The Intramonth Momentum Cycle*

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Comments Welcome

Abstract

US equity momentum returns accrue almost entirely in just six trading days each month. We show this concentration arises from investors' dash-for-cash: the need to raise cash before month-end payment deadlines leads to selling pressure on loser stocks a few days before month-end. A value-weighted WML strategy invested only during days $t-9$ to $t-4$ relative to the last trading day turns \$1 into \$18.78 over 1980–2025, compared to \$2.40 for the rest of the month. The concentration is driven entirely by losers: in stock-level regressions with firm and date fixed effects, bottom-decile losers underperform by an additional 7.2 basis points per day during these six days, while winners show no corresponding pattern. This effect remains stable across subperiods and concentrates among liquid stocks, precisely where institutional liquidity needs would be most visible, suggesting a structural rather than behavioral origin. TAQ data confirm that net selling pressure in losers spikes during the window and reverses at month-start. We achieve causal identification by exploiting the SEC's May 2024 transition to T+1 settlement. This reform eliminated the settlement-mismatch friction and, as predicted, shifted the pre-month-end selling pressure precisely one day later. The timing of momentum crash risk further supports this mechanical view: crashes concentrate at month-start, after the monthly payment cycle has cleared, when loser reversals are the sharpest. Our evidence points to a simple mechanical driver for the momentum premium: systematic month-end liquidity needs. These findings suggest that momentum is less about slow information diffusion and more about the fundamental plumbing of the equity market.

JEL Classification: G11, G12, G14, G23

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1 Introduction

Momentum, the tendency of past winners to outperform past losers, is one of the most extensively documented patterns in financial economics. Since Jegadeesh and Titman (1993), hundreds of papers have confirmed momentum profits in equities across dozens of markets and over long historical samples. Two broad classes of explanations have emerged. Behavioral theories attribute momentum to gradual information diffusion or investor underreaction (Hong and Stein, 1999; Daniel et al., 1998). Risk-based theories argue that momentum compensates investors for exposure to crash risk or other priced factors; Daniel and Moskowitz (2016) and Barroso and Santa-Clara (2015) document the crash risk and propose strategies to manage it. Despite three decades of research, no consensus has been reached.

We offer a simple "plumbing" explanation for equity momentum in U.S. markets. Rather than asking *why* momentum exists, we ask *when*, and the answer to the second question resolves the first. The bulk of the value-weighted momentum premium in U.S. equities accrues during just six trading days per month. These are precisely the days when, as Etula et al. (2020) document, institutions sell assets to raise cash ahead of month-end settlement. When forced to liquidate, institutions disproportionately sell past losers. This concentrated selling depresses loser prices during a predictable calendar window, mechanically generating the winner-loser spread.

To isolate this effect, we construct a long-run series of daily winner-minus-loser returns from 1980 through 2025, using standard momentum breakpoints. Motivated by the dash-for-cash mechanism documented by Etula et al. (2020), we decompose each month into a six-day pre-month-end window (henceforth "PreTOM") spanning trading days $t-9$ through $t-4$ relative to the last trading day, and the remaining approximately fifteen days. A \$1 investment in 1980 that captures only the window-period WML returns and holds cash otherwise grows to \$18.78 by 2025, compared to \$2.40 for the complementary strategy and \$45.06 for the full WML portfolio (Figure 1). The window is not cherry-picked. Sliding a six-day window across the second half of the trading month, the mean loser excess return declines monotonically from near zero mid-month to a trough at PreTOM (-11.1 bp/day), before partially recovering at month-end (Figure 4; Section 4.2.3 provides the formal analysis).

The concentration is asymmetric and entirely loser-driven. In portfolio-level returns, losers underperform the market by 44 basis points per month during the pre-month-end window, while earning returns indistinguishable from zero on all other trading days (Figure 2). Winners show no such calendar pattern (Figure 3). Momentum profits, in this sense, are not about winners winning. They are about losers losing at predictable times.

These portfolio-level patterns remain robust when moving to a more granular stock-level panel of over 53 million observations. By accounting for both the unique characteristics of individual firms and broad daily market swings, we ensure that the results are not driven by idiosyncratic company traits or macroeconomic shocks. This confirms that the intramonth cycle is a pervasive feature of the equity market, rather than a byproduct of aggregate risk or specific firm fundamentals. In this more rigorous specification, bottom-decile momentum losers underperform by an additional 7.2 basis points per day (value-weighted) during the six-day window ($t = -3.08$), while winners show no corresponding pattern. The effect is concentrated among liquid losers, exactly those stocks institutions would target when they need to raise cash quickly. To test this liquidity channel, we add a bid-ask spread interaction in equal-weighted regressions, where smaller stocks that drive the BAS variation receive equal weight. The triple interaction Loser $\times$ PreTOM $\times$ BAS is positive and significant: the window effect is strongest among stocks with narrow spreads.

The effect is stable across time. Splitting the sample at the midpoint (July 2002), the window effect is significant in both halves: -5.8 bps in 1980–2002 and -8.5 bps in 2002–2025. If anything, it has grown stronger as institutional assets have increased. This contrasts sharply with the well-documented attenuation of overall U.S. momentum (Bhattacharya et al., 2017; Jegadeesh and Titman, 2023): the non-window component has weakened, but the window component has not. The persistence is consistent with a structural friction rather than a behavioral anomaly that arbitrageurs would erode (McLean and Pontiff, 2016).

The pre-month-end price pressure reverses. Adding a post-window indicator (days $t+1$ to $t+3$ at month-start) to the panel regression, the Loser $\times$ Post coefficient is +8.21. A formal test of full reversal cannot be rejected. Price pressure that fully reverses is difficult to reconcile with permanent risk compensation. The reversal does not imply there is no monthly momentum premium. The rebound falls at month-start, which is part of the rest-of-month component. That is partially why the rest-of-month component contributes so little to cumulative wealth ($2.40 terminal value) relative to the window-only strategy ($18.78; Figure 1). TAQ data confirm the selling pressure directly. Net selling pressure in losers spikes during the pre-month-end window and reverses to net buying at month-start.

The settlement reform provides a natural experiment of the mechanism. Under T+2 settlement, a one-day mismatch between fund redemption payments (T+1) and equity settlement (T+2) compelled funds to sell one day earlier than pure settlement would require, making $t-4$ empirically the effective last day of the selling window. The SEC's May 2024 transition to T+1, characterized by regulators as a major change in U.S. market infrastructure (Securities and Exchange Commission, 2023; Depository Trust & Clearing Corporation, 2024), eliminated this mismatch entirely, giving funds one extra day. In a DiD comparing $t-4$ against $t-3$ before and after the reform, the interaction is +69.4 basis points ($t = 2.36$, $p = 0.018$): $t-4$ recovers as funds no longer need it under T+1, while $t-3$ absorbs selling pressure as the deadline under the new regime. Falsification tests using placebo days and dates all return zero.

A separate set of results addresses the concern that the pre-month-end window's strong performance reflects a lucky draw: that momentum crashes simply happened to fall outside the window by coincidence. It is not. To avoid confounding between PreTOM and month-start, we compare each window against remaining trading days only. PreTOM accounts for 30.9% of crash days (WML < -200 basis points) versus its 33.3% share of non-month-start trading days ($z = -1.27$, $p = 0.20$).[1] The pre-month-end window is not unusually crash-free.

[1] The result is robust across thresholds. At -100 bps: 31.8% vs. 33.3% ($z = -1.26$, $p = 0.21$). At -300 bps: 29.9% vs. 33.3% ($z = -1.24$, $p = 0.22$). PreTOM crash frequency is proportional at every threshold.

What is unusual is month-start (t+1 to t+3), which accounts for a disproportionate share of crash days compared with non-PreTOM trading days. Month-start is when reinvestment flows are expected to support loser prices; when those flows are unusually large, the rebound overshoots and becomes a crash. Our mechanism also generates a prediction that existing explanations of momentum crashes cannot make: within a crash episode, losses should concentrate at month-start rather than during PreTOM.

The COVID crash of February–May 2020 is particularly instructive. The framework of Daniel and Moskowitz (2016) requires a prolonged bear market to build the conditions for a momentum crash: extended losses that concentrate short positions before a sharp reversal. COVID provided no such buildup. The market decline was sudden, followed by an immediate V-shaped recovery. Yet momentum crashed severely (Figure 1). Our mechanism offers a natural explanation: the same institutional selling that generates PreTOM profits becomes the setup for month-start crashes when it is extreme. During COVID, PreTOM selling pressure on losers was an order of magnitude larger than normal. The violent rebound at month-start, as this extreme selling reversed, concentrated losses precisely at the turn of the month. Over the four-month episode, the pre-month-end window earned *positive* cumulative returns (+1,424 bps), while the −9,515 basis point cumulative loss fell disproportionately at month-start. No monthly-frequency framework can generate this prediction. The plumbing of the settlement cycle can.

The calendar concentration and the reversal evidence pose distinct challenges to the two dominant classes of momentum explanations. Behavioral theories, whether based on gradual information diffusion (Hong and Stein, 1999), underreaction (Barberis et al., 1998), or overconfidence (Daniel et al., 1998), predict that momentum returns should accrue continuously as information is slowly incorporated into prices. Information does not arrive on a settlement schedule. The fact that the bulk of the premium concentrates in six specific days tied to institutional cash management, and is absent on the remaining fifteen, is difficult to reconcile with any model in which momentum reflects the speed of belief updating. Risk-based theories face a different problem. If momentum compensates investors for bearing crash risk or exposure to a priced factor (Daniel and Moskowitz, 2016; Barroso and Santa-Clara, 2015), the returns should be permanent, as they represent compensation for holding a risky asset. Instead, losers decline during the pre-month-end window and rebound at month-start, with the full reversal test failing to reject. The premium is not compensation. It is temporary price pressure. Crash risk itself concentrates in a different calendar window than profits, further weakening the link between the momentum premium and crash exposure.

Several additional findings complete the picture. The window effect is present every month, not just at quarter-ends, ruling out window dressing as the primary explanation. In December, the effect weakens because tax-loss selling depletes the pool of losers by mid-month, before the pre-month-end window begins. The effect is also robust to restricting the sample to S&P 500 constituents and is distinct from mechanical portfolio rebalancing.

Our paper relates to several strands of literature. A growing literature attributes momentum to institutional trading frictions. Lou (2012) and Vayanos and Woolley (2013) emphasize the role of performance-driven flows to delegated asset managers: past returns generate investor inflows that induce managers to trade in the direction of prior performance, producing momentum. Our evidence points to a different source of trading pressure: calendar-driven liquidity demand. Most directly, we build on Etula et al. (2020), who document that institutional investors sell stocks broadly before month-end to raise cash. Their finding is a *level* effect: the entire market dips. We document a distinct *cross-sectional* pattern: selling pressure concentrates in past losers, generating the momentum premium as a byproduct of institutional liquidity management. Conceptually, our framework contrasts with Cochrane et al. (2008), who show that in a frictionless two-tree endowment economy, dividend shocks generate momentum-like return dynamics through symmetric changes in discount rates affecting both winners and losers. Our mechanism instead operates through asymmetric calendar-driven selling of losers only. We also contribute to the debate over whether momentum has weakened (Bhattacharya et al., 2017; Jegadeesh and Titman, 2023). Our decomposition shows that the non-window component of momentum has indeed attenuated, while the window component persists. This is consistent with a structural institutional-mechanics origin rather than a behavioral anomaly that arbitrage would erode.

The remainder of the paper is organized as follows. Section 2 reviews the related literature. Section 3 describes our data and empirical design. Section 4 presents the main results. Section 5 distinguishes between tax-loss selling and dash-for-cash. Section 6 provides direct evidence on the mechanism, including TAQ selling pressure, reversal, crash risk separation, and the T+1 settlement experiment. Section 7 concludes.

2 Related Literature

Momentum: behavioral vs. risk-based vs. mechanical. While the momentum literature has traditionally been divided between behavioral theories of underreaction (Hong and Stein, 1999; Barberis et al., 1998; Daniel et al., 1998) and risk-based models of crash compensation (Daniel and Moskowitz, 2016; Barroso and Santa-Clara, 2015; Avramov et al., 2016), our work shifts the focus toward the mechanical "plumbing" of the market. The momentum premium, first documented by Jegadeesh and Titman (1993) and since confirmed across international markets (Rouwenhorst, 1998; Griffin et al., 2003; Chui et al., 2010), asset classes (Asness et al., 2013), and long historical samples (Geczy and Samonov, 2016), has resisted a unified explanation precisely because both behavioral and risk-based theories leave important patterns unexplained. Behavioral theories predict gradual accrual as information diffuses; risk-based theories predict permanent compensation. Neither predicts that the premium should concentrate in six settlement-linked days and then reverse.

Recent evidence has increased this tension. Bhattacharya et al. (2017) find that U.S. momentum profits became statistically insignificant after the late 1990s. Chordia et al. (2014) document a broad attenuation coinciding with increased trading activity. Jegadeesh and Titman (2023), in a 30-year retrospective, find momentum alive in developed markets outside the United States but weakened domestically. Our decomposition offers a resolution: the non-window component of momentum has indeed attenuated, while the window component, driven by institutional settlement frictions, has not.

Institutional trading and dash for cash. Etula et al. (2020) document a "dash for cash" pattern: institutional investors sell stocks in the days before month-end to meet liquidity needs arising from fund redemptions, margin requirements, and settlement deadlines. This generates a predictable dip in aggregate equity returns followed by a reversal at the turn of the month. Their finding builds on earlier work documenting the turn-of-month effect (Ariel, 1987; McConnell and Xu, 2008; Ogden, 1990).

