The Unintended Consequences of Rebalancing*

Campbell R. Harvey† Michele G. Mazzoleni‡ Alessandro Melone§

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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.

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†Fuqua School of Business, Duke University and NBER. E-mail: cam.harvey@duke.edu.
‡Capital Group. E-mail: mazzoleni.research@gmail.com.
§Fisher College of Business, The Ohio State University. E-mail: melone.11@osu.edu.

"*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)

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. Moreover, since rebalancing costs recur annually, their true present value is substantially larger. At the same time, we show that simple randomization in rebalancing schedules can reduce these costs to about half a basis point, underscoring that much of the burden arises from mechanical rebalancing pressures.

We leverage four datasets to link our rebalancing signals to actual investor trades. First, we use weekly CFTC futures positions and show that hedgers sell (buy) equities when they are overweight (underweight) relative to bonds. We then exploit CFTC's weekly Large Trader Net Position Changes and ANcerno's daily data on institutional equity transactions, which reveal that asset managers and pension funds act as rebalancers. Finally, ICI mutual fund flows show that mutual funds sell equities and buy bonds when equities become overweight. Taken together, these diverse sources confirm that institutional investors' trading behavior is broadly consistent with our interpretation.

We conduct several additional 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. Finally, we document that the Threshold and Calendar signals also extend to international equity markets.

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. Andonov, Eiling, and Xu (2024) extend the TDFs evidence to international capital markets, showing that these funds frequently engage in contrarian rebalancing between domestic and foreign equities. 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. Parker and Sun (2025) document that trading by TDFs acted as a significant stabilizing force in U.S. equity markets during the COVID-19 pandemic. Lu and Wu (2025) find that rebalancing pressures play a significant role in the transmission of monetary shocks to the stock market. 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.

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

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 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 2 presents our main evidence on the relationship between rebalancing activities and aggregate price dynamics. In Section 3, we conduct several validation analyses for the economic interpretation of our rebalancing signals. Section 4 uses rebalancing signals to construct a portfolio that exploits market reversals. Section 5 discusses both the costs and benefits of rebalancing. Some concluding remarks are offered in the final section.

[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.

1 Rebalancing: Motivation, Measurement, and Interpretation

1.1 Evidence on Institutional Rebalancing Practices

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.[4] 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. Figure 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.

[4] 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 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.

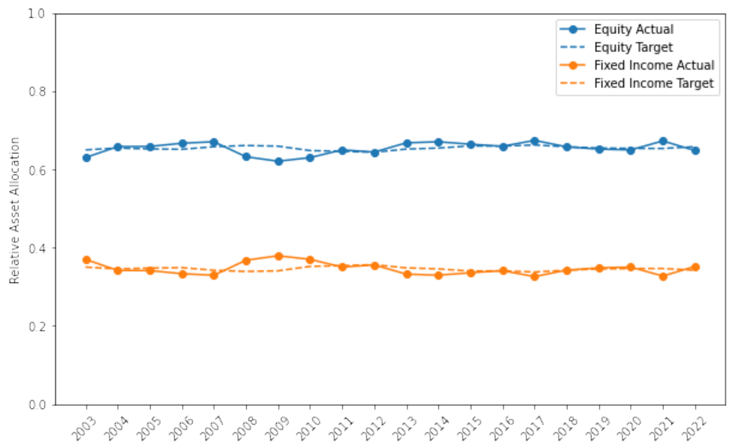


Figure 1: U.S. Defined Benefit Pension Funds' Asset Allocation Over Time. This figure shows the average relative allocations by fiscal year across U.S. defined benefit pension funds produced by the Center for Retirement Research at the Boston College and available at Public Plans Data. Equity allocations 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.

Rebalancing frequency varies across investor types and often reflects cash flow management. For instance, pension funds, which typically face greater outflows than inflows, tend to rebalance at month-end to raise capital for benefit payments (e.g., Etula et al., 2020). Mutual funds, by contrast, experience continuous inflows and outflows and may rebalance daily to adjust allocations, e.g., by deploying inflows into underweight assets.[5]

Benchmark design also shapes rebalancing practices, as managers seeking to minimize tracking error often align with their benchmark's schedule. Practices can vary: Vanguard's TDF benchmarks used to rebalance daily, the S&P 500 Target Date Index series monthly, and the Morningstar Target Risk Series quarterly.[6] Rebalancing is often implemented through derivatives such as futures and swaps.

[5]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).

[6]For example, as Vanguard reports in relation to its TDFs: "In practice, we first use daily cash flows to maintain portfolio level allocations. If daily cash flows are insufficient to bring the portfolios within the Threshold band of the target asset allocation, we then buy and sell securities to realign the funds' asset allocation back with the target" (see Vanguard).

Evidence from public pension plans provides additional insights into institutional practices. A Seattle City Employees' Retirement System memo (September 2020) reports that most rebalancing is conducted "synthetically" by an overlay manager using futures tied to major equity benchmarks (e.g., S&P 500, MSCI EAFE) and U.S. Treasuries, with periodic use of physical securities to adjust notional exposure. The overlay manager noted that most clients rebalance at month-end to minimize tracking error versus benchmarks—also rebalanced monthly—or within a few days of month-end to align with external cash flows. Similarly, a Sacramento County Employees' Retirement System memo (February 2024) describes how State Street Global Advisors rebalances the total fund through a hybrid approach combining calendar- and threshold-based rules: rebalancing occurs quarterly at quarter-end unless tolerance bands are breached mid-quarter. A February 2018 San Francisco Employees' Retirement System memo highlights the role of tolerance bands, cash flows, and tracking error in overlay program design, while a 2015 Montgomery County Public Schools memo documents a month-end overlay-based rebalancing policy.[7]

These institutional case studies are in line with broader survey evidence and related empirical research. 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). Related discussions on the merits of different rebalancing approaches appear in research by Meketa Investment Group, one of the largest institutional investment advisory firms (Benham, Obregon, and Simanovich, 2018)), in studies by Vanguard Group on TDF rebalancing (Zhang et al., 2022; Zhang and Ahluwalia, 2024), and in a 2018 discussion note by Norges Bank Investment Management (see Norges). Both Vanguard and Norges Bank adopt a threshold-based rebalancing approach.

[7] Documentation can be found here: SCERS; SFERS; Montgomery.

1.2 Measuring Rebalancing Activity

Rule-Based Rebalancing: Threshold and Calendar Approaches. Building on our research on institutional rebalancing policies, we construct two measures of rebalancing activity by focusing on the most widely used rule-based approaches: threshold rebalancing and calendar rebalancing. *Threshold rebalancing* seeks to minimize transaction costs by allowing portfolio weights to drift within tolerance bands around target allocations. When an asset's weight deviates from its target by more than a preset threshold—for example, two percentage points—the portfolio is rebalanced. *Calendar rebalancing*, by contrast, follows a deterministic schedule, typically monthly or quarterly. Notice that while the timing of Calendar rebalancing is predetermined, the magnitude of the rebalancing trades remains unknown. 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 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. The equity allocation is a function of trailing equity and bond market returns. At any point in time t, portfolio weights w are updated as a function of past weights, equity returns, and bond returns:

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

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. After one period, the deviation from the target equity allocation is given by $w_{t+1}(w_t; R_{t+1}^{SP}; R_{t+1}^{10Y}) - 60\%$. 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).[8] Appendix B provides a detailed explanation of their construction. Thus, 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.

We highlight two key parameters for constructing and testing our signals: (i) the rebalancing range used in the Threshold signal's construction and (ii) the range of days when the Calendar signal is expected to display the strongest predictability. We posit two hypotheses. First, the relevant range for the Threshold signal should cluster around 2 percentage points, consistent with institutional rebalancing practices and published guidance by large investors such as Norges and Vanguard. Second, that the predictability of the Calendar signal should concentrate toward month-end, when pension funds typically face liquidity needs. We test these hypotheses next.

