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Abstract

Institutional investors engage in trillions of dollars of regular portfolio rebalancing, often based on calendar schedules or deviations from allocation targets. We document that such rebalancing has a market-wide impact and generates predictable price patterns. When stocks are overweight, funds sell stocks and buy bonds, leading to a decrease in equity returns of 17 basis points over the next day. Our results are robust to controls for momentum, reversals, and macroeconomic information. Importantly, we estimate that current rebalancing practices cost investors about $16 billion annually—or $200 per U.S. household. Moreover, the predictability of these trades enables certain market participants to profit by front-running the orders of large institutional funds. While rebalancing remains a fundamental tool for investors, our findings highlight the costs associated with prevailing strategies and emphasize the need for innovative approaches to mitigate these costs.

Keywords: Rebalancing, Institutional Investors, Return Dynamics, Price Pressures, Reversal.
JEL codes: G11, G12, G23.

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"JPMorgan Says Stocks to Suffer \$150 Billion Rebalancing Sales"
Bloomberg (June 15, 2023)
"Pension Rebalancing Threatens to Spur \$26 Billion Equity Selloff"
Bloomberg (September 29, 2022)
"Big investors to shift billions from bonds into stock markets"
Financial Times (March 11, 2022)

1 Introduction

For more than three decades, investment managers have employed regular rebalancing—selling stocks and purchasing bonds when equities outperform bonds, and vice versa—as a key strategy to align portfolio weights with their target allocations.[1] Although this rebalancing activity is often perceived as a significant driver of aggregate price fluctuations, the academic literature has only recently begun to investigate whether and why this is the case. For example, Parker, Schoar, and Sun (2023) find that, while rebalancing by target date funds (TDFs) influences the cross-sectional pattern of returns across stocks, the aggregate effects are likely to be negligible given the current size of TDFs. However, most investors—including pension, sovereign wealth, and mutual funds—have relatively tight mandates and maintain stable asset shares (see, e.g., Gabaix and Koijen, 2021). Therefore, as prices fluctuate over time, these funds must buy losers and sell winners, which indicates a potentially broader and stronger rebalancing impact on aggregate dynamics.

In this paper, we study the market-wide economic implications of rebalancing. While rebalancing is a core strategy for maintaining portfolio diversification and managing liquidity, our results highlight that existing rebalancing policies induce significant predictability, costing investors billions of dollars every year. Furthermore, mechanical rebalancing enables certain traders to front-run the predictable orders of large funds, generating significant risk-adjusted profits. A key challenge in testing the implications of rebalancing lies in constructing measures of rebalancing activity that can capture the various frequencies at which different investors rebalance. Indeed, while some investors may rebalance quarterly, others do so monthly or even daily. Many adjust their portfolios when asset weights deviate beyond a specified percentage from their target allocation. To develop comprehensive measures of rebalancing activity, we analyze weight deviations in balanced equity/bond portfolios.

Consider a portfolio with 60% of its capital invested in the S&P 500 Index and 40% in 10-year U.S. Treasury note. We calculate weight deviations of this simulated 60/40 portfolio

[1] See, e.g., Perold and Sharpe (1988) for an early contribution on rebalancing.

using daily futures returns during the period 1997–2023. When stocks outperform bonds, they become overweight, and rebalancers must sell stocks and buy bonds to realign portfolio weights to their target allocations. Thus, weight deviations represent a natural proxy for rebalancing activities: the larger the deviation, the greater the likelihood and the potential magnitude of rebalancing.

We compute weight deviations from portfolio targets using two rule-based rebalancing approaches, Threshold and Calendar, that reflect the investment policies of different institutions. The Threshold approach adjusts positions when portfolio weights exceed predetermined distances from targets, reflecting the idea that allowing for portfolio drifts within defined ranges helps minimize transaction costs. Furthermore, many institutional investors have regular cash flow needs at the beginning of every month (see, e.g., Etula, Rinne, Suominen, and Vaittinen, 2020). For example, mature pension funds often sell assets at month-end to raise cash for member benefit payments. The Calendar approach captures these scheduled rebalancing activities. Both Threshold and Calendar are easy to compute, available in real-time, and applicable for any frequency with available return data. The Threshold signal captures faster intra-month rebalancing, while the Calendar signal captures slower month-end rebalancing.

Using these rebalancing signals, we provide novel evidence on U.S. aggregate price dynamics related to rebalancing activities. We find a one-standard-deviation increase in the Threshold (Calendar) signal leads to a *decrease* in equity returns of approximately 16 basis points (bps) (17 bps) and an *increase* in bond returns of about 4 bps (2 bps) over the next trading day. Rebalancing pressures revert almost entirely within two weeks, consistent with the fact that rebalancing is a by-product of institutional investors' mandates that likely conveys little information about market fundamentals. Our results are robust to including controls for momentum, reversals, macroeconomic activity, and sentiment indicators. We argue that these results are conservative. Without actual daily trades from all rebalancers, our rebalancing signals only proxy for a representative rebalancer's activity. Consequently, the documented effects likely represent a lower bound of the true impact we would observe if we knew the precise timing of individual investors' rebalancing activities.

A back-of-the-envelope calculation using our predictability results estimates that the rebalancing costs borne by institutional investors can exceed 8 bps per year. For a market potentially exceeding \$20 trillion in size, rebalancing pressures could translate into an annual cost of \$16 billion, or about \$200 per U.S. household each year. To put these numbers in perspective, these costs are higher than those institutional investors pay to invest passively across equity and bond markets. In other words, rebalancing a balanced equity/bond portfolio might cost more than the fees to access those markets in the first place. Further, since rebalancing costs recur annually, their true present value is substantially larger.

We conduct several analyses to validate the economic interpretation of our rebalancing signals. First, we identify seasonal patterns in the predictability of the Threshold and Calendar signals, observing that Calendar predictability is strong at month-end but absent at other times and that the predictive power and economic significance of both signals increase as the quarter-end approaches. These patterns are consistent with month- or quarter-end trades motivated by liquidity needs or benchmark tracking, rather than risk or behavioral factors. Second, we demonstrate that our signals predict equity and bond excess returns with opposite signs, indicating trades in both markets consistent with our interpretation. Third, we find that the predictive power of these signals became significant in the early 2000s, which reflects changes in pension fund allocations, cash flow demands, and 2006 legislation affecting the TDF industry. Fourth, we show that our rebalancing predictions apply to large- and small-cap stocks but not to value and growth stocks, aligning with funds targeting specific equity market segments. Fifth, we document that the Threshold and Calendar signals also extend to international equity markets. We further validate our rebalancing signals using Commodity Futures Trading Commission (CFTC) data on futures trading positions.

Finally, mechanical rebalancing offers certain investors the opportunity to front-run the predictable trades of large funds. To explore the potential economic value of these front-running strategies, we construct a managed portfolio that replicates the trades of an investor anticipating rebalancing activities. This portfolio uses our Threshold and Calendar signals to develop a cross-asset trading strategy. This strategy involves taking either a long position in S&P 500 futures while shorting 10-year Treasury note futures, or vice versa, based on the rebalancing signals. The managed portfolio constructed using these rebalancing signals delivers significant positive alphas and achieves a Sharpe ratio exceeding 1 over the 1997 to 2023 sample period.

Our work contributes to a growing literature on the effects of rebalancing by institutional investors.[2] Da, Larrain, Sialm, and Tessada (2018) document market-wide price pressure for stocks and bonds in Chile following recommendations for asset reallocation. Camanho, Hau, and Rey (2022) show that aggregate fund flows prompted by global portfolio rebalancing affect exchange rate dynamics. Peng and Wang (2023) document that mutual funds have persistent factor demand that forces them to frequently rebalance their portfolios' factor exposures, which leads to predictable stock-level trading and price pressure. Parker, Schoar, and Sun (2023) demonstrate that rebalancing by TDFs influences the fund flow patterns across mutual funds and the cross-sectional patterns of returns across stocks. Chen (2024) shows that active mutual funds rebalance their portfolios by selling shares in recently well-performing positions, in line with diversification and risk management motives. Sammon and Shim (2025) find that index funds incur adverse selection costs from rebalancing in response to stock market composition changes, buying at high prices when firms issue shares and selling at low prices when firms repurchase them. Our paper provides the first evidence of aggregate price effects for U.S. stocks and bonds arising from portfolio rebalancing activity.

This paper is also broadly related to the literature on price pressures. Since the work of Shleifer (1986) and Harris and Gurel (1986), an important strand of the literature has focused on event studies (e.g., index inclusion or new regulations) to understand cross-sectional price patterns; however, the literature has only recently started to explore potential aggregate price effects.[3] If aggregate demand is inelastic, shifts in institutional demand can generate large price impact (Koijen and Yogo, 2019; Gabaix and Koijen, 2021; Pavlova and Sikorskaya, 2023). Li, Pearson, and Zhang (2021) document that flows based on IPO regulations influence the Chinese aggregate stock market. Jansen (2021) investigates the effect of long-term investors demand shifts on government bond yields. Bretscher, Schmid, Sen, and Sharma (2024) study the price impact of demand shocks for the corporate bond market both for large institutions and at the aggregate level. Haddad, Huebner, and Loualiche (2024) find that the rise of passive investing over the last 20 years has lowered the elasticity

[2] Buffa, Vayanos, and Woolley (2022) provide a theoretical model to study the equilibrium effects of rebalancing.

[3] Warther (1995) and Edelen and Warner (2001) are two notable early contributions documenting a positive relationship between aggregate flows and *concurrent* aggregate market returns. Another interesting early paper is Ritter and Chopra (1989), who attributes the turn-of-the-year effect—the fact that returns on small firms are unusually high in January—to buying pressure from individuals reinvesting the proceeds of December's tax-motivated sales and from institutional investors shifting their portfolio allocations to small, risky stocks after year-end window dressing.

of aggregate demand. Most closely related to our paper, Hartzmark and Solomon (2025) find that uninformed, predictable buying pressures from dividend payments are associated with higher aggregate market returns. In addition, Chen, Noronha, and Singal (2006) and Petajisto (2011) find that index funds incur substantial costs due to mechanically buying stocks at elevated prices following index inclusion and selling them at depressed prices after index deletion. Our contribution is to show that mechanical rebalancing exerts a significant *market-wide* price impact. We then use our regression estimates to quantify the economic costs of current rebalancing activity.

The paper is organized as follows. In the next section, we provide institutional details on rebalancing and construct our return-based rebalancing proxies. Section 3 presents our main evidence on the relationship between rebalancing activities and aggregate price dynamics. In Section 4, we conduct several validation analyses for the economic interpretation of our rebalancing signals. Section 5 uses rebalancing signals to construct a portfolio that exploits market reversals. Section 6 discusses both the costs and benefits of rebalancing. Some concluding remarks are offered in the final section.

2 Rebalancing: Motivation, Measurement, and Interpretation

2.1 Background on Rebalancing

We define *rebalancing* as the activity of selling recent winners and buying recent losers to restore portfolio weights to their target allocations. In a multi-asset context, a 60/40 equity/bond portfolio is a commonly employed target asset allocation; for an early reference, see Ambachtsheer (1987), and for a more recent discussion, see Rattray, Granger, Harvey, and Van Hemert (2020). For example, large pension plans and sovereign wealth funds commonly target the 60/40 asset mix (e.g., Chambers, Dimson, and Ilmanen, 2012). Also, Gabaix and Koijen (2021) document that, on average, pension funds hold 60% in equities. Target allocations can be derived from theoretical considerations—such as TDF glide paths—or can be decided by investment committees based on multiple inputs, as with public pension funds.

As the value of risky assets fluctuate over time, so do their relative allocations or weights within a portfolio. This simple observation carries important asset management implications. In fact, most institutional investors, such as pension funds or mutual funds, are expected—as stipulated by their investment policies—to maintain their asset weights within certain ranges.For example, Figure 1 in Gabaix and Koijen (2021) documents that the relative equity share in the portfolios of institutional investors remains relatively stable over time. Appendix Figure D.1 complements these findings by focusing on U.S. defined benefit (DB) pension funds. Over the last two decades, the relative allocations to public equity and fixed income have closely tracked their stated targets, resembling the classic 60/40 portfolio and suggesting that public pension funds must regularly engage in rebalancing.

Rebalancing frequency varies by investor type: some trade quarterly, monthly, or even daily. This variation often relates to cash flow management, as many institutional investors have liquidity needs at the start of the month (e.g., Etula et al., 2020). For instance, pension funds tend to experience more outflows than inflows and must conduct regular trades to raise capital for benefit payments, so they often rebalance at month-end. In contrast, mutual funds, which face inflows and outflows throughout the month, may rebalance daily to adjust allocations (e.g., using inflows to buy underweight assets).[4]

A fund's chosen benchmark also influences rebalancing frequency. Portfolio managers that want to minimize tracking error may match the frequency of their benchmark. This frequency can vary. For instance, while Vanguard's TDF benchmarks were rebalanced daily, the S&P 500 Target Date Index series are rebalanced monthly, and the Morningstar Target Risk Series are rebalanced quarterly. In addition, rebalancing can be executed through various instruments, including derivatives like futures and swaps. These highly liquid instruments allow funds to efficiently adjust their exposures to capital market risks.

Rebalancers include various institutional investors, such as public and private pension funds, endowments, sovereign wealth funds, asset managers, and wealth managers. In the U.S. retirement industry, as of year-end 2022, DB plans, defined contribution (DC) plans, and individual retirement accounts (IRAs) held $37.8 trillion, according to data from the Federal Reserve's Financial Accounts database. Other types of asset owners may also have

[4]For example, a prospectus for a BlackRock balanced fund reports: "(...) the Fund's portfolio may be brought closer to the Fund's target asset allocation either through the direction of daily cash flows to suitable underlying funds or by interim rebalancings" (see SEC report).

an influence. Among sovereign wealth funds, the Norges Bank Investment Management, which targets approximately a 70/30 equity/bond portfolio, alone held slightly more than 1% of the U.S. stock market at the end of year 2023. U.S. university endowments also accounted for almost $1 trillion at the end of fiscal year 2021, holding about 0.5% of the stock market assuming a 25% allocation to U.S. public equities, according to data from the National Center for Education Statistics.

2.2 Measuring Rebalancing Activity

Rule-Based Rebalancing: Threshold and Calendar Approaches. To construct comprehensive rebalancing activity measures, we focus on two popular rule-based rebalancing approaches: Threshold and Calendar.[5] *Threshold rebalancing* builds on the idea that transaction costs can be minimized by allowing a portfolio to drift within defined ranges from its target allocation. When an asset's weight deviates from its target by a specified percentage—e.g., a 2% weight deviation—the portfolio manager rebalances the positions. *Calendar rebalancing*, instead, follows a deterministic schedule, occurring on a daily basis or towards month- or quarter-end. Notice that while the timing of Calendar rebalancing is predetermined, the magnitude of the rebalancing trades remains unknown. In particular, coordination mechanisms, portfolio reporting rules, beginning-of-the-month cash flow needs, and portfolio managers' aversion to tracking error with respect to their benchmark, among other factors, may explain month-end rebalancing. Different rebalancing approaches are not mutually exclusive, so portfolio managers may combine them.