A large literature establishes that institutional trading drives momentum returns. Grinblatt et al. (1995) document that mutual funds are momentum traders, buying past winners and selling past losers. Sias (2004) shows that institutional herding (correlated trading across institutions) contributes to momentum, with institutional demand positively related to past returns. Lou (2012) demonstrates that mutual fund flow-driven trading explains a large fraction of momentum profits: funds experiencing inflows buy past winners, while outflow-driven selling concentrates in past losers. Vayanos and Woolley (2013) provide the main theoretical model of flow-based institutional momentum: in their delegated asset management framework, performance-driven flows generate positive-feedback trading that produces momentum and subsequent reversal. Both papers attribute momentum to flows reacting to past performance. Our mechanism differs: the causal chain runs from calendar-driven liquidity needs to selective loser selling, rather than from past performance to flows to trading. Lou's analysis operates at the monthly frequency and does not identify *when within the month* flow-driven selling occurs. This selling concentrates in six specific days tied to the settlement cycle. The T+1 natural experiment provides causal identification, linking flow-driven momentum directly to the mechanics of trade settlement. Puckett and Yan (2011) use daily institutional trading data to show that institutions' interim trades (between quarterly snapshots) exhibit significant momentum-chasing behavior. Warther (1995) documents the link between aggregate fund flows and market returns, establishing the flow-return channel at the macro level.

Our paper extends the dash-for-cash framework from the market level to the cross-section. While Etula et al. (2020) show that institutions sell broadly before month-end, this selling is not uniform across stocks. Institutions disproportionately sell past losers, generating the cross-sectional return pattern known as momentum. The fire-sale mechanism is closely related to Coval and Stafford (2007), who show that mutual funds facing outflows engage in forced selling that generates substantial temporary price pressure followed by predictable reversals.

Why losers? Liquidity pressure does not compel institutions to sell any particular stock. It compels them to sell something. Akepanidtaworn et al. (2023) offer a direct answer. Using data on institutional portfolios averaging $573 million, they show that institutional investors exhibit clear skill in their buying decisions but sell in a heuristic, non-strategic manner. Their selling decisions underperform even random selling strategies. When institutions face liquidity pressure, they reach for the easiest sell. Under time pressure, even sophisticated portfolio managers fall back on simple rules of thumb, and past losers, which have already declined and carry no unrealized gain, are the path of least resistance. Tax considerations reinforce this selection. Past losers carry unrealized losses that can be harvested to offset gains elsewhere, providing an additional incentive to sell them first when liquidity pressure arises (Constantinides, 1984; Grinblatt and Moskowitz, 2004). This mechanism is distinct from window dressing, the deliberate sale of embarrassing holdings before reporting dates to improve portfolio appearance (Lakonishok et al., 1991; He et al., 2004; Meier and Schaumburg, 2014). Carhart et al. (2002) document a related but distinct pattern, "leaning for the tape," in which funds inflate quarter-end prices of existing holdings by buying rather than selling. Wang (2024) extends this evidence to fund families. Window dressing and portfolio pumping are strategic, reputation-motivated behaviors tied to quarterly reporting. The selective selling we document occurs every month and is better characterized as a heuristic response to liquidity pressure.

Calendar effects. Calendar effects in stock returns have been documented extensively, from the January effect (Keim, 1983; Reinganum, 1983) to day-of-week patterns (French, 1980) and the turn-of-month effect (Ariel, 1987; Lakonishok and Smidt, 1988). Ogden (1990) attributes the turn-of-month effect to the clustering of cash payments (dividends, salaries, interest) around month-end, generating predictable buying pressure at the turn of the month. Our contribution is to show that momentum itself has a calendar structure, and that this structure maps directly onto the institutional liquidity calendar identified by Etula et al. (2020). The T+1 settlement natural experiment further links the pattern to the mechanics of trade settlement, providing evidence that goes beyond calendar correlation.

Market plumbing and intermediary constraints. Our paper contributes to a growing literature showing that institutional frictions, the "plumbing" of financial markets, generate asset pricing phenomena previously attributed to behavioral or risk-based stories. Cochrane et al. (2008) show that in a frictionless two-tree endowment economy, dividend shocks alter relative asset supplies and generate momentum-like return dynamics through symmetric discount-rate changes affecting both winners and losers. Our mechanism instead operates through asymmetric selling pressure on losers driven by calendar liquidity needs, producing effects that are entirely one-sided and that reverse. Duffie (2010) argues that slow-moving capital, constrained by settlement lags, regulatory frictions, and organizational inertia, explains many apparent anomalies. He and Krishnamurthy (2013) show that intermediary balance sheet constraints affect asset prices through funding channels rather than information. Du et al. (2018) demonstrate that covered interest parity deviations, once considered impossible in efficient markets, arise from institutional frictions in the settlement and funding of cross-currency trades. Kutai et al. (2025) show that settlement netting on the Israeli government bond exchange reduced liquidity stress during the March 2020 crisis relative to OTC

Treasury markets, providing direct evidence that settlement mechanics shape market outcomes during stress. Our paper extends this perspective to momentum: the cross-sectional return pattern long attributed to underreaction or crash risk is, at least in part, a byproduct of the equity settlement cycle.

Settlement cycle. U.S. equity settlement has shortened progressively: from T+3 (adopted 1993) to T+2 (compliance September 5, 2017) to T+1 (May 28, 2024). Each shortening reduces the lead time institutions need to convert stock sales into cash before month-end. The 2024 transition was particularly significant: both the SEC and DTCC characterized it as a major change in U.S. market infrastructure, requiring coordinated adjustments across trading, clearing, and funding systems (Securities and Exchange Commission, 2023; Depository Trust & Clearing Corporation, 2024). We exploit the T+2→T+1 transition as our primary natural experiment, and use the earlier T+3→T+2 transition as a supporting test. To our knowledge, this is the first paper to use settlement-cycle changes for asset pricing identification.

3 Data and Methodology

3.1 Data Sources

We use three primary data sources. First, for portfolio-level analysis, we obtain daily returns of the ten momentum-sorted portfolios from Kenneth French's data library.[2] These portfolios sort all NYSE, AMEX, and NASDAQ stocks into deciles based on cumulative returns over months −12 through −2, skipping the most recent month. From the same source we obtain daily Fama-French factors, including the market excess return ($r_t^m - r_t^f$) and the risk-free rate (r_t^f, the one-month Treasury bill rate). Our portfolio-level sample spans 1980–2025.

Second, for stock-level analysis, we construct a panel of daily stock returns from CRSP

[2] Available at https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

merged with momentum decile assignments and bid-ask quotes. The stock-level panel contains approximately 53.3 million stock-day observations spanning 1980–2025, with momentum deciles assigned using fixed monthly sorts (held constant within each calendar month).

Third, for direct evidence on institutional trading, we obtain daily measures of selling pressure from the WRDS Intraday Indicators dataset, derived from NYSE TAQ data and covering 2003–2022.[3] These include net selling pressure and the sell share of volume. We merge these measures with the CRSP panel at the stock-day level.

3.2 Key Variables

Trading day index. For each month, we index trading days backward from the last trading day. The last trading day is $t = 0$, the penultimate is $t = -1$, and so on. Our pre-month-end window ("PreTOM") consists of days $t = -9$ through $t = -4$, corresponding to the second-to-last week of the month. This window aligns with the period of elevated institutional selling documented by Etula et al. (2020).

Momentum portfolios. The winner portfolio consists of stocks in the top momentum decile; the loser portfolio consists of stocks in the bottom decile. The WML (winner-minus-loser) return is the daily difference. We examine both value-weighted (VW) and equal-weighted (EW) portfolio returns.

Loser indicator. In stock-level regressions, $\text{Loser}_{i,d}$ is an indicator equal to one if stock i is in the bottom momentum decile on date d. The variable PreTOM_d indicates whether date d falls in the $[t-9, t-4]$ window, where t denotes the within-month event-time index defined above. The interaction $\text{Loser}_{i,d} \times \text{PreTOM}_d$ is our key variable, capturing the additional return earned by losers during the window.

[3] See `https://wrds-www.wharton.upenn.edu/pages/grid-items/wrds-intraday-indicators/`.

Bid-ask spread. From CRSP daily bid and ask quotes, we compute the percentage bid-ask spread as $\text{BAS}_{i,d} = (A_{i,d} - B_{i,d})/M_{i,d}$, where A is the ask price, B is the bid price, and M is the midpoint.

Selling pressure. From TAQ, we construct: (i) net selling pressure, defined as the share of total dollar volume initiated by sellers minus the share initiated by buyers; and (ii) sell share of volume, the fraction of volume from seller-initiated trades.

Settlement transitions. If the pre-month-end selling window is driven by settlement mechanics, exogenous changes to the settlement cycle should shift the window's boundaries. U.S. equity settlement shortened from T+3 to T+2 (compliance September 5, 2017) and from T+2 to T+1 (May 28, 2024).[4] Under each regime, the effective selling deadline depends on the interaction between equity settlement and fund redemption payment timing (see Section 6.2 for details). We exploit these transitions as natural experiments in Section 6.2. For the T+2→T+1 test, we define PostT1_d as an indicator for dates on or after May 28, 2024, and "Core PreTOM" as days $t-8$ through $t-4$, the overlap between the T+2 and T+1 pre-month-end selling windows. For the T+3→T+2 test, we define PostT2_d analogously for dates on or after September 5, 2017.

3.3 Empirical Design

Our stock panel regressions take the form:

$$r_{i,d} - r^f_d = \alpha_i + \delta_d + \beta_1 \,\text{Loser}_{i,d} + \beta_2 \,\text{Loser}_{i,d} \times \text{PreTOM}_d + \varepsilon_{i,d} \tag{1}$$

where d indexes trading dates, α_i and δ_d are firm and date fixed effects, and standard errors are double-clustered by firm and date. We estimate both equal-weighted (EW) and value-weighted (VW) specifications. In the VW specification, observations are weighted by

[4] The T+3 to T+2 transition was mandated by SEC Rule 15c6-1(a) (Securities and Exchange Commission, 2017). The T+2 to T+1 transition was mandated by Securities and Exchange Commission (2023).

lagged market capitalization within each momentum decile-date cell, so that the regression coefficients reflect the returns of portfolios that overweight larger, more liquid stocks.

4 Main Results

4.1 The Window Effect in Portfolio Returns

We begin with the portfolio-level evidence. Figure 3 plots average daily excess returns for momentum winners, losers, and the WML spread during the pre-month-end window ($t-9$ to $t-4$) versus the rest of the month. The WML spread is large and positive during the pre-month-end window and close to zero on all other trading days, with the difference driven almost entirely by losers rather than winners.

To illustrate the economic magnitude of this concentration, Figure 1 decomposes the momentum premium into window and non-window components. Each day's value-weighted WML return (top decile minus bottom decile, from Kenneth French's momentum portfolios) is assigned to one of two mutually exclusive buckets based on the trading-day index t: the "window" return on days $t-9$ through $t-4$, and the "rest" return on all other days. Compounding each component separately from $1 on January 2, 1980 reveals a stark divergence. By 2025, the window-only strategy has grown to $18.78 while the rest-only strategy reaches just $2.40.[5] The two strategies track each other through the early 2000s before diverging, consistent with the non-window component of momentum weakening over time while the window component persists.

The asymmetry is entirely loser-driven. Figure 2 isolates the loser portfolio. Losers underperform the market by 44.4 basis points per month during the pre-month-end window ($t = -3.24$) but earn returns indistinguishable from zero on all other trading days (-8.8 bps, $t = -0.39$). Figure 3 confirms that winners show no special pre-month-end pattern: their

[5] Using French's daily-rebalanced momentum portfolios instead of fixed monthly sorts yields $15.9 and $2.2 respectively. The qualitative pattern is identical.

daily returns are similar in both windows. Momentum, at the portfolio level, is about losers losing during six predictable days each month. The pattern is robust across subperiods: Appendix Figures A2 and A3 show that the loser PreTOM underperformance and the WML window concentration are present in both the 1980–2002 and 2002–2025 halves of the sample. Appendix Figure A1 provides the full daily decomposition, plotting mean excess returns for each trading day t separately for losers and winners.

4.2 Stock-Level Evidence

The portfolio results establish that the concentration is driven by losers, not winners. To quantify the effect at the stock level and rule out a wide range of confounds, we estimate panel regressions with firm and date fixed effects. The firm fixed effects absorb any time-invariant stock characteristics, such as size, illiquidity premia, or persistent return differences across stocks. The date fixed effects absorb all market-wide variation on a given day, including aggregate risk premia, macroeconomic news, and any calendar anomaly affecting all stocks equally.

Table 1 presents estimates of equation (1). In the value-weighted specification, the coefficient on Loser $\times$ PreTOM is -7.2 basis points per day ($t = -3.08$). Over six trading days, this implies losers underperform by approximately 43 basis points per month solely during the window, a magnitude sufficient to account for the entire monthly momentum premium. The equal-weighted estimate is smaller (-2.6 bps, $t = -1.85$) because equal-weighting dilutes the effect across illiquid micro-cap stocks that do not participate in institutional selling, a point we clarify below with bid-ask spread interactions.

4.2.1 Liquidity

If the window effect is driven by institutional selling, it should concentrate where institutions trade: among liquid stocks.

Table 2 adds the contemporaneous bid-ask spread and its interactions. In the equal-weighted specification, the triple interaction Loser × PreTOM × BAS is large and positive (30.4, $t = 2.57$), indicating that the window effect concentrates among liquid losers: stocks with narrow spreads show large pre-month-end declines, while illiquid stocks exhibit little selling pressure. This is precisely what the dash-for-cash hypothesis predicts: when institutions need to raise cash quickly, they sell stocks they *can* sell, not stocks that happen to be cheap. The value-weighted interaction is also positive and significant (+58.8, $t = 2.34$), confirming the liquidity channel holds regardless of weighting scheme.

Since value-weighting naturally captures the institutional-trading channel, we adopt it as our primary specification for all remaining analyses.

