Internet Appendix for "The Intramonth Momentum Cycle"

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This Internet Appendix contains supplementary material for "The Intramonth Momentum Cycle." It includes: (IA.1) data construction and sample formation, (IA.2) holding period analysis, (IA.3) transaction cost decomposition, (IA.4) T+1 settlement falsification tests, (IA.5) sliding window analysis, (IA.6) tail trimming analysis, (IA.7) crash-day concentration methodology, (IA.8) international evidence methodology, (IA.9) full international country-level results, (IA.10) subperiod PreTOM concentration analysis, (IA.11) selling recency (fresh vs. stale losers), (IA.12) window dressing falsification, (IA.13) dividend cycle within-quarter detail, (IA.14) liquidity shock panel regression full specification, (IA.15) beta controls, (IA.16) T+3 to T+2 settlement transition, (IA.17) winner window effect, (IA.18) S&P 500 membership robustness, (IA.19) long-horizon reversion identifying the PreTOM-specific component, and (IA.20) additional figures.

IA.1 Data Construction and Sample Formation

The daily stock-level panel used in the main analysis is constructed as follows.

1. **CRSP input data.** We obtain the CRSP daily stock file from WRDS in Flat File Format 2.0 (CIZ). The file spans December 29, 1978 through December 31, 2025.[1]

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[1] Observations from 1978–1979 are retained in order to construct momentum signals for the first valid holding months in 1980.

2. **CRSP sample restrictions.** We restrict the CRSP sample to U.S. common operating-company equities listed on the NYSE, AMEX, or Nasdaq, and retain only regular-way, active observations.[2]

3. **Trading-day panel construction.** Using the CRSP trading calendar, we expand each security's panel so that all trading days between its first and last observed trading day are included. Trading days without an observed CRSP record remain in the panel as missing rows. After applying the common-stock and exchange/trading-status filters, the sample contains 59,917,630 observations on 23,827 securities. Trading-day expansion increases this to 60,910,165 observations. Table IA.1 reports the corresponding attrition.

4. **Month-relative trading-day index.** Within each month, trading days are indexed so that the last trading day is labeled $T = 0$, the second-to-last is $T = -1$, and so on through $T = -9$ for the tenth-to-last trading day. Earlier trading days in the same month are indexed $T = 1, 2, \ldots$.

5. **Momentum construction.** For each stock-month, we compute 12–2 momentum from daily returns:
$$M_{i,m} = \prod_{s=m-12}^{m-2} (1 + r_{i,s}) - 1.$$
The resulting stock-month signal is assigned to all daily observations in holding month m.

6. **Momentum validity.** A momentum window is treated as valid only if it contains no trading-calendar-added empty rows and no missing-return indications according to the CRSP variable `DlyRetMissFlg`.[3] We then retain only observations with valid momentum and non-missing lagged market capitalization. Of the 60,910,165 rows

[2] In the CIZ format, these restrictions are implemented sequentially as follows: `ShareType='NS'`, `SecurityType='EQTY'`, `SecuritySubType='COM'`, `USIncFlg='Y'`, `IssuerType` in {`ACOR`, `CORP`}, `PrimaryExch` in {`N`, `A`, `Q`}, `ConditionalType='RW'`, and `TradingStatusFlg='A'`. Legacy CRSP share-code filters such as 10 and 11 are not available in the same way in CIZ, so we use the equivalent CIZ security-type and trading-status fields instead.

[3] In the baseline specification, a day is admissible only if `DlyRetMissFlg` is either absent or equal to `NA`. Thus, windows are excluded if they contain any day with `DlyRetMissFlg` in {`MV`, `NS`, `NT`, `RA`, `GP`, `MP`, `DG`, `DM`, `DP`}.

in the expanded panel, 52,479,222 satisfy the momentum-validity requirement. After requiring non-missing lagged market capitalization, the final CRSP-based analysis sample contains 52,437,348 observations on 22,642 securities. The earliest date with valid momentum is January 2, 1980. Table IA.2 reports the corresponding attrition. At the stock-month level, 2,505,762 stock-months satisfy the momentum-validity requirement; the excluded observations consist of 304,805 stock-months with insufficient formation history, 63,184 stock-months containing disallowed return-status flags, and 47,116 stock-months containing trading-calendar-added empty observations.

7. **Momentum deciles and portfolio weights.** We assign each stock-month to a momentum decile using Kenneth French's NYSE 2–12 prior-return breakpoints, aligned to the month immediately preceding the holding month. All stock-months that survive the post-momentum filters are successfully matched to a breakpoint date and receive a non-missing decile assignment. For the portfolio analysis, weights are computed within each (*date*, *decile*) cell using lagged market capitalization:

$$w_{i,d}^{(q)} = \frac{\mathrm{MCAP}_{i,d-1}}{\sum_{j \in q(d)} \mathrm{MCAP}_{j,d-1}},$$

where $q(d)$ denotes the set of securities in the relevant decile on date d, and $\mathrm{MCAP}_{i,d-1}$ is security i's market capitalization on the previous trading day. These lagged market-cap weights are included in the final analysis panel.

8. **Additional daily characteristics.** We merge S&P 500 membership from the CRSP index constituents database. We also merge daily factors from Kenneth French's data library (*Fama/French 3 Factors*), from which we use the daily risk-free rate (`RF`) and the daily market return (`Mkt`) in the analysis. In addition, we construct the bid-ask spread measure

$$\mathrm{BAS}_{i,d} = \frac{\mathrm{Ask}_{i,d} - \mathrm{Bid}_{i,d}}{(\mathrm{Ask}_{i,d} + \mathrm{Bid}_{i,d})/2}.$$

The S&P 500 membership indicator is available for all observations; 5,440,227 daily rows correspond to index members and 46,997,121 correspond to non-members. The BAS variable is non-missing for 45,998,824 out of 52,437,348 observations, corresponding to 87.72% coverage.

9. **TAQ sell-pressure measures.** We merge daily sell-pressure measures derived from WRDS TAQ intraday indicator data into the CRSP panel using `PERMNO`-date. The TAQ data are available from September 10, 2003 through October 27, 2022, so coverage is nonzero only within this period. The merge is performed as a left merge, so the number of daily panel rows is unchanged. Within the full 1980–2025 panel, 17,778,629 observations have non-missing net selling pressure and seller-initiated volume share, corresponding to 33.90% of the sample. Restricting to the TAQ-available period, the panel contains 18,105,868 observations on 9,407 securities, of which 98.19% have non-missing sell-pressure measures.

10. **Final panel.** The final dataset is a daily `PERMNO`-date panel spanning January 2, 1980 through December 31, 2025. It contains CRSP returns and market-cap variables, momentum measures and momentum deciles, the month-relative trading-day index, lagged market-cap portfolio weights, S&P 500 membership, daily factor variables, bid-ask spreads, and TAQ-based sell-pressure measures.

Table IA.1: CRSP Sample Construction

Step	Rows	Unique PERMNO
Deduplicated CRSP input	87,304,208	37,368
Common-stock filter	61,022,853	23,834
Exchange/status filter	59,917,630	23,827
Trading-day expansion	60,910,165	23,827

Table IA.2: Momentum Construction and Attrition

Step	Rows	Unique PERMNO
Input panel with month-relative T	60,910,165	23,827
After valid momentum requirement	52,479,222	22,644
After lagged market-cap filter	52,437,348	22,642

IA.2 Holding Period Analysis

A related question is whether the PreTOM concentration depends on the choice of holding period. Our baseline uses a one-month holding period ($K = 1$), which is standard in the factor zoo literature but shorter than the 3–12 month holding periods emphasized in Jegadeesh and Titman (1993). Table IA.3 addresses this by varying K from 1 to 12 months while keeping the formation period fixed at 12 months with a one-month skip, using NYSE-breakpoint decile assignments throughout. For $K > 1$, we implement the overlapping-portfolio construction of Jegadeesh and Titman (1993): the strategy holds K cohorts simultaneously, each formed in a different past month and each held for K months with fixed composition, and takes the equal-weighted average of their returns on each trading day. This is the standard approach for extending holding periods in the momentum literature (Carhart, 1997; Jegadeesh and Titman, 2001). Standard errors use Newey-West with $K - 1$ lags to account for the autocorrelation induced by the overlapping cohorts.

The PreTOM component is statistically significant at the 1% level for every holding period examined, while the Rest component is never significant and deteriorates monotonically as K increases. By $K = 9$, Rest returns are sufficiently negative that PreTOM wealth exceeds total strategy wealth. By $K = 12$, the Rest component is negative, and the PreTOM share reaches 139%—meaning the six pre-month-end trading days generate more wealth than the full strategy, while all remaining trading days destroy it. The PreTOM concentration is not a feature of short holding periods. If anything, it becomes more pronounced as K increases.

This monotonicity is consistent with the month-end cash-demand mechanism. The information-driven component of momentum (which operates uniformly across trading days) decays quickly as the formation signal becomes stale, while the flow-driven PreTOM component (which reflects a monthly institutional cycle) persists as long as funds continue to hold stale losers.