Extracting Predictive Signals from Rebalancing Processes. We simulate the daily dynamics of 60/40 equity/bond portfolios rebalanced with Threshold and Calendar methodologies. The Threshold methodology rebalances a portfolio back to target weights when the

[5] According to a recent survey of rebalancing policies conducted by the National Association of State Retirement Administrators (NASRA)—a national organization with over 50 members representing $3.5 trillion in AUM—all public pension funds in the survey use either a predetermined schedule rebalancing policy, a threshold-based approach triggered when an allocation range is breached, or a combination of the two (see NASRA). Furthermore, see related discussions in a publication by Meketa Investment Group, one of the largest institutional investment advisory firms (Benham, Obregon, and Simanovich, 2018), and in research by Vanguard Group, the largest TDF manager (Zhang et al., 2022; Zhang and Ahluwalia, 2024).

weights deviate beyond a set distance from their targets, while the Calendar methodology rebalances to target weights on the last business day of each month.

We extract Threshold and Calendar rebalancing signals by measuring the *distance* of the equity allocation from its target at the end of the previous trading day. That is, we use information available up to day $t-1$ to predict returns on day t and subsequent days. These signals are functions of trailing equity and bond market returns; Appendix B provides a detailed explanation of their construction. For example, if the equity market outperforms the bond market by 10% on a single day within the 60/40 portfolio, both rebalancing signals should increase by approximately 2.26%. The only exceptions to this rule occur when rebalancing is triggered—either because the equity weight breaches its predefined range (Threshold signal) or because day t is the last business day of the month (Calendar signal).[6]

Our first hypothesis is that both Threshold and Calendar signals should negatively predict equity market returns and positively predicts Treasury market returns. Positive values for these signals indicate overweight positions in equities and equivalent underweight positions in bonds, which would trigger rebalancing. Our second hypothesis is that the predictability of the Calendar signal should concentrate towards the end of a month, consistent with the idea that the flow-performance relationship is stronger when investors do rebalance (see, e.g., Chevalier and Ellison, 1997; Lou, 2012):

We highlight two critical parameters for constructing and testing our signals: the rebalancing range associated with the Threshold signal's construction, and the range of days when we expect the Calendar signal to display the most predictability. Next, we provide preliminary evidence consistent with our hypotheses for different calibrations of these two parameters.

Signal Calibrations and Univariate Predictive Regressions. We formally define a Threshold signal by Threshold Signal$_t^\delta$, where δ indicates the rebalancing range (i.e., portfolio rebalancing occurs when the distance of a portfolio weight from its target exceeds δ). To evaluate different calibrations of Threshold Signal$_t^\delta$, we run the following regression for

[6] Consider a 60/40 portfolio in dollars. If the equity market increases by 10% and the bond market remains unchanged, the portfolio value becomes $66 + 40 = \$106$. The equity allocation is now $66/106 = 62.26\%$. To restore the original allocation, we need to rebalance by trading $0.60 \times 0.40 \times 10\% = 2.4\%$ of the initial \$100 portfolio value—i.e., sell \$2.4 of equities and buy \$2.4 of bonds.

different values of δ:

$$Ret_{t+1} = \gamma_0 + \gamma_1 \text{Threshold Signal}_t^{\delta} + \epsilon_{t+1} \ , \tag{1}$$

where Ret_{t+1} is the difference between S&P 500 and 10-year Treasury note futures returns. Detailed information about the data sources is provided in Appendix A. In Figure 1, we show the $t-$statistics of the γ_1 coefficient as a function of the chosen δ value, which in effect determines how often a threshold rebalancer may realign their portfolio weights.

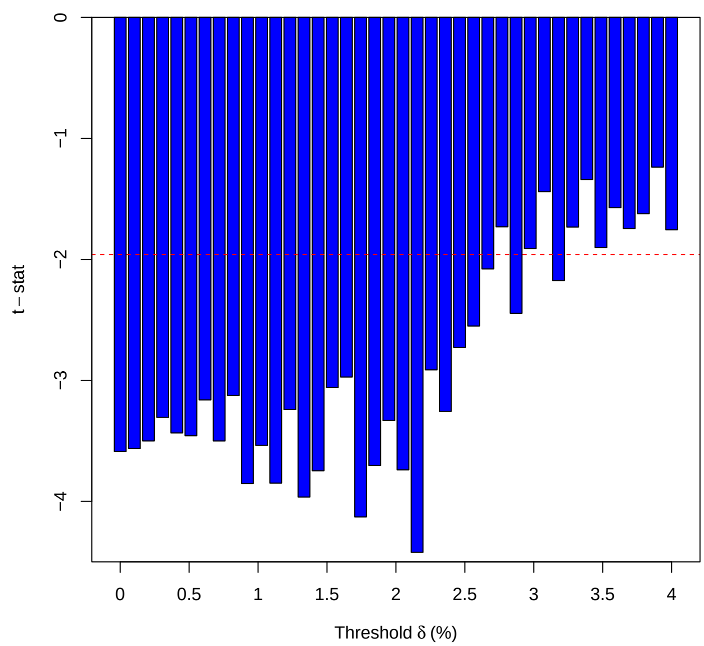


Figure 1: Threshold Calibrations and Predictability. This figure shows the $t-$statistics for the predictive coefficient in (1) for different values of the threshold rebalancing range δ. The dependent variable is the difference between the S&P 500 and the 10-year Treasury note futures returns. $t-$statistics are based on heteroskedasticity-consistent standard errors. Daily observations. The sample period is 1997-09-10 to 2023-03-17.

We focus on two results. First, consistent with our first hypothesis, the Threshold signal is negatively related to subsequent daily S&P 500 returns in excess of the 10-year Treasury note. Second, the predictability of the signal fades for values of δ above 2.5%, an intuitive result when viewed through the lenses of rebalancing frequency. When $\delta = 0$, the 60/40 portfolio rebalances 252 times per year (i.e., every business day). When $\delta = 1.1\%$, rebalancing occurs about once per month, and at $\delta = 2.5\%$ it happens about once per quarter. Given the necessity of managing cash flows, rebalancing less than once per quarter on average is unlikely.

In the remainder of this paper, we adopt a Threshold signal that is defined as the average of Threshold signals computed using δ values that span the range 0%-2.5% with increments of 0.1%.[7] Formally,

$$\text{Threshold signal}_t = \frac{1}{N}\sum_{\delta=0}^{2.5\%} \text{Threshold signal}_t^{\delta} \; . \tag{2}$$

Averaging different rebalancing calibrations approximates what a heterogeneous group of investors might implement while also reducing the set of potential predictors.[8] Consistent with these observations, introducing the Threshold signal in (2) yields a t-statistic for the predictive coefficient exceeding 4 (in absolute terms), which is higher than the median t-statistics across the range of δ values used to construct the aggregate signal.

A second important parameter in our study is the range of days when the Calendar rebalancing effect is expected to materialize. To investigate this variable, we estimate the following predictive models:

$$Ret_{t+1} = \beta_0 + \beta_1 \text{Calendar Signal}_t + \beta_2 \text{Calendar Signal}_t \cdot \text{Dummy}_t^{\text{N Days}} + \beta_3 \text{Dummy}_t^{\text{N Days}} + \epsilon_{t+1} \; , \tag{3}$$

where $\text{Dummy}_t^{\text{N Days}}$ is a dummy variable that takes the value of 1 during the last N-days of a month. Hence, (3) allows us to test whether the predictive power of Calendar signal concentrate towards month-end, as we expect.

In line with with the second hypothesis, we find that the Calendar signal is negatively related to future S&P 500 returns in excess of the 10-year Treasury note, with this predictability concentrated in the final days of the month. Figure 2 shows the t-statistics for the predictive coefficient β_2 in (3). Calendar predictability peaks in the last four days of

[7]While economically meaningful, one might be concerned about the fact that this signal calibration uses the whole sample. To address this, we repeated the analysis using only the first half of the sample and found qualitatively similar results, with predictability becoming insignificant for values of δ greater than 2.5%.

[8]Chinco and Fos (2021) find that this heterogeneity can be a source of computational complexity. Our results indicate robust and consistent predictability associated with the Threshold signal for economically meaningful rebalancing ranges.

the month, consistent with liquidity-driven trading by pension funds. Moreover, Figure 2 suggests that funds attempt to minimize market impact by avoiding trades on the very last day—or spreading trades over several days. Therefore, our focus for the rest of the paper is the interaction between the Calendar signal and the last week of the month, labeled as week4_t, which corresponds to $\text{Dummy}_t^{5\text{ Days}}$.[9]

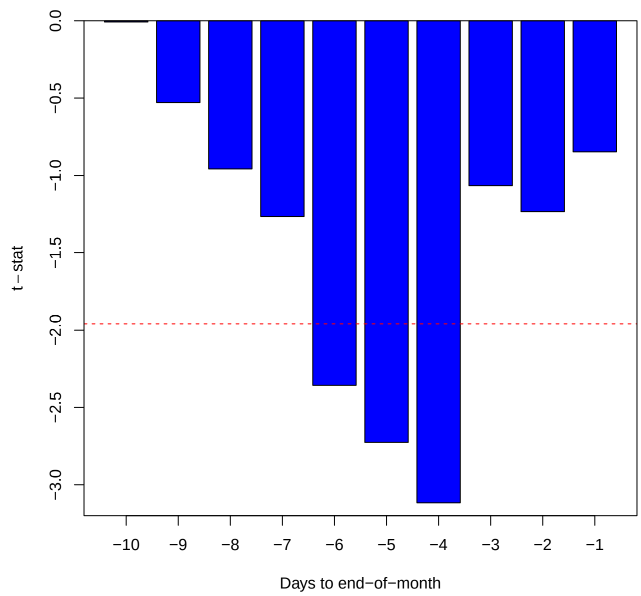


Figure 2: Calendar Signals and End-of-Month Effect. This figure shows the $t-$statistics for the predictive coefficient β_2 in (3) for different values of $\text{Dummy}_t^{\text{N Days}}$. The dependent variable is the difference between S&P 500 and 10-year Treasury note futures returns. $t-$statistics are based on heteroskedasticity-consistent standard errors. Daily observations. The sample period is 1997-09-10 to 2023-03-17.

2.3 Interpreting Rebalancing Signals

In Appendix Figure C.1, we plot the time-series of the Threshold and Calendar signals. Both series display high-frequency movements around periods of market turmoil. The Calendar

[9]This effect is distinct from the turn-of-the-month anomaly (e.g., Ariel, 1987; Lakonishok and Smidt, 1988), which refers to the observation that the U.S. stock index performs significantly better from the last trading day of the month through either the first three (Lakonishok and Smidt, 1988) or nine (Ariel, 1987) trading days of the following month. Ogden (1990) attributes this pattern to investors reinvesting cash payments—including wages, dividends, interest, and principal payments—at the turn of each calendar month.

signal shows the greatest absolute deviations, which are due to intra-month market volatility combined with an end-of-month rebalancing approach. We find that the median rebalancing frequency of the Threshold signal is about 16 times per year, higher than the 12 times per year of the Calendar approach. The average values of the Threshold and Calendar signals are positive, reflecting the fact that S&P 500 returns in excess of the 10-year Treasury note average about 3% per year in our sample. As a result, rebalancers tend to sell equities and buy bonds more often. Additionally, the signals have a positive correlation of approximately 0.60, as both are influenced by the same equity and bond market returns.

By construction, the Threshold and Calendar signals are positively correlated with trailing equity excess returns computed over different time frames. Since the Threshold signal tends to rebalance more frequently than the Calendar signal, it should be more closely related to short-term rather than long-term trailing excess returns.

In Appendix Table D.1, we report the estimated coefficients from regressing Threshold and Calendar signals onto trailing excess returns of selected horizons. The sums of the coefficients for each regression are close to 0.24, which reflects our decision to simulate a 60/40 portfolio's dynamics.[10] The Threshold signal displays its highest sensitivities to short horizon trailing returns, as is consistent with its higher turnover statistics. The Calendar signal displays a hump-shaped relationship that reflects how its horizon grows every month until the last business day. Hence, the Threshold signal and Calendar signal resemble the actions of a more frequent rebalancer and a less frequent rebalancer, respectively.

3 Rebalancing Pressures

3.1 Rebalancing and Cross-Asset Return Predictability

Many factors can affect aggregate returns. For example, time-series momentum appears as an ubiquitous driver of return dynamics (see, e.g., Moskowitz, Ooi, and Pedersen, 2012).

[10]Since $60\% \times 40\% = 0.24$, we can approximate the S&P 500 weight deviation from its target allocation as $\approx 0.24(R^E - R^B)$, where $R^E - R^B$ measures the equity excess returns since the last rebalancing. Importantly, from a predictive standpoint, our decision to simulate 60/40 portfolios rather than other allocations—such as 50/50 or 70/30—does not affect our results qualitatively. From an economic perspective, an equal-allocation portfolio implies the largest potential portfolio deviations and, therefore, the highest rebalancing pressures.

Furthermore, asset volatility is a well-know predictor of future returns, including at high-frequency (e.g., Nagel, 2012), and sentiment is an important driver of returns, especially at short-horizons (e.g., Da, Engelberg, and Gao, 2015). Thus, multivariate regressions are the natural setting to study if and how rebalancing activity affects future returns. Finally, we also want to understand whether Threshold and the Calendar signals contain different informative predictive content, i.e., if they are jointly significant predictors of future cross-asset returns.

To this end, we run the cross-asset predictive multivariate regression:

$$Ret_{t+1} = \beta_0 + \beta' RebalancingSignal_t + \psi Momentum_t + \zeta Ret_t + \gamma' X_t + \epsilon_{t+1} \ , \tag{4}$$

where, for the benchmark analysis, *Ret* is the difference between S&P 500 and 10-year Treasury note futures returns. We naturally refer to this analysis as *cross-asset* (or, abbreviated, XA) return predictability.

The $RebalancingSignal_t$ vector contains the Threshold and the Calendar signal constructed in Section 2.2; the Calendar signal is also interacted with a dummy variable taking the value of 1 the last week (i.e., 5 days) of any month or 0 otherwise. Momentum and rebalancing signals have a correlation higher than 67% (see Table C.1) but yield opposite predictions, so controlling for momentum in our setting is important. As trailing returns over different horizons convey distinct information (see, e.g., Goulding, Harvey, and Mazzoleni, 2023), we calculate fast, medium, and slow momentum signals. Since we find that the fast momentum signal lacks predictive power in our specification, we construct our momentum signal, $Momentum_t$, by averaging the medium and slow momentum signals.[11] We also control for trailing one-day returns, Ret_t.

The vector X_t contains three categories of control variables motivated by prior research. First, as proxies for aggregate volatility, we use the Chicago Board Options Exchange (CBOE) daily market volatility index (VIX), which measures the implied volatility of S&P 500 index options, together with the ICE BofA MOVE index, which tracks fixed income

[11] Momentum fast is calculated as the average of the signs of trailing 1 to 10 daily excess returns; momentum medium averages the signs of 11 to 20 daily excess returns; momentum slow averages the signs of 21, 42, 63, 126, and 252 daily excess returns. In Appendix Table D.3, we report robustness results using these three distinct momentum signals.

market option volatility. The inclusion of the MOVE index is motivated by the fact that we study both stock and bond return dynamics. Second, as controls for macroeconomic conditions, we use the news-based measure of economic policy uncertainty developed by Baker, Bloom, and Davis (2016) and the real-time business conditions index constructed in Aruoba, Diebold, and Scotti (2009). Finally, as sentiment proxy, we include the daily news-based sentiment index constructed in Shapiro, Sudhof, and Wilson (2022). In Appendix Table C.1, we report the correlation among all the predictors in our benchmark specification.

