Internet Appendix for
"The Liquidity-Demand Component of the Factor Zoo"

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Abstract

This Internet Appendix reports supplementary evidence for "The Liquidity-Demand Component of the Factor Zoo." The evidence is organized around the paper's main identifying claims. First, we show that the PreTOM concentration is not an artifact of window choice, sample period, or return adjustment. Second, we test alternative dispensability measures and show that distance from the 52-week high is the cleanest single-characteristic proxy. Third, we report additional T+1 settlement-reform, ETF, stock-level, and within-leg evidence. Fourth, we characterize the persistent component under alternative filters. Finally, we address factor redundancy, external-library replication, multiple testing, and full factor-level classifications.

Roadmap.

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Issue	*Evidence*	*Result*
Window choice	Permutation and bootstrap window tests	The cash-demand window is where factor returns disperse most
Dispensability proxy	Alternative constructions and multiple-testing bootstrap	Distance from the 52-week high remains the best single-characteristic proxy
Settlement timing	Inference comparison, placebo dates, pre-period starts	Sign and timing are robust
Selling pressure	TAQ order flow, stock-level, and within-leg evidence	Dispensable stocks face extra seller-initiated trading before month-end
Factor construction	Official JKP portfolios and independent libraries	The asymmetry does not depend on our decile construction
Factor redundancy	PCA, pruning, effective rank, theme weighting	Redundancy is symmetric across windows; the return concentration is not
Persistent component	Triple-intersection identification filters	The persistent factors concentrate in investment, accruals, profitability, and related q-theory and mispricing variables

Table IA.1: Variable Definitions

Object	Definition	First use
$\delta_{i,m}$	Stock i's dispensability score at month-end m, computed from distance from the 52-week high	Section 3.1
d_f	Factor f's average short-minus-long exposure to stock-level dispensability	Section 3.1
LDS_m	Monthly return spread measuring the realized PreTOM price concession on dispensable stocks	Section 4.1
β_f^{LDS}	Time-series exposure of factor f to LDS_m	Section 4.3
d_e	ETF e's holdings-weighted exposure to stock-level dispensability	Section 6.4
PreTOM	Trading days $\tau{-}9$ through $\tau{-}4$, where $au = 0$ is month-end	Section 2.2
Rest	Trading days outside PreTOM	Section 2.2
Post	Trading days $\tau{-}3$ through $\tau{+}3$	Section 2.2

IA.1 Bootstrap and Permutation Inference

Table IA.2: Bootstrap Test of PreTOM Concentration

Test statistic	Actual	Null mean (sd)	Null 95th	p-value
Factor count ($\|\text{Pre}\| > \|\text{Rest}\|$)	107/153	86.5 (15.1)	111	0.102
Mean absolute share	0.617	0.531 (0.046)	0.608	0.031
Cross-factor variance ratio	**4.50**	1.66 (0.95)	3.56	**0.017**

Notes: 10,000 bootstrap iterations. In each iteration, we randomly assign 6 of ∼21 trading days per month as "placebo PreTOM" and recompute all test statistics. The variance ratio measures how much more cross-sectional dispersion exists in PreTOM factor returns than in Rest: $\text{Var}(\overline{R}_f^{\text{Pre}})/\text{Var}(\overline{R}_f^{\text{Rest}})$ across 153 factors. Sample: 1980–Jan 2025 market-adjusted, the window required for the bootstrap implementation. The headline concentration count of 117/153 (Table IA.6) uses the full 1963–2025 raw/VW JKP sample. For exact reproducibility, all bootstrap and permutation tests fix the random seed (`20260513` in the Python pipeline; `20260507` in the Stata replication); at $B = 5{,}000$ month-block draws the resulting intervals and t-statistics are stable across seeds to two decimal places.

Table IA.3: Unconditional Mean of LDS_m by Trading-Day Window

	Mean (bps/day)	t-stat (HC1)	N days
Mid-month placebo $[\tau-15, \tau-10]$	-0.36	(-0.15)	4,529
PreTOM $[\tau-9, \tau-4]$	$+6.82^{***}$	$(+3.05)$	4,530
Post $[\tau-3, \tau+3]$	-6.34^{***}	(-2.96)	5,285

Notes: Unconditional mean of $\text{LDS}_m = D10 - D1$ in bps/day across three within-month windows, 1963–2025. HC1 heteroskedasticity-robust standard errors. $^{*},^{**},^{***}$ denote $10\%, 5\%, 1\%$ significance.

The anchor cross-sectional specification uses inverse-variance WLS, where the weight on each factor is the inverse of the analytical variance of Δ_f. Table IA.12 reports the slope under alternative weighting choices: equal-weighted OLS, WLS with weights winsorized at 1/99 and 5/95, WLS with weight caps at 10× and 20× the median weight, a theme-equal regression, and the range of leave-one-theme-out and leave-one-factor-out WLS slopes. The estimates remain positive across these specifications, indicating the sign of the settlement shift does not depend on a small number of high-precision factors.

Table IA.4: Alternative LDS Exclusion Rules

Panel A: Exclusion summary and panel-regression coefficients

	Correlation with full LDS			PreTOM		Rest		
Exclusion rule	mean	min	max	β	t	β	t	N
Full LDS (no exclusion)	1.00	1.00	1.00	+ 0.514	(+15.49)	−0.003	(−0.12)	83,117
Theme-wide own-stock exclusion	0.77	0.41	0.97	+ 0.450	(+9.98)	+ 0.022	(+0.72)	83,117

Panel B: Theme-wide exclusion – correlation with full LDS *by JKP theme*

Theme	Corr.	Theme	Corr.	Theme	Corr.	Theme	Corr.
Other	0.41	Profitability	0.74	Profit Growth	0.81	ST Reversal	0.93
Value	0.59	Momentum	0.77	Quality	0.83	LT Reversal	0.97
Low Risk	0.59	Seasonality	0.79	Accruals	0.84		
Investment	0.69	Debt Issuance	0.81	Size	0.92		

Notes: Panel A reports the cross-factor panel coefficient on $d_f \times$ LDS under two exclusion rules. "Full LDS" uses the full CRSP universe; "Theme-wide own-stock exclusion" removes the union of D_1 and D_{10} holdings across all factors in the same JKP theme as f each month. After each exclusion, the remaining universe is re-ranked by dispensability and the NYSE-breakpoint deciles are recomputed before constructing the $D_{10} - D_1$ PreTOM spread. "Correlation with full LDS" in Panel A averages the per-theme correlation across the matched 1979–2025 sample. Panel B reports the per-theme correlation between the theme-excluded LDS series and the full-universe LDS. All specifications: factor and month fixed effects, standard errors two-way clustered by factor and month, matched sample 1979–2025. The 52-week-high characteristic (which defines d_f) is excluded from the panel throughout.

Table IA.5: Binomial Test: PreTOM Share Above Uniform Benchmark

	Observed	Null
Number of factors	153	153
Factors with PreTOM share > 29%	117	—
Share of factors exceeding benchmark	76.5%	50.0%
Binomial p-value (two-sided)	< 0.001	
Normal-approximation z	6.55	

Notes: Each factor's PreTOM share is the fraction of its absolute monthly return earned in the six PreTOM days, $|\overline{R}^{\text{Pre}}| \cdot 6 \,/\, (|\overline{R}^{\text{Pre}}| \cdot 6 + |\overline{R}^{\text{Rest}}| \cdot 15)$. The benchmark 29% $= 6/21$ is the share of trading days in PreTOM. The test we report is a sign test on whether the per-factor PreTOM share exceeds this benchmark: under symmetric noise around the benchmark, the probability of any single factor's share exceeding 29% is 0.5, and the binomial null $H_0 : p = 0.5$ is what asymmetric concentration must reject. Observed: 117of 153factors (76.5%) exceed 29%. The binomial sign test rejects at $p < 0.001$ ($z = 6.55$). This exceeds what calendar-time alone would produce. Sample: all 153JKP factors, VW deciles, NYSE breakpoints, market-adjusted, 1963–Dec 2025.

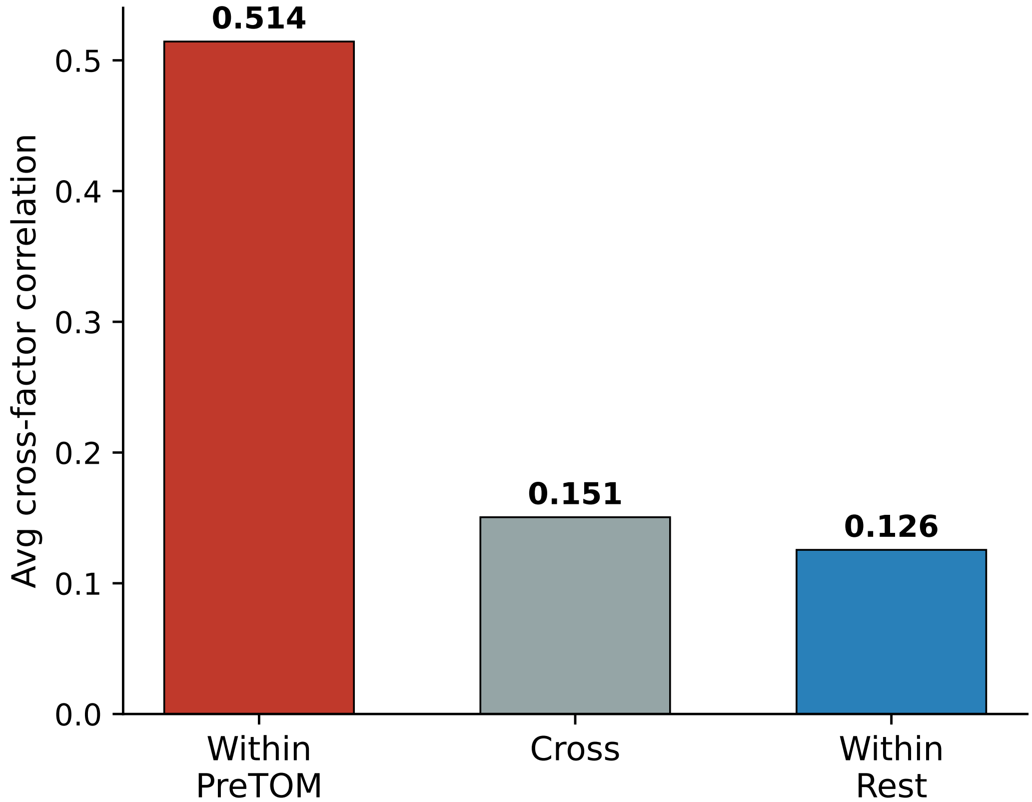

Figure IA.1: Cross-factor pairwise correlation between trading days, 1963–Dec 2025. For each trading-day position from month-end ($\tau-0$ through $\tau-20$) we average daily long–short returns across all calendar months, giving a 153-dimensional cross-factor vector for each position; we then correlate these vectors across position pairs and average within categories. Bars show the average within-PreTOM correlation (pairs of positions both inside the $[\tau-9, \tau-4]$ window), the average within-Rest correlation (pairs of positions both outside), and the average cross correlation (one position inside and one outside). PreTOM days share a common cross-factor pattern of returns; Rest days do not.

