The Intramonth Momentum Cycle*

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April 30, 2026

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Abstract

U.S. equity momentum returns concentrate in just six trading days each month, the window ending four days before month-end. We show this concentration arises from investors' month-end cash demand: predictable payment obligations create demand for settled cash, leading investors to sell, and the stocks they sell are their losers. A value-weighted WML strategy invested only during these six days turns \$1 into \$18.78 over 1980–2025, compared with \$2.37 during the rest of the month. The concentration is asymmetric: bottom-decile losers underperform by an additional 7.2 basis points per day during the window, while winners show no corresponding pattern. The SEC's May 2024 transition from T+2 to T+1 equity settlement provides causal identification: the predicted one-day shift in the selling window appears in individual stocks, the momentum spread, and mutual fund returns. Three episodes of acute fund outflows confirm the broader mechanism: when investors need cash, they sell their losers; the same loser-driven pattern replicates across 19 developed markets. The result also revisits Carhart's past-loser fund underperformance: the momentum-loading component is realized largely in the PreTOM window, while expense drag operates throughout the month. Crashes concentrate at month-start, not during PreTOM. The findings recast momentum as a feature of equity market plumbing rather than a property of investor beliefs or priced risk.

JEL Classification: G11, G12, G14, G23

Keywords: Momentum, month-end cash demand, institutional trading, calendar effects, settlement cycle, market microstructure

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*We thank Itamar Drechsler, Amit Goyal, and Dimitri Vayanos for helpful comments, and seminar participants at the Hong Kong Polytechnic University and Aalto University brown-bag seminars. We thank Filipp Dokienko and Eeli Tuovinen for excellent research assistance. All errors are our own.

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1 Introduction

"... Most prominent is the momentum in short-term returns, ... which in my view is the biggest challenge to market efficiency."

— Eugene F. Fama, "Two Pillars of Asset Pricing," Nobel Prize Lecture (2014)

Momentum is the most pervasive anomaly in financial markets. Since Jegadeesh and Titman (1993), the momentum premium has been documented in equities across dozens of markets and over more than a century of history, and momentum has become a cornerstone of systematic factor investing, anchoring industry mandates that exceed USD 6 trillion globally (Gupta and Doole, 2025). Yet, despite three decades of research, no one agrees on why it exists. Behavioral theories trace momentum to gradual information diffusion and investor underreaction; risk-based theories argue the premium compensates for exposure to priced firm-level or macroeconomic risks.[1]

We offer a simple plumbing explanation. Rather than asking *why* momentum exists, we ask *when* within the month it is earned. The timing distinguishes among theories in ways the monthly average premium does not. Over 1980–2025, \$1 invested in the value-weighted winner-minus-loser momentum strategy (WML) only during PreTOM (pre-turn-of-month), a six-day window ending four trading days before month-end, grew to \$18.78; the same dollar invested during the rest of the month grew to \$2.37 (Figure 1). The concentration is one-sided: loser portfolios underperform the market by 9.5 basis points per day during PreTOM, while winners show no comparable pattern (Figure 2).

Stock-level panel regressions on 53 million CRSP observations with firm and day fixed effects confirm the return asymmetry: bottom-decile losers underperform by an additional 7.2 basis points per day during PreTOM, while winners show no comparable pattern. The effect is strongest among liquid losers, consistent with institutions selling positions that can be unwound at low cost. The PreTOM component has not weakened over time; the apparent attenuation of U.S. momentum (Bhattacharya et al., 2017; Jegadeesh and Titman, 2023) is entirely in the rest-of-month component. The same loser-driven signature appears across 19 developed markets.

[1]See, e.g., Hong and Stein (1999) and Daniel et al. (1998) for behavioral explanations; Johnson (2002) and Chordia and Shivakumar (2002) for risk-based explanations.

The PreTOM window aligns with the period when investors raise cash ahead of month-end (Etula et al., 2020). We document that the selling pressure falls disproportionately on past losers. Losers are salient underperformers, often carry tax losses, and are disproportionately non-dividend-paying—any of which makes them the natural first sale when cash is needed. Two findings support cash management over information- or risk-based explanations: TAQ data show elevated net selling pressure on past losers during PreTOM, and daily mutual fund flow pressure concentrates on losers during the same window.

If the PreTOM concentration reflects transitory selling pressure rather than fundamentals, the loser-vs-non-loser gap should narrow once the cash-raising window closes. Losers recover roughly 70 percent of the PreTOM drawdown within a week, and TAQ trade-direction data trace the same pattern: current losers are net sold during PreTOM and net bought in the days that follow. The rebound is partial; it identifies transitory price pressure without implying that the momentum premium cancels within the month.

The SEC's May 2024 transition from T+2 to T+1 equity settlement provides causal identification of the calendar concentration. If loser underperformance reflects settlement-driven cash management, shortening the settlement cycle should shift the selling window closer to month-end. Before the reform, loser underperformance was concentrated in the six days ending four trading days before month-end; after the reform, the same concentration ends one day later, with the third trading day before month-end now showing the negative loser returns that previously appeared on the fourth. Placebo tests on other trading days and on false reform dates return null.

Acute cash needs identify the same loser-selling asymmetry outside the monthly cycle. During fund-outflow episodes in 2008 and March 2020, past-loser funds and loser stocks fell sharply while winners showed no comparable response. In March 2020, value-weighted past-loser funds lost 26% against 9% for past-winner funds; UMD (the Fama–French momentum factor, long winners and short losers) earned 18% the same month. A fund-month panel confirms the pattern: aggregate outflows hit past-loser funds but not past-winner funds.

The same calendar structure appears in the momentum factor and in mutual fund performance. UMD earns 5.51 basis points per day during PreTOM, compared with 1.36 basis points during the rest of the month, again driven by the loser leg. Revisiting Carhart (1997), we find that past-loser fund underperformance reflects loser-stock exposure plus expense drag. The loser-stock component is realized largely during PreTOM and disappears once loser-stock returns are controlled for; the expense-ratio component is spread through the month.

Momentum crashes occur in a different part of the month. Crash days concentrate at month-start, not during PreTOM, ruling out crash avoidance as the source of the six-day premium. This intramonth separation complements Daniel and Moskowitz (2016): the profit window and the crash window are distinct parts of the monthly cash cycle.

Our paper relates most directly to the literature linking institutional flows to price pressure. Coval and Stafford (2007) document price pressure from forced mutual-fund trading, Lou (2012) connects fund flows to momentum, and Vayanos and Woolley (2013) model performance-driven flows as the engine of equilibrium momentum. Grinblatt et al. (1995), Sias (2004), and Puckett and Yan (2011) document momentum-chasing by institutions, and Lou and Polk (2022) show how arbitrage in momentum strategies itself affects returns. We identify the cross-sectional counterpart of this mechanism: settlement-driven cash demand at month-end falls disproportionately on past losers and produces the short-leg component of momentum in a six-day window.

A second body of work documents calendar structure in returns. Ogden (1990) and Lakonishok and Smidt (1988) document the turn-of-month effect, and Etula et al. (2020) show that month-end institutional selling generates the market-level pattern. Adjacent work documents monthly seasonalities (Heston and Sadka, 2008, 2010), infrequent rebalancing (Bogousslavsky, 2016, 2021), intraday-overnight decompositions (Lou et al., 2019; Barardehi et al., 2026), same-weekday continuation (Keloharju et al., 2016, 2021; Da and Zhang, 2025), and calendar structure in specific anomalies (Birru, 2018; Cao et al., 2021; Hartzmark and Solomon, 2013, 2025). We identify a specific institutional clock—settlement-induced cash demand before month-end—that concentrates selling on past losers and generates the majority of the momentum premium in six trading days, with causal identification from the T+1 reform.

Two broader literatures provide context. Institutional frictions and the limits of arbitrage shape asset prices through funding constraints (Shleifer and Vishny, 1997; Brunnermeier and Pedersen, 2009), slow-moving capital (Duffie, 2010; He and Krishnamurthy, 2013; Mitchell et al., 2007), and demand-system frameworks (Koijen and Yogo, 2019; Gabaix and Koijen, 2021); Kutai et al. (2025) show that settlement mechanics shape outcomes during stress. The cross-sectional asymmetry of anomaly returns is also well documented: Stambaugh et al. (2012), Hong et al. (2000), Avramov et al. (2013), and Engelberg et al. (2018) show that anomaly profits including momentum concentrate on the short leg, attributed variously to slower information diffusion, credit distress, and news clustering. The mechanism documented here, settlement-driven cash demand, produces short-side concentration in momentum without invoking mispricing or slow information diffusion.

The rest of the paper documents the return concentration, identifies the selling-pressure mechanism, and tests its predictions across settlement reform, fund-level persistence, and momentum crashes.

2 Data and Methodology

2.1 Data Sources

We use five primary data sources. First, for both portfolio-level and stock-level analysis, we construct daily momentum decile portfolios from CRSP using fixed monthly sorts: all NYSE, AMEX, and NASDAQ stocks are ranked into deciles based on cumulative returns over months -12 through -2, using NYSE return breakpoints. Decile assignments are held constant within each calendar month. From Kenneth French's data library we obtain daily Fama-French factors and the risk-free rate.

Our sample begins in 1980, consistent with the modern institutional-flow literature (Lewellen, 2011; Lou, 2012; Coval and Stafford, 2007). Reliable trade-based daily prices for NASDAQ stocks become available in November 1982. The stock-level panel merges the CRSP daily return panel with momentum decile assignments and bid-ask quotes, yielding 53.3 million stock-day observations over 1980–2025.

Second, 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. These include net selling pressure and the sell share of volume.

Third, we use daily fund flows from Morningstar matched with quarterly fund holdings from the CRSP Mutual Fund Holdings database, spanning 2010–2023. The matched sample covers approximately 30% of mutual fund total net assets in CRSP and Morningstar.

Fourth, we use the CRSP Mutual Fund Database for fund-level evidence on Carhart persistence. Monthly returns span 1962–2025 (long-horizon replication); daily returns span

September 1998–2025 (within-month decomposition). The sample restricts to actively managed U.S. equity diversified funds (CRSP objective code ED%, excluding index funds and ETFs) with assets under management of at least \$10 million.

Fifth, for international evidence, we construct analogous daily momentum decile portfolios for 19 developed markets using Compustat Global, applying size-conditional within-country breakpoints. Construction details and country-by-country results appear in the Online Appendix.

Although our sample begins in 1980, the cross-sectional pattern of selling losers predates it. Asem (2009) documents dividend-driven differences in momentum portfolios from 1927, and loser underperformance is well-documented across the long sample. What our analysis shows is the emergence of *intramonth timing* in this underperformance: losers underperform the market across the full month before 1962, but the underperformance increasingly concentrates in PreTOM thereafter, alongside the rise in U.S. institutional equity ownership from below 10% pre-1962 to 67% by 2010 (Blume and Keim, 2012). The PreTOM concentration first becomes statistically significant in 1962–1980 (D1 loser−Mkt difference: −5.46 bps/day, $t = -2.80$ value-weighted; −6.27, $t = -2.90$ equal-weighted), the conventional starting point of the momentum literature (Jegadeesh and Titman, 1993). Online Appendix Section IA.10 reports the full subperiod evidence.

