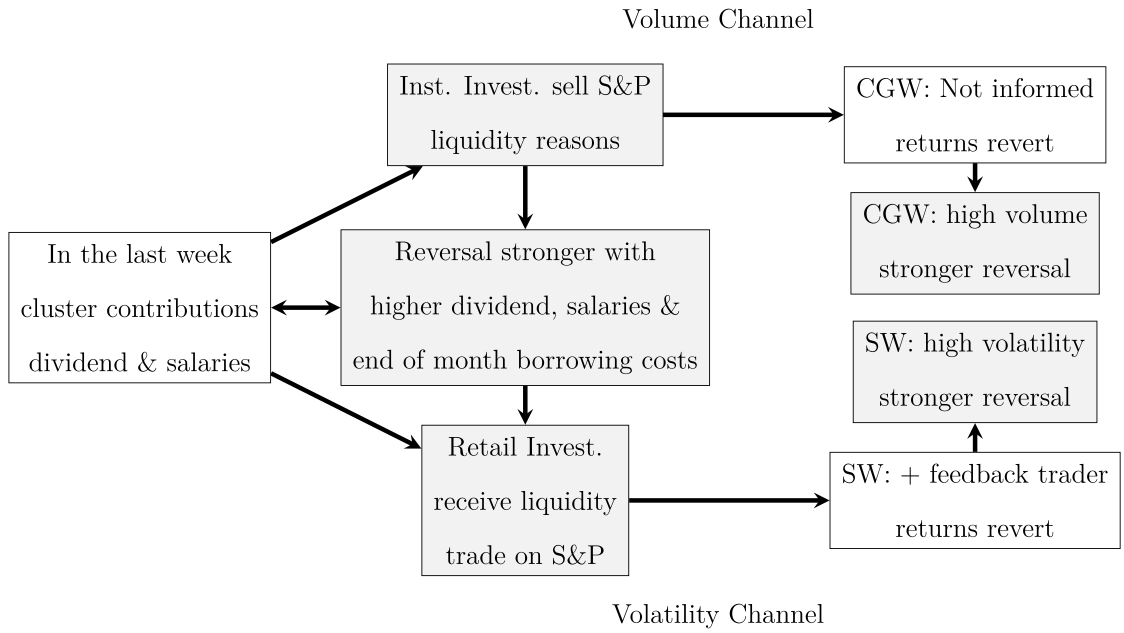


In Section 4.3, we consider trading fees and show that the results do not change qualitatively. In Appendix B.5, we plot the excess return portfolio obtained from the time series reversal against each predictor. In Appendix B.6, we report the results allowing short selling in the reversal strategy. We observe that overall, the performance deteriorates consistently with the end-of-the-month payment cycle explanation.

3 Explanation

In this Section, we provide evidence that the end-of-the-month payment cycle is likely the economic channel behind the novel reversal pattern. Figure 7 graphically describes the mechanism through which the market-specific settlement convention triggers the documented pattern.

Figure 7: **Mechanism Channel behind Time Series Reversal**
This Figure summarizes the mechanism channels through which the end-of-the-month payment cycle determines the reversal pattern. The shaded boxes are empirically tested in the next Sessions. We abbreviate Campbell et al. (1993) with CGW and Sentana and Wadhwani (1992) with SW.



3.1 Direct Evidence

In this session, we provide evidence that the reversal pattern is stronger in months with higher end-of-month disbursement and borrowing cost. Consistent with the end-of-the-month payment cycle explanation, when institutional investors face larger liquidity needs or worse liquidity conditions, they resort more on the equity market to recoup the end of month liquidity needs.

To study how the reversal pattern changes according to shifts in dividends, salary payments and borrowing costs, we perform a Threshold Autoregressive Regression (TAR) on the logarithmic difference of monthly real S&P dividends available from Shiller's website, Δdiv_t, on monthly seasonally adjusted U.S. salary (compensation of Employees Wage and Salary Disbursements) from FRED, Δsal_t, and on the end of month change in Fed Funds from FRED, $\Delta ff_{w=4,t}$:

$$r_{t+1} = \begin{cases} \alpha + \gamma_1 \; r_{w=4,t} + \epsilon_{t+1} & if \quad -\infty < \Delta div_t \; (\Delta sal_t, \; \Delta ff_{w=4,t}) \leq \tau \\ \alpha + \gamma_2 \; r_{w=4,t} + \epsilon_{t+1} & if \qquad \tau < \Delta div_t \; (\Delta sal_t, \; \Delta ff_{w=4,t}) < \infty \end{cases} \quad (12)$$

where τ is the threshold parameter estimated within the TAR algorithm either on dividends, Δdiv_t, or on salaries, Δsal_t, or on Fed funds $\Delta ff_{w=4,t}$. The coefficients γ_1 and γ_2 capture, respectively, the reversal pattern in periods of smaller and larger cash disbursement and end of month borrowing costs.

Figure 8: **Payment Cycle and Reversal Pattern: Direct Evidence**
The figure reports the estimated coefficients and the robust 95% confidence intervals for the following TAR regressions:

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

where τ is the threshold parameter estimated within the TAR algorithm either on monthly dividend changes, Δdiv_t, or on salaries, Δsal_t, or on the end of month change in Fed Funds , $\Delta ff_{w=4,t}$. The estimated threshold for the TAR based on Δdiv_t is 0.003, on Δsal_t is 0.001 and on $\Delta ff_{w=4,t}$ is 0.001. The sample period goes from January 1975 to December 2020.

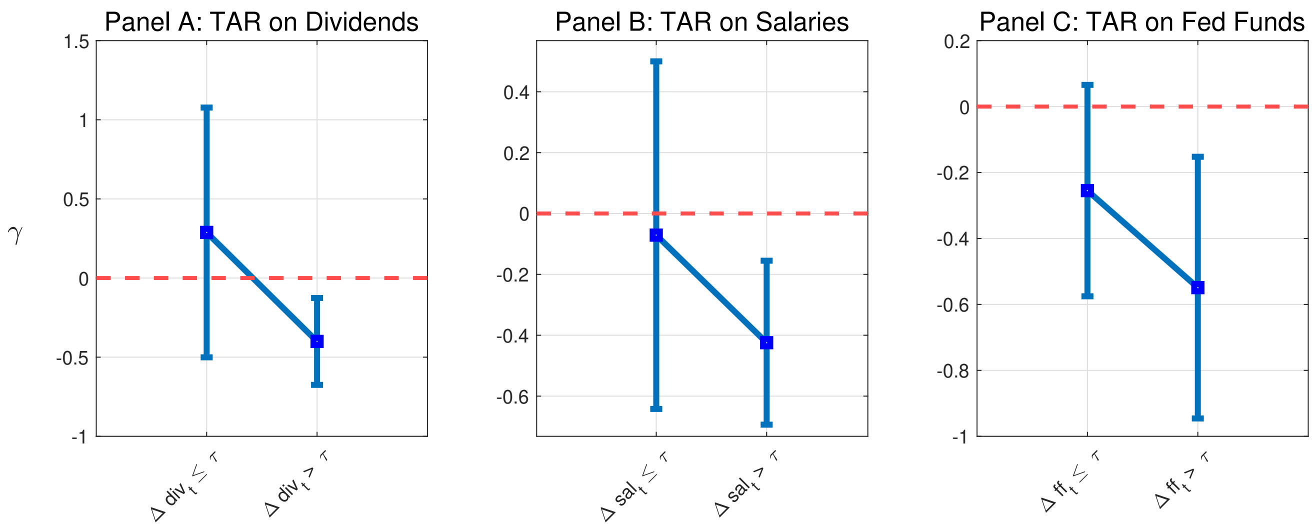
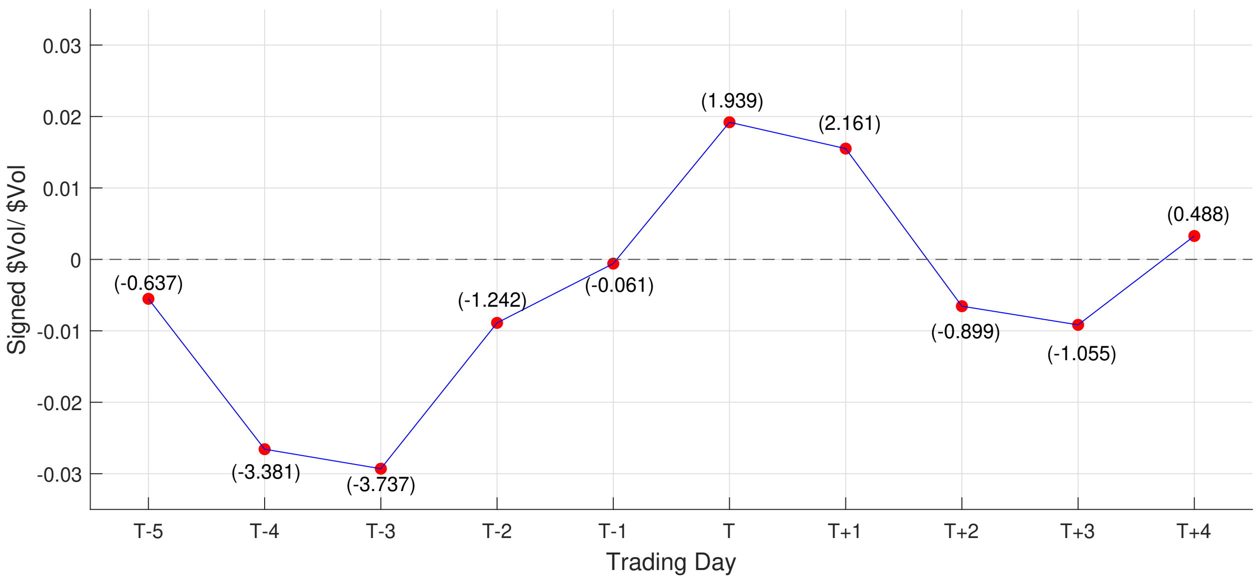


Figure 8 reports the estimated coefficients and associated 95% robust confidence interval for both TAR regressions. The results show that when there is an increase in salaries and dividends as well as increase of end of month borrowing costs, the reversal pattern spikes consistently with the payment cycle explanation. In the next subsections, we explore the end-of-month payment cycle channel, disentangling between liquidity suppliers (institutional investors) and takers (retail investors).

3.2 Volume Channel

The market-specific settlement convention forces institutional investors to have massive liquidity needs at the end of the month. As short-term and equity debt borrowing costs increase during the end of the month - Etula et al. (2020), institutional investors may engage in end-of-the-month liquidity trading to pay dividends, salaries, and contributions. We analyze the ANcerno dataset from 2000 to 2010 to investigate the institutional trading activity on the S&P 500 constituents and its most popular traded ETFs (SPY, VOO and IVY). Considering the daily order imbalance (ratio between signed dollar volume and dollar volume), we find consistent results with Etula et al. (2020). Specifically, as shown in Figure 9, institutions are systematically net sellers is the last trading week of the month.[9]

Figure 9: **S&P 500 Institutional Order Imbalance at the end of the Month**
This Figure reports the average institutional investors' order imbalance around the turn of a month, (where T is the last trading day of the month) on S&P 500 constituents and its major ETFs. A negative value of the ratio implies that, on average, institutional investors are net sellers. In parenthesis, we report the associated t-statistic against the null hypothesis of a 0 ratio (Institutional investors are neither net buyers nor sellers). The Data is ANcerno, and the sample period goes from January 2000 to December 2010.



[9]ANcerno contains trade-level observations for hundreds of institutional investors. For a more detailed description of the ANcerno Dataset and the historical constituents of the S&P 500, see Appendix C.1. Results do not change by considering calendar days instead of trading days. In Appendix C.1.3, we use data from Commodity Futures Trading Commission (CFTC) to corroborate the results established with the ANcerno dataset.

In order to corroborate the non-informational nature of the institutional investors' trading activity at the end of the month, we empirically test the Campbell et al. (1993) model. Their model has 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, we 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 the stock price movement is not linked to fundamental news. Hence, the reversal pattern should be accentuated with a surge of trading volume when investors trade in the market for liquidity reasons.

To empirically test the Campbell et al. (1993) model, we collect from GFD weekly S&P 500 volume data from January 1975 to December 2020, and we measure the last week's volume through the following metric:

$$\Delta vol_t = \frac{VOL_{w=4,t} - VOL_{w=3,t}}{\sum_{i=1}^{4} VOL_{w=i,t}} \tag{13}$$

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

$$r_{t+1} = \begin{cases} \alpha + \gamma_1 \; r_{w=4,t} + \epsilon_{t+1} & if \quad -\infty < \Delta vol_t \leq \tau \\ \alpha + \gamma_2 \; r_{w=4,t} + \epsilon_{t+1} & if \qquad \tau < \Delta vol_t < \infty \end{cases} \tag{14}$$

where τ is the threshold parameter estimated within the TAR algorithm. The results, reported in Table 4, 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.2.1, we show that the threshold condition $\Delta vol_t > \tau$ likely indicates a month with a high trading activity in the last week of the month (Panel A Figure 1.C and Table 2.C). The TAR model establishes a change in the regime behavior of return autocorrelation depending on the end-of-the-month volume: a large market activity in the last week is associated with a stronger reversal pattern.[10] In the second step we control that volume impacts the return dynamic through the return correlation rather than directly. We define the following binary variable based on the estimated threshold τ:

$$\mathbb{1}_{\Delta vol_t} = \begin{cases} 1 & if \quad \Delta vol_t > \tau \\ 0 & otherwise \end{cases} \tag{15}$$

and consider the following Predictive Regression (PR):

$$r_{t+1} = \alpha + \gamma\, r_{w=4,t} + \beta\, \mathbb{1}_{\Delta vol_t} + \psi\, (r_{w=4,t} \times \mathbb{1}_{\Delta vol_t}) + \varepsilon_{t+1} \tag{16}$$

The results reported in Table 4 show that $r_{w=4,t}$ has stand-alone predicting power, while $\mathbb{1}_{\Delta vol_t}$ alone does not predict future return. Therefore our 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 we jointly consider the two variables and their interaction, we 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 4 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.

[10] We divide for the monthly volume to address the concern that our results are driven by specific monthly seasonality. We find consistent results by considering a different volume variable specification in Appendix C.2.2. In Appendix C.2.4, we show that the impact of volume on reversal is throughout the entire month ahead.

Table 4: Volume Channel
In the first panel of the Table, we 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; $r_{4,t}$ 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, we 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 parenthesis, we 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 $\Delta_{vol_t} < \tau$	-0.047	$\mathbb{1}_{\Delta vol_t > \tau}$		-0.001	-0.001
	(-0.150)			(-0.259)	(-0.141)
$r_{w=4,t}$ if $\Delta_{vol_t} \geq \tau$	-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%

By comparing the values obtained by the TAR and PR estimations, we can observe that both in terms of the magnitude of the coefficient (-0.438 in the TAR and -0.386 in the PR) and R^2 (same value of 2.07%), the two models produce similar statistics, suggesting that results are robust whether we consider threshold regression or interaction relationship between returns and volume. In terms of t-statistics, the TAR model, due to its non-linear optimizer algorithm, reduces the estimation errors.[11] Overall, the results presented in Table 4 are consistent with the Campbell et al. (1993) theoretical model: high trading volume is associated with a reversal

[11] To address the concern of using an estimated regressor in equation (16), we confirm the significance of the interaction term coefficient through a two-step bootstrapping procedure.

pattern, supporting the hypothesis that the institutional investors' trading activity at the end of the month is due to non-informational reasons.