Table 1 reports results for different specifications of the multivariate predictive regression (4). We use heteroskedasticity-consistent standard errors.[12] In Column (1), both Threshold and Calendar signals significantly predict future daily XA returns, with associated t-statistics around 4. The negative signs for both signals are consistent with their role as rebalancing indicators: when stocks outperform bonds, stocks become overweight in portfolios and need to be sold. Thus, rebalancers act as macro-contrarians, as the TDF evidence in Parker, Schoar, and Sun (2023) suggests.[13] This, in turn, exerts downward pressure on XA returns. By contrast, momentum positively predicts daily returns, consistent with the literature.

Columns (2) to (4) report results for regression (4) including as controls proxies for volatility, macro conditions, and sentiment, respectively. This analysis shows that, while some regressors (e.g., volatility and economic uncertainty) partially explain future return dynamics, the two rebalancing signals remain strong predictors alongside momentum. Finally, we also include all regressors jointly. Column (5) reports this result showing that Threshold and Calendar are highly significant determinants of future XA returns.[14]

[12]We have also computed Newey-West HAC standard errors for all the main empirical results. These unreported standard errors imply even higher $t-$values, suggesting our reported results are conservative.

[13]Using individual portfolio data from Sweden, Calvet, Campbell, and Sodini (2009) find that households are, on average, macro-contrarians. More recently, Gabaix, Koijen, Mainardi, Oh, and Yogo (2023) find that U.S. households, by contrast, are on average pro-cyclical investors, with the important exception of ultra-high-net-worth individuals.

[14]Appendix Table D.2 uses the return differential between the S&P 500 Index and the Bloomberg Aggregate Bond Index, showing qualitatively and quantitatively similar results that indicate our findings are not specific to the financial instrument used to analyze rebalancing pressures. Appendix Table D.4 shows that using changes in the control variables ($\Delta X_t = X_t - X_{t-1}$) leads to similar results. Furthermore, Appendix Table D.5 shows that replacing these economic uncertainty and sentiment indexes with, respectively, the uncertainty index constructed in Bekaert, Engstrom, and Xu (2022) and the FEARS index constructed in Da, Engelberg, and Gao (2015) has little effect on the results. We thank the authors for making their FEARS time series available to us.

Table 1: Cross-Asset Predictive Regressions

This table reports estimates for the multivariate predictive regression (4). *Ret* is the difference between S&P 500 and 10-y Treasury note futures returns. Threshold and Calendar signals are constructed as described in Section 2.2. Momentum is computed by averaging the sign of 11 to 20, and 21, 42, 63, 126, and 252 trailing equity returns in excess of the 10-year Treasury note. VIX is the CBOE equity option-implied volatility index (divided by 100); MOVE is the U.S. bond market option-implied volatility index (divided by 100); Econ Uncertainty is the news-based measure of economic policy uncertainty from Baker, Bloom, and Davis (2016); Econ Activity is the Aruoba, Diebold, and Scotti (2009) real-time business conditions index; Sentiment is the daily news-based sentiment index constructed in Shapiro, Sudhof, and Wilson (2022). Values in parentheses are heteroskedasticity-consistent standard errors. Constant estimates are not tabulated. Daily observations. The sample period is 1997-09-10 to 2023-03-17.

	Ret_{t+1}				
	(1)	(2)	(3)	(4)	(5)
Threshold	-0.4127^{***}	-0.4200^{***}	-0.4240^{***}	-0.4274^{***}	-0.4202^{***}
	(0.1104)	(0.1107)	(0.1067)	(0.1087)	(0.1098)
Calendar	0.0580	0.0725	0.0598	0.0571	0.0707
	(0.0701)	(0.0679)	(0.0690)	(0.0705)	(0.0680)
week4	0.0002	0.0001	0.0002	0.0002	0.0002
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Calendar ∗week4	-0.3048^{***}	-0.3057^{***}	-0.3045^{***}	-0.3053^{***}	-0.3053^{***}
	(0.0804)	(0.0803)	(0.0802)	(0.0802)	(0.0804)
Momemtum	0.0023^{***}	0.0024^{***}	0.0023^{***}	0.0024^{***}	0.0024^{***}
	(0.0006)	(0.0007)	(0.0006)	(0.0006)	(0.0007)
Ret	−0.0147	−0.0107	−0.0142	−0.0129	−0.0113
	(0.0286)	(0.0285)	(0.0281)	(0.0283)	(0.0284)
VIX		0.0097^{*}			0.0088
		(0.0053)			(0.0062)
MOVE		-0.0022^{**}			-0.0020^{*}
		(0.0011)			(0.0011)
EPU			0.0005^{*}		0.0002
			(0.0003)		(0.0004)
ADS			0.0001		0.0001
			(0.0002)		(0.0002)
Sentiment				−0.0016	−0.0003
				(0.0012)	(0.0013)
Observations	6,223	6,223	6,223	6,223	6,223
Adjusted R^2	0.0232	0.0248	0.0237	0.0235	0.0244

The predictability of the rebalancing signals is both statistically and economically significant: a one-standard-deviation decrease in the Threshold (Calendar) signal is associated with an increase in XA returns of about 20 bps (19.4 bps) over the next trading day, and vice versa. This is remarkable if compared to other daily return predictability results. For example, Da, Engelberg, and Gao (2015) find that one-standard-deviation increase in their investor sentiment measure, FEARS, predicts an increase of 7.1 bps in the S&P 500. Or, more recently, Hartzmark and Solomon (2025) document a 3.2 bps increase in aggregate market returns for a one-standard-deviation increase in dividend payout. Furthermore, positive rebalancing signal values significantly predict future negative returns, while negative values significantly predict future positive returns, i.e., predictability is not concentrated in bad times. Finally, we find that the predictability associated with Threshold is stronger when the signal magnitude is larger, aligning with its economic interpretation.

These results suggest that investors may incur meaningful costs when rebalancing. To quantify these costs, we adopt a two-step approach. First, we estimate the cost in percentage terms by multiplying the price impact by the simulated rebalancing trade. Specifically, we estimate the costs for a hypothetical calendar rebalancer that rebalances their portfolio during the last week of each month, and a hypothetical threshold rebalancer that rebalances their portfolio whenever the weight deviates by more than 2.5% from its target. The results indicate that the calendar rebalancer incurs an annualized cost of approximately 8 bps, while the threshold rebalancer faces an annualized cost of about 13 bps. In the case of the Calendar strategy, we calculate the price impact using the predictive coefficient from a regression of the difference between S&P 500 and 10-year Treasury note futures returns on the lagged Calendar signal. We then multiply this value by the average absolute distance from the target during the past week, multiplied by 12 (the number of trades per year). We follow a similar procedure for the Threshold strategy and find that annualized costs range from 6 bps to 19 bps, depending on the calibration of the threshold signal ($\delta = 0$ to 2.5%), with an average value of 13 bps. To be conservative, we use 8 bps in the subsequent calculations for all rebalancing.

Consider the economic context of our 8 bps estimate. First, institutional investors typically pay about 3 bps per year to invest passively across equity and bond markets. This implies that mechanical rebalancing is nearly three times as costly as accessing these markets in the first place. Second, Chen, Noronha, and Singal (2006) quantify the losses incurred by index fund investors due to cross-sectional price pressures around the effective dates of index additions and deletions. They find that, on average, S&P 500 index investors lose approximately 4 bps per year. In addition, as TDFs and balanced funds are expected to grow (e.g., Parker, Schoar, and Sun, 2023), the costs associated with mechanical rebalancing could rise substantially over time.

Finally, to convert the costs into dollar terms, we multiply the percentage cost by the estimated dollar size of rebalancers. According to the Federal Reserve's Financial Accounts, U.S. retirement assets—including public and private DB and DC plans and IRAs but excluding Social Security—totaled \$37.8 trillion at year-end 2022. By our calculations, more than \$20 trillion of these assets may have been invested in public equity and debt.[15] Thus, current rebalancing policies cost approximately \$16 billion per year. Furthermore, about two-thirds of U.S. households have a financial stake in the U.S. retirement system, according to the Survey of Consumer Finances (SCF). Given that there were about 127 million households in the U.S., as reported by the Census Bureau in 2022, the annual cost of rebalancing per household reaches almost \$200.

3.2 Price Impact

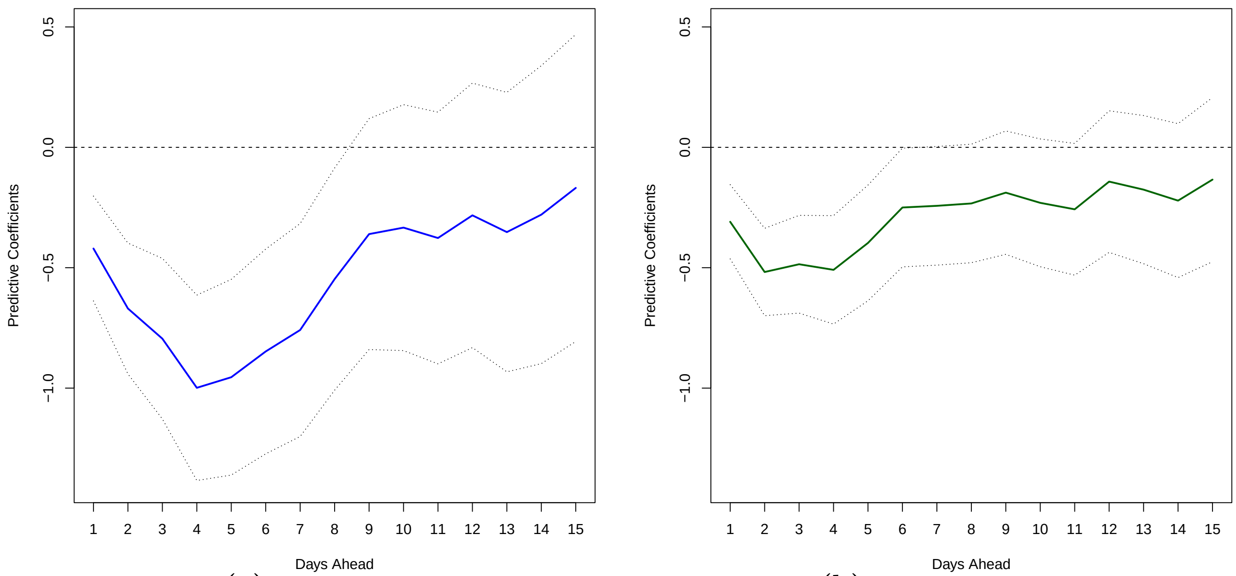
Threshold and Calendar signals are proxies for rebalancing activity, largely reflecting institutional mandates and expected to convey limited information about market fundamentals. Nevertheless, several models predict that even uninformed trades can influence prices (see, e.g., Grossman and Miller, 1988; De Long, Shleifer, Summers, and Waldmann, 1990 for early work, or more recently, Vayanos and Vila, 2021; Gabaix and Koijen, 2021).

We investigate the persistence of rebalancing price pressures by running the regression:

$$Ret_{t+1:t+i} = \beta_0 + \beta' RebalancingSignal_t + \psi Momentum_t + \zeta Ret_t + \epsilon_{t+i} \;, \tag{5}$$

[15] According to a 2023 study by the Congressional Research Service (CRS), of the \$14 trillion in public DB and DC plans, approximately \$7.2 trillion is allocated to public equity and fixed income. In private DC plans, which total \$8.1 trillion, about \$6.8 trillion is invested in TDFs or directly in equities and fixed income. Additionally, an estimated \$2.3 trillion in private DB plans and \$4.8 trillion in IRAs may be allocated to public equity and debt. For the full report, see CRS Report.

where $Ret_{t+1:t+i}$ are cumulative log returns up to $t+i$. To address potential inference issues related to overlapping observations, we follow Ang and Bekaert (2007) and use conservative standard errors from reverse regressions to compute confidence bands, as proposed by Hodrick (1992). Furthermore, Appendix Figure 3 shows results for non-overlapping returns.



(a) Threshold

(b) Calendar ∗week4

Figure 3: Rebalancing and Horizon of Cross-Asset Return Predictability. This figure shows coefficient estimates and 95% confidence intervals for Threshold and Calendar signals for the multivariate predictive regression (5). Confidence bands are computed using Hodrick (1992) standard errors. Daily observations. The sample period is 1997-09-10 to 2023-03-17.

Figure 3 shows the estimated coefficients for Threshold in Panel (a) and Calendar in Panel (b) from the multivariate predictive regression (5), along with their 95% confidence intervals. Point estimates reach their trough in Day 4 and Day 2 for Threshold and Calendar, respectively, before nearly reverting within 15 days. The predictive coefficients become statistically indistinguishable from zero at the 5% level by Day 9 for Threshold and Day 8 for Calendar.

Increasing the predictability horizon of (5), while introducing significant noise to our estimates, reveals that point estimates for both rebalancing signals would completely revert within less than two months. Thus, while our point estimates indicate that rebalancing pressures are not quickly reversed in full, this evidence suggests that these pressures eventually dissipate. As discussed in Hartzmark and Solomon (2025), although reversals have been extensively studied in the cross-section, understanding the speed and extent to which a market-level pattern like ours should reverse remains an important avenue for future research.

3.3 External Validity

We shared our preliminary empirical results with a group representing a global network of public pensions. The director suggested that we host a roundtable with 16 different pensions and present our preliminary findings. Held June 19, 2024, the meeting featured CIOs and other senior executives representing approximately $2 trillion in pension assets.

At first, the discussion only touched on general rebalancing information. Are there target allocations? How frequently is rebalancing conducted? Is rebalancing performed on a Calendar or Threshold basis? If on the former, how often do you rebalance? If on the latter, what are the thresholds? Would derivatives be used for rebalancing? What market considerations, if any, might delay or accelerate rebalancing? Based on the information we gathered, all pensions had systematic rebalancing procedures, with some variation across Calendar- and Threshold-based approaches.

We then presented our evidence that rebalancing induces predictability. Many pensions acknowledged that they were aware of this phenomenon. When we explained that potential front-runners could exploit such predictability, one pension replied, “We know about that.” Others agreed. When we suggested a more dynamic rebalancing policy might reduce the potential for front-running, one pension remarked, “It is easier for us to task our alpha desk with addressing this predictability than to try to convince our investment committee to change our rebalancing policy.”

In summary, pensions in our roundtable sample rebalance mechanically based on Calendar and Threshold rules. They understand these policies induce predictability and believe that traders will front-run their rebalancing. At least some of the funds appear to front-run their own rebalancing (and potentially that of others). Finally, the funds perceive changing rebalancing policies as very challenging given institutional constraints.

3.4 Robustness

Different Portfolio Weights. Our decision to simulate 60/40 portfolios rather than other calibrations simply influences the magnitude of the estimated predictive coefficients. To illustrate this point, in Appendix Table D.6 we replicate the results in Column (1) of Table 1 using rebalancing signals derived from a simulated 86%/14% equity/bond portfolio. These estimates shows that the new signals exhibit similar statistical power as the original ones, while being roughly twice in magnitude. This is exactly what we expected, since the magnitude of the 86/14 rebalancing signals is approximately half that of those calculated using the 60/40 calibration.[16]

The Role of Reversal. A potential concern is whether alternative reversal signals could subsume the predictive content of Threshold and Calendar. To study this question, we test two reversal measures. First, inspired by Nagel (2012), we construct a short-term reversal signal as the $5-$day trailing XA returns. Second, following Fama and French (1996), we calculate a long-term reversal signal as the $5-$year trailing returns (i.e., 1260 days) skipping the last year.