2.2 Key Variables

Trading day index and calendar windows. We define a within-month trading day index T where the last trading day of each month is $T = 0$, the penultimate is $T = -1$, and so on. Each calendar day receives a single T value: negative when counted backward from month-end, positive when counted forward from month-start. The two ranges partition disjoint subsets of the month. The pre-turn-of-month window (PreTOM) consists of the six trading days $T \in [-9, -4]$; the rest-of-month window (Rest) consists of all other trading days. We use PreTOM_t, Rest_t, and Post_t as indicators for the corresponding windows, with Post_t covering the seven-day window $T \in [-3, +3]$ surrounding month-end.

Momentum portfolios. We define WML as the daily VW return on the top momentum decile (D10) minus the daily VW return on the bottom decile (D1), where value weights within each (day, decile) cell are lagged market capitalizations normalized to sum to one. We also report equal-weighted variants.

Bid-ask spread. From CRSP daily bid and ask quotes, we compute the percentage bid-ask spread as $\text{BAS}_{i,t} = (\text{Ask}_{i,t} - \text{Bid}_{i,t})/\text{Midpoint}_{i,t}$.

Selling pressure. From the WRDS Intraday Indicators dataset described above, we use two measures: (i) net selling pressure (sell share minus buy share of dollar volume); and (ii) sell share of volume.

Settlement transitions. U.S. equity settlement shortened from T+3 to T+2 on September 5, 2017, and from T+2 to T+1 on May 28, 2024.[2] We use these transitions for the difference-in-differences analysis of Section 5.

3 Main Results

3.1 Portfolio-Level Evidence

We begin with the value-weighted WML portfolio and decompose its cumulative return by trading-day position within the month. We classify each trading day as PreTOM or Rest and compound returns within each window separately from \$1 on January 2, 1980. Figure 1 shows a stark divergence: by 2025, the PreTOM-only strategy has grown to \$18.78 while the Rest-only strategy reaches just \$2.37.[3] The two strategies track each other through the early 2000s before diverging, consistent with the Rest component of momentum weakening over time while the PreTOM component persists.

The asymmetry in returns is overwhelmingly loser-driven. Figure 2 plots average daily market-adjusted returns for momentum winners, losers, and the WML spread during Pre-

[2]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).

[3]Using French's daily-rebalanced momentum portfolios yields \$15.52 and \$2.07 respectively. Daily rebalancing reassigns deciles every day on a sliding 12-month formation window, so the cohort defined as "losers" shifts continuously. Our fixed monthly sort holds the cohort constant within each calendar month, which more closely tracks the institutional positions that face month-end selling pressure. The qualitative pattern is identical under either convention.

TOM and Rest. Losers underperform the market by 9.5 basis points per day during PreTOM ($t = -4.47$) but earn returns indistinguishable from zero during Rest (-2.4 bps/day, $t = -1.62$). Winners show no comparable PreTOM differential. Momentum premiums are mostly about losers losing at predictable times and less about winners winning. This asymmetry is robust across subperiods.[4]

Table 1 formalizes Figure 2 using daily Fama–MacBeth cross-sectional regressions. For each trading day t, we estimate

$$\text{ExRet}_{i,t} = \sum_{d=1}^{10} b_{d,t}\, \mathbf{1}\{D_{i,t} = d\} + u_{i,t} \tag{1}$$

across all CRSP common stocks, with no intercept and observations weighted by lagged market capitalization. $\text{ExRet}_{i,t} \equiv r_{i,t} - r_t^m$ is the daily market-adjusted return, r_t^m is the CRSP value-weighted market return, and $\mathbf{1}\{D_{i,t} = d\}$ indicates membership in momentum decile $d \in \{1, \dots, 10\}$.

We then test whether the loser and winner premia differ across calendar windows by regressing each daily series on a PreTOM indicator:

$$b_{d,t} = c_0^d + c_1^d\, \text{PreTOM}_t + v_{d,t}, \qquad d \in \{1, 10\}. \tag{2}$$

The constant c_0^d is the average market-adjusted return of decile d on Rest days; $c_0^d + c_1^d$ is the PreTOM average; c_1^d is the PreTOM–Rest differential.

Table 1 reports the estimates. For losers ($d = 1$), the Rest-day average is $c_0^1 = -2.42$ basis points per day and the PreTOM average is $c_0^1 + c_1^1 = -9.54$ basis points; the PreTOM–Rest differential is $c_1^1 = -7.12$ ($t = -2.76$). For winners ($d = 10$), the Rest-day average is essentially zero (-0.04 bps), the PreTOM average is $+0.61$ bps, and the differential is $c_1^{10} = +0.65$ ($t = 0.40$). The PreTOM concentration is one-sided, overwhelmingly on the loser leg, which is difficult to reconcile with explanations that act symmetrically on winners and losers, including symmetric risk-based or mispricing accounts.

The remaining analyses use the stock-level panel framework, which accommodates firm and day fixed effects, multi-way interactions, and stock-day covariates.

[4] Online Appendix Figure IA.4 plots the same decomposition for the 1980–2002 and 2002–2025 halves of the sample; both show the loser PreTOM underperformance and WML PreTOM concentration.

3.2 Stock-Level Evidence

The portfolio evidence shows the concentration is loser-driven. We now test this at the stock level on the full panel of 53 million CRSP common-stock-day observations (1980–2025), where firm and day fixed effects absorb confounds that portfolio aggregation cannot. We estimate the panel regression

$$\mathrm{ExRet}_{i,t} = \beta_1 \,\mathrm{Loser}_{i,t} + \beta_2 \,\mathrm{Loser}_{i,t} \times \mathrm{PreTOM}_t + \mu_i + \delta_t + \varepsilon_{i,t}, \tag{3}$$

where $\mathrm{ExRet}_{i,t} \equiv r_{i,t} - r_t^m$ is the daily excess return over the market of stock i on day t (in basis points), with $r_{i,t}$ the stock's daily return and r_t^m the value-weighted CRSP market return that day. $\mathrm{Loser}_{i,t}$ is an indicator equal to one if stock i is in the bottom momentum decile on day t. PreTOM_t is an indicator equal to one if day t falls in the $[T-9, T-4]$ window; the standalone PreTOM indicator is absorbed by δ_t. μ_i and δ_t are firm and day fixed effects, and standard errors are double-clustered by firm and day. The coefficient of interest is β_2: the additional underperformance of losers on PreTOM days relative to losers outside PreTOM. We also report equal-weighted estimates.

Table 2 presents the baseline estimates. In the value-weighted specification, the Loser × PreTOM coefficient is $\beta_2 = -7.15$ basis points per day ($t = -3.08$). The equal-weighted β_2 is smaller (-2.55 bps, $t = -1.85$). The gap between value-weighted and equal-weighted estimates previews the bid-ask-spread evidence below: the PreTOM effect concentrates where institutions trade, and equal-weighting dilutes it across illiquid micro-caps where they do not.

3.2.1 Liquid Losers Drive the PreTOM Underperformance

We now ask whether the PreTOM hit on losers concentrates among liquid D1 stocks, the prediction implied by the institutional-selling channel. We restrict the sample to bottom-decile stocks and estimate

$$\mathrm{ExRet}_{i,t} = \beta \,\mathrm{PreTOM}_t + \gamma_1 \,\mathrm{BAS}_{i,t} + \gamma_2 \,\mathrm{PreTOM}_t \times \mathrm{BAS}_{i,t} + \mu_i + \delta_{m(t)} + \varepsilon_{i,t}, \quad i \in \mathrm{D1}, \tag{4}$$

where $\mathrm{BAS}_{i,t}$ is the daily bid-ask spread of stock i on day t as a fraction of the quote midpoint. μ_i are firm fixed effects and $\delta_{m(t)}$ are year-month fixed effects, allowing the standalone

PreTOM coefficient to be identified within month. Standard errors are double-clustered by firm and day. The coefficient γ_2 measures how the within-D1 PreTOM effect varies with the bid-ask spread.

Table 3 reports the estimates. We focus on the value-weighted specification; equal-weighted estimates are reported alongside. In VW (column 2), $\gamma_2 = +53.73$, statistically significant at the 10% level ($t = 1.92$). The base PreTOM coefficient at zero spread is $\beta = -9.11$ ($t = -3.00$); the positive interaction implies the loser hit attenuates as the bid-ask spread rises: the PreTOM effect concentrates in liquid losers, where institutional selling can execute at low cost. To illustrate: at the median D1 bid-ask spread of 3.1%, the PreTOM marginal effect is -7.4 bps/day; at the 75th percentile of 9.3%, it attenuates to -4.1 bps/day. In equal-weighting, $\gamma_2 = +31.48$ ($t = 2.47$): the interaction is smaller in magnitude but more precisely estimated, because EW preserves the wide BAS variation across micro-cap losers that VW down-weights. Liquid losers bear the PreTOM underperformance; illiquid losers less so. We use value-weighted returns for the remainder of the analysis.

3.2.2 The PreTOM Effect Persists and Strengthens Over Time

A natural concern is that the PreTOM 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 PreTOM effect should be stronger in the first half of the sample and attenuate or vanish in the second. The opposite is true.

Table 4 splits the panel at the midpoint (July 2002). The Loser×PreTOM coefficient appears in both halves and strengthens over time: $\beta_2 = -5.76$ bps ($t = -2.31$) in 1980–2002 and $\beta_2 = -8.50$ bps ($t = -2.20$) in 2002–2025. Two regimes share a common feature: PreTOM remains the cluster of days on which losers most clearly underperform non-losers, and the magnitude of the PreTOM widening (β_2) has grown 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.

Three alternative explanations are ruled out. The PreTOM window itself is not cherry-picked: a sliding six-day window analysis (Online Appendix Figure IA.1) shows that $[T-9, T-4]$

is the unique trough in loser returns across the second half of the trading month, with mean market-adjusted loser returns declining monotonically from near zero at mid-month to a trough at PreTOM (-11.32 bps/day, $t = -3.53$). Quarter-end window dressing (Brown, 2017) is not the driver: restricting to non-quarter-end months produces a Loser $\times$ PreTOM coefficient of -7.5 bps ($t = -2.66$), essentially identical to the full-sample estimate. Passive beta exposure is also ruled out: the WML portfolio has essentially zero net market beta ($\beta_{WML} \approx -0.08$), the triple interaction Loser $\times$ PreTOM $\times$ β is indistinguishable from zero, and beta exposure is continuous across days while the calendar concentration is discrete. Additional robustness, including S&P 500 membership splits, alternative holding periods, and transaction-cost adjustments, appears in the Online Appendix.

4 The Mechanism

4.1 Selling Pressure During PreTOM

Section 3.2.1 showed that the PreTOM effect concentrates in liquid losers. We now use intraday trade-direction data to test directly whether losers experience elevated selling pressure during PreTOM. The data come 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.

We estimate the analogue of equation (3) with selling pressure as the dependent variable:

$$\mathrm{NSP}_{i,t} = \beta_1 \,\mathrm{Loser}_{i,t} + \beta_2 \,\mathrm{Loser}_{i,t} \times \mathrm{PreTOM}_t + \mu_i + \delta_t + \varepsilon_{i,t}, \tag{5}$$

where $\mathrm{NSP}_{i,t}$ is daily net selling pressure (sell volume minus buy volume, divided by total volume) on a $[-1, 1]$ scale, with higher values indicating more selling pressure. μ_i and δ_t are firm and day fixed effects, and standard errors are double-clustered by firm and day. β_2 captures how much more strongly losers are sold on PreTOM days than on Rest days.