4.2.2 Subperiod Stability

A natural concern is that the window effect reflects an artifact of earlier, less liquid markets, such as thin trading, wider spreads, and less institutional participation, that has since disappeared as markets modernized. Many well-documented anomalies do attenuate over time as arbitrage capital grows and markets become more efficient (McLean and Pontiff, 2016; Greenwood and Sammon, 2025). If so, the window effect should be stronger in the first half of the sample and attenuate or vanish in the second. The opposite is true.

Table 3 splits the sample at the midpoint (July 2002) into two equal halves. The window effect is present in both: −5.8 bps ($t = -2.31$) in the first half and −8.5 bps ($t = -2.20$) in the second. The increase in magnitude is consistent with growing institutional assets amplifying month-end selling pressure over time. An illiquidity explanation predicts the opposite pattern: if thin, less-efficient pre-2002 markets drove the effect, it should attenuate as spreads tightened and markets modernized (McLean and Pontiff, 2016). The strengthening rules this out. The Loser main effect, which captures average daily underperformance outside the window, roughly doubles from the first half to the second, yet the window component is significant throughout. The well-documented attenuation of U.S. momentum (Bhattacharya et al., 2017; Jegadeesh and Titman, 2023) appears to reflect erosion of its non-window component, while the institutional-mechanics component persists. Unlike anomalies driven by mispricing, the window effect reflects a structural "plumbing" friction that is not easily arbitraged away: institutions face recurring, non-discretionary cash needs at month-end regardless of whether arbitrageurs are aware of the pattern or positioned to trade against it.

A related concern is that the persistence of PreTOM profits reflects compensation for crash risk. If momentum crashes disproportionately fell in the pre-month-end window, the strategy's apparent profitability would simply be a tail-risk premium. We address this directly in Section 6.3: crash days fall in the PreTOM window at roughly the rate expected under a uniform distribution, neither more nor less than in other non-month-start windows. What is structurally unusual is month-start, where crash days are overrepresented by 43%.

4.2.3 Window Uniqueness

A natural concern is that the PreTOM window $[t-9, t-4]$ was selected ex post to maximize the effect. We address this by sliding a six-day window across the second half of the trading month and computing the raw mean market-adjusted VW loser return within each window. We restrict to windows starting on or after trading day 7 (approximately mid-month) to ensure that all days within each window belong to the same monthly portfolio assignment, avoiding contamination from portfolio re-formation at month-start.

Figure 4 shows the result. The mean loser-market return is near zero for mid-month windows, declines monotonically as the window shifts toward month-end, and troughs at PreTOM (days 14–19): -7.7 basis points per day ($t = -3.59$, Newey-West). No other window starting position produces a comparably negative estimate. The decline into PreTOM and partial recovery at month-end are exactly what the dash-for-cash mechanism predicts: selling pressure builds as month-end approaches, peaks during PreTOM, and eases in the final days.

4.3 Reversal

If the pre-month-end loser underperformance reflects temporary selling pressure rather than permanent risk compensation, prices should recover once the selling subsides.

Table 4 tests this prediction by adding a Loser × Post indicator (days t+1 to t+3 at month-start) to the baseline return regression. The Loser × PreTOM coefficient is -5.51 ($t = -2.32$) and Loser × Post is +8.22 ($t = 2.40$): losers underperform during the pre-month-end window and outperform at month-start. A test of full reversal ($6\times\beta_{\text{PreTOM}}+3\times\beta_{\text{Post}} = 0$) cannot be rejected ($F = 0.19$, $p = 0.66$), consistent with the pre-month-end price decline being fully offset by the post-window rebound.

This sell-then-rebound cycle distinguishes our mechanism from risk-based explanations. If the pre-month-end loser underperformance were compensation for bearing risk, the returns should be permanent. Investors would earn the premium precisely because they are exposed to the risk during those days, and there would be no reason for prices to snap back afterward. The fact that loser prices decline during the window and then recover at month-start indicates temporary price pressure, not permanent risk compensation. This dynamic closely parallels Coval and Stafford (2007), who show that mutual funds facing outflows engage in forced selling that generates substantial price pressure followed by predictable reversals, and is consistent with the broader evidence that non-informational demand shocks produce temporary price dislocations (Shleifer and Vishny, 1997; Wurgler and Zhuravskaya, 2002).

A potential concern is that full reversal contradicts the existence of a positive monthly momentum premium: if loser prices decline and then recover, how does the premium survive? The resolution lies in where the reversal falls. The month-start rebound (days t+1 to t+3) is already inside the rest-of-month bucket. It is precisely why that component earns so little relative to the window-only strategy ($2.40 versus $18.78; Figure 1). The full reversal result is not a threat to our mechanism but a direct consequence of it.

4.4 Transaction Costs

Novy-Marx and Velikov (2016) show that momentum is among the most expensive anomalies to implement, with bid-ask spreads and market impact consuming much of the gross return. A natural question is whether the PreTOM concentration survives realistic trading costs.

We decompose the standard value-weighted momentum strategy, rebalanced monthly into decile 10 (winners) minus decile 1 (losers), into PreTOM and rest-of-month components. The portfolio is identical; only the accounting window differs. Daily value-weighted returns on days $t=-9$ to $t=-4$ are compounded into the PreTOM component, and remaining days into the rest. Transaction costs are computed following the spirit of Novy-Marx and Velikov (2016). Each month, we identify stocks that change momentum decile assignment. For each such stock, we charge one full quoted bid-ask spread, (ask − bid) / midpoint, averaged across trading days in the month. This round-trip cost covers the entry and exit trades associated with rebalancing. Stocks that remain in the same decile incur zero cost. The strategy-level cost is the value-weighted average across turnover stocks, summed over both sides of the long-short.[6]

Table 5 reports the results. Over the full sample (1980–2025), gross WML averages +88.8 bps per month, of which +56.8 bps (64%) accrues during PreTOM. Transaction costs of 112 bps per month, driven by the wide spreads of small, illiquid losers, more than eliminate the gross return, leaving a net of −23.2 bps. This is the Novy-Marx and Velikov (2016) problem: unrestricted momentum is expensive.

The picture changes substantially post-decimalization (2001–2025). Gross WML falls to +35.0 bps per month, but the PreTOM component averages +53.3 bps (152% of gross). The rest-of-month component is *negative* (−16.9 bps).[7] Transaction costs drop to 13.9 bps

[6] Our cost measure is conservative. Novy-Marx and Velikov (2016) use the Hasbrouck (2009) effective spread, which is typically smaller than the quoted spread because many trades receive price improvement. The quoted spread overstates execution costs for small liquidity demanders but understates price impact for large trades. Monthly turnover averages 20.9% for losers and 26.2% for winners.

[7] The PreTOM and rest-of-month components are compounded separately within each month and do not sum exactly to the gross return due to cross-product terms.

per month as spreads tighten, yielding a net return of +21.1 bps. In recent markets, the standard monthly-rebalanced momentum strategy is marginally profitable, and all of its net return originates in the PreTOM window.

We stress that this decomposition characterizes the source of net profits, not a trading recommendation. A strategy that trades *only* during the PreTOM window would require entering and exiting positions twice per month, roughly doubling turnover costs. Designing a cost-efficient hybrid, for example holding the full month but overweighting during PreTOM, is beyond the scope of this paper but a natural direction for practitioners.

5 Tax-Loss Selling vs. Dash for Cash

A natural alternative is that the pre-month-end selling of losers reflects tax-motivated trading rather than institutional liquidity needs. Grinblatt and Moskowitz (2004) show that the capital gains "overhang" is a key predictor of momentum returns, with the loser momentum effect roughly 2.5 times larger in December than in other months. Brown (2017) documents that momentum returns concentrate in the third month of calendar quarters, attributing the pattern to tax-loss selling and window dressing by delegated managers. If tax-loss selling is the primary driver of the pre-month-end loser effect, the pattern should amplify in December and at quarter-ends.

Our evidence points in the opposite direction. The PreTOM effect is present every month, with no quarter-end amplification, and is sharply *attenuated* in December (Appendix Figure A4). Tax-loss harvesting should amplify the PreTOM effect in December by intensifying selling of losers before year-end. Dash-for-cash predicts the opposite: tax-loss selling in early December front-runs the usual PreTOM selling pressure, attenuating the window effect. We find attenuation, not amplification.

Two tests address the tax-loss alternative directly. First, restricting the sample to non-quarter-end months, where tax-loss selling is least relevant, the Loser $\times$ PreTOM coefficient is -7.5 bps ($t = -2.66$), virtually identical to the full-sample estimate (Table 6). Second, interacting Loser × PreTOM with a quarter-end indicator produces a small, insignificant triple interaction (Table A1): there is no systematic quarter-end amplification, consistent with a monthly liquidity cycle rather than quarterly reporting incentives.

December is the decisive test. Mutual fund capital gains distribution record dates cluster in mid-December.[8] Investors who learn estimated distribution sizes in November harvest offsetting losses in the first two weeks of December, well before our window opens around December 17–26. By the time PreTOM begins, much of the selling pressure on losers has already occurred. The mechanism predicts attenuation, and that is exactly what we find. Loser PreTOM returns in December average +0.18% per month ($t = 0.28$), indistinguishable from zero, compared to -0.67% across all months ($t = -3.25$). September, where tax-loss incentives are weaker, produces the deepest underperformance in the sample (-2.37%, $t = -3.36$).

Our finding complements Grinblatt and Moskowitz (2004). Tax-loss selling amplifies December's monthly loser underperformance, but this selling occurs earlier in the month, front-running the institutional selling that would normally concentrate in PreTOM (Appendix Figure A4). December illustrates this displacement clearly. Despite being among the stronger months for momentum at the monthly frequency (+137 bps, ranking fifth in our sample), December produces near-zero PreTOM underperformance. September presents the mirror image: the deepest PreTOM underperformance in the sample coincides with strong total momentum, consistent with the mechanism operating without seasonal disruption.

This is not a contradiction: December demonstrates that loser selling can generate a strong monthly premium even when displaced from the PreTOM window. The settlement cycle determines the timing in normal months; tax deadlines override that timing in December. Both channels route through the same friction, selective institutional liquidation of past

[8]For example, 65% of Vanguard's 2023 year-end distribution record dates fell between December 14 and 19 (Vanguard, *Final Estimated Year-End Capital Gains Distributions*, December 2023, available at https://investor.vanguard.com).

losers, and both generate momentum. The mechanism is the selling itself, not the specific days.

6 Mechanism

6.1 TAQ Selling Pressure

If the window effect reflects institutional selling of losers, we should observe elevated selling pressure in loser stocks during the $[t-9, t-4]$ window. We test this using intraday data from the WRDS TAQ Intraday Indicators dataset, which provides daily measures of buy- and sell-initiated volume classified by the Lee-Ready algorithm. The sample covers 2003–2022, yielding approximately 17.9 million stock-day observations.

Table 7 regresses selling pressure on Loser, PreTOM, and their interaction, with firm and date fixed effects. The Loser $\times$ PreTOM coefficient on net selling pressure is 0.0020 ($t = 2.50$), and on the sell share of volume 0.0010 ($t = 2.50$). When a stock enters the bottom momentum decile, it experiences more selling during the pre-month-end window than the same stock does outside the window or when it is not classified as a loser. Extending the specification to include a post-window indicator (days t+1 to t+3), the selling-buying cycle is clear: Loser $\times$ PreTOM is positive (+0.0014, net selling) while Loser $\times$ Post is negative (-0.0028, $t = -2.55$, net buying). Losers face abnormal selling pressure before month-end and abnormal buying pressure at month-start, consistent with temporary price pressure followed by reversal.

6.2 T+1 Settlement Natural Experiment

The preceding evidence establishes a strong association between the institutional settlement calendar and the timing of momentum returns, but it is ultimately correlational. An alternative explanation could attribute the calendar concentration to any monthly cycle, whether behavioral, informational, or macroeconomic, that happens to coincide with the pre-month-end window. To move toward a causal interpretation, we exploit a regulatory change that shifted the settlement deadline by exactly one day: the SEC's May 28, 2024 transition from T+2 to T+1 equity settlement.[9]

Prior to the 2024 reform, open-end mutual funds faced a settlement mismatch: fund redemptions required cash payment on a T+1 basis while sales of portfolio securities settled on T+2 (Securities and Exchange Commission, 2023). To meet redemption payments on time, funds were compelled to sell portfolio securities one day earlier than pure settlement would require. This mismatch made day $t-4$ empirically the effective last selling day: a sale on $t-4$ settles on $t-2$, one day ahead of a T+1 redemption payment due on $t-1$. The 2024 reform eliminated this mismatch entirely by aligning equity settlement with fund redemption settlement at T+1. Both the SEC and DTCC characterize the transition as a major change in U.S. market infrastructure, requiring coordinated adjustments across trading, clearing, and funding systems (Securities and Exchange Commission, 2023; Depository Trust & Clearing Corporation, 2024). With no need to pre-sell, the effective deadline shifted one day later to $t-3$. The key prediction is one-sided: day $t-3$ should absorb additional selling pressure that could not occur there under T+2.

The pattern that held for 45 years vanishes after May 2024. In the 533 months before the transition, compounded loser returns during the PreTOM window ($t-9$ to $t-4$) averaged -46.5 basis points per month ($t = -3.29$). In the 19 months after, the same window averages $+12.5$ basis points ($t = 0.36$, insignificant). With only 19 post-event months, this could reflect noise rather than a structural break.

The day-by-day return profile resolves this ambiguity. Figure 5 plots the difference in mean loser market-adjusted returns (Post-T+1 minus Pre-T+1) at each trading day t. The new settlement deadline at $t-3$ absorbs -27 basis points of additional selling pressure, exactly as predicted. Day $t-4$ shifts by $+43$ basis points, suggesting institutions abandoned

[9] U.S. equity settlement shortened progressively from T+3 to T+2 (September 5, 2017) and from T+2 to T+1 (May 28, 2024). We exploit the T+2→T+1 transition as our primary natural experiment. The earlier T+3→T+2 transition provides a supporting test; results are reported in Appendix Table A3.

the old deadline rapidly rather than partially retaining it. Day $t{-}2$ also turns negative, suggesting some selling spills beyond the new deadline; the DiD comparing $t{-}4$ to $t{-}3$ is therefore conservative. All other days show differences indistinguishable from zero. The pattern did not disappear. It shifted.