Table IA.3: PreTOM Concentration by Holding Period

	$K = 1$	$K = 3$	$K = 6$	$K = 9$	$K = 12$
Panel A: Loser − Market (bps/month)					
PreTOM	-56.8^{***}	-55.9^{***}	-51.8^{***}	-48.4^{***}	-44.4^{***}
	(−4.44)	(−4.76)	(−4.63)	(−4.34)	(−4.22)
Rest	−34.0	−31.7	−24.3	−16.7	−9.5
	(−1.52)	(−1.50)	(−1.27)	(−0.92)	(−0.54)
Panel B: Winner − Market (bps/month)					
PreTOM	3.5	0.7	2.3	0.6	−1.1
	(0.45)	(0.10)	(0.32)	(0.09)	(−0.15)
Rest	−0.7	−6.5	−8.3	−9.5	−12.9
	(−0.06)	(−0.53)	(−0.70)	(−0.81)	(−1.16)
Panel C: WML (bps/month)					
PreTOM	61.4^{***}	58.2^{***}	55.6^{***}	50.4^{***}	44.4^{***}
	(3.59)	(3.85)	(3.86)	(3.60)	(3.38)
Rest	38.4	29.8	19.5	10.6	−0.4
	(1.37)	(1.12)	(0.78)	(0.44)	(−0.02)
Panel D: Wealth ($1 invested, 1980–2025)					
$PreTOM	18.78	16.91	15.81	12.43	9.33
$Rest	2.37	1.79	1.25	0.86	0.53
$Total	44.46	30.28	19.76	10.71	4.93
PreTOM share	77%	83%	93%	105%	139%

Notes. Momentum portfolios use the French 12-month formation period with a one-month skip and NYSE breakpoints for decile assignment. The holding period K varies from 1 to 12 months. For $K > 1$, the strategy holds K overlapping portfolios simultaneously and takes the equal-weighted average of their returns. Panels A–C report mean monthly compounded returns in basis points; t-statistics in parentheses use Newey-West standard errors with $K - 1$ lags. Market-adjusted returns subtract the raw market return. Panel D reports cumulative wealth from $1 invested over 1980–2025. PreTOM share = log($PreTOM)/ log($Total) × 100. Sample: 1980–2025.

IA.3 Transaction Cost Decomposition

Novy-Marx and Velikov (2016) show that momentum is among the most expensive anomalies to implement. We decompose the standard value-weighted momentum strategy into PreTOM and Rest components. Transaction costs are computed following Novy-Marx and Velikov (2016): each stock that changes momentum decile incurs a round-trip cost equal to one full quoted bid-ask spread (half-spread to liquidate the position plus half-spread to enter the replacement). Costs are value-weighted within each leg and summed over the long (winner) and short (loser) sides of the long-short.[4]

Table IA.4 reports the results. Over the full sample (1980–2025), gross WML averages +91.3 bps per month, of which +59.7 bps (65%) accrues during PreTOM. Buy-and-hold rebalancing costs of 79.9 bps per month leave a net return of +11.5 bps. A PreTOM-only strategy that enters and exits each month faces a full round-trip cost of 317.1 bps, making it unviable in the full sample due to pre-decimalization spreads. Post-decimalization (2001–2025), quoted spreads shrink dramatically (losers 24.4 bps, winners 14.8 bps), reducing the full round-trip cost to 39.2 bps. The PreTOM-only strategy earns +54.1 bps gross and +14.9 bps net of costs. The Rest strategy is negative both gross (−26.9 bps) and net (−66.1 bps). In recent markets, all net return originates in the PreTOM window.

[4]Our cost measure is conservative. Novy-Marx and Velikov (2016) use the Hasbrouck (2009) effective spread, which is typically smaller than the quoted spread. Monthly turnover averages 20.9% for losers and 26.2% for winners.

Table IA.4: Transaction Cost Decomposition of Monthly Momentum Returns

	Gross (bps/mo)	TC (bps/mo)	Net (bps/mo)
Panel A: Full sample (1980–2025)			
Buy-and-hold WML	+91.3	79.9	+11.5 (0.35)
PreTOM component	+59.7*** (3.60)		
Rest component	+32.4 (1.12)		
PreTOM-only strategy	+59.7	317.1	−257.5 (−11.34)
Rest-only strategy	+32.4	317.1	−284.8 (−8.99)
Panel B: Post-decimalization (2001–2025)			
Buy-and-hold WML	+25.1	10.1	+15.0 (0.29)
PreTOM component	+54.1** (2.07)		
Rest component	−26.9 (−0.59)		
PreTOM-only strategy	+54.1	39.2	+14.9 (0.56)
Rest-only strategy	−26.9	39.2	−66.1 (−1.43)

Notes: The table decomposes monthly returns of the standard value-weighted WML strategy (long decile 10, short decile 1, rebalanced monthly using fixed momentum decile breakpoints from CRSP) into PreTOM ($T-9$ to $T-4$) and rest-of-month components. Daily value-weighted returns within each window are compounded to monthly frequency. Transaction costs are computed following Novy-Marx and Velikov (2016) using quoted bid-ask spreads. "Buy-and-hold" charges one full quoted spread for each stock that changes momentum decile (monthly turnover: losers 21.0%, winners 26.3%). "PreTOM-only" and "Rest-only" strategies additionally incur a full round-trip spread on all portfolio stocks each month, since the investor enters and exits the entire long-short position within the month. Post-decimalization, mean quoted spreads are 24.4 bps (losers) and 14.8 bps (winners), making the PreTOM-only strategy viable net of costs. t-statistics in parentheses, placed beneath the number being tested. $^{**}p < 0.05$, $^{***}p < 0.01$.

IA.4 T+1 Settlement Falsification Tests

Two falsification tests confirm that the T+1 settlement result is specific to the boundary days the mechanism predicts. 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 boundary shifted, produces a DiD of -2.3 ($t = -0.08$). Second, *placebo dates*: the same $T-4$ vs. $T-3$ comparison using fake event dates spread across 1999–2015 (May 28 of 1999, 2005, 2011, 2013, and 2015), each well removed from major market disruptions, returns DiDs ranging from -13.6 to $+3.7$ with $|t| \leq 1.27$. All falsifications are indistinguishable from zero, in contrast to the $+85.9$ ($t = 2.78$) for the actual May 2024 reform. Table IA.5 reports the full results.

Table IA.5: T+1 Settlement: Falsification Tests

Test	DiD	t-stat	p-value	Prediction
Real: Losers, $T-4$ vs. $T-3$, May 2024	**+85.93**	**2.78**	**0.005**	**Nonzero**
Placebo days (losers, May 2024):				
$T-6$ vs. $T-7$	−2.33	−0.08	0.936	Zero
Placebo dates (losers, $T-4$ vs. $T-3$):				
May 28, 2015	+3.74	+0.22	0.825	Zero
May 28, 2013	+2.84	+0.19	0.851	Zero
May 28, 2011	+3.19	+0.23	0.815	Zero
May 28, 2005	−10.04	−0.82	0.412	Zero
May 28, 1999	−13.57	−1.27	0.205	Zero

Notes: Falsification tests for the T+1 settlement DiD reported in the main paper. 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 shift is predicted. Placebo dates use fake event dates when no regulatory change occurred. All falsification interactions are small and statistically insignificant. Sample: 1980–2025.

IA.5 Sliding Window Analysis

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.

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 ($T \in [-9, -4]$): -11.32 basis points per day ($t = -3.53$, 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 month-end cash-demand mechanism predicts.

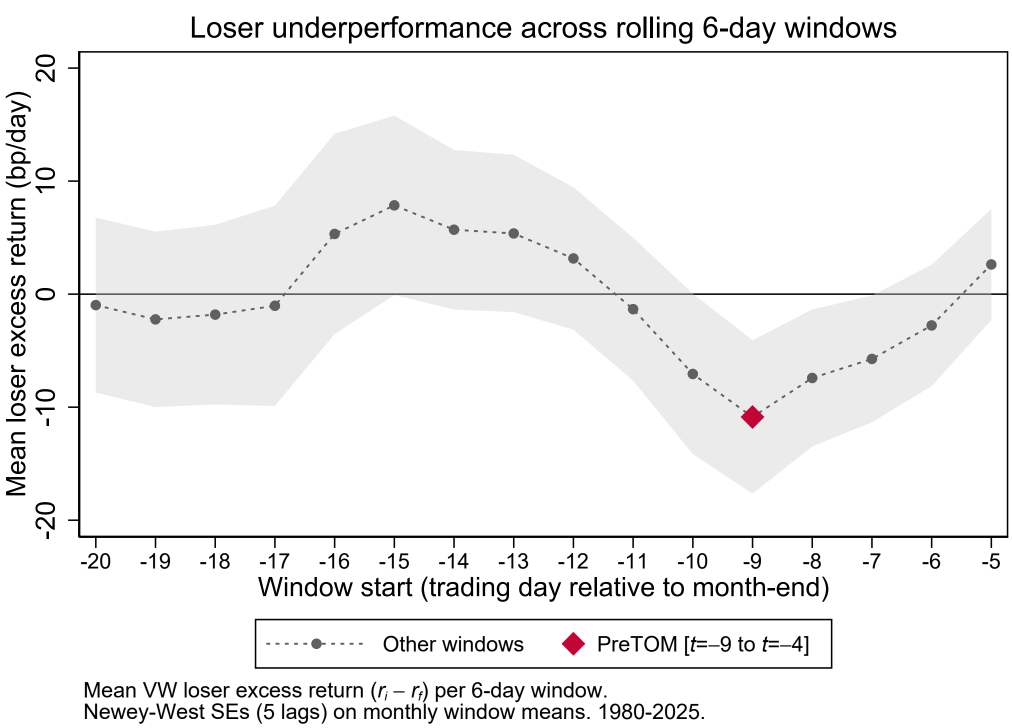

Figure IA.1: Sliding six-day window analysis. Each point plots the mean daily market-adjusted VW loser return for a six-day window starting at the indicated trading day. The trough occurs at PreTOM (days 14–19). Sample: 1980–2025.