Table 5, Panel A, reports estimates of equation (5) and an analogous specification with the sell share of volume as the dependent variable. On PreTOM days, losers experience an additional 0.2 percentage points of net selling pressure relative to non-losers, beyond the Rest-day baseline gap ($\beta_2 = +0.0020$, $t = 2.50$, on the $[-1, 1]$ scale; sell-share coefficient

+0.0010, $t = 2.50$).[5]

A complementary measure of selling pressure comes from mutual fund flows. Following Coval and Stafford (2007) and Lou (2012), we construct stock-specific flow pressures by attributing each fund's daily flows to its holdings as of the previous quarter-end, then aggregating across funds and normalizing by market capitalization. Figure 3 shows average flow pressure during PreTOM by momentum decile. The pattern is monotonic: losers (D1) face the strongest outflow pressure (−9.9 basis points), while winners (D10) experience slight inflow pressure (+0.5 bps).

4.2 Short-Term and Long-Term Reversal

If the PreTOM concentration reflects transitory selling pressure rather than fundamental news, the loser-vs-non-loser gap that opens during PreTOM should partially close once the cash-raising window ends. We test this by extending equation (3) on the full panel with a Loser × Post interaction:

$$\text{ExRet}_{i,t} = \beta_1 \,\text{Loser}_{i,t} + \beta_2 \,\text{Loser}_{i,t} \times \text{PreTOM}_t + \beta_3 \,\text{Loser}_{i,t} \times \text{Post}_t + \mu_i + \delta_t + \varepsilon_{i,t}. \quad (6)$$

Both β_2 and β_3 are measured against the same baseline: the loser-vs-non-loser gap on Rest days (captured by β_1), within trading days (day FE absorbs market-wide effects). β_2 is the additional widening of that gap on PreTOM days; β_3 is the additional widening (or, here, narrowing) on Post days.

Table 6 reports the estimates. The PreTOM widening is $\beta_2 = -5.59$ basis points per day ($t = -2.07$); the Post-window narrowing is $\beta_3 = +3.36$ basis points per day ($t = 1.24$), positive but not individually significant. The contrast between the two windows is large and highly significant: $\beta_3 - \beta_2 = +8.94$ basis points per day ($t = 3.30$, $p < 0.001$). Whatever drives the loser-vs-non-loser gap wider during PreTOM closes back up during the surrounding seven-day window. Cumulated over the windows, the Post-window narrowing of the gap ($7\beta_3 = +23.5$ basis points) recovers about 70 percent of the PreTOM widening

[5] Lee–Ready trade signing is measured with error, so signed order-imbalance estimates are attenuated toward zero. The classic benchmark is about 85% accuracy (Odders-White, 2000); recent TAQ evidence finds similar raw Lee–Ready accuracy, rising from 86% to 92% after latency adjustment (Holden et al., 2023). We therefore interpret the imbalance coefficient as conservative.

($6\beta_2 = -33.5$ basis points).[6] The 70 percent describes the cross-sectional loser-vs-non-loser gap, not absolute loser prices: the gap opens during PreTOM and closes during Post, even as the loser cohort continues to underperform the broader market over longer horizons. The mechanism predicts cross-sectional selling pressure, not the disappearance of momentum itself.

The same reversal appears in trade-direction data. Panel B of Table 5 adds a Loser $\times$ Post interaction to the TAQ specification of equation (5). The Post interaction flips sign: $\beta_3 = -0.0028$ ($t = -3.11$) on net selling pressure and -0.0014 ($t = -2.80$) on the sell share. The contrast $\beta_3 - \beta_2$ is highly significant: the same losers that are sold heavily during the six PreTOM days are bought back during the surrounding Post window. The trade-direction reversal mirrors the return reversal documented above.

The Post-window rebound traces the immediate unwind of PreTOM selling pressure. Stocks that fall in D1 across multiple past PreTOM windows accumulate the pressure cycle after cycle; if that pressure is transitory, the accumulation should mean-revert at longer horizons. Cumulative returns from non-PreTOM days, which reflect information rather than flow, should not. We confirm both predictions in Online Appendix Table IA.19: in a within-firm panel of 43.5 million stock-days, past PreTOM returns accumulated while a stock was in D1 revert about three times more strongly than past PreTOM returns accumulated outside D1 (Wald $p = 0.0006$); past non-PreTOM returns show no equivalent reversion. The long-horizon reversal of past returns documented by Jegadeesh and Titman (1993) loads more strongly on the PreTOM component than on returns from other days.

4.3 Why Losers Face Selling Pressure During PreTOM

Sections 4.1 and 4.2 established that PreTOM selling pressure falls disproportionately on losers and unwinds transitorily. Why losers specifically? Three channels, institutional selling under time pressure, tax-loss harvesting, and the dispensability of low-dividend stocks when cash buffers drain, point to the same answer: losers are dispensable on multiple margins.

[6] Fixing the loser cohort across the month boundary, so that each month's D1 stocks are tracked through the subsequent Post window, yields a similar reversal contrast ($\beta_3 - \beta_2 = +8.66$ vs. $+9.10$ contemporaneous, untabulated). The result is not driven by cohort turnover.

4.3.1 Institutional Selling of Losers

Three pieces of evidence in Sections 3.2.1–4.1 already point to institutional selling: the PreTOM effect concentrates in liquid losers, in S&P 500 stocks where institutions hold positions, and shows up directly as elevated net selling pressure in TAQ trade-direction data. Within the bottom decile, the institutional-selling story makes a more specific prediction: the most salient liquidation candidates are the *most recent* losers. Faced with compressed month-end cash demands, managers gravitate toward positions most salient as losers, the ones that have fallen most recently (Akepanidtaworn et al., 2023). Stocks in the freshest-loss tercile (defined by the most negative returns over months -3 to -1) underperform the stalest-loss tercile by 4.5 basis points per day during PreTOM ($F = 7.15$, $p = 0.008$). The effect survives controls for bid-ask spreads and size (Online Appendix Table IA.9).

4.3.2 Tax-Related Selling

Tax considerations can make losers attractive to sell (Constantinides, 1984; Grinblatt and Moskowitz, 2004), but they can't *fully* account for the monthly PreTOM concentration. The effect remains in months when tax and window-dressing motives should be weakest: excluding quarter-end months yields a Loser $\times$ PreTOM coefficient of -7.5 bps/day ($t = -2.66$), essentially identical to the full-sample estimate. December, the month with the strongest tax incentive, does not absorb the pattern: D1 losers underperform the market by -12.65 bps/day during December PreTOM ($t = -2.10$).[7] PreTOM operates as a monthly cash-management cycle independent of tax pressure. Full estimates appear in Online Appendix Section IA.12.

4.3.3 Dividend Income

Losers generate less dividend income. Among D1 stock-months, 84.0% are non-payers, compared with 67.6% among D10 stock-months. Selling losers therefore entails less foregone dividend income, making them more dispensable when investors need cash. Among quarterly dividend payers, the same logic produces a within-cycle prediction: PreTOM selling

[7] A separate mid-December pattern of negative D1 returns (-14.92 bps/day in the second week, $t = -1.99$) is consistent with tax-loss harvesting timed to mutual-fund capital-gains distributions (Sialm and Starks, 2012), but operates outside PreTOM and does not absorb the monthly cycle.

pressure on losers should be lowest in the month a stock pays its dividend, when holders have just received cash, and highest later in the dividend cycle, when that cash buffer has been depleted. The prediction is loser-specific; winners are not the positions sold to resolve cash demand.

The TAQ data are consistent with this pattern. Loser net selling pressure during PreTOM rises monotonically across the dividend cycle, from 0.18 percentage points in the dividend month to 0.57 percentage points two months later, with the latter statistically significant ($t = 2.12$). Winner net selling pressure during PreTOM is statistically flat across the same months ($F = 0.38$, $p = 0.68$). Return-based specifications and full estimates appear in Online Appendix Section IA.13 and Table IA.11.

These three channels, institutional dispensability, tax timing, and dividend-buffer dynamics, are complementary, not competing. Each gives investors an independent reason to liquidate losers before month-end, and the channels jointly index the same stocks, losers held by institutions facing cash needs.

5 Causal Identification: The T+1 Settlement Reform

5.1 Stock-Level Evidence

The previous evidence is ultimately correlational. We now exploit the SEC's May 28, 2024 transition from T+2 to T+1 equity settlement, which directionally shifts the precautionary selling window toward month-end.

The PreTOM window we use, $[T-9, T-4]$, follows Etula et al. (2020), who establish that institutional cash-raising for month-end obligations concludes at $T-4$ in their sample.[8] The reform reduces settlement time by one day, giving funds an extra day of leeway in their cash-raising cycle. We therefore expect the right edge of the cash-raising window to shift from $T-4$ toward $T-3$.

[8]This boundary also appears in our full 1980–2025 sample. A sliding six-day window analysis (Online Appendix Figure IA.1) shows that $[T-9, T-4]$ is the unique trough in loser market-adjusted returns across the second half of the trading month: mean returns decline monotonically from near zero at mid-month to a trough at PreTOM (-11.32 bps/day, $t = -3.53$, Newey-West) before partially recovering at month-end. No other six-day window in the second half of the month produces a comparably negative estimate. Because the right edge of the cash-raising window is identified independently in our data, the T+1 prediction below is not a consequence of inherited window definitions.

Figure 4 plots the post-vs-pre difference in mean loser market-adjusted returns at each trading day T. The two boundary days move in opposite directions: $T-4$ becomes substantially less negative after the reform, while $T-3$ becomes substantially more negative. Other days lie near zero. The pattern suggests the right edge of the cash-raising window has moved one day later, from $T-4$ to $T-3$. We test this directly below.

The DiD compares $T-4$ and $T-3$ against early-month controls $[T+5, T+8]$, which experience the same post-2024 time-series shocks but are plausibly unaffected by settlement mechanics. Days closer to month-end $(T-2, T-1)$ are contaminated by post-PreTOM reversal and unsuitable as controls.[9] We estimate

$$\begin{aligned}\mathrm{ExRet}_t = \alpha + \beta_{-4}\,\mathbf{1}[T=-4] + \beta_{-3}\,\mathbf{1}[T=-3] + \beta_{\mathrm{Post}}\,\mathrm{Post}_t \\ + \theta_{-4}\,\mathbf{1}[T=-4]\times\mathrm{Post}_t + \theta_{-3}\,\mathbf{1}[T=-3]\times\mathrm{Post}_t + \varepsilon_t, \quad (7)\end{aligned}$$

where ExRet_t is the value-weighted loser portfolio market-adjusted return on day t, Post_t indicates dates from June 1, 2024 onward, and the omitted reference is $[T+5, T+8]$. May 2024 is excluded from both pre- and post-samples to avoid contamination at the regime boundary. The headline test is $\theta_{-4} - \theta_{-3} > 0$: the PreTOM window edge moves from $T-4$ to $T-3$ under the reform.

Table 7, Panel A reports raw cell means: the loser mean at $T-4$ shifts from -8.4 bps/day pre-reform to $+49.4$ post-reform; at $T-3$, from -5.2 to -33.4; the early-month control shifts only modestly. Panel B converts these into DiD coefficients. The two days move in opposite directions, neither individually significant given the 19-month post-reform sample. Pooling them tightens the test: $\theta_{-4} - \theta_{-3} = +85.9$ basis points ($t = 2.68$, $p = 0.007$). Restricting the pre-period to the T+2 era alone (September 2017 to April 2024) yields a similar $+85.7$ ($t = 2.31$).