Signal Calibrations and Univariate Predictive Regressions. We 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 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, and Threshold Signal$_t^\delta$ is constructed as in (B.1). Detailed information about the data sources is provided in Appendix A. In Figure 2, 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.

We focus on two results. First, consistent with our interpretation, the Threshold signal is negatively related to subsequent daily S&P 500 returns in excess of the 10-year Treasury note. Second, the signal's predictive power peaks around 2 percentage points and declines

[8] 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.

for values of δ above 2.5%. This evidence aligns with our first hypothesis, which is supported by institutional practices of large funds, and is intuitive when viewed through the lens 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.

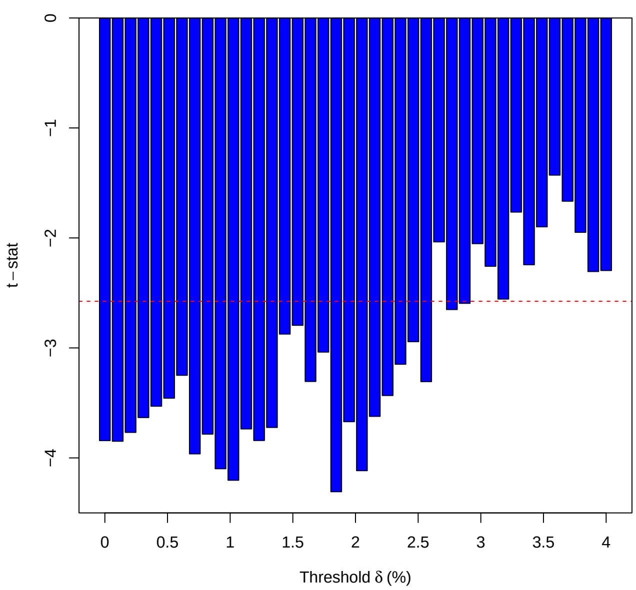


Figure 2: Threshold Calibrations and Predictability. This figure shows the $t-$statistics for the predictive coefficient in (1) for different values of the threshold rebalancing range δ. The dependent variable is the difference between the S&P 500 and the 10-year Treasury note futures returns. $t-$statistics are based on heteroskedasticity-consistent standard errors. The dashed red line denotes the 1% critical value. Daily observations. The sample period is 1997-09-10 to 2023-03-17.

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%.[9] Formally,

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

[9] We obtain similar results when averaging over the range 0%–2%. Also, one might be concerned that our calibration exploits information from the full sample. To address this, we re-estimated the signal using only the first half of the sample and found qualitatively similar results, with predictability becoming insignificant for δ values above 2.5%.

Averaging different rebalancing calibrations approximates what a heterogeneous group of investors might implement while also reducing the set of potential predictors.[10] 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.

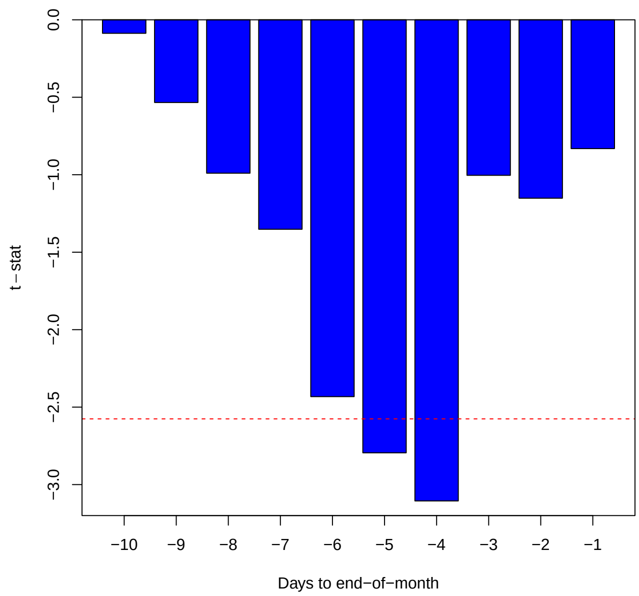


Figure 3: Calendar Signals and End-of-Month Effect. This figure shows the $t-$statistics for the predictive coefficient β_2 in (3) for different values of $\text{Dummy}_t^{\text{N Days}}$. $\text{Dummy}_t^{\text{N Days}}$ is a dummy variable that takes the value of 1 during the last $N-$days of the month. 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. The dashed red line denotes the 1% critical value. Daily observations. The sample period is 1997-09-10 to 2023-03-17.

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:

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

[10] 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.

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, and Calendar Signal_t is constructed as in (B.2). 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 3 shows the t-statistics for the predictive coefficient β_2 in (3). Calendar predictability peaks in the last four days of the month, consistent with liquidity-driven trading by pension funds. Moreover, Figure 3 suggests that funds attempt to minimize market impact by avoiding trades on the very last day while 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 $\text{Dummy}_t^{\text{5 Days}}$.[11]

1.3 Interpreting Rebalancing Signals

Appendix Figure C.1 plots the time-series of the Threshold and Calendar signals, while Appendix Table C.1 shows summary statistics. Both series display high-frequency movements around periods of market turmoil. The Calendar 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. The two signals are positively correlated, with a correlation coefficient of approximately 60%.

By construction, the Threshold and Calendar signals are positively correlated with trailing equity excess returns computed over different time frames. Since the Threshold signal

[11] 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.

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.[12] 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.

2 Rebalancing Pressures

This section documents market-wide pressures associated with rebalancing activity. We examine the price impact on stocks and bonds around rebalancing signals, analyze how institutional investors adjust their trading in response, and draw on conversations with pension fund leaders to provide further institutional context on the relevance of rebalancing pressures.

2.1 Return-Based Evidence of Rebalancing

2.1.1 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). 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

[12]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.

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:

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

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 1.2; 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.2) 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.[13] 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 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 condi-

[13] 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.

tions, 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.2, 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.[14] 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.[15] 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.[16]

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 (19.2 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

[14]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.

[15]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.

[16]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.

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 1.2. 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); EPU is the news-based measure of economic policy uncertainty from Baker, Bloom, and Davis (2016); ADS 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	-0.4144^{***}	-0.4208^{***}	-0.4254^{***}	-0.4254^{***}	-0.4226^{***}
	(0.1148)	(0.1164)	(0.1098)	(0.1133)	(0.1139)
Calendar	0.0553	0.0689	0.0572	0.0542	0.0666
	(0.0709)	(0.0686)	(0.0696)	(0.0713)	(0.0686)
week4	0.0002	0.0002	0.0002	0.0002	0.0002
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Calendar $*$week4	-0.3029^{***}	-0.3036^{***}	-0.3026^{***}	-0.3032^{***}	-0.3033^{***}
	(0.0808)	(0.0808)	(0.0805)	(0.0806)	(0.0808)
Momemtum	0.0023^{***}	0.0024^{***}	0.0024^{***}	0.0025^{***}	0.0024^{***}
	(0.0006)	(0.0007)	(0.0006)	(0.0006)	(0.0007)
Ret	-0.0203	-0.0167	-0.0198	-0.0192	-0.0173
	(0.0289)	(0.0289)	(0.0281)	(0.0287)	(0.0286)
VIX		0.0090^{*}			0.0076
		(0.0053)			(0.0062)
MOVE		-0.0020^{*}			-0.0019^{*}
		(0.0011)			(0.0011)
EPU			0.0005^{*}		0.0002
			(0.0003)		(0.0004)
ADS			0.0000		0.0001
			(0.0002)		(0.0002)
Sentiment				-0.0016	-0.0003
				(0.0012)	(0.0013)
Observations	6,226	6,226	6,226	6,226	6,226
Adjusted R^2	0.0239	0.0252	0.0243	0.0242	0.0248