IA.6 Tail Trimming Analysis

A key concern is whether PreTOM profitability is structural or driven by a few extreme days. We address this by progressively trimming the worst days from each window's return distribution and recomputing the mean. Figure IA.2 shows the result. PreTOM mean WML is +10.2 bps untrimmed and rises to +17.2 bps after removing the worst 1% of days, confirming that the effect is structural and not driven by outliers. In contrast, month-start mean WML flips from −4.4 bps to +6.2 bps after the same 1% trim: approximately 15 extreme days drive the entire negative month-start average. This asymmetry confirms that PreTOM profits and month-start crashes have distinct statistical signatures: PreTOM is a persistent daily effect, while month-start negativity is concentrated in rare tail events.

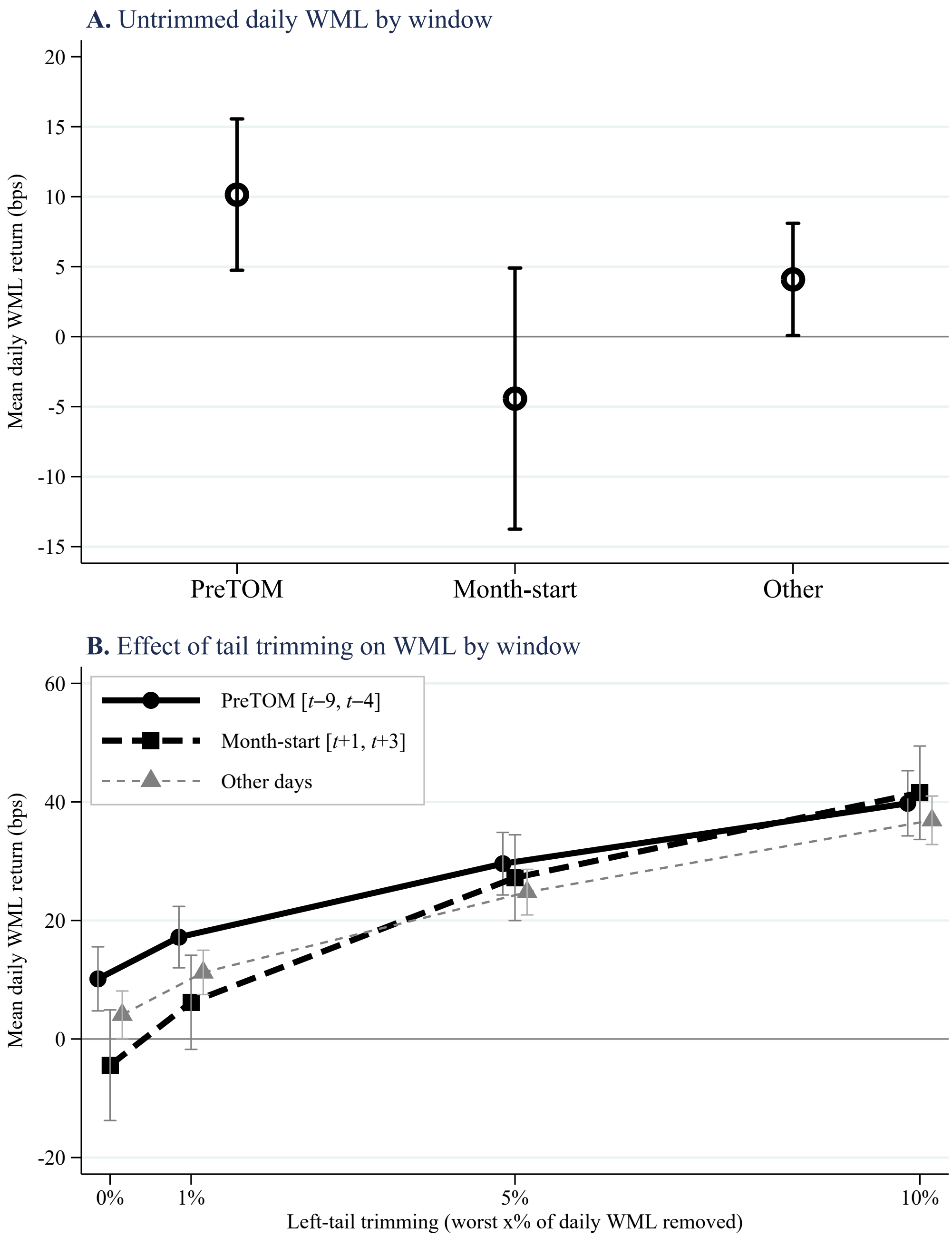

Figure IA.2: Mean daily WML return by calendar window after progressively trimming the worst days from each window's distribution. Left panel: pre-month-end ($T-9$ to $T-4$). Right panel: month-start ($T+1$ to $T+3$). PreTOM mean WML rises from +10.2 to +17.2 bps after 1% trimming (structural), while month-start flips from -4.4 to +6.2 bps (driven entirely by $\sim$15 tail events). Sample: 1980–2025, value-weighted.

IA.7 Crash-Day Concentration: Calendar-Share Methodology

This appendix details the calendar-share construction and proportions z-test summarized in Section 8 of the main paper.

Crash-day classification. A trading day is a crash day if the value-weighted WML return falls below -200 basis points. Robustness at -100 and -300 basis-point thresholds is reported in the figures.

Comparison universes. To prevent the PreTOM and month-start windows from contaminating each other, we compare each window's crash share against its calendar share within a comparison universe that excludes the other window. For PreTOM, the universe is non-month-start trading days (PreTOM days plus other days, excluding $T \in [+1, +3]$). For month-start, the universe is non-PreTOM trading days (month-start days plus other days, excluding $T \in [-9, -4]$). The calendar share is the fraction of trading days in the universe that fall in the window of interest. Under the null that crashes are spread proportionally across the calendar, the observed share equals the calendar share.

Test statistic. For each window w and threshold, let $p_{\text{obs}} = n_{\text{crash},w}/n_{\text{crash}}$ be the observed share of crash days in window w and p_{exp} be the calendar share. The standard one-sample proportions z-statistic is

$$z = \frac{p_{\text{obs}} - p_{\text{exp}}}{\sqrt{p_{\text{exp}}(1 - p_{\text{exp}})/n_{\text{crash}}}},$$

two-sided p-values from the standard normal.

Excluded episodes. The robustness reported in the body excludes 11 months that contain famous momentum-crash episodes: January 2001, October–November 2001, and November 2002 (the Daniel–Moskowitz 2016 cluster); March–May 2009; and February–May 2020 (COVID dislocation).

IA.8 International Evidence: Methodology

This appendix details the construction of the international momentum decile portfolios summarized in Section 6.2 of the main paper.

Sample. Daily stock returns are from Compustat Global for 19 developed markets: Australia, Austria, Belgium, Denmark, Finland, France, Germany, Hong Kong, Ireland, Italy, the Netherlands, New Zealand, Norway, Portugal, Singapore, Spain, Sweden, Switzerland, and the United Kingdom. The sample begins in 1990 for most countries and in 1993 for Hong Kong and Switzerland, where Compustat coverage is thin in the early 1990s. We exclude Japan, where momentum returns are approximately zero over our sample period (Fama and French, 2012; Asness et al., 2013), and Canada, for which Compustat Global coverage is limited.

Decile assignments. Within each country-month, we rank stocks into momentum deciles using cumulative returns over months -12 through -2. Following the U.S. convention, we use *size-conditional* breakpoints: decile cutoffs are computed from stocks above the within-country median market capitalization at the prior month-end, then all stocks (including small-cap) are assigned to deciles based on those cutoffs. This avoids decile assignments being driven by micro-cap noise. For countries with fewer than 50 large-cap stocks in a given month (Austria, Belgium, Finland, Ireland, New Zealand, Portugal, and Singapore), we pool breakpoints within the broader region. Decile assignments are fixed within each calendar month.

Returns. Value-weighted portfolio returns use lagged month-end market capitalization as weights. We subtract each country's local market excess return (from Kenneth French's regional factor files) to obtain market-adjusted returns. The dependent variable in equation (10) is the day-d value-weighted loser-decile return in excess of the local market in country c.

IA.9 International Evidence: Full Country Table

Table IA.6: International Evidence: All Countries — Losers − Market (bps/day)

	PreTOM		Rest of Month		Difference	
Country	Mean	t	Mean	t	Mean	t
Norway	−11.12	(−3.43)	−0.03	(−0.01)	−11.10	(−2.82)
Netherlands	−5.48	(−1.45)	3.32	(1.49)	−8.80	(−2.05)
Sweden	−4.56	(−1.32)	3.95	(1.89)	−8.51	(−2.20)
Ireland	−5.26	(−0.90)	2.80	(0.72)	−8.06	(−1.09)
Finland	−5.60	(−1.46)	2.19	(0.75)	−7.79	(−1.66)
Switzerland	−3.49	(−0.81)	3.54	(1.50)	−7.03	(−1.42)
Belgium	−6.93	(−2.27)	−0.00	(−0.00)	−6.93	(−1.71)
Hong Kong	−7.40	(−2.14)	−0.72	(−0.33)	−6.68	(−1.61)
UK	−4.87	(−1.69)	0.41	(0.20)	−5.28	(−1.40)
Denmark	−3.97	(−1.21)	0.62	(0.29)	−4.60	(−1.15)
France	−5.40	(−1.94)	−0.91	(−0.42)	−4.49	(−1.28)
New Zealand	−3.95	(−0.96)	−0.11	(−0.04)	−3.84	(−0.72)
Germany	−5.66	(−2.17)	−1.91	(−0.91)	−3.75	(−1.11)
Spain	−2.42	(−0.89)	0.46	(0.25)	−2.88	(−0.89)
Australia	−5.10	(−1.97)	−2.60	(−1.42)	−2.50	(−0.81)
Italy	−3.17	(−1.01)	−2.10	(−1.07)	−1.07	(−0.28)
Singapore	5.57	(1.97)	3.81	(1.83)	1.76	(0.53)
Austria	−1.01	(−0.30)	−2.85	(−1.12)	1.84	(0.44)
Portugal	0.93	(0.24)	−5.03	(−2.02)	5.95	(1.34)
Pooled	−4.19	(−5.28)	0.28	(0.52)	−4.47	(−4.60)

Notes: Daily VW portfolio returns from Compustat Global, 1990–2025 (HKG/CHE from 1993). NYSE-style breakpoints (above-median mcap). Countries with <50 qualifying stocks use regional breakpoints. Market-adjusted using Kenneth French regional factors. Sorted by Difference. Individual t-statistics clustered by month; pooled includes country FE, clustered by country-month.