3.3 Volatility Channel

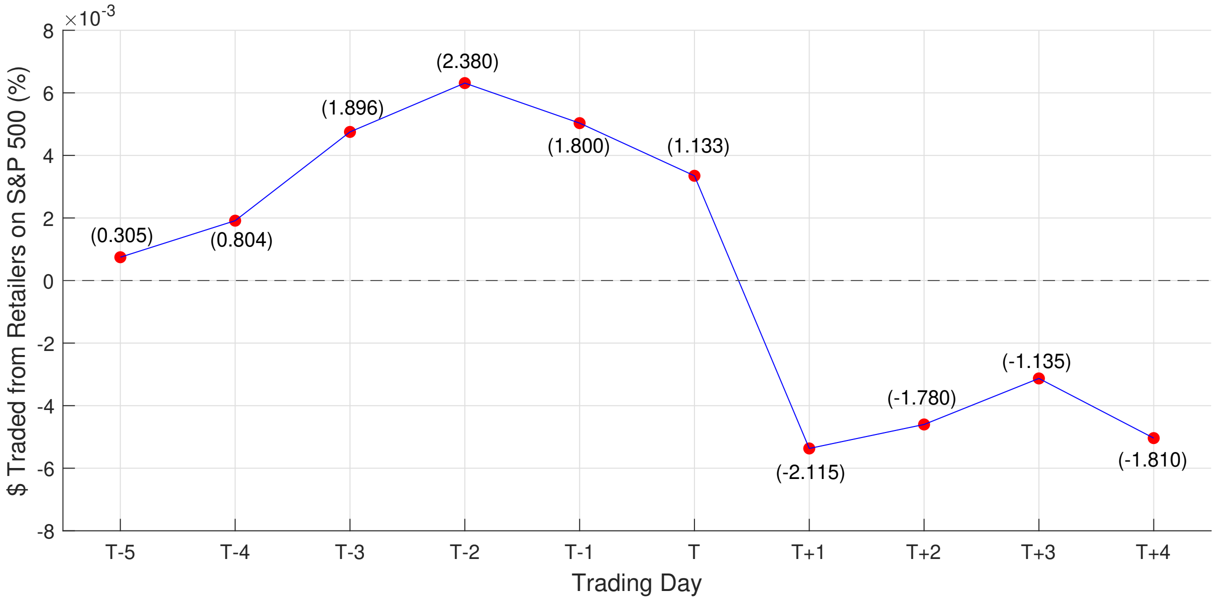
In this Session, we investigate whether retail investors, the recipient of most of the end-of-the-month liquidity, can potentially impact the reversal pattern. We use a novel dataset from Nasdaq Data Link (Retail Trading Activity Tracker) to study retail investment on the S&P 500. Specifically, for each instrument traded at Nasdaq, we 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. We 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.[12] In Figure 10, we report the average daily retail importance of the S&P 500 in the last and firt 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)).[13] Sentana and Wadhwani (1992) shows 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.

[12]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.

[13]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 10: **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. We 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, we 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, we 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:

$$\Delta vix_t = vix_{w=4,t} - vix_{w=3,t} \tag{17}$$

where $vix_{w=4,t}$ is the i^{th} weekly logarithmic VIX price. We perform the analogous two-step procedure in Section 3.2 (defined in equations (14) and (16)) using Δvix_t and $\mathbb{1}_{\Delta vix_t}$.

The results presented in Table 5 are qualitatively equivalent to the ones presented in Table 4: 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). The predictive regression 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. Our 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 negative market autocorrelation.

Table 5: Volatility Channel

In the first panel of the Table, we 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; $r_{4,t}$ 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, we 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 parenthesis, we 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 $\Delta_{vix_t} < \tau$	-0.072	$\mathbb{1}_{\Delta vix_t > \tau}$		-0.005	-0.002
	(-0.370)			(-0.799)	(-0.312)
$r_{w=4,t}$ if $\Delta_{vix_t} \geq \tau$	-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 5 are slightly larger than the ones in Table 4 (the coefficient attached to $r_{w=4,t}$ is around -0.6 with high volatility, while -0.4 with high volume), suggesting that the negative autocorrelation is stronger when there is high uncertainty. A possible explanation is that the estimated threshold in Table 5 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 1.C). We can conclude that the volume (volatility) channel is more (less) likely to be active but has a lower (higher) average impact on the time series reveral. In economic terms, institutional 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.

The results presented in Tables 4 and 5 show that an increased volume and volatility in the last week of the month could explain the reversal pattern between $r_{w=4,t}$ and r_{t+1}.[14] The two channels, volume and volatility, are micro-funded and consistent with a market-based-payment cycle theory. At the end of the month, institutional investors trade to pay salaries, dividends, interests, and contributions (volume channel). The liquidity is received by retail investors, who, therefore, trade more in the S&P 500 following the institutional investor trend (volatility channel).

It is worth noticing that Δvix_t is linked with market activity rather than the business cycle. In Figure 2.C, we graphically investigate Δvol_t and Δvix_t over time and find no precise relationship with the National Bureau of Economic Research (NBER) recession periods. Therefore, periods with high Δvix_t do not necessarily imply periods of economic downturn.

In Appendix C.3, we investigate potential different explanations from the end-of-the-month payment cycle and find no suggestive results. Specifically, in Appendix C.3.1, we investigate whether the overconfidence of market participants can be the economic source behind the reversal pattern. In Appendix C.3.4 and C.3.5, we investigate whether option expiration in the third week of the month and quarterly rebalancing could be plausible explanations.

[14] The two channels are likely not mutually exclusive as volume and volatility are strongly correlated. In Appendix C.2.5, we jointly study the volume and volatility channels.

3.4 Properties of Time Series Reversal

3.4.1 Reversal and Business Cycle

We argue that the end-of-the-month payment cycle, an exogenous market rule constant over time, is a non-informational shock that forces market participants to trade for liquidity reasons, consequently leading to a reversal pattern. Therefore, we expect that the reversal pattern is less subject to business cycle variations as during periods of uncertainty and distress, market participants likely consider price movements as permanent shocks, Wang (1994), Llorente et al. (2002) and Cujean and Hasler (2017).[15]

We test this hypothesis by studying the negative correlation in relationship with peaks and troughs in the U.S. economy. We use the NBER dates of peaks and troughs, and we 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), we consider the following specification:

$$r_t = \alpha + \sum_{l=2}^{-1} \beta^P_{t-l}\, I^P_{t-l} + \sum_{l=2}^{-1} \beta^T_{t-l}\, I^T_{t-l} + \epsilon_t \tag{18a}$$

$$\hat{r}_t = \alpha + \sum_{l=2}^{-1} \beta^P_{t-l}\, I^P_{t-l} + \sum_{l=2}^{-1} \beta^T_{t-l}\, I^T_{t-l} + \epsilon_t \tag{18b}$$

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 (18a)) and in the estimated equity risk premium (in equation (18b)) from a cyclical peak (trough). As the equity market is forward-looking, we consider an asymmetric window that includes 2 months before a peak (trough) and 1 month after.

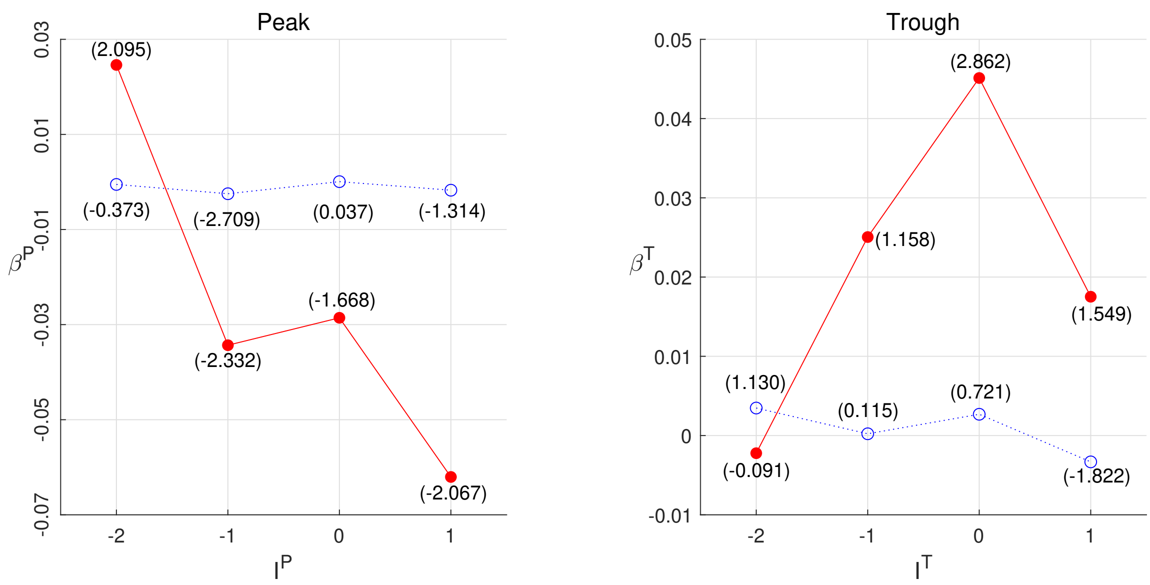
[15] In Wang (1994) and Llorente et al. (2002), trading due to private information causes persistent price movements that counteract temporary price pressure, potentially leading to momentum. In Cujean and Hasler (2017) model, investors use different forecasting models. As economic conditions worsen, 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 hence returns immediately revert.

In Figure 11, we report the estimated coefficients of I^P (left Panel) and I^T (right Panel); the coefficients obtained from (18a) are in a solid red line, while the coefficients of (18b) 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 the business cycle. The coefficients estimated from equation (18b) are, on average, 1 magnitude smaller than the corresponding ones estimated from (18a) and, most of the time, are not significant. Interestingly, the coefficients from the regression equation (18b) 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 11: **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 (18a) are in a solid red line, while the coefficients of (18b) are in a blue dotted line. For each coefficient estimated marked with a dot, we report robust Newey and West (1987) t-statics in parenthesis. The sample period goes from January 1975 to December 2020.



Overall, the results in Figure 11 are consistent with the hypothesis that the negative serial correlation is only marginally affected by variation in the business cycle. We find that, if anything, the serial correlation is more robust during periods of expansion. The TAR analysis reported in Appendix C.4.1and the Out-of-Sample results support the cyclical nature of the time series reversal pattern.

The results could be rationalized by the fact that the mechanism channels determining the reversal pattern weaken during recession periods. Institutional investors increase precautionary cash reserves in bad times, Campello, Giambona, Graham, and Harvey (2011), and market participants are in general more cautious in investing in the stock market consistent with a "flight-to-quality" effect (e.g.Næs, Skjeltorp, and Ødegaard (2011) and Longstaff (2002). Therefore, institutional investors likely avoid selling in the market to pay the end-of-the-month contributions as potentially very risky and expensive, and retail investors are naturally less likely to trade in the stock market.

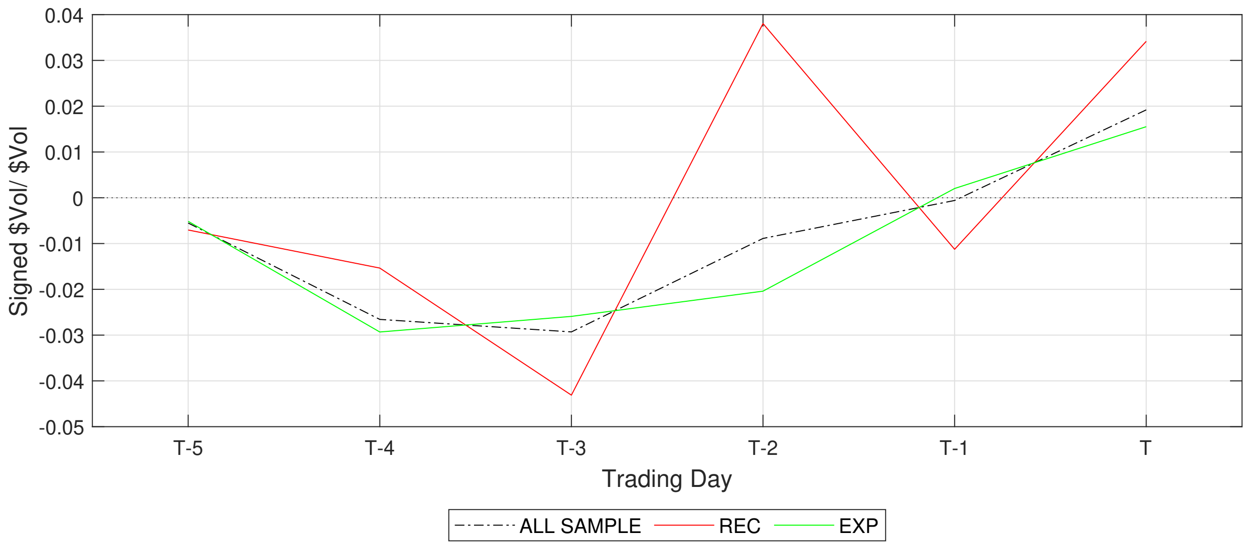
The above reasoning is corroborated by analyzing the institutional trading activity during expansion and recession periods. We propose in Figure 12 the daily order imbalance (ratio between signed dollar volume and dollar volume) considering the full sample 2000-2010 (black-dotted line), only during expansion (green-solid line) and recession periods (red-solid line).[16] The erratic Institutional behavior during recession periods is difficult to rationalize and suggests that Institutional investors trade in these hectic periods for market-contingent purposes.

The results presented here and in Section 3.3 lead to an important implication for reversal studies. It is common to consider negative correlation patterns as a proxy for market-making activities, Dai et al. (2023). The findings in the literature suggest that reversal is more robust during uncertain periods as the risk premium associated with liquidity provision predictably rises, Nagel (2012).[17] However, based on the evidence presented here, market-making becomes so risky

[16]During the sample considered (2000-2010), 26 out of 132 months are marked in recession according to the NBER indicator function. Table 17.C reports the associated t-statistics against a 0 ratio for the estimation results in Figure 12. We do not test the behavior of retail investors during recession periods as in the available sample (January 2016-January 2023) only two months (March and April 2020) are classified in recession.

[17]In Appendix C.4.3, we show that, contrary to the Nagel (2012) cross sectional based reversal strategy, the

Figure 12: **S&P 500 Institutional Order Imbalance over Business Cycle**
This Figure reports the average institutional investors' order imbalance in the last 8 days of a month (where T is the last day of the month) on S&P 500 constituents and its major ETFs. A negative value of the ratio implies that, on average, institutional investors are net sellers. We report the full sample 2000-2010 (black-dashed line), only during expansion (green-solid line) and recession periods (red-solid line). The Data is ANcerno, and the sample period goes from January 2000 to December 2010.



that investors do not engage in liquidity provision when the economy is in recession, so reversal patterns disappear. Therefore, reversal patterns could potentially be used as liquidity-driven indicators regarding the state of the economy.