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 indicate that investors may incur meaningful costs when rebalancing. To quantify these costs, we adopt a two-step procedure. First, we estimate costs in percentage terms by multiplying the estimated price impact by the average rebalancing trade. Specifically, we measure price impact using the predictive regression in equation (4), estimated over periods in which rebalancing trades are expected to occur—namely, the last week of the month for Calendar rebalancing, or the subsample of days for which the rebalancing signal exceeds a given threshold for Threshold rebalancing. We then multiply the estimated price impact by the average absolute distance to target at the time of rebalancing and by the number of rebalancing trades per year.[17] For the Calendar strategy, the implied annual costs are $\widehat{\text{Price Impact}} \times \text{Average Trade Size} \times \text{Trades per Year} = |-0.39| \times 1\% \times 12 \approx 5$ bps. Applying the same procedure to the Threshold strategy yields annualized costs ranging from 6 to 27 bps across δ values between 0 and 2.5%, with an average of 15 bps.[18]

To estimate rebalancing costs, we make assumptions about the timing of trades under both rebalancing rules. For the Calendar strategy, focusing on the last week of the month is natural, as institutional investors typically rebalance at month- or quarter-end. The timing is inherently more nuanced for the Threshold strategy. However, discussions with market participants indicate that discretion in practice is limited. In particular, when rebalancing is delegated to overlay managers—as suggested by institutional evidence discussed above—execution tends to follow standardized procedures with limited scope for opportunistic timing. To be conservative, we also consider a scenario in which managers rebalance

[17] An alternative specification estimates a single regression using the full sample and interacts the rebalancing signal with an indicator equal to one during rebalancing periods, either in the last week of the month or when the signal exceeds a threshold. Results are largely the same.

[18] Etula et al. (2020) document that pension funds must sell securities at least four business days before month-end to meet benefit payments. Consistent with their findings, a Calendar rebalancer trading on day $T-4$ would incur a cost of roughly 9 bps. Costs are also higher in the post-PPA period (i.e., after 2006).

before the signal fully breaches the threshold, when the average trade size is approximately 1%, similar to the Calendar case. Under this assumption, implied costs are about 11 bps. Averaging between the Calendar and Threshold estimates yields an annual rebalancing cost of approximately 8 bps, which we use in subsequent calculations.

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; Parker and Sun, 2025), the costs associated with mechanical rebalancing could rise substantially over time.[19]

As a further benchmark, we consider a *random rebalancing* strategy that rebalances once per month on a randomly chosen day, yielding the same expected frequency of 12 rebalancing events per year as our Calendar approach. We simulate the strategy 10,000 times and report average costs across simulations. Appendix Figure D.2 displays the distribution of economic costs. The average cost is 0.6 bps (median of 0.5 bps), and never reaches 8 bps.[20] These results indicate that, all else equal, investors may be able to meaningfully reduce rebalancing costs by avoiding the specific days on which other institutions concentrate their trading activity.

Finally, to translate these costs in 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.[21] Thus, current

[19] According to the Investment Company Institute (ICI), total U.S. retirement assets reached $45.8 trillion as of June 30, 2025—an increase of more than 15% since 2023; see ICI.

[20] We deliberately allow random rebalancing dates to fall within the final week of the month, coinciding with Calendar rebalancing. When we exclude the final week from the random selection, the resulting costs are even smaller.

[21] 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

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.

2.1.2 Price Pressures

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:

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

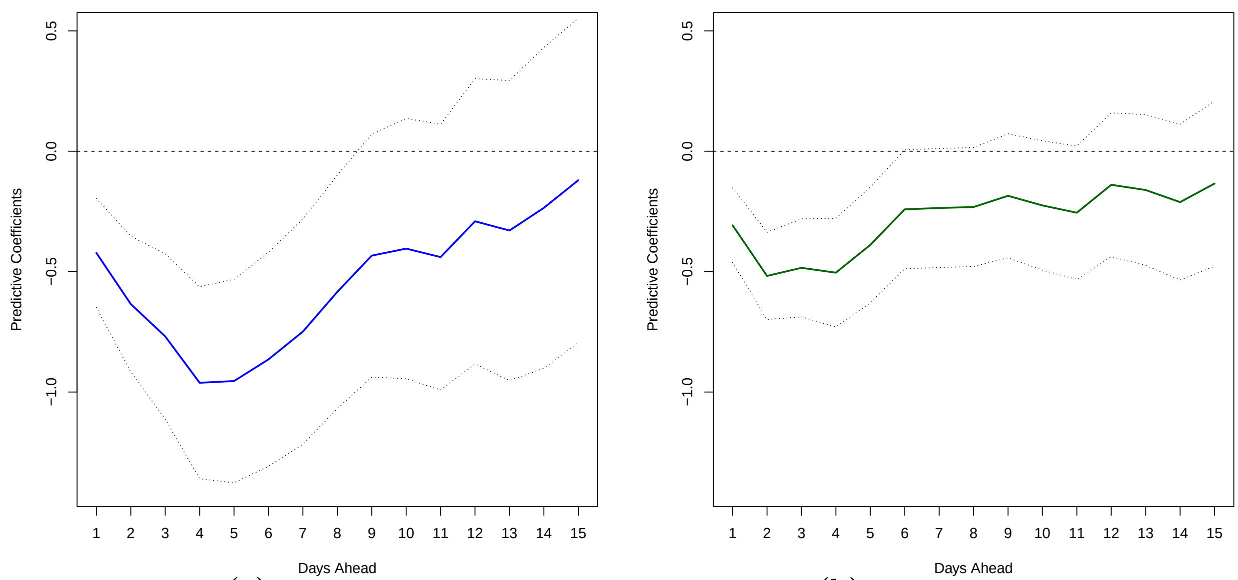
where $Ret_{t+1:t+i}$ are cumulative log returns up to $t+i$. To address potential inference issues related to overlapping observations, we follow Ang and Bekaert (2007) and use conservative standard errors from reverse regressions to compute confidence bands, as proposed by Hodrick (1992). Furthermore, Appendix Figure 4 shows results for non-overlapping returns.

Figure 4 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 6 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

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.

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.



(a) Threshold **(b)** Calendar $*$ week4

Figure 4: 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.

2.1.3 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.5 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.[22]

Alternative Controls. Appendix Table D.6 shows results when we consider alternative control variables in our main predictive regression Table 1. Specifically, in Columns (1) to (3) of Table D.6, we replace our main economic uncertainty and sentiment indexes with, respectively, the uncertainty indexes constructed in Bekaert, Engstrom, and Xu (2022) and the FEARS index constructed in Da, Engelberg, and Gao (2015) and show that it has little effect on the results.[23]

Furthermore, we include the aggregate retail attention (ARA) index proposed by Da, Hua, Hung, and Peng (2025) as a control, since attention-induced contrarian trading may offer an alternative explanation for the market-wide pressures we document. Da et al. (2025) show that ARA negatively predicts market returns, with stronger predictive power during periods of high volatility and illiquidity—precisely when rebalancing-driven predictability is also more pronounced. Moreover, ARA tends to spike at month-end, and when recent excess returns are more salient, as captured by the Threshold signal. Column (4) of Table D.6 reports the results, which remain largely unchanged after including ARA, suggesting that our findings reflect a distinct dimension of return predictability.

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

[22] 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.

[23] We thank the authors for making their FEARS time series available to us.

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 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.[24]

2.2 Rebalancing and Institutional Investors' Trades

We leverage four datasets to directly examine how our rebalancing signals relate to investors' trades.