Table IA.6: Subperiod Stability of |Pre| > |Rest| Count

Sample	N	|Pre| > |Rest|	Share
Full (1963–2025)	153	117	76.5%
1963–1993	153	109	71.2%
1994–2025	153	113	73.9%

Notes: For each of the 153 JKP factors and each subperiod, we compute the average daily long–short return inside the PreTOM window ($\tau-9$ to $\tau-4$) and outside it. The third column counts the number of factors whose absolute PreTOM daily return exceeds their absolute Rest daily return. Under the two-sided binomial null that PreTOM and Rest are equally likely to contain a factor's larger absolute daily LS return, the expected count is $153 \times 0.5 = 76.5$ with standard deviation $\sqrt{153 \times 0.25} = 6.18$; the observed full-sample count of 117 gives $z = (117 - 76.5)/6.18 = 6.55$ ($p < 10^{-10}$). The two-half z-statistics are 5.25 (1963–1993) and 5.90 (1994–2025). The count is similar in both halves of the sample. VW deciles, NYSE breakpoints.

Table IA.7: PreTOM Share of Total Factor Returns by JKP Theme

Theme	N	Factors with |Pre| > |Rest| (count)	(%)	PreTOM (bps/d)	Pre − Rest t-stat	Rest (bps/d)	Ret. share (%)
Low Risk	20	13 / 20	65	−2.66	−2.76	+0.38	74
Profit Growth	5	4 / 5	80	+3.17	+2.66	+0.72	64
Quality	7	7 / 7	100	+1.72	+2.27	+0.43	62
Profitability	21	19 / 21	90	+4.56	+2.69	+1.35	58
Debt Issuance	8	6 / 8	75	−1.82	−2.08	−0.63	54
Value	9	7 / 9	78	+3.06	+2.01	+1.27	49
Momentum	7	7 / 7	100	+5.96	+1.74	+2.95	45
Seasonality	10	8 / 10	80	+1.52	+1.02	+0.85	42
Size	2	2 / 2	100	−1.87	−1.79	+1.33	36
ST Reversal	1	1 / 1	100	+2.75	+2.25	−2.29	32
Other	27	20 / 27	74	−0.50	−1.96	+0.52	28
Investment	27	17 / 27	63	−0.88	+0.39	−1.17	23
LT Reversal	1	0 / 1	0	+1.28	+1.71	−1.76	22
Accruals	8	6 / 8	75	−0.32	+0.65	−0.73	15
Total	**153**	**117 / 153**	**77**				

Notes: VW NYSE-breakpoint JKP decile portfolios, 1963–Dec 2025. Returns are the $D10 - D1$ long–short with no per-factor sign flip. PreTOM is $[\tau-9, \tau-4]$; Rest is the complement. The "Ret. share" column scales absolute PreTOM and Rest average daily returns by their trading-day counts. The Pre − Rest t-statistic stacks factor-months within each theme and clusters by month. All 14 JKP themes are shown. Subperiod stability is in Table IA.6.

Table IA.8: Subperiod Stability of Theme-Level PreTOM vs. Rest

Theme	N	1963–1993 PreTOM (bps/d)	1963–1993 Rest (bps/d)	1963–1993 Pre−Rest t-stat	1994–2025 PreTOM (bps/d)	1994–2025 Rest (bps/d)	1994–2025 Pre−Rest t-stat
Low Risk	20	−2.87	+0.34	−3.73	−2.45	+0.27	−1.42
Profit Growth	5	+3.17	+1.45	+1.48	+3.09	+0.08	+2.37
Profitability	21	+3.62	+1.17	+2.72	+5.44	+1.62	+1.92
Quality	7	+0.97	+0.86	+0.25	+2.44	+0.01	+2.33
Debt Issuance	8	−2.04	−0.58	−2.74	−1.54	−0.60	−0.94
Value	9	+3.29	+1.55	+1.97	+2.86	+1.00	+1.24
Momentum	7	+6.34	+4.57	+1.31	+5.60	+1.35	+1.49
Seasonality	10	+1.06	+1.05	+0.03	+1.97	+0.71	+1.11
Size	2	−1.15	+1.12	−1.80	−2.57	+1.27	−1.14
ST Reversal	1	+4.07	−4.63	+4.86	+1.48	−0.24	+0.44
Other	27	−0.85	+0.27	−2.00	−0.16	+0.72	−1.05
Investment	27	−2.44	−1.05	−1.89	+0.62	−1.20	+1.42
LT Reversal	1	−1.37	−2.93	+0.89	+3.84	−0.35	+1.43
Accruals	8	−1.82	−0.33	−2.35	+1.12	−1.15	+2.40

Notes: Same construction as Table IA.7 in the main paper, split into two equal-length subperiods. Returns are unsigned $D10 - D1$ in bps/day; the Pre−Rest t-stat is the pooled (factor × day) difference-in-means t on a PreTOM dummy with standard errors clustered by date. The pattern is similar across halves: themes whose Pre−Rest t-stat is significant in 1963–1993 (Low Risk, Profitability, Debt Issuance, Value, Other, Accruals) retain the same sign in 1994–2025 for all but Accruals (which flips). Quality strengthens after 1993 (+2.33 vs. +0.25). Profit Growth becomes significant after 1993 (+2.37 vs. +1.48). VW deciles, NYSE breakpoints.

Table IA.9: Post-on-PreTOM Reversal Slope by $|d_f|$ Tercile

Subset	N	$\hat{\beta}$ (t-stat)	R^2
All factors	144	-0.19 (-2.67)	0.048
Q1: low $\lvert d_f \rvert$	48	+0.50 (+4.57)	0.312
Q2: middle $\lvert d_f \rvert$	48	-0.01 (-0.13)	0.000
Q3: high $\lvert d_f \rvert$	48	-0.50 (-4.53)	0.309

Notes: Cross-sectional regression of each factor's average daily Post-window return on its average daily PreTOM return, $\bar{R}_f^{\text{Post}} = \alpha + \beta \bar{R}_f^{\text{Pre}} + \varepsilon_f$, estimated within $|d_f|$ terciles of the 144-factor universe (factors with both window statistics available). The reversal slope is positive (continuation) in the low-$|d_f|$ tercile, approximately zero in the middle, and large negative (reversal) in the high-$|d_f|$ tercile.

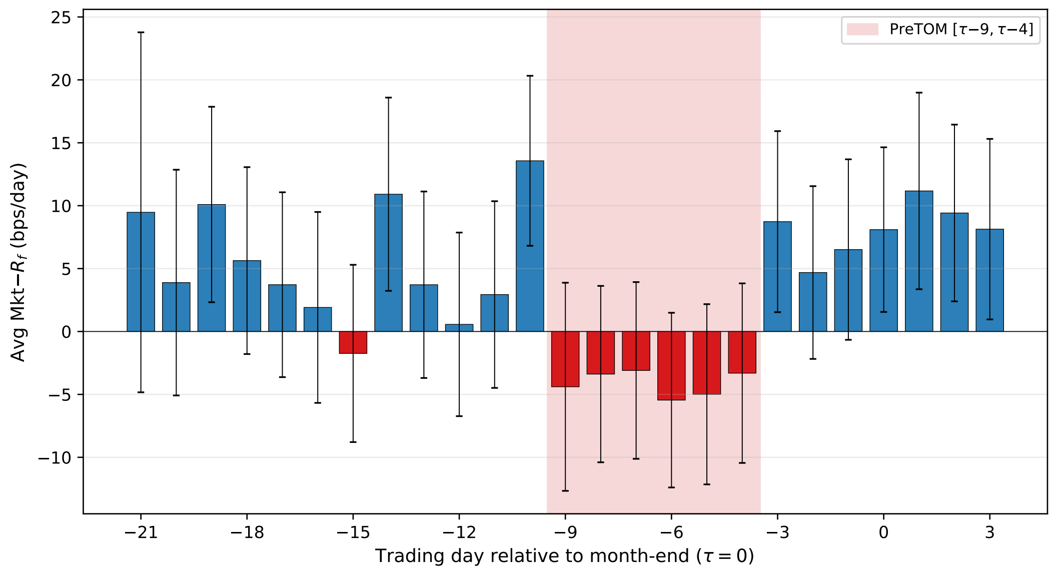

Figure IA.2: Unconditional CRSP value-weighted excess market return (Mkt$-R_f$, daily basis points) by trading-day position relative to the last trading day of the month ($\tau = 0$), 1963–Dec 2025. Bars are shaded blue/red by sign; whiskers are 95% confidence intervals. The red band marks the canonical PreTOM window $[\tau{-}9, \tau{-}4]$; days $\tau{+}1$ to $\tau{+}3$ are the first three trading days of the following month. This is the market-return panel previously shown alongside main-paper Figure 2.

Table IA.10: T+1 Settlement Reform: Permutation Test

	Actual	Permutation 95th	p-value
DiD magnitude (bps)	+16.9	+8.0	**0.006**
$\|t\|$-statistic	4.56	6.46	0.266

Notes: 1,000 permutation iterations. In each iteration, we randomly assign one of the valid month-indices as the "reform date" and re-estimate the detrended DiD across all 153 factors. The actual DiD of +16.9 bps exceeds 99.4% of permuted DiDs ($p = 0.006$). The $|t|$-statistic is less extreme ($p = 0.266$) because some random cutoffs split the sample at trend breaks that mechanically produce large t-stats.

Table IA.11: T+1 Cross-Sectional Test: Inference Comparison

Spec	Slope (bps)	Inference	Statistic	One-sided p
	+33.4	Theme-clustered analytical	$t = +1.78$	0.038
OLS $\hat{\Delta}_f \sim d_f$	+33.4	Month-block bootstrap	$t = +1.24$	0.107
	+33.4	Placebo reform-date randomization	93.3th pctile	0.067
	+47.9	Theme-clustered analytical	$t = +2.45$	0.007
WLS $\hat{\Delta}_f \sim d_f$	+47.9	Month-block bootstrap	$t = +1.43$	0.076
	+47.9	Placebo reform-date randomization	**99.6th pctile**	**0.004**

Notes: Three inference frameworks for the same cross-sectional test: signed factor return DiD $\hat{\Delta}_f = \hat{\pi}_{f,\tau-3} - \hat{\pi}_{f,\tau-4}$ regressed on dispensability loading d_f across 152 JKP factors. *Theme-clustered analytical* groups factors by JKP theme (14 clusters) and applies the standard cluster-robust SE; it captures within-theme correlation but conditions on the per-factor point estimates. *Month-block bootstrap* resamples the pre- and post-reform months separately ($B = 5{,}000$), recomputing $\hat{\Delta}_f$ inside each draw; it additionally captures first-stage estimation uncertainty from the 19-month post-reform window, with $t = \hat{b}/\mathrm{SE}_{\mathrm{boot}}$. *Placebo reform-date randomization* draws 1,000 pseudo-reform dates uniformly from 1990–2015 (all 80/19-month placebo windows fully within the T+3 settlement regime, well clear of both the September 2017 T+3→T+2 and May 2024 T+2→T+1 transitions); the same DiD machinery is applied to each placebo and the actual May 2024 slope is compared to the placebo distribution. All three rows within each panel report the same anchor slope (OLS +33.4, WLS +47.9); the inference methods differ only in how they estimate its standard error. The three procedures address different sources of uncertainty; the placebo distribution preserves the cross-sectional dependence structure of the data, and we use it as the inference for the factor-level T+1 test.