Panel B isolates the time-of-month shift but cannot rule out a generic post-2024 repricing affecting all stocks at $T-4$ and $T-3$. Panel C addresses this with a stock-level triple-

[9] Using $T-2$ as the control yields similar estimates (untabulated).

difference contrasting D1 against D10 at the same days:

$$\mathrm{ExRet}_{i,t} = \theta^L_{-4}\,\mathrm{Loser}_{i,t} \times \mathbf{1}[T=-4] \times \mathrm{Post}_t + \theta^L_{-3}\,\mathrm{Loser}_{i,t} \times \mathbf{1}[T=-3] \times \mathrm{Post}_t + Z'_{i,t}\gamma + \mu_i + \delta_t + \varepsilon_{i,t}, \quad (8)$$

where $Z_{i,t}$ contains the lower-order $\mathrm{Loser}_{i,t}$, $\mathrm{Loser}_{i,t} \times \mathbf{1}[T=m]$, and $\mathrm{Loser}_{i,t} \times \mathrm{Post}_t$ terms; the $\mathbf{1}[T=m]$, Post_t, and $\mathbf{1}[T=m] \times \mathrm{Post}_t$ effects are absorbed by δ_t. The sample is restricted to days $T=-4$, $T=-3$, and the early-month control window, with early-month days as the omitted day reference and D10 as the omitted decile reference.

The shift is loser-specific: $\theta^L_{-4} - \theta^L_{-3} = +196$ basis points ($t = 2.20$, $p = 0.028$).[10]

5.2 The Earlier T+3→T+2 Transition

The earlier T+3→T+2 transition (September 2017) produces a directional shift but no statistical effect (DiD = +17.0 bps, $t = 0.83$; Online Appendix Table IA.16). This is consistent with the mechanism: the 2017 reform shortened equity settlement by one day but left the fund-equity settlement gap at one day, so loser-selling concentration would partially migrate but should not fully shift. Only the May 2024 reform closed the gap entirely.[11]

6 Validation Beyond the Monthly Cycle

6.1 Liquidity Shocks and the Selection of Losers

The mutual fund flow evidence establishes that loser stocks face elevated selling pressure during PreTOM in normal times. If month-end cash demand is the correct mechanism, the same asymmetry should appear whenever institutions need cash: losers should fall harder than winners during exogenous liquidity shocks regardless of calendar timing. The fund-level pattern follows mechanically: loser-tilted funds hold what the market sells.

[10] Panel C exceeds Panel B because the triple-difference contrasts D1 against D10 directly. If markets at $T-4$ and $T-3$ experienced any cross-sectional shock affecting both D1 and D10 after May 2024, Panel B understates the loser-specific component while Panel C nets it out. Placebo tests on non-boundary days ($T-6$ vs. $T-7$) and on placebo regime dates (May 2018, May 2020) return zero (Online Appendix Table IA.5).

[11] The SEC and DTCC publicly characterized T+1 as a major change to U.S. market infrastructure (Securities and Exchange Commission, 2023; Depository Trust & Clearing Corporation, 2024).

We test this using three episodes of acute aggregate outflows between 1998 and 2025: September 2008, October 2008 (GFC), and March 2020 (COVID-19). At the start of each year, we sort actively managed U.S. equity funds into deciles on prior 12-month return; assignments are held constant within the calendar year. The sort is effectively by momentum loading: D10 funds hold past winners and D1 funds hold past losers (Carhart, 1997), and D1 and D10 classifications are ex ante to each month's returns. Table 8, Panel A, reports value-weighted monthly returns alongside aggregate outflows. The asymmetry is consistent across episodes and largest in the biggest shocks. March 2020 was the worst D1 month in the sample: D1 funds returned −26.34% against D10's −8.90%, a 17.44 percentage-point spread on outflows of 1.16% of assets.

A fund-month panel regression (Table 8, Panel B) confirms the channel while absorbing style differences across loser, winner, and middle deciles:

$$R_{j,m}-R^f_m = \alpha+\beta_0\,\text{Outflow}_m+F'_m\gamma+\sum_{d\in\{\text{D1},\text{D10}\}} D_{d,j,y}\,(\beta_{1,d}+\beta_{2,d}\,\text{Outflow}_m+F'_m\delta_d)+\mu_j+\varepsilon_{j,m}, \tag{9}$$

where $F_m = (\text{MKT}_m, \text{SMB}_m, \text{HML}_m)'$, $\gamma = (\gamma_1,\gamma_2,\gamma_3)'$, and $\delta_d = (\delta_{1,d},\delta_{2,d},\delta_{3,d})'$ are the decile-specific factor-loading shifts. $R_{j,m}$ is fund j's return in month m and R^f_m is the risk-free rate; $D_{\text{D1},j,y}$ and $D_{\text{D10},j,y}$ indicate whether fund j falls in the loser or winner decile during year y, the year containing month m (reference group D2–D9); decile assignments are held constant within each calendar year; Outflow_m is aggregate net flows as a share of lagged assets; μ_j are fund fixed effects; and standard errors are double-clustered by fund and month. Past-loser and past-winner funds differ in market beta and in size and value tilts; the δ_d vector absorbs these factor-loading differences, so $\beta_{2,d}$ is identified from outflow-driven variation orthogonal to systematic factor exposure. The middle-decile baseline identifies β_0 and makes $\beta_{2,\text{D1}}$ and $\beta_{2,\text{D10}}$ directly comparable. Past-loser funds lose 0.63 pp per percentage point of aggregate outflow ($t = -2.11$); past-winner funds show no response (−0.05 pp, $t = -0.19$). Loser-tilted funds bear the hit because they hold the stocks the market is selling.

6.2 International Evidence

We test whether the PreTOM loser effect extends beyond U.S. equities using daily momentum decile portfolios for 19 developed markets from Compustat Global, 1990–2025.[12] Within each country-month, we rank stocks into momentum deciles on cumulative returns over months -12 through -2, value-weight by lagged market cap, and subtract the local market excess return from Kenneth French's regional factor files.

Table 10 reports the pooled regression

$$\text{ExRet}_{c,d} = \alpha_c + \beta\,\text{PreTOM}_d + \varepsilon_{c,d}, \tag{10}$$

where $\text{ExRet}_{c,d}$ is the day-d value-weighted loser-decile return in excess of the local market in country c, PreTOM_d is the indicator for trading days $T \in [-9, -4]$ (Rest days are the omitted reference), α_c are country fixed effects, and standard errors are clustered by country-month. The coefficient β measures the PreTOM-minus-Rest gap in loser excess returns within country. Losers underperform the local market by 4.5 bps per day more during PreTOM than during the rest of the month ($t = -4.60$). The asymmetry is loser-driven: winners show no differential PreTOM concentration (+0.74 bps, $t = 0.78$); the WML spread differs by +5.3 bps ($t = 4.27$). The effect is largest in Norway, Hong Kong, and Belgium, with Germany, Finland, and the Netherlands close behind; Japan, where momentum is known to be weak (Fama and French, 2012; Asness et al., 2013), shows nothing. Country-by-country results are in Internet Appendix IA.9.

7 Revisiting Carhart: Fund Persistence as a PreTOM Phenomenon

In his seminal paper, Carhart (1997) showed that past-loser funds persistently underperform, and that two components, negative momentum loading (they hold last year's losers) and high expense ratios, account for almost all of what prior literature had attributed to skill or luck.

We revisit Carhart's persistence result because our mechanism predicts an intramonth

[12] Countries, sample periods, and methodology details (size-conditional breakpoints, regional pooling for small markets) are described in Internet Appendix IA.8. We exclude Japan, where momentum is approximately zero over our sample, and Canada, for which Compustat Global coverage is limited.

structure for the first of these two components. Institutions sell loser stocks during PreTOM to raise cash, and mutual funds that hold those stocks lose value during the same six days, every month. The negative UMD loading of past-loser funds should therefore be earned almost entirely during PreTOM, while expense-ratio drag operates uniformly across all trading days. Past-loser fund persistence, in this view, is the fund-level counterpart of the stock-level selling mechanism we document.

Four testable predictions follow. The momentum-driven component of past-loser fund underperformance should concentrate in PreTOM. It should be absorbed by controlling for loser-stock returns. It should shift by one day following the T+1 settlement reform. And it should combine with expense drag to account for total D1 underperformance, leaving no residual. We find all four.

7.1 The Factor's Intramonth Profile

We begin with the factor itself. The Fama–French UMD factor earns +5.51 bps/day during PreTOM ($t = 3.76$) and +1.36 bps/day during the roughly fifteen remaining trading days ($t = 1.43$). Only the PreTOM leg is statistically distinguishable from zero. Over 1980–2025, a dollar invested in UMD only on PreTOM days grows to \$5.51; invested only on Rest days it grows to \$2.26 (Table 9, Panel A). Any fund that loads on UMD collects that loading almost entirely in six days per month.

7.2 Replicating Carhart at Monthly Frequency

We replicate Carhart's results. We sort actively managed equity funds into deciles each year on prior 12-month return and estimate decile-level monthly alphas using

$$R_m^{Dk} - R_m^f = \alpha_{Dk} + \beta_{Dk}\,\text{MKT-RF}_m + s_{Dk}\,\text{SMB}_m + h_{Dk}\,\text{HML}_m + u_{Dk}\,\text{UMD}_m + \varepsilon_m, \quad (11)$$

where R_m^{Dk} is the equal-weighted month-m return on decile Dk, and the four-factor specification is reported alongside the three-factor version (omitting UMD). Past-loser funds (D1) load on UMD with a beta of -0.22 to -0.29 in every subperiod from 1963 to 2025, and underperform the three-factor benchmark by −0.55%/month ($t = -6.38$; Table 9, Panel B).[13] Past-winner funds (D10) show weak and inconsistent outperformance that fades in recent decades. The loser leg is structural; the winner leg is not.

7.3 Intramonth Decomposition of D1 Fund Underperformance

The intramonth decomposition reveals what concentrates and what does not. Using daily CRSP mutual fund returns, available from September 1998 onward when CRSP first reports daily NAV-implied fund returns, D1's PreTOM three-factor alpha is −2.50 bps/day ($t = -2.03$). Controlling for the raw loser-stock return absorbs it to −0.64 bps/day, no longer significant (Table 9, Panel C). Outside PreTOM, the three-factor alpha of −2.43 bps/day ($t = -2.77$) is only partially absorbed when the loser return is added (−1.54, $t = -2.21$). The momentum-driven component concentrates in PreTOM; non-momentum drift persists in both windows.

The estimates also reveal a symmetric cross-sectional pattern. D1 funds load on the loser return with $\beta_{\text{Loser}} = +0.27$, roughly the effective share of their portfolio in loser stocks. D10 funds load with $\beta_{\text{Loser}} = -0.18$, mirroring D1 with the opposite sign. D10's raw PreTOM alpha (+0.20 bps/day) reflects loser-avoidance benefit rather than stock-picking; once the loser return is added, D10's alpha turns slightly negative (−1.05 bps/day), like D1's. The D1−D10 spread reflects a single mechanism: the loser-stock cycle drives D1 returns down through ownership and D10 returns up through avoidance.

7.4 Expense Ratios and the Three-Way Decomposition

A three-way decomposition adding expense ratios further isolates the source of D1 underperformance (Table 9, Panel D). After controlling for both the loser-stock return and the expense ratio, D1 funds show no detectable alpha in either window: +2.01 bps/day in PreTOM ($t = 1.41$) and −0.42 bps/day in Rest ($t = -0.45$). The two channels jointly account for D1 underperformance.