Table IA.7: International Evidence: All Countries — Winners − Market (bps/day)

	PreTOM		Rest of Month		Difference	
Country	Mean	t	Mean	t	Mean	t
Norway	2.33	(0.62)	6.62	(3.25)	−4.29	(−1.03)
Netherlands	6.05	(1.50)	3.15	(1.52)	2.90	(0.63)
Sweden	4.87	(1.58)	6.01	(3.35)	−1.14	(−0.30)
Ireland	5.87	(1.31)	−2.16	(−0.79)	8.03	(1.48)
Finland	5.81	(1.66)	2.87	(1.22)	2.94	(0.69)
Switzerland	6.33	(2.29)	2.99	(1.66)	3.35	(1.01)
Belgium	−2.97	(−0.92)	7.23	(2.26)	−10.20	(−2.14)
Hong Kong	0.16	(0.05)	2.67	(1.29)	−2.51	(−0.61)
UK	3.53	(1.17)	3.11	(1.84)	0.41	(0.12)
Denmark	5.93	(1.82)	6.20	(3.13)	−0.27	(−0.07)
France	2.99	(1.21)	2.52	(1.41)	0.47	(0.14)
New Zealand	7.96	(1.83)	2.91	(1.24)	5.05	(1.00)
Germany	8.15	(2.29)	5.30	(2.66)	2.85	(0.79)
Spain	6.33	(2.32)	4.76	(2.68)	1.57	(0.47)
Australia	7.13	(2.77)	5.02	(2.92)	2.11	(0.64)
Italy	6.04	(2.47)	4.33	(2.56)	1.71	(0.56)
Singapore	7.18	(2.11)	0.18	(0.09)	7.01	(1.68)
Austria	1.58	(0.44)	4.56	(1.66)	−2.98	(−0.66)
Portugal	3.54	(0.87)	6.84	(2.27)	−3.30	(−0.62)
Pooled	4.69	(6.05)	3.95	(7.96)	0.74	(0.78)

Notes: Same specification as Table IA.6. Countries sorted in the same order as the losers table for comparability. The winner PreTOM–Rest difference is insignificant in the pooled sample ($t = 0.78$) and in all but one individual country, confirming the PreTOM effect is loser-driven.

IA.10 Subperiod PreTOM Concentration: VW versus EW

Table IA.8 reports daily PreTOM and Rest mean returns for D1 (loser−Mkt) and WML by historical subperiod under both value-weighting (Panel A) and equal-weighting (Panel B). PreTOM days are 29% of the trading month, so a return process spread proportionally across days would produce PreTOM and Rest means within sampling error of each other.

Three patterns warrant note. First, in VW the PreTOM and Rest loser returns are statistically indistinguishable in 1927–1940 (−5.43 vs −4.86) and 1940–1962 (−2.75 vs −2.45); concentration emerges only from 1962 onward, when PreTOM separates sharply from Rest (−10.09 vs −4.63 in 1962–1980; −12.18 vs −6.68 in 1980–2002; −7.12 vs +1.50 in 2002–2025). The timing tracks the scaling of institutional ownership in U.S. equities. Second, the WML PreTOM concentration achieves statistical significance against Rest only in the most recent subperiod, driven by the collapse of Rest-of-month WML to negative territory; PreTOM-day WML returns themselves are positive in every subperiod from 1927 onward. Third, the EW results show no clean PreTOM concentration in any subperiod, consistent with the institutional cash-management channel operating on the larger, more liquid stocks captured by value-weighting, while EW is dominated by small-stock noise that hosts a separate (behavioral, dividend-information) channel of the kind documented by Asem (2009).

Table IA.8: Subperiod Analysis of D1 (Loser−Mkt) Returns: PreTOM versus Rest

	Value-weighted		Equal-weighted		
Period	PreTOM	Rest	PreTOM	Rest	Inst. Own.
1927–1962	−3.75	−3.42	+8.31	+11.60	< 10%
	(−1.79)	(−2.31)	(3.06)	(5.29)	
1962–1980	−10.09***	−4.63	−3.74***	+2.53	15–30%
	(−5.25)	(−3.40)	(−1.54)	(1.33)	
1980–2002	−12.18*	−6.68	+5.92	+8.85	30–55%
	(−5.91)	(−3.72)	(2.25)	(3.76)	
2002–2025	−7.12**	+1.50	+2.42	+3.00	55–72%
	(−2.17)	(0.62)	(0.65)	(1.17)	

Notes. Daily mean returns of the D1 (loser−Mkt) portfolio in basis points per day, by historical subperiod and weighting scheme. The market benchmark is the value-weighted CRSP index. PreTOM is the trading-day window $T \in [-9, -4]$ before month-end; Rest is all other trading days. Newey-West t-statistics with 21-day bandwidth in parentheses. *Asterisks on PreTOM cells denote significance of the PreTOM−Rest difference at 10%, 5%, 1%*, not significance of the level relative to zero. The PreTOM concentration first becomes statistically significant in 1962–1980, alongside the rise of U.S. institutional equity ownership. Aggregate institutional ownership figures are approximate ranges from Blume and Keim (2012) and the NYSE Fact Book; D1-specific institutional ownership (from Thomson Reuters 13F holdings) is unavailable before 1980.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

IA.11 Selling Recency: Fresh Losers Bear Disproportionate PreTOM Pressure

This section reports the detail behind the fresh-versus-stale loser result summarized in Section 4.4.3 of the main paper. Within the bottom momentum decile, we measure "freshness" as the cumulative return over the most recent three months ($\text{ret}_{3,1}$), standardized cross-sectionally within D1 each month and sign-flipped so that higher values indicate worse recent performance. All stocks in D1 share similar 12-month losses (the sorting variable), so freshness captures the *timing* of the loss, not its magnitude: fresh losers (bottom tercile, mean $\text{ret}_{3,1} = -33.8\%$) and stale losers (top tercile, mean $\text{ret}_{3,1} = +14.9\%$) have nearly identical 12-month returns (-56.3% vs. -45.2%).

Table IA.9 reports the regressions. Panel A splits D1 into terciles; fresh losers underperform stale losers by 4.5 bps per day during PreTOM ($F = 7.15$, $p = 0.008$). Panel B uses a continuous freshness measure: the PreTOM $\times$ freshness effect is -1.8 bps per standard deviation ($t = -2.38$), strengthening after bid-ask spread controls (from -1.5 without). The effect vanishes in December: the December $\times$ PreTOM $\times$ freshness interaction is $+3.8$ ($t = 1.61$), leaving the total December effect at $+1.7$ ($t = 0.74$). Outside December the effect strengthens to -2.1 ($t = -2.72$), consistent with tax-loss harvesting depleting the fresh-loser pool before PreTOM begins.

Table IA.9: PreTOM Returns by Loser Freshness

	Coefficient	t-statistic	p-value
Panel A: Tercile split within D1 losers			
PreTOM × Fresh (bottom tercile $\text{ret}_{3,1}$)	-3.30^{**}	(−2.17)	0.030
PreTOM × Stale (top tercile $\text{ret}_{3,1}$)	+1.24	(1.02)	0.308
Test Fresh = Stale		$F = 7.15, \quad p = 0.008$	
Panel B: Continuous freshness measure			
Without BAS controls (N = 9,954,220)			
PreTOM × fresh_z	-1.51^{**}	(−2.10)	0.036
With BAS controls (N = 9,029,730)			
PreTOM × fresh_z	-1.77^{**}	(−2.38)	0.017
PreTOM × BAS	$+33.1^{**}$	(2.30)	0.021
Panel C: December falsification (with BAS controls)			
PreTOM × fresh_z (non-December)	-2.07^{***}	(−2.72)	0.007
December × PreTOM × fresh_z	+3.77	(1.61)	0.107
Total December effect (sum)	+1.70	(0.74)	0.459

Notes: Sample consists of bottom-decile (D1) momentum losers only, 1980–2025. Freshness is measured by $\text{ret}_{3,1}$ (cumulative return over months −3 through −1), standardized within D1 each month and sign-flipped so that higher values indicate worse recent performance. Panel A splits D1 into terciles by freshness; PreTOM × Fresh and PreTOM × Stale are the window effects for the bottom and top terciles, and the F-test examines their equality. Panel B uses the continuous standardized measure, with and without bid-ask spread (BAS) controls. Panel C interacts the continuous measure with a December indicator and reports the total December effect (non-December coefficient plus the December interaction). All specifications include firm and date fixed effects; standard errors are double-clustered by firm and date. Returns in basis points per day. Momentum deciles use NYSE breakpoints applied to all NYSE, AMEX, and NASDAQ stocks in CRSP; assignments are held constant within each calendar month. $^{**}p < 0.05$, $^{***}p < 0.01$.