3.4.2 Reversal and Stock Characteristics

If the payment cycle is the friction causing the documented pattern, it is reasonable to expect that institutional investors would try selling stocks to minimize price impact and transaction costs. In order to investigate this hypothesis, we analyze all common stocks traded on either the NYSE or the NASDAQ markets using the daily CRSP file covering the period from January 1985 to December 2020. For each stock's time series, we calculate the average Amihud illiquidity ratio and average price to proxy transaction costs, and then we categorize the stocks into quintiles

time series reversal return is negatively correlated to the implied volatility index.

based on these measures.[18] The results for value-weighted indexes formed on each metric are presented in Figure 13.

Consistently with the economic mechanism discussed in the previous subsections, we find that the reversal pattern is stronger for high-priced and liquid stocks. In contrast, the positive serial correlation pattern for illiquid and low-priced stocks is consistent with stale price theories (the differences in estimated coefficients for both quintiles are significant at 5% significance level).

Overall, the evidence reported in Figure 13 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.4.4, we compare the time series and cross-sectional approaches to corroborate our 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. While we regard the reversal pattern as an anomaly, our analysis suggests that the demand shock is due to a settlement convention rather than behavioral biases. Furthermore, the novel characteristics of the reversal pattern, which differ from the established cross-sectional findings,

[18]From CRSP, we select only the common traded stocks with exchange variable *EXCHG* equal to either 11, 12, or 14. The Amihud illiquidity ratio for each stock is calculated at a monthly frequency:

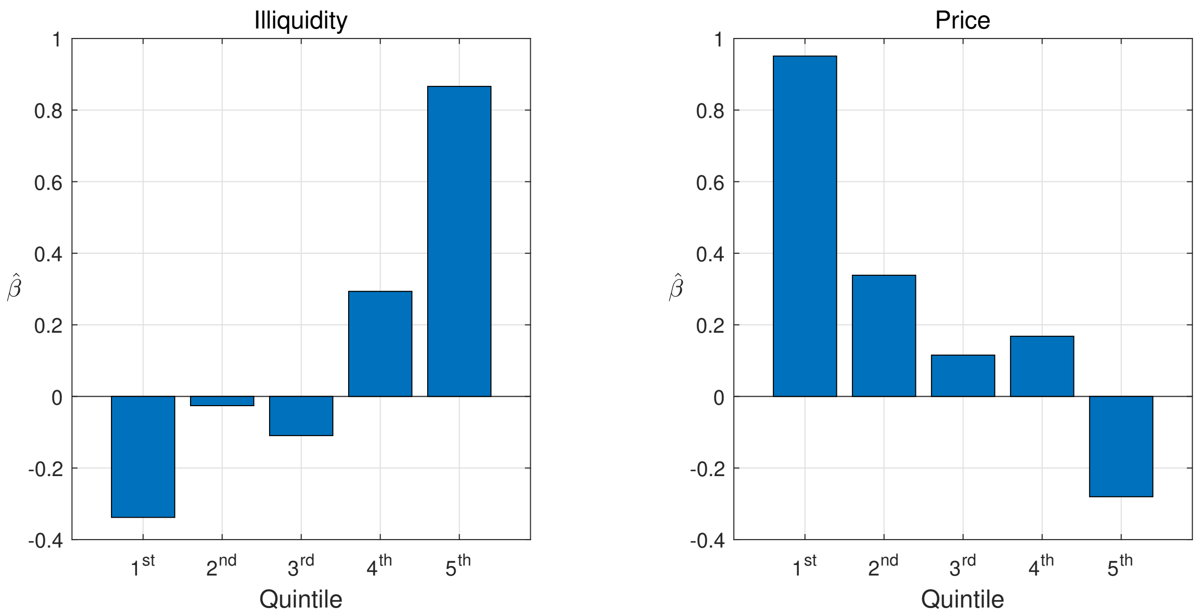
$$AH_t = \frac{1}{D}\sum_{i=1}^{D}\frac{|r_{d=i,t}|}{\$VOL_{d=i,t}}$$

where D is the number of daily trading records in month t (for each month, we 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. We then consider normal returns to construct the portfolios. In Appendix C.4.4, we construct portfolios sorting every month and we find analogous results.

Figure 13: **Stock Characteristics and Serial Correlation**
This Figure reports the estimated β coefficient of the following prediction equations:

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

where $r_{t+1}^{sc_q}$ ($r_{t+1}^{sc_q} = \frac{1}{N}\sum_{i=1}^{N} r_{t+1}^{i \in sc_q} = \frac{1}{N}\sum_{i=1}^{N} p_t^{i \in sc_q} - p_{t-1}^{i \in sc_q}$) is one month ahead return of the equally value-weighted return of a portfolio sorted into quintiles q on stock characteristic sc and $r_{w=4,t}^{sc_q}$ is analogously obtained by considering the last week return. 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, and the sample period goes from January 1985 to December 2020.



pose a challenge in interpreting the novel documented pattern as a compensation mechanism for providing liquidity. Notably, *if* the time series reversal were 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 providing liquidity is less risky.

4 Robustness

4.1 Evidence from other U.S. indexes

In the main body of the paper, we presented our results analyzing the S&P 500. Here we study whether the negative market correlation characterizes the other two major American indexes: the Dow Jones Industrial Average (DOW) and the Nasdaq Composite Index (Nasdaq). Table

6 reports the In-Sample predicting regression estimated coefficient, the Out-of-sample R^2, the expansion and recession Out-of-sample R^2. The results for the DOW are qualitatively similar to the one presented for the S&P 500, while we do not find a negative correlation pattern in the Nasdaq.

Table 6: 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. In the first column, we report the estimated coefficient of the In-Sample predicting equation:

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

In the second column, we report 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. In the third and fourth columns, we 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

We can observe that when the In-Sample estimated coefficient is statistically significant (S&P 500 and DOW), the Out-of-Sample predictability is positive and meaningful. The results here proposed are consistent with the evidence and argument in Section 3.4.2. 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 $R^{2,OS}$), suggesting that the reversal pattern is indeed caused by the 30 American most capitalized stocks forming the DOW and included on the S&P 500. At the same time, we do not find statistically significant results for the Nasdaq as the index includes more than 3700 stocks and the illiquid and small-cap stock are likely not target of the end-of-the-month non-informational trading activity.

For the DOW, we propose the analysis of the Volume and Volatility channels in Table 7. The results are qualitatively equal to the ones reported in Section 3 for the S&P 500, corroborating the market-based explanation.

To further show that the reversal pattern is a consequence of the unique characteristics of the American market, we provide evidence that at the international level - Appendix C.3.2 - and on commodities - Appendix C.3.3, there is no evidence of a time series reversal pattern. The findings can be rationalized by the fact that institutional investors have less concentrated ownership in international indexes. Additionally, it's worth considering that the scale of financial transactions associated with the payment cycle in foreign countries is considerably smaller when compared to the United States.

Table 7: Volume and Volatility Channel on DOW

In this Table, we analyze the volume and volatility channels on the Dow Jones Industrial Average (DOW). In Panel A, we 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, we 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 parenthesis, we report robust Newey and West (1987) t-statistics. In Panel B, we 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 $\Delta_{vol_t} < \tau$	-0.215	$\mathbb{1}_{\Delta vol_t > \tau}$		-0.009	-0.008	$r_{w=4,t}$ if $\Delta_{vix_t} < \tau$	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 $\Delta_{vol_t} \geq \tau$	-0.779	$r_{w=4,t} \times \mathbb{1}_{\Delta vol_t > \tau}$			-0.524	$r_{w=4,t}$ if $\Delta_{vix_t} \geq \tau$	-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%

4.2 Mixing Reversal with Momentum

In the main body of the paper, we have discussed the striking difference between our proposed predictor $r_{w=4,t}$ and the "Momentum" approach. Given their different peculiarities and characteristics, we analyze in this section whether mixing the two approaches could benefit the Out-of-Sample forecasting power. Specifically, we use the predicting power of $r_{w=4,t}$ in expansion times and the momentum in bad times. We run the Out-Sample-Sample exercise simultaneously for both $r_{w=4,t}$ and r_{t-12}; we 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 otherwise.[19]

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}:

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

In the first column, we report the out-of-sample $R^{2,OS}$, in the second and third columns $R^{2,OS}_{exp}$ and $R^{2,OS}_{rec}$. 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.

$R^{2,OS}$	$R^{2,OS}_{exp}$	$R^{2,OS}_{rec}$
$1.545^{\star\star\star}$	1.840	0.546

We report the Out-Sample Analysis results in Table 8. Mixing $r_{w=4,t}$ with r_{t-12} substantially

[19] We condition on I^{rec}_{t-1} instead of I^{rec}_t as NBER data on expansion and recession is released with a one month lag.

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, we 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 previously presented strategies 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 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 annum.

To take into account higher trading fees before the new millennium, we set a conservative fee of 10 bps per transaction, at least twenty times higher than the actual ones[20]. 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 strategy incurs only a holding cost-management fee of 3 bps per month.

The net of fees results are reported in Table 9: the left panel reports the Utility Gains, and

[20]By trading each month, the annual transaction fees paid in our 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.

the right panel reports the Monetary Gains. For both exercises, the values are qualitatively similar to the ones reported in Tables 2 and 3. The negative market serial correlation delivers gains for both risk-averse and risk-neutral agents, even net of fees. Therefore the negative serial correlation discussed here can be considered a market inefficiency not only in the classical sense but even under the definition of minimally rational markets.

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	
	$r_{w=4,t}$	$\bar{r}_t$		$r_{w=4,t}$	$\bar{r}_{S\$P500}$
$U(p)(\%)$	4.662	3.463	$\$\bar{r}(\%)$	4.112	3.786
Sharpe Ratio	0.316	0.190	Sharpe Ratio	0.394	0.251

4.4 Implications for the Aggregate Market Elasticity

The findings discussed in the main body of the paper suggest that institutional investors trade in the last week of the month for liquidity reasons. Therefore, the non-informational demand flow of institutional investors can be used to estimate the aggregate market price multiplier. Reminiscent of Ben-David, Li, Rossi, and Song (2022), the daily flow of institutional investors is defined as:

$$flow_{d=i,t} = \left(\sum_c \frac{\$signed\ vol_{d,c}}{MktCap_c} \right) \times 10 \tag{20}$$

where c stands for a company belonging to the S&P 500, $\$signedvol_{d,c}$ is the daily difference between institutional investors buy and sell in day d on stock c and finally $MarketCap_c$ is the daily market valuation of company c.[21] By using the quasi-exogenous variation of institutional investors' flow on the last week of the month, we have a causal identification strategy to estimate

[21] The ratio is multiplied by 10 as Hu, Jo, Wang, and Xie (2018) argue that the ANcerno dataset, although representative of institutional investors' behavior, maps between 8 to 12% of CRSP volume.

the price impact:

$$ret_{d=i,t} = \alpha + \phi flow_{d=i,t} + \beta X_{d=I,t} + \epsilon_{d=I,t} \tag{21}$$

where $ret_{d=i,t}$ is the daily index return, X_d is a set of control variables, and $\epsilon_{d=i,t}$ captures price shocks due to fundamental news.

Table 10: Aggregate Market Elasticity
This Table reports the estimated aggregate market elasticity $(-\frac{1}{\phi})$ and associated robust p-value obtained by the following regression:

$$ret_{d=i,t} = \alpha + \phi flow_{d=i,t} + \beta X_{d=I,t} + \epsilon_{d=I,t}$$

where $ret_{d=i,t}$ is the daily index return, $flow_{d=i,t}$ is the daily institutions investors flow (equation (20)), X_d is a set of control variables, and $\epsilon_{d=I,t}$ captures price shocks due to fundamental news. To capture non-informational trading of institutional investors, we only last week of the month's returns. The daily institutions investors flow is constructed by using the ANcerno dataset, the time window considered goes from January 2000 to December 2010.

Baseline	Control for Δvol_d	Control for Δvix_d
0.414***	0.412***	1.358***

Table 10 reports market elasticity $(-\frac{1}{\phi})$ following Gabaix and Koijen (2021). The estimated elasticity aligns with existing literature, ranging from 0.4 to 1.4. Moreover, the flow variable exhibits near orthogonality to daily changes in institutional investors' volume, indicating a low correlation between daily market position and changes in liquidity provision. We control for daily changes in market volatility to mitigate potential concerns about measuring fundamental news. Despite an increase in market elasticity, the estimated value remains significantly below the one suggested by frictionless neoclassical asset pricing models, which is around 20 according to Gabaix and Koijen (2021).[22]

The identification strategy outlined in (21) conforms to existing literature but introduces innovative elements. It assesses institutional investors' holdings on a daily basis by observing their trading activity, in contrast to measuring monthly changes in asset holdings. Additionally, it employs the frequent liquidity trading caused by the payment cycle friction instead of relying on infrequent events like index inclusions and exclusions, which may lead to substantial demand

[22]By considering daily volume and volatility instead of daily changes, the results are almost identical to the baseline regression. By running regression (21) excluding the last trading week, the estimated elasticity goes from 0.608 (baseline regression) to 1.758 (controlling for volatility).

and supply fluctuations.

5 Discussion

In this session, we qualitatively discuss which institutional investors are more exposed to end-of-month liquidity needs. By answering this question, we obtain implications to better underpin the payment cycle as the explanation channel behind the time series reversal.

As shown in the main body of the paper, the last week of the month is a particularly frenetic week in which most market participants have liquidity needs. However, among the different institutional investors e.g., pension, mutual, and hedge funds- pension funds are more likely to be the institutional investors behind the end-of-the-month payment cycle friction. The reason behind this is threefold. First, pension funds can impact the aggregate market dynamic, managing approximately $35 − 40 trillion in assets, of which around 40% invested in the equity market.[23] Second, in the last week of the month, pension funds have enormous liquidity needs to pay benefits. Thirdly and most importantly, pension funds have a short-term cash flow problem as predicting and matching inflows and outflows is very hard in this industry. This is why American pension funds have negative cash flow, as shown in Figure 14 Panel A.[24] To address cash flow issues, pension funds have increased their exposure to riskier assets, such as equity and real estate, to pay outflow with higher performance. By arguing that pension funds are the leading institutional investors involved in end-of-the-month liquidity trading, we establish the following implications:

Implication 1: *Why do institutional investors not anticipate their liquidity needs?*

It is not new inside the pension fund industry that pension funds may raise cash to pay benefits by selling assets due to negative short-term cash flows; in their jargon, it has been labeled selling

[23]Data on Pension fund assets under management and asset allocation are from OECD *Pension Markets in Focus.*

[24]Many industries reports corroborate this evidence, See for example Figure 1 of Goldman Sachs report Cash Flow Matching: The Next Phase of Pension Plan Management

risk.[25] Pension funds have the incentive to wait until the last week of the month to minimize inefficiencies associated with selling for liquidity needs as the in- and outflow clusters in the last part of the month - they receive the contributions paid by companies around the 22nd of each month, and they pay benefits the last day of the month.

Implication 2: *Why is the time series reversal cyclical?*

Precautionary cash holdings increase during periods of uncertainty (Figure 14 Panel B) to mitigate cashflow problems. Moreover, pension funds, like many others, fly to liquidity during uncertain periods by increasing their exposure to bills and bonds and reducing their exposure to the equity market. Therefore, during uncertainty, pension funds increase liquidity buffers to match cash flow problems, and their relative importance on the equity market decreases.