The day-level evidence is visually compelling but faces an obvious confounder: any change in macroeconomic conditions or momentum portfolio behavior after May 2024 could drive the result. We design a DiD that isolates the sharpest prediction of the settlement mechanism. The test compares two adjacent trading days, $t{-}4$ and $t{-}3$, before and after the T+1 transition. Under T+1, day $t{-}3$ becomes the new settlement deadline and should absorb selling pressure that was previously spread across earlier days. Both days share the same macro environment, the same market conditions, and the same universe of loser stocks on any given month. Any broad shift in loser returns cancels out. What remains is specific to the settlement deadline. We estimate:

$$r_d^{\text{loser}} - r_d^{\text{mkt}} = \alpha + \beta_1\, \mathbf{1}[t{=}{-4}]_d + \beta_2\, \text{PostT1}_d + \beta_3\, \mathbf{1}[t{=}{-4}]_d \times \text{PostT1}_d + \varepsilon_d \qquad (2)$$

where $\mathbf{1}[t{=}{-4}]$ indicates the T+2-era deadline day (versus $t{-}3$, the control), PostT1 indicates dates after May 28, 2024, and the sample is restricted to loser portfolio returns on days $t = -4$ and $t = -3$ only. The coefficient of interest is β_3: a positive estimate indicates that $t{-}4$ improved relative to $t{-}3$ after T+1, consistent with $t{-}3$ absorbing selling pressure as the deadline under T+1.

Table 8 reports the 2×2 cell means and the DiD estimate. Before T+1, both days carried similar selling pressure: $t{-}4$ averaged -8.8 bps and $t{-}3$ averaged -4.2 bps ($\beta_1 = -4.5$, $t = -0.68$, insignificant). After T+1, they diverge sharply: $t{-}3$ drops to -30.6 bps as it absorbs selling pressure under the new settlement regime, while $t{-}4$ flips to $+34.4$ bps. The DiD interaction is $+69.4$ basis points ($t = 2.36$, $p = 0.018$). Day $t{-}3$, the deadline under T+1, absorbed selling pressure precisely as predicted. The PostT1 main effect is -26.3

($t = -1.21$), indicating that $t-3$, the omitted day, became more negative after the reform. This is consistent with $t-3$ absorbing selling pressure as the new deadline under T+1, and is precisely the variation the DiD interaction isolates.

We run three falsification tests using the same DiD specification. First, *placebo days*: running the identical $t-4$ vs. $t-3$ DiD but shifted to $t-6$ vs. $t-7$, two days well inside both the T+2 and T+1 selling windows where no deadline shifted, produces a DiD of +1.0 ($t = 0.04$). Second, *placebo dates*: the same $t-4$ vs. $t-3$ comparison using fake event dates of May 2020 and May 2018, when no regulatory change occurred, yields DiDs of -0.9 ($t = -0.03$) and -3.5 ($t = -0.16$). All three falsifications are indistinguishable from zero (Table A2).

The post-T+1 period covers only 19 months (June 2024–December 2025), yielding just 19 observations per cell. The DiD estimate is conservative: Column 2 of Table 8 restricts the pre-period to the T+2 era alone (September 2017–May 2024), when $t-4$ was the effective deadline. The DiD strengthens to +78.8 bps ($t = 2.13$), confirming that the full-sample baseline understates the effect due to dilution from T+3-era observations.[10] The earlier T+3→T+2 transition (September 2017) produces a positive but insignificant DiD (+4.0 bps, $t = 0.19$): the core PreTOM window weakened slightly after the reform, as expected if T+2 reduced but did not eliminate the settlement mismatch (Appendix Table A3).

6.3 Momentum Crashes

A natural concern is that PreTOM's strong performance reflects luck: momentum crashes happened to fall outside the window by coincidence. We classify a trading day as a "crash day" if VW WML falls below -200 basis points. To avoid confounding PreTOM and month-start, we compare each window against remaining trading days only: PreTOM is compared

[10] Redefining the PreTOM window to track the settlement regime ($[t-9, t-3]$ under T+2, $[t-9, t-2]$ under T+1) yields a marginally stronger Loser × PreTOM coefficient (-8.3 bps, $t = -3.35$ vs. -7.2, $t = -3.08$), but the extra-day interactions are individually insignificant due to limited post-regime-change samples. We retain the fixed $[t-9, t-4]$ window throughout.

against non-month-start days, and month-start against non-PreTOM days.[11] PreTOM accounts for 30.9% of crash days versus its 33.3% calendar share ($z = -1.27$, $p = 0.20$): crashes arrive in PreTOM at the expected rate. What *is* unusual is month-start, which accounts for a disproportionate share of crash days at every threshold from -100 to -300 bps (Figure 6). The same institutional payment cycle that generates PreTOM selling channels reinvestment flows to month-start; when reinvestment buying is unusually strong, the loser rebound overshoots and becomes a crash. Figure 7 displays both dimensions jointly: crash probability is elevated precisely at month-start, while mean WML is highest during PreTOM. Trimming just the worst 1% of days confirms the asymmetry (Figure 8): PreTOM mean WML rises from +9.7 to +17.4 bps (structural), while month-start flips from -4.4 to +5.3 bps (driven entirely by tail events).

Our mechanism also predicts that within a crash episode, losses should concentrate at month-start rather than during PreTOM. We decompose cumulative WML losses during three momentum crash episodes identified following the framework of Daniel and Moskowitz (2016).[12] In every case, PreTOM's share of losses is at or below its calendar share: 29% of $-2{,}204$ bps in 2001, 22% of $-12{,}785$ bps in 2009. COVID is particularly instructive. The Daniel and Moskowitz (2016) framework requires a prolonged bear market that loads losers with high beta before a market rebound triggers the crash; the 2001 and 2009 episodes fit this pattern. COVID provided no such buildup: the market decline was sudden and followed by an immediate V-shaped recovery, yet momentum crashed severely (Figure 1). Their framework cannot explain this episode. Ours can: extreme forced selling during PreTOM drove loser prices far below fundamental value, setting up a violent month-start reversal when

[11] Calendar share is the fraction of trading days that fall in a given window within the relevant comparison universe. For PreTOM, we exclude month-start days from both numerator and denominator; for month-start, we exclude PreTOM days. If crashes were spread evenly across the month, each window's share of crash days would equal its calendar share. We test whether the observed share differs from this benchmark using a standard proportions z-test.

[12] August 2001–March 2002, January–September 2009, and February–May 2020 (COVID). The first two episodes fall within the Daniel and Moskowitz (2016) sample; COVID postdates it but exhibits the same momentum crash pattern. The date ranges are ours, chosen to span the full period of sustained momentum losses in each episode.

those positions snapped back. PreTOM earned *positive* returns (+1,424 bps) throughout, while month-start absorbed −6,090 bps (64% of the total loss) as losers surged. No prolonged buildup is needed; the institutional cash cycle generates both the profit and the crash.

6.4 Rebalancing

A natural alternative is mechanical portfolio rebalancing. Harvey et al. (2025) document that calendar-driven rebalancing by pension funds and target-date funds generates predictable price pressure of approximately 17 basis points per day at month-ends and quarter-ends. Several features distinguish our findings. First, the Harvey et al. effect operates at the *aggregate* level (equities vs. bonds), while our effect is *cross-sectional* (which stocks within equities bear disproportionate selling pressure). Second, they show their signals are robust to momentum controls, indicating empirical distinctness. Third, our BAS and TAQ results point to a stock-selection channel rather than broad asset-class rotation. The two mechanisms are complementary: aggregate rebalancing pressure may amplify cross-sectional selling by increasing the urgency of month-end liquidation.

6.5 Index Rebalancing

If past losers systematically lose weight in major benchmarks, mechanical selling by passive funds could produce the pattern. We test this directly by splitting the sample into S&P 500 constituent stocks and non-constituent stocks. The window effect is present in both groups. In the value-weighted specification, Loser × PreTOM is −4.6 bps ($t = -2.53$) among non-S&P 500 stocks and −8.8 bps ($t = -2.71$) among S&P 500 stocks. The interaction Loser × PreTOM × S&P500 is small and insignificant (−2.5, $t = -0.82$). The window effect operates equally inside and outside the major index, ruling out passive index rebalancing as the driver. Table A4 in the Appendix reports the full results.

6.6 Turn-of-the-Month Effect

Our pre-month-end window ($t-9$ to $t-4$) is distinct from the classic turn-of-month window ($t = 0$ through $t+3$). The two windows do not overlap. Re-estimating our baseline specification excluding turn-of-month days, the Loser $\times$ PreTOM coefficient is unchanged. Adding TOM day controls interacted with Loser produces no meaningful attenuation. The pre-month-end momentum concentration is a separate phenomenon from the well-documented turn-of-month effect.

7 Conclusion

The momentum premium has a simple structure: it accrues almost entirely during six trading days before month-end, and it is driven entirely by losers. Over four decades, the bulk of the value-weighted winner-minus-loser return in U.S. equities has concentrated in this predictable calendar window. Outside it, the momentum premium is indistinguishable from zero.

The mechanism is institutional dash-for-cash. Funds facing month-end liquidity needs disproportionately liquidate past losers during a predictable calendar window. TAQ data confirm the selling pressure spike and its reversal at month-start. The 2024 T+1 settlement reform shifted the selling deadline by exactly one day, as predicted. And crash days concentrate at month-start rather than during the profit window, a separation that follows directly from the same institutional payment cycle that generates the premium.

These findings are difficult to reconcile with existing explanations. Behavioral theories require that information arrive on a settlement schedule; it does not. Risk-based theories require that the price decline be permanent compensation for bearing risk; it reverses. The concentration of the entire premium in six specific days, tied not to news or risk but to the mechanics of trade settlement, points toward a simpler explanation: momentum is a byproduct of how institutional investors manage cash.

A natural question is whether momentum is special. We doubt it. The approach developed here, decomposing factor returns by day-of-month and asking when within the month anomaly profits actually accrue, can be applied broadly. Many cross-sectional return patterns share a short leg populated by stocks that institutions would rationally sell first under liquidity pressure. If the intramonth structure documented here generalizes, it would suggest that a meaningful fraction of what the literature calls anomaly returns reflects not slow-moving information or priced risk, but the predictable rhythm of institutional cash management. Distinguishing plumbing from economics is, we believe, one of the more productive directions open to empirical asset pricing.

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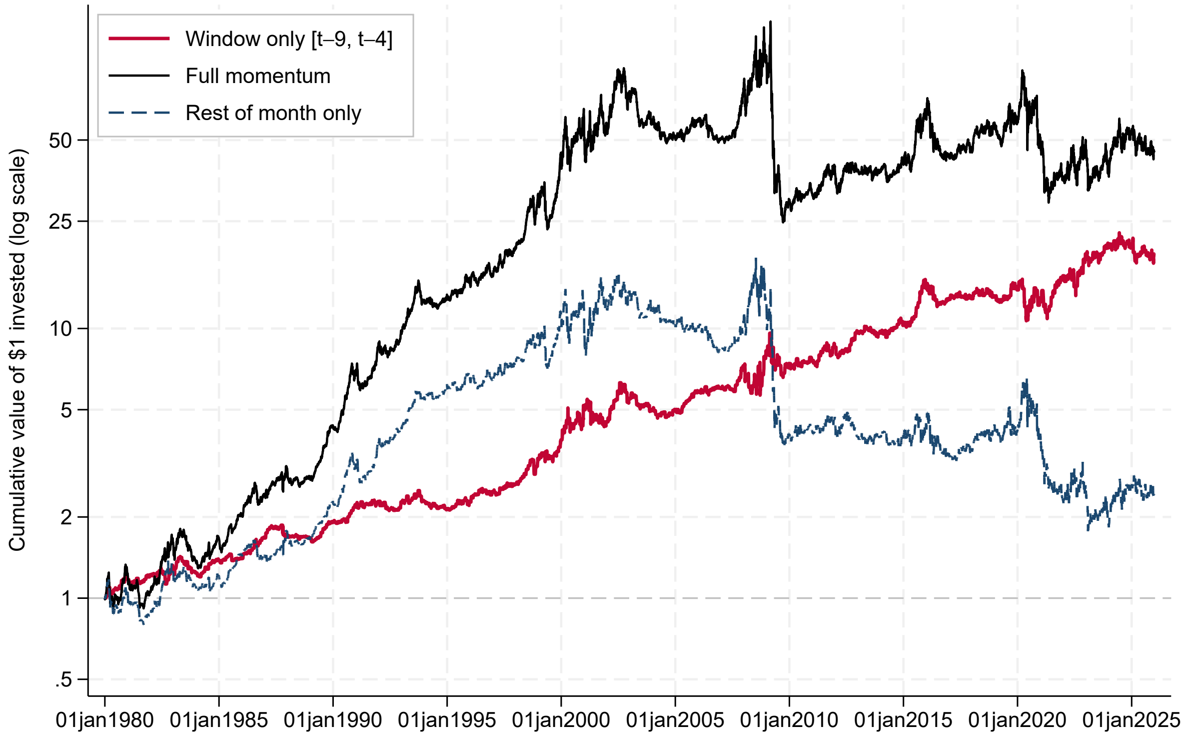


Figure 1: Cumulative wealth from $1 invested in three momentum strategies using fixed monthly decile assignments. Stocks are sorted into momentum deciles based on cumulative returns over months −12 through −2 relative to formation, with decile assignments held constant within each calendar month. WML is the daily winner return (decile 10) minus the loser return (decile 1), both in excess of the risk-free rate. Trading days within each month are indexed backward from the last trading day ($t = 0$). The *Window-only* strategy earns the WML return on days $t-9$ through $t-4$ and earns zero (cash) on all other days. The *Rest-only* strategy earns the WML return on all days *except* $t-9$ through $t-4$ and earns zero during the window. The *Full WML* strategy earns the WML return every day. Cumulative wealth is computed as $W_T = \prod_{d=1}^{T}(1 + r_d^s)$, where r_d^s is the strategy return on day d. All three strategies start at $1 on January 2, 1980. Terminal values (December 31, 2025): Window-only $18.78, Full $45.06, Rest-only $2.40.