Table IA.12: T+1 Cross-Sectional Test: Weighting Robustness

Specification	N	Slope (bps)	t	Weight rule
OLS (equal-weighted)	152	+33.41	+2.88	1 / factor
WLS, cell-mean dispersion SE	152	+52.62	+4.01	$1/\widehat{\mathrm{SE}}(\Delta_f)^2$ (from cell-mean SD)
WLS, weights winsorized at 1/99	152	+52.56	+4.00	clip(w, p1, p99)
WLS, weights winsorized at 5/95	152	+51.72	+3.93	clip(w, p5, p95)
WLS, weights capped at 10x median	152	+52.62	+4.01	$\min(w, 10\,\mathrm{median}(w))$
WLS, weights capped at 20x median	152	+52.62	+4.01	$\min(w, 20\,\mathrm{median}(w))$
Theme-equal regression	14	+64.80	+2.08	theme means, equal-weighted
Leave-one-theme-out WLS, min	152	+42.88	—	min over 14 themes
Leave-one-theme-out WLS, max	152	+70.34	—	max over 14 themes
Leave-one-factor-out WLS, min	152	+49.66	—	min over 152 factors
Leave-one-factor-out WLS, max	152	+56.16	—	max over 152 factors

Notes: Cross-sectional regression of per-factor signed DiD $\Delta_f = \pi_{f,au-3} - \pi_{f,au-4}$ on the dispensability loading d_f across 152 JKP factors (the 52-week-high self-loading factor excluded). The WLS weight in every row of this table is $1/\widehat{\mathrm{SE}}(\Delta_f)^2$, where $\widehat{\mathrm{SE}}(\Delta_f)$ is computed from the dispersion of pre/post-period cell means for $\tau - 4$ and $\tau - 3$. This is a different variance estimator from the main-paper Table 4 Panel B WLS anchor (+47.9, $t = +2.45$), which uses the analytical inverse variance of Δ_f implied by the per-factor day-level DiD regression. The two estimators yield slopes in the same direction and same order of magnitude (+47.9 vs. +52.6) but are not identical because they place different weights on factors with sparse post-reform months. "Theme-equal" first averages Δ_f and d_f within each JKP theme (14 themes) and runs the regression on theme means. Leave-one-theme-out and leave-one-factor-out report the range of WLS slopes across all single-element exclusions. Pre-period: T+2 era (Sept 5, 2017–Apr 30, 2024). Post-period: T+1 era (June 1, 2024–Dec 31, 2025). May 2024 dropped.

IA.2 Alternative Dispensability Constructions

This section asks whether the main result depends on the exact dispensability proxy. The main paper uses one characteristic: distance from the 52-week high. Composite measures can raise in-sample fit, but they also risk importing profitability, quality, or earnings-streak premia that exist outside PreTOM. We therefore treat the 52-week-high measure as the baseline and report composites as robustness checks. Table IA.13 reports the cross-factor R^2 and clustered t-statistic from the main-paper specification across alternative dispensability constructions.

Table IA.13: Alternative Dispensability Measures

	PreTOM		Rest	
Construction	R^2	t	R^2	t
Panel A: Main specification and components				
Price / 52-week high only — main specification	**0.586**	**8.02**	**0.025**	**1.04**
Financial safety (QMJ-safety) alone	0.473	5.11	0.000	−0.15
Panel B: Composite measures (robustness only)				
52-week high + QMJ-safety	0.667	9.40	0.005	0.59
52-week high + Z-score	0.562	7.19	0.017	0.82
52-week high + F-score	0.591	11.39	0.079	2.01
52-week high + QMJ	0.656	11.04	0.041	1.64
52-week high + QMJ-safety + profitability	0.707	9.21	0.030	1.39

Notes: The main paper uses the single-characteristic 52-week-high specification. Composite measures are reported only as robustness checks. We do not use them as the baseline because they can import non-PreTOM profitability or quality premia into the dispensability measure. Each row reports a cross-factor regression of average daily PreTOM (Rest) long-short return on the indicated dispensability construction. All 153 JKP factors. t-statistics clustered by JKP theme (14 clusters). NYSE breakpoints, VW deciles, market-adjusted, 1980–Jan 2025.

B.1. Stock-Level Residualization of the Dispensability Score

Table IA.14 asks whether the 52-week-high measure is only a repackaging of standard characteristics. Each month, we residualize the stock-level dispensability measure on reversal, prior 11-month return, market beta, idiosyncratic volatility, and QMJ-safety, then rebuild the factor-level short-minus-long loading from the residual. The residualized loading continues to explain a large share of the PreTOM cross-section: the PreTOM R^2 is 0.356 with $t = +6.36$, compared with 0.629 for the baseline measure. About 57% of the baseline PreTOM explanatory power remains after residualization. The Rest-window fit remains small and statistically insignificant, with $R^2 = 0.020$ and $t = +0.93$. Standard characteristics attenuate the 52-week-high signal but do not explain the relation between dispensability exposure and PreTOM factor returns. We retain the single-characteristic specification as the headline measure for its parsimony and direct economic interpretation; the residualized version is reported here as a robustness check.

Table IA.14: Residualized d_f: Standard-Characteristic Controls

	PreTOM		Rest	
Dispensability measure	R^2	t	R^2	t
Baseline d_f (52-week high only)	0.629	+9.20	0.030	+0.95
Residualized d_f	**0.356**	**+6.36**	0.020	+0.93

Notes: The baseline d_f uses the stock-level distance-from-52-week-high measure. The residualized version first projects the stock-level measure each month on reversal, prior 11-month return, market beta, idiosyncratic volatility, and QMJ-safety, and then constructs d_f from the residual. The table reports cross-factor regressions of mean factor returns on each loading separately in PreTOM and Rest. Factor-level loadings use value-weighted NYSE-breakpoint D1–D10 averages of the stock-level score; the single-characteristic 52-week-high factor is excluded (self-loading). t-statistics clustered by JKP theme (14 clusters). Sample: 1963–Dec 2025.

IA.3 Raw (Unadjusted) Return Results

Baseline factor returns in the main paper are raw value-weighted $D10 - D1$ long–short returns; the risk-free rate cancels in the long–short. Table IA.15 reports a market-adjusted robustness check and confirms a similar cross-sectional fit.

Table IA.15: Cross-Sectional Regression on Dispensability: Raw Returns

	PreTOM		Rest	
	R^2	t	R^2	t
Raw $D10 - D1$ (baseline)	0.659	9.63	0.013	0.91
Market-adjusted	0.586	8.02	0.025	1.04

Notes: Cross-factor regressions using the single-characteristic dispensability loading d_f (52-week high only) as in the main text. The baseline row uses raw $D10 - D1$ returns; the market-adjusted row adjusts each decile leg for the market before differencing. All 153 JKP factors. t-statistics clustered by JKP theme. NYSE breakpoints, VW deciles, 1980–Jan 2025.

IA.4 Per-Factor T+1 DiD Estimates

Table IA.16 reports the detrended dispensable-leg difference-in-differences estimate $\hat{\delta}_f = \hat{\pi}_f^{-4} - \hat{\pi}_f^{-3}$ for each of the 153 JKP factors, computed on the factor's dispensable leg (D1 if $d_f > 0$, D10 if $d_f < 0$) using the panel specification of equation (12) of the main text with a linear time trend in the pre-period. This is the dispensable-leg specification; the main text's Panel C of Table 4 and Figure 3 use the parallel signed-factor-return specification $\Delta_f = \pi_{f,au-3} - \pi_{f,au-4}$ on $R_f = D10 - D1$. The two specifications agree directionally but differ numerically because they sign the per-factor DiD relative to different reference legs.

Table IA.16: Per-Factor T+1 Settlement DiD Estimates

Factor	Theme	d_f	$\hat{\delta}_f$ (bps)	t_f	Category
taccruals_at	Accruals	+0.39	+38.2	+2.73	Residual
taccruals_ni	Accruals	+0.26	+35.9	+2.57	Residual
oaccruals_at	Accruals	+0.23	+88.9	+6.36	Residual
oaccruals_ni	Accruals	+0.20	−0.1	−0.01	No signal
dsale_dsga	Accruals	+0.15	+7.6	+0.55	Residual
dgp_dsale	Accruals	+0.07	−45.3	−3.24	Residual
dsale_dinv	Accruals	+0.06	−9.6	−0.69	Residual
dsale_drec	Accruals	−0.03	+13.6	+0.97	Residual
dbnetis_at	Debt Issuance	+0.23	+11.5	+0.69	Residual
eqnpo_12m	Debt Issuance	+0.21	+48.2	+2.90	Liquidity-demand
netis_at	Debt Issuance	−0.17	+98.4	+5.92	No signal
debt_gr3	Debt Issuance	−0.20	+13.4	+0.81	Residual
chcsho_12m	Debt Issuance	−0.29	−44.2	−2.66	Residual
eqnetis_at	Debt Issuance	−0.38	+36.7	+2.21	No signal
netdebt_me	Debt Issuance	−0.79	−19.6	−1.18	Liquidity-demand
debt_me	Debt Issuance	−0.85	+73.4	+4.42	Liquidity-demand
be_gr1a	Investment	+0.43	−4.0	−0.83	Residual
at_gr1	Investment	+0.32	−4.3	−0.88	No signal
nfna_gr1a	Investment	+0.31	+2.2	+0.45	Residual
sale_gr3	Investment	+0.26	+8.8	+1.80	Residual
col_gr1a	Investment	+0.24	−16.2	−3.32	Liquidity-demand
sale_gr1	Investment	+0.22	−5.3	−1.08	Liquidity-demand

Table IA.16 continued

Factor	Theme	d_f	$\hat{\delta}_f$ (bps)	t_f	Category
ncoa_gr1a	Investment	$+0.21$	-29.6	-6.08	No signal
tax_gr1a	Investment	$+0.20$	-10.6	-2.17	Liquidity-demand
noa_gr1a	Investment	$+0.19$	$+23.2$	$+4.76$	No signal
saleq_gr1	Investment	$+0.19$	$+34.5$	$+7.06$	Liquidity-demand
lnoa_gr1a	Investment	$+0.18$	-6.1	-1.26	No signal
nncoa_gr1a	Investment	$+0.17$	-23.7	-4.86	No signal
coa_gr1a	Investment	$+0.15$	-45.8	-9.38	No signal
ppeinv_gr1a	Investment	$+0.15$	-3.8	-0.78	Residual
emp_gr1	Investment	$+0.13$	$+1.2$	$+0.24$	Residual
capx_gr3	Investment	$+0.13$	-20.0	-4.09	No signal
capx_gr2	Investment	$+0.13$	$+15.8$	$+3.24$	No signal
ncol_gr1a	Investment	$+0.11$	-16.0	-3.29	Residual
capx_gr1	Investment	$+0.11$	$+91.7$	$+18.79$	No signal
inv_gr1a	Investment	$+0.09$	-18.6	-3.81	No signal
lti_gr1a	Investment	$+0.07$	-19.2	-3.94	Residual
sale_emp_gr1	Investment	$+0.06$	-1.4	-0.29	Residual
sti_gr1a	Investment	$+0.06$	$+5.0$	$+1.02$	Residual
inv_gr1	Investment	-0.02	$+0.8$	$+0.17$	Residual
cowc_gr1a	Investment	-0.07	$+16.7$	$+3.41$	Residual
fnl_gr1a	Investment	-0.12	-9.9	-2.02	Residual
noa_at	Investment	-0.26	$+21.3$	$+4.37$	Residual
ret_60_12	LT Reversal	$+0.58$	$+12.9$	—	Residual
zero_trades_126d	Low Risk	$+0.44$	$+118.0$	$+9.86$	Market-mechanical

