Internet Appendix for "The Intramonth Momentum Cycle"

Daniel Nathan, Matti Suominen, and Joni Tasa*

This Internet Appendix contains supplementary material for "The Intramonth Momentum Cycle." It includes: (IA.1) data construction details, (IA.2) holding period analysis, (IA.3) transaction cost decomposition, (IA.4) settlement falsification tests, (IA.5) sliding window analysis, (IA.6) tail trimming analysis, (IA.7) partial reversal, and (IA.8) full international country-level results.

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]

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

*Nathan: Hong Kong Polytechnic University (daniel.nathan@polyu.edu.hk). Suominen and Tasa: Aalto University School of Business (matti.suominen@aalto.fi, joni.tasa@aalto.fi).

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

[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.

filters, the sample contains 59,917,630 observations on 23,827 securities. Trading-day expansion increases this to 60,910,165 observations. Table 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 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 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

[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`}.

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 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 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

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 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 $K > 1$, the strategy holds K overlapping portfolios simultaneously, each initiated in a different month, and takes the equal-weighted average of their returns. Standard errors use Newey-West with $K-1$ lags to account for the mechanical autocorrelation induced by overlapping portfolios.

The PreTOM component is statistically significant at the 1% level for every holding period examined, while the rest-of-month component is never significant and deteriorates monotonically as K increases. By $K = 9$, rest-of-month returns are sufficiently negative that PreTOM wealth exceeds total strategy wealth. By $K = 12$, the rest-of-month 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 dash-for-cash 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 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 = $\log(\$\text{PreTOM}) / \log(\$\text{Total}) \times 100$. Sample: 1980–2025.

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-of-month components. Transaction costs are computed following Novy-Marx and Velikov (2016): each month, we charge one full quoted bid-ask spread for each stock that changes momentum decile assignment. The strategy-level cost is the value-weighted average across turnover stocks, summed over both sides of the long-short.[4]

Over the full sample (1980–2025), gross WML averages +88.8 bps per month, of which +56.8 bps (64%) accrues during PreTOM. Transaction costs of 112 bps per month more than eliminate the gross return. Post-decimalization (2001–2025), gross WML falls to +35.0 bps per month, but the PreTOM component averages +53.3 bps (152% of gross). Transaction costs drop to 13.9 bps, yielding a net return of +21.1 bps. In recent markets, all net return originates in the PreTOM window.

4 T+1 Settlement Falsification Tests

Three falsification tests confirm that the T+1 settlement result is specific to the settlement deadline. First, *placebo days*: running the identical $T-4$ vs. $T-3$ DiD but shifted to $T-6$ vs. $T-7$, two days well inside both the T+2 and T+1 selling windows where no deadline shifted, produces a DiD of +6.6 ($t = 0.24$). Second, *placebo dates*: the same $T-4$ vs. $T-3$ comparison using fake event dates of May 2020 and May 2018, when no regulatory change occurred, yields DiDs of -0.4 ($t = -0.01$) and -1.9 ($t = -0.08$). All three falsifications are indistinguishable from zero.

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 (days 14–19): -7.7 basis points per day ($t = -3.59$, Newey-West). No other window starting position produces a comparably negative estimate. The decline into PreTOM and partial recovery at month-end are exactly what the dash-for-cash mechanism predicts.

[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.