[13] Choi and Zhao (2021) document that full-month fund persistence disappears post-1994. Our Panel B is consistent with their finding for the winner–loser spread in 2011–2025 (+0.23%/month, $t = 1.07$). The disappearance is asymmetric: D1 underperformance remains significant in every subperiod, with a UMD loading that has strengthened to $\beta = -0.29$ ($t = -8.4$) in 2011–2025. The spread narrows because the winner leg has lost its modest outperformance, not because the loser leg has improved.

Loser exposure does most of the work in PreTOM. The loser-return control alone absorbs PreTOM alpha from −2.29 to −0.45, while in Rest the same control absorbs from −2.25 to −1.50—only partial absorption outside PreTOM. Expense ratios are negatively related to fund returns in both windows, with a larger coefficient in PreTOM (−1.80, $t = -2.49$) than in Rest (−0.79, $t = -1.66$); the cross-window difference is consistent with high-expense funds tilting toward losers.

7.5 Fund-Level T+1 Evidence

The T+1 settlement reform confirms causality at the fund level. Following the SEC's May 2024 transition from T+2 to T+1 settlement, D1 fund underperformance migrates from $T-4$ to $T-3$ (DiD = +25.4 bps, $t = 2.15$; Table 9, Panel E), mirroring the stock-level shift documented in Table 7. The same exogenous shock that shifts stock-level selling by one day shifts fund-level underperformance by one day. While Carhart documented which funds load on momentum, we show that the momentum-loading component of past-loser fund underperformance is realized in the PreTOM window.

8 PreTOM Profits Are Not Crash-Avoidance

A natural concern is that PreTOM's strong performance reflects luck rather than mechanism: if momentum crashes happened to land outside PreTOM by coincidence, the premium would be a calendar artifact. A trading day is classified as a "crash day" if VW WML falls below −200 basis points, and we compare crash incidence against calendar share within a comparison universe that excludes the other window (PreTOM against non-month-start days, month-start against non-PreTOM days), so the two effects do not contaminate each other.[14] PreTOM accounts for 30.8% of crash days against its 33.3% calendar share ($z = -1.32$, $p = 0.19$): crashes arrive in PreTOM at the expected rate, and the PreTOM premium is not generated by crash avoidance.

Month-start is where crashes concentrate. Month-start days hold a disproportionate share of crash days at every threshold from −100 to −300 bps (Figure 5). The pattern is not driven by famous episodes: excluding the 2001 cluster (Daniel and Moskowitz, 2016), the March–

[14] Calendar-share construction and the proportions z-test are described in Internet Appendix IA.7.

May 2009 crash, and the COVID dislocation (February–May 2020) leaves the month-start share at 20.4% across $N = 685$ remaining crash days ($z = 4.61$). Tail-trimming preserves PreTOM profits but flattens month-start returns: PreTOM gains are structural, month-start crashes are tail-driven (Online Appendix Figure IA.2). Figure 6 displays both dimensions jointly: crash probability peaks at month-start, while mean WML peaks in PreTOM.

9 Conclusion

The momentum premium is mostly a six-day phenomenon. Seventy-seven percent of WML's cumulative log return is earned during the six trading days before month-end (PreTOM), which comprise just 29% of the trading month. A dollar invested in WML only on PreTOM days grew to $18.78 between 1980 and 2025; the same dollar invested on the remaining fifteen days grew to $2.37; over the full sample WML grew to $44.46. The premium is driven by past losers; winners contribute nothing distinctive.

The mechanism has two pieces. The timing comes from month-end cash demand: predictable payment obligations force investors to raise cash before settlement clears, concentrating selling pressure in the days leading up to the deadline. The cross-sectional incidence falls on losers because they are dispensable on multiple margins—non-dividend-paying, tax-favored for liquidation, and salient under institutional risk reduction. Three pieces of evidence connect mechanism to result: TAQ trade-direction data show institutional sell pressure on losers concentrated in PreTOM; the May 2024 T+1 settlement reform shifted the selling window by one day, with placebo tests returning null; and the loser-asymmetric pattern reproduces in 19 developed international markets and in three episodes of acute fund outflows (September 2008, October 2008, March 2020).

The findings reframe momentum as a feature of market microstructure rather than a property of investor beliefs or risk. The same approach may generalize: many cross-sectional anomalies share a short leg populated by stocks investors would sell first under liquidity pressure, and if the intramonth structure documented here extends to those anomalies, a portion of cross-sectional return predictability may turn out to be a settlement-cycle phenomenon.

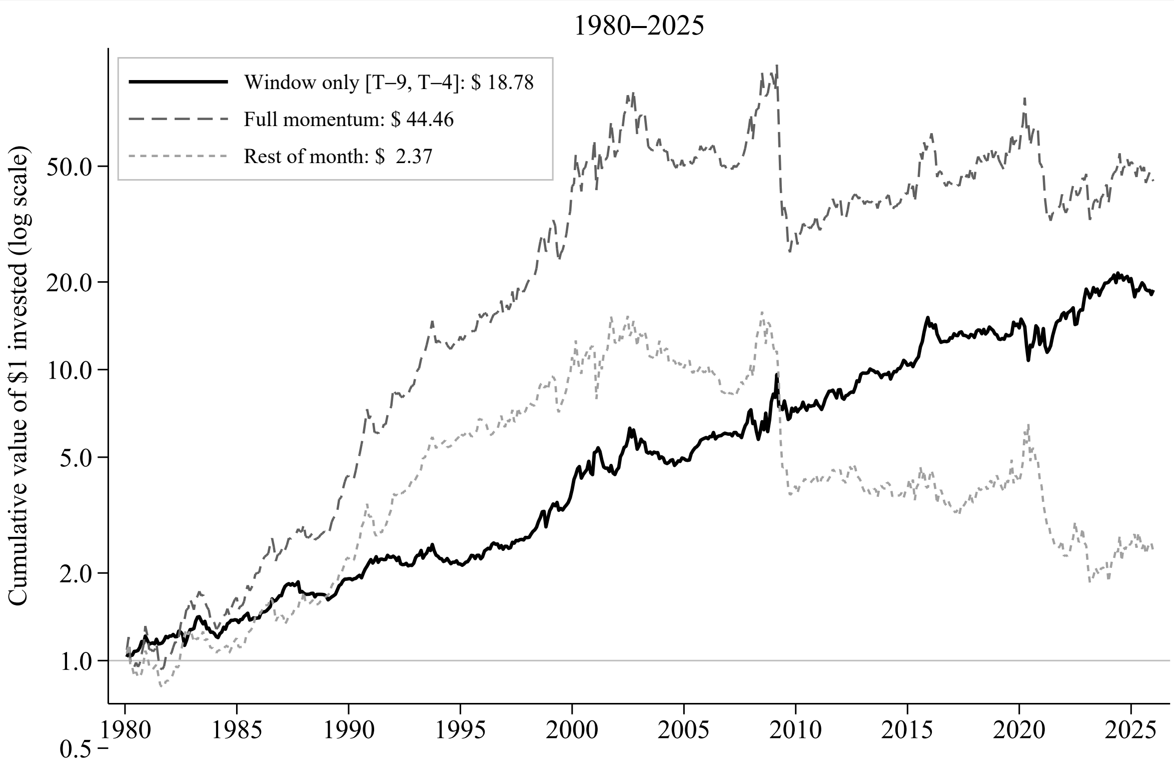

Figure 1: Cumulative wealth from $1 invested in three momentum strategies: WML earned only during PreTOM ($T-9$ to $T-4$), WML earned only during Rest (i.e., the approximately 15 trading days outside the PreTOM window), and WML earned every day. T indexes trading days relative to month-end, with T=0 the last trading day of the month. Value-weighted daily returns. Decile assignments are held constant within each calendar month and are formed by ranking all NYSE, AMEX, and NASDAQ stocks in CRSP on cumulative returns over months -12 through -2 using NYSE breakpoints. Sample: 1980–2025.

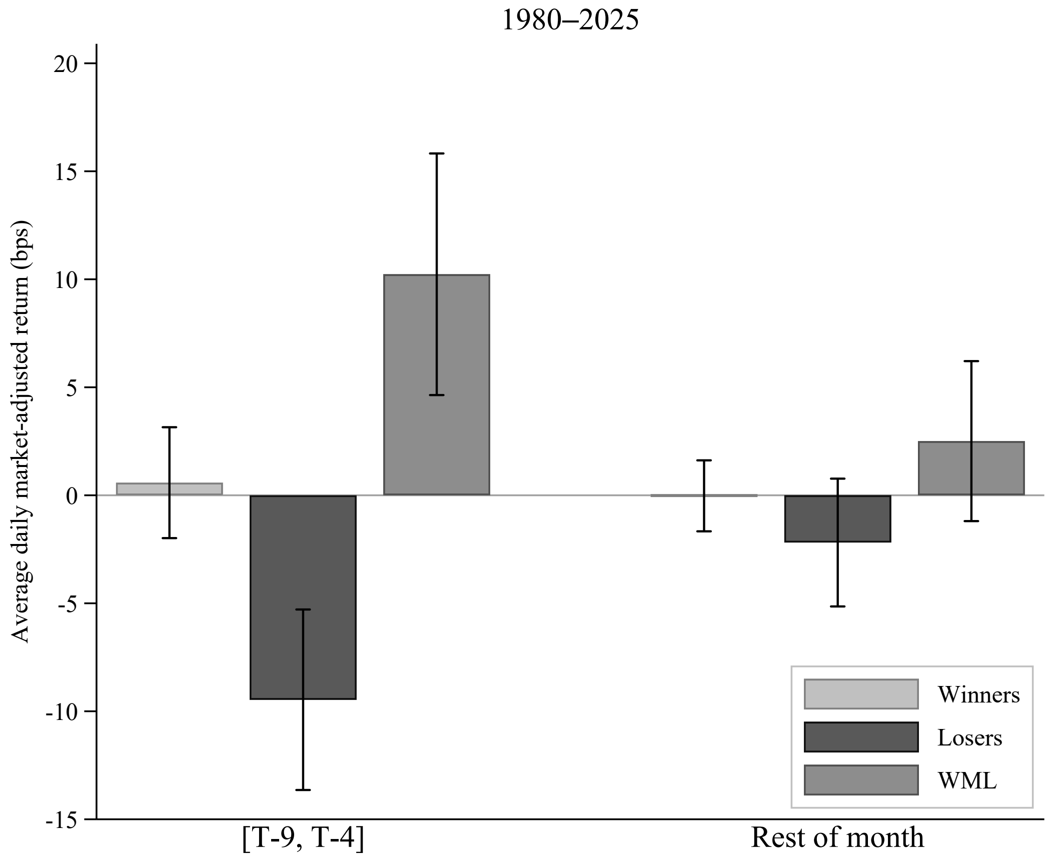

Figure 2: Average daily market-adjusted returns (basis points) of momentum winners, losers, and WML during PreTOM ($T-9$ to $T-4$) versus Rest. Whiskers denote 95% confidence intervals. Value-weighted. Momentum deciles use NYSE breakpoints applied to all NYSE, AMEX, and NASDAQ stocks in CRSP; assignments are held constant within each calendar month. Sample: 1980–2025.