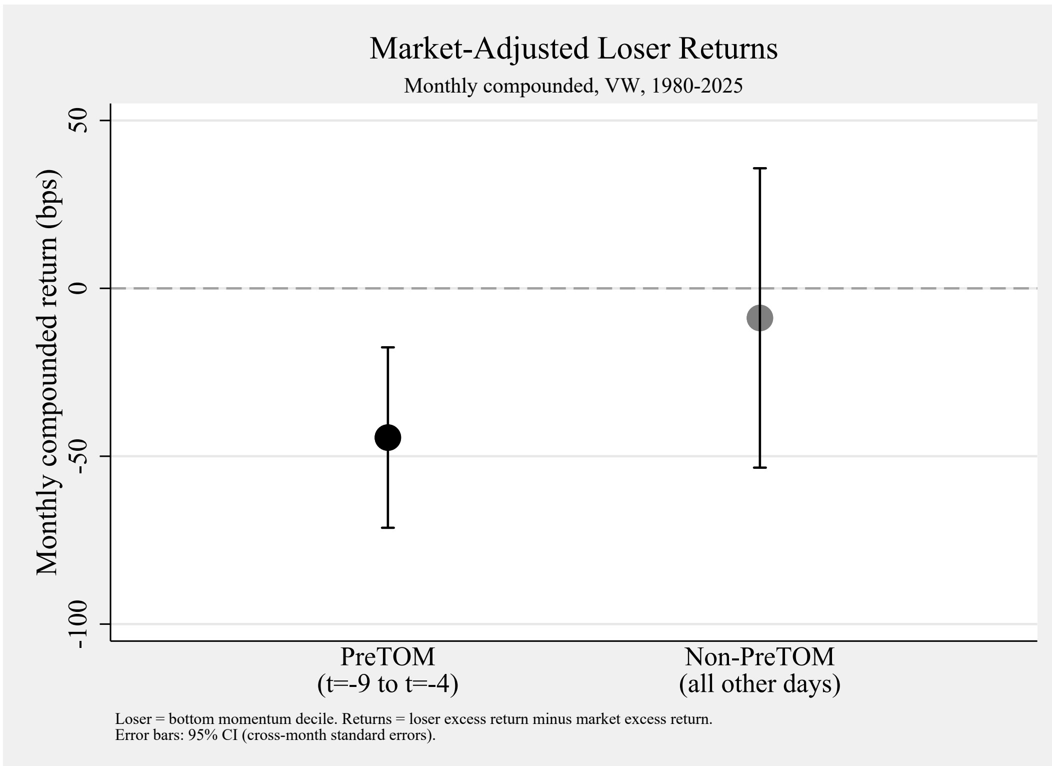


Figure 2: Market-adjusted monthly loser returns during the PreTOM window versus the rest of the month. For each calendar month, daily market-adjusted loser returns (loser portfolio return minus market excess return) are compounded separately within the PreTOM window (days $t-9$ to $t-4$) and the non-PreTOM window (all other trading days) to produce two monthly return observations. Bars show the time-series average of these monthly compounded returns across 552 months (1980–2025), in basis points. Whiskers denote 95% confidence intervals computed from the time-series standard deviation of monthly compounded returns divided by $\sqrt{552}$. Data are value-weighted returns of the bottom momentum decile portfolio from Kenneth French's data library. Losers underperform the market by 44.4 basis points per month during PreTOM ($t = -3.24$) but earn returns indistinguishable from zero on other days (-8.8 bps, $t = -0.39$).

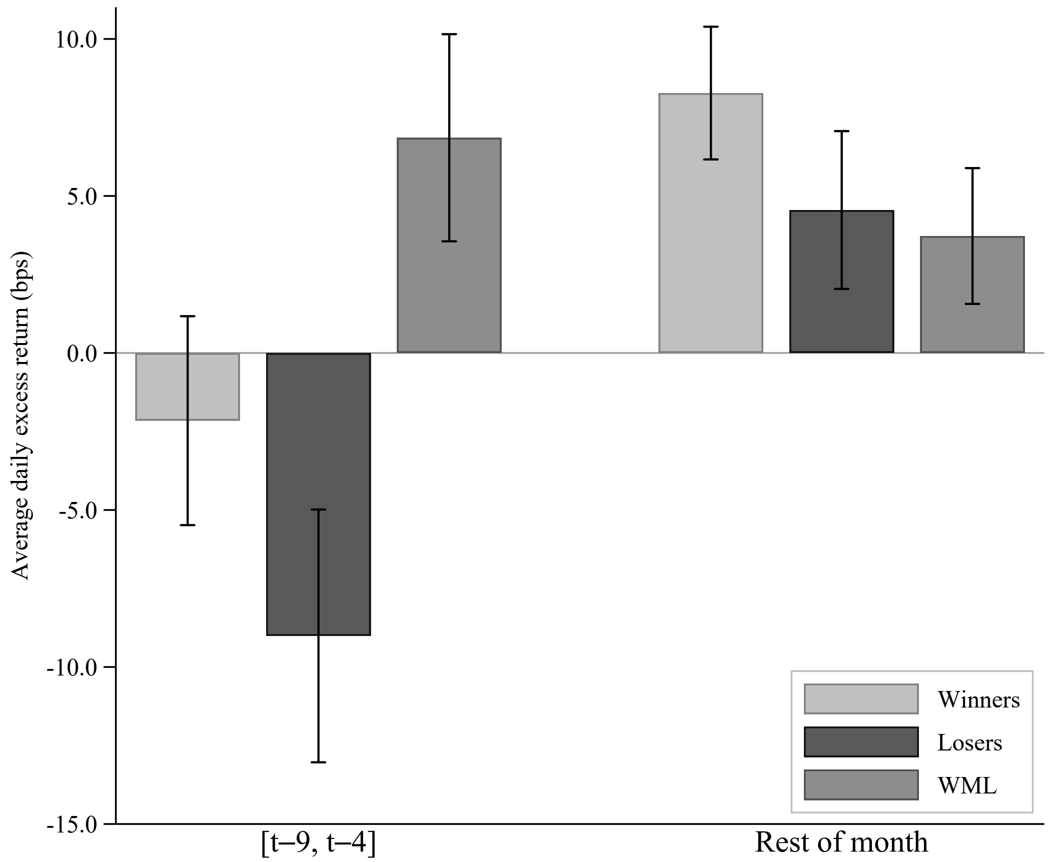


Figure 3: Average daily excess returns (basis points) of momentum winners, losers, and WML during the pre-month-end window ($t-9$ to $t-4$) versus the rest of the month. Each bar shows the unconditional time-series mean of daily returns across all trading days in the indicated window. Whiskers denote 95% confidence intervals. Data are daily value-weighted returns of the top and bottom momentum decile portfolios from Kenneth French's data library. Sample: 1980–2025.

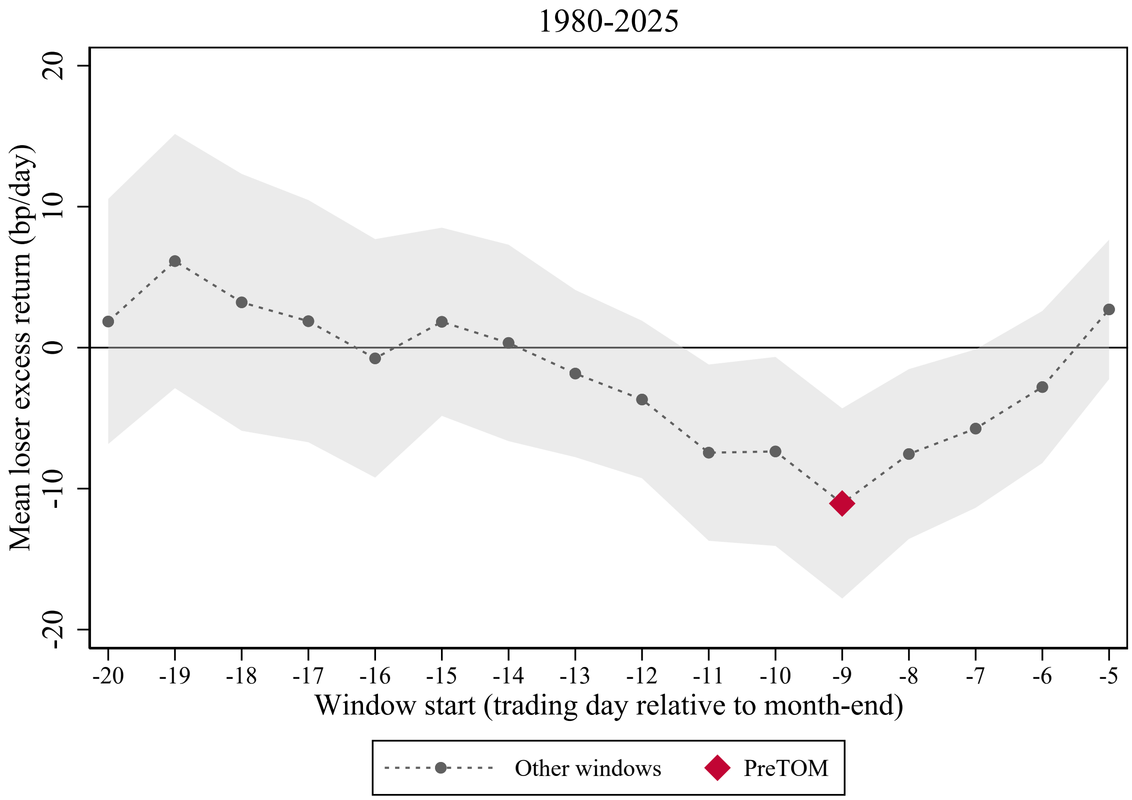


Figure 4: Buildup of loser underperformance toward month-end. Each point plots the mean VW loser excess return ($r_i - r_f$) within a sliding six-day window. The x-axis indicates the window start day relative to month-end (0 = last trading day). The loser excess return is positive at mid-month and declines monotonically, reaching its trough at PreTOM ($t{-}9$ to $t{-}4$, diamond; -11.1 bp/day, $t = -3.21$). The partial recovery toward the last trading day is consistent with the post-window reversal documented in Table 4. Only months with all six days in the window are included. Newey-West standard errors (5 lags) on monthly window means. Sample: 1980–2025.

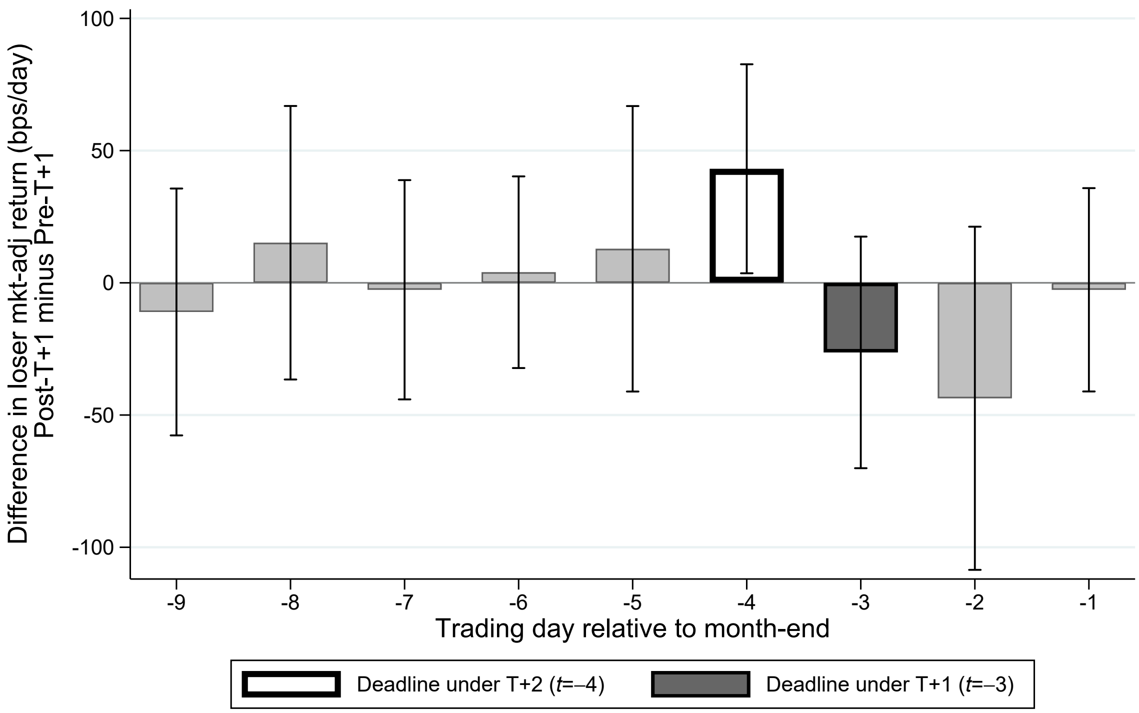


Figure 5: Each bar shows the difference in mean daily market-adjusted VW loser returns (Post-T+1 minus Pre-T+1) at each trading day t, with 95% confidence intervals. Under T+2, day $t{-}4$ was the effective settlement deadline; it shifts by +43 bps after the reform as selling pressure migrates away. Under T+1, day $t{-}3$ becomes the new deadline and absorbs −27 bps of additional selling pressure. All other days are indistinguishable from zero. Sample: 1980–2025 (533 months pre, 19 months post).