Table D.7 evalutes the predictive power of these two reversal measures. Column (1) shows that short-term reversal significantly predict future daily XA returns and displays the expected negative sign, although its effect is relatively small: a one-standard-deviation increase in short-term reversal leads to an increase in XA returns of about 1.1 bps over the next trading day. This finding complements previous work focused on stock returns alone (e.g., Nagel, 2012). In contrast, as shown in Column (3), long-term reversal does not appear to predict XA returns at a daily frequency. In columns (2), (4), and (5), we expand

[16]For example, if the equity market achieves a 10% excess return, the deviation of the S&P 500 from a 60% target allocation is computed as:

$$60\% \times 40\% \times 10\% = 0.24 \times 10\% = 2.4\%$$

In contrast, the deviation from an 86% target is:

$$86\% \times 14\% \times 10\% \approx 0.12 \times 10\% = 1.2\%$$

Thus, selecting a different target allocation, such as an 86/14 equity/bond mix, effectively narrows the δ range used to construct the Threshold signal.

our main empirical specification by adding the two reversal measures. Including either or both variables does not change our interpretation of the Threshold and Calendar signals. Instead, the short-term reversal measure is not significant in the joint regression in Column (2), suggesting that our rebalancing proxies capture its effect.[17]

4 Validation of Rebalancing Signals

Rule-based rebalancing policies are a function of past returns. Thus, whether our signals merely reflect fundamental risks or behavioral factors correlated with past returns rather than capturing rebalancing activity is a valid concern. In Section 3.1, we already demonstrate that factors such as momentum, reversal, volatility, macroeconomic activity, and sentiment do not explain the return predictability associated with our signals.

This section further investigates the economic interpretation of our rebalancing signals through six analyses. First, we document seasonal patterns in the predictability of the Threshold and Calendar signals and find that (i) Calendar predictability is strong at month-end but absent at other times, and (ii) both signals' predictive power and economic significance increase toward the quarter-end. These seasonal patterns align with month- or quarter-end trades driven by liquidity needs or benchmark tracking considerations rather than risk or behavioral factors. Second, we show that our signals independently predict both equity and bond excess returns, suggesting trades occur in both markets, consistent with our interpretation. Third, we find that the signals' predictive power became significant in the early 2000s, coinciding with shifts in pension fund allocations, cash flow needs, and 2006 legislation affecting the Target Date Fund industry. Fourth, we demonstrate that our rebalancing predictions extend to large- and small-cap stocks but do not extend to value and growth stocks, consistent with the fact that many funds have target allocations to small and large capitalization stocks but few have targets to growth and value. Fifth, we show that the Threshold and Calendar signals extend to international equity returns. Lastly, we

[17] Appendix Table D.8 investigates whether the end-of-month return patterns documented in Graziani (2024) relate to our findings. We construct the end-of-month reversal signal (EoM Rev), defined as the return between the fourth Friday's close and the month-end close, and find that it has very low correlation with our Calendar and Threshold signals (–0.062 and 0.038, respectively); in addition, EoM Rev is statistically insignificant and does not affect the predictability of our rebalancing signals.

further validate our rebalancing signals using CFTC data on futures trading positions.

4.1 Seasonal Patterns

In Panel A of Table 2, Column (2) indicates that the predictability of the Calendar signal concentrates at month-end, while outside of these days, Calendar does not exhibit predictive power (Column (1)). In Column (3), we demonstrate that this finding does not apply to the Threshold signal. This distinction validates their interpretation: despite a 60.2% correlation (see Appendix Table C.1), these results show that the signals capture two distinct rebalancing pressures.

Panel B of Table 2 shows that the predictability of our rebalancing signals varies across the months within a quarter. Specifically, we divide the sample into three groups: the first months of each quarter (January, April, July, and October), the second months of each quarter (February, May, August, and November), and the third months of each quarter (March, June, September, and December). Estimating our baseline regression conditional on these samples reveals that the predictive power and economic significance of rebalancing signals increase toward end-of-quarter.

The seasonal patterns in both the Threshold and Calendar signals align with the broader tendency of capital markets to rebalance at least quarterly. For instance, performance reports are often prepared quarterly, motivating portfolio managers to rebalance their allocations according to this schedule. While portfolio managers may not strictly adhere to a single rebalancing strategy—for instance, they might employ a mix of Threshold and Calendar indicators—there is a collective tendency to adjust portfolios at least once per quarter. The conditional estimates of the rebalancing signals' coefficients reflect this behavior.

4.2 Dissecting Cross-Asset Predictability

If Threshold and Calendar are valid proxies for rebalancing activity, they should also predict aggregate stocks and bonds *individually*. Specifically, Threshold and Calendar should *negatively* predict equity excess returns and *positively* predict bond excess returns. To test this, we run our benchmark regression (4) when Ret_{t+1} is either S&P 500 or 10-year Treasury

Table 2: Seasonal Patterns

This table reports estimates for the multivariate predictive regression (4). *Ret* is the difference between S&P 500 and 10-y Treasury note futures returns. Threshold and Calendar signals are constructed as described in Section 2.2. Values in parentheses are heteroskedasticity-consistent standard errors. Constant estimates as well as Calendar, week4, Momentum, and one-day trailing returns are not tabulated. Daily observations. The sample period is 1997-09-10 to 2023-03-17.

Panel A: Seasonal Patterns at Month-End

	Ret_{t+1}		
	(1)	(2)	(3)
Threshold	-0.3326^{***}	-0.4127^{***}	-0.4520^{***}
	(0.1073)	(0.1097)	(0.1249)
Calendar	-0.0760	0.0580	0.0693
	(0.0572)	(0.0694)	(0.0732)
Calendar ∗week4		-0.3048^{***}	-0.3345^{***}
		(0.0791)	(0.0937)
Threshold ∗week4			0.1323
			(0.1567)
Observations	6,223	6,223	6,223
Adjusted R^2	0.0124	0.0232	0.0233

Panel B: Seasonal Patterns Across the Months of Each Quarter

	Ret_{t+1}		
	1st Month of Q	2nd Month of Q	3rd Month of Q
	(1)	(2)	(3)
Threshold	-0.2238	-0.3649^{**}	-0.7044^{***}
	(0.1956)	(0.1599)	(0.2128)
Calendar ∗week4	-0.2431	-0.3483^{***}	-0.3587^{***}
	(0.1574)	(0.1060)	(0.1301)
Observations	2,077	2,051	2,095
Adjusted R^2	0.0101	0.0230	0.0454

note futures returns.

Table 3: Dissecting Cross-Asset Return Predictability

This table reports estimates for the multivariate predictive regression (4). *Ret* is the S&P 500 futures excess returns (first two columns) or 10-y Treasury note futures excess returns (last two columns). Values in parentheses are heteroskedasticity-consistent standard errors. Constant estimates are not tabulated. Appendix Table D.9 reports the coefficient estimates for all regressors. Daily observations. The sample period is 1997-09-10 to 2023-03-17.

	$\text{Ret}_{t+1}^{S\&P500}$		Ret_{t+1}^{10-y}	
	(1)	(2)	(3)	(4)
Threshold	-0.3225^{***}	-0.3301^{***}	0.0902^{***}	0.0901^{***}
	(0.1015)	(0.1005)	(0.0244)	(0.0248)
Calendar	0.0435	0.0561	-0.0145	-0.0145
	(0.0655)	(0.0634)	(0.0113)	(0.0112)
week4	0.0005	0.0005	0.0004^{***}	0.0004^{***}
	(0.0004)	(0.0004)	(0.0001)	(0.0001)
Calendar $*$week4	-0.2672^{***}	-0.2676^{***}	0.0376^{***}	0.0377^{***}
	(0.0753)	(0.0753)	(0.0126)	(0.0126)
Momemtum	0.0017^{***}	0.0018^{***}	-0.0005^{***}	-0.0005^{***}
	(0.0005)	(0.0006)	(0.0001)	(0.0001)
Ret	-0.0211	-0.0179	-0.0064	-0.0067
	(0.0259)	(0.0256)	(0.0061)	(0.0061)
Controls	NO	YES	NO	YES
Observations	6,223	6,223	6,223	6,223
Adjusted R^2	0.0225	0.0242	0.0078	0.0072

Table 3 reports the results. Columns (1) and (2) show results for equity, and Columns (3)-(4) for bonds. As expected, when stocks are overweight, future stock returns are lower, while future bond returns are higher, and vice versa. This effect is statistically significant for both rebalancing proxies, even after including controls. Economically, a one-standard-deviation decrease in the Threshold (Calendar) signal corresponds to an increase in equity returns of about 15.6 bps (17 bps) and a decrease in bond returns of about 4.4 bps (2.4 bps) over the next trading day.[18]

4.3 Long-Term Evidence

There are several reasons to believe that Threshold and Calendar signals were less relevant prior to the 2000s. First, portfolios are more diversified today than they used to be in the past, and higher diversification should imply more rebalancing.[19] Second, liquidity needs have also changed, which requires pension funds to regularly sell assets to pay member benefits at the beginning of each month.[20] Finally, the TDF industry's growth may have also contributed to rebalancing's rising importance. The 2006 Pension Protection Act (PPA) designated TDFs and balanced funds as default options in DC plans, which helped propel their growth and attract new savers to such contrarian strategies. Since TDFs inherently engage in rebalancing, as demonstrated by Parker, Schoar, and Sun (2023), we would expect stronger rebalancing pressures in recent years.

To test our hypothesis, in Table 4, we employ a longer dataset starting in the mid-1960s. We use daily U.S. equity market total returns from Kenneth French's database and estimate daily 10-year Treasury note total returns using Federal Reserve Board Treasury data. In the first column, we present whole-sample evidence. In the second and third columns, we split the sample at September 10, 1997, which coincides with the start date of our evidence in Table 1. The number of observations differs between Table 4 and 1 (6,421 vs. 6,223) due to variations in trading days between CRSP and Bloomberg futures data.

The evidence reported aligns with our expectations. While Column (1) shows that

[18] Pitkäjärvi, Suominen, and Vaittinen (2020) explore cross-asset predictability, demonstrating that past bond returns predict future equity market returns, and past equity market returns predict future bond market returns. Our findings complement their results by revealing that the *same* (rebalancing) signals convey predictive power for *both* equities and bonds.

[19] Until the early 1990s, pension funds were mostly invested in fixed-income securities due to stricter regulations, better funding conditions, and a higher interest rate environment. As interest rates declined, pension plans began shifting large portions of their portfolios away from bonds and toward equities. For example, the 2014 report *"State Public Pension Investments Shift Over Past 30 Years"* by the Pew Charitable Trusts shows that, until the 1980s, over 80% of public pension fund assets were invested in cash and bonds; see report.

[20] Due to changing demographics, most U.S. DB pension funds began experiencing negative cash flows by the early 2000s (see, e.g., OECD reports *Pension Markets in Focus*).

Table 4: Long-Term Evidence

This table reports estimates for the multivariate predictive regression (4) by using a longer dataset. *Ret* is the difference between daily U.S. equity total returns from Kenneth French's database and daily 10-year Treasury note total returns calculated using U.S. Treasury yield curve data from Gürkaynak, Sack, and Wright (2007). Threshold and Calendar signals are constructed as described in Section 2.2. Momentum is computed by averaging the sign of 11 to 20, and 21, 42, 63, 126, and 252 trailing equity returns in excess of the 10-year Treasury note. The data spans from 1961-06-16 to 2023-03-17 (the entire sample is used in the first column of the table). For consistency with our previous estimations, the estimations in the second column end on 1997-09-09, while those in the third column begin on 1997-09-10. Values in parentheses are heteroskedasticity-consistent standard errors. Constant estimates are not tabulated. Daily observations.

	Ret_{t+1}		
	(1)	(2)	(3)
Sample	1961-2023	1961-1997	1997-2023
Threshold	-0.1809^{***}	-0.0157	-0.3685^{***}
	(0.0620)	(0.0576)	(0.1103)
Calendar	0.0259	-0.0204	0.0573
	(0.0411)	(0.0495)	(0.0612)
week4	0.0004	0.0005^{**}	0.0000
	0.0002	(0.0002)	(0.0004)
Calendar $*$week4	-0.1536^{***}	-0.0284	-0.2569^{***}
	(0.0471)	(0.0596)	(0.0670)
Momemtum	0.0013^{***}	0.0004	0.0020^{***}
	(0.0003)	(0.0003)	(0.0005)
Ret	0.0216	0.1433^{***}	-0.0144
	(0.0192)	(0.0245)	(0.0280)
Observations	15,291	8,870	6,421
Adjusted R^2	0.0053	0.0204	0.0170

Threshold and Calendar signals are significant predictors of future XA returns, splitting the sample allows for a deeper understanding of aggregate dynamics. Over the past approximately 30 years, the rebalancing coefficients are both quantitatively large and statistically significant, whereas they are indistinguishable from zero over the preceding four decades. These findings support the view that Threshold and Calendar signals effectively capture the behavior of large groups of rebalancers. Finally, we note that the estimates for the period 1997-2023 closely resemble those presented in Table 1, providing an additional robustness check for our main results.

4.4 Rebalancing Pressures across Equity Indices

Some TDFs have specific allocations to large- and small-capitalization stocks, suggesting that the impact of rebalancing pressures may extend beyond aggregate markets. For example, PGIM Target Date and BlackRock LifePath funds allocate capital explicitly between large-cap and small-cap stocks. Recent work by Pavlova and Sikorskaya (2023) further motivates our analysis, showing that investor demand is highly sensitive to changes in the composition of the Russell 1000 and Russell 2000 indices. Although such allocations apply only to a subset of institutional investors, they enable us to test our empirical strategy across different equity indices.

To study this rebalancing mechanism, we apply the empirical framework outlined in Section 2, with a few modifications. To emulate TDF design, we analyze a portfolio invested in the Russell 1000 and Russell 2000 indices. To reflect typical allocations, the portfolio maintains a 90%/10% split between the Russell 1000 and Russell 2000 rather than the conventional 60/40 allocation for stock/bond portfolios. Our analysis begins in August 2006, when TDFs started to come into broad use.

We also conduct a falsification test by examining rebalancing pressures across growth and value stocks using the Russell 1000 Value and Russell 1000 Growth indices. Since institutional investors do not generally target allocations between these two market segments, we expect Threshold and Calendar signals to be insignificant predictors of excess returns between value and growth stocks.

The results reported in Panel A of Table 5 offer some insights. For large- and small-cap stocks, the Threshold and Calendar signals exhibit predictive power consistent with our rebalancing interpretation. However, their statistical and economic significance is smaller than that reported in Table 4, aligning with our observation that only a subset of institutional investors may target allocations within specific segments of the U.S. equity market. Finally, as expected, the rebalancing signals show no predictive power for excess returns between value and growth stocks.

Table 5: Rebalancing across Equity Indices

In Column (1), we predict the returns of the Russell 1000 Index (R1K) in excess of the Russell 2000 Index (R2K). In Columns (2), we predict the returns of the Russell 1000 Value Index (R1K Value) in excess of the Russell 1000 Growth Index (R1K Growth). Threshold and Calendar signals are constructed within their respective equity segments. We use momentum and one-day trailing returns as controls. Values in parentheses are heteroskedasticity-consistent standard errors. Constant and control estimates are not tabulated. Daily observations. The sample period is 2006-08-16 to 2023-03-17.