IA.12 Window Dressing Falsification

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 window dressing 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 not absorbed by December tax-driven selling.

Two tests address the window dressing alternative directly, both reported in Table IA.10. First, restricting the sample to non-quarter-end months, where window dressing is least relevant, the Loser × PreTOM coefficient is -7.5 bps ($t = -2.66$), virtually identical to the full-sample estimate. Second, interacting Loser × PreTOM with a quarter-end indicator produces a small, insignificant triple interaction: there is no systematic quarter-end amplification, consistent with a monthly liquidity cycle rather than quarterly reporting incentives.

A parallel test isolates December, the month in which tax-loss harvesting is most concentrated. Restricting the sample to non-December months yields a Loser × PreTOM coefficient of -7.03 bps ($t = -2.86$, $N = 48.85$ million), virtually identical to the full-sample estimate of -7.15. The PreTOM concentration is not driven by December tax-loss selling.

Table IA.10: Window Dressing Falsification

	(1) Non-QE months	(2) Full sample, QE interaction	(3) Full sample baseline
Loser	4.132***	4.039***	2.609**
	(2.68)	(2.62)	(2.04)
Loser × PreTOM	−7.523***	−7.496***	−7.151***
	(−2.66)	(−2.65)	(−3.08)
Loser × QtrEnd		−4.249	
		(−1.48)	
Loser × PreTOM × QtrEnd		0.990	
		(0.18)	
Constant	4.636***	3.442***	3.442***
	(33.84)	(29.93)	(29.42)
Fixed effects	Firm, Date	Firm, Date	Firm, Date
Observations	35,417,562	53,324,145	53,324,145
Within R^2	0.0000	0.0000	0.0000

Notes. Dependent variable is daily excess return in basis points. All specifications are value-weighted using lagged market-capitalization weights. Column (1) restricts the sample to non-quarter-end months (Jan, Feb, Apr, May, Jul, Aug, Oct, Nov); window dressing would be least relevant in these months, yet the Loser × PreTOM coefficient is essentially identical to the full-sample estimate. Column (2) estimates the full sample with quarter-end interactions; QtrEnd equals one in March, June, September, December. The triple interaction Loser × PreTOM × QtrEnd is small and statistically indistinguishable from zero, indicating no quarter-end amplification. Column (3) reproduces the full-sample baseline from Table 1 of the main paper for reference. All specifications include firm and date fixed effects. t-statistics (in parentheses) are computed from 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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Sample: 1980–2025.

IA.13 Dividend Cycle: Within-Quarter Detail

This section reports the detail behind the dividend-buffer channel summarized in Section 4.3.3 of the main paper. A dividend payment delivers a cash buffer that drains over the months until the next payment. If holders rely on dividend cash to meet month-end obligations, PreTOM selling pressure on a stock should be lowest in the month it pays its dividend (full buffer) and highest in the month before its next payment (drained buffer). The mechanism is the same dispensability channel that runs through the rest of the paper: institutions sell positions they can spare, and a stock whose holders just received cash is more spared than one whose holders are running on the previous quarter's dividend. The prediction therefore applies specifically to losers (winners are not the positions sold to resolve cash demand), and we should see the dividend-cycle pattern in PreTOM loser selling, not in winner selling.

We test this within D1 and D10 quarterly payers. With $\text{Month}_{i,t} \in \{1,2,3\}$ indexing the position of day t within stock i's dividend quarter ($m = 1$: dividend month; $m = 2$: one month after; $m = 3$: two months after), we estimate

$$\begin{aligned}\text{ExRet}_{i,t} = {} & \alpha\,\text{Loser}_{i,t} + \sum_{m=1}^{3} \beta_m^L\,\text{Loser}_{i,t} \times \text{PreTOM}_t \times \mathbf{1}[\text{Month}_{i,t} = m] \\ & + \sum_{m=1}^{2} \beta_m^W\,\text{PreTOM}_t \times \mathbf{1}[\text{Month}_{i,t} = m] + \sum_{m=1}^{2} \lambda_m\,\text{Loser}_{i,t} \times \mathbf{1}[\text{Month}_{i,t} = m] \\ & + \sum_{m=1}^{2} \theta_m\,\mathbf{1}[\text{Month}_{i,t} = m] + \mu_i + \delta_t + \varepsilon_{i,t}. \end{aligned} \tag{IA.1}$$

Month 3 is the omitted reference for the lower-order Month and Loser × Month interactions. Standard errors are two-way clustered by firm and date. The standalone $\text{Loser}_{i,t}$ captures the within-firm time-varying component of decile membership; firm fixed effects μ_i absorb only its firm-level mean. Date fixed effects δ_t absorb the standalone PreTOM_t indicator. Table IA.11 reports the estimates in Panel B (returns) and Panel C (TAQ).[5]

Both predictions hold in the TAQ data. Panel C of Table IA.11 reports the loser coef-

[5] Coefficients β_m^L report the loser-specific Loser × PreTOM × Month effect in each dividend cycle month rather than as differentials from Month 3; the saturated triple-interaction structure identifies all three m jointly with the $\alpha\,\text{Loser}_{i,t}$ standalone. Winner coefficients β_m^W for $m \in \{1,2\}$ are PreTOM × Month effects for non-losers relative to the Month 3 reference. The TAQ analog replaces $\text{ExRet}_{i,t}$ with $\text{NSP}_{i,t}$ and relabels $\beta \to \gamma$; the right-hand side is identical.

ficients rising monotonically across the cycle: $\gamma_1^L = +0.0018$ ($t = 0.70$), $\gamma_2^L = +0.0051$ ($t = 1.84$), $\gamma_3^L = +0.0057$ ($t = 2.12$). The winner coefficients are statistically flat: $\gamma_1^W = +0.0001$ ($t = 0.06$), $\gamma_2^W = +0.0016$ ($t = 0.77$); the joint test $\gamma_1^W = \gamma_2^W = 0$ does not reject ($F = 0.38$, $p = 0.68$). The dividend-cycle pattern is loser-specific.

Panel B (returns) is directionally consistent but underpowered to detect cross-month differences. Loser coefficients are $\beta_1^L = -6.3$ bps/day ($t = -1.32$), $\beta_2^L = -10.6$ ($t = -1.98$), $\beta_3^L = -7.7$ ($t = -1.57$); the joint Wald does not reject equality across months ($F = 0.31$, $p = 0.73$). Winner coefficients are flat ($\beta_1^W = -4.4$, $\beta_2^W = -0.9$). Trade-direction is more informative than returns at this sample size, consistent with the broader pattern that institutional selling shows more directly in TAQ flows than in daily returns.

Table IA.11: Dividend Income and PreTOM Selling Pressure

Panel A: Dividend Payer Composition

	D1 Losers	D10 Winners
Non-payer	84.0%	67.6%
Quarterly payer	8.8%	23.2%
Other (semi-annual, annual, monthly)	7.2%	9.2%

Panel B: Within-Quarter Returns (Quarterly Payers, D1 ∪ D10)

	Month 1 (just paid)	Month 2 (1 mo after)	Month 3 (about to pay)
Winners: PreTOM × Month_m	−4.35	−0.87	0
	(−1.48)	(−0.28)	(ref.)
Losers: Loser × PreTOM × Month_m	−6.28	−10.56**	−7.74
	(−1.32)	(−1.98)	(−1.57)
N		2,449,358	

Panel C: Within-Quarter TAQ Net Selling Pressure (Quarterly Payers, D1 ∪ D10)

	Month 1 (just paid)	Month 2 (1 mo after)	Month 3 (about to pay)
Winners: PreTOM × Month_m	+0.0001	+0.0016	0
	(0.06)	(0.77)	(ref.)
Losers: Loser × PreTOM × Month_m	+0.0018	+0.0051*	+0.0057**
	(0.70)	(1.84)	(2.12)
N		768,018	

Notes: Panel A reports the share of stock-month observations by dividend frequency classification (CRSP distributions, modal frequency). Panels B and C restrict to quarterly dividend payers within D1 (loser decile) and D10 (winner decile) momentum portfolios. Month 1 = the dividend-payment month; Month 2 = one month after payment; Month 3 = about to pay again. Both panels report estimates from the triple-interaction specification of equation (IA.1); Panel C uses the same right-hand side with $\text{NSP}_{i,t}$ replacing $\text{ExRet}_{i,t}$ on the left. The "Winners" row reports β_m^W, the PreTOM × Month_m coefficient identified from D10 (winners are the omitted-loser baseline); Month 3 is the omitted reference for these coefficients. The "Losers" row reports β_m^L, the Loser × PreTOM × Month_m coefficient, which measures the additional loser-specific PreTOM effect in month m above the winner counterpart. All specifications include firm and date fixed effects; standard errors are double-clustered by firm and day. Panel B is value-weighted by lagged 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. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

IA.14 Liquidity Shock Panel Regression: Full Specification

This section reports the full coefficient set for the fund-month panel regression of equation (9) summarized in Table 8, Panel B of the main paper. Bold rows highlight the outflow main effect (β_0), the decile-specific outflow interactions ($\beta_{2,d}$), and the implied total outflow response by decile group.

Table IA.12: Liquidity Shock Panel Regression: Full Specification

Pooled fund-month regression of equation (9); reference group = middle-decile funds (D2–D9).