Implication 3: *Why the pattern clusters in the U.S.?*

Differently from the American pension funds, international pension funds have a substantially lower amount of assets under management (Figure 14 Panel C), invest abroad, presumably in the US (Figure 14 Panel D),and generally do not have negative cash flows (Figure 14 Panel E). Therefore, this is likely the motivation for why, internationally, evidence of the reversal pattern is weak - Table 11.C in the Appendix: the pension funds might not have the size to impact the local market or prefer financing by selling foreign equity. Interestingly, we 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.

Implication 4: *Policy Implications for the New retirement account rules*

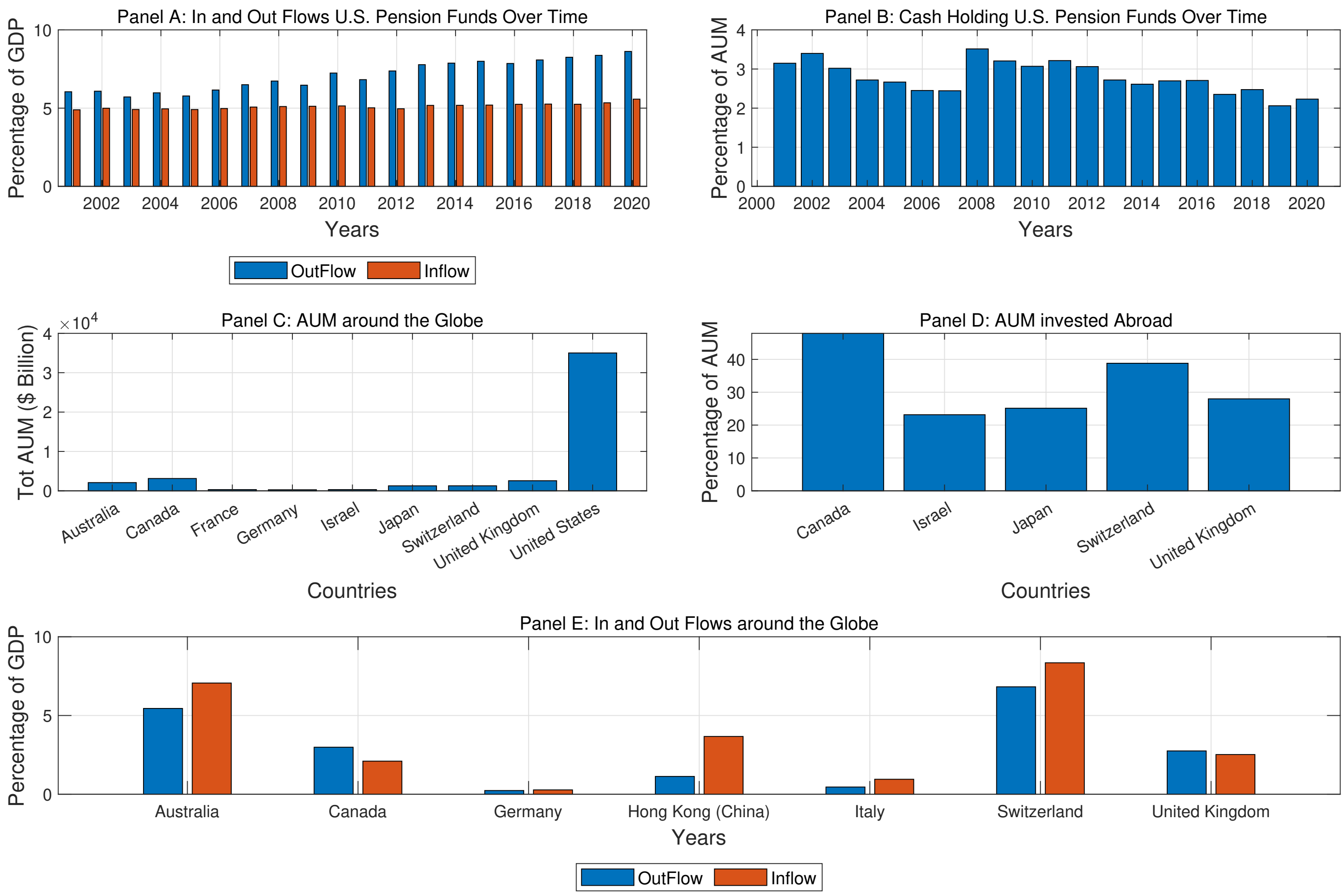
In recent years, the U.S. government has enacted regulations aimed at facilitating and reducing penalties and taxes on early withdrawals from 401(k) retirement plans.[26] While these measures intend to help Americans facing financial difficulties, especially during extreme negative shocks (severe hospitalization, divorces, and other major events), the higher flexibility to deviate from

[25] See for example Agilis - Pension Investing: How to Invest When Cash Flow is Negative

[26] In 2024, *Secure* 2.0 is designed to waive many early-withdrawal tax penalties

preset schedules granted by these reforms poses further challenges for pension funds in managing their cash flow as outflows become even less predictable. Consequently, the discussed reversal pattern is expected to intensify in the near future. Ultimately, this study advocates for measures to alleviate end-of-month liquidity needs for institutional investors, thereby limiting both their liquidity-driven trading and riskier asset allocation.

Figure 14: **Pension Funds Characteristics**
Panel A 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) in the U.S. Panel B shows the percentage of Asset Under Management (AUM) on Cash Holding for the American Pension Funds. Panel C shows the AUM (Billion of $) for some representative countries in 2022. Panel D shows the percentage of AUM invested abroad in 20222 for some representative countries. Panel E compares the annual pension benefit flows against the contributions into pension plans for some representative countries in 2022. The Data is OECD *Pension Markets in Focus*.



6 Conclusion

The paper documents a novel 1-month reversal pattern at the time series level. The empirical evidence is statistically significant both In and Out-of-Sample. Moreover, it delivers sizable gains both in utility and monetary terms. The reversal pattern is robust and economically meaningful as it maintains its predictive power by considering different Out-of-Sample windows, return specifications, indexes, and trading fees.

We provide evidence to support the end-of-the-month payment cycle as the economic source behind the documented pattern. We first document a direct link between the reversal pattern and the amount of dividends and salaries paid at the end of the month. Secondly, by jointly considering theoretical models and recent empirical findings, we show how the non-informational trading of institutional and retail investors fosters the reversal pattern. Thirdly, in line with a non-informational return shock resulting from trading activity, our findings show that the reversal pattern is stronger both In-sample and Out-of-Sample during economic expansions, as price fluctuations during times of distress are not short-lived. Finally, consistently with an institutional investors' strategy to minimize trading costs and fees when trading to recoup end-of-month liquidity, we provide evidence that time series reversal characterizes high-priced and liquid stocks.

Significantly, the findings presented in this paper offer novel insights into how and why the aggregate American market reverses price pressure. Our findings align with the permanent-transitory decomposition framework introduced by Poterba and Summers (1988). However, our research furnishes compelling evidence that the transitory shock's source is due to market friction rather than behavioral biases. The temporary shocks due to non-informational predictable price pressure help explain why we observe stock market price movements even without news on the stock's fundamental value.

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Appendices

A Appendix Section 2

A.1 Settlement Convention in the U.S.

Trade settlement is the conclusive phase of a two-step process at the end of a financial transaction. In this process, the buyer takes actual possession of the securities, and the seller receives payment for the transaction. While the formal agreement is made on the transaction date, the actual transfer of ownership and cash is delayed on the settlement date - SEC Rule 17.

The rule is designed to prevent free-riding trading from cash account owners. These accounts are the standard accounts for normal retail investors in which the investor must pay the full amount for securities purchased - SEC Cash Account Bulletin. However, institutional and professional investors can open a margin account to have more freedom in their trading strategies. A margin account is a particular account that allows traders to borrow money and other financial assets from a broker to trade in the financial markets. The professional trader deposits the collateral amount on the account, stipulated by the broker's trading conditions, after which they can conduct trading on margin in assets borrowed from the broker - SEC Margin Account Bulletin. Among many structural differences between cash and margin accounts, margin accounts do not have a real settlement period as the proceeding of a trade is immediately available. This is a necessary prerequisite for both market-making and arbitrage activities.

A.2 Summary Statistics

In this session, we 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 1.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.3 Controlling for Friday Effect

In this session, we consider whether the reversal pattern is due to the specific choice of the end of the week (Friday) as the closing price. To study whether the negative correlation does not depend on the specific day chosen but instead on the end-of-the-month market activity, we consider the following specifications:

$$r_{d=t-i,t} = p_t - p_{d=t-i,t} \qquad 0 < i \leq 20 \tag{22}$$

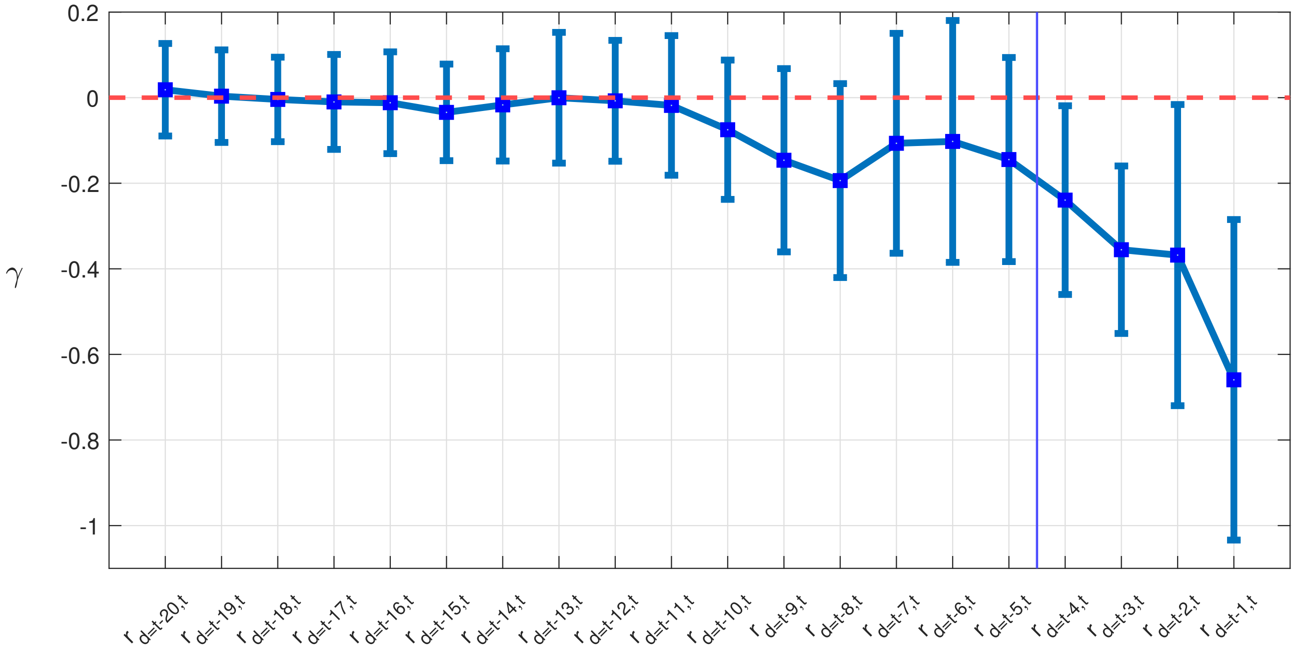
where $p_{d=t-i,t}$ is the $t-i$ last day closing price of the month.[27] Figure 1.A shows that a Friday effect does not cause the results. Importantly, the reversal pattern is statically significant for all the returns constructed in the last week of the month (from $r_{d=t-4,t}$ to $r_{d=t-1,t}$), whereas by increasing the time period considered the predictability is lost. Furthermore, the predictability of the last day of the month can be explained by institutional investors' use of Margin accounts and the potential role of retail investors in the reversal pattern.

[27]When the trading days in a month are less than a specific i^{th} price, we take the first closing price of the month.

Figure 1.A: **Reversal Pattern using Daily Prices**
This Figure reports the estimated coefficient and the 95% Newey and West (1987) robust confidence interval of the following predictive equations:

$$r_{t+1} = \alpha + \gamma\ r_{d=t-i,t} + \epsilon_{t+1} \qquad 0 < i \leq 20$$

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



A.4 Predictability after First Week of the Month

This Session investigates whether the time serial reversal pattern displayed in Figure 3 exclusively depends on the ability of $r_{w=4,t}$ to predict the one ahead week return. Therefore, we consider the following predicting equation to exclude the first-week effect:

$$r_{w=1,t+1} = \alpha + \gamma\ r_{w=4,t} + \epsilon_{t+1} \tag{23}$$

where $r_{w=1,t+1} = p_{t+1} - p_{w=1,t+1}$. The estimated coefficient is -0.222, and the Newey and West (1987) t-statistic is -2.320. Therefore, the result suggests that the reversal pattern does not depend solely on a turn-of-the-month effect studied in the literature.

A.5 Placebo Test around 15^{th} of the Month

In this session, we conduct a Placebo test to verify that the market activity in the last week of the month determines the negative serial correlation. We consider the 15^{th} of each month - a second common payment date - as the end of the month.[28] We 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. By performing a similar Placebo test (Figure A4 and Table A1 of their Internet Appendix), Etula et al. (2020) find a reversal pattern comparable in magnitude to the one reported between returns from $T-8$ to $T-4$ and $T-3$ to $T-1$ even though financing in the short-term bond, equity, and longer-term debt capital markets is relatively cheap in the middle of the month (around $T+7$ in Figures 2 and 3 in Etula et al. (2020)). The different results can be explained by the fact that daily returns are generally statistically negative, capturing liquidity-making and price-pressure effects.