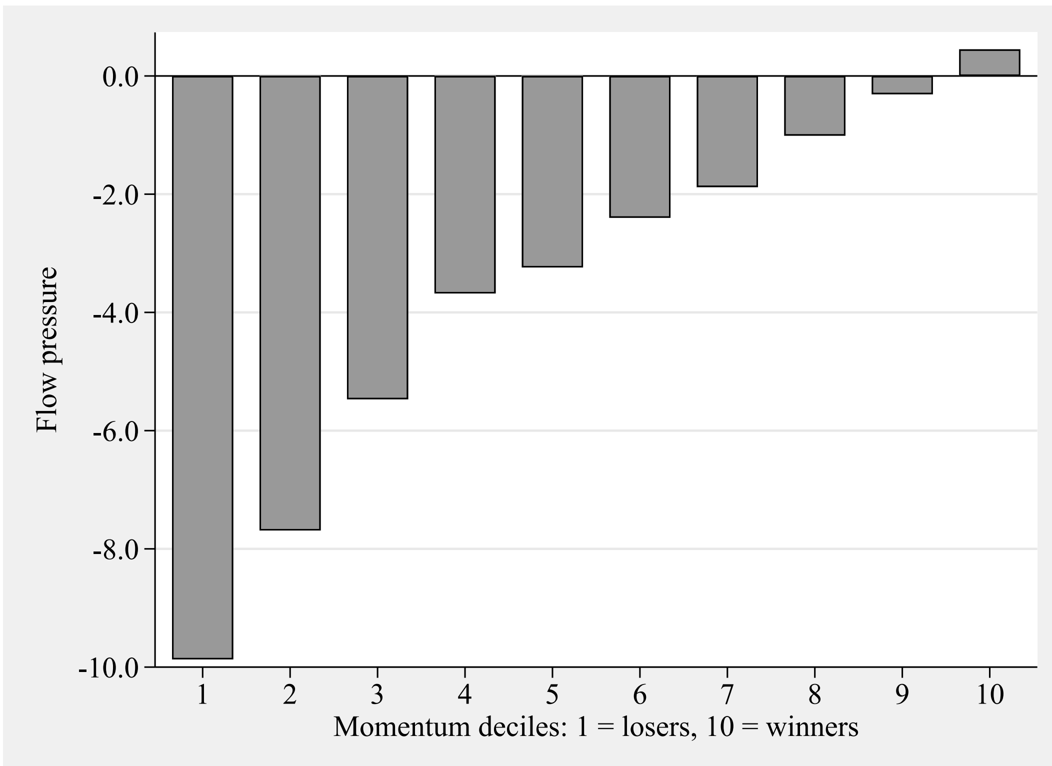

Figure 3: Cumulative mutual fund flow pressure during PreTOM ($T-9$ to $T-4$) by momentum decile. Flow pressure is calculated from daily mutual fund flows allocated to stocks in proportion to prior-quarter holdings, normalized by market capitalization. Momentum deciles use NYSE breakpoints applied to all NYSE, AMEX, and NASDAQ stocks in CRSP; assignments are held constant within each calendar month. Sample: 2010–2023.

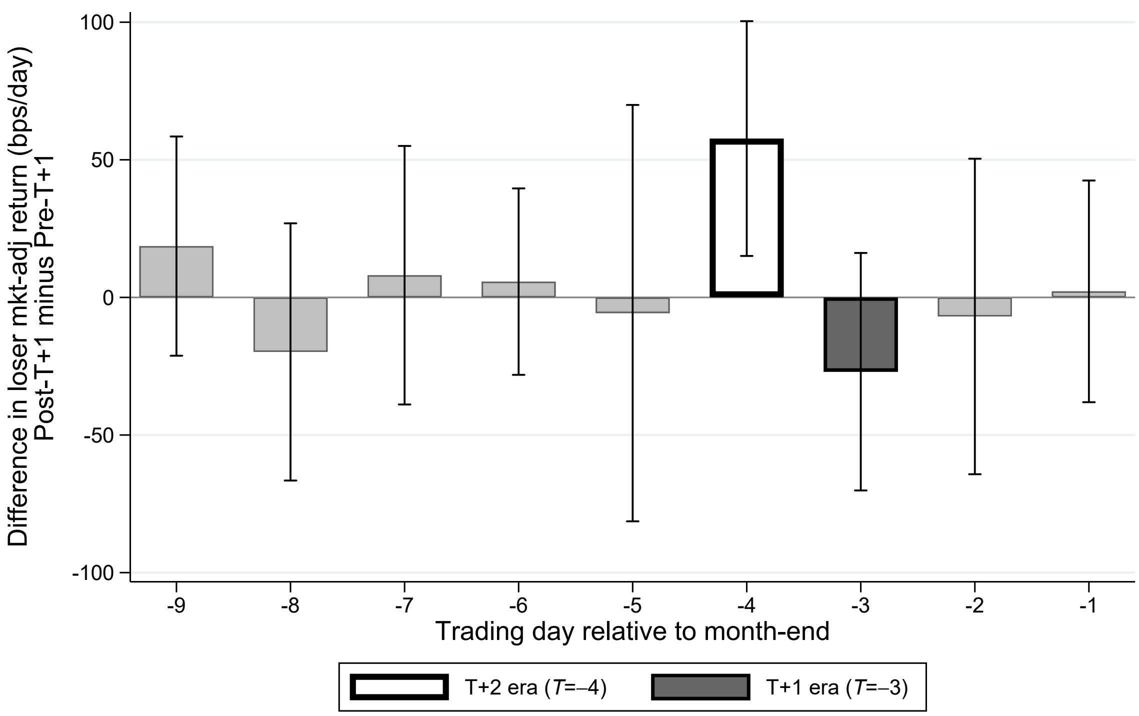

Figure 4: Difference in mean daily market-adjusted VW loser returns (Post-T+1 minus Pre-T+1) at each trading day t, with 95% confidence intervals. The SEC transitioned from T+2 to T+1 settlement on May 28, 2024. Momentum deciles use NYSE breakpoints applied to all NYSE, AMEX, and NASDAQ stocks in CRSP; assignments are held constant within each calendar month. Sample: 1980–2025 (533 months pre, 19 months post).

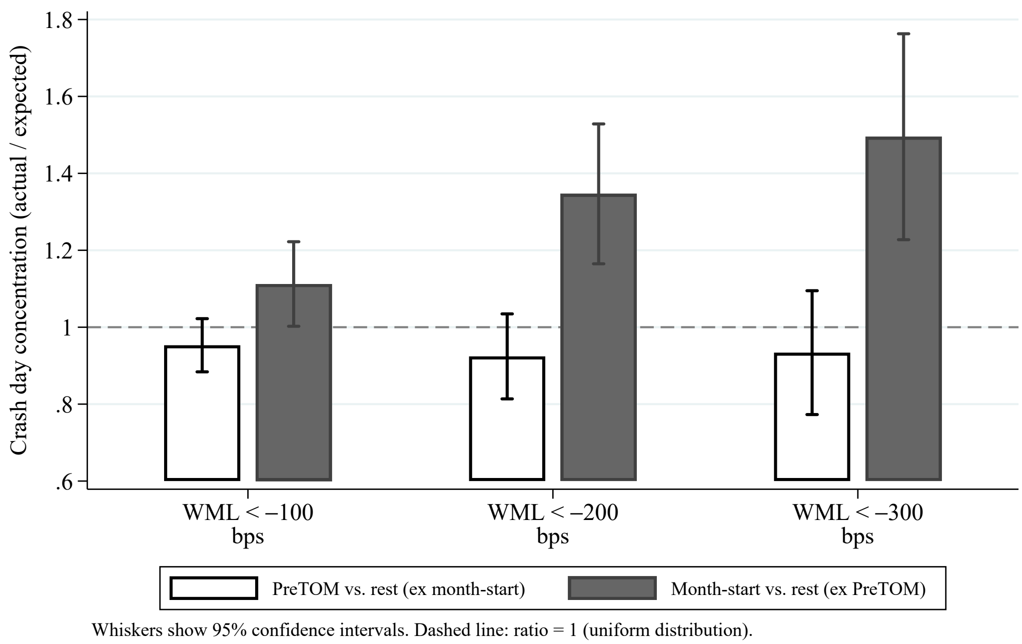

Figure 5: Crash day concentration by calendar window. Each point plots the ratio of actual crash-day share to calendar share, with 95% confidence intervals. Under uniform distribution, all points equal one (dashed line). Value-weighted. Momentum deciles use NYSE breakpoints applied to all NYSE, AMEX, and NASDAQ stocks in CRSP; assignments are held constant within each calendar month. Sample: 1980–2025.

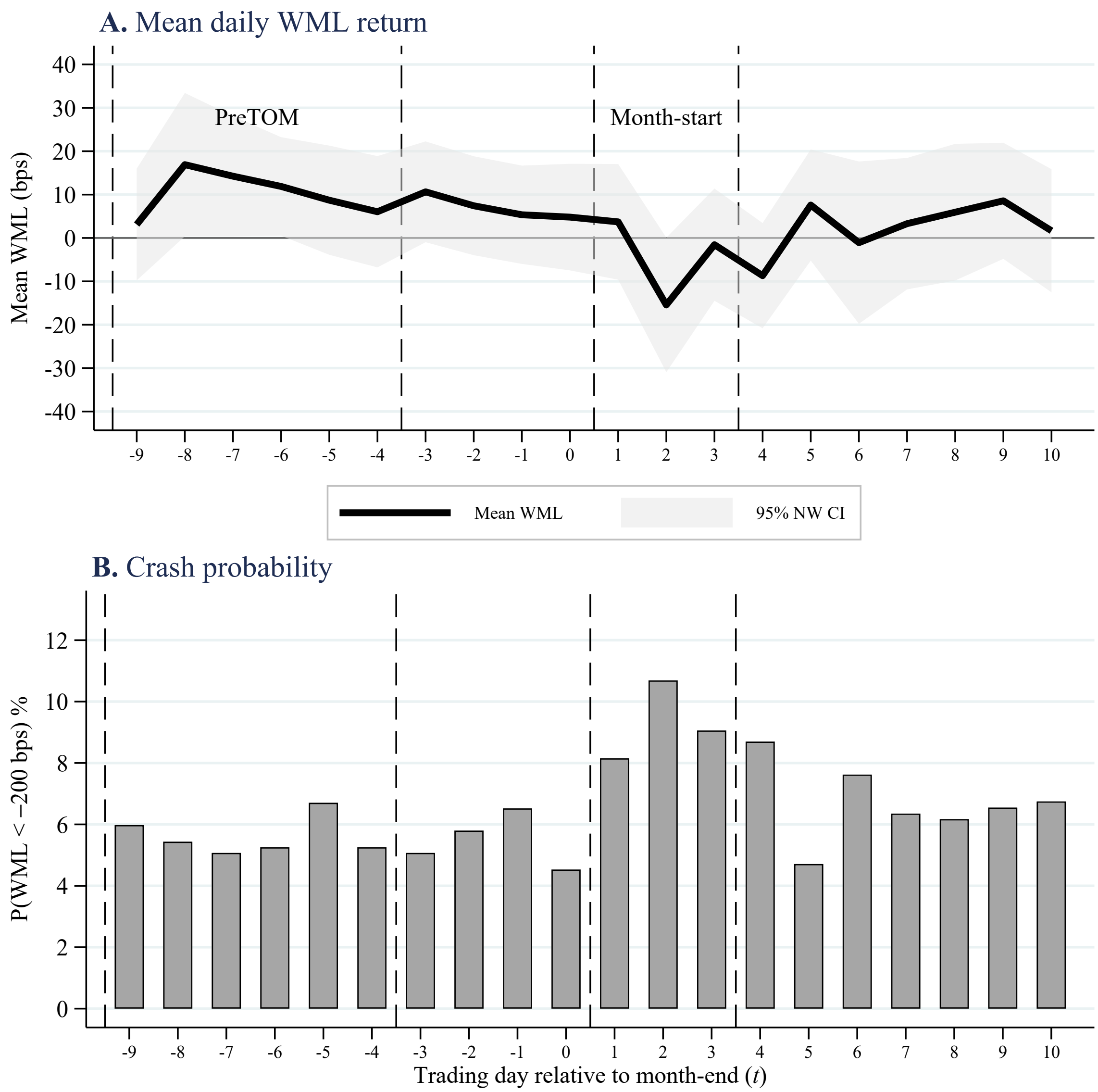

Figure 6: Panel A plots mean daily WML return with Newey-West 95% confidence bands by trading day T relative to month-end. Panel B plots crash probability, defined as Pr(WML $<$ -200 bps). Dashed vertical lines mark the PreTOM window ($T-9$ to $T-4$) and the month-start window ($T+1$ to $T+3$). Value-weighted. Momentum deciles use NYSE breakpoints applied to all NYSE, AMEX, and NASDAQ stocks in CRSP; assignments are held constant within each calendar month. Sample: 1980–2025.