	(1) R1K / R2K	(2) R1K Value / R1K Growth
Threshold	-0.2054^{***}	-0.0339
	(0.0597)	(0.0478)
Calendar $*$week4	-0.1174^{*}	-0.0678
	(0.0683)	(0.0654)
Observations	4,175	4,175
Adjusted R^2	0.0094	0.0023

4.5 Spillover Effects in International Equity

We expect international equity prices to be similarly affected by rebalancing activities as U.S. equities. Allocations in international equities can constitute half or more of the size of allocations to domestic equities. Additionally, the returns of domestic and international equities are positively correlated. This implies that when an investor needs to rebalance their domestic equity positions, it is likely that they also need to rebalance their international equity positions.

To extend our analysis to international equities, we modify our empirical specification to account for different closing times across stock markets. As international markets close before the U.S. stock market, one-day U.S. equity returns are highly and *positively* correlated with the subsequent one-day returns of international equity indices. We control for the two-day trailing returns of the S&P 500 in order to characterize cross-market serial correlations. Since our rebalancing signals depend on trailing returns, we lag them by one day. While introducing this lag might reduce predictive power, it helps disentangle the positive cross-market correlation due to time differences from the rebalancing effects we aim to measure.

Table D.10 shows that both Threshold and Calendar signal coefficients are negative and significant, with magnitudes similar to the ones reported in Table 1. The R^2 from the predictive regression is approximately 2.5%, indicating that the total variation explained is also similar. Overall, this evidence suggests that rebalancing signals based on the dynamics of U.S. equity and bond markets are predictive of the returns of international equity markets.

4.6 Rebalancing and Traders Positions

We further validate our rebalancing signals through publicly available futures trading positions from the Commodity Futures Trading Commission (CFTC). Futures trading positions provide insights into trades associated with a key financial instrument used in rebalancing processes and risk management. Most importantly, the availability of CFTC data on a weekly basis is crucial for our analysis, as most rebalancing effects manifest within a month. Traditional quarterly data sources (e.g., 13F filings) would not fully capture these dynamics.

Our analysis investigates weekly position changes for different types of traders. The CFTC requires all large traders to identify as either commercial or non-commerical. The former report using futures for hedging purposes. The weekly Commitment of Traders (COT) reports detail the aggregate long and short positions of futures market participants for these trader types. Following the previous literature (e.g., Bessembinder, 1992; De Roon, Nijman, and Veld, 2000; Moskowitz, Ooi, and Pedersen, 2012), we refer to commercial traders as *hedgers* and to non-commercial traders as *speculators*.

We posit that hedgers primarily act as rebalancers, as they must hedge or "close" the tracking risk that arises when a portfolio drifts from its target allocation. To eliminate this tracking risk, rebalancers must buy underweight assets and sell overweight assets. Hence, hedgers' trades are not mainly motivated by speculation—although this channel cannot be entirely ruled out—but are instead driven by risk considerations. Conversely, speculators act as liquidity providers and are unlikely to be influenced by tracking risk, as they typically have no strict mandate to follow a benchmark.[21]

We use the CFTC data on S&P 500 and 10-year Treasury futures to construct a variable that captures the trading behavior of hedgers and speculators. Following Kang, Rouwenhorst, and Tang (2020), we compute net trading Q as the cross-asset net position change between $t+1$ and t, scaled by open interest (i.e., the total number of contracts outstanding) in week t. We calculate this measure separately for both hedgers and speculators.

We test whether net trading positions are predicted by the rebalancing signals constructed as described in Section 2.2, with a modification to address the frequency mismatch between the rebalancing signals and traders' positions. Specifically, our rebalancing signals are based on daily data, while traders' positions are reported weekly and reflect information up to Tuesday. To reconcile this mismatch, we adjust the dummy variable "week4" so that it equals 1 if at least one observation in a given week falls within the last week of the month, and 0 otherwise. Additionally, we restrict our sample to the post-Pension Protection Act (PPA) period, during which rebalancing mechanisms are stronger and parameter estimates are more reliable.

Table 6 reports the results. Column (1) shows that hedgers positions are negatively related to Threshold and Calendar, while Column (3) shows a positive relationship between speculators positions and rebalancing proxies. When stocks are overweight (underweight) compared to bonds, hedgers need to sell (buy) equity, and speculators take the opposite position of the trade, consistent with our interpretation. Furthermore, Column (2) and (4) show that these effects are robust even after controlling for past trading positions.

To further explore how rebalancing pressures relate to trades, we use the Large Trader Net Position Changes data. This report categorizes net position changes for financial futures traders into four groups: dealer/intermediary, asset manager/institutional, leveraged funds, and other reportables.[22] We aggregate trades from the first two categories into a single group,

[21] As in, e.g., Nagel (2012), this notion of liquidity providers is not restricted to designated market makers.

[22] The Large Trader Net Position Changes dataset, published by the CFTC on June 30, 2011, identifies the daily average aggregate net position changes for large traders across 35 futures markets during a specified week and is provided in a one-time report covering the period from January 2009 to May 2011. Further

Table 6: Weekly Trades and Rebalancing Signals

This table reports results from regressing weekly traders position changes on the rebalancing signals plus controls. We use CFTC Commitments of Traders (COT) data on commercial (hedgers) and non-commercial (speculators) traders' positions to compute weekly position changes. Hedgers (Speculators) net trading Q_{t+1} is the cross-asset net position change at time $t+1$ scaled by open interest in week t. Threshold and Calendar signals are constructed as described in Section 2.2. Values in parentheses are heteroskedasticity- and autocorrelation-consistent standard errors. Constant estimates are not tabulated. Weekly observations.

	Hedgers Q_{t+1}		Speculators Q_{t+1}	
	(1)	(2)	(3)	(4)
Threshold	-0.5346^{**}	-0.4967^{*}	0.5855^{**}	0.4849^{*}
	(0.2658)	(0.2638)	(0.2545)	(0.2625)
Calendar	0.2555	0.2542	0.0387	0.0668
	(0.2083)	(0.2120)	(0.1758)	(0.1840)
week4	-0.0050^{**}	-0.0047^{**}	0.0062^{***}	0.0061^{***}
	(0.0022)	(0.0023)	(0.0020)	(0.0020)
Calendar $*$week4	-0.7265^{***}	-0.7559^{***}	0.3475^{*}	0.3672^{*}
	(0.2210)	(0.2195)	(0.1955)	(0.1998)
Hedgers Q_t		-0.0730^{**}		
		(0.0358)		
Speculators Q_t				-0.1093^{***}
				(0.0379)
Observations	863	862	863	862
Adjusted R^2	0.0316	0.0358	0.0437	0.0546

labeled as institutional investors, which encompasses pension funds, endowments, insurance companies, mutual funds, large banks, and dealers in financial securities. Leveraged funds typically include hedge funds and other types of money managers, such as commodity trading advisors. We calculate net trading Q for these two groups as the cross-asset net position change for the week, scaled by the weekly average of Large Trader Net Position Changes.

Table D.11 presents the results of a predictive regression that uses our rebalancing signals to forecast cross-asset net trading by large traders. The first column shows that when stocks outperform bonds, institutional investors, on average, sell stocks and purchase bonds, while leveraged funds take the opposite position. These results offer a more granular perspective on the findings reported in Table 6 and are broadly consistent with the characterization of Threshold and Calendar as rebalancing activity measures.

Previous work has found that flows are characterized by a strong factor structure (e.g., Edelen, 1999; Gabaix, Koijen, Mainardi, Oh, and Yogo, 2023). Our findings suggest that rebalancing activity may be a potential determinant of flows.

5 Front-Running Rebalancers

We construct a simple, implementable real-time trading strategy by combining Threshold and Calendar signals. This strategy simulates the actions of an investor who, based on rebalancing signals, enters the equity and bond markets as a front-runner. On average, this investor buys equities and sells bonds after bonds have relatively outperformed and buys bonds while selling equities after equities have outperformed.

The trading strategy takes a position in a S&P 500 futures contract and an opposite position in a 10-year Treasury note futures contract as follows:

$$R_t^{\text{Strategy}} = (R_t^{\text{SP500}} - R_t^{10T}) \cdot w_t^{\text{Strategy}} \ ,$$

where the portfolio weight w_t^{Strategy} is defined as the average of modified versions of the Threshold and Calendar signals. The Threshold signal is rescaled to $-\frac{\text{Threshold Signal}_t}{1.5\%}$ to

details can be found on the CFTC website.

ensure that both rebalancing signals contribute approximately equal risk to the trading strategy. We take the negative of the signal, since a positive Threshold signal indicates that S&P 500 is overweight relative to the 10-year Treasury note.

While the Threshold strategy can take a position on any day of the month, the Calendar strategy focuses on the end-of-month effect. Therefore, the Calendar signal is modified to $sign\left(-\text{Calendar Signal}_t\right)$ if t falls within the last week of a month, to capture the "week4" effect. Furthermore, on the first business day of a new month, the modified Calendar signal is set to $sign\left(\text{Calendar Signal}_{-4}\right)$ to capture potential reversal effects. On any other day, the modified version of the signal is set to zero.

Panel A of Table 7 summarizes the trading strategy's statistics. The rebalancing-based strategy generates annualized average returns of approximately 9.9%, with a Sharpe ratio just above 1, much higher than the 0.38 and 0.50 of the equity and bond markets, respectively, during our sample period. Importantly, our strategy is robust to the inclusion of transaction costs. Following the assumptions of Harvey et al. (2018), we estimate that the Sharpe ratio net of transaction costs remains close to 1.

This performance cannot be explained by several standard factor models. In particular, Panel B of Table 7 shows the alphas from regressing the R_t^{Strategy} on the market portfolio (in excess of the risk-free asset), the Carhart (1997) four-factor model, the Fama and French (2015) five-factor model, or the Hou, Xue, and Zhang (2015) $q-$factor model. The alphas are positive, of significant magnitude, and highly significant, with a $t-$statistic above 4 for all combinations of factor models. This evidence supports our interpretation that rebalancing signals effectively times cross-asset returns rather than increasing exposure to systematic risk factors.

The strategy exhibits a high positive skewness of 5.14. This suggests strong performance during periods of heightened volatility, when the strategy takes larger positions, and market liquidity is lower. It is consistent with the evidence in Figure 4, which plots the cumulative log returns from investing \$1 in the front-running strategy along with the performance of \$1 invested in the R_t^{SP500} portfolio. In particular, the global financial crisis (GFC) of 2008–2009 and the 2020 COVID-19 crisis stand out as significant contributors to cumulative returns. But the economic significance of our strategy does not rely solely on these two extreme events: even after excluding the September 2008 to March 2009 and March 2020 periods,

Table 7: Performance of Front-Running Trading Strategies

This table reports performance results for the rebalancing-based strategy R_t^{Strategy} constructed as described in Section 5. Panel A reports several summary statistics. Panel B reports the alphas from regressing R_t^{Strategy} on the excess market returns (CAPM), on the four-factor Carhart (1997) model (C4), on the five-factor Fama and French (2015) (FF5), or on the Hou, Xue, and Zhang (2015) $q-$factors (HXZ). Panel C reports R_t^{Strategy} over high- and low-friction regimes, defined using the sample median of several variables; the columns labeled "H" ("L") correspond to the sample period with above (below) median friction level. Idiosyncratic volatility (ivol) is calculated as the cross-sectional standard deviation of individual CRSP stock returns; liquidity risk is the BofA GFSI Liquidity Risk measure; VIX is the CBOE equity option-implied volatility index (divided by 100); MOVE is the U.S. bond market option-implied volatility index (divided by 100); Econ Uncertainty is the news-based measure of economic policy uncertainty from Baker, Bloom, and Davis (2016). Means, volatilities, and alphas are expressed in annualized percentage. Values in parentheses are heteroskedasticity-consistent standard errors. Daily observations. The sample period is 1997-09-10 to 2023-03-17.

Panel A: Descriptive Statistics

	Ex. Returns (in % p.a.)	Volatility (in % p.a.)	Sharpe Ratio	Skewness
R_t^{SP500}	7.62	20.03	0.38	-0.07
R_t^{10T}	2.91	5.88	0.50	0.01
R_t^{Strategy}	9.92	9.20	1.08	5.14

Panel B: Alphas (in % p.a.)

	CAPM	C4	FF5	HXZ
α	9.39***	9.42***	9.30***	9.23***
	(1.78)	(1.79)	(1.75)	(1.75)

Panel C: High- and Low-Friction Periods (in % p.a.)

	ivol		liquidity risk		VIX		MOVE		Econ Uncertainty	
	H	L	H	L	H	L	H	L	H	L
R_t^{Strategy}	7.77***	2.36***	8.73***	1.85***	8.10***	1.82***	7.28***	2.63***	7.29***	2.63***
	(1.73)	(0.65)	(1.64)	(0.95)	(1.73)	(0.56)	(1.67)	(0.72)	(1.64)	(0.79)

the strategy's Sharpe ratio remains elevated at 0.90.

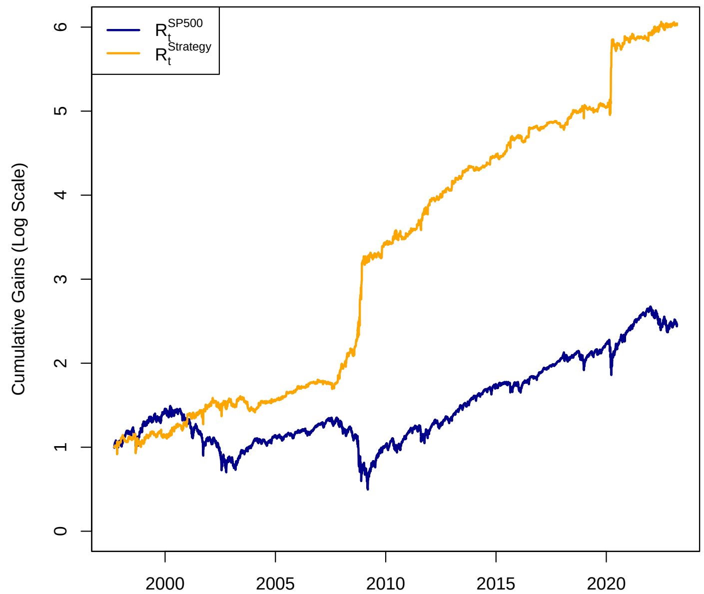


Figure 4: Front-Running Strategy Performance Over Time. This figure shows the cumulative gains of \$1 invested in the rebalancing-based strategy, R_t^{Strategy}, constructed as described in Section 5, alongside the performance of \$1 invested in the R_t^{SP500} portfolio. R_t^{Strategy} is rescaled to match the volatility of R_t^{SP500}. Daily observations. The sample period is 1997-09-10 to 2023-03-17.

Limits to arbitrage are critical for front-running strategies to be profitable. Indeed, as valuations shift, rebalancers must adjust their positions to maintain target allocations, while constrained liquidity providers cannot fully absorb the rebalancing pressures and instead trade more slowly (see, e.g., Ben-David, Franzoni, and Moussawi, 2012; Gârleanu and Pedersen, 2013; Vayanos and Vila, 2021). Front-runners anticipate these dynamics and exploit the predictable price impact. However, we emphasize that front-running the rebalancing is not a risk-free strategy. Trading ahead of rebalancers is risky due to uncertainty in both the timing and magnitude of the rebalancing trades (e.g., Dou, Kogan, and Wu, 2023).