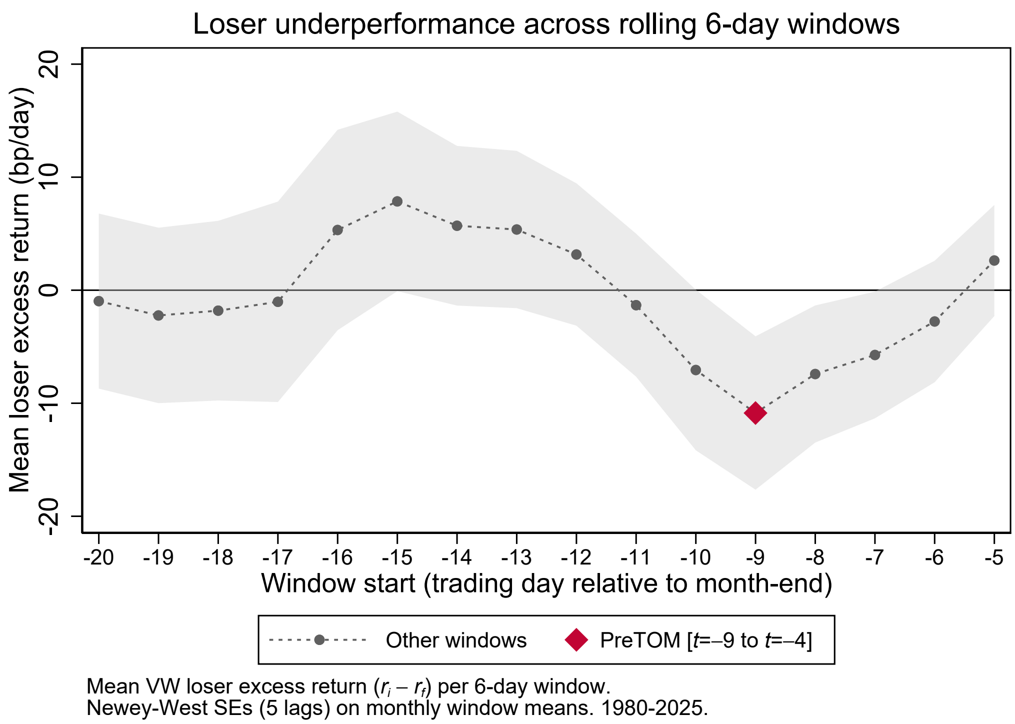

Figure 1: Sliding six-day window analysis. Each point plots the mean daily market-adjusted VW loser return for a six-day window starting at the indicated trading day. The trough occurs at PreTOM (days 14–19). Sample: 1980–2025.

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 2 shows the result. PreTOM mean WML is +9.7 bps untrimmed and rises to +17.5 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 −4.2 bps to +5.5 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.

7 Partial Reversal

If the pre-month-end loser underperformance reflects temporary selling pressure, prices should partially reverse once the selling subsides. We test this by adding a Loser × Post indicator for the seven days surrounding month-end ($T-3$ to $T+3$) to the baseline return regression. The Loser × PreTOM coefficient is −5.59 ($t = -2.07$) and Loser × Post is +3.36 ($t = 1.24$): losers show a positive but insignificant partial reversal around the turn of the month. The point estimate is consistent with temporary price pressure, as expected if the price impact is partly non-informational (Coval and Stafford, 2007), though the effect is not statistically distinguishable from zero.

8 International Evidence: Full Country Table

International Momentum Portfolio Construction

We construct daily momentum decile portfolios for 19 developed markets outside the United States using Compustat Global. The construction mirrors the U.S. methodology as closely as possible. Below we describe each step in detail.

Step 1: Data extraction. From Compustat Global daily security file (`comp.g_secd`), we extract all observations with non-missing positive closing prices (`prccd > 0`) for common equity securities (`tpci = '0'`) domiciled in the 19 sample countries, from January 1990 onward. For Hong Kong and Switzerland, we begin the sample in January 1993 due to thin Compustat coverage in the early 1990s (fewer than 70 common stocks).