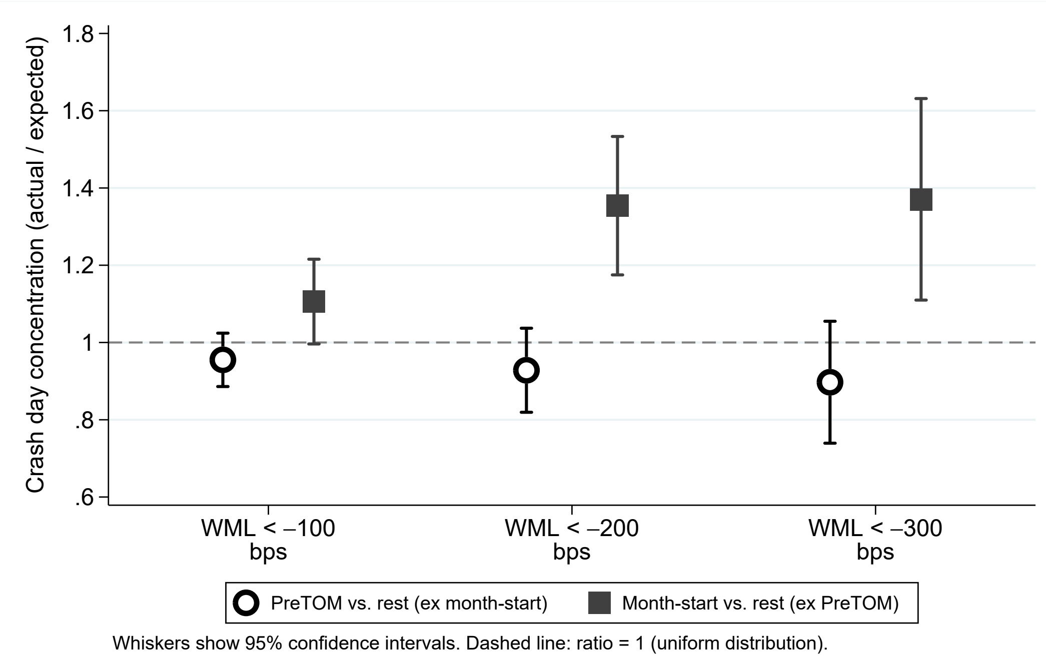


Figure 6: Crash day concentration by calendar window. Each point plots (actual share of crash days in window) / (window's calendar share), with 95% confidence intervals. To avoid confounding, each window is compared against remaining trading days only: PreTOM against non-month-start days, and month-start against non-PreTOM days. Under the null that crashes are uniformly distributed, all points equal one (dashed line). Month-start is overrepresented at every threshold. PreTOM is indistinguishable from its expected share at all thresholds. Sample: 1980–2025, value-weighted.

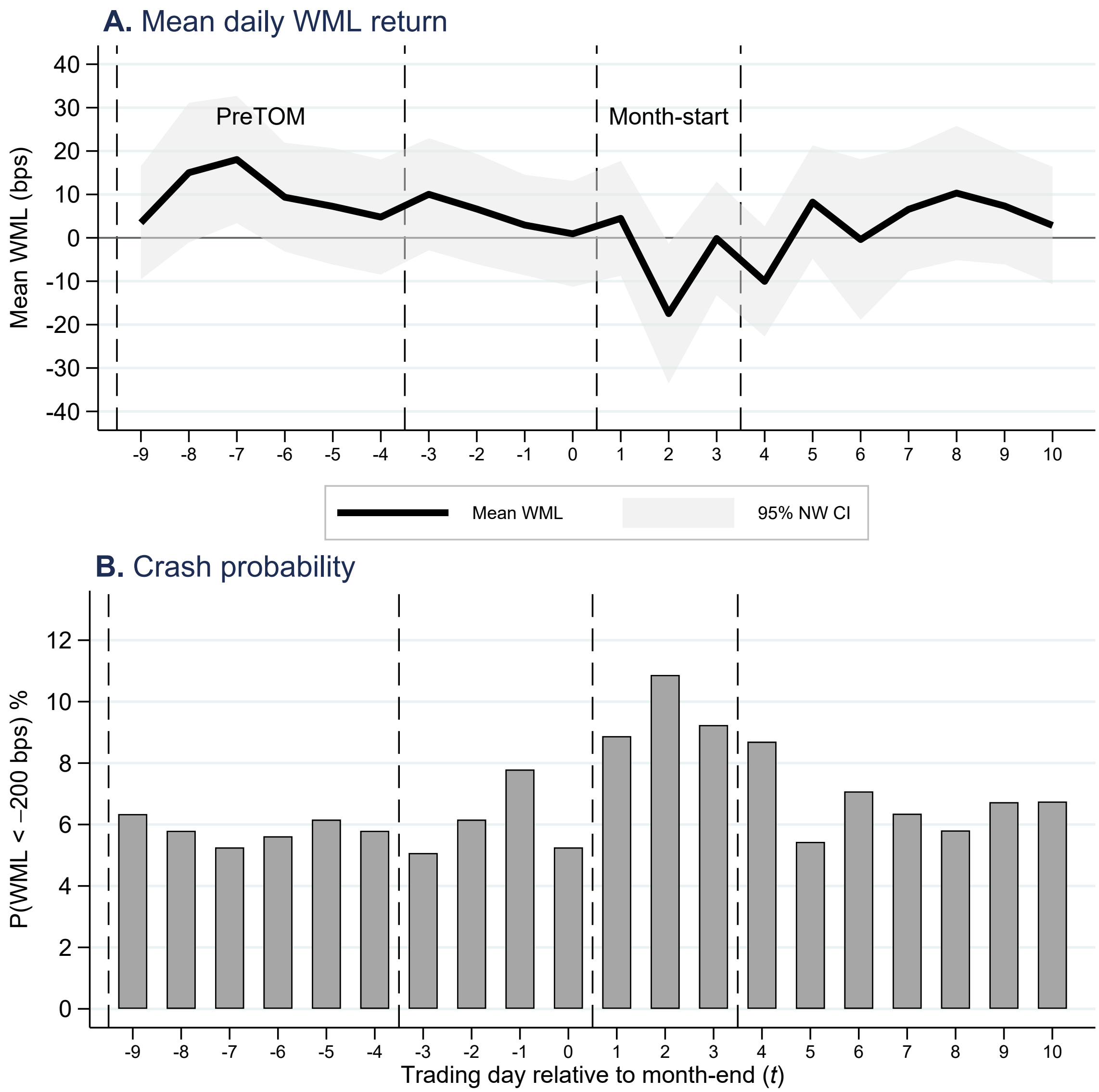


Figure 7: Panel A plots mean daily WML return with Newey-West 95% confidence bands by trading day t relative to month-end. Panel B plots crash probability, defined as Pr(WML $<$ -200 bps). Dashed vertical lines mark the PreTOM window ($t-9$ to $t-4$) and the month-start window ($t+1$ to $t+3$). PreTOM features positive average returns and crash frequency near its calendar share. Month-start features negative average returns and structurally elevated crash probability. Profit and crash risk are temporally separated. Sample: 1980–2025, value-weighted.

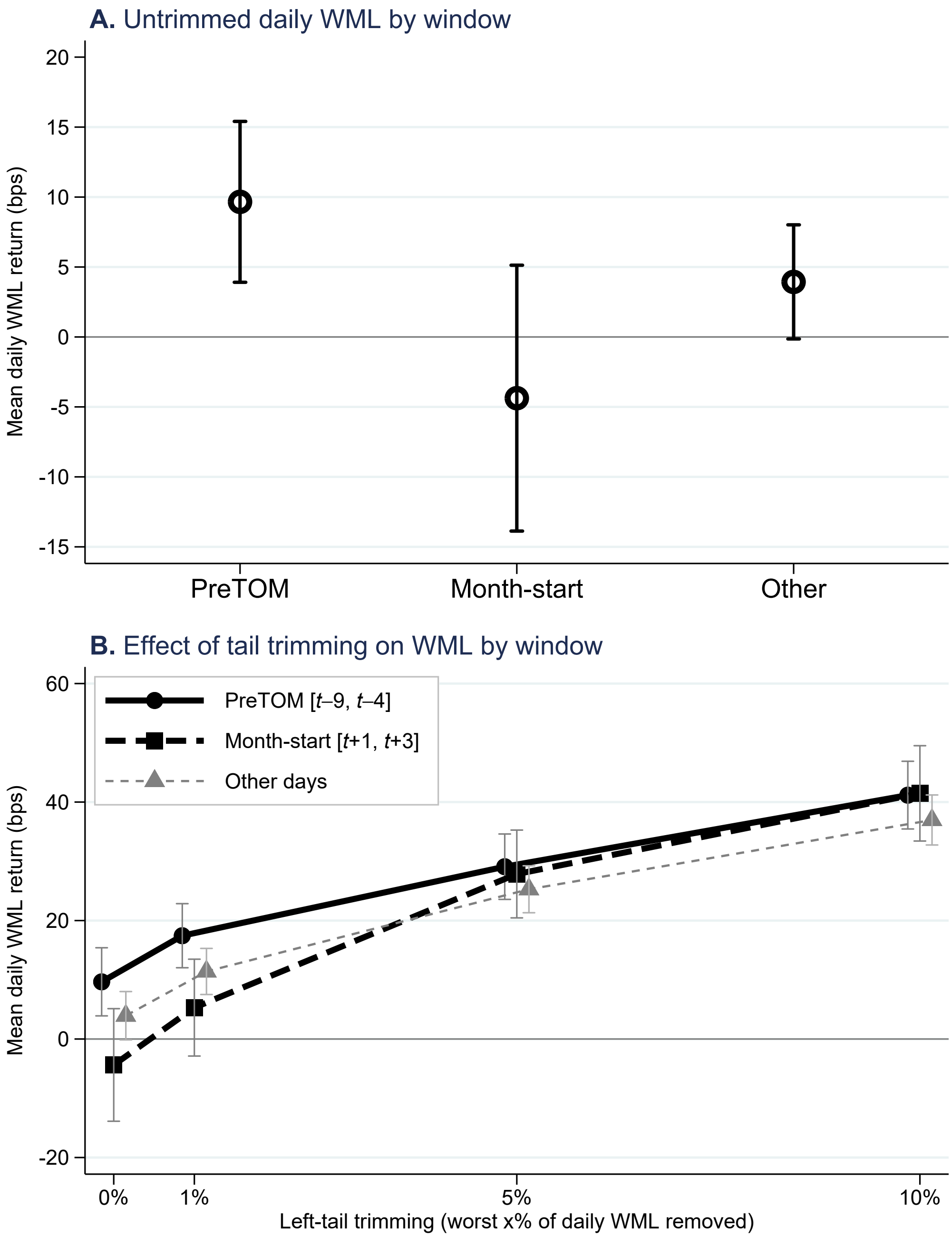


Figure 8: Mean daily WML return by calendar window after progressively trimming the worst days from each window's distribution. Left panel: pre-month-end ($t-9$ to $t-4$). Right panel: month-start ($t+1$ to $t+3$). PreTOM mean WML is positive at every trimming threshold, rising from +9.7 untrimmed to +17.4 after a 1% trim. Month-start mean flips sign from -4.4 to +5.3 after removing just the worst 1% of days. Sample: 1980–2025, value-weighted.

Table 1: Baseline Window Effect on Daily Returns

	(1) Equal Weighted	(2) Value Weighted
Loser	8.022***	2.609**
	(0.717)	(1.279)
Loser × PreTOM	-2.550*	-7.151***
	(1.376)	(2.322)
Constant	5.629***	3.442***
	(0.108)	(0.117)
Observations	53,324,145	53,324,145
Within R^2	0.0000	0.0000

Notes. Dependent variable is daily excess return in basis points. Loser equals one for stocks in the bottom momentum decile. PreTOM equals one during the six-day pre-month-end window (trading days $t-9$ to $t-4$). All specifications include firm and date fixed effects. Standard errors (in parentheses) are two-way clustered by firm and date. VW uses lagged market-capitalization weights within each decile-date cell. Sample: CRSP common stocks, 1980–2025.

Table 2: Window Effect and Bid-Ask Spread

	(1) Equal Weighted	(2) EW + BAS	(3) Value Weighted	(4) VW + BAS
Loser	8.022***	7.161***	2.609**	5.808***
	(0.717)	(0.993)	(1.279)	(1.643)
Loser × BAS		27.635***		−196.989***
		(9.258)		(14.430)
Loser × PreTOM	-2.550*	-5.118***	-7.151***	-8.836***
	(1.376)	(1.747)	(2.322)	(2.992)
Loser × PreTOM × BAS		30.411**		58.771**
		(11.842)		(25.117)
Observations	53,324,145	46,559,900	53,324,145	46,559,900
Within R^2	0.0000	0.0001	0.0000	0.0001

Notes. Dependent variable is daily excess return in basis points. Columns 1 and 3 reproduce the baseline from Table 1 on the full sample. Columns 2 and 4 restrict to the subsample with non-missing bid-ask spreads. BAS is the contemporaneous bid-ask spread as a fraction of the quote midpoint. A positive coefficient on Loser × PreTOM × BAS indicates that the window effect is weaker for illiquid (high-spread) stocks, i.e., concentrated among liquid losers. All specifications include firm and date fixed effects. Standard errors (in parentheses) are two-way clustered by firm and date.

Table 3: Subperiod Stability of the Window Effect

	(1) 1980–2002	(2) 2002–2025
Loser	0.345	6.063***
	(1.292)	(2.081)
Loser × PreTOM	-5.762**	-8.503**
	(2.497)	(3.858)
Observations	30,596,232	22,727,911
Within R^2	0.0000	0.0001

Notes. Dependent variable is daily excess return in basis points. Value-weighted specifications throughout. Sample split at midpoint (July 2002). All specifications include firm and date fixed effects. Standard errors (in parentheses) are two-way clustered by firm and date.