Table 1: Calendar-Conditional Momentum-Decile Premia: Fama–MacBeth Estimates

	Losers (D1)	Winners (D10)
Rest premium (c_0^d)	-2.424	-0.036
	(1.496)	(0.859)
PreTOM differential (c_1^d)	-7.116^{***}	$+0.646$
	(2.547)	(1.638)
PreTOM premium ($c_0^d + c_1^d$)	-9.540^{***}	$+0.610$
	(2.134)	(1.334)
Sample	1980–2025	1980–2025
Newey–West lags	21	21
Observations (T)	11,595	11,595

Notes. Daily Fama–MacBeth estimates from equations (1)–(2). Stage 1 regresses stock-level market-adjusted returns on momentum-decile indicators with no intercept, value-weighted by lagged market capitalization, across all CRSP common stocks each trading day. Stage 2 regresses the daily decile coefficient on a PreTOM indicator with Newey–West standard errors at 21 lags. PreTOM is the trading-day window $T \in [-9, -4]$. Sample: 1980–2025. Coefficients in basis points. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 2: Loser PreTOM Underperformance: Baseline Panel Regression

	(1) VW	(2) EW
Loser (β_1)	2.609**	8.022***
	(1.279)	(0.717)
Loser × PreTOM (β_2)	−7.151***	−2.550*
	(2.322)	(1.376)
Sample	Full panel	Full panel
Firm FE, Date FE	✓	✓
Observations	53,324,145	53,324,145

Notes. Estimates of equation (3) on the full CRSP panel of NYSE/AMEX/NASDAQ stocks, 1980–2025. Dependent variable is the stock's daily excess return over the value-weighted CRSP market, $\text{ExRet}_{i,d} = r_{i,d} - r_d^m$, in basis points. $\text{Loser}_{i,d}$ is an indicator equal to one if stock i is in the bottom momentum decile on date d. PreTOM_d is an indicator for the six trading days $[T-9, T-4]$ before month-end (absorbed by date fixed effects). All specifications include firm and date fixed effects. Standard errors (in parentheses) are two-way clustered by firm and date. Column 1 weights observations by lagged market capitalization within decile-date. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3: PreTOM Effect on Losers and the Bid-Ask Spread (Market-Adjusted)

	(1) VW	(2) VW + BAS	(3) EW	(4) EW + BAS
PreTOM	-7.294***	-9.108***	-2.214	-4.351**
	(2.334)	(3.040)	(1.895)	(2.148)
BAS		-333.183***		-2.608
		(20.655)		(15.104)
PreTOM × BAS		53.730*		31.480**
		(27.952)		(12.719)
Observations	10,140,216	9,214,471	10,140,216	9,214,471
Within R^2	0.0001	0.0004	0.0000	0.0000

Notes. Sample: bottom-decile (D1) momentum stocks, 1980–2025. Dependent variable is $\text{ExRet}_{i,d}$ in basis points (defined in eq. 3). PreTOM is an indicator for the six trading days $[T-9, T-4]$ before month-end. BAS is the daily bid-ask spread of stock i on date d as a fraction of the quote midpoint. All specifications include firm and year-month fixed effects. Standard errors (in parentheses) are two-way clustered by firm and date. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4: Subperiod Stability of the PreTOM 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. Estimates of equation (3) on subperiods. 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. Momentum deciles use NYSE breakpoints applied to all NYSE, AMEX, and NASDAQ stocks in CRSP; assignments are held constant within each calendar month.

Table 5: Selling Pressure During PreTOM and Post: Full Sample with Loser Interactions

	Panel A: PreTOM only		Panel B: PreTOM + Post	
	Net Sell Pressure	Sell Share	Net Sell Pressure	Sell Share
	(1)	(2)	(3)	(4)
Loser (β_1)	0.0122***	0.0061***	0.0122***	0.0061***
	(0.0010)	(0.0005)	(0.0010)	(0.0005)
Loser × PreTOM (β_2)	0.0020**	0.0010**	0.0014*	0.0007*
	(0.0008)	(0.0004)	(0.0008)	(0.0004)
Loser × Post (β_3)			−0.0028***	−0.0014***
			(0.0009)	(0.0005)
Sample	Full panel	Full panel	Full panel	Full panel
Fixed effects	Firm, Date	Firm, Date	Firm, Date	Firm, Date

Notes. Estimates of equation (5) on the full panel of CRSP/TAQ stocks, 2003–2022. Dependent variables: net sell pressure = (sell volume − buy volume)/total volume, in $[-1, 1]$; sell share = sell volume/total volume, in $[0, 1]$. Trade direction is assigned using the Lee–Ready algorithm (WRDS Intraday Indicators). $\text{Loser}_{i,d}$ is an indicator for the bottom momentum decile. PreTOM_d is an indicator for $[T-9, T-4]$ before month-end; Post_d is an indicator for $[T-3, T+3]$ around month-end. Both date-level indicators are absorbed by the date fixed effect; their interactions with Loser are identified from cross-decile within-date variation. Firm and date fixed effects. Standard errors (in parentheses) are two-way clustered by firm and date. The contrast $\beta_3 - \beta_2$ in Panel B is highly significant: same losers heavily sold in PreTOM are bought back in Post. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 6: Partial Reversal of PreTOM Loser Underperformance

	(1) VW
Loser (β_1)	1.043
	(1.901)
Loser $\times$ PreTOM (β_2)	-5.585^{**}
	(2.698)
Loser $\times$ Post (β_3)	3.356
	(2.708)
$\beta_3 - \beta_2$	$+8.94^{***}$
	($t = 3.30$)
Sample	Full panel
Firm FE, Date FE	✓
Observations	53,324,145

Notes. Estimates of equation (6) on the full CRSP panel, 1980–2025. Dependent variable is the daily excess return over the value-weighted CRSP market, $\text{ExRet}_{i,d}$, in basis points. $\text{Loser}_{i,d}$ is an indicator for the bottom momentum decile. PreTOM_d is an indicator for $[T-9, T-4]$ before month-end. Post_d is an indicator for $[T-3, T+3]$ around month-end. Both PreTOM and Post are date-level and absorbed by the date fixed effect. Value-weighted by lagged market capitalization. Firm and date fixed effects. Standard errors (in parentheses) are two-way clustered by firm and date. Cumulative widening: $6\beta_2 = -33.5$ bps over six PreTOM days; cumulative narrowing $7\beta_3 = +23.5$ bps over seven Post days; recovery ratio $\approx 70\%$. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 7: T+1 Settlement Difference-in-Differences

Panel A: Cell Means (loser-decile market-adjusted return, bps/day)

	Pre-T+1 / Post-T+1
Early-month $[T{+}5, T{+}8]$ (control)	-5.1 / $+5.0$
$T-3$	-5.2 / -33.4
$T-4$	-8.4 / $+49.4$

Panel B: Portfolio-Level DiD (early-month control)

	(1) Pre-period: T+2 era only (Sep 2017–May 2024)	(2) Pre-period: full history (1980–May 2024)
β_{-4}: $\mathbf{1}[T=-4]$	-22.25	-3.39
	(16.82)	(4.82)
β_{-3}: $\mathbf{1}[T=-3]$	-19.30	-0.18
	(14.36)	(5.49)
β_{Post}: Post_t	$+6.59$	$+10.09$
	(21.33)	(18.67)
θ_{-4}: $\mathbf{1}[T=-4] \times \text{Post}_t$	$+66.56^{*}$	$+47.71$
	(38.54)	(34.53)
θ_{-3}: $\mathbf{1}[T=-3] \times \text{Post}_t$	-19.10	-38.22
	(31.83)	(28.66)
$\theta_{-4} - \theta_{-3}$ (one-day shift)	$+85.66^{**}$	$+85.93^{***}$
	(37.07)	(32.06)
Observations	297	1,653

Notes. Estimates of equation (7). Dependent variable is the daily market-adjusted value-weighted loser portfolio return in basis points. Treated days are $T-4$ and $T-3$; control days are early-month $[T{+}5, T{+}8]$, averaged to one observation per month, so each month contributes three observations: $T-4$, $T-3$, and one early-month-control mean. May 2024 is excluded from both pre- and post-samples to avoid contamination at the regime boundary, so the post-T+1 window begins June 1, 2024. Column 1 uses the T+2 era (Sep 2017 to Apr 2024) as the pre-period; Column 2 uses 1980 to Apr 2024. Panel A reports cell means. Panel B reports portfolio-level OLS coefficients with Newey-West standard errors in parentheses (NW(10) lags). Newey-West t-statistics on the differential are stable across NW(5), NW(10), and NW(21) lag choices. Momentum deciles use NYSE breakpoints applied to all NYSE, AMEX, and NASDAQ stocks in CRSP; assignments are held constant within each calendar month. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 7: T+1 Settlement Difference-in-Differences (continued)

Panel C: Stock-Level Triple-Difference (D1 and D10, firm + day FE, early-month control)	Pre-period: 1980 to Apr 2024
θ^L_{-4}: $\text{Loser}_{i,t} \times \mathbf{1}[T=-4] \times \text{Post}_t$	$+161.24^{**}$
	(73.23)
θ^L_{-3}: $\text{Loser}_{i,t} \times \mathbf{1}[T=-3] \times \text{Post}_t$	-35.07
	(52.70)
$\theta^L_{-4} - \theta^L_{-3}$ (one-day shift)	$+196.32^{**}$
	(89.32)
Observations	4,907,237

Notes. Stock-level triple-difference of equation (8). Sample: D1 (loser) and D10 (winner) decile stocks; pre-period 1980 to Apr 2024, post-period from June 1, 2024 (May 2024 excluded). Dependent variable is the daily excess return in basis points. Value-weighted by lagged market capitalization. Standard errors two-way clustered by firm and date. Momentum deciles use NYSE breakpoints applied to all NYSE, AMEX, and NASDAQ stocks in CRSP; assignments are held constant within each calendar month. See Table 7 for details. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 8: Liquidity Shocks and Asymmetric Loser Selling