Variable	Coefficient	t-stat
$D_{\text{D1},j,y}$ ($\beta_{1,\text{D1}}$)	-1.324^{***}	(-9.39)
$D_{\text{D10},j,y}$ ($\beta_{1,\text{D10}}$)	$+1.288^{***}$	($+9.14$)
Outflow$_{\mathbf{m}}$ ($\boldsymbol{\beta_0}$, middle-decile response)	**-0.339^{***}**	**(-3.30)**
$D_{\text{D1},j,y}$ × Outflow$_m$ ($\beta_{2,\text{D1}}$)	**-0.291**	**(-1.03)**
$D_{\text{D10},j,y}$ × Outflow$_m$ ($\beta_{2,\text{D10}}$)	**$+0.293$**	**($+1.10$)**
MKT$_m$ (γ_1)	$+0.901^{***}$	($+83.75$)
$D_{\text{D1},j,y}$ × MKT$_m$ ($\delta_{1,\text{D1}}$)	$+0.129^{***}$	($+3.36$)
$D_{\text{D10},j,y}$ × MKT$_m$ ($\delta_{1,\text{D10}}$)	-0.107^{***}	(-2.92)
SMB$_m$ (γ_2)	$+0.124^{***}$	($+8.62$)
$D_{\text{D1},j,y}$ × SMB$_m$ ($\delta_{2,\text{D1}}$)	$+0.018$	($+0.28$)
$D_{\text{D10},j,y}$ × SMB$_m$ ($\delta_{2,\text{D10}}$)	$+0.234^{**}$	($+2.55$)
HML$_m$ (γ_3)	$+0.078^{***}$	($+6.00$)
$D_{\text{D1},j,y}$ × HML$_m$ ($\delta_{3,\text{D1}}$)	$+0.013$	($+0.19$)
$D_{\text{D10},j,y}$ × HML$_m$ ($\delta_{3,\text{D10}}$)	-0.148^{***}	(-2.61)
Implied total response to 1 pp of aggregate outflow:		
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

Notes. Estimates of equation (9), the single pooled fund-month panel regression with fund fixed effects and standard errors double-clustered by fund and month. Bold rows highlight the outflow main effect (β_0), the decile-specific outflow interactions ($\beta_{2,d}$), and the implied total outflow response by decile group, which are the coefficients summarized in Table 8, Panel B. Reference group is middle-decile funds (D2–D9). Sample: CRSP Mutual Fund Database, actively managed U.S. equity diversified funds (objective code ED, AUM ≥ \$10M, excluding index funds and ETFs), 1998–2025. Funds are sorted annually into deciles on prior 12-month return. The Outflow variable is coded as the magnitude of outflows (positive in outflow months). $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

IA.15 Beta Controls

This section reports the beta-controlled regressions referenced in the main text. The concern is that the Loser$\times$PreTOM effect could be a mechanical transmission of the aggregate market's own PreTOM underperformance through higher loser betas, rather than targeted institutional selling of losers. We use 60-month rolling CAPM betas from the Jensen et al. (2023) global factor data, demeaned within date (value-weighted for VW, equal-weighted for EW and TAQ). The full specification adds β, PreTOM$\times\beta$, Loser$\times\beta$, and Loser$\times$PreTOM$\times\beta$ to the baseline. The triple interaction is the coefficient that would capture beta-amplification of loser selling if the channel were mechanical.

Tables IA.13, IA.14, and IA.15 show the results for value-weighted returns, equal-weighted returns, and TAQ net selling pressure respectively. Column 1 is the baseline; column 2 adds the PreTOM$\times\beta$ interaction in isolation to show its marginal contribution; column 3 is the saturated specification with the standalone β and all lower-order interactions included. Across all three, the headline Loser$\times$PreTOM coefficient is essentially unchanged from the baseline and the triple interaction is statistically indistinguishable from zero. The PreTOM$\times\beta$ coefficient is negative and significant in returns but null in TAQ selling pressure, consistent with a price-level channel rather than a flow-level channel: high-beta stocks mechanically track the market's PreTOM drop in prices, but are not sold harder on net during PreTOM. The window effect is a flow effect on losers that lives on top of, not through, the market's own calendar structure.

Table IA.13: Adding Stock-Level Beta as a Control to Table 1 (VW)

	(1) Baseline	(2) + PreTOM × Beta	(3) Full
Loser	2.609**	2.915**	2.691**
	(2.04)	(2.21)	(2.33)
Loser × PreTOM	−7.151***	−6.771***	−7.215***
	(−3.08)	(−3.08)	(−3.60)
Beta (demeaned)			0.935
			(0.95)
PreTOM × Beta		−2.785*	−3.758**
		(−1.68)	(−2.05)
Loser × Beta			0.499
			(0.37)
Loser × PreTOM × Beta			2.648
			(1.19)
Observations	53,324,145	43,368,519	43,368,519
Within R^2	0.0000	0.0000	0.0000

Notes. Dependent variable is daily excess return in basis points. All specifications are value-weighted (lagged market-cap), with stock and date fixed effects. t-statistics (in parentheses) are computed from standard errors two-way clustered by stock and date. Beta is the 60-month rolling CAPM beta from Jensen et al. (2023), demeaned within each date using value weights. Sample: CRSP common stocks, 1980–2025; columns 2–3 restrict to the subsample with non-missing beta. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table IA.14: Adding Stock-Level Beta as a Control to Table 1 (EW)

	(1) Baseline	(2) + PreTOM × Beta	(3) Full
Loser	8.022***	8.332***	8.520***
	(11.19)	(11.62)	(12.97)
Loser × PreTOM	−2.550*	−2.566**	−2.472**
	(−1.85)	(−1.97)	(−2.00)
Beta (demeaned)			1.507***
			(2.75)
PreTOM × Beta		−3.259***	−3.997***
		(−3.27)	(−3.39)
Loser × Beta			−1.133*
			(−1.65)
Loser × PreTOM × Beta			0.364
			(0.29)
Observations	53,324,145	43,368,519	43,368,519
Within R^2	0.0000	0.0000	0.0000

Notes. Dependent variable is daily excess return in basis points. All specifications are equal-weighted, with stock and date fixed effects. t-statistics (in parentheses) are computed from standard errors two-way clustered by stock and date. Beta is the 60-month rolling CAPM beta from Jensen et al. (2023), demeaned within each date. Sample: CRSP common stocks, 1980–2025; columns 2–3 restrict to the subsample with non-missing beta. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table IA.15: Beta as Control in TAQ Selling Pressure (Table 7)

	(1) Baseline	(2) + PreTOM × Beta	(3) Full
Loser	0.0122***	0.0126***	0.0121***
	(20.33)	(21.00)	(17.29)
Loser × PreTOM	0.0020**	0.0011	0.0018**
	(2.50)	(1.38)	(2.25)
Beta (demeaned)			0.0047***
			(7.83)
PreTOM × Beta		0.0018***	−0.0007
		(4.50)	(−1.75)
Loser × Beta			0.0005
			(0.83)
Loser × PreTOM × Beta			0.0003
			(0.43)
Observations	17,861,276	15,972,786	15,972,786
Within R^2	0.0002	0.0002	0.0002

Notes. Dependent variable is daily net selling pressure (sell-initiated minus buy-initiated share of volume), TAQ data 2003–2022, approximately 17.9 million stock-day observations. All specifications include stock and date fixed effects. t-statistics (in parentheses) are computed from standard errors two-way clustered by stock and date. Beta is the 60-month rolling CAPM beta from Jensen et al. (2023), demeaned within each date. Columns 2–3 restrict to the subsample with non-missing beta. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

IA.16 T+3 to T+2 Settlement Transition

An earlier settlement reform, the September 5, 2017 transition from T+3 to T+2 equity settlement, provides a useful calibration. Its mechanics differ from the May 2024 T+1 reform: the 2017 reform shortened the equity settlement cycle while leaving the fund redemption cycle at T+1 unchanged. This compressed the fund/equity settlement gap from two days to one but did not eliminate it. Our mechanism therefore predicts a *partial* migration of the precautionary selling day from $T-4$ toward $T-3$: right-signed but smaller in magnitude than the 2024 experiment and likely statistically insignificant given the attenuated treatment and limited post-reform data.

Table IA.16 reports the analogous boundary-day DiD. The $T-4$ vs. $T-3$ DiD is +17.0 basis points ($t = 0.83$, $p = 0.41$): the sign is correct, but the magnitude is about a fifth of the 2024 coefficient (+84.7) and not statistically significant, exactly the "right-signed, attenuated, insignificant" pattern the partial-mismatch story predicts. Only the 2024 reform, which fully aligned the two cycles at T+1, eliminated the mismatch and produced the large and significant one-day shift documented in the main paper. The calibration across the two regimes strengthens the causal reading: the size of the remaining settlement gap maps monotonically into the size of the PreTOM day migration.

Table IA.16: T+3→T+2 Settlement Boundary-Day Difference-in-Differences

Panel A: 2×2 Cell Means

	Pre-T+2 (1980–Aug 2017)	Post-T+2 (Sep 2017–2025)	Diff
$T-3$	−2.5 ($n = 452$)	−23.1 ($n = 100$)	−20.7
$T-4$	−5.7 ($n = 452$)	−9.4 ($n = 100$)	−3.7
Diff ($T-4$ minus $T-3$)	−3.3	+13.7	**+17.0**

Panel B: DiD Regression

	Coefficient	Robust SE	t-stat	p-value
$\mathbf{1}[T{=}-4]$	−3.26	5.98	−0.54	0.586
Post T+2	−20.66	13.99	−1.48	0.140
$\mathbf{1}[T{=}-4] \times$ Post T+2	+16.99	20.49	0.83	0.407
Constant	−2.46	4.44	−0.55	0.579
Observations		1,104		
R^2		0.0032		

Notes: Boundary-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 in the main paper. 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.