We examine how periods with different levels of friction affect how our strategy performs. As discussed in, e.g., Gromb and Vayanos (2010), limits to arbitrage can arise from a variety of frictions. First, we consider idiosyncratic volatility (ivol), which is widely considered to be a major implementation cost of short arbitrage (Pontiff, 1996, 2006). We follow the model-free approach of Garcia, Mantilla-García, and Martellini (2014) to compute ivol at a daily frequency as the cross-sectional standard deviation of individual CRSP stock returns.[23] We also examine several aggregate risk and uncertainty measures. These include: the Bank of America Global Financial Stress Index (GFSI) Liquidity Risk, which measures funding stress in the global financial system through spread-based relationships in rates, credit, and currencies; VIX and MOVE, the option-implied volatility measures for the U.S. stock and bond market, respectively; and the news-based measure of economic policy uncertainty from Baker, Bloom, and Davis (2016).

Panel C of Table 7 reports the (percentage) annualized performance of our strategy during high (H) and low (L) friction periods, defined based on the sample median of the limits of arbitrage proxy used. The analysis shows that front-running strategies perform better during high friction periods—characterized by elevated volatility, low liquidity, and heightened uncertainty—than low friction periods. This indicates that the profitability of our strategies increases when sophisticated investors and liquidity providers face greater constraints.

6 Discussion

Implications? Given the economic significance of rebalancing costs, institutional investors should consider reassessing their rebalancing policies. First, the use of deterministic or systematic policies can lead to price impact. These pressures will likely intensify in the future as TDFs and other balanced funds come into broader use. Much of the institutional industry relies on Calendar or Threshold policies. This increases the likelihood that these investors will trade in the same direction at the same time and induces a mechanical predictability in returns that encourages front-running. Second, changing the design of benchmarks, such as end-of-month rebalancing, could have a major effect on rebalancing strategies. Those portfolio managers that tend to minimize tracking risk would immediately evolve their strategies to adjust to new benchmarks. Third, institutional investors should be wary of hedge funds and other investors that may anticipate their actions and attempt to profit from them. We simu-

[23] Garcia, Mantilla-García, and Martellini (2014) show that their measure is a consistent and asymptotically efficient estimator for aggregate idiosyncratic volatility. Furthermore, they find that the correlation between cross-sectional volatility and the model-based ivol as computed in Ang, Hodrick, Xing, and Zhang (2006) is above 99%.

late trading strategies in liquid futures that have yielded consistent and relatively large alpha over the last two decades; in addition, our own conversations with market participants have confirmed that hedge funds do deploy front-running strategies. Fourth, because rebalancing costs are borne by balanced funds, they remain hidden from individual investors who tend to focus on a fund's explicit fees. Yet these costs represent a clear drag on performance—one that can be mitigated, as discussed next.

Can these rebalancing costs be reduced? We are the first to document the market-wide economic implications of rebalancing strategies for equity/bond portfolios—the core allocation of institutional investors. This raises the question of whether more efficient rebalancing approaches exist beyond the commonly used Threshold and Calendar strategies. Answering this question requires theoretical, empirical, and institutional considerations that are beyond the scope of this paper. All else being equal, one could envision a cost-mitigating strategy that avoids pre-scheduled rebalancing—for example, by introducing a random component to trade execution (e.g., Huddart, Hughes, and Levine, 2001). Yet, rebalancing is a coordination exercise. The actions of individual rebalancers could impact the decisions of other rebalancers, while the actions of liquidity providers and other sophisticated investors could further influence strategy designs.[24] Furthermore, agency problems should not be ignored, as the design of benchmarks appears to play an important role in informing rebalancing decisions.

Investors can also attempt to mitigate rebalancing costs through more active portfolio management. For instance, Blume and Edelen (2004) show that index funds can substantially enhance their performance by trading in advance of index additions and deletions. In a similar spirit, balanced funds could potentially profit by anticipating trades driven by rebalancing pressures. This is also consistent with insights shared during the pension fund roundtable discussion mentioned earlier.

What do investors gain from rebalancing? While we have documented rebalancing's costs, it also has important benefits. First, rebalancing helps investors maintain diversifica-

[24] E.g., Bessembinder, Carrion, Tuttle, and Venkataraman (2016) show that traders competition may reduce the price impact of predictable trades.

tion across asset classes, keeping portfolio risk aligned with their risk tolerance. Without it, a balanced 60/40 equity/bond portfolio would drift to 80/20 within about 10 years and eventually become 100% equity. Second, rebalancing is a valuable tool for institutional investors to better manage cash flows. For example, cash-flow-negative DB funds require frequent rebalancing to ensure they can pay member benefits at the beginning of each month. Conversely, TDFs may rebalance to better manage cash inflows. Lastly, a utility analysis we conducted demonstrates that both Threshold and Calendar rebalancing generate utility gains for a mean-variance investor when benchmarked against a buy-and-hold portfolio. For a level of risk aversion of 3, Threshold rebalancing generates extra utility gains of about 18 bps, while Calendar rebalancing generates approximately 10 bps.[25] Hence, investors benefit from rebalancing in general. However, our paper suggests that a particular type of rebalancing—a mechanical rebalancing—induces potentially unnecessary costs, thereby harming investors.

7 Conclusion

We present the first evidence of aggregate price effects for U.S. stocks and bonds driven by portfolio rebalancing activity. Using daily U.S. data, we construct two return-based proxies for rebalancing behavior. When stocks outperform bonds, resulting in an overweight allocation to stocks within a balanced portfolio, rebalancers sell stocks and purchase bonds to restore target portfolio weights. On average, these rebalancing pressures lead equity returns to fall by more than 16 bps and bond returns to increase by approximately 4 bps the following day. The opposite effect occurs when bonds outperform stocks. This cross-asset return predictability cannot be explained by past returns, volatility measures, macroeconomic conditions, or sentiment indicators. Moreover, rebalancing pressures largely revert in less than two weeks, suggesting that rebalancing trades carry limited informational content about asset fundamentals.

[25] We simulate three portfolios with the same data and sample period (1997–2023) used in our main empirical analysis: a buy-and-hold portfolio with an initial equity allocation of 60% that does not rebalance; a portfolio that rebalances when the equity allocation breaches a 2.5% threshold; and a portfolio that rebalances at month-end. We compute the average utility associated with these portfolios as: $\bar{U} = \bar{r} - 0.5\gamma\bar{\sigma}^2$, where γ represents the level of risk aversion, and $\bar{r}$ and $\bar{\sigma}^2$ represent the sample average returns and variance of the portfolio, respectively. Finally, we compute the difference in utility between each rebalancing strategy and the no-rebalancing portfolio.

We provide several analyses to validate the economic interpretation of our rebalancing signals. We document (i) seasonal patterns consistent with a rebalancing interpretation, (ii) predictability in both equity and bond markets, (iii) increased predictability over the past two decades, reflecting the growth in the number of funds engaging in rebalancing, (iv) predictability across equity indices, (v) international evidence, and (vi) CFTC futures trades that align with rebalancing mechanisms.

Importantly, our results suggest that current rebalancing policies cost investors billions of dollars every year. We estimate these costs to be approximately \$16 billion per year, or \$200 per U.S. household. As rebalancing pressures are expected to grow in the future with the expansion of TDFs and other balanced funds, these costs could increase substantially.

Furthermore, mechanical rebalancing offers certain investors the opportunity to front-run the predictable trades of large funds—a fact that, based on our conversations with several large institutional investors, is well-known to both pension funds and hedge funds. To explore the potential economic value of these front-running strategies, we construct a managed portfolio that replicates the trades of a front-runner exploiting rebalancing signals. This portfolio generates substantial positive alpha and achieves a Sharpe ratio greater than 1. Our analysis indicates that this strategy performs particularly well during periods of heightened volatility, when sophisticated investors face greater constraints, consistent with theories on the limits to arbitrage.

Overall, our findings highlight the importance of studying institutional investor trading to better understand asset price dynamics. Institutional investors operate under specific investment horizons, face unique constraints, and respond to distinct incentive structures, all of which influence how and when they trade (Haddad and Muir, 2025). Recognizing these features is essential for capturing the broader impact of their behavior on market outcomes.

We conclude by emphasizing that, while the objective of this paper is to quantify the economic costs associated with mechanical rebalancing, rebalancing remains a fundamental tool for ensuring portfolio diversification, managing liquidity, and generating utility gains for mean-variance investors compared to a non-rebalanced portfolio. Therefore, designing more effective rebalancing policies that preserve the benefits of rebalancing while minimizing its costs seems like a priority for future researchers and investors.

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Internet Appendix

A Data Sources

We obtain daily prices for the E-mini S&P 500 Index and the 10-year Treasury note from Bloomberg. We select the two futures contracts with the shortest maturity (tickers: ES1 Index and ES2 Index for the E-mini S&P 500 and TY1 Comdty and TY2 Comdty for the 10-year Treasury note). Based on these contracts' roll schedule, we then compute the daily returns of the front-month futures contract. The E-mini S&P 500 contracts expire on the third Friday of March, June, September, and December. The last trading day for the Treasury note futures is the seventh business day preceding the last business day of the delivery month. Our series and empirical analyses start September 10, 1997, when the first E-mini S&P 500 price data is available.

From Bloomberg we also obtain daily index data for the S&P 500 Total Return Index, the Bloomberg U.S. Aggregate Bond Total Return Index, and international equities (MSCI ACWI ex USA Net Total Return Index (USD)), as well as implied volatility measures for the equity market (VIX Index) and the Treasury bond market (MOVE Index).

B Technical Details on the Construction of Rebalancing Signals

Consider a balanced equity/bond portfolio, where equity consists of S&P500 futures and bond consists of 10-year U.S. Treasury note futures. This portfolio is rebalanced following approach j, where $j = T, C$, indicating Threshold and Calendar, respectively. We denote by w_t^j the proportion of the portfolio invested in equity at time t and by $(1 - w_t^j)$ the proportion invested in bonds. Target weights follow a common 60/40 allocation. Thus, at time $t = 0$, 60% of the portfolio is invested in S&P500 and 40% in the 10-year U.S. Treasury note, i.e., $w_t^j = 60\%$.

At any time t, weights are updated as a function of past weights, equity returns, and bond returns. Specifically, after one period we have:

$$w_{t+1}^j(w_t^j; R_{t+1}^{SP}; R_{t+1}^{10Y}) = \frac{w_t^j(1 + R_{t+1}^{SP})}{w_t^j(1 + R_{t+1}^{SP}) + (1 - w_t^j)(1 + R_{t+1}^{10Y})}$$

where R_{t+1}^{SP} and R_{t+1}^{10Y} indicate the returns earned by the S&P500 and the 10-year Treasury note, respectively.

In the absence of rebalancing, no trading takes place and the following holds true:

$$w_{t+1}^{j} = w_{t+1}^{j}(w_t^j; R_{t+1}^{SP}; R_{t+1}^{10Y})$$

Weights are allowed to drift until a portfolio is rebalanced and portfolio weights are brought back to their targets.

According to the Threshold approach, portfolio rebalancing takes place when portfolio weights exceed their targets by more than δ:

$$w_{t+1}^{T} = \begin{cases} 60\% & \text{if } \left| w_t^T - 60\% \right| \geq \delta, \\ w_{t+1}^{T}(w_t^T; R_{t+1}^{SP}; R_{t+1}^{10Y}) & \text{otherwise.} \end{cases}$$

According to the Calendar approach, rebalancing simply takes place on the last business day of every month:

$$w_{t+1}^{C} = \begin{cases} 60\% & \text{if } t \text{ is the last business day of the month,} \\ w_{t+1}^{C}(w_t^C; R_{t+1}^{SP}; R_{t+1}^{10Y}) & \text{otherwise.} \end{cases}$$

Lastly, we can define the rebalancing signals as weight deviations from target. Specifically, the Threshold signal is defined as:

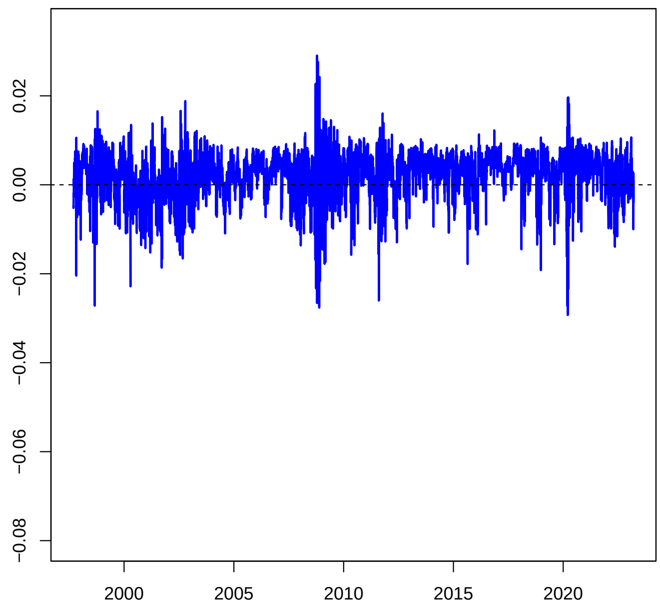
$$\text{Threshold signal}_t^{\delta} = w_{t+1}^{T}(w_t^T; R_{t+1}^{SP}; R_{t+1}^{10Y}) - 60\%$$

where δ denotes the threshold adopted to rebalance the portfolio. The Calendar signal is defined as:

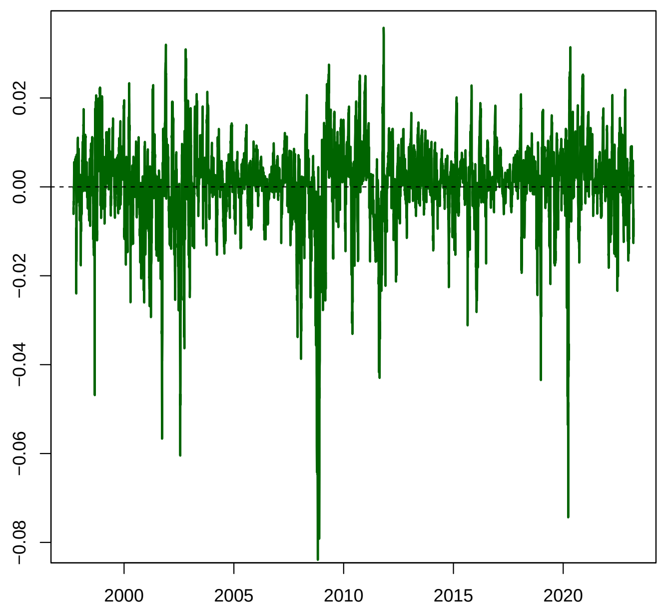
$$\text{Calendar signal}_t = w_{t+1}^{C}(w_t^C; R_{t+1}^{SP}; R_{t+1}^{10Y}) - 60\%$$

where the portfolio is rebalanced on a monthly cadence.

C Summary Statistics



(a) Threshold Signal



(b) Calendar Signal

Figure C.1: Rebalancing Signals. This figure shows the two return-based rebalancing measures constructed as described in Section 2.2. Daily observations. The sample period is 1997-09-10 to 2023-03-17.

Table C.1: Correlation Matrix for Different Predictors

This table reports the correlation matrix for the signals used in our main predictive regressions. Threshold and Calendar signals are constructed as described in Section 2.2. Momentum is computed by averaging the sign of 11 to 20, and 21, 42, 63, 126, and 252 trailing equity returns in excess of the 10-year Treasury note. Controls include: VIX is the CBOE equity option-implied volatility index; MOVE is the U.S. bond market option-implied volatility index; Econ Uncertainty is the news-based measure of economic policy uncertainty from Baker, Bloom, and Davis (2016); Econ Activity is the Aruoba, Diebold, and Scotti (2009) real-time business conditions index; Sentiment is the daily news-based sentiment index constructed in Shapiro, Sudhof, and Wilson (2022). Daily observations. The sample period is 1997-09-10 to 2023-03-17.