First, we use publicly available futures positions from the Commodity Futures Trading Commission (CFTC). Futures positions provide insight into trading in key instruments used for rebalancing and risk management. 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 argue that hedgers primarily act as rebalancers: to mitigate tracking risk when portfolios

[24] 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.

drift from their target allocations, they buy underweight assets and sell overweight assets.

We use CFTC data on S&P 500 and 10-year Treasury futures to construct a variable capturing the trading behavior of hedgers and speculators, starting in August 2006. 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 and examine the relation between future net trading positions and current rebalancing signals.

The first part of Figure 5 shows that future hedger positions are negatively related to both Threshold and Calendar signals, whereas speculators display a positive relation. When equities are overweight (underweight) relative to bonds, hedgers sell (buy) equities and speculators take the opposite side, consistent with our interpretation.

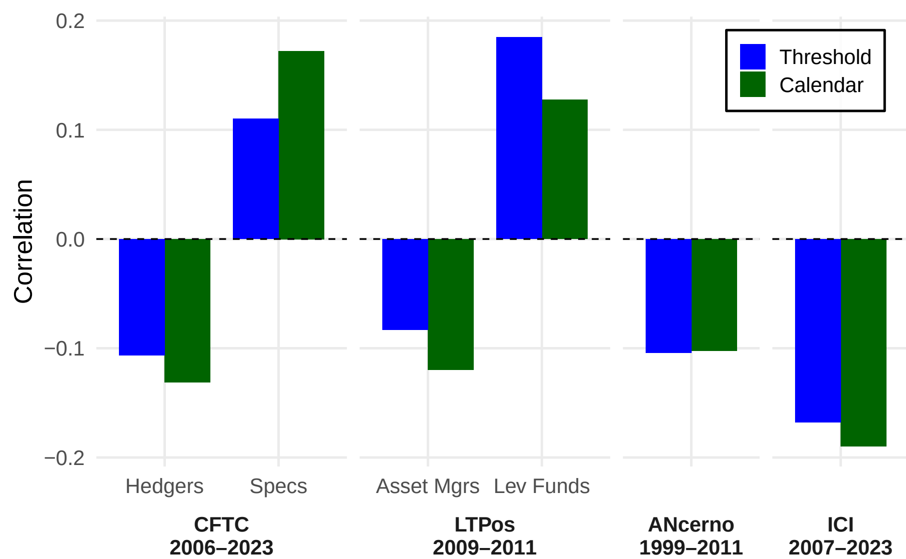


Figure 5: Rebalancing Signals and Trading Positions. This figure shows the correlation between various institutional investors' trades and (lagged) rebalancing signals.

To further investigate which institutional investors trade in the direction of rebalancing pressures and which take the opposite side, we exploit the Large Trader Net Position Changes dataset. Published by the CFTC on June 30, 2011, this one-time report covers the period from January 2009 to May 2011 and provides the daily average aggregate net position changes for large traders across 35 futures markets. The report classifies financial futures traders into four groups: dealers/intermediaries, asset managers/institutional investors, leveraged funds, and other reportables. According to the CFTC, the dataset captures at least 80% of open interest in futures markets.[25] We focus on asset managers—which include pension funds, endowments, insurance companies, mutual funds, and portfolio/investment managers whose clients are primarily institutional—and on leveraged funds, which typically comprise hedge funds and other money managers such as commodity trading advisors.

The second group in Figure 5 reports the correlation between weekly net trading by these two groups and lagged Threshold and Calendar signals. On average, asset managers sell equities and buy bonds when equities are overweight, whereas leveraged funds tend to take the opposite side of these trades. Because the CFTC data are available only at weekly frequency, they inevitably aggregate substantial within-week dynamics: hedge funds that temporarily trade in the same direction as pensions for a few days and subsequently unwind their positions would appear as providing liquidity over the full week. Thus, the evidence should not be interpreted as ruling out front-running or other short-horizon strategies. Rather, these results offer a more granular counterpart to our first-panel findings and remain broadly consistent with viewing the Threshold and Calendar signals as capturing rebalancing activity—where some hedge funds act as liquidity providers to pensions, while others may be aligned with them at higher frequencies that our data cannot detect.

Then, we use the Ancerno (formerly Abel Noser) dataset, which reports daily, trade-level equity transactions for hundreds of institutional investors. As documented by Puckett and Yan (2011), the sample includes institutions such as CalPERS and the YMCA Retirement Fund and, in aggregate, accounts for about 8% of daily CRSP trading volume. For our analysis, we focus on the period from January 1999 to September 2011, which corresponds to the years in which pension plan sponsors can be identified, and we restrict attention to trades in S&P 500 constituents to align with our empirical design. While limited, these data provide a rare window into high-frequency pension fund trading; other (public) sources offer only quarterly or annual aggregates (e.g., 13F filings and CRSP/Thomson Reuters holdings).

The third part of Figure 5 reports the correlation between the aggregate buy ratio—the dollar value of the ANcerno institutional buy transactions divided by the sum of buy and

[25]Further details can be found on the CFTC website.

sell dollar values—and our lagged rebalancing signals. Consistent with our interpretation, the pattern indicates that pension plans act as rebalancers. Moreover, the magnitude of this correlation is comparable to that for CFTC hedgers in the first panel, further validating the economic content of these data.

Finally, we also use estimated weekly net equity flows from the Long-Term Mutual Fund Flows data provided by the Investment Company Institute (ICI), defined as U.S. total equity flows minus bond flows. These data are available starting in January 2007. The fourth grouping in Figure 5 shows that, on average, when equities are overweight relative to bonds, mutual funds sell equities and buy bonds, consistent with our interpretation.

2.3 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.[26] 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

[26]Interestingly, in a March 2024 episode of the podcast *Flirting with Models*, an executive at one of the world's largest hedge funds described a front-running rebalancing strategy as an example of a widely used systematic portfolio approach. Listen to the episode here.

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 Further Validation of Rebalancing Signals

This section further investigates the economic interpretation of our rebalancing signals through five 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. Lastly, we show that the Threshold and Calendar signals extend to international equity returns.

3.1 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

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 1.2. 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	-0.3281^{***}	-0.4144^{***}	-0.4789^{***}
	(0.1113)	(0.1148)	(0.1308)
Calendar	-0.0778	0.0553	0.0735
	(0.0582)	(0.0709)	(0.0749)
Calendar $*$week4		-0.3029^{***}	-0.3511^{***}
		(0.0808)	(0.0963)
Threshold $*$week4			0.2137
			(0.1620)
Observations	6,226	6,226	6,226
Adjusted R^2	0.0130	0.0239	0.0244

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	-0.2723	-0.4153^{**}	-0.5845^{***}
	(0.2075)	(0.1666)	(0.2083)
Calendar $*$ week4	-0.2509	-0.3487^{***}	-0.3400^{***}
	(0.1590)	(0.1062)	(0.1300)
Observations	2,078	2,052	2,097
Adjusted R^2	0.0110	0.0234	0.0469

Threshold signal. This distinction validates their interpretation: despite a correlation higher than 60% (see Appendix Table C.2), 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.

3.2 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 note futures returns.

Table 3 reports the results.[27] 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-

[27]In untabulated analysis provided to us by a major asset manager, using the 3:30 PM price to compute stock and bond returns instead of the closing price leads to largely the same results.

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.