Table IA.16 continued

Factor	Theme	d_f	$\hat{\delta}_f$ (bps)	t_f	Category
zero_trades_21d	Low Risk	+0.42	+67.5	+5.64	Market-mechanical
zero_trades_252d	Low Risk	+0.42	+132.6	+11.08	Market-mechanical
rmax5_rvol_21d	Low Risk	+0.18	−5.4	−0.45	Market-mechanical
iskew_ff3_21d	Low Risk	+0.08	−33.1	−2.76	Market-mechanical
iskew_hxz4_21d	Low Risk	+0.07	−28.2	−2.35	Market-mechanical
iskew_capm_21d	Low Risk	+0.07	−8.9	−0.74	Market-mechanical
rskew_21d	Low Risk	+0.04	−45.1	−3.77	Market-mechanical
beta_dimson_21d	Low Risk	−0.34	+0.2	+0.02	Market-mechanical
ami_126d	Low Risk	−0.45	+0.5	+0.05	Market-mechanical
betadown_252d	Low Risk	−0.47	−67.0	−5.59	Market-mechanical
rmax1_21d	Low Risk	−0.52	−13.8	−1.15	Market-mechanical
rmax5_21d	Low Risk	−0.61	−28.7	−2.40	Market-mechanical
beta_60m	Low Risk	−0.62	−51.3	−4.29	Market-mechanical
ivol_ff3_21d	Low Risk	−0.76	−50.6	−4.23	Market-mechanical
bidaskhl_21d	Low Risk	−0.78	−25.8	−2.15	Market-mechanical
ivol_hxz4_21d	Low Risk	−0.78	−39.9	−3.33	Market-mechanical
ivol_capm_21d	Low Risk	−0.79	−24.5	−2.04	Market-mechanical
rvol_21d	Low Risk	−0.79	−29.6	−2.47	Market-mechanical
ivol_capm_252d	Low Risk	−0.93	−37.4	−3.12	Market-mechanical
ret_12_1	Momentum	+0.96	+72.1	+6.04	Liquidity-demand
ret_9_1	Momentum	+0.88	+1.3	+0.10	Liquidity-demand
ret_6_1	Momentum	+0.76	+5.7	+0.48	Liquidity-demand
ret_3_1	Momentum	+0.55	+24.6	+2.06	Residual

Table IA.16 continued

Factor	Theme	d_f	$\hat{\delta}_f$ (bps)	t_f	Category
ret_12_7	Momentum	+0.46	+46.1	+3.86	Liquidity-demand
resff3_12_1	Momentum	+0.26	−18.4	−1.54	Residual
resff3_6_1	Momentum	+0.22	+47.5	+3.98	Residual
market_equity	Other	+0.72	+90.5	+10.52	Residual
dolvol_126d	Other	+0.35	+30.1	+3.51	Residual
at_turnover	Other	+0.29	−9.3	−1.09	Residual
age	Other	+0.28	+96.9	+11.27	Residual
opex_at	Other	+0.24	−16.6	−1.94	Residual
cash_at	Other	+0.24	−31.0	−3.61	Residual
eq_dur	Other	+0.17	−19.1	−2.22	Residual
corr_1260d	Other	+0.09	+17.6	+2.05	Residual
aliq_at	Other	+0.09	−19.2	−2.23	Residual
capex_abn	Other	+0.05	+129.0	+15.00	Liquidity-demand
tangibility	Other	+0.00	−22.1	−2.57	Residual
ni_ar1	Other	−0.01	+2.5	+0.29	Residual
rd5_at	Other	−0.02	−5.6	−0.65	Residual
rd_sale	Other	−0.02	−10.0	−1.16	Residual
pi_nix	Other	−0.02	−21.4	−2.49	Residual
coskew_21d	Other	−0.04	−63.8	−7.43	Residual
earnings_variability	Other	−0.16	−15.8	−1.83	Residual
dolvol_var_126d	Other	−0.34	−10.9	−1.27	Residual
turnover_var_126d	Other	−0.36	+11.4	+1.33	Residual
ival_me	Other	−0.37	+35.0	+4.07	Residual

Table IA.16 continued

Factor	Theme	d_f	$\hat{\delta}_f$ (bps)	t_f	Category
aliq_mat	Other	−0.40	+24.1	+2.80	No signal
ocfq_saleq_std	Other	−0.42	−21.0	−2.45	Liquidity-demand
ni_ivol	Other	−0.46	−34.4	−4.00	Residual
turnover_126d	Other	−0.47	−27.5	−3.20	Residual
rd_me	Other	−0.61	−10.3	−1.20	Residual
betabab_1260d	Other	−0.63	−62.1	−7.23	Residual
bev_mev	Other	−0.70	+27.2	+3.17	Residual
niq_be_chg1	Profit Growth	+0.21	+2.2	+0.22	Liquidity-demand
ni_inc8q	Profit Growth	+0.19	−17.0	−1.70	Residual
niq_at_chg1	Profit Growth	+0.16	+26.7	+2.68	Liquidity-demand
saleq_su	Profit Growth	+0.13	−26.6	−2.67	Residual
ocf_at_chg1	Profit Growth	+0.10	+16.7	+1.68	Residual
qmj	Profitability	+1.21	+7.0	+0.88	Liquidity-demand
mispricing_perf	Profitability	+1.13	+100.1	+12.58	Liquidity-demand
niq_at	Profitability	+0.83	+80.7	+10.15	Liquidity-demand
ni_be	Profitability	+0.83	+83.3	+10.48	Liquidity-demand
ebit_bev	Profitability	+0.80	+93.2	+11.72	Liquidity-demand
niq_be	Profitability	+0.71	+58.1	+7.31	Liquidity-demand
ni_me	Profitability	+0.70	+86.6	+10.89	Liquidity-demand
qmj_prof	Profitability	+0.68	+54.7	+6.87	Liquidity-demand
ebit_sale	Profitability	+0.68	+82.5	+10.37	Liquidity-demand
ope_bel1	Profitability	+0.58	+85.3	+10.72	Liquidity-demand
op_at	Profitability	+0.51	+103.0	+12.95	Liquidity-demand

Table IA.16 continued

Factor	Theme	d_f	$\hat{\delta}_f$ (bps)	t_f	Category
op_atl1	Profitability	+0.51	+75.6	+9.51	Liquidity-demand
ope_be	Profitability	+0.50	+86.5	+10.88	Liquidity-demand
fcf_me	Profitability	+0.43	+63.0	+7.92	No signal
cop_at	Profitability	+0.35	+19.2	+2.41	Residual
gp_at	Profitability	+0.34	+11.7	+1.47	Liquidity-demand
cop_atl1	Profitability	+0.33	+8.9	+1.12	Liquidity-demand
gp_atl1	Profitability	+0.31	+5.4	+0.68	Liquidity-demand
niq_su	Profitability	+0.14	−1.7	−0.21	Liquidity-demand
ebitda_mev	Profitability	+0.07	+102.3	+12.86	No signal
ocf_me	Profitability	−0.02	+75.2	+9.45	No signal
qmj_safety	Quality	+1.68	+110.8	+5.84	Liquidity-demand
z_score	Quality	+0.68	+47.1	+2.48	Liquidity-demand
f_score	Quality	+0.30	−15.8	−0.83	Residual
qmj_growth	Quality	+0.23	−14.2	−0.75	Liquidity-demand
mispricing_mgmt	Quality	+0.15	−34.6	−1.83	Residual
kz_index	Quality	−0.57	−9.5	−0.50	Residual
o_score	Quality	−1.26	+20.7	+1.09	Liquidity-demand
ret_1_0	ST Reversal	+0.49	+67.6	—	Residual
seas_1_1na	Seasonality	+0.85	+43.1	+4.08	Liquidity-demand
seas_2_5na	Seasonality	+0.28	+16.1	+1.52	Residual
seas_1_1an	Seasonality	+0.16	+30.9	+2.92	Liquidity-demand
seas_6_10na	Seasonality	+0.14	+14.0	+1.32	Liquidity-demand
seas_2_5an	Seasonality	+0.09	−30.0	−2.83	No signal

Table IA.16 continued

Factor	Theme	d_f	$\hat{\delta}_f$ (bps)	t_f	Category
seas_11_15na	Seasonality	+0.07	+82.9	+7.84	Residual
seas_6_10an	Seasonality	+0.06	−27.1	−2.56	Residual
seas_16_20na	Seasonality	+0.04	+26.1	+2.47	Residual
seas_11_15an	Seasonality	+0.03	+10.3	+0.97	Liquidity-demand
seas_16_20an	Seasonality	+0.01	+43.8	+4.14	No signal
at_me	Size	−0.36	+20.9	+7.32	Residual
at_be	Size	−0.47	+15.2	+5.32	Residual
prc_highprc_252d	Value	+1.44	+127.5	+6.60	Liquidity-demand
prc	Value	+1.23	+122.7	+6.35	Liquidity-demand
ocf_at	Value	+0.67	+92.9	+4.81	Residual
sale_bev	Value	+0.47	−4.3	−0.22	Residual
eqnpo_me	Value	+0.22	+96.4	+4.99	Residual
eqpo_me	Value	−0.11	−24.8	−1.28	Residual
div12m_me	Value	−0.11	+5.8	+0.30	Residual
sale_me	Value	−0.58	+31.9	+1.65	No signal
be_me	Value	−0.68	+21.3	+1.10	No signal

IA.5 Additional Robustness Tests

E.1. Alternative Window Definitions

We test the sensitivity of our results to the PreTOM window definition. Table IA.17 reports the d_f cross-sectional R^2 for windows of 5, 6, and 7 days.

Table IA.17: Cross-Sectional R^2 by Window Definition

Window	Days	PreTOM R^2	PreTOM t
$\tau-8$ to $\tau-4$ (5 days)	5	0.623	9.21
$\tau-9$ to $\tau-4$ (baseline)	6	0.659	9.63
$\tau-10$ to $\tau-4$ (7 days)	7	0.681	9.96

Notes: Cross-factor regression of average daily PreTOM long–short return on dispensability loading, varying the window definition. The baseline 6-day window ($\tau-9$ through $\tau-4$) is selected from the cross-day correlation structure (Figure 2 in the main text), not optimized over R^2.