	Threshold	Calendar	Momentum	VIX	MOVE	Econ Uncertainty	Econ Activity	Sentiment
Threshold	1							
Calendar	0.602	1						
Momentum	0.672	0.676	1					
VIX	-0.348	-0.408	-0.496	1				
MOVE	-0.249	-0.243	-0.384	0.653	1			
EPU	-0.066	-0.132	-0.152	0.448	0.112	1		
ADS	0.069	0.156	0.194	-0.323	-0.192	-0.280	1	
NewsSentiment	0.094	0.134	0.255	-0.546	-0.318	-0.563	0.202	1

D Additional Results

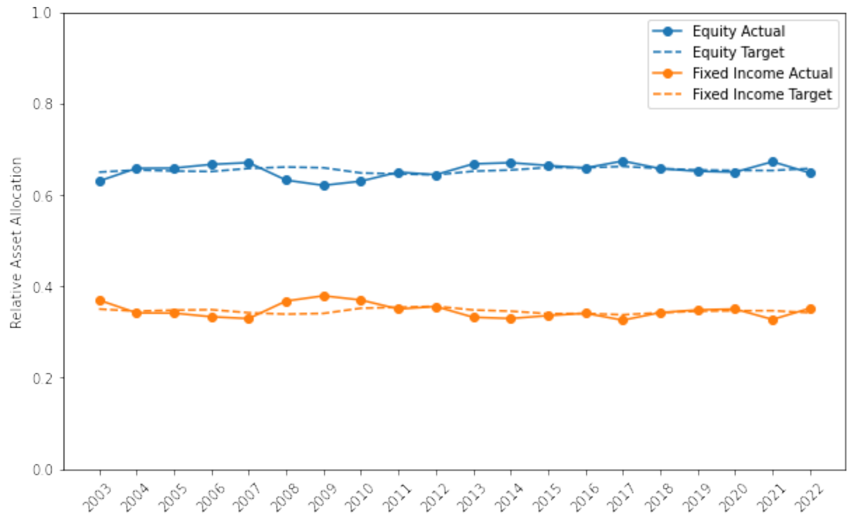
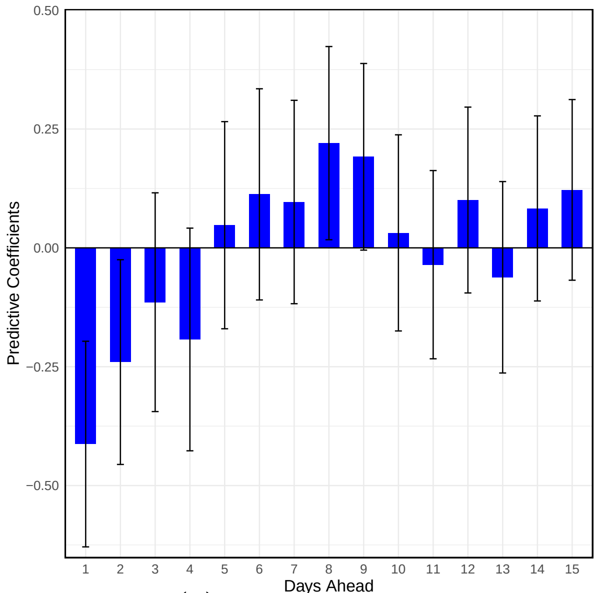
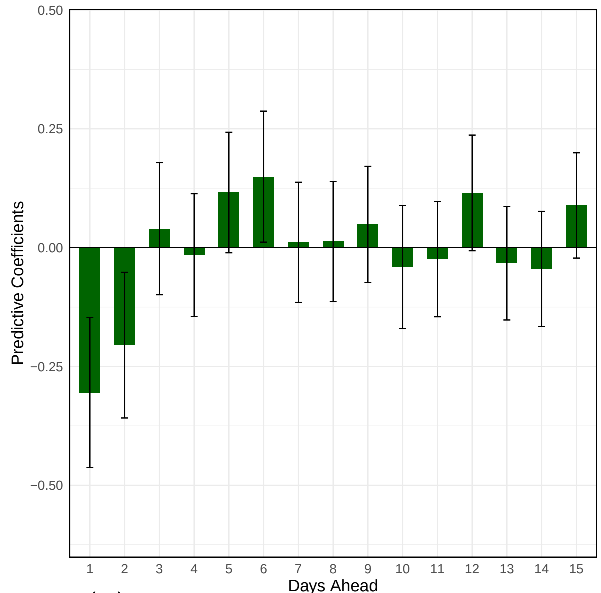


Figure D.1: U.S. Defined Benefit Pension Funds' Asset Allocation Over Time. This figure shows the average relative allocations by fiscal year across U.S. defined benefit pension funds produced by the Center for Retirement Research at the Boston College and available at Public Plans Data. Equity allocations include investments in domestic and international public equity markets. Fixed income includes cash allocations in addition to bonds. Relative allocations are computed by normalizing portfolio weights for the sum of equity and fixed income allocations. As of the end of fiscal year 2022, public equity and fixed income allocations amounted to about 64% of total portfolio weights. Annual observations. The sample period is 2003 to 2022.



(a) Threshold Signal



(b) Calendar Signal $*$Week4 Dummy

Figure D.2: Rebalancing and Horizon of Cross-Asset Return Predictability: Non-Overlapping Returns. This figure shows coefficient estimates and 95% heteroskedasticity-consistent confidence intervals for threshold and calendar signals for the multivariate predictive regression (4). We predict non-overlapping returns n days ahead, with $n = 1 : 15$. Daily observations. The sample period is 1997-09-10 to 2023-03-17.

Table D.1: Explaining Rebalancing Signals with Trailing Returns

This table reports the estimates from regressing Threshold and Calendar on the trailing returns of S&P 500 futures in excess of the trailing returns of 10-year Treasury note futures. Threshold and Calendar signals are constructed as described in Section 2.2. The horizon of the trailing returns is indicated in the table. Values in parentheses are heteroskedasticity- and autocorrelation-robust standard errors. Constant estimates are not tabulated. Daily observations. The sample period is 1997-09-10 to 2023-03-17.

	Threshold Signal	Calendar Signal
1-Day Returns	0.1466***	0.0023
	(0.0100)	(0.0030)
2-Day Returns	0.0278***	0.0041
	(0.0030)	(0.0050)
3-Day Returns	0.0134***	0.0024
	(0.0040)	(0.0040)
4-Day Returns	0.0129***	−0.0027
	(0.0020)	(0.0070)
5-Day Returns	0.0177***	0.0298***
	(0.0020)	(0.0070)
10-Day Returns	0.0145***	0.0611***
	(0.0020)	(0.0060)
15-Day Returns	0.0051***	0.0607***
	(0.0020)	(0.0050)
21-Day Returns	0.0061**	0.0502***
	(0.0020)	(0.0070)
42-Day Returns	0.0025	0.0133*
	(0.0020)	(0.0070)
63-Day Returns	0.0001	0.0024
	(0.0010)	(0.0050)
126-Day Returns	0.0000	0.0010
	(0.0010)	(0.0030)
252-Day Returns	0.0020***	0.0014
	(0.0010)	(0.0020)
Adjusted R^2	0.8020	0.7194

Table D.2: Cross-Asset Predictive Regressions Using Index Returns

This table reports estimates for the multivariate predictive regression (4). *Ret* is the difference between S&P 500 Index and Bloomberg Aggregate Bond Index returns. Threshold and Calendar signals are constructed as described in Section 2.2. Momentum is computed by averaging the sign of 11 to 20, and 21, 42, 63, 126, and 252 trailing equity returns in excess of the 10-year Treasury note. VIX is the CBOE equity option-implied volatility index (divided by 100); MOVE is the U.S. bond market option-implied volatility index (divided by 100); Econ Uncertainty is the news-based measure of economic policy uncertainty from Baker, Bloom, and Davis (2016); Econ Activity is the Aruoba, Diebold, and Scotti (2009) real-time business conditions index; Sentiment is the daily news-based sentiment index constructed in Shapiro, Sudhof, and Wilson (2022). Values in parentheses are heteroskedasticity-consistent standard errors. Daily observations. The sample period is 1997-09-10 to 2023-03-17.

			Ret_{t+1}		
	(1)	(2)	(3)	(4)	(5)
Threshold	-0.3970^{***}	-0.4048^{***}	-0.4137^{***}	-0.4131^{***}	-0.4039^{***}
	(0.1199)	(0.1203)	(0.1163)	(0.1182)	(0.1195)
Calendar	0.0570	0.0743	0.0597	0.0560	0.0734
	(0.0740)	(0.0715)	(0.0729)	(0.0744)	(0.0716)
week4	0.0006	0.0006	0.0006	0.0006	0.0006
	(0.0005)	(0.0004)	(0.0005)	(0.0005)	(0.0005)
Calendar ∗week4	-0.3189^{***}	-0.3199^{***}	-0.3187^{***}	-0.3194^{***}	-0.3194^{***}
	(0.0866)	(0.0863)	(0.0863)	(0.0863)	(0.0864)
Momemtum	0.0021^{***}	0.0023^{***}	0.0023^{***}	0.0023^{***}	0.0023^{***}
	(0.0006)	(0.0007)	(0.0007)	(0.0007)	(0.0007)
Ret	−0.0299	−0.0255	−0.0289	−0.0279	−0.0265
	(0.0311)	(0.0311)	(0.0306)	(0.0308)	(0.0309)
VIX		0.0117^{**}			0.0108
		(0.0060)			(0.0070)
MOVE		-0.0023^{**}			-0.0021^{*}
		(0.0012)			(0.0012)
EPU			0.0007^{**}		0.0003
			(0.0003)		(0.0004)
ADS			0.0000		0.0001
			(0.0002)		(0.0002)
Sentiment				−0.0018	0.0003
				(0.0013)	(0.0013)
Observations	6,223	6,223	6,223	6,223	6,223
Adjusted R^2	0.0238	0.0258	0.0247	0.0242	0.0255

Table D.3: Cross-Asset Predictive Regressions: Dissecting Momentum

This table reports estimates for the multivariate predictive regression (4). *Ret* is the difference between S&P 500 and 10-year Treasury note futures returns. Threshold and Calendar signals are constructed as described in Section 2.2. Momentum fast is calculated as the average of the signs of trailing 1 to 10 daily excess returns; momentum medium averages the signs of 11 to 20 daily excess returns; momentum slow averages the signs of 21, 42, 63, 126, and 252 daily excess returns. VIX is the CBOE equity option-implied volatility index (divided by 100); MOVE is the U.S. bond market option-implied volatility index (divided by 100); Econ Uncertainty is the news-based measure of economic policy uncertainty from Baker, Bloom, and Davis (2016); Econ Activity is the Aruoba, Diebold, and Scotti (2009) real-time business conditions index; Sentiment is the daily news-based sentiment index constructed in Shapiro, Sudhof, and Wilson (2022). Values in parentheses are heteroskedasticity-consistent standard errors. Constant estimates are not tabulated. Daily observations. The sample period is 1997-09-10 to 2023-03-17.

			Ret_{t+1}		
	(1)	(2)	(3)	(4)	(5)
Threshold	-0.4624^{***}	-0.4695^{***}	-0.4704^{***}	-0.4732^{***}	-0.4686^{***}
	(0.1185)	(0.1196)	(0.1170)	(0.1182)	(0.1193)
Calendar	0.0498	0.0657	0.0529	0.0514	0.0639
	(0.0742)	(0.0697)	(0.0724)	(0.0737)	(0.0696)
week4	0.0002	0.0002	0.0002	0.0002	0.0002
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Calendar $*$week4	-0.3011^{***}	-0.3023^{***}	-0.3012^{***}	-0.3021^{***}	-0.3019^{***}
	(0.0808)	(0.0807)	(0.0806)	(0.0806)	(0.0806)
Momemtum fast	0.0005	0.0005	0.0005	0.0005	0.0005
	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)
Momemtum medium	0.0012^{***}	0.0011^{***}	0.0011^{***}	0.0011^{***}	0.0011^{***}
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Momemtum slow	0.0010^{**}	0.0012^{**}	0.0012^{***}	0.0013^{***}	0.0012^{**}
	(0.0004)	(0.0005)	(0.0004)	(0.0004)	(0.0005)
Ret	-0.0135	-0.0098	-0.0134	-0.0121	-0.0104
	(0.0281)	(0.0281)	(0.0277)	(0.0279)	(0.0280)
VIX		0.0095^{*}			0.0088
		(0.0053)			(0.0062)
MOVE		-0.0022^{**}			-0.0021^{*}
		(0.0011)			(0.0011)
EPU			0.0005^{*}		0.0002
			(0.0003)		(0.0004)
ADS			0.0001		0.0001
			(0.0002)		(0.0002)
Sentiment				-0.0016	-0.0002
				(0.0012)	(0.0013)
Observations	6,223	6,223	6,223	6,223	6,223
Adjusted R^2	0.0233	0.0247	0.0237	0.0235	0.0244

Table D.4: Cross-Asset Predictive Regressions Using Changes

This table reports estimates for the multivariate predictive regression (4). *Ret* is the difference between S&P 500 and 10-year Treasury note futures returns. Threshold and Calendar signals are constructed as described in Section 2.2. Momentum is computed by averaging the sign of 11 to 20, and 21, 42, 63, 126, and 252 trailing equity returns in excess of the 10-year Treasury note. All control variables are expressed in changes. Controls include: VIX is the CBOE equity option-implied volatility index (divided by 100); MOVE is the U.S. bond market option-implied volatility index (divided by 100); Econ Uncertainty is the news-based measure of economic policy uncertainty from Baker, Bloom, and Davis (2016); Econ Activity is the Aruoba, Diebold, and Scotti (2009) real-time business conditions index; Sentiment is the daily news-based sentiment index constructed in Shapiro, Sudhof, and Wilson (2022). Values in parentheses are heteroskedasticity-consistent standard errors. Daily observations. The sample period is 1997-09-10 to 2023-03-17.

	Ret_{t+1}			
	(1)	(2)	(3)	(4)
Threshold	-0.4039^{***}	-0.4186^{***}	-0.4114^{***}	-0.4082^{***}
	(0.1103)	(0.1096)	(0.1107)	(0.1095)
Calendar	0.0583	0.0596	0.0583	0.0600
	(0.0700)	(0.0682)	(0.0700)	(0.0679)
week4	0.0001	0.0002	0.0002	0.0001
	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Calendar ∗week4	-0.3057^{***}	-0.3044^{***}	-0.3048^{***}	-0.3052^{***}
	(0.0809)	(0.0803)	(0.0804)	(0.0808)
Momemtum	0.0022^{***}	0.0023^{***}	0.0023^{***}	0.0022^{***}
	(0.0006)	(0.0006)	(0.0006)	(0.0006)
Ret	0.0205	−0.0127	−0.0150	0.0228
	(0.0470)	(0.0282)	(0.0286)	(0.0470)
ΔVIX	0.0309			0.0314
	(0.0372)			(0.0381)
ΔMOVE	0.0122^{*}			0.0124^{*}
	(0.0070)			(0.0070)
ΔEPU		−0.0005		−0.0005
		(0.0004)		(0.0004)
ΔADS		−0.0010		−0.0010
		(0.0039)		(0.0040)
ΔSentiment			−0.0025	−0.0030
			(0.0116)	(0.0114)
Observations	6,223	6,223	6,223	6,223
Adjusted R^2	0.0252	0.0235	0.0231	0.0254

Table D.5: Cross-Asset Predictive Regressions: Alternative Controls

This table reports estimates for the multivariate predictive regression (4). *Ret* is the difference between S&P 500 and 10-year Treasury note futures returns. Threshold and Calendar signals are constructed as described in Section 2.2. Momentum is computed by averaging the sign of 11 to 20, and 21, 42, 63, 126, and 252 trailing equity returns in excess of the 10-year Treasury note. VIX is the CBOE equity option-implied volatility index (divided by 100); MOVE is the U.S. bond market option-implied volatility index (divided by 100); ra^{BEX} and unc^{BEX} are, respectively, the risk aversion and economic uncertainty indexes costructed in Bekaert, Engstrom, and Xu (2022); FEARS is the Financial and Economic Attitudes Revealed by Search index constructed in Da, Engelberg, and Gao (2015). Values in parentheses are heteroskedasticity-consistent standard errors. Daily observations.