	$\text{Ret}_{t+1}^{\text{S\&P 500}}$		$\text{Ret}_{t+1}^{\text{10-y}}$	
	(1)	(2)	(3)	(4)
Threshold	-0.3302^{***}	-0.3261^{***}	0.0842^{***}	0.0841^{***}
	(0.1062)	(0.1049)	(0.0269)	(0.0270)
Calendar	0.0424	0.0441	-0.0129	-0.0148
	(0.0665)	(0.0645)	(0.0116)	(0.0113)
week4	0.0005	0.0005	0.0004^{***}	0.0004^{***}
	(0.0004)	(0.0004)	(0.0001)	(0.0001)
Calendar $*$ week4	-0.2667^{***}	-0.2671^{***}	0.0362^{***}	0.0372^{***}
	(0.0758)	(0.0762)	(0.0128)	(0.0127)
Momemtum	0.0018^{***}	0.0018^{***}	-0.0005^{***}	-0.0005^{***}
	(0.0005)	(0.0006)	(0.0001)	(0.0001)
Ret	-0.0223	0.0030	-0.0020	-0.0027
	(0.0264)	(0.0430)	(0.0065)	(0.0093)
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

deviation decrease in the Threshold (Calendar) signal corresponds to an increase in equity returns of about 15.9 bps (16.9 bps) and a decrease in bond returns of about 4.1 bps (2.3 bps) over the next trading day.[28]

3.3 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.[29] Second, liquidity needs have also changed, which requires pension funds to regularly sell assets to pay member benefits at the beginning of each month.[30] 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. 6,226) due to variations in trading days between CRSP and Bloomberg futures data.

[28] 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.

[29] 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.

[30] 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 1.2. 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

The evidence reported aligns with our expectations. While Column (1) shows that 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.[31]

3.4 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 1, 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

[31] We have extended the sample through 2025 and find that the results become even stronger.

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 2006-08-17 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

3.5 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 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:

$$R_{t+1}^{\text{Strategy}} = (R_{t+1}^{\text{S\&P 500}} - R_{t+1}^{\text{10-y}}) \cdot w_t^{\text{Strategy}} \ ,$$

where the portfolio weight w_t^{Strategy} is defined as the average of modified versions of the Threshold and Calendar signals defined in Appendix B (see Eqs. (B.1)–(B.2)). We modify

Threshold signal by rescaling to $-\frac{\text{Threshold Signal}_t}{1.5\%}$ so that the two rebalancing signals have the same risk contribution to the strategy; in our sample, both signals exhibit an annualized volatility of 11.6%. The signal is multiplied by -1 because a positive Threshold value indicates that the 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 $sign\,(-\text{Calendar Signal}_t)$ 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 (see Figure 4). On any other day, the modified version of the signal is set to zero.

Panel A of Table 6 summarizes the trading strategy's statistics. The rebalancing-based strategy generates annualized average returns of approximately 10%, with a Sharpe ratio above 1, much higher than the 0.35 and 0.48 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 6 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 5.23. 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 6, 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

Table 6: Performance of Front-Running Trading Strategies

This table reports performance results for the rebalancing-based strategy R_t^{Strategy} constructed as described in Section 4. 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); EPU 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}	7.11	20.05	0.35	-0.08
R_t^{10T}	2.92	6.13	0.48	0.03
R_t^{Strategy}	10.20	9.17	1.11	5.23

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

	CAPM	C4	FF5	HXZ
α	9.61***	9.64***	9.49***	9.43***
	(1.77)	(1.78)	(1.74)	(1.75)

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

	ivol		liquidity risk		VIX		MOVE		EPU	
	H	L	H	L	H	L	H	L	H	L
R_t^{Strategy}	15.68***	5.09***	17.96***	3.79**	16.50***	3.91***	14.85***	5.55***	15.16***	5.24***
	(3.44)	(1.28)	(3.33)	(1.85)	(3.44)	(1.11)	(3.32)	(1.43)	(3.26)	(1.56)

events: even after excluding the September 2008 to March 2009 and March 2020 periods, the strategy's Sharpe ratio remains elevated at 0.90.

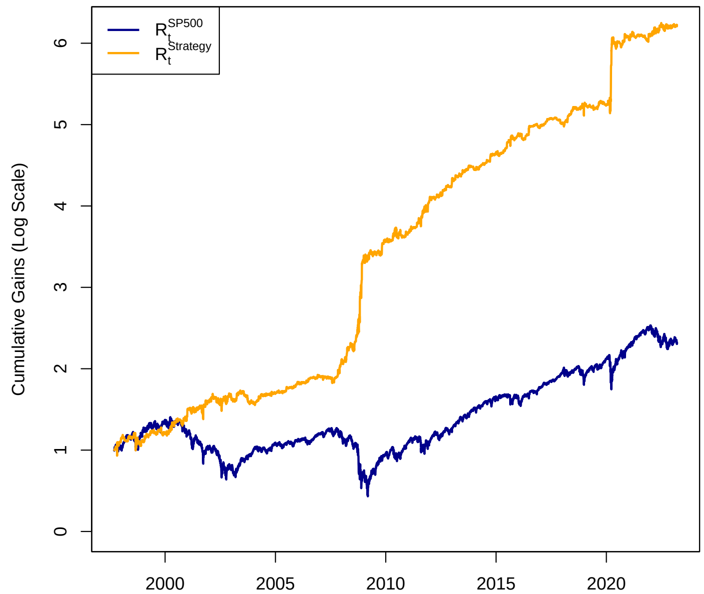


Figure 6: Front-Running Strategy Performance Over Time. This figure shows the cumulative gains of \$1 invested in the rebalancing-based strategy, R_t^{Strategy}, constructed as described in Section 4, alongside the performance of \$1 invested in the R_t^{SP500} portfolio. R_t^{Strategy} is rescaled to 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.[32] 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 6 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 result is important as it suggests that our strategy is more profitable when liquidity providers are more constrained and price impact is larger, consistent with our interpretation.

5 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

[32] 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%.

other investors that may anticipate their actions and attempt to profit from them. We simulate 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. 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).

To explore this idea, Section 2.1 analyzed random rebalancing strategies that preserve the typical annual rebalancing frequency while eliminating predictable price pressures. We find that these strategies reduce estimated costs substantially—to about half a basis point on average—compared with roughly 8 basis points for conventional rule-based approaches. These results indicate that a significant share of rebalancing costs arises from concentrated trading on predictable dates.

Three considerations are worth emphasizing. First, while random rebalancing substantially reduces transaction costs, it induces an average tracking error of approximately 35 bps. For a standard 60/40 equity–bond portfolio with an annualized volatility of 12% in our sample, this corresponds to about 3% of total portfolio volatility. Although this magnitude may appear small in absolute terms, its relevance varies across institutions. Investors operating under tight benchmark-tracking mandates may find even modest deviations costly, whereas others have greater flexibility. For example, Norges publicly reports a tracking error limit of 1.25% (see Norges).

Second, rebalancing decisions interact with the liability side of the balance sheet. Institutions with predictable end-of-month cash outflows may need to liquidate assets to meet liabilities. If a random rebalance occurs early in the month, such investors forgo the return on the rebalanced portfolio relative to cash over the remainder of the month, effectively incurring an additional opportunity cost.

Third, rebalancing is ultimately a coordination exercise. The actions of individual rebalancers can influence those of others, while liquidity providers and sophisticated investors may further affect the effectiveness of any given strategy.[33] Optimal rebalancing policies are therefore likely to depend on investor size: smaller investors may rebalance more opportunistically, whereas larger investors must consider the market impact of their own trades, making aggregate liquidity conditions a central determinant of rebalancing costs.

Finally, 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.[34] 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 diversification 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,

[33] For example, Bessembinder, Carrion, Tuttle, and Venkataraman (2016) show that trader competition can mitigate the price impact of predictable trades.

[34] Khanjar (2025) studies bond indices and reaches similar conclusions.

while Calendar rebalancing generates approximately 10 bps.[35] 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.

6 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.