E.3. Chen-Zimmermann Factor Library

As an independent cross-validation, we replicate the PreTOM concentration test using 179 factors from the Chen and Zimmermann (2021) Open Asset Pricing database (all-stock breakpoints, daily VW decile returns, 1927–2024). Because the Chen-Zimmermann library follows each original paper's methodology rather than a unified framework, this test confirms that the PreTOM pattern is not an artifact of the JKP construction.

Table IA.18: PreTOM Concentration in Chen-Zimmermann Factors

	JKP (153 factors)	Chen-Zimmermann (179 factors)
Factors with $\lvert\text{Pre}\rvert > \lvert\text{Rest}\rvert$	109/153 (71%)	55/179 (31%)
Momentum D1 PreTOM (bps)	−70.0	−66.7
Momentum WML PreTOM (bps)	+62.5	+91.4

Notes: Chen-Zimmermann factors use all-stock breakpoints (not NYSE), which inflate both PreTOM and Rest returns via micro-cap contamination. Despite this difference, the PreTOM concentration pattern is similar. The momentum estimates are close across the two libraries. The JKP count 109/153 (71%) is computed over the CZ-matched sample window (1927–2024 intersection); the headline JKP count 117/153 (76.5%) in Table IA.7 of the main paper is computed over the full 1963–Dec 2025 sample.

E.4. Pre-2002 Rest-Window Leakage Diagnostic

The within-half replication (Table 4 in the main text) shows a small but significant Rest-window R^2 of 0.121 ($t = 2.60$) in 1980–2002 that vanishes post-2002 ($R^2 = 0.075$, $t = -1.87$). We decompose the Rest window into near-Rest ($\tau-3$ through $\tau-1$, the three days immediately following the PreTOM window) and far-Rest ($\tau-20$ through $\tau-10$) to localize the leakage.

Table IA.19: Rest-Window Leakage by Sub-Window and Period

	1980–2002		2003–Jan 2025	
Sub-window	R^2	t	R^2	t
Near-Rest ($\tau-3$ to $\tau-1$)	0.49	+5.5	—	−5.9
Far-Rest ($\tau-20$ to $\tau-10$)	0.07	—	—	—

Notes: The pre-2002 Rest significance concentrates entirely in the near-Rest window ($\tau-3$ through $\tau-1$), not in trading days far from the PreTOM boundary. After decimalization in 2001, the near-Rest coefficient reverses sign ($t = -5.9$), consistent with faster price discovery containing the institutional impact inside the six-day PreTOM window. Far-Rest is insignificant in both subperiods, consistent with the pre-2002 leakage reflecting slow price adjustment rather than a broader month-long mechanism.

E.5. Day-by-Day Return Profile

Table IA.20 reports the average signed long–short return across 153 JKP factors for each intramonth phase, decomposing the monthly return into its calendar components.

Table IA.20: Daily Return Profile: Signed Long-Short Spread by Trading-Day Position

Phase	Days	Avg LS (bps/day)	t
PreTOM ($\tau-9$ to $\tau-4$)	6	+2.51	+9.94
Recovery ($\tau-3$ and $\tau+1$)	2	+3.48	+10.92
Last day ($T0$)	1	−4.83	−6.83
Core Rest (remaining ∼12 d)	12	+1.46	+12.95
Monthly contributions (bps/month)			
PreTOM zone (8 days)	8	+22.0 (≈ 60% of monthly total)	
Core Rest + last day (13 days)	13	+12.7 (≈ 40% of monthly total)	

Notes: Average daily signed long-short return across 153 JKP factors, grouped by intramonth phase. Each factor is signed by its full-sample mean LS direction. "Recovery" includes $\tau-3$ (the first Rest day after PreTOM ends within the same month) and $\tau+1$ (the first trading day of the following month). Core Rest excludes $\tau-3$, $\tau+1$, and $T0$. Cross-factor t-statistics. VW deciles, NYSE breakpoints, 1980–Jan 2025.

IA.6 Within-Half Replication

Table IA.21 replicates the core d_f cross-sectional regression independently in each half of the sample (1980–2002 and 2003–Jan 2025), re-estimating both dispensability loadings and factor premia within each half.

Table IA.21: Within-Half Replication: $d_f \rightarrow$ Daily LS Returns

		λ_f (Pre−Rest)		PreTOM		Rest	
Period	N	R^2	t	R^2	t	R^2	t
1980–2002 (H1)	152	0.557	7.16	0.597	6.72	0.121	2.60
2003–Jan 2025 (H2)	153	0.423	9.93	0.381	6.17	0.075	−1.87

Notes: Cross-factor regressions of daily long–short return on d_f, estimated independently in each half. dispensability loadings are recomputed within each half using only that half's stock-level characteristics and VW decile assignments; λ_f = PreTOM mean − Rest mean. t-statistics are clustered by JKP theme (14 clusters).

IA.7 Dispensability Out-of-Sample Test

Table IA.22 tests whether dispensability loadings estimated in one half of the sample predict PreTOM concentration in the other half.

Table IA.22: Dispensability Out-of-Sample Test

d_f formed in	λ_f from	R^2	t	Type
Panel A: Predicting λ_f				
1980–2002	1980–2002	0.557	—	In-sample
2003–Jan 2025	2003–Jan 2025	0.423	—	In-sample
1980–2002	2003–Jan 2025	**0.448**	**+9.04**	**Out-of-sample**
2003–Jan 2025	1980–2002	**0.584**	**+10.19**	**Out-of-sample**
Panel B: Predicting PreTOM mean				
1980–2002	2003–Jan 2025	0.436	+7.64	Out-of-sample
2003–Jan 2025	1980–2002	0.583	+8.24	Out-of-sample
Panel C: Predicting Rest mean (falsification)				
1980–2002	2003–Jan 2025	0.051	−1.64	Out-of-sample
2003–Jan 2025	1980–2002	0.092	+2.66	Out-of-sample
Panel D: d_f stability				
Corr(d_f^{H1}, d_f^{H2}) across 153factors			+0.954	

Notes: d_f is formed independently in each half-sample using only that half's stock-level characteristics and VW decile assignments. λ_f is estimated independently in each half from time-series regressions on daily LS returns. t-statistics are clustered by JKP theme (14 clusters).

Interpretation. What is being held fixed in the out-of-sample test is each factor's *characteristic tilt*, d_f, not the identity of the stocks inside its deciles. The specific stocks sitting in D1 or D10 of any factor turn over continuously: momentum's worst losers in 1985 (US Steel, Bethlehem Steel) are not its worst losers in 2015 (Chesapeake Energy, J.C. Penney). What persists is the mechanical relationship between each factor's *sorting rule* and the dispensability characteristic. Sorting on past returns pulls stocks that are far from their 52-week high and financially fragile into D1 in every decade, because large recent losers are almost by definition far from their highs and frequently in distress. Sorting on book-to-market pulls similar stocks into D10. Sorting on corporate investment or accruals is essentially orthogonal to dispensability. These rule-to-characteristic relationships are structural features of the sorting variables themselves; the cross-factor correlation in d_f across halves of +0.954(Panel D) reflects that stability. The 0.448 out-of-sample R^2 in Panel A is therefore not a claim that dispensable stocks remained the same over 45 years, but that each sorting variable's interaction with dispensability did, which is what links pre-period d_f loadings to post-period PreTOM concentration.

IA.8 Decomposing the PreTOM Premium: CAPM Beta vs. Residual

Table IA.23 decomposes each factor's PreTOM loading λ_f into a CAPM-implied component (the spread in market betas between the long and short legs, multiplied by the market's own PreTOM differential) and a residual. The Low Risk theme accounts for almost all of its PreTOM loading through the beta channel; economic factors (profitability, momentum, investment) are predominantly residual.

Table IA.23: Decomposing the PreTOM Premium: CAPM Beta vs. Residual

	N	Beta share	Residual share	Residual t
All factors	153	53%	47%	+5.93
Excl. Low Risk	133	33%	67%	+9.06
Excl. Low Risk + Other	106	20%	80%	+11.74
By JKP theme				
Low Risk	20	160%	−60%	—
Other	27	98%	2%	—
Profitability	21	41%	59%	—
Momentum	7	30%	70%	—
Quality	7	24%	76%	—
Investment	27	−33%	133%	—
Profit Growth	5	−4%	104%	—
Accruals	8	1%	99%	—

Notes: For each factor f, we decompose λ_f into a CAPM-implied component $[\beta(\text{D10}) - \beta(\text{D1})] \times (-10.0)$, where -10.0 bps/day is the market's own PreTOM−Rest differential, and a residual. Beta share = mean signed beta-implied / mean signed actual, where each factor is signed by its own PreTOM direction. Residual t = cross-factor t-statistic of the signed residual. VW decile portfolios, NYSE breakpoints, 1980–Jan 2025. Full-sample CAPM betas estimated from daily portfolio returns on the market.

IA.9 Is the PreTOM Premium a Shorting Premium?

Drechsler and Drechsler (2014) argue that short-selling costs explain many cross-sectional anomalies. Table IA.24 tests whether short interest relative to institutional ownership (SIRIO), a proxy for shorting costs, subsumes d_f's PreTOM explanatory power.

Table IA.24: Is the PreTOM Premium a Shorting Premium? Dispensability vs. SIRIO

Dep. var.	Predictors	R^2	$t(d_f)$	$t(\text{SIRIO}_f)$
PreTOM mean return				
pre_avg	SIRIO_f alone	0.115	—	−5.17
pre_avg	d_f alone	0.659	+9.63	—
pre_avg	Both	0.682	+9.35	−1.94
Rest mean return (falsification)				
rest_avg	SIRIO_f alone	0.021	—	−1.53
rest_avg	d_f alone	0.013	+0.91	—
rest_avg	Both	0.027	+0.61	−1.13

Notes: SIRIO_f = time-series mean of the VW average SIRIO (short interest / institutional ownership) of the JKP-signed short leg minus long leg, for each of 153 factors. Positive SIRIO_f means the short leg is more expensive to short, consistent with the Drechsler and Drechsler (2014) hypothesis. All t-statistics theme-clustered (14 JKP themes). VW deciles, NYSE breakpoints, 1980–Jan 2025.

IA.10 Within-Theme Standard Error Correction for the DiD Estimator

This section reports the within-theme covariance correction for theme-level summaries of the T+1 DiD. The main paper reports the theme means descriptively in Table 4 Panel A; the corrected t-statistics are reported here. The main causal test in the paper is the cross-sectional slope of Δ_f on d_f across the 152 individual factor estimates (Table 4 Panel B), which does not aggregate within themes and therefore does not require this correction.

Naive baseline. A naive cross-factor t-statistic $\bar{\delta}/(s_\delta/\sqrt{N_{\text{th}}})$ treats the N_{th} factor-level estimates within a theme as independent. Within a JKP theme this assumption is strong: factors in the same theme share underlying stocks, identical sample-period construction, and the same NYSE-breakpoint sorting, so their $\hat{\delta}_f$'s are mechanically correlated. Profitability, for example, contains 21 factors built from overlapping subsets of operating-profitability, gross-profit, and cash-flow ratios; their per-factor T+1 shifts move together far more than independent draws would imply.