Table 4: Post-Window Reversal in Loser Returns

	Full Sample
Loser	0.967
	(1.394)
Loser × PreTOM	-5.508^{**}
	(2.373)
Loser × Post	8.215^{**}
	(3.419)
Observations	53,324,145
Within R^2	0.0000
Reversal test:	
$6 \times \hat{\beta}_{\text{PreTOM}} + 3 \times \hat{\beta}_{\text{Post}}$	$= -8.40$
F-statistic	0.19
p-value	0.66

Notes. Dependent variable is daily excess return in basis points. Loser equals one for bottom-decile momentum stocks (fixed monthly sorting). PreTOM equals one during trading days $t-9$ to $t-4$ relative to month-end ($t = 0$). Post equals one during trading days $t+1$ to $t+3$ at month-start. The reversal test evaluates whether the cumulative PreTOM decline (6 days × $\hat{\beta}_{\text{PreTOM}}$) is fully offset by the post-window rebound (3 days × $\hat{\beta}_{\text{Post}}$). Failure to reject indicates full reversal, consistent with temporary price pressure. Value-weighted (lagged market cap). Firm and date fixed effects. Standard errors (in parentheses) clustered by firm and date. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: Transaction Cost Decomposition of Monthly Momentum Returns

	Gross WML (bps/mo)	PreTOM (bps/mo)	Rest (bps/mo)	TC (bps/mo)	Net WML (bps/mo)
Full sample (1980–2025)	+88.8	+56.8 [64%]	+32.8 [36%]	112.1	−23.2
Post-decimalization (2001–2025)	+35.0	+53.3 [152%]	−16.9	13.9	+21.1

Notes: The table decomposes monthly returns of the standard value-weighted WML strategy (long decile 10, short decile 1, rebalanced monthly using Kenneth French's momentum decile breakpoints) into PreTOM (t=−9 to t=−4) and rest-of-month components. The portfolio is identical across columns; only the accounting window differs. Daily value-weighted returns within each window are compounded to monthly frequency. Transaction costs are computed as follows. Each month, we identify stocks that change momentum decile assignment ("turnover stocks"). For each turnover stock, we charge one full quoted bid-ask spread, defined as (ask − bid) / midpoint, averaged across trading days in the month. This round-trip cost covers the entry and exit trades associated with portfolio rebalancing. Stocks that remain in the same decile incur zero cost. The strategy-level cost is the value-weighted average across turnover stocks, summed over both the long and short sides. Our cost measure is conservative: following Novy-Marx and Velikov (2016), quoted spreads overestimate effective execution costs because they assume market orders. Percentages in brackets show each component's share of gross WML.

Table 6: Window Effect in Non-Quarter-End Months

	(1) Non-QE, Value Weighted
Loser	4.132***
	(1.539)
Loser × PreTOM	-7.523***
	(2.828)
Constant	4.636***
	(0.137)
Observations	35,417,562
Within R^2	0.0000

Notes. Dependent variable is daily excess return in basis points. Value-weighted. Sample restricted to non-quarter-end months (Jan, Feb, Apr, May, Jul, Aug, Oct, Nov). All specifications include firm and date fixed effects. Standard errors (in parentheses) are two-way clustered by firm and date.

Table 7: Selling Pressure During PreTOM — Firm and Date Fixed Effects

	Panel A: Baseline		Panel B: With Post Reversal	
	Net Sell Pressure	Sell Share	Net Sell Pressure	Sell Share
	(1)	(2)	(3)	(4)
Loser	0.0122***	0.0061***	0.0128***	0.0064***
	(0.0006)	(0.0003)	(0.0006)	(0.0003)
Loser × PreTOM	0.0020**	0.0010**	0.0014*	0.0007*
	(0.0008)	(0.0004)	(0.0008)	(0.0004)
Loser × Post			−0.0028***	−0.0014***
			(0.0011)	(0.0005)
Fixed effects	Firm, Date	Firm, Date	Firm, Date	Firm, Date
Observations	17,861,276	17,861,276	17,861,276	17,861,276
Adj. R^2	0.0361	0.0361	0.0361	0.0361

Notes. OLS regressions of daily selling pressure on loser status and its interactions with the PreTOM window ($t \in [-9, -4]$) and the post-window period ($t \in [+1, +3]$). Net sell pressure = (sell volume − buy volume) / total volume; sell share = sell volume / total volume. Trade direction assigned using Lee-Ready (WRDS Intraday Indicators). Panel A shows the baseline specification. Panel B adds the post-window interaction, revealing that the elevated selling pressure during PreTOM reverses to net buying at month-start. Sample: 2003–2022, approximately 17.9 million stock-day observations (extracted from the main CRSP panel). Firm and date fixed effects included. Standard errors double-clustered by firm and date in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 8: T+1 Settlement Deadline-Day Difference-in-Differences

Panel A: 2×2 Cell Means

	Pre-T+1 (1980–May 2024)	Post-T+1 (Jun 2024–2025)	Diff
$t{-}3$ (deadline under T+1)	−4.2	−30.6	−26.3
	($n = 532$)	($n = 20$)	
$t{-}4$ (deadline under T+2)	−8.8	+34.4	+43.1
	($n = 533$)	($n = 19$)	
Diff ($t{-}4$ minus $t{-}3$)	−4.5	+64.9	**+69.4**

Panel B: DiD Regression

	(1) Full baseline 1980–2025	(2) T+2 only Sep 2017–2025
$\mathbf{1}[t{=}{-}4]$	−4.53	−13.92
	(6.67)	(23.82)
Post T+1	−26.32	−14.23
	(21.84)	(27.24)
$\mathbf{1}[t{=}{-}4]$ × Post T+1	+69.45**	+78.84**
	(29.40)	(37.43)
Observations	1,104	200
R^2	0.0038	0.0170

Notes: Deadline-day difference-in-differences test of the T+2 to T+1 settlement transition (May 28, 2024). Dependent variable: daily market-adjusted VW loser portfolio return (bps). Sample restricted to trading days $t = -4$ and $t = -3$ only. Panel A shows raw cell means. Panel B reports the DiD regression with robust standard errors. Column 1 uses the full 1980–2025 sample. Column 2 restricts the pre-T+1 baseline to the T+2 era only (September 2017–May 2024), the period during which $t{-}4$ was the effective settlement deadline. The DiD strengthens from +69.4 to +78.8, confirming that the full-sample estimate is conservative due to dilution from T+3-era observations when $t{-}4$ carried less selling pressure. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Appendix

Table A1: Quarter-End Amplification of the Window Effect

	(1) Value Weighted
Loser	4.039***
	(1.544)
Loser × PreTOM	-7.496***
	(2.828)
Loser × PreTOM × QtrEnd	0.990
	(5.369)
Loser × QtrEnd	-4.249
	(2.867)
Constant	3.442***
	(0.115)
Observations	53,324,145
Within R^2	0.0000

Notes. Dependent variable is daily excess return in basis points. Value-weighted. QtrEnd equals one in March, June, September, December. A significant Loser × PreTOM × QtrEnd would indicate amplification at quarter-ends, consistent with window dressing. All specifications include firm and date fixed effects. Standard errors (in parentheses) are two-way clustered by firm and date.

Table A2: T+1 Settlement: Falsification Tests

Test	DiD	t-stat	p-value	Prediction
Real: Losers, $t{-}4$ vs. $t{-}3$, May 2024	**+69.45**	**2.36**	**0.018**	**Nonzero**
Placebo days (losers, May 2024):				
$t{-}6$ vs. $t{-}7$	+6.63	0.24	0.810	Zero
Placebo dates (losers, $t{-}4$ vs. $t{-}3$):				
May 28, 2020	−0.39	−0.01	0.990	Zero
May 28, 2018	−1.89	−0.08	0.933	Zero

Notes: Falsification tests for the T+1 settlement DiD (Table 8). All tests use the same specification: market-adjusted VW loser returns regressed on a day indicator, a post-event indicator, and their interaction, with robust standard errors. Placebo days shift the comparison to $t{-}6$ vs. $t{-}7$, two days interior to both the T+2 and T+1 selling windows where no deadline shifted. Placebo dates use fake event dates when no regulatory change occurred. All falsification interactions are small and statistically insignificant. Sample: 1980–2025.

Table A3: T+3→T+2 Settlement Deadline-Day Difference-in-Differences

Panel A: 2×2 Cell Means

	Pre-T+2 (1980–Aug 2017)	Post-T+2 (Sep 2017–2025)	Diff
$t{-}3$	−2.1 ($n = 452$)	−19.2 ($n = 100$)	−17.1
$t{-}4$	−4.9 ($n = 452$)	−18.0 ($n = 100$)	−13.1
Diff ($t{-}4$ minus $t{-}3$)	−2.8	+1.2	**+4.0**

Panel B: DiD Regression

	Coefficient	Robust SE	t-stat	p-value
$\mathbf{1}[t{=}{-}4]$	−2.82	6.61	−0.43	0.670
Post T+2	−17.08	14.83	−1.15	0.250
$\mathbf{1}[t{=}{-}4]$ × Post T+2	+4.02	21.06	0.19	0.849
Constant	−2.09	4.93	−0.42	0.671
Observations		1,104		
R^2		0.0030		

Notes: Deadline-day difference-in-differences test of the T+3 to T+2 settlement transition (September 5, 2017). Dependent variable: daily market-adjusted VW loser portfolio return (bps). Sample restricted to trading days $t = -4$ and $t = -3$ only, the same pair used in the T+1 test (Table 8). The DiD is near zero and insignificant, as expected: the 2017 reform reduced the settlement mismatch but did not eliminate it, so the $t{-}4/t{-}3$ pair did not diverge. Robust standard errors. Sample: 1980–2025.

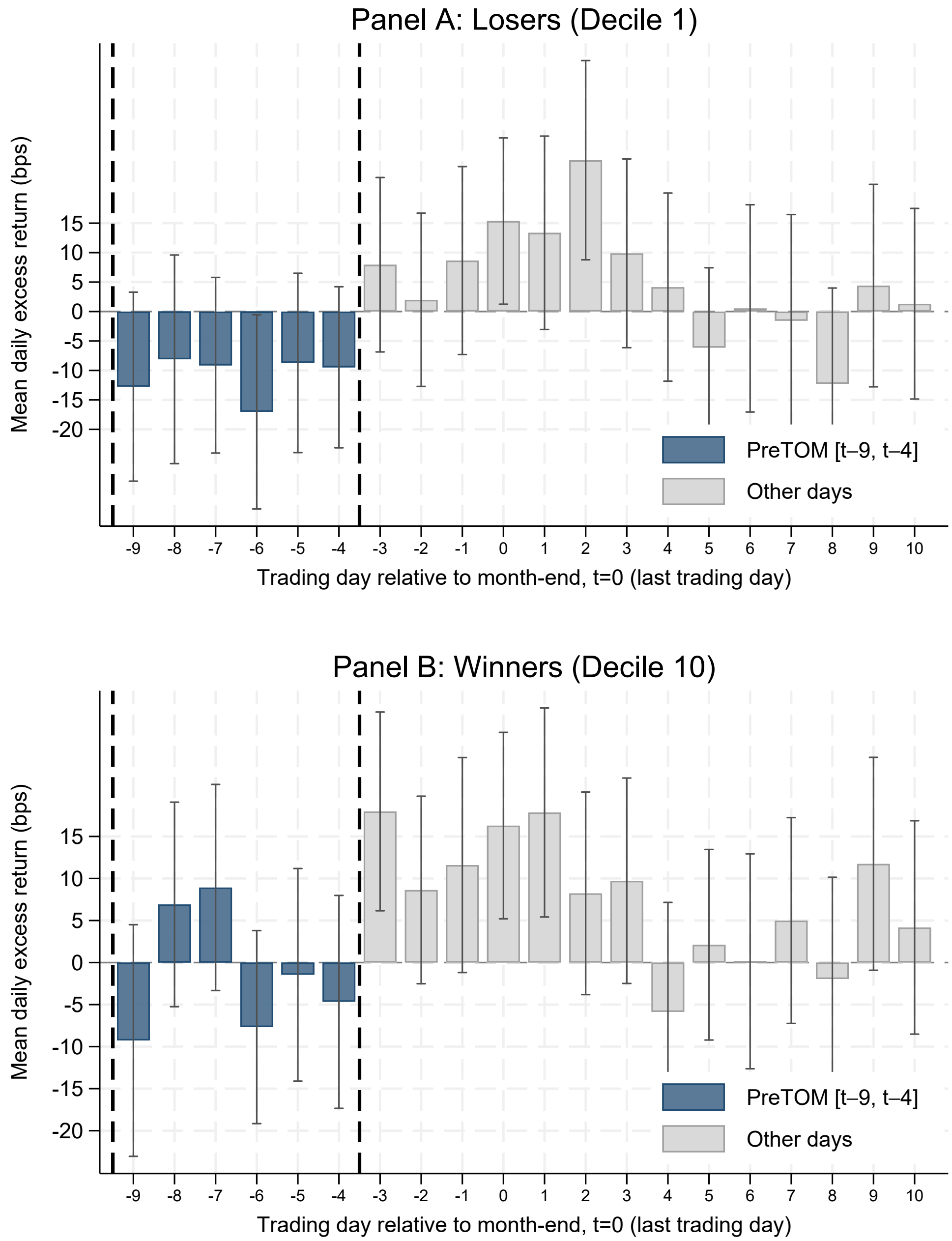


Figure A1: Mean daily excess returns of loser and winner decile portfolios by trading day. Panel A plots the average daily excess return (in basis points) of the loser portfolio (decile 1) for each trading day t relative to month-end. Panel B plots the same for winners (decile 10). Bars corresponding to the PreTOM window ($t-9$ through $t-4$) are highlighted. Losers exhibit systematically negative returns during the PreTOM window, averaging approximately -11 bps per day, while winners show no comparable pattern. Data are value-weighted daily returns from Kenneth French's momentum decile portfolios, 1980–2025.