We show that institutional investors' trading behavior is broadly consistent with our interpretation. To further validate the economic content of our rebalancing signals, we conduct several additional analyses. Specifically, we document (i) seasonal patterns consistent with a rebalancing motive, (ii) return predictability in both equity and bond markets, (iii) a marked increase in predictability over the past two decades, reflecting the growth of funds engaging in rebalancing, (iv) predictability across equity indices, and (v) corroborating international evidence.

Importantly, our results suggest that current rebalancing policies cost investors billions

[35] 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.

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 construct continuous return series for the E-mini S&P 500 futures (ES) and the 10-year U.S. Treasury note futures (TY) using Bloomberg's nearby contracts. Specifically, ES1 refers to the front-month E-mini S&P 500 futures contract and ES2 to the second-nearest contract; similarly, TY1 denotes the front-month 10-year Treasury note futures contract and TY2 the second-nearest contract. These are reported by Bloomberg as excess return price indices, which serve as the building blocks for our continuous series. To generate continuous returns, we stitched together the first and second nearby contracts for each market while accounting for the relevant expiry calendar. Our rule specifies that positions roll from the front contract (ES1 or TY1) to the second contract (ES2 or TY2) at the end of the month preceding the contract's expiry month. From the first day of the expiry month until the expiry date, returns are based on the second contract, while before this window and after expiry they are based on the front contract. This methodology produces continuous time series that avoid discontinuities at contract expiration and reflect an easily replicable rolling convention. Lastly, a holiday was identified whenever both front contracts, TY1 and ES1, were reported as N/A in Bloomberg, indicating that neither futures market had traded on that date. In addition, we explicitly marked September 12–14, 2001, as exchange closures. During this period ES1 displayed no prices, while ES2 appeared to carry stale values. 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:

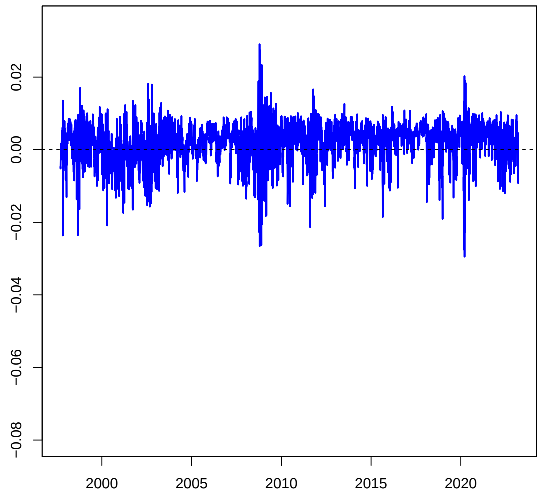
$$\text{Threshold signal}_{t+1}^{\delta} = w_{t+1}^T(w_t^T; R_{t+1}^{SP}; R_{t+1}^{10Y}) - 60\% \tag{B.1}$$

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

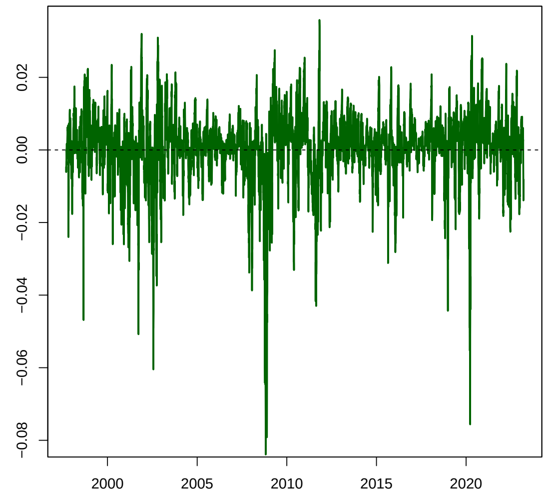
$$\text{Calendar signal}_{t+1} = w_{t+1}^C(w_t^C; R_{t+1}^{SP}; R_{t+1}^{10Y}) - 60\% \tag{B.2}$$

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 rebalancing measures constructed as described in Section 1.2. Daily observations. The sample period is 1997-09-10 to 2023-03-17.

Table C.1: Rebalancing Signals: Summary Statistics

This table reports summary statistics for the two rebalancing measures constructed as described in Section 1.2. Mean and standard deviation (SD) are annualized. Daily observations. The sample period is 1997-09-10 to 2023-03-17.

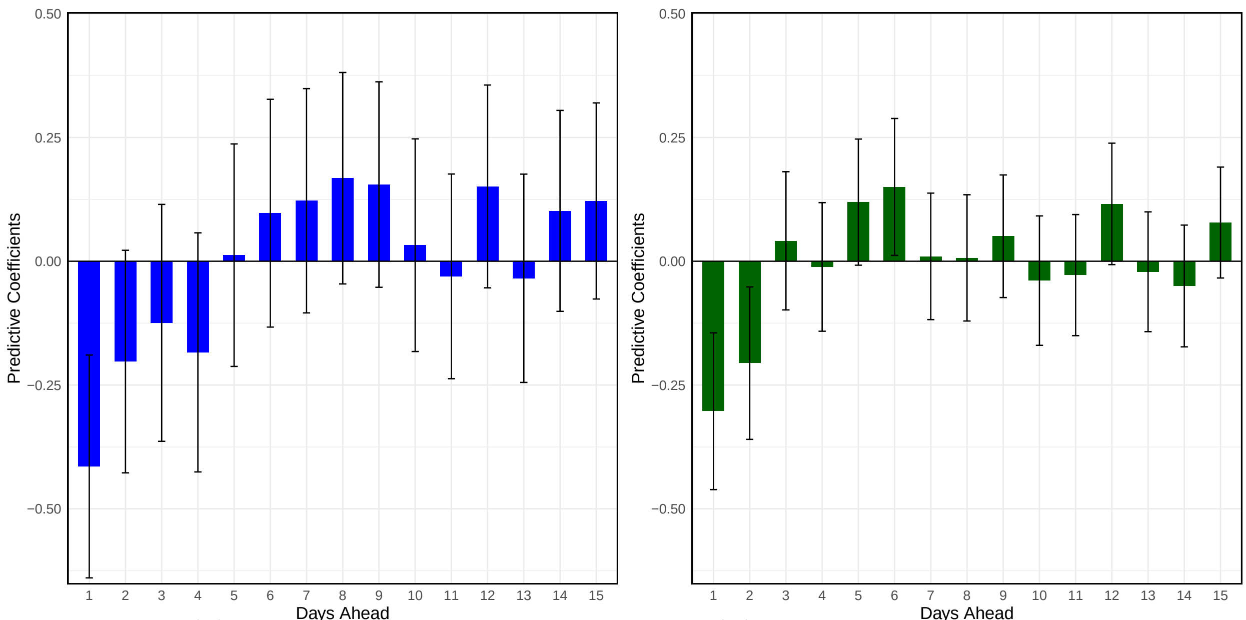
	Mean	SD	AR1	Skewness	Exc. Kurtosis
Threshold Signal	0.49	0.08	0.61	-0.98	2.69
Calendar Signal	0.18	0.16	0.91	-1.43	6.27

Table C.2: 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 1.2. 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; EPU is the news-based measure of economic policy uncertainty from Baker, Bloom, and Davis (2016); ADS 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	0.605	1						
Momentum	0.676	0.676	1					
VIX	-0.353	-0.408	-0.489	1				
MOVE	-0.252	-0.239	-0.373	0.630	1			
EPU	-0.062	-0.129	-0.146	0.443	0.117	1		
ADS	0.058	0.156	0.190	-0.323	-0.187	-0.278	1	
Sentiment	0.101	0.130	0.247	-0.530	-0.333	-0.560	0.200	1

D Additional Results



(a) Threshold Signal **(b)** Calendar Signal $*$ Week4 Dummy

Figure D.1: 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.