Correction. Let $\hat{\varepsilon}_{f,m}$ denote the monthly residual from the per-factor regression $y_{f,m} = \alpha_f + \beta_f\, \mathbf{1}[\text{Post-T+1}]_m + \gamma_f\, m + \varepsilon_{f,m}$, where $y_{f,m} = R^{au-4}_{f,m} - R^{au-3}_{f,m}$ is the monthly $\tau-4$-minus-$\tau-3$ differential for factor f and m is a linear time trend. (This is the monthly companion to the daily DiD specification reported as equation 12 in the main text, used here to construct theme-clustered t-statistics.) Let $\hat{\rho}_{fg}$ denote the Pearson correlation of the two residual time-series across months. We compute the cross-factor mean's variance as

$$\text{Var}(\bar{\delta}) \;=\; \frac{1}{N_{\text{th}}^2}\, \mathbf{1}^\top \widehat{\Sigma}_\delta\, \mathbf{1}, \qquad \widehat{\Sigma}_{\delta,fg} \;=\; \text{se}(\hat{\delta}_f)\,\text{se}(\hat{\delta}_g)\,\hat{\rho}_{fg}, \tag{1}$$

and report $t = \bar{\delta}/\sqrt{\text{Var}(\bar{\delta})}$.

When residuals are highly correlated within a theme, $\widehat{\Sigma}_\delta$ has large off-diagonal mass, $\text{Var}(\bar{\delta})$ is materially larger than the naive s_δ^2/N_{th} formula assumes, and the resulting t-statistic is correspondingly smaller. This collapses N_{th} correlated factor estimates into an effective independent sample size reflecting the cross-factor information content.

Magnitude. The correction is substantial. Table IA.25 reports both the naive and the covariance-corrected theme-level t-statistic alongside the mean Δ_f reproduced from Table 4 Panel A. For Profitability the naive t is +7.67 (treating 21 factor estimates as independent draws); the within-theme covariance correction yields $t = +2.14$. For Value, naive $t = +5.24$

versus corrected $t = +2.56$. For Investment, where the per-factor estimates are nearly orthogonal, the per-factor mean is large but the corrected t-statistic is close to zero, because the within-theme covariance absorbs almost all of the apparent precision. The correction reduces the theme-level t-statistics by removing the significance attributable to within-theme correlation.

Table IA.25: Theme-Level T+1 DiD: Naive vs. Covariance-Corrected t-Statistics

Theme	N	Mean Δ_f (bps)	Naive t	Corrected t
Investment	27	+80.9	+7.89	−0.04
Profit Growth	5	+66.6	+3.61	+1.42
Momentum	7	+64.4	+1.78	+1.30
Seasonality	10	+59.8	+2.07	+1.55
Profitability	21	+54.5	+7.67	+2.14
Accruals	8	+53.9	+2.03	+1.58
Low Risk	20	+39.1	+3.43	+1.20
Other	27	+20.1	+1.50	+0.78
Quality	7	+18.2	+0.69	+0.51
Value	8	−17.7	−5.24	−2.56
Debt Issuance	8	−35.4	−1.65	−1.20

Notes: Mean Δ_f values are reproduced from Table 4 Panel A. The naive t treats the N factor-level estimates within each theme as independent draws. The corrected t applies equation (1) and absorbs within-theme correlation in the per-factor residuals. Themes with high within-theme correlation (Profitability, Investment, Low Risk) see the largest attenuation; themes with near-orthogonal per-factor estimates (Quality, Momentum, Debt Issuance) see modest attenuation. Size, ST Reversal, and LT Reversal omitted ($N < 2$).

IA.11 ETF Evidence

ETFs provide a portfolio-level test using real-money holdings. If dispensability identifies the stocks sold during the cash-demand window, ETFs with greater holdings-weighted dispensability should earn lower PreTOM returns and should exhibit the same T+1 timing shift as factor portfolios.

For each ETF, we compute holdings-weighted dispensability, d_e. ETFs with higher d_e hold more stocks far below their 52-week highs.[1] These ETFs earn lower PreTOM returns:

[1] Formally, $d_e = T_e^{-1} \sum_t \sum_i w_{ei,t}\, \delta_{i,t}$, where $w_{ei,t}$ is ETF e's portfolio weight on stock i on day t and $\delta_{i,t}$ is stock i's dispensability score. We restrict the level test to U.S. equity broad, style, factor, and cap-based ETFs (CRSP objective code EDY or EDC), dropping country-specific, narrow-commodity, narrow-biotech, leveraged, and alternative-strategy funds; with TNA $\geq$ \$10M and at least 18 months of PreTOM history, the filter retains 541 of the original 927 ETFs.

the FF3-controlled slope from

$$\bar{R}_e^{\text{PreTOM}} \;=\; \alpha \;+\; \beta\, d_e \;+\; \beta_{\text{Mkt}}\hat{\beta}_e^{\text{Mkt}} \;+\; \beta_{\text{SMB}}\hat{\beta}_e^{\text{SMB}} \;+\; \beta_{\text{HML}}\hat{\beta}_e^{\text{HML}} \;+\; u_e \tag{2}$$

is -10.59 basis points per day ($t = -2.03$, Table IA.26, Figure IA.3). The Rest slope is small and positive ($+4.33$, $t = +1.80$), consistent with post-window reversal rather than a persistent expected-return relation.

The T+1 reform provides a timing test. High-d_e ETFs exhibit the predicted shift from $\tau{-}4$ to $\tau{-}3$, parallel to the factor-level result. For the 416 ETFs with both pre- and post-reform return windows, we compute the within-month $\tau{-}4$ minus $\tau{-}3$ return differential $y_{e,r}$, separately pre- and post-reform, and estimate

$$y_{e,r} \;=\; \alpha + \beta\, d_e + \gamma\, \text{Post}_r + \delta\,(d_e \times \text{Post}_r) + X_e'\Gamma_r + u_{e,r}, \tag{3}$$

with per-ETF FF3 betas and their interactions with Post_r, SE clustered by ETF. The DiD is $\hat{\delta} = +36.9$ ($t = +2.22$): high-d_e ETFs' $\tau{-}4$ versus $\tau{-}3$ differential rose by an additional $+36.9$ basis points after the reform. The factor-level settlement shift documented in Section 5 thus appears in ETF baskets on the predicted days. The DiD uses a broader cross-section than the level test: its inclusion requirement is four years of pre-reform $\tau{-}4$ data per ETF, but it does not impose the broad/style/factor/cap-based name filter. The additional ETFs are predominantly sector funds (CRSP objective code `EDS`) plus some country-specific and narrow-thematic funds. The broader universe is appropriate because the DiD is identified within ETF. The specification ladder (Table IA.27), on the broader 735-ETF sample without the FF3-beta requirement, gives $+46.2$ ($t = +4.26$, HC3) and $+46.2$ ($t = +3.82$, ETF-clustered) without FF3 controls; on the matched FF3 sample the controlled DiD is $+36.9$ ($t = +2.22$). The post-reform ETF window is shorter than the 19-month factor-level window of Section 5 because the ETF analysis additionally requires same-month FF3-beta estimation; the two analyses are not directly comparable on window length.

The remainder of this appendix reports the ETF-level T+1 specification ladder. The main paper reports the final row of the ladder; earlier rows show that the sign and economic magnitude are present before adding controls and clustering.

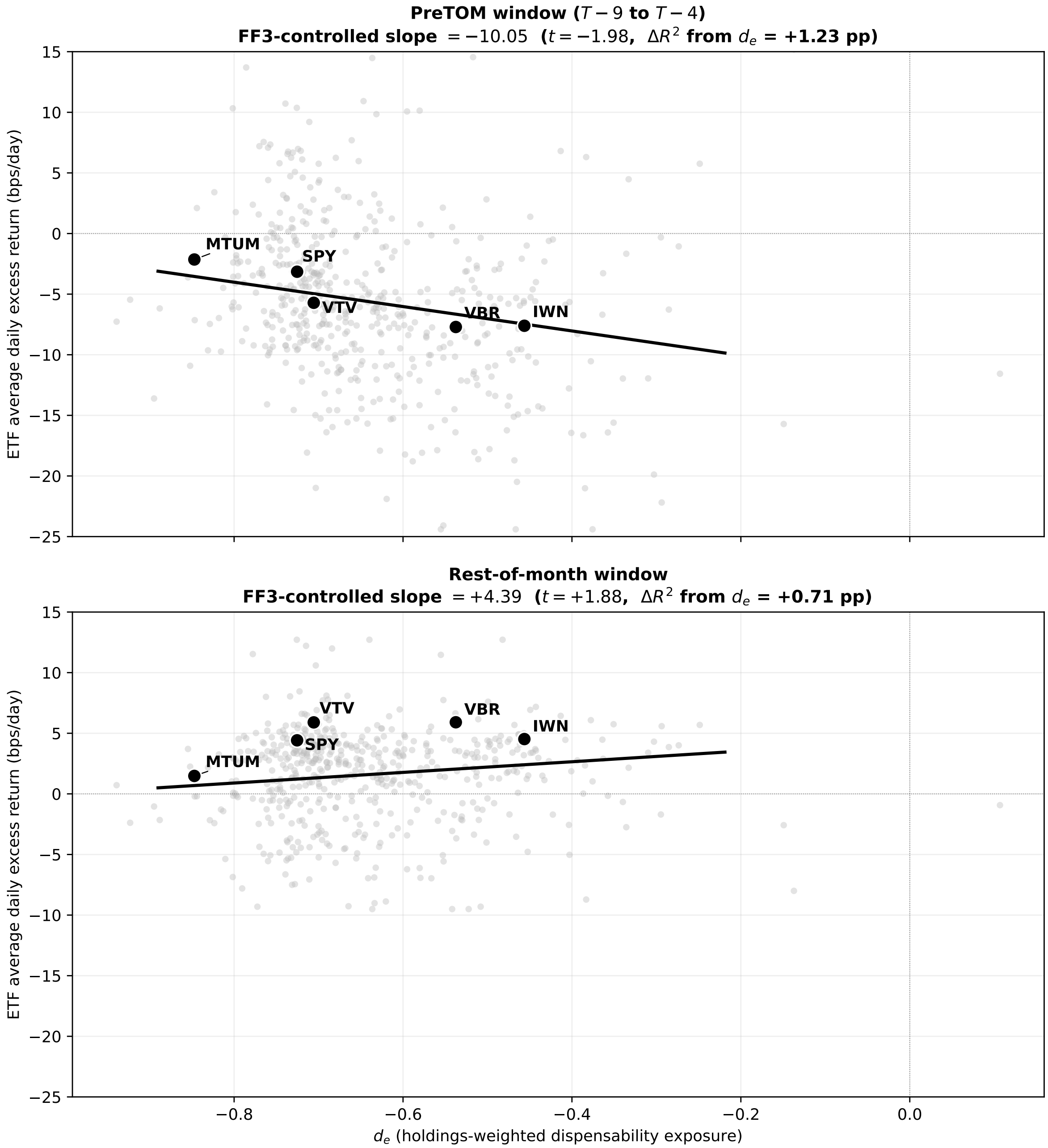

Figure IA.3: 541 U.S. equity broad, style, factor, and cap-based ETFs (TNA $\geq$ \$10M, $\geq$ 18 months of PreTOM history, 1998–Jan 2025). x-axis: holdings-weighted ETF-level dispensability d_e (winsorized 1/99). y-axis: ETF average daily excess return in bps/day (winsorized 0.5/99.5). Top panel: PreTOM ($\tau-9$ to $\tau-4$); bottom: rest of month. The black line is the FF3-controlled slope on d_e, anchored at the cross-section mean. Titles report slope, t-statistic (HC1), and ΔR^2 over the FF3-only model.