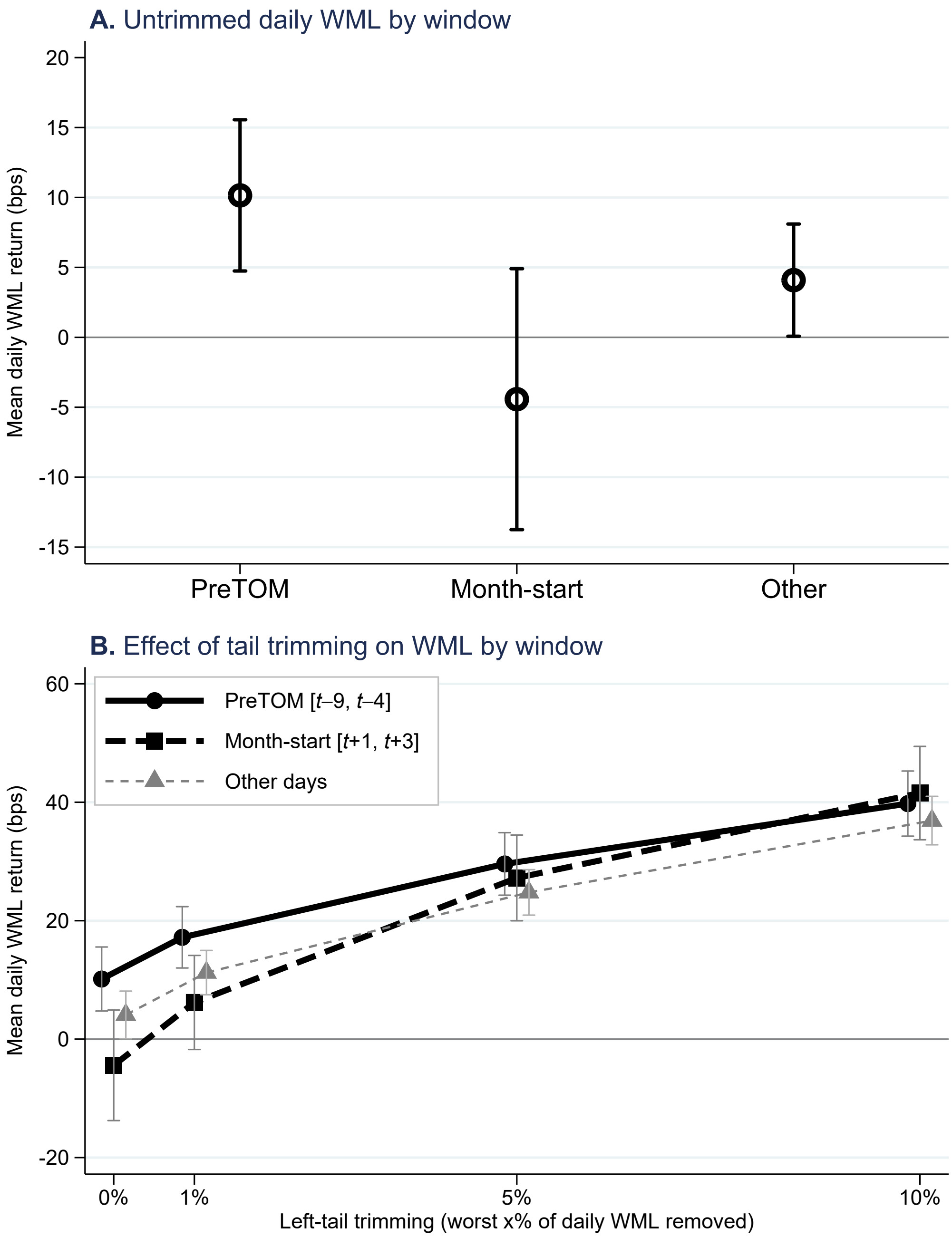

Figure 2: Mean daily WML return by calendar window after progressively trimming the worst days from each window's distribution. Left panel: pre-month-end ($T-9$ to $T-4$). Right panel: month-start ($T+1$ to $T+3$). PreTOM mean WML rises from +9.7 to +17.4 bps after 1% trimming (structural), while month-start flips from -4.4 to +5.3 bps (driven entirely by $\sim$15 tail events). Sample: 1980–2025, value-weighted.

Step 2: Return computation. We compute daily total returns from Compustat's adjusted price and total return factor:

$$\text{AdjPrice}_{i,d} = \frac{\texttt{prccd}_{i,d}}{\texttt{ajexdi}_{i,d}} \times \texttt{trfd}_{i,d}, \qquad r_{i,d} = \frac{\text{AdjPrice}_{i,d}}{\text{AdjPrice}_{i,d-1}} - 1.$$

We winsorize returns at −99% and +1,000% to remove obvious data errors. Market capitalization is $\texttt{prccd} \times \texttt{cshoc}$ (shares outstanding, in millions).