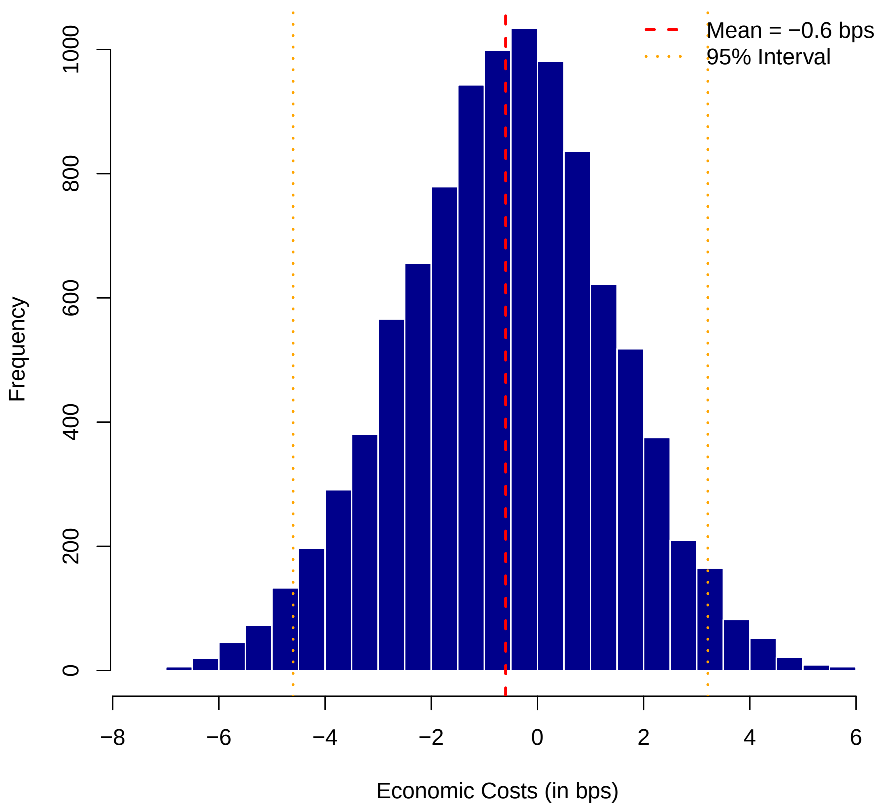


Figure D.2: Economic Costs of Random Monthly Rebalancing. This figure shows the distribution of economic costs for a randomly rebalanced portfolio that rebalances once per month on a randomly selected day. We simulate the strategy 10,000 times and report the resulting distribution of costs. Daily observations. 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 1.2. 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 1.2. 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); EPU is the news-based measure of economic policy uncertainty from Baker, Bloom, and Davis (2016); ADS 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	6,226	6,226	6,226	6,226	6,226
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 1.2. 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); EPU is the news-based measure of economic policy uncertainty from Baker, Bloom, and Davis (2016); ADS 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	-0.4789^{***}	-0.4864^{***}	-0.4858^{***}	-0.4851^{***}	-0.4859^{***}
	(0.1237)	(0.1260)	(0.1210)	(0.1233)	(0.1243)
Calendar	0.0449	0.0592	0.0480	0.0463	0.0573
	(0.0747)	(0.0702)	(0.0728)	(0.0742)	(0.0700)
week4	0.0002	0.0002	0.0002	0.0002	0.0002
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Calendar $*$week4	-0.2986^{***}	-0.2995^{***}	-0.2986^{***}	-0.2994^{***}	-0.2992^{***}
	(0.0811)	(0.0810)	(0.0808)	(0.0809)	(0.0809)
Momemtum fast	0.0006	0.0007	0.0006	0.0006	0.0006
	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)
Momemtum medium	0.0013^{***}	0.0012^{***}	0.0012^{***}	0.0012^{***}	0.0012^{***}
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Momemtum slow	0.0010^{**}	0.0011^{**}	0.0011^{***}	0.0012^{***}	0.0011^{**}
	(0.0004)	(0.0005)	(0.0004)	(0.0004)	(0.0005)
Ret	-0.0184	-0.0148	-0.0183	-0.0177	-0.0155
	(0.0282)	(0.0284)	(0.0276)	(0.0281)	(0.0281)
VIX		0.0085			0.0074
		(0.0053)			(0.0062)
MOVE		-0.0021^{**}			-0.0020^{*}
		(0.0011)			(0.0011)
EPU			0.0005		0.0002
			(0.0003)		(0.0004)
ADS			0.0000		0.0001
			(0.0002)		(0.0002)
Sentiment				-0.0014	-0.0002
				(0.0012)	(0.0013)
Observations	6,226	6,226	6,226	6,226	6,226
Adjusted R^2	0.0241	0.0253	0.0245	0.0243	0.0250

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 1.2. 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); EPU is the news-based measure of economic policy uncertainty from Baker, Bloom, and Davis (2016); ADS 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	-0.4049^{***}	-0.4217^{***}	-0.4122^{***}	-0.4103^{***}
	(0.1148)	(0.1135)	(0.1152)	(0.1136)
Calendar	0.0570	0.0570	0.0557	0.0589
	(0.0709)	(0.0687)	(0.0708)	(0.0685)
week4	0.0002	0.0002	0.0002	0.0002
	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Calendar $*$week4	-0.3048^{***}	-0.3024^{***}	-0.3029^{***}	-0.3043^{***}
	(0.0812)	(0.0806)	(0.0808)	(0.0810)
Momemtum	0.0023^{***}	0.0023^{***}	0.0023^{***}	0.0023^{***}
	(0.0006)	(0.0006)	(0.0006)	(0.0006)
Ret	0.0031	-0.0179	-0.0207	0.0057
	(0.0463)	(0.0283)	(0.0289)	(0.0461)
ΔVIX	0.0191			0.0196
	(0.0367)			(0.0375)
ΔMOVE	0.0135^{*}			0.0138^{*}
	(0.0071)			(0.0072)
ΔEPU		-0.0006		-0.0006^{*}
		(0.0004)		(0.0004)
ΔADS		-0.0010		-0.0010
		(0.0039)		(0.0040)
ΔSentiment			-0.0044	-0.0041
			(0.0115)	(0.0113)
Observations	6,226	6,226	6,226	6,226
Adjusted R^2	0.0257	0.0243	0.0238	0.0261

Table D.5: 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 1.2. 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.6: 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 1.2. 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. 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) available from 2004-07-01 to 2016-12-30; ARA is the aggregate retail attention index constructed in Da et al. (2025) available from 2004-07-01 to 2019-12-31. Values in parentheses are heteroskedasticity-consistent standard errors. Daily observations.