Table IA.26: ETF Evidence: Cross-Section and T+1 Settlement Reform

Panel A: ETF holdings exposure predicts PreTOM returns (541 ETFs)

	PreTOM		Rest of month	
Predictor	Bivariate	FF3-controlled	Bivariate	FF3-controlled
d_e (winsorized 1/99)	-14.74^{***}	-10.59^{**}	$+0.86$	$+4.33^{*}$
	(-5.09)	(-2.03)	$(+0.63)$	$(+1.80)$
β^{Mkt}		-1.34		$+1.96^{**}$
		(-1.04)		$(+2.49)$
β^{SMB}		-0.51		-1.96^{***}
		(-0.39)		(-2.84)
β^{HML}		-7.50^{***}		$+0.30$
		(-5.07)		$(+0.41)$
ΔR^2 from d_e		+1.23 pp		+0.71 pp
R^2	6.3%	27.6%	0.1%	10.8%
ETFs N	541	541	541	541

Panel B: ETF holdings exposure predicts the T+1 timing shift (416 ETFs)

Predictor	Bivariate	FF3×Post-controlled
d_e (winsorized 1/99)	$+82.0^{***}$	$+36.9^{**}$
	$(+6.46)$	$(+2.22)$
R^2	10.4%	45%
ETFs N	416	416

Panel A notes. Cross-sectional regressions of ETF average daily PreTOM and Rest returns on holdings-weighted dispensability d_e. Sample: 541 U.S. equity broad, style, factor, and cap-based ETFs, 1998–Jan 2025. FF3-controlled columns include full-sample ETF betas on Mkt-RF, SMB, and HML. ETF-universe filters (CRSP objective codes, name screens) are documented in the Internet Appendix.

Panel B notes. Cross-sectional regressions of the ETF-level T+1 timing-shift DiD on d_e. Sample: 416 ETFs with both pre- and post-reform return windows around the May 28, 2024 settlement reform. Returns and d_e are winsorized as described in the Internet Appendix. HC1 robust standard errors. $^{*}p<0.10$, $^{**}p<0.05$, $^{***}p<0.01$.

Table IA.27: ETF-Level T+1 DiD: Specification Ladder

Specification	N ETFs	Controls	SE	DiD	t
Raw OLS, individual obs.	733	none	HC3	+92.4	+6.84
Collapsed by ETF, equal-weighted	735	none	ETF cluster	+46.2	+3.82
Main specification	416	FF3×Post	ETF cluster	**+36.9**	**+2.22**

Notes: Cross-sectional DiD regressions of the per-ETF ($\tau-4$) minus ($\tau-3$) return differential on holdings-weighted stock-level dispensability exposure, post-reform minus pre-reform. Returns are market-adjusted bps/day, winsorized 0.5/99.5. The first row pools the raw stock–day observations (N includes multiple per-month observations per ETF) and reports HC3 SE. The second row collapses to the per-ETF DiD scalar before running the cross-section and clusters by ETF; the slope is smaller because collapsing equal-weights each ETF rather than weighting by data density. The third row, the main paper's specification, restricts to the 416 ETFs with both pre- and post-reform return windows and adds FF3-beta × reform-period interactions. The main paper reports the final row.

IA.12 The Stambaugh-Yu-Yuan Mispricing Composite

Data and sign convention. We use the MGMT and PERF clusters from Stambaugh and Yuan (2017), covering 148 of our 153 factors.[2] The MGMT cluster aggregates net stock issues, composite equity issues, accruals, net operating assets, asset growth, and investment. The PERF cluster aggregates momentum, distress, O-score, gross profitability, and return on assets. In SYY, a higher composite score predicts lower returns (overpriced stocks). At the factor level we compute the value-weighted $D_{10}-D_1$ score difference, matching the $\bar{R}^{\text{PreTOM}}_{\text{D10},m} - \bar{R}^{\text{PreTOM}}_{\text{D1},m}$ return convention used throughout the paper. Under this convention, factors whose long leg is more overpriced (positive MGMT_f or PERF_f) earn lower returns, so the predicted SYY coefficient is negative.

Window-by-window horse race. The main paper reports the cross-factor horse race in Table 8 using bootstrap inference on the canonical $D_{10}-D_1$ specification. The numbers in that table are the canonical record for MGMT and PERF.

Window asymmetry between MGMT and dispensability. The horse race in Table 8 reveals a window asymmetry between the two channels. In PreTOM, d_f alone explains a large share of the cross-factor variation, while MGMT and PERF add only modest incremental fit ($\Delta R^2 \approx 0.08$ for each). In Rest, the ordering reverses: d_f is statistically indistinguishable

[2] The SYY composite requires the 11 underlying anomaly variables to be simultaneously available at the stock-month level. A small number of JKP factors (e.g., *ni_inc8q*, *rd5_at*, *div12m_me*) have D1 or D10 portfolios whose overlap with the SYY stock panel is too thin to produce a reliable VW D_1-D_{10} MGMT/PERF gap, leaving 148 factors with usable loadings.

from zero, and MGMT explains roughly a third of the cross-factor Rest variation. PERF behaves similarly to MGMT in the joint regression because the two share several underlying constituents; its incremental fit beyond MGMT is small.

Implications. Our decomposition complements the mispricing literature. After accounting for the PreTOM component, MGMT's Rest explanatory power becomes visible because the calendar-bound friction that contaminates monthly returns is no longer in the dependent variable. Return predictability in the factor zoo splits across two windows: liquidity-demand pressure in PreTOM and corporate-policy characteristics in Rest. The Stambaugh, Yu, and Yuan composite, by averaging across both, understates the strength of each.

IA.13 Formal Methodology: Characteristic-Loading Framework

This appendix formalizes the characteristic-loading framework used in the main paper. It states the construction in full mathematical detail and reproduces the characteristic-selection logic that identifies distance from the 52-week high as the leading characteristic for cross-factor PreTOM premia. The corresponding informal exposition appears in Sections 3 and 3.5 of the main paper.

From Stock Characteristics to Factor-Level Exposure

We begin by asking which firm characteristic organizes the cross section of factor returns during the PreTOM window. Our goal is not to form a new traded factor. Rather, we use firm characteristics to measure each anomaly portfolio's exposure to the type of stocks that institutions are likely to liquidate when they face predictable month-end cash demands.

Let $f = 1, \dots, F$ index the 153 JKP long-short factors, and let $c \in \mathcal{C}$ denote a candidate firm characteristic. For each stock i and month m, we first standardize the characteristic cross-sectionally:

$$z^c_{i,m} = \frac{c_{i,m} - \bar{c}_m}{\sigma_m(c)}. \tag{4}$$

The standardization makes characteristics comparable across months and across signals measured in different units. Throughout, $c_{i,m}$ is observed at the end of month $m-1$ and used to form the portfolios that earn month-m returns; the index m refers to the return month.

For each factor f, let $S_{f,m}$ and $L_{f,m}$ denote its short and long legs in month m, and let $w^S_{i,f,m}$ and $w^L_{i,f,m}$ denote the corresponding within-leg value weights. We define factor f's loading on characteristic c as the value-weighted short-minus-long difference in characteristic scores:

$$d^c_{f,m} \;=\; \sum_{i \in S_{f,m}} w^S_{i,f,m}\, z^c_{i,m} \;-\; \sum_{i \in L_{f,m}} w^L_{i,f,m}\, z^c_{i,m}. \tag{5}$$

We then average this exposure over time:

$$d^c_f \;=\; \frac{1}{M}\sum_{m=1}^{M} d^c_{f,m}. \tag{6}$$

Thus, d^c_f measures whether the short leg of factor f contains stocks with higher values of characteristic c than its long leg. A high value of d^c_f means that the factor is short the characteristic and therefore benefits if stocks with high c underperform.

For each factor f, we estimate its incremental return during the PreTOM window:

$$R_{f,d} \;=\; \alpha_f + \lambda_f \cdot \mathbf{1}\{d \in \text{PreTOM}\} + \varepsilon_{f,d}, \tag{7}$$

where $R_{f,d}$ is the daily return on factor f and PreTOM denotes trading days $T-9$ through $T-4$ relative to the last trading day of the month. The coefficient λ_f is the factor's incremental daily return during the PreTOM window.

The central cross-factor test is:

$$\lambda_f \;=\; a + b_c \cdot d^c_f + u_f. \tag{8}$$

If characteristic c organizes exposure to the PreTOM liquidation shock, then factors whose short legs load more heavily on c should earn larger PreTOM returns. The prediction is therefore $b_c > 0$.

This procedure gives each candidate characteristic the same opportunity to explain the cross section of PreTOM factor returns. The object of interest is not the return on a standalone characteristic portfolio. It is the ability of a firm characteristic to explain which existing anomaly portfolios load on the PreTOM shock.

Selecting the Characteristic

We implement this procedure for a broad set of candidate firm characteristics. For each c, we compute d^c_f across the 153 JKP factors and estimate equation (8) in the full sample and in two subperiods, 1980–2002 and 2003–2025.

The results identify distance from the 52-week high as the dominant and most stable organizing characteristic. Let

$$d^{52}_{i,m} \;=\; -\, z_m\!\left(\frac{P_{i,m}}{H^{252}_{i,m}}\right), \tag{9}$$

where $P_{i,m}$ is the stock price and $H^{252}_{i,m}$ is the stock's 252-trading-day high. The negative sign ensures higher values correspond to stocks trading farther below their 52-week highs. We refer to this variable as distance-from-high dispensability.

The corresponding factor-level loading is

$$d^{52}_f \;=\; \frac{1}{M}\sum_{m=1}^{M}\left[\sum_{i\in S_{f,m}} w^S_{i,f,m}\, d^{52}_{i,m} \;-\; \sum_{i\in L_{f,m}} w^L_{i,f,m}\, d^{52}_{i,m}\right]. \tag{10}$$

A factor with high d^{52}_f is short stocks that are farther from their 52-week highs than the stocks in its long leg. If month-end cash demand induces institutions to sell positions that are easiest to justify liquidating, then such factors should earn higher returns during PreTOM.