Step 3: Monthly compounding. For each security-month with at least 15 valid trading days, we compound daily returns to obtain a monthly return. Security-months with fewer than 15 days are dropped.

Step 4: Momentum signal. For each security-month, we compute the cumulative return over months −12 through −2 (skipping the most recent month), requiring at least 8 of the 10 monthly returns to be non-missing:

$$\text{Mom}_{i,m} = \exp\Big(\sum_{k=2}^{11} \log(1 + r_{i,m-k}^{\text{monthly}})\Big) - 1.$$

Step 5: Decile assignment with size-conditional breakpoints. At the end of each month m, within each country (or breakpoint group), we: (i) identify stocks with market capitalization above the within-country median; (ii) compute momentum decile breakpoints from this large-cap subsample only (analogous to NYSE breakpoints); (iii) assign all stocks to deciles 1–10 based on those cutoffs; (iv) for countries with fewer than 50 large-cap stocks, pool breakpoints within the broader region.

Step 6: Daily portfolio returns. Decile assignments formed at the end of month m are held fixed throughout month $m+1$. Value-weighted returns use month-m end-of-month market capitalization as weights.

Step 7: Trading day index and market adjustment. Within each country-month, trading days are indexed backward from the last trading day ($T = 0$). PreTOM is $T = -9$ through $T = -4$. We subtract the local market excess return from Kenneth French's regional daily factor files.

Table 4: 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)
Switzerland	−3.49	(−0.81)	3.54	(1.50)	−7.03	(−1.42)
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)
France	−5.40	(−1.94)	−0.91	(−0.42)	−4.49	(−1.28)
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)
Belgium	−1.53	(−0.37)	0.94	(0.37)	−2.47	(−0.51)
Denmark	−4.88	(−1.32)	−2.48	(−0.94)	−2.39	(−0.56)
Finland	−4.01	(−0.94)	−1.90	(−0.62)	−2.11	(−0.43)
Singapore	−3.17	(−0.88)	−2.38	(−0.97)	−0.79	(−0.18)
New Zealand	−3.96	(−0.98)	−3.31	(−1.11)	−0.65	(−0.14)
Italy	−1.68	(−0.63)	−1.49	(−0.79)	−0.19	(−0.06)
Ireland	−0.79	(−0.12)	−1.29	(−0.32)	0.50	(0.07)
Austria	1.49	(0.33)	0.16	(0.05)	1.33	(0.26)
Portugal	2.77	(0.56)	−0.73	(−0.23)	3.50	(0.60)
Pooled	−4.18	(−4.20)	0.28	(0.55)	−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 5: 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)
Switzerland	6.33	(2.29)	2.99	(1.66)	3.35	(1.01)
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)
France	2.99	(1.21)	2.52	(1.41)	0.47	(0.14)
Germany	8.15	(2.29)	5.30	(2.66)	2.85	(0.79)
Australia	7.13	(2.77)	5.02	(2.92)	2.11	(0.64)
Pooled	4.69	(6.47)	3.95	(8.17)	0.74	(0.78)

Notes: Same specification as the losers table above. Reports the nine largest countries plus the pooled estimate. Winner Difference column is insignificant in all individual countries and pooled ($t = 0.78$), confirming the effect is loser-driven.

References

Coval, Joshua and Erik Stafford, "Asset Fire Sales (and Purchases) in Equity Markets," *Journal of Financial Economics*, 2007, *86* (2), 479–512.

Jegadeesh, Narasimhan and Sheridan Titman, "Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency," *Journal of Finance*, 1993, *48* (1), 65–91.

Novy-Marx, Robert and Mihail Velikov, "A Taxonomy of Anomalies and Their Trading Costs," *Review of Financial Studies*, 2016, *29* (1), 104–147.