A.6 Closing Price Robustness Check

In the main body of the paper, we use closing price to construct the predictor $r_{w=4,t} = p_t - p_{w=4,t}$. In this Session, we control whether the reversal pattern between the last week's return and the one month ahead depends on a closing price effect. To mitigate this concern, we consider high (low) daily prices recorded during the last trading week of the month as these prices are formed during the daily market activity. Hence, the right-hand side returns here considered are:

$$\begin{aligned} r^H_{d=t-i,t} &= p^H_t - p^H_{d=t-i,t} \\ r^L_{d=t-i,t} &= p^L_t - p^L_{d=t-i,t} \end{aligned} \tag{24}$$

where p^H_t (p^L_t) is the high (low) log-price during the last trading day of month t and $p^H_{d=t-i,t}$ ($p^L_{d=t-i,t}$)is the high (low) price during the $(t-i)^{th}$ trading day in month t. Figure 2.A reports

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

the estimation results of the standard predicting equation:

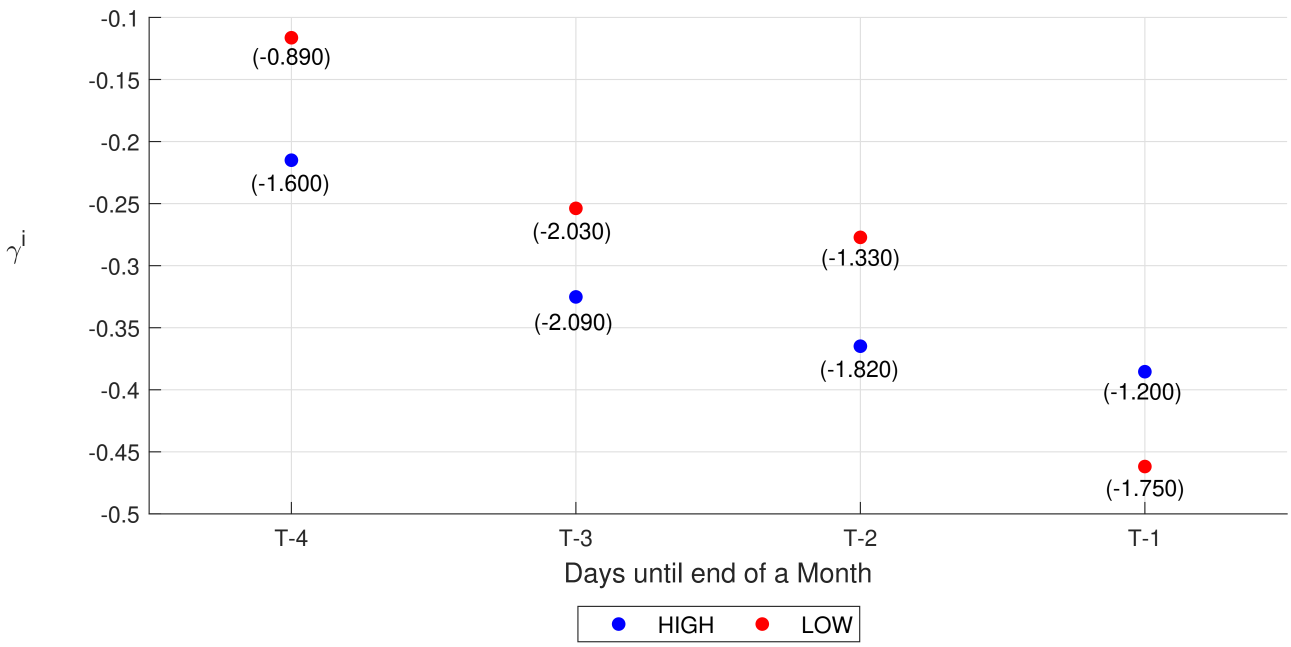
$$r_{t+1} = \alpha + \gamma^i \ r^i_{d=t-i,t} + \epsilon_{t+1} \tag{25}$$

where $r^i_{d=t-i}$ is the last week's return defined in equation (24) that does not incorporate closing price effects on the predicting variable. Considering the returns using high and low prices, the estimated coefficients are negative and only for $t - i = 4$ not statistically significant for both $r^H_{d=t-i,t}$ and $r^L_{d=t-i,t}$. Overall, the results show that daily closing market effects do not crucially affect the monthly reversal.

Figure 2.A: **High and Low end of the Month Return**
This Figure reports the estimated coefficient of the following predictive equation:

$$r_{t+1} = \alpha + \gamma^i \ r^i_{d=t-i,t} + \epsilon_{t+1}$$

where $r^i_{d=t-i,t}$ is the last week's return defined as the difference between the high (low) end-of-the-month closing price and the $(t-d)^{th}$ trading day high (low) price. In parenthesis, we report Newey and West (1987) robust t-statistics. The sample period goes from January 1975 to December 2020.



A.7 Multi - Month Predictability

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

$$r^{'}_{w=i,t+2} = \alpha + \gamma \; r_{w=4,t} + \epsilon_{t+1} \tag{26}$$

and

$$r_{t+2} = \alpha + \gamma \; r_{w=4,t} + \epsilon_{t+1} \tag{27}$$

where $r^{'}_{w=i,t+2} = p_{w=i,t+2} - p_{t+1}$ and $r_{t+2} = p_{t+2} - p_{t+1}$. The results reported in Table 2.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 2.A: Two Month Ahead Predictability
In this Table, we report the estimated coefficient of the following Predictive regressions

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

and

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

where $r^{'}_{w=i,t+2} = p_{w=i,t+2} - p_{t+1}$ and $r_{t+2} = p_{t+2} - p_{t+1}$. In parenthesis, we 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}
0.006	0.077	0.079	0.028	0.075
(0.130)	(1.320)	(0.840)	(0.250)	(0.660)

A.8 Controlling For Others Predictors

A.8.1 Controlling for Weekly Returns

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

$$r_{t+1} = \alpha + \gamma \; r_{w=4,t} + \beta_1 \; r_{w=3,t} + \beta_2 \; r_{w=2,t} + \beta_3 \; r_{w=1,t} + \epsilon_{t+1} \tag{28}$$

and standard weekly returns:

$$r_{t+1} = \alpha + \gamma\ r_{w=4,t} + \beta_1\ r^{''}_{w=4,t} + \beta_2\ r^{''}_{w=3,t} + \beta_3\ r^{''}_{w=2,t} + \beta_4\ r^{''}_{w=1,t} + \epsilon_{t+1} \tag{29}$$

where $r_{w=i,t} = p_t - p_{w=i,t}$ and $r^{''}_{w=i,t} = p_{w=i,t} - p_{w=i-1,t}$. The results reported in Table 3.A show that the predictability channel of $r_{w=4,t}$ is robust to controlling for either *intramonthly* or standard weekly returns.

Table 3.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 parenthesis, we 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, we control for a set of economic variables commonly used by the forecasting literature, Welch and Goyal (2008). Data is available from Amit Goyals website, and in Table 4.A, we briefly describe each variable. The predictive regression is:

$$r_{t+1} = \alpha + \gamma \; r_{w=4,t} + \beta \; EV_t^i + \epsilon_{t+1} \tag{30}$$

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 our proposed predictor $r_{4,t}$.

Table 4.A: Economic Variables Description
This table briefly describes the standard economic variables used in the forecasting literature, Welch and Goyal (2008). The data source is Amit's Goyal Website.

	Description
D12	Dividends are 12-month moving sums of dividends paid on the S&P 500 index.
E12	Earnings are 12-month moving sums of earnings on the S&P 500 index.
BM	Ratio of book value to market value for the Dow Jones Industrial Average.
TBL	3- Month Treasury Bill in the Secondary Market Rate.
AAA	Corporate Bond Yields on class AAA.
BAA	Corporate Bond Yields on class BAA.
LTY	Long-term government bond yield.
NTIS	12 months moving sums ratio of NYSE listed stocks net issues to total year-end market cap.
RFREE	Treasury-bill rate.
INFL	Inflation is the Consumer Price Index (All Urban Consumers) lagged 1 month.
LTR	Long-term government bond return.
CORPR	Long-term corporate bond return.
SVAR	Stock Variance is computed as sum of squared daily returns on the S&P 500 500.

Table 5.A: Reversal Pattern and Economic Variables
In this Table, we report 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 parenthesis, we report robust Newey and West (1987) t-statics. The sample period goes from January 1975 to December 2020.

	$\hat{\alpha}$	$r_{w=4,t}$	EV_t^i
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)

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). Therefore, in this session, we 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 respectively). To not introduce measurement errors, we directly use the variables available from the authors' website and study the statistical relationship between January 1980 to December 2017. The predictive regression is:

$$r_{t+1} = \alpha + \gamma \ r_{w=4,t} + \beta \ A_t^i + \epsilon_{t+1} \tag{31}$$

where r_{t+1} is the $t+1$ monthly excess return; $r_{w=4,t}$ is the 4^{th} weekly return at 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 our 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. Subsequently, this net buying flow slows down, so the price tends to revert. In contrast, we provide evidence of a reversal dynamic induced by the negative price pressure of the end-month payment cycle.

Table 6.A: Reversal Pattern and Investors' Attention
In this Table, we report 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 parenthesis, we 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	1.88%	3.75%	1.93%	2.63%

A.8.4 Controlling for Cross-Sectional Factors

In this Session, we 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. We firstly check that the short serial correlation is not captured by the three Fama French factors augmented by Momentum and Short Reversal available in the Kenneth R. French website:

$$r_{t+1} = \alpha + \gamma\, r_{w=4,t} + \beta_i F_{i,t} + \varepsilon_{t+1} \tag{32}$$

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

$$r_{t+1} = \alpha + \gamma\, r_{w=4,t} + \beta_i PC_{i,t} + \varepsilon_{t+1} \tag{33}$$

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.

Table 7.A: Reversal Pattern and Factor Anomalies
This table reports in the first row 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 row, we 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 parenthesis, we 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 in the Zhou 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	2.63		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

A.9 Return Autocorrelation Across Frequencies

Figure 3.A: **Return Density at Different Frequencies**
The Figure displays the kernel density of daily, weekly, monthly, and quarterly *standardized* returns (solid blue line) and the distribution of a normal standard variable (red dashed line). The time window is from January 1975 to December 2020.

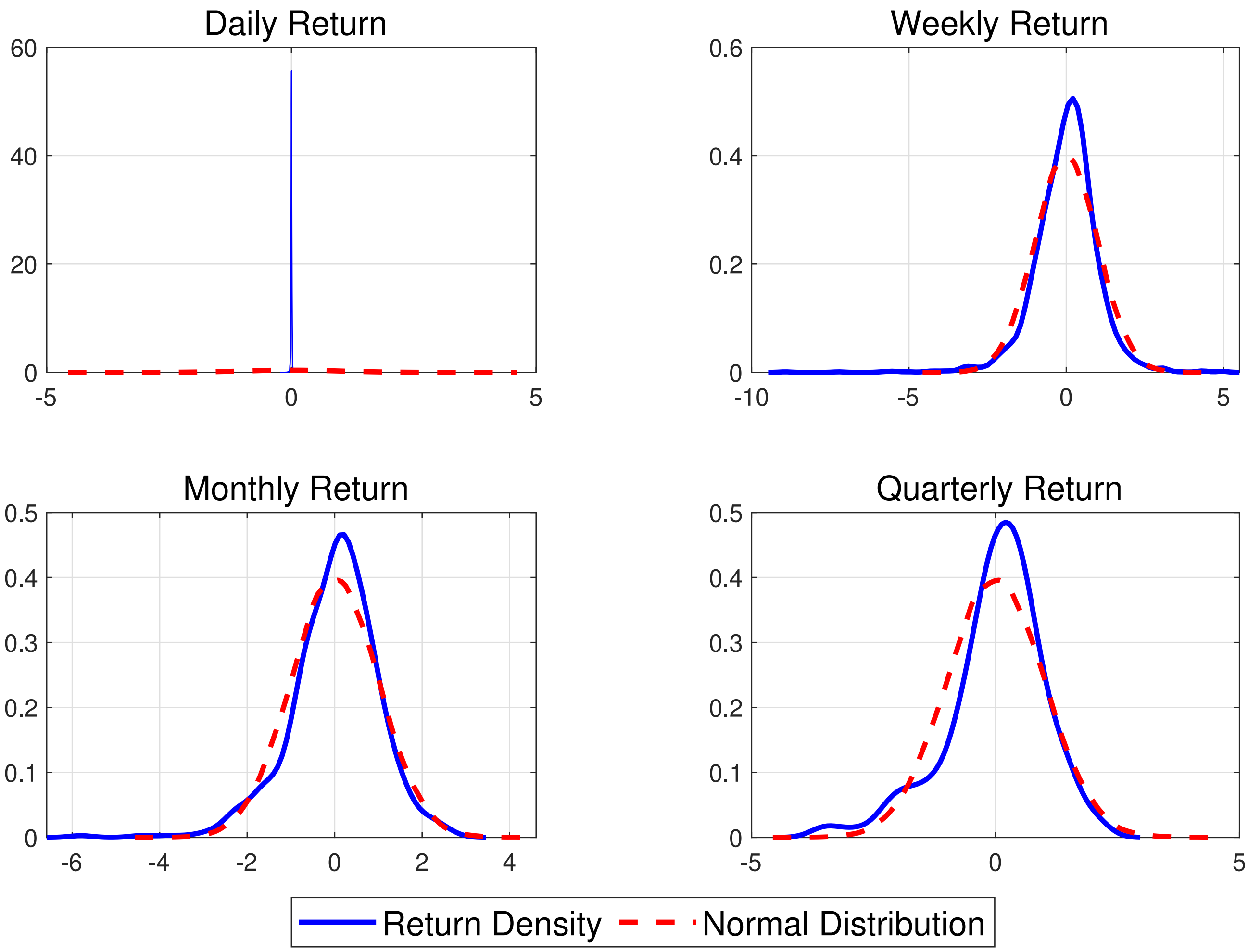
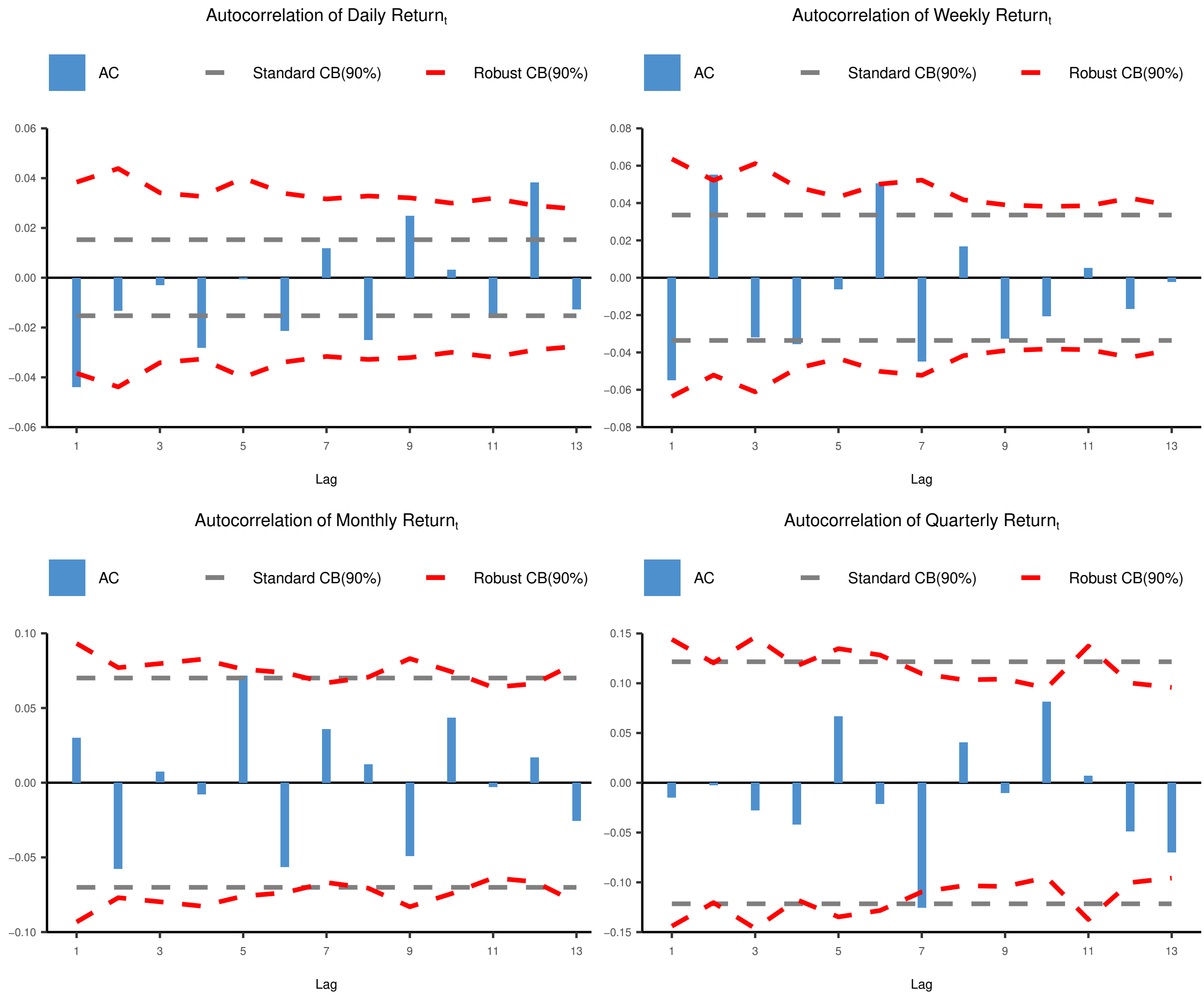


Figure 4.A: **Return AutoCorrelation at Different Frequencies**
The Figure displays the estimated autocorrelation of daily, weekly, monthly, and quarterly returns (up to 13 lags in blue bars). In each plot, we report the standard (solid grey line) and robust Dalla, Giraitis, and Phillips (2020) (red dashed line) 10% confidence bands. The time window is from January 1975 to December 2020.