Panel A: Momentum Fund Returns During Liquidity Crisis Episodes

Episode	D1 Return (%)	D10 Return (%)	D1−D10 (pp)	Outflow (% AUM)
Sep 2008 (GFC)	−15.30	−6.68	−8.63	+0.82
Oct 2008 (GFC)	−24.49	−12.40	−12.10	+1.58
Mar 2020 (COVID)	−26.34	−8.90	−17.44	+1.16

Panel B: Fund-Month Panel Regression — Outflow Response by Decile, 1998–2025

Decile group	Outflow response	t-stat
Middle deciles (D2–D9): β_0	−0.339***	(−3.30)
D1 (past-losers): $\beta_0 + \beta_{2,\text{D1}}$	−0.630**	(−2.11)
D10 (past-winners): $\beta_0 + \beta_{2,\text{D10}}$	−0.046	(−0.19)
Within $R^2 = 0.695$		Obs. = 2,091,952

Panel C: Stock-Level Momentum Portfolio Returns, Same Three Episodes

Episode	D1 (Losers) (%)	D10 (Winners) (%)	D10−D1 (pp)
Sep 2008 (GFC)	−25.90	−15.42	+10.48
Oct 2008 (GFC)	−26.05	−15.12	+10.93
Mar 2020 (COVID)	−27.96	−9.77	+18.19

Notes. Panel A reports value-weighted (by lagged TNA) monthly returns on D1 and D10 fund portfolios during three acute-outflow episodes, alongside aggregate mutual fund net outflows (magnitude, as % of one-month-lagged assets). Panel B reports the implied total return response to a one-percentage-point increase in aggregate outflows, by decile group, from a single pooled fund-month panel regression of equation (9) with fund fixed effects, decile-specific factor controls (MKT, SMB, HML), and standard errors double-clustered by fund and month; the reference group is middle-decile funds (D2–D9). Online Appendix Table IA.12 reports the full coefficient set. Sample for Panels A and B: CRSP Mutual Fund Database, actively managed U.S. equity diversified funds (objective code ED, AUM $\geq$ \$10M, excluding index funds and ETFs), 1998–2025. Funds are sorted annually into deciles on prior 12-month return. Panel C reports compounded VW monthly returns on stock-level momentum decile portfolios (NYSE breakpoints, fixed monthly sorts on cumulative returns over months −12 through −2); the D10−D1 column is the percentage-point spread between winner and loser deciles. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 9: UMD Factor Decomposition and Carhart Replication

Panel A: Daily UMD returns by calendar window, 1980–2025

	Mean (bps/day)	t-stat	\$1 cumulative	Days
PreTOM ($T-9$ to $T-4$)	5.51	3.76	\$5.51	3,183
Rest of month	1.36	1.43	\$2.26	8,412
Full month	2.55	2.71	\$12.44	11,595

Panel B: Monthly fund decile alphas across subperiods (% per month, EW) — replication of Carhart (1997) including recent data

	1963–1993 (Carhart)	1994–2025 (Post)	2011–2025 (Modern)	Full (1963–2025)
3-Factor alpha (FF3):				
D1 (past losers)	-0.61^{***}	-0.49^{***}	-0.45^{***}	-0.55^{***}
	(-4.72)	(-4.32)	(-3.76)	(-6.38)
D10 (past winners)	-0.19^{*}	-0.01	-0.22	-0.09
	(-1.73)	(-0.08)	(-1.63)	(-1.03)
D10−D1	$+0.50^{***}$	$+0.48^{**}$	$+0.23$	$+0.49^{***}$
	(3.14)	(2.54)	(1.07)	(3.96)
4-Factor alpha (FF3 + UMD):				
D1 alpha	-0.37^{***}	-0.31^{***}	-0.27^{***}	-0.37^{***}
	(-3.05)	(-3.32)	(-2.87)	(-4.90)
D1 UMD β	-0.24^{***}	-0.24^{***}	-0.29^{***}	-0.22^{***}
	(-5.20)	(-7.37)	(-8.35)	(-7.80)
D10−D1 alpha	$+0.07$	$+0.09$	-0.13	$+0.09$
	(0.47)	(0.56)	(-0.86)	(0.87)

Notes: Panel A decomposes the Fama–French daily UMD factor into PreTOM and Rest-of-month components, 1980–2025. Panel B reports estimates of equation (11) for CRSP equity-diversified mutual funds (ED, AUM $\geq$ \$10M, excluding index funds and ETFs), sorted annually on prior 12-month return into deciles; equal-weighted; monthly returns winsorized at 1/99. The D10−D1 row reports the alpha from a separately estimated regression of the monthly D10−D1 spread portfolio return on the factors, which restricts to months in which both deciles are non-empty; it therefore need not equal the algebraic difference of the D10 and D1 alphas, which use all months where the respective decile is non-empty. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 9: UMD Factor Decomposition and Carhart Replication (continued)

Panel C: D1 and D10 fund daily alphas (bps/day) by calendar window, with raw loser-return control (1998–2025)

	D1 (Losers)		D10 (Winners)	
Specification	α	β_{Loser}	α	β_{Loser}
PreTOM only				
FF3 only	−2.50**	—	+0.20	—
	(−2.03)		(+0.18)	
FF3 + Loser	−0.64	+0.27***	−1.05	−0.18***
	(−0.62)	(+10.7)	(−0.99)	(−8.9)
Rest of the month				
FF3 only	−2.43***	—	+0.03	—
	(−2.77)		(+0.04)	
FF3 + Loser	−1.54**	+0.28***	−0.55	−0.18***
	(−2.21)	(+19.3)	(−0.81)	(−13.7)
Full sample				
FF3 only	−2.46***	—	+0.04	—
	(−3.48)		(+0.06)	
FF3 + Loser	−1.29**	+0.27***	−0.73	−0.18***
	(−2.25)	(+21.3)	(−1.28)	(−15.9)

Panel D: D1 (losers only) fund alpha — stepwise absorption by Loser return and expense ratio

	(1) FF3	(2) +Loser	(3) +Exp	(4) +Loser+Exp
PreTOM days ($N = 1{,}150{,}005$)				
α (bps/day)	−2.29*	−0.45	−0.33	+2.01
	(−1.90)	(−0.46)	(−0.19)	(+1.41)
β_{Loser}	—	+0.262***	—	+0.263***
	—	(+15.4)	—	(+15.4)
Exp β (per 1%)	—	—	−1.43	−1.80**
	—	—	(−1.58)	(−2.49)
Rest of the days ($N = 2{,}868{,}045$)				
α (bps/day)	−2.25***	−1.50**	−0.85	−0.42
	(−2.82)	(−2.36)	(−0.72)	(−0.45)
β_{Loser}	—	+0.265***	—	+0.265***
	—	(+28.4)	—	(+28.4)
Exp β (per 1%)	—	—	−1.02*	−0.79
	—	—	(−1.70)	(−1.66)

Notes: D1 (loser decile) and D10 (winner decile) are equal-weighted daily fund portfolios, 1998–2025; daily fund returns outside $[-50\%, +50\%]$ are dropped. Panel C: HAC(5) time-series regressions; Loser is the VW bottom-momentum-decile stock return from the CRSP panel; β_{Loser} is the fund's effective loser weight. Panel D: fund-day panel within D1 with standard errors clustered by date; expense ratio reported per 1% annual. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 9: UMD Factor Decomposition and Carhart Replication (continued)

Panel E: T+1 settlement DiD on D1 fund portfolio (CRSP daily, 1998–2025)

	Simple	With FF3
Intercept	-3.35	-3.01^{*}
	(-0.92)	(-1.79)
Post-T+1	$+17.65$	-1.90
	$(+1.20)$	(-0.38)
$\mathbf{1}_{t=-4}$	-0.43	-0.31
	(-0.06)	(-0.09)
Post-T+1 $\times \mathbf{1}_{t=-4}$	$+13.53$	$+6.77$
	$(+0.59)$	$(+0.70)$
$\mathbf{1}_{t=-3}$	$+21.79^{***}$	$+3.50$
	$(+2.67)$	$(+0.98)$
Post-T+1 $\times \mathbf{1}_{t=-3}$	-35.82	-18.66^{*}
	(-1.64)	(-1.92)
DiD ($\beta_{P\times-4} - \beta_{P\times-3}$)	$+49.35^{**}$	$+25.42^{**}$
	$(+2.08)$	$(+2.15)$
N	1,965	1,965

Notes: Portfolio-level analogue of equation (7) applied to the equal-weighted D1 (loser-decile) fund portfolio, 1998–2025. Treated days are $T = -4$ and $T = -3$ relative to month-end; the control is early-month days $[T{+}5, T{+}8]$ (matching Table 7). The PostT1 indicator equals one for dates on or after May 28, 2024, the SEC's transition from T+2 to T+1 equity settlement. Standard errors clustered by date are reported in parentheses. The DiD coefficient $\beta_{P\times-4} - \beta_{P\times-3}$ measures the predicted one-day shift in the selling window from $T{-}4$ to $T{-}3$ following the reform. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 10: International Evidence: PreTOM Returns across Developed Markets

	PreTOM (bps/day)	Rest (bps/day)	Difference (bps/day)
Panel A: Pooled regression (19 countries, 1990–2025)			
Losers − Market	-4.19^{***}	+0.28	-4.47^{***}
	(−5.28)	(0.52)	(−4.60)
Panel B: Country estimates, sorted by PreTOM Loser excess return			
Norway	-11.12^{***}	−0.03	-11.10^{***}
	(−3.43)	(−0.01)	(−2.82)
Hong Kong	-7.40^{**}	−0.72	−6.68
	(−2.14)	(−0.33)	(−1.61)
Belgium	-6.93^{**}	−0.00	-6.93^{*}
	(−2.27)	(−0.00)	(−1.71)
Germany	-5.66^{**}	−1.91	−3.75
	(−2.17)	(−0.91)	(−1.11)
Finland	−5.60	+2.19	-7.79^{*}
	(−1.46)	(0.75)	(−1.66)
Netherlands	−5.48	+3.32	-8.80^{**}
	(−1.45)	(1.49)	(−2.05)
France	-5.40^{*}	−0.91	−4.49
	(−1.94)	(−0.42)	(−1.28)
Ireland	−5.26	+2.80	−8.06
	(−0.90)	(0.72)	(−1.09)
Australia	-5.10^{**}	−2.60	−2.50
	(−1.97)	(−1.42)	(−0.81)
UK	-4.87^{*}	+0.41	−5.28
	(−1.69)	(0.20)	(−1.40)
Reversed-sign reference (excluded from pooled sample):			
Japan	$+3.84^{***}$	+0.31	$+3.53^{**}$
	(3.05)	(0.44)	(2.54)

Notes: Daily VW returns from Compustat Global, 1990–2025 (HKG/CHE from 1993). Momentum deciles use cumulative returns over months −12 through −2 with NYSE-style breakpoints (above-median market cap; small markets pool regionally). Market-adjusted using Kenneth French's regional factors. PreTOM denotes $T-9$ through $T-4$; Rest is the omitted reference. PreTOM and Rest columns are within-country means; Difference is β from equation (10). t-statistics clustered by country-month (Panel A) and by month (Panel B). Japan, excluded from the pooled sample (Fama and French, 2012; Asness et al., 2013), uses VW bottom-quintile returns from a database compiled by one of the authors. The full 19-country table is in the Online Appendix.

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