	Ret_{t+1}			
	(1)	(2)	(3)	(4)
Threshold	-0.4493^{***}	-0.4375^{***}	-0.4226^{**}	-0.3731^{**}
	(0.1152)	(0.1134)	(0.1719)	(0.1537)
Calendar	0.1059^{*}	0.0599	0.1000	0.1100
	(0.0616)	(0.0704)	(0.1134)	(0.0980)
week4	0.0001	0.0001	0.0003	0.0003
	(0.0004)	(0.0004)	(0.0006)	(0.0005)
Calendar $*$week4	-0.3048^{***}	-0.3075^{***}	-0.4011^{***}	-0.3823^{***}
	(0.0807)	(0.0813)	(0.1309)	(0.1173)
Momemtum	0.0025^{***}	0.0026^{***}	0.0020^{**}	0.0016^{**}
	(0.0006)	(0.0007)	(0.0010)	(0.0008)
Ret	-0.0115	-0.0208	-0.0087	-0.0223
	(0.0289)	(0.0290)	(0.0389)	(0.0350)
ra^{BEX}	0.0009			
	(0.0006)			
unc^{BEX}		0.0007		
		(0.0007)		
FEARS			0.0009	
			(0.0007)	
ARA				0.0001
				(0.0060)
Observations	6,124	6,124	3,149	3,903
Adjusted R^2	0.0300	0.0249	0.0298	0.0270

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 1.2. 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		-0.4313^{***}		-0.5644^{***}	-0.5446^{***}
		(0.1256)		(0.1140)	(0.1542)
Calendar		0.0694		0.0632	0.0691
		(0.0707)		(0.0840)	(0.0839)
week4		0.0001		0.0001	0.0001
		(0.0004)		(0.0005)	(0.0005)
Calendar ∗week4		-0.3077^{***}		-0.2835^{***}	-0.2858^{***}
		(0.0814)		(0.0966)	(0.0978)
Momemtum		0.0024^{***}		0.0025^{***}	0.0025^{***}
		(0.0006)		(0.0007)	(0.0008)
Short-Term Reversal	-0.0377^{***}	−0.0122			−0.0054
	(0.0136)	(0.0195)			(0.0236)
Long-Term Reversal			−0.0004	−0.0001	−0.0001
			(0.0004)	(0.0004)	(0.0004)
Observations	6,473	6,226	5,218	5,218	5,218
Adjusted R^2	0.0057	0.0240	−0.0001	0.0263	0.0262

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 1.2. 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.

	$\text{Ret}_{t+1}^{S\&P500}$ - Ret_{t+1}^{10-y}			$\text{Ret}_{t+1}^{S\&P500}$	Ret_{t+1}^{10-y}
	(1)	(2)	(3)	(4)	(5)
EoM Rev	−0.0159		−0.0209	−0.0178	0.0031
	(0.0154)		(0.0157)	(0.0146)	(0.0032)
Threshold		−0.4185***	−0.4116***	−0.3271***	0.0845***
		(0.1157)	(0.1163)	(0.1077)	(0.0272)
Calendar		0.0554	0.0469	0.0351	−0.0118
		(0.0714)	(0.0729)	(0.0686)	(0.0118)
week4		0.0001	0.0001	0.0005	0.0004***
		(0.0004)	(0.0004)	(0.0004)	(0.0001)
Calendar ∗week4		−0.3052***	−0.3050***	−0.2687***	0.0363***
		(0.0812)	(0.0812)	(0.0763)	(0.0128)
Momemtum		0.0023***	0.0024***	0.0019***	−0.0005***
		(0.0006)	(0.0006)	(0.0006)	(0.0001)
Ret		−0.0196	−0.0203	−0.0225	−0.0022
		(0.0292)	(0.0292)	(0.0267)	(0.0065)
Observations	6,173	6,173	6,173	6,173	6,173
Adjusted R^2	0.0003	0.0241	0.0247	0.0236	0.0074

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	-0.3302^{***}	-0.3250^{***}	-0.3344^{***}	-0.3272^{***}	-0.3261^{***}
	(0.1062)	(0.1062)	(0.1048)	(0.1067)	(0.1049)
Calendar	0.0424	0.0428	0.0433	0.0430	0.0441
	(0.0665)	(0.0666)	(0.0646)	(0.0664)	(0.0645)
week4	0.0005	0.0005	0.0005	0.0005	0.0005
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Calendar $*$week4	-0.2667^{***}	-0.2674^{***}	-0.2664^{***}	-0.2667^{***}	-0.2671^{***}
	(0.0758)	(0.0763)	(0.0757)	(0.0758)	(0.0762)
Momemtum	0.0018^{***}	0.0018^{***}	0.0018^{***}	0.0018^{***}	0.0018^{***}
	(0.0005)	(0.0006)	(0.0006)	(0.0005)	(0.0006)
Ret	-0.0223	0.0015	-0.0209	-0.0229	0.0030
	(0.0264)	(0.0431)	(0.0259)	(0.0265)	(0.0430)
VIX		0.0211			0.0217
		(0.0342)			(0.0351)
MOVE		0.0082			0.0083
		(0.0067)			(0.0067)
EPU			-0.0004		-0.0004
			(0.0003)		(0.0003)
ADS			-0.0006		-0.0005
			(0.0035)		(0.0036)
Sentiment				-0.0061	-0.0063
				(0.0103)	(0.0101)
Observations	6,226	6,226	6,226	6,226	6,226
Adjusted R^2	0.0229	0.0239	0.0229	0.0228	0.0239

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

	Ret_{t+1}				
	(1)	(2)	(3)	(4)	(5)
Threshold	0.0842^{***}	0.0799^{***}	0.0873^{***}	0.0850^{***}	0.0841^{***}
	(0.0269)	(0.0269)	(0.0270)	(0.0270)	(0.0270)
Calendar	−0.0129	−0.0141	−0.0137	−0.0127	−0.0148
	(0.0116)	(0.0116)	(0.0114)	(0.0116)	(0.0113)
week4	0.0004^{***}	0.0004^{***}	0.0004^{***}	0.0004^{***}	0.0004^{***}
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Calendar ∗week4	0.0362^{***}	0.0374^{***}	0.0360^{***}	0.0362^{***}	0.0372^{***}
	(0.0128)	(0.0128)	(0.0127)	(0.0128)	(0.0127)
Momemtum	-0.0005^{***}	-0.0005^{***}	-0.0005^{***}	-0.0005^{***}	-0.0005^{***}
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Ret	−0.0020	−0.0015	−0.0030	−0.0022	−0.0027
	(0.0065)	(0.0093)	(0.0064)	(0.0065)	(0.0093)
VIX		0.0020			0.0020
		(0.0067)			(0.0066)
MOVE		-0.0054^{***}			-0.0055^{***}
		(0.0017)			(0.0017)
EPU			0.0002^{***}		0.0003^{***}
			(0.0001)		(0.0001)
ADS			0.0005		0.0005
			(0.0006)		(0.0007)
Sentiment				−0.0017	−0.0021
				(0.0031)	(0.0031)
Observations	6,226	6,226	6,226	6,226	6,226
Adjusted R^2	0.0074	0.0102	0.0087	0.0072	0.0117

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 1.2. 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); EPU is the news-based measure of economic policy uncertainty from Baker, Bloom, and Davis (2016); ADS 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	-0.2723^{***}	-0.2773^{***}	-0.2738^{***}	-0.2766^{***}	-0.2749^{***}
	(0.0870)	(0.0857)	(0.0870)	(0.0868)	(0.0865)
Calendar	0.0810^{*}	0.0855^{**}	0.0810^{*}	0.0801^{*}	0.0818^{*}
	(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	-0.2060^{***}	-0.2055^{***}	-0.2056^{***}	-0.2061^{***}	-0.2055^{***}
	(0.0535)	(0.0539)	(0.0536)	(0.0535)	(0.0539)
Momemtum	0.0004	0.0003	0.0004	0.0005	0.0003
	(0.0003)	(0.0004)	(0.0003)	(0.0003)	(0.0004)
2-day Trailing Returns	0.0708^{***}	0.0727^{***}	0.0703^{***}	0.0710^{***}	0.0707^{***}
	(0.0145)	(0.0141)	(0.0145)	(0.0145)	(0.0143)
VIX		0.0035			0.0011
		(0.0043)			(0.0047)
MOVE		-0.0014^{*}			-0.0011
		(0.0008)			(0.0009)
EPU			0.0005^{**}		0.0004
			(0.0002)		(0.0003)
ADS			0.0001		0.0001
			(0.0002)		(0.0002)
Sentiment				-0.0008	-0.0001
				(0.0009)	(0.0009)
Observations	6,097	6,097	6,097	6,097	6,097
Adjusted R^2	0.0255	0.0262	0.0263	0.0255	0.0265