B Appendix Section 2.2

B.1 Technical Indicators

We 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 function is based on a moving average approach:

$$\mathbb{1}_{MA(1,12),t} = \begin{cases} 1 & if\ p_t \geq \frac{1}{12}\sum_{i=0}^{11} p_{t-i} \\ 0 & if p_t < \frac{1}{12}\sum_{i=0}^{11} p_{t-i} \end{cases} \tag{34}$$

The second technical indicator is based on momentum:

$$\mathbb{1}_{MOM(1,12),t} = \begin{cases} 1 & if\ p_t \geq p_{t-i12} \\ 0 & if p_t < p_{t-12} \end{cases} \tag{35}$$

B.2 Value Weighted Return Analysis

In the main body of the text, we have considered index returns ($r_{t+1} = p_{t+1} - p_t$) as the monthly reference returns to study its correlation with $r_{w=4,t} = p_t - p_{4,t}$. In this session, we consider excess value-weighted returns as the dependent variable. Studying the relationship between $r_{w=4,t}$ and excess value-weighted returns allows comparing our 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, we 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, we can test the negative market correlation in different samples. We 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, we 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, our 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, we consider value-weighted returns as r_{t+1}. In each Panel, in the first column, we report the coefficient attached to $r_{w=4,t}$ in the In-Sample regression:

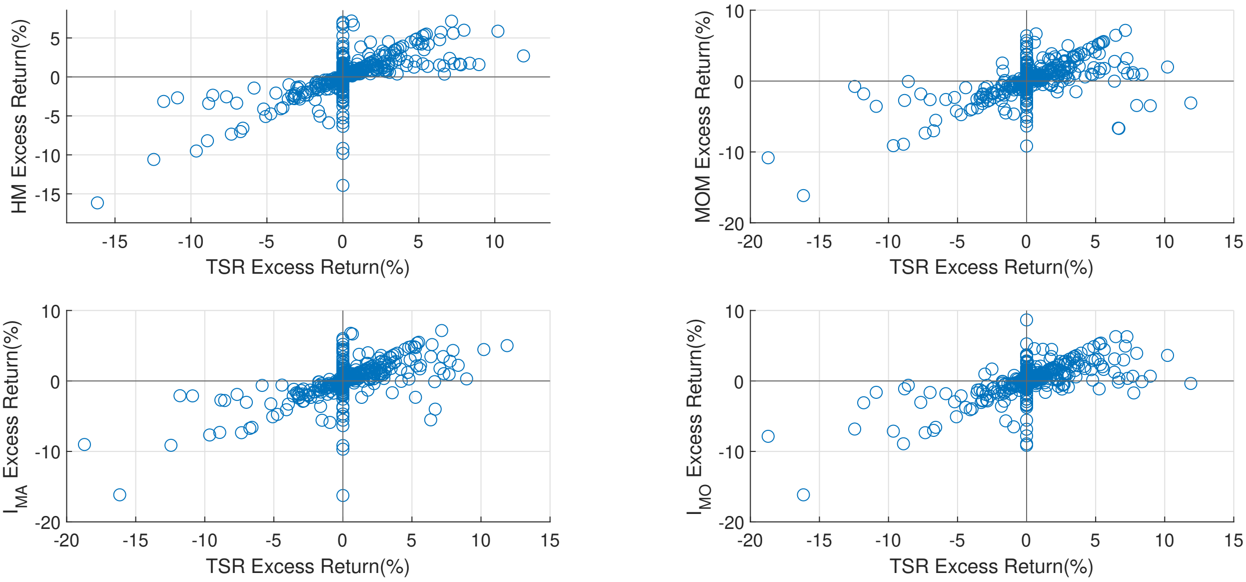
$$r_{t+1} = \alpha + \gamma \, r_{w=4,t} + \epsilon_{t+1}$$

In parenthesis, we report robust Newey and West (1987) t-statistics. In the second column, we 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, we 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**
The 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.

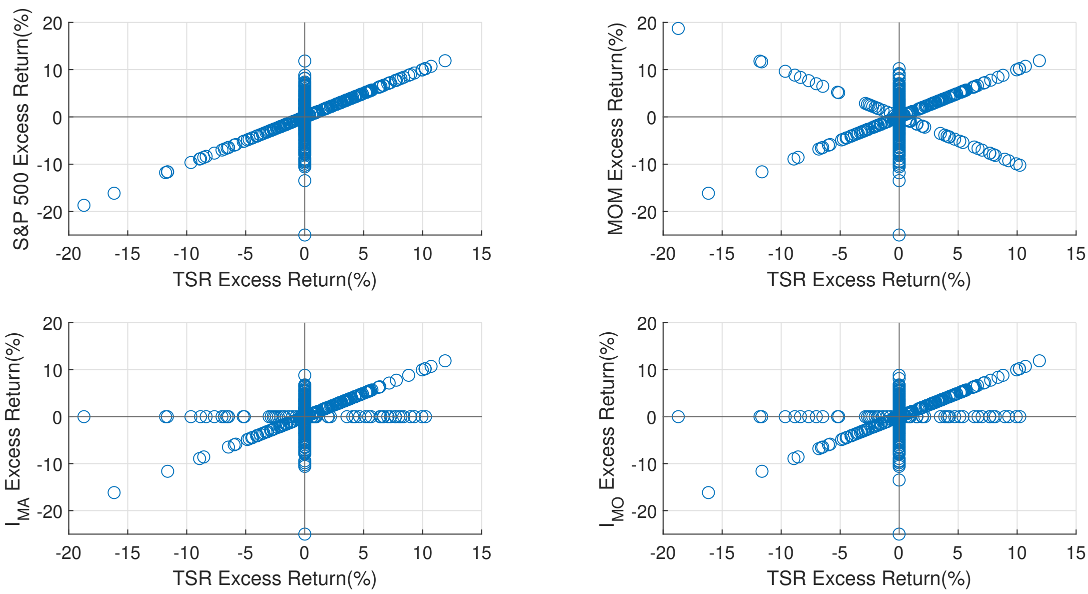


B.4 Short Selling TSR - Utility Gains

In this Session, we 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 returns go from 5.184 to 5.028, and the variance increases from 0.106 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**
The 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 Short Selling TSR - Monetary Gains

In this Session, we study the effect of short selling on a trading strategy based on the time series reversal. Therefore we consider

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

where $\$r_{w=4,t}$ is the trading strategy considered in the main body of the paper, $\$r^s_{w=4,t}$ 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 2.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 3.B: **Monetary Gains over Time**
The 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.

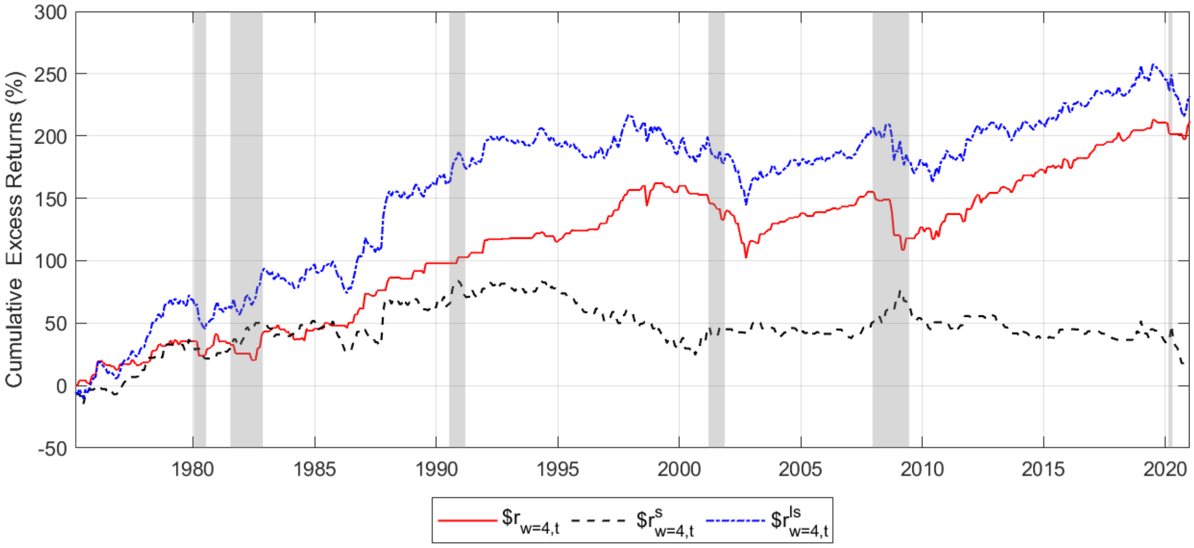


Table 2.B shows that allowing short selling minimally improves average returns but substantially increases variance. Hence, the Sharper ratio drastically deteriorates from 0.439 to 0.335. Figure 3.B shows that the short-selling gains focus on recession periods. The evidence is more reconcilable with a compensation for liquidity provision rather than an end-of-the-month payment cycle price pressure.

C Appendix Section 3

C.1 End of Month Institutional Behavior on S&P 500

C.1.1 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.

C.1.2 ANcerno Dataset: Data Description

We obtained the daily ANcerno dataset from 1997 to 2010 included. As the first three years have very few limited observations, we consider only data from 2000 onwards - a common practice in the literature Hu et al. (2018). The variables in our dataset are:

- *clientcode*: Ancerno defined Client identifier. Each client gets a unique code. It is impossible to reverse engineering Client names.
- *clientmgrcode*: Ancerno defined Client Manager identifier. The identifier allows grouping all trades the same broker executes, even across clients.
- *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.

Using the 8-digit CUSIP identifier, we created a sample focusing only on trades of stocks listed in the S&P 500 and its most prominent ETFs (SPY, VOO, IVY). The historical constituents of the S&P 500 from 2000 to 2010 and their CUSIPs were obtained from Compustat.

C.1.3 End of Month Institutional Behavior: CFTC data

In this Session, we use data from Commodity Futures Trading Commission (CFTC) to corroborate the results established with the ANcerno dataset. We 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, we 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.C: 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.C, we report the delta between the last two weeks of the month for both net buys and sells across the different investor classes.[29] 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 funds provide liquidity as $\Delta Buy - \Delta Sell$ is positive, whereas others (among which retail investors) sell futures linked to the S&P 500 consistently with the positive feedback trader hypothesis.

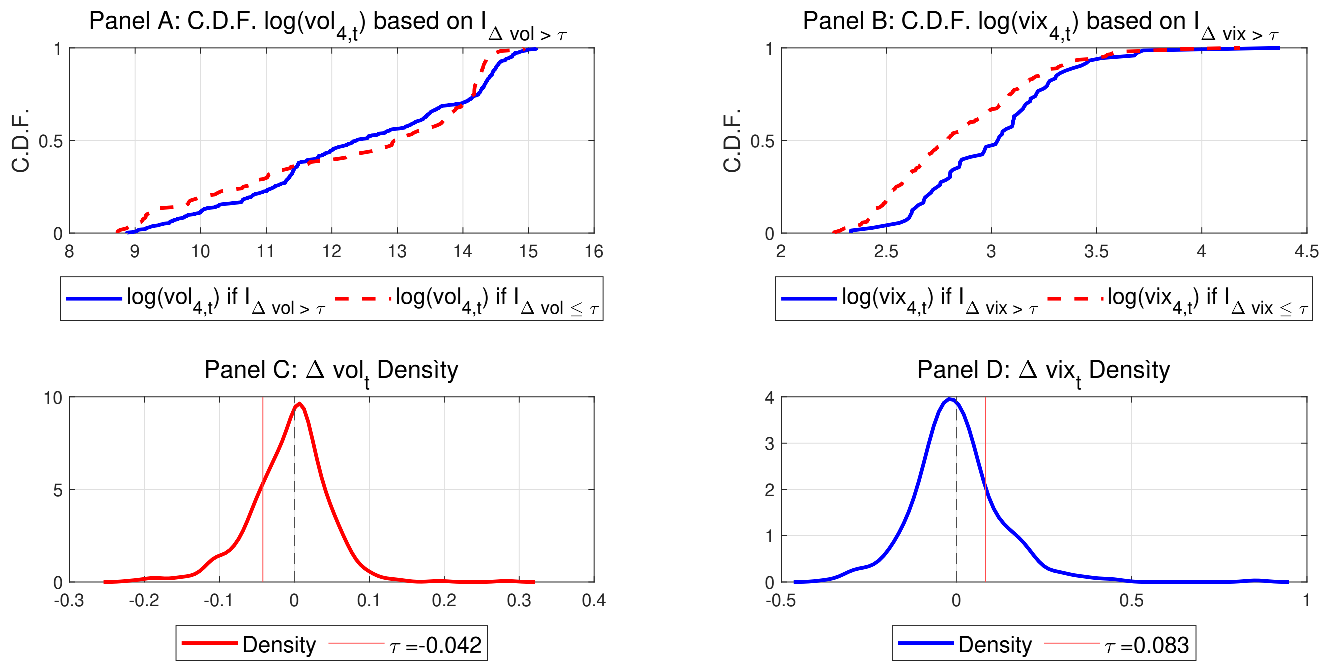
[29]CFTC Methodology website: "A traders increase in a net long position or decrease in a net short position can be viewed as net buys. Similarly, a traders decrease in a net long position or increase in a net short position can be viewed as net sells. For each reporting week, the values reported are the simple average of that weeks daily aggregate net buys and net sells "

C.2 Volume and Volatility Channels

C.2.1 Volume and Volatility Variables

This Appendix discusses the statistical properties of the two variables introduced in Section 3: Δvol_t and Δvix_t. In Panel A (B) of Figure 1.C, we 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, we 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.

Figure 1.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.