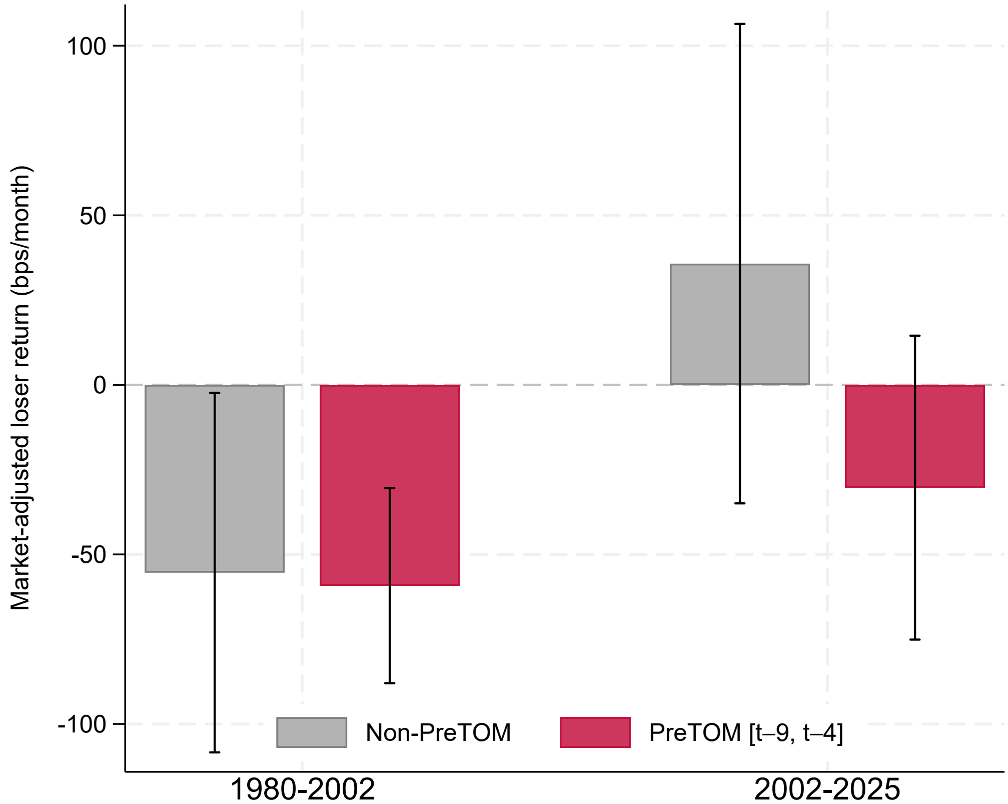


Figure A2: Market-adjusted monthly loser returns during the PreTOM window versus the rest of the month, by subperiod. Returns are computed as in Figure 2: daily market-adjusted loser returns are compounded separately within the PreTOM window ($t-9$ to $t-4$) and non-PreTOM days for each calendar month. Bars show the time-series mean of monthly compounded returns (in basis points); whiskers denote 95% confidence intervals. The PreTOM loser underperformance is present in both the 1980–2002 and 2002–2025 subperiods. Data are value-weighted returns from Kenneth French's momentum decile portfolios.

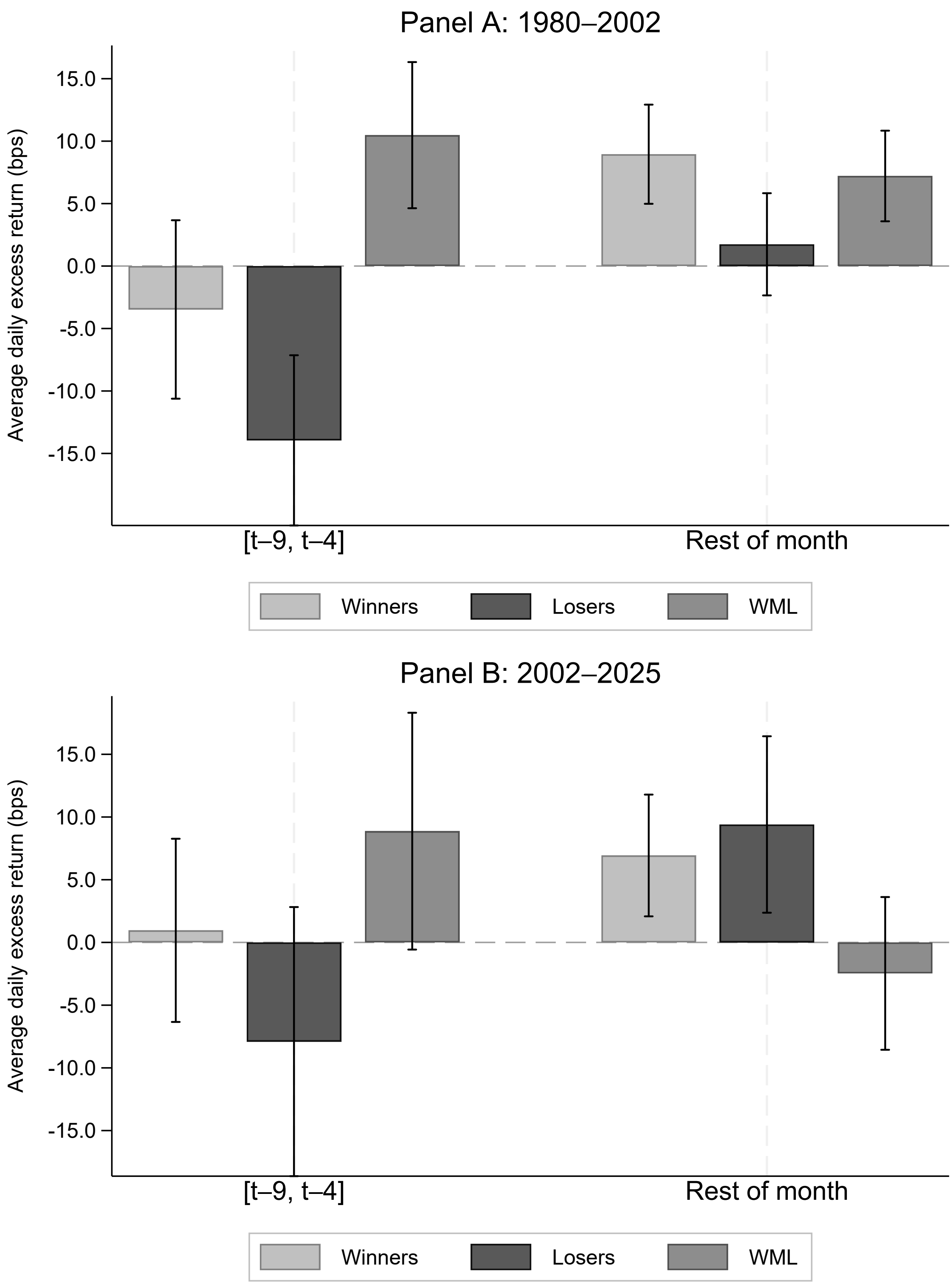
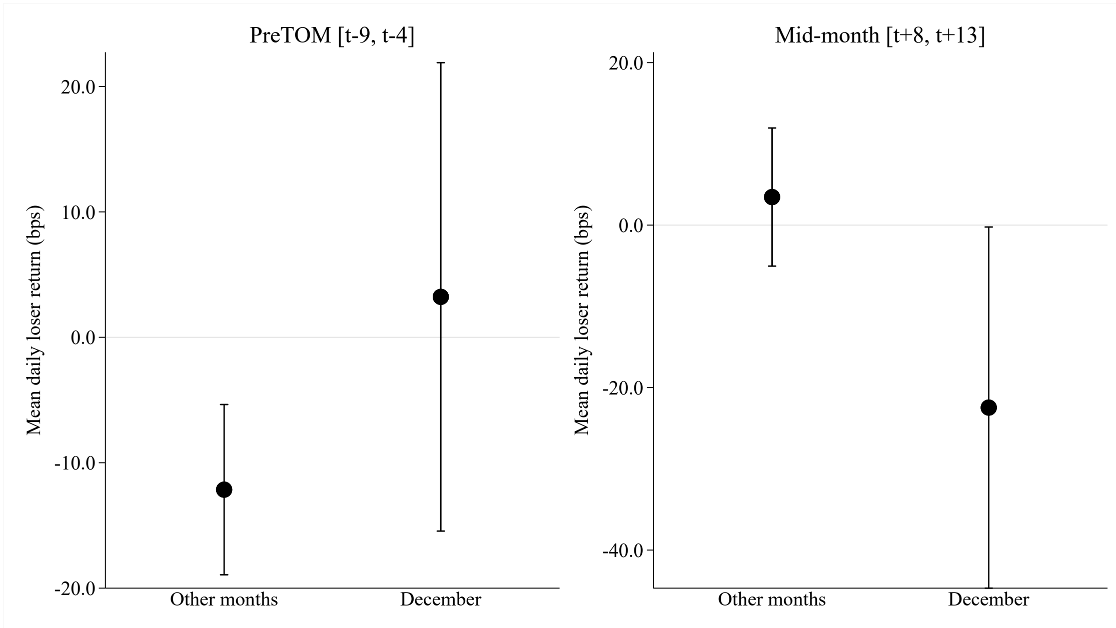


Figure A3: Average daily excess returns (basis points) of momentum winners, losers, and WML during the pre-month-end window ($t-9$ to $t-4$) versus the rest of the month, by subperiod. Bars show time-series means; whiskers denote 95% confidence intervals. The loser-driven asymmetry is present in both the 1980–2002 and 2002–2025 subperiods: losers underperform during the window while winners show no consistent pattern. Data are daily value-weighted returns from Kenneth French's momentum decile portfolios.

Panel A: Excess Returns ($r_i - r_f$)



Panel B: Market-Adjusted Returns ($r_i - r_{mkt}$)

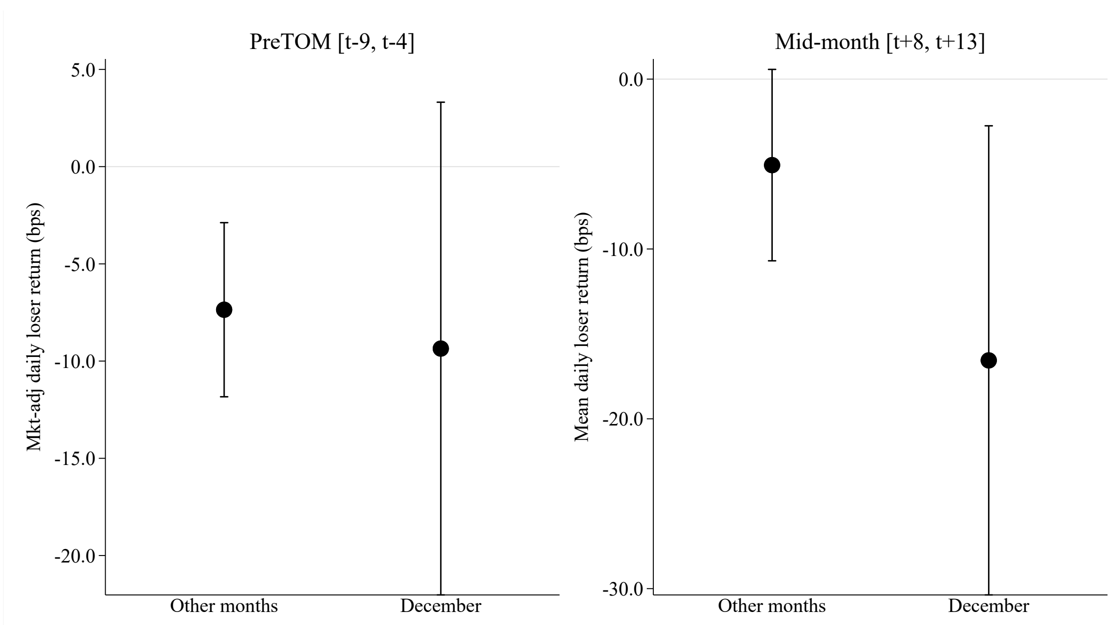


Figure A4: December displacement of loser selling pressure. Each panel compares mean daily loser returns during the pre-month-end window ($t-9$ to $t-4$, left) and the first two weeks of the month (right) in December versus all other months. Panel A uses excess returns ($r_i - r_f$); Panel B uses market-adjusted returns ($r_i - r_{mkt}$). In other months, losers underperform during PreTOM and are flat at mid-month. In December, the PreTOM effect is attenuated while mid-month returns are sharply negative. Tax-loss selling, concentrated in early-to-mid December around mutual fund distribution record dates, depletes the pool of available losers before the PreTOM window opens. Whiskers denote 95% confidence intervals. Value-weighted returns, 1980–2025.

Table A4: Window Effect and S&P 500 Membership

	Non-S&P 500	S&P 500	Full Sample
	(1)	(2)	(3)
Loser	1.806*	4.018**	2.429**
	(0.980)	(1.803)	(1.103)
Loser × PreTOM	−4.622**	−8.769***	−5.916**
	(1.825)	(3.237)	(2.307)
Loser × S&P 500			0.408
			(1.603)
Loser × PreTOM × S&P 500			−2.520
			(3.060)
Observations	47,863,849	5,460,280	53,324,145
Within R^2	0.0000	0.0000	0.0000

Notes. Dependent variable is daily excess return in basis points. Value-weighted using lagged market-capitalization weights. Columns (1) and (2) restrict the sample to non-S&P 500 and S&P 500 constituent stocks, respectively. Column (3) estimates the full sample with an S&P 500 interaction; an insignificant Loser × PreTOM × S&P 500 coefficient indicates that the window effect does not differ across index membership. All specifications include firm and date fixed effects. Standard errors (in parentheses) are two-way clustered by firm and date. Sample: 1980–2025.