IA.17 Winner Window Effect

The asymmetry of the PreTOM effect, entirely loser-driven, is confirmed by running the baseline regression on winners instead of losers. Table IA.17 reports the winner analogue of Table 1 of the main paper. Neither the Winner main effect nor the Winner × PreTOM interaction is statistically distinguishable from zero in the value-weighted specification, confirming that winners show no differential PreTOM concentration.

Table IA.17: Winner Window Effect on Daily Returns

	EW	VW
Winner	-0.23^{***}	0.04
	(-3.29)	(0.40)
Winner × PreTOM	-1.27	1.55
	(-0.82)	(0.76)
Fixed effects	Firm, Date	Firm, Date
Observations	53,324,149	53,324,149
Within R^2	0.0000	0.0000

Notes. Dependent variable is daily excess return in basis points. Value-weighted (VW) regressions use lagged market-capitalization weights. t-statistics (in parentheses) are computed from standard errors double-clustered by firm and date. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Sample: CRSP common stocks, 1980–2025.

IA.18 S&P 500 Membership Robustness

A natural concern is that the PreTOM effect is concentrated among small-cap or thinly traded stocks. The effect is also present among S&P 500 constituents: the Loser × PreTOM coefficient is -8.77 ($t = -2.71$) among S&P 500 stocks and -4.62 ($t = -2.53$) among non-constituents, with no statistically significant difference between the two groups (triple interaction $t = -0.82$). The effect is not confined to small or illiquid stocks.

Table IA.18: Window Effect and S&P 500 Membership

	Non-S&P 500 (1)	S&P 500 (2)	Full Sample (3)
Loser	1.806*	4.018**	2.429**
	(1.84)	(2.23)	(2.20)
Loser × PreTOM	−4.622**	−8.769***	−5.916**
	(−2.53)	(−2.71)	(−2.56)
Loser × S&P 500			0.408
			(0.25)
Loser × PreTOM × S&P 500			−2.520
			(−0.82)
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. All specifications include firm and date fixed effects. t-statistics (in parentheses) are computed from standard errors two-way clustered by firm and date. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Sample: CRSP common stocks, 1980–2025.

IA.19 Long-Horizon Reversion: Identification of the PreTOM-Specific Component

The short-horizon Post-window narrowing documented in the main paper shows that the loser-vs-non-loser gap that opens during PreTOM closes within the surrounding seven days. The same mechanism implies a longer-horizon prediction: cumulative pressure from past PreTOM windows should mean-revert at horizons of several months to two years, while cumulative returns over non-PreTOM days, which reflect information and fundamentals rather than transitory flow pressure, should not. The asymmetric prediction tightens the test: identification comes from the contrast between the two predictors rather than the absolute level of either.

We focus on the D1 loser decile. Panel A of Table IA.19 reports daily time-series regressions on the value-weighted D1 portfolio:

$$\text{ExRet}_t = \alpha + \beta_1\,\text{CumPT}_t + \beta_2\,\text{CumNPT}_t + \beta_3\,\text{CumRec}_t + \beta_4\,\text{PreTOM}_t + \beta_5\,\text{ExRet}_{t-1} + \varepsilon_t, \tag{IA.2}$$

where $\text{CumPT}_t = \sum_{s=t-480}^{t-60} \text{ExRet}_s \cdot \mathbf{1}\{s \in \text{PreTOM}\}$ sums distant past returns on PreTOM days only; $\text{CumNPT}_t = \sum_{s=t-480}^{t-60} \text{ExRet}_s \cdot \mathbf{1}\{s \notin \text{PreTOM}\}$ sums distant past returns on non-PreTOM days; and $\text{CumRec}_t = \sum_{s=t-60}^{t-1} \text{ExRet}_s$ is the recent 60-day cumulative excess return. The distant window runs from 60 to 480 trading days prior (approximately three to twenty-four months). The regression is estimated with Newey–West standard errors at 21 lags. The prediction is $\beta_1 < 0$ and $\beta_2 \approx 0$, with the Wald test of $\beta_1 = \beta_2$ rejecting symmetric reversion.

The pattern holds in the standard D1 portfolio ($\beta_1 = -0.0033$, $t = -2.32$; Wald $t = -2.41$) and strengthens when the portfolio is restricted to stocks with persistent past D1-PreTOM exposure. Conditioning today's portfolio on stocks that were in D1 on at least three past PreTOM days (out of approximately 120 in the distant window) drives β_1 to -0.0043 ($t = -3.06$) and the Wald statistic to $t = -3.04$, with effectively no loss in portfolio size (575 vs. ~ 500 stocks/day; only one percent of D1 market capitalization is removed). Results are stable across thresholds from ≥ 1 through ≥ 30; we report ≥ 3 as the primary specification because it removes stocks with essentially zero past D1-PreTOM exposure while preserving 99 percent of D1 market capitalization. Within the ≥ 3 universe, CumPT_t has a time-series standard deviation of 1,779 basis points; the implied cross-sectional spread between $\pm 1\sigma$ tails is 15.4 basis points per day, roughly 39 percentage points annualized. Conditioning on past D1 status also drives β_2 to zero (from $+0.0002$ to -0.0001), removing the trace of conventional medium-horizon momentum that contaminated the unfiltered specification (Jegadeesh and Titman, 1993).

Panel B identifies the same reversion within-firm, with firm and day fixed effects absorbing stock-specific means and aggregate day-level shocks. The key step is to decompose each stock's past PreTOM returns by its own past D1 status: $\text{CumPT}^{\text{PL}}_{i,t}$ sums past PreTOM returns on days when stock i was itself in D1, and $\text{CumPT}^{\text{PNL}}_{i,t}$ sums past PreTOM returns from periods when the stock was not. Analogous quantities $\text{CumNPT}^{\text{PL}}_{i,t}$ and $\text{CumNPT}^{\text{PNL}}_{i,t}$ decompose past non-PreTOM returns. The panel regression is

$$\begin{aligned}\text{ExRet}_{i,t} = \alpha_i + \delta_t \; &+ b_1\,\text{CumPT}^{\text{PL}}_{i,t} + b_2\,\text{CumPT}^{\text{PNL}}_{i,t} \\ &+ b_3\,\text{CumNPT}^{\text{PL}}_{i,t} + b_4\,\text{CumNPT}^{\text{PNL}}_{i,t} + b_5\,\text{CumRec}_{i,t} + b_6\,\text{Loser}_{i,t} + \varepsilon_{i,t},\end{aligned} \tag{IA.3}$$

estimated on all momentum deciles (43.5 million stock-days), value-weighted by lagged market capitalization, with standard errors two-way clustered by firm and day.

Past PreTOM returns accumulated while the stock was in D1 ($b_1 = -0.00111$, $t = -4.99$) revert about three times more strongly than past PreTOM returns accumulated while the stock was outside D1 ($b_2 = -0.00038$, $t = -2.65$), with the Wald test of equality rejecting at $p = 0.0006$. Past non-PreTOM returns show no equivalent asymmetry: b_3 is indistinguishable from zero in D1 and b_4 is marginal outside D1. The marginal b_4 is consistent with a small generic long-horizon reversal in non-loser stocks that firm fixed effects do not fully absorb; its magnitude is about 60 percent of b_2.

If the negative coefficient on CumPT^{PL} reflected generic mean-reversion of persistent underperformers, the analogous $\text{CumNPT}^{\text{PL}}$ should also be negative and large; it is not. The reversion loads specifically on the component of past returns that accumulated during PreTOM windows, when flow pressure was active. Standard persistent-regressor concerns (Stambaugh, 1999; Ferson et al., 2003) affect both predictors similarly given their parallel construction and difference out in the Wald test.

Table IA.19: Long-Horizon Reversion of PreTOM Loser Pressure

Panel A: Portfolio Time Series (D1, value-weighted)				
Portfolio	Avg stocks/day	β_1: CumPT	β_2: CumNPT	Wald: β_1=β_2
Standard D1 (no filter)	~ 500	-0.0033^{**}	$+0.0002$	$t = -2.41^{**}$
		(-2.32)	$(+0.30)$	
Persistent ≥ 3 (primary)	575	-0.0043^{***}	-0.0001	$t = -3.04^{***}$
		(-3.06)	(-0.06)	
Persistent ≥ 30	400	-0.0036^{***}	-0.0000	$t = -2.43^{**}$
		(-2.63)	(-0.03)	
Persistent ≥ 110	35	-0.0019	-0.0006	$t = -0.90$
		(-1.44)	(-0.96)	

Panel B: Stock-Level Panel (all deciles, firm + date FE, VW)		
Variable	Estimate (t-stat)	
b_1: $\text{CumPT}^{\text{PL}}_{i,t}$ (past PreTOM while in D1)	-0.00111^{***}	(-4.99)
b_2: $\text{CumPT}^{\text{PNL}}_{i,t}$ (past PreTOM while not in D1)	-0.00038^{***}	(-2.65)
b_3: $\text{CumNPT}^{\text{PL}}_{i,t}$ (past non-PreTOM while in D1)	-0.00013	(-0.79)
b_4: $\text{CumNPT}^{\text{PNL}}_{i,t}$ (past non-PreTOM while not in D1)	-0.00023^{*}	(-1.88)
b_5: $\text{CumRec}_{i,t}$	-0.00253^{***}	(-7.14)
b_6: $\text{Loser}_{i,t}$	-2.16^{**}	(-2.24)
Wald test: $b_1 = b_2$	$F = 11.85$, $p = 0.0006$	
Difference ($b_1 - b_2$)	-0.00073^{***}	(-3.44)
Observations (stock-days)	43,463,404	