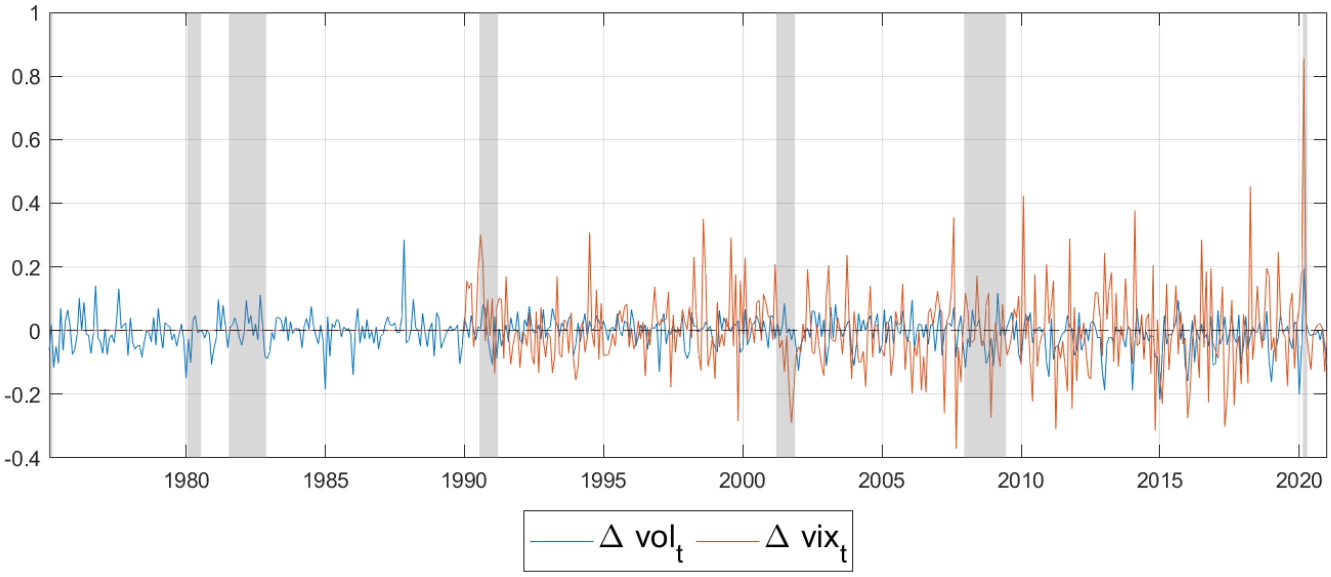
The statistical analysis reported in Table 2.C corroborates the visual inspection in Figure 1.C. In Panel C (D), we report the estimated density function of Δvol_t (Δvix_t).

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, we 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 2.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, we 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 2.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.2.2 Different Metrics of Volume and Variance

In this session, we present evidence that the results presented in Sections 3.2 and 3.3 are robust to different volume and volatility variables specifications. Here, we consider the following:

$$\Delta vol_t = vol_{w=4,t} - vol_{w=43,t} \qquad \Delta vix_t = vix_{w=4,t} - vix_t \tag{36}$$

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, we report the results of the following Threshold Autoregressive Regression (TAR):

$$r_{t+1} = \begin{cases} \alpha + \gamma_1\ r_{w=4,t} + \epsilon_{1,t+1} & if\ \ -\infty < \Delta vol_t \leq \tau \\ \alpha + \gamma_2\ r_{w=4,t} + \epsilon_{2,t+1} & if\ \ \ \ \ \tau < \Delta vol_t < \infty \end{cases}$$

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 $\Delta vol_t = vol_{w=4,t} - vol_{w=3,t}$. In the second panel, we 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 parenthesis, we 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 $\Delta_{vol_t} < \tau$	-0.090	$\mathbb{1}_{\Delta vol_t > \tau}$		-0.001	-0.001
	(-0.320)			(-0.247)	(-0.132)
$r_{w=4,t}$ if $\Delta_{vol_t} \geq \tau$	-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, we report the results of the following Threshold Autoregressive Regression (TAR):

$$r_{t+1} = \begin{cases} \alpha + \gamma_1 \ r_{w=4,t} + \epsilon_{1,t+1} & if \ -\infty < \Delta vix_t \leq \tau \\ \alpha + \gamma_2 \ r_{w=4,t} + \epsilon_{2,t+1} & if \qquad \tau < \Delta vix_t < \infty \end{cases}$$

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, we 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 parenthesis, we 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 $\Delta_{vix_t} < \tau$	-0.076	$\mathbb{1}_{\Delta vix_t > \tau}$		-0.005	0.020
	(-0.360)			(-0.592)	(1.950)
$r_{w=4,t}$ if $\Delta_{vix_t} \geq \tau$	-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.2.3 Evidence from Bloomberg Data

In this Subsession, we use volume data from Bloomberg to corroborate our results reported in the main body of the paper. Differently from price series, volume series can differ as different data providers have different rules in counting the number of transactions.

Table 5.C: Volume Channel: Bloomberg Data Robustness Check
In the Table, we report the results of the following Threshold Autoregressive Regression (TAR) for the different Δvol_t specifications :

$$r_{t+1} = \begin{cases} \alpha + \gamma_1 \ r_{w=4,t} + \epsilon_{1,t+1} & if \ -\infty < \Delta vol_t \leq \tau \\ \alpha + \gamma_2 \ r_{w=4,t} + \epsilon_{2,t+1} & if \qquad \tau < \Delta vol_t < \infty \end{cases}$$

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. In the first column we consider the specification $\Delta vol_t = \frac{VOL_{w=4,t} - VOL_{w=3,t}}{\sum_{i=1}^{4} VOL_{w=i,t}}$ and in the second column $\Delta vol_t = vol_{w=4,t} - vol_{w=3,t}$.In parenthesis, we report robust t-statics. The sample period goes from January 1990 to December 2020, and the volume data is obtained from Bloomberg.

τ	-0.105	-0.442
α	0.005	0.005
	(2.200)	(2.270)
$r_{w=4,t}$ if $\Delta_{vol} < \tau$	0.851	0.645
	(0.780)	(0.660)
$r_{w=4,t}$ if $\Delta_{vol} \geq \tau$	-.0326	-0.323
	(-2.140)	(-2.090)
Obs.	371	371

C.2.4 Volume and Volatility Channels throughout One-Month Ahead

This Session investigates whether the volume and volatility channels discussed in Section 3 apply throughout the month. For each return $r'_{w=i,t+1}$ ($r'_{w=i,t+1} = p_{w=i,t+1} - p_t, \quad \forall\ 0 < i \leq 4$), we estimate Threshold Autoregressive Regressions (TARs) based on volume Δvol_t (volatility Δvix_t):

$$r'_{w=i,t+1} = \begin{cases} \alpha + \gamma_1\ r_{w=4,t} + \epsilon_{t+1} & if\ \ -\infty < \Delta vol_t\ \ (\Delta vix_t) \leq \tau \\ \alpha + \gamma_2\ r_{w=4,t} + \epsilon_{t+1} & if\ \ \qquad \tau < \Delta vol_t\ \ (\Delta vix_t) < \infty \end{cases} \tag{37}$$

The results reported in Table 6.C show that the mechanisms described in Sections 3.2 and 3.3 hold throughout the month. The negative serial correlation is stronger for each $r'_{w=i,t+1}$ when there is an increased volume or volatility in the last week of the previous month (only for $r'_{w=3,t+1}$ we find that a decrease in volume implies a stronger serial correlation).

Table 6.C: Volume and Volatility Channel troughout One-Month Ahead

In this Table, we analyze the volume and volatility channels on returns that gradually become one month ahead returns ($r'_{w=i,t+1} = p_{w=i,t+1} - p_t, \quad \forall\ 0 < i \leq 4$). For each $r'_{w=i,t+1}$, we report the results of the following Threshold Autoregressive Regressions (TARs) based on volume Δvol_t (volatility Δvix_t) :

$$r'_{w=i,t+1} = \begin{cases} \alpha + \gamma_1\ r_{w=4,t} + \epsilon_{t+1} & if\ \ -\infty < \Delta vol_t\ \ (\Delta vix_t) \leq \tau \\ \alpha + \gamma_2\ r_{w=4,t} + \epsilon_{t+1} & if\ \ \qquad \tau < \Delta vol_t\ \ (\Delta vix_t) < \infty \end{cases}$$

where $r_{w=4,t}$ is the 4^{th} weekly return at month t; τ is the estimated TAR threshold estimated on the volume variable $\Delta vol_t = \frac{VOL_{w=4,t} - VOL_{w=3,t}}{\sum_{i=1}^{4} VOL_{w=i,t}}$ (volatility variable $\Delta vix_t = vix_{w=4,t} - vix_{w=3,t}$). In parenthesis, we report robust t-statics. The sample period goes from January 1975 to December 2020 for TARs based on volume and from January 1990 to December 2020 for TARs based on volatility

	$r'_{1,t+1}$		$r'_{2,t+1}$		$r'_{3,t+1}$		$r'_{4,t+1}$	
	Δvol_t	Δvix_t	Δvol_t	Δvix_t	Δvol_t	Δvix_t	Δvol_t	Δvix_t
τ	0.008	-0.089	-0.026	0.086	-0.003	0.117	-0.039	0.083
α	0.002	0.003	0.003	0.003	0.006	0.006	0.006	0.005
	(2.980)	(2.600)	(2.460)	(1.720)	(3.520)	(2.660)	(2.830)	(2.150)
$r_{w=4,t}$ if $\Delta_i \leq \tau$	-0.041	0.203	-0.010	0.107	-0.485	0.165	0.071	0.127
	(-0.470)	(0.790)	(-0.040)	(0.580)	(-1.910)	(0.810)	(0.190)	(0.560)
$r_{w=4,t}$ if $\Delta_i > \tau$	-0.215	-0.166	-0.221	-0.647	0.037	-1.198	-0.346	-0.791
	(-1.950)	(-1.940)	(-1.950)	(-3.670)	(0.190)	(-3.450)	(-2.240)	(-3.500)
Obs	551	371	551	371	551	371	551	371

C.2.5 Volume and Volatility Channels

In Section 3, we have studied volume and volatility channels individually. As the two channels are likely to be interdependent, this session analyzes the negative market serial correlation considering jointly volume and volatility. We estimate the following predictive regression:

$$\begin{aligned} r_{t+1} =& \alpha + \gamma\ r_{w=4,t} + \beta_1 \mathbb{1}_{\Delta vol_t} + \beta_2 \mathbb{1}_{\Delta vix_t} + \psi_1\ (r_{w=4,t} \times \mathbb{1}_{\Delta vol_t}) \\ &+ \psi_2\ (r_{w=4,t} \times \mathbb{1}_{\Delta vix_t}) + \psi_3\ (\mathbb{1}_{\Delta vol_t} \times \mathbb{1}_{\Delta vix_t}) + \xi(r_{w=4,t} \times \mathbb{1}_{\Delta vol_t} \times \mathbb{1}_{\Delta vix_t}) + \varepsilon_{t+1} \end{aligned} \tag{38}$$

where Δvol_t Δvix_t are the indicator variables based on the threshold regressions defined respectively in Sections 3.2 and 3.3.

Table 7.C: Volume and Volatility Channel
This Table reports the estimated interaction coefficients between $r_{4,t}$ and the volume and volatility indicator variables of the following predictive regression:

$$\begin{aligned} r_{t+1} =& \alpha + \gamma\ r_{w=4,t} + \beta_1 \mathbb{1}_{\Delta vol_t} + \beta_2 \mathbb{1}_{\Delta vix_t} + \psi_1\ (r_{w=4,t} \times \mathbb{1}_{\Delta vol_t}) \\ &+ \psi_2\ (r_{w=4,t} \times \mathbb{1}_{\Delta vix_t}) + \psi_3\ (\mathbb{1}_{\Delta vol_t} \times \mathbb{1}_{\Delta vix_t}) + \xi(r_{w=4,t} \times \mathbb{1}_{\Delta vol_t} \times \mathbb{1}_{\Delta vix_t}) + \varepsilon_{t+1} \end{aligned}$$

where r_{t+1} is the t + 1 monthly excess return; $r_{w=4,t}$ is the 4^{th} weekly return at month t; Δvol_t Δvix_t are the indicator function based on the threshold regressions defined respectively in Sections 3.2 and 3.3. In parenthesis, we report robust Newey and West (1987) t-statics. The sample period goes from January 1990 to December 2020.

$(r_{w=4,t} \times \mathbb{1}_{\Delta vol_t})$	$(r_{w=4,t} \times \mathbb{1}_{\Delta vix_t})$	$(r_{w=4,t} \times \mathbb{1}_{\Delta vol_t} \times \mathbb{1}_{\Delta vix_t})$
-1.218	-0.614	0.933
(-2.722)	(-1.867)	(1.602)

Table 7.C reports the interaction coefficients between $r_{w=4,t}$ and the volume and volatility indicator variables (ψ_1, ψ_2, and ξ). The results confirm that the negative serial correlation is stronger when there is a higher volume or volatility, as both the coefficients attached to $(r_{w=4,t} \times \mathbb{1}_{\Delta vol_t})$ and $(r_{w=4,t} \times \mathbb{1}_{\Delta vix_t})$ are negative and statistically significant. The magnitude of the coefficients is in line with the one reported in Sections 3.2 and 3.3: the negative correlation is stronger with higher end-of-the-month volatility rather than volume. When both indicator variables are set to 1, hence the two channels are contemporaneously working, the market autocorrelation is still strongly negative as it is the sum of both volume and volatility indicators (negative and statistically significant), and the coefficient attached to the overall joint effect (ξ)

(positive but only almost statistically significant).

C.3 Potential Other Explanation of Reversal Pattern

C.3.1 Over-Confidence Channel

Based on the theoretical models and the empirical findings, we 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, we study whether the overconfidence of market participants could be the economic source behind our results.

To measure overconfidence in the stock market, we 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).[30] 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).

We run a TAR regression

$$r_{t+1} = \begin{cases} \alpha + \gamma_1 \; r_{w=4,t} + \epsilon_{t+1} & if \;\; -\infty < BF_t^i \leq \tau \\ \alpha + \gamma_2 \; r_{w=4,t} + \epsilon_{t+1} & if \;\;\;\;\;\; \tau < BF_t^i < \infty \end{cases} \tag{39}$$

where BF^i is either $SENT$ or $SENT^{\perp}$. Table 8.C shows that the negative correlation does not depend on the Sentiment level as both and above the threshold, the correlation is negative and likely significant. Moreover, if we consider a higher sentiment as a measure of overconfidence,

[30]To not introduce measurement errors, we 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. We 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.

the behavioral channel proposed in Odean (1998) is less likely to be a plausible explanation of our findings as the negative serial correlation is statistically stronger when the BF^i values are below the estimated threshold.

Table 8.C: Over-Confidence Channel

In this Table, we report the results of the following Threshold Autoregressive Regression (TAR):

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

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 parenthesis, we 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 $SENT_t < \tau$	-0.558	$r_{w=4,t}$ if $SENT_t^{\perp} < \tau$	-0.519
	(-1.895)		(-2.499)
$r_{w=4,t}$ if $SENT_t \geq \tau$	-0.273	$r_{w=4,t}$ if $SENT_t^{\perp} \geq \tau$	-0.248
	(-1.822)		(-1.525)
Obs.	551	Obs.	551
R^2	1.78%	R^2	1.82%

To corroborate our results, we perform the standard predictive regression $r_{t+1} = \alpha + \gamma \ r_{w=4,t} + \beta BF_t^i + \epsilon_{t+1}$. We show that controlling for each BF^i, the magnitude and significance of γ do not change. Table 9.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 9.C: Over-Confidence Channel: Predictive Regression
In this Table, we report 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 parenthesis, we 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 Evidence on International Indexes

In this Session, we 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 and relative information regarding geographical regions and time windows are reported in Table 10.C.