	Ret_{t+1}		
	(1)	(2)	(3)
Threshold	-0.4669^{***}	-0.4514^{***}	-0.4523^{***}
	(0.1071)	(0.1638)	(0.1592)
Calendar	0.1136^{*}	0.0941	0.2065^{**}
	(0.0624)	(0.1120)	(0.0946)
week4	0.0001	0.0003	0.0001
	(0.0004)	(0.0006)	(0.0006)
Calendar $*$week4	-0.2986^{***}	-0.3971^{***}	-0.3596^{***}
	(0.0801)	(0.1303)	(0.1325)
Momemtum	0.0023^{***}	0.0022^{**}	0.0006
	(0.0006)	(0.0010)	(0.0009)
Ret	0.0028	0.0022	0.0204
	(0.0281)	(0.0378)	(0.0389)
ra^{BEX}	0.0012		-0.0069
	(0.0008)		(0.0184)
unc^{BEX}	-0.0012		-0.0041^{**}
	(0.0011)		(0.0020)
FEARS		0.0009	0.0020
		(0.0007)	(0.0016)
VIX			-0.0014
			(0.0012)
MOVE			0.0007
			(0.0007)
Observations	6,121	3,147	3,122
Adjusted R^2	0.0314	0.0299	0.0454

Table D.6: Cross-Asset Predictive Regressions: Different Portfolio Weights

This table reports estimates for the multivariate predictive regression (4). *Ret* is the difference between S&P 500 and 10-year Treasury note futures returns. Threshold and Calendar signals are constructed as described in Section 2.2. Momentum is computed by averaging the sign of 11 to 20, and 21, 42, 63, 126, and 252 trailing equity returns in excess of the 10-year Treasury note. Values in parentheses are heteroskedasticity-consistent standard errors. Daily observations. The sample period is 1997-09-10 to 2023-03-17.

	Ret_{t+1}
Threshold	-0.8008***
	(0.179)
Calendar	0.1750
	(0.130)
week4	0.0000
	(0.000)
Calendar $*$week4	-0.6061***
	(0.162)
Momentum	0.0012***
	(0.000)
Observations	6,223
Adjusted R^2	0.0220

Table D.7: Cross-Asset Predictive Regressions: The Role of Reversal

This table reports estimates for the multivariate predictive regression (4). *Ret* is the difference between S&P 500 and 10-year Treasury note futures returns. Threshold and Calendar signals are constructed as described in Section 2.2. Momentum is computed by averaging the sign of 11 to 20, and 21, 42, 63, 126, and 252 trailing equity returns in excess of the 10-year Treasury note. Short-Term Reversal are the trailing 5−day returns; Long-Term Reversal are the trailing 5−year (i.e., 1260 days) returns with the last year skipped. Values in parentheses are heteroskedasticity-consistent standard errors. Constant estimates are not tabulated. Daily observations. The sample period is 1997-09-10 to 2023-03-17.

			Ret_{t+1}		
	(1)	(2)	(3)	(4)	(5)
Threshold		-0.4063^{***}		-0.5448^{***}	-0.5298^{***}
		(0.1231)		(0.1112)	(0.1501)
Calendar		0.0740		0.0582	0.0627
		(0.0703)		(0.0834)	(0.0837)
week4		0.0001		0.0001	0.0001
		(0.0004)		(0.0005)	(0.0005)
Calendar ∗week4		-0.3104^{***}		-0.2817^{***}	-0.2835^{***}
		(0.0812)		(0.0968)	(0.0982)
Momemtum		0.0023^{***}		0.0025^{***}	0.0025^{***}
		(0.0006)		(0.0007)	(0.0007)
Short-Term Reversal	-0.0366^{***}	−0.0140			−0.0041
	(0.0136)	(0.0195)			(0.0237)
Long-Term Reversal			−0.0003	−0.0001	−0.0001
			(0.0004)	(0.0004)	(0.0004)
Observations	6,470	6,223	5,215	5,215	5,215
Adjusted R^2	0.0054	0.0235	−0.0001	0.0258	0.0256

Table D.8: Cross-Asset Predictive Regressions: End-of-Month Reversal

This table reports estimates for the multivariate predictive regression (4). The dependent variable is the difference between S&P 500 futures excess returns and 10-year Treasury note futures excess returns (Columns (1) to (3)), S&P 500 futures excess returns in Column (4), or 10-year Treasury note futures excess returns in Column (5). EoM Rev is constructed as in Graziani (2024), defined as the realized return between the closing price on the fourth Friday of the month and the monthly closing price of the S&P 500 *index*. Threshold and Calendar signals are constructed as described in Section 2.2. Momentum is computed by averaging the sign of 11 to 20, and 21, 42, 63, 126, and 252 trailing equity returns in excess of the 10-year Treasury note. VIX is the CBOE equity option-implied volatility index (divided by 100); MOVE is the U.S. bond market option-implied volatility index (divided by 100); Econ Uncertainty is the news-based measure of economic policy uncertainty from Baker, Bloom, and Davis (2016); Econ Activity is the Aruoba, Diebold, and Scotti (2009) real-time business conditions index; Sentiment is the daily news-based sentiment index constructed in Shapiro, Sudhof, and Wilson (2022). Values in parentheses are heteroskedasticity-consistent standard errors. Daily observations. The sample period is 1997-09-10 to 2023-03-17.

	$\text{Ret}^{S\&P500}_{t+1}$ - Ret^{10-y}_{t+1}			$\text{Ret}^{S\&P500}_{t+1}$	Ret^{10-y}_{t+1}
	(1)	(2)	(3)	(4)	(5)
EoM Rev	−0.0173		−0.0234	−0.0194	0.0040
	(0.0154)		(0.0156)	(0.0146)	(0.0031)
Threshold		−0.4165***	−0.4135***	−0.3228***	0.0907***
		(0.1111)	(0.1113)	(0.1024)	(0.0245)
Calendar		0.0570	0.0481	0.0354	−0.0128
		(0.0706)	(0.0719)	(0.0674)	(0.0115)
week4		0.0001	0.0001	0.0005	0.0004***
		(0.0004)	(0.0004)	(0.0004)	(0.0001)
Calendar ∗week4		−0.3055***	−0.3056***	−0.2687***	0.0369***
		(0.0809)	(0.0809)	(0.0758)	(0.0126)
Momemtum		0.0023***	0.0024***	0.0018***	−0.0005***
		(0.0006)	(0.0006)	(0.0006)	(0.0001)
Ret		−0.0142	−0.0142	−0.0208	−0.0066
		(0.0288)	(0.0288)	(0.0261)	(0.0061)
Observations	6,170	6,170	6,170	6,170	6,170
Adjusted R^2	0.0004	0.0234	0.0241	0.0233	0.0079

Table D.9: Dissecting Cross-Asset Return Predictability

This table reports estimates for the multivariate predictive regression (4). *Ret* is the S&P 500 futures excess returns in Panel A; Panel B reports results for 10-year Treasury note futures excess returns. Values in parentheses are heteroskedasticity-consistent standard errors. Constant estimates are not tabulated. Daily observations. The sample period is 1997-09-10 to 2023-03-17.

Panel A: S&P 500 in excess of cash

			Ret_{t+1}		
	(1)	(2)	(3)	(4)	(5)
Threshold	−0.3225***	−0.3295***	−0.3351***	−0.3370***	−0.3301***
	(0.1015)	(0.1017)	(0.0976)	(0.0998)	(0.1005)
Calendar	0.0435	0.0578	0.0455	0.0426	0.0561
	(0.0655)	(0.0633)	(0.0645)	(0.0658)	(0.0634)
week4	0.0005	0.0005	0.0005	0.0005	0.0005
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Calendar ∗week4	−0.2672***	−0.2680***	−0.2669***	−0.2676***	−0.2676***
	(0.0753)	(0.0752)	(0.0751)	(0.0751)	(0.0753)
Momemtum	0.0017***	0.0019***	0.0018***	0.0019***	0.0018***
	(0.0005)	(0.0006)	(0.0006)	(0.0006)	(0.0006)
Ret	−0.0211	−0.0172	−0.0205	−0.0193	−0.0179
	(0.0259)	(0.0258)	(0.0254)	(0.0256)	(0.0256)
VIX		0.0096**			0.0085
		(0.0049)			(0.0056)
MOVE		−0.0021**			−0.0019*
		(0.0010)			(0.0010)
EPU			0.0006**		0.0002
			(0.0003)		(0.0003)
ADS			0.0001		0.0001
			(0.0002)		(0.0002)
Sentiment				−0.0016	−0.0001
				(0.0011)	(0.0011)
Observations	6,223	6,223	6,223	6,223	6,223
Adjusted R^2	0.0225	0.0244	0.0233	0.0229	0.0242

Panel B: 10-year Treasury note in excess of cash

	Ret_{t+1}				
	(1)	(2)	(3)	(4)	(5)
Threshold	0.0902***	0.0905***	0.0889***	0.0904***	0.0901***
	(0.0244)	(0.0244)	(0.0242)	(0.0243)	(0.0248)
Calendar	−0.0145	−0.0147	−0.0143	−0.0145	−0.0145
	(0.0113)	(0.0111)	(0.0112)	(0.0114)	(0.0112)
week4	0.0004***	0.0004***	0.0004***	0.0004***	0.0004***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Calendar ∗week4	0.0376***	0.0376***	0.0376***	0.0376***	0.0377***
	(0.0126)	(0.0126)	(0.0126)	(0.0125)	(0.0126)
Momemtum	−0.0005***	−0.0005***	−0.0005***	−0.0005***	−0.0005***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Ret	−0.0064	−0.0065	−0.0063	−0.0064	−0.0067
	(0.0061)	(0.0061)	(0.0061)	(0.0061)	(0.0061)
VIX		−0.0000			−0.0003
		(0.0010)			(0.0013)
MOVE		0.0001			0.0002
		(0.0003)			(0.0003)
EPU			0.0000		0.0001
			(0.0001)		(0.0001)
ADS			−0.0000		0.0000
			(0.0000)		(0.0000)
Sentiment				0.0000	0.0002
				(0.0003)	(0.0003)
Observations	6,223	6,223	6,223	6,223	6,223
Adjusted R^2	0.0078	0.0075	0.0076	0.0076	0.0072

Table D.10: Cross-Asset Predictive Regressions: International Equity

This table reports estimates for the multivariate predictive regression (4) for international equity returns. *Ret* is the difference between MSCI ACWI ex U.S. Index and the U.S. 3-month Treasury bill. Threshold and Calendar signals are constructed as described in Section 2.2. Momentum is computed by averaging the sign of 11 to 20, and 21, 42, 63, 126, and 252 trailing equity returns in excess of the 10-year Treasury note. VIX is the CBOE equity option-implied volatility index (divided by 100); MOVE is the U.S. bond market option-implied volatility index (divided by 100); Econ Uncertainty is the news-based measure of economic policy uncertainty from Baker, Bloom, and Davis (2016); Econ Activity is the Aruoba, Diebold, and Scotti (2009) real-time business conditions index; Sentiment is the daily news-based sentiment index constructed in Shapiro, Sudhof, and Wilson (2022). Values in parentheses are heteroskedasticity-consistent standard errors. Constant estimates are not tabulated. Daily observations. The sample period is 1997-09-10 to 2023-03-17.

	Ret_{t+1}				
	(1)	(2)	(3)	(4)	(5)
Threshold	-0.2711^{***}	-0.2764^{***}	-0.2727^{***}	-0.2755^{***}	-0.2739^{***}
	(0.0870)	(0.0857)	(0.0870)	(0.0868)	(0.0865)
Calendar	0.0809^{*}	0.0856^{**}	0.0811^{*}	0.0801^{*}	0.0821^{*}
	(0.0453)	(0.0427)	(0.0447)	(0.0457)	(0.0433)
week4	0.0007^{**}	0.0007^{**}	0.0007^{**}	0.0007^{**}	0.0007^{**}
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Calendar ∗week4	-0.2062^{***}	-0.2059^{***}	-0.2060^{***}	-0.2065^{***}	-0.2059^{***}
	(0.0535)	(0.0539)	(0.0536)	(0.0535)	(0.0539)
Momemtum	0.0004	0.0003	0.0005	0.0005	0.0003
	(0.0003)	(0.0004)	(0.0003)	(0.0003)	(0.0004)
2-day Trailing Returns	0.0708^{***}	0.0726^{***}	0.0702^{***}	0.0709^{***}	0.0707^{***}
	(0.0145)	(0.0141)	(0.0145)	(0.0145)	(0.0143)
VIX		0.0036			0.0013
		(0.0043)			(0.0047)
MOVE		-0.0015^{*}			-0.0011
		(0.0008)			(0.0009)
Econ Uncertainty			0.0004^{**}		0.0004
			(0.0002)		(0.0003)
Econ Activity			0.0001		0.0001
			(0.0002)		(0.0002)
Sentiment				-0.0008	-0.0001
				(0.0009)	(0.0009)
Observations	6,098	6,096	6,096	6,096	6,096
Adjusted R^2	0.0254	0.0262	0.0263	0.0255	0.0265

Table D.11: Large Trader Net Position Changes

We use Large Trader Net Position Changes data on institutional investors (various asset managers, dealers, and large banks) and leveraged funds traders' positions to compute weekly position changes. Net trading Q_{t+1} is the cross-asset net position change at time $t+1$ scaled by the daily average Large Trader Net Position Changes. Threshold and Calendar signals are constructed as described in Section 2.2. Values in parentheses are heteroskedasticity- and autocorrelation-robust standard errors. Constant estimates are not tabulated. Weekly observations.

	Institutional Q_{t+1}		Leveraged Funds Q_{t+1}	
Threshold	-7.1937^{**}	-7.2294^{**}	6.5095^{**}	5.2542^{*}
	(3.0081)	(3.0142)	(2.8948)	(2.8694)
Calendar	2.8903	2.8967	-1.7132	-0.5008
	(1.8024)	(1.8501)	(1.7711)	(1.6889)
week4	0.0281	0.0236	0.0065	0.0159
	(0.0265)	(0.0275)	(0.0256)	(0.0271)
Calendar∗week4	-4.9856^{**}	-4.5700^{**}	1.7881	0.5959
	(2.1963)	(2.2834)	(2.1214)	(2.2829)
Institutional Q_t		-0.0017		
		(0.0392)		
Leveraged Funds Q_t				-0.2609^{***}
				(0.0560)
Observations	125	124	125	124
Adjusted R^2	0.0737	0.0523	0.0253	0.1231