Notes. Predictors are rolling cumulative returns over the distant window $[t{-}480, t{-}60]$: CumPT_t sums returns on past PreTOM days ($T{-}9$ through $T{-}4$); CumNPT_t sums returns on past non-PreTOM days; CumRec_t sums all returns over the recent $[t{-}60, t{-}1]$ window. Panel A reports daily time-series regressions on the indicated value-weighted D1 portfolio with a PreTOM dummy and the portfolio's own one-day lagged return as additional controls (Newey-West standard errors, 21 lags). The persistent-$\geq k$ portfolios restrict today's D1 to stocks that were also in D1 on at least k PreTOM days within the distant window (out of approximately 120 such days). Panel B reports the stock-level panel regression of equation (IA.3). Predictors decompose past cumulative returns by whether stock i was itself in D1 on each past day: CumPT^{PL} ($\text{CumPT}^{\text{PNL}}$) sums past PreTOM returns when stock i was (was not) in D1 on day s, and analogously for non-PreTOM days. Sample includes all momentum deciles. Firm and date fixed effects; 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. Sample: 1980–2025. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

IA.20 Additional Figures

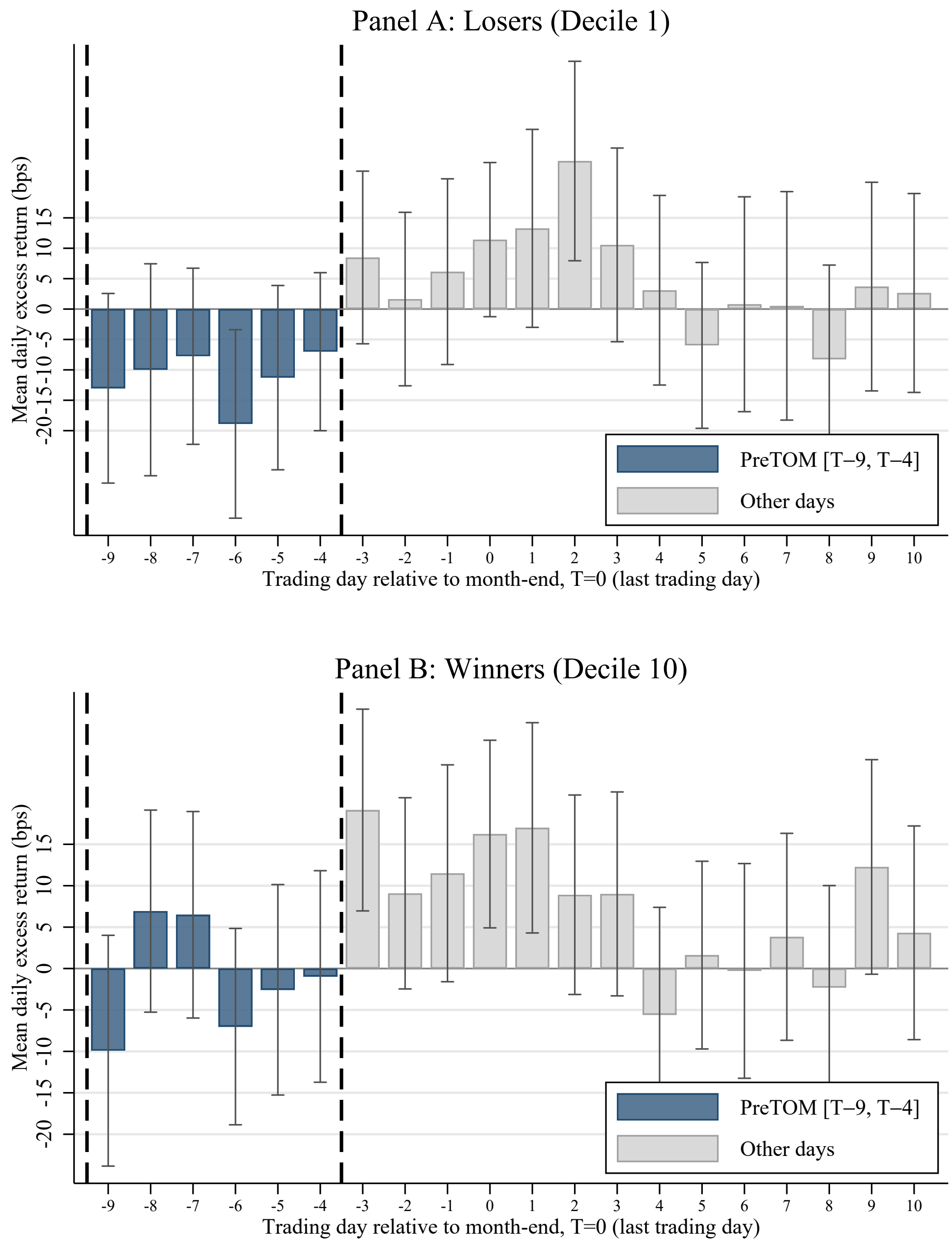

Figure IA.3: Mean daily excess returns (basis points) of loser and winner decile portfolios by trading day t relative to month-end. Panel A: loser portfolio (decile 1). Panel B: winners (decile 10). Bars corresponding to the PreTOM window ($T-9$ through $T-4$) are highlighted. Data are value-weighted daily returns using fixed monthly decile assignments from CRSP. Sample: 1980–2025.

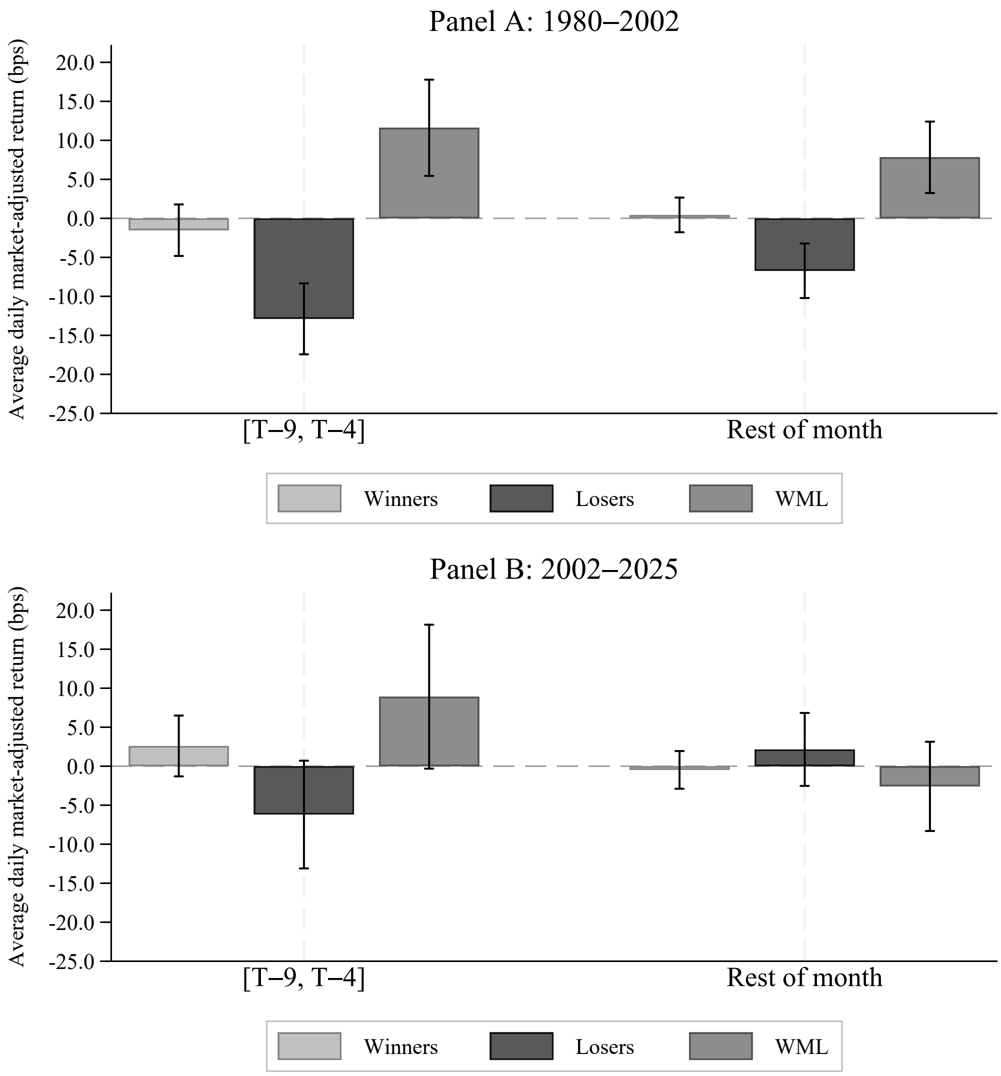

Figure IA.4: Average daily market-adjusted returns (basis points) of momentum winners, losers, and WML during PreTOM ($T-9$ to $T-4$) versus Rest, by subperiod. Market-adjusted returns are $r_i - r_{mkt}$ for winners and losers; WML is unchanged. Bars show time-series means; whiskers denote 95% confidence intervals. Data are daily value-weighted returns using fixed monthly decile assignments from CRSP.

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