Table 10.C: Indices around the World: Descriptive Statistics
This table reports the list of international indices. For each index, we 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

In the first two rows of Table 11.C, we report for each index the estimated coefficient and associated t-statistics of the following predictive regression:

$$r_{t+1} = \alpha + \gamma \, r_{w=4,t} + \epsilon_{t+1} \tag{40}$$

The results show a negative relationship even though not statically significant. The results are consistent with a more diluted institutional investors' ownership on international indexes. Finally, the amount of money involved in the payment cycle in foreign countries is likely lower than in the U.S.. Interestingly, the country with the most similarities to the United States, England, has a negative and almost significant coefficient.

Table 11.C: Last week predictability around the World
In the first row of the Table, we report 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, we 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 parenthesis, we 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)

C.3.3 Evidence on Commodities

In this Subsection, we control whether there is a negative serial correlation pattern in the commodity market. The commodities indices considered are reported in Table 12.C.

Table 12.C: Commodities: Descriptive Statistics
This table reports the list of commodity indexes. For each financial instrument, we report the Bloomberg ISIN, the underlying commodity and the time window considered. The data provider is Bloomberg.

ISIN	Underlying Commodity	Initial Date	End Date
USCRANSW	Oil	28/02/1991	31/12/2020
GC1 COMB	Gold	29/10/1993	31/12/2020
W 1 COMB	Wheat	29/10/1993	31/12/2020

Table 13.C reports the results of the standard predicting equation. The lack of significance suggests that the reversal pattern is a peculiarity of the American indexes.

Table 13.C: Last week predictability on Commodity Indexes
The Table reports the coefficient attached to last week return of the following predictive regression for the commodities reported in Table 12.C:

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

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 parenthesis, we report robust Newey and West (1987) t-statics.

	Oil	Gold	Wheat
α	0.002	0.005	0.002
	(0.420)	(2.130)	(0.410)
$r_{w=4,t}$	0.314	-0.205	-0.018
	(0.870)	(-1.230)	(-0.070)
Obs.	358	326	326
$R^2(\%)$	1.50	0.52	0.00

C.3.4 Option Expiration Effect

In this Session, we address the concern that our results could possibly be driven by the S&P 500 option expiration on the third Friday of the month. Specifically, Cao, Chordia, and Zhan (2021) argues that the expiration triggers a selling pressure due to re-balancing activities, and the magnitude increases with volatility. The intuition is that investors are more likely to liquidate the option-exercise-created positions in the more risky and volatile stocks.

In Table 14.C, we show that the reversal pattern discussed in the main body of the paper does not depend on increased volatility in the third week of the month. Specifically, we show both with a TAR regression and with a linear predicting equation any effect of the third-week volatility, $vix_{w=3,t}$ on the pattern. We obtain similar results by considering a change in volatility between the third and second week, $\Delta vix' = vix_{w=3,t} - vix_{w=2,t}$.

Table 14.C: Volatility Channel: Option Expiration Effect
In the first column of the Table, we report the results of the following Threshold Autoregressive Regression (TAR):

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

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 third Friday vix price ,$vix_{w=3,t}$. In the second column, we report the results of the following predictive regression:

$$r_{t+1} = \alpha + \gamma \; r_{w=4,t} + \beta \; vix_{w=3,t} + \varepsilon_{t+1}$$

In parenthesis, we report robust Newey and West (1987) t-statics. The sample period goes from January 1990 to December 2020.

	r_{t+1}		r_{t+1}
τ	3.174		
α	0.005	α	-0.018
	(2.150)		(-0.690)
$r_{w=4,t}$ if $\Delta_{vix'_t} < \tau$	-0.103	$r_{w=4,t}$	-0.273
	(-0.500)		(-2.330)
$r_{w=4,t}$ if $\Delta_{vix'_t} < \tau$	-0.388	$vix_{w=3,t}$	0.008
	(-1.600)		(0.840)
Obs	371		371

C.3.5 Quarterly Robustness Check

In this Session, we investigate whether the reversal pattern between $r_{w=4,t}$ and r_{t+1} is a consequence of quarterly rebalancing and reports. First, we split the full sample (January 1975 - December 2020) between end-of- and non-end-of-quarter months. The results presented in Table 15.C show that for both subsamples, the serial correlation is negative and statistically significant, therefore the pattern documented in the main body of the paper could not be rationalized only due to a "quarter effect". However, the results suggest that at the of quarter the reversal patter is stronger consistent with the intuition that when institutional investors face stronger liquidity constraints, they increase the non informational short selling.

Table 15.C: Reversal Pattern and End of Quarter Effect
This table reports the correlation coefficient of:

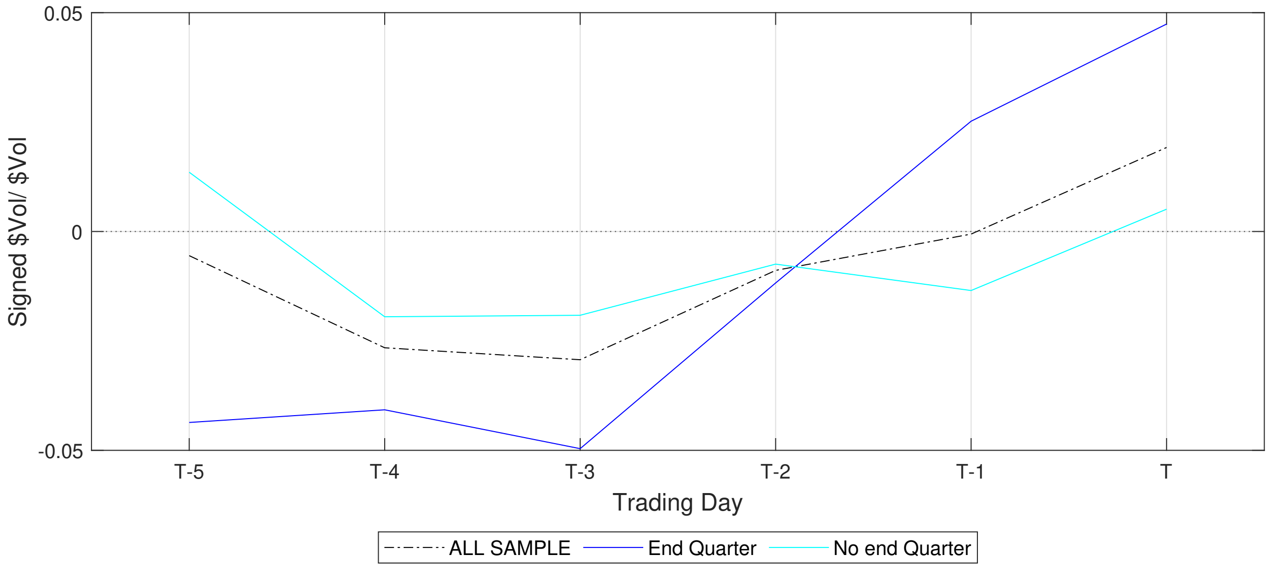
$$r_{t+1} = \alpha + \gamma \, r_{w=4,t} + \varepsilon_{t+1}$$

subsampling between non-end of quarter (*No end Q.*) and quarter end months (*Only end Q.*). In parenthesis, we report robust Newey and West (1987) t-statics. The sample period goes from goes from January 1975 to December 2020,

No end Q.	-0.257	Only end Q.	-0.581
	(-2.300)		(-1.920)

To further corroborate our findings we study end-of-and non-end-of-quarter month institutional behavior using the ANcerno Dataset. Consistent with the findings reported in Table 15.C, Figure 3.C displays no structural changes in the two subsamples.

Figure 3.C: **S&P 500 Institutional Order Imbalance and Quarter Effect**
This Figure reports the average institutional investors' order imbalance in the last 5 trading days of a month (where T is the last trading day of the month) on S&P 500 constituents and its major ETFs. A negative value of the ratio implies that, on average, institutional investors are net sellers. We report the full sample 2000-2010 (black-dashed line), only at the end of quarter months (red-solid line) and the remaining months (green-solid line). The Data is ANcerno, and the sample period goes from January 2000 to December 2010.



C.4 Properties of Time Series Reversal

C.4.1 Market Correlation over Business Cycle

In this session, we analyze the market autocorrelation between $r_{w=4,t}$ and r_{r+1} in relationship with the business cycle. We consider the following TAR regression:

$$r_{t+1} = \begin{cases} \alpha + \gamma_1 \; r_{w=4,t} + \epsilon_{1,t+1} & if \;\; I_t^{rec} = 0 \\ \alpha + \gamma_2 \; r_{w=4,t} + \epsilon_{2,t+1} & if \;\; I_t^{rec} = 1 \end{cases} \tag{41}$$

where I_t^{rec} is the NBER indicator function that takes a value of 1 when month t is in recession and 0 otherwise. The results reported in Table 16.C corroborate the findings reported in Section 3.4.1. The negative market serial correlation is more robust when there is no recession.

Table 16.C: Return Autocorrelation over Business Cycle
This table reports the coefficients obtained by following TAR regression:

$$r_{t+1} = \begin{cases} \alpha + \gamma_1 \; r_{w=4,t} + \epsilon_{1,t+1} & if \;\; I_t^{rec} = 0 \\ \alpha + \gamma_2 \; r_{w=4,t} + \epsilon_{2,t+1} & if \;\; I_t^{rec} = 1 \end{cases}$$

where I_t^{rec} is the NBER indicator function that takes a value of 1 when month t is in recession and 0 otherwise. Robust t-statistics are reported in parenthesis. The sample period goes from January 1975 to December 2020.

α		$r_{w=4,t}$ if $I_t^{rec} = 0$	$r_{w=4,t}$ if $I_t^{rec} = 1$
0.004		-0.373	-0.174
(2.140)		(-2.890)	(-0.450)
Obs.	551		
R^2	1.70%		

C.4.2 Institutional Investment over the Business Cycle

Table 17.C: S&P 500 Institutional Signed Investment over Business Cycle
This table reports the average institutional investors' ratio between signed $ volume and dollar volume in the last 8 days of a month (where T is the last day of the month) on S&P 500 constituents and its major ETFs for the full sample 2000-2010 (first column), only during recession (second column) and periods expansion (third column). In parenthesis, we report the associated t-statistic against the null hypothesis of a 0 ratio (Institutional investors are neither net buyers nor sellers). The Data is ANcerno, and the sample period goes from January 2000 to December 2010.

	All Sample	Recession	Expansion
T-7	-0.005	-0.006	-0.005
	(-0.590)	(-0.357)	(-0.482)
T-6	-0.021	-0.026	-0.020
	(-1.525)	(-1.398)	(-1.197)
T-5	-0.024	-0.067	-0.014
	(-1.863)	(-2.582)	(-0.970)
T-4	-0.025	0.024	-0.037
	(-2.851)	(1.554)	(-3.818)
T-3	-0.019	-0.032	-0.016
	(-2.031)	(-1.820)	(-1.455)
T-2	-0.011	0.041	-0.024
	(-1.387)	(3.005)	(-2.693)
T-1	-0.004	-0.015	-0.001
	(-0.331)	(-0.400)	(-0.070)
T	0.019	0.034	0.016
	(1.939)	(1.493)	(1.411)

C.4.3 TSR performance and VIX

In light of Nagel (2012), we here jointly report the cumulative excess returns obtained from the TSR and the implied volatility index VIX.

Figure 4.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 stategy goes from January 1975 to December 2020, for data availability the VIX series starts from January 1990.

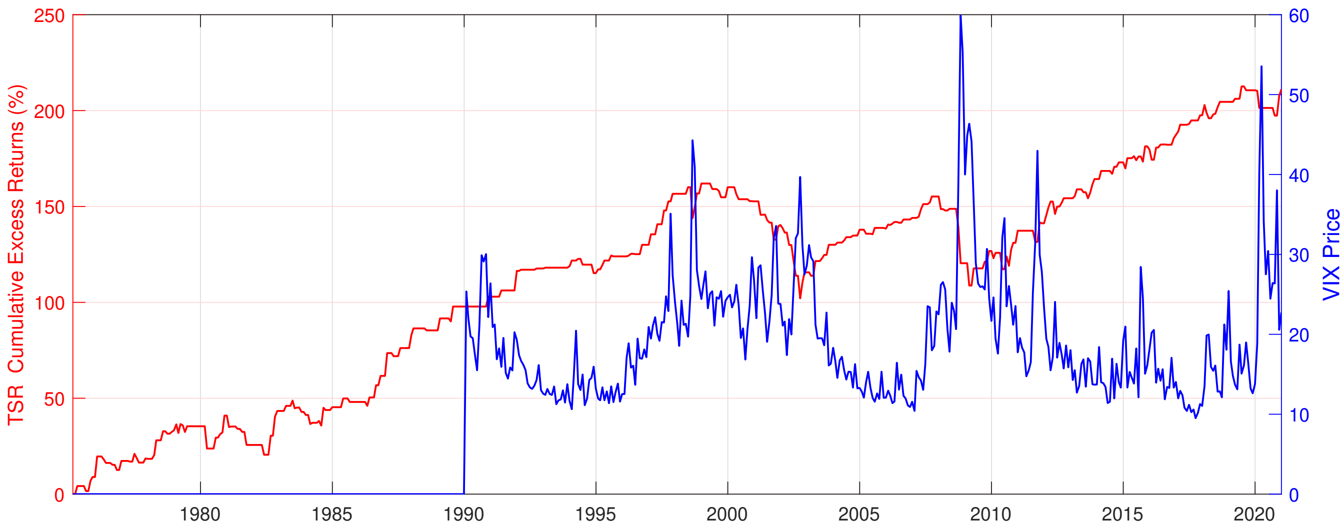


Figure 4.C shows that the TSR reversal strategy return is not positively correlated to the VIX index corroborating that, differently from the cross-sectional approach in Nagel (2012), the last week of the month does not proxy a compensation factor for liquidity provision.

C.4.4 Time Series and Cross-Sectional Approach

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

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

$$r_{t+1}^{sc_q} = \alpha + \beta r_{w=4,t}^{sc_q} + \epsilon_{t+1} \tag{42}$$

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. 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, we regress cross-sectionally:

$$r_{t+1}^{i \in sc_q} = \alpha + \beta^{CS} r_{w=4,t}^{i \in sc_q} + \epsilon_{t+1} \tag{43}$$

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).

In Figure 5.C, we 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 3.4.2, 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).

Figure 5.C: **Time Series and Cross-Sectional Approach**
The top panel of this Figure reports the β coefficient of the following prediction equations:

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

where $r_{t+1}^{sc_q}$ ($r_{t+1}^{sc_q} = \frac{1}{N}\sum_{i=1}^{N} r_{t+1}^{i \in sc_q}$) is one month ahead return of the equally value-weighted return of a portfolio sorted into quintile q on stock characteristic sc and $r_{w=4,t}^{sc_q}$ is analogously obtained by considering the last week return. The bottom panel reports the average coefficient over time of the following cross-sectional estimation:

$$r_{t+1}^{i \in sc_q} = \alpha + \beta^{CS} r_{w=4,t}^{i \in sc_q} + \epsilon_{t+1}$$

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. The stock characteristics considered are the Amihud illiquidity measure (the fifth being the most illiquid portfolio)and stock price. 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.