Empirically, d^{52}_f is the only characteristic that strongly and stably explains PreTOM returns in both subperiods. In the full sample, the regression of λ_f on d^{52}_f produces an R^2 of 0.58. The relation is not confined to one era: the R^2 is 0.48 in 1980–2002 and 0.30 in 2003–2025. No other characteristic reaches $R^2 \geq 0.30$ in both subperiods.

This stability is important. Some characteristics explain PreTOM returns in the full sample but not consistently across eras. Quality, financial safety, and idiosyncratic volatility have substantial explanatory power in the early sample but weaken sharply after 2003. Momentum has explanatory power in the late sample but is much weaker in the early sample. Distance from the 52-week high is the only characteristic that remains strong in both periods.

We therefore use d^{52}_f as the baseline measure of factor-level dispensability exposure. The interpretation is an exposure interpretation: distance from the 52-week high measures whether a portfolio is short the stocks most susceptible to predictable month-end liquidation pressure. It need not be a standalone traded factor in every subperiod. The relevant prediction is that existing anomaly portfolios with larger d^{52}_f load more strongly on the PreTOM shock.

IA.14 Full Factor-by-Factor Classification

We classify each factor according to the source of its return pattern. Liquidity-demand-component factors have returns primarily aligned with the PreTOM dispensability component. Persistent factors retain significant returns outside that component. Opposite-signed LD factors have returns offset by exposure to dispensable stocks. Market-beta-mechanical factors load on the unconditional market return rather than on dispensability. Factors with no persistent signal do not meet the persistent-component threshold. Table IA.28 reports the complete classification for all 153 JKP factors: factor name, JKP theme, dispensability loading, PreTOM and Rest daily long–short returns (bps/day), their t-statistics, and the classification.

Table IA.28: Complete Factor Classification (153 JKP Factors)

Factor	Theme	d_f	Pre (bps)	Rest (bps)	t_{Pre}	t_{Rest}	t_{Full}	Category
taccruals_at	Accruals	+0.39	+0.4	−1.3	+0.36	−1.76	−1.28	No signal
taccruals_ni	Accruals	+0.26	+0.1	−0.7	+0.10	−0.72	−0.53	No signal
oaccruals_at	Accruals	+0.23	−3.1	−3.1	−2.11	−3.53	−4.06	Residual
oaccruals_ni	Accruals	+0.20	−1.2	−2.5	−1.00	−3.30	−3.29	Residual
dsale_dsga	Accruals	+0.15	+1.5	−1.6	+1.03	−1.70	−0.90	No signal
dgp_dsale	Accruals	+0.07	+2.7	−0.1	+1.95	−0.18	+1.04	No signal
dsale_dinv	Accruals	+0.06	+2.1	+1.5	+1.77	+1.60	+2.35	No signal
dsale_drec	Accruals	−0.03	−0.5	−0.3	−0.53	−0.54	−0.77	No signal
dbnetis_at	Debt Issuance	+0.23	+0.7	−1.3	+0.72	−1.86	−1.20	No signal
eqnpo_12m	Debt Issuance	+0.21	+3.7	+1.2	+2.30	+1.36	+2.54	Liquidity-demand
netis_at	Debt Issuance	−0.17	−1.7	−3.0	−1.25	−3.76	−3.67	Residual
debt_gr3	Debt Issuance	−0.20	+0.2	−0.2	+0.21	−0.59	−0.35	No signal
chcsho_12m	Debt Issuance	−0.29	−4.0	−1.9	−2.52	−2.24	−3.50	Residual
eqnetis_at	Debt Issuance	−0.38	−2.8	−2.2	−1.64	−2.07	−2.65	Residual
netdebt_me	Debt Issuance	−0.79	−4.3	+0.4	−2.51	+0.15	−1.28	No signal
debt_me	Debt Issuance	−0.85	−4.6	+2.1	−2.12	+1.53	+0.05	No signal
be_gr1a	Investment	+0.43	+0.5	−1.3	+0.35	−1.52	−0.97	No signal
at_gr1	Investment	+0.32	−0.2	−1.9	−0.21	−2.23	−1.96	Residual
nfna_gr1a	Investment	+0.31	+1.9	+1.3	+1.91	+1.73	+2.43	No signal
sale_gr3	Investment	+0.26	+2.0	−0.1	+1.25	−0.14	+0.60	No signal
col_gr1a	Investment	+0.24	+4.6	+0.3	+3.40	−0.16	+1.64	No signal
sale_gr1	Investment	+0.22	+3.6	−1.5	+2.14	−1.64	−0.10	No signal

Table IA.28 continued

Factor	Theme	d_f	Pre (bps)	Rest (bps)	t_{Pre}	t_{Rest}	t_{Full}	Category
ncoa_gr1a	Investment	+0.21	−0.7	−2.2	−0.56	−2.88	−2.66	Residual
tax_gr1a	Investment	+0.20	+3.3	−1.0	+2.23	−1.26	+0.31	No signal
noa_gr1a	Investment	+0.19	−2.1	−2.8	−1.52	−3.20	−3.62	Residual
saleq_gr1	Investment	+0.19	+4.5	−0.2	+2.60	−0.40	+1.14	No signal
lnoa_gr1a	Investment	+0.18	−0.2	−3.0	−0.23	−3.33	−3.02	Residual
nncoa_gr1a	Investment	+0.17	−1.3	−2.0	−1.01	−2.48	−2.53	Residual
coa_gr1a	Investment	+0.15	−0.1	−1.9	−0.12	−2.38	−2.06	Residual
ppeinv_gr1a	Investment	+0.15	−2.2	−1.4	−1.61	−1.46	−2.16	No signal
emp_gr1	Investment	+0.13	−2.5	−0.7	−1.63	−0.77	−1.53	No signal
capx_gr3	Investment	+0.13	−1.7	−2.1	−1.26	−2.44	−2.63	Residual
capx_gr2	Investment	+0.13	−1.3	−2.3	−1.01	−2.73	−2.70	Residual
ncol_gr1a	Investment	+0.11	−1.5	+0.5	−1.39	+0.57	−0.28	No signal
capx_gr1	Investment	+0.11	−1.0	−2.2	−0.85	−2.14	−2.24	Residual
inv_gr1a	Investment	+0.09	−0.8	−2.3	−0.64	−2.19	−2.26	Residual
lti_gr1a	Investment	+0.07	−0.8	−0.4	−0.82	−1.14	−1.40	No signal
sale_emp_gr1	Investment	+0.06	+3.8	−1.7	+3.11	−2.03	−0.06	Opposite-signed
sti_gr1a	Investment	+0.06	−1.0	−0.2	−1.12	−0.55	−1.10	No signal
inv_gr1	Investment	−0.02	−0.4	−1.8	−0.34	−1.86	−1.78	No signal
cowc_gr1a	Investment	−0.07	−4.6	−2.1	−3.89	−2.51	−4.26	Residual
fnl_gr1a	Investment	−0.12	−1.3	−1.0	−1.36	−1.42	−1.94	No signal
noa_at	Investment	−0.26	−4.5	−3.2	−3.85	−3.96	−5.70	Residual
ret_60_12	LT Reversal	+0.58	+3.1	−1.5	+1.77	−1.15	−0.13	No signal
zero_trades_126d	Low Risk	+0.44	+0.2	−1.8	+0.07	−0.84	−0.71	Market-mechanical

Table IA.28 continued

Factor	Theme	d_f	Pre (bps)	Rest (bps)	t_{Pre}	t_{Rest}	t_{Full}	Category
zero_trades_21d	Low Risk	+0.42	−0.1	−1.6	−0.06	−0.85	−0.75	Market-mechanical
zero_trades_252d	Low Risk	+0.42	+0.9	−1.5	+0.37	−0.78	−0.50	Market-mechanical
rmax5_rvol_21d	Low Risk	+0.18	−1.6	−2.6	−1.08	−2.83	−3.18	Market-mechanical
iskew_ff3_21d	Low Risk	+0.08	+0.4	+1.2	+0.42	+2.39	+2.25	Market-mechanical
iskew_hxz4_21d	Low Risk	+0.07	+0.0	+1.7	+0.03	+3.42	+2.99	Market-mechanical
iskew_capm_21d	Low Risk	+0.07	+0.2	+0.6	+0.17	+1.14	+1.03	Market-mechanical
rskew_21d	Low Risk	+0.04	+0.6	+0.4	+0.57	+1.04	+1.17	Market-mechanical
beta_dimson_21d	Low Risk	−0.34	−3.8	+1.9	−1.61	+0.78	−0.29	Market-mechanical
ami_126d	Low Risk	−0.45	+0.1	−1.0	+0.04	−0.43	−0.34	Market-mechanical
betadown_252d	Low Risk	−0.47	−1.4	+2.5	−0.54	+1.26	+0.71	Market-mechanical
rmax1_21d	Low Risk	−0.52	−5.0	−0.7	−2.05	−0.33	−1.35	Market-mechanical
rmax5_21d	Low Risk	−0.61	−5.5	−0.9	−1.99	−0.60	−1.54	Market-mechanical
beta_60m	Low Risk	−0.62	−5.3	+4.3	−1.78	+2.23	+0.91	Market-mechanical
ivol_ff3_21d	Low Risk	−0.76	−6.7	−0.7	−2.67	−0.36	−1.65	Market-mechanical
bidaskhl_21d	Low Risk	−0.78	−4.5	−0.3	−1.77	−0.37	−1.16	Market-mechanical
ivol_hxz4_21d	Low Risk	−0.78	−6.4	−0.7	−2.57	−0.34	−1.64	Market-mechanical
ivol_capm_21d	Low Risk	−0.79	−6.9	−1.2	−2.63	−0.46	−1.71	Market-mechanical
rvol_21d	Low Risk	−0.79	−6.2	+0.1	−2.14	+0.02	−1.06	Market-mechanical
ivol_capm_252d	Low Risk	−0.93	−7.9	−1.0	−2.75	−0.53	−1.74	Market-mechanical
ret_12_1	Momentum	+0.96	+10.3	+2.6	+3.62	+1.48	+3.24	Liquidity-demand
ret_9_1	Momentum	+0.88	+8.5	+2.5	+3.09	+1.62	+3.10	Liquidity-demand
ret_6_1	Momentum	+0.76	+5.6	+2.8	+2.10	+1.73	+2.66	Liquidity-demand
ret_3_1	Momentum	+0.55	+4.2	+2.4	+1.74	+1.64	+2.35	No signal

Table IA.28 continued

Factor	Theme	d_f	Pre (bps)	Rest (bps)	t_{Pre}	t_{Rest}	t_{Full}	Category
ret_12_7	Momentum	+0.46	+6.6	+2.3	+3.18	+1.51	+2.97	Liquidity-demand
resff3_12_1	Momentum	+0.26	+3.4	+2.9	+2.25	+2.50	+3.28	Residual
resff3_6_1	Momentum	+0.22	+2.8	+0.7	+1.97	+0.74	+1.64	No signal
market_equity	Other	+0.72	+0.8	+1.2	+0.49	+0.61	+0.78	No signal
dolvol_126d	Other	+0.35	−1.0	+0.7	−1.01	+0.09	−0.44	No signal
at_turnover	Other	+0.29	+3.0	+0.7	+1.63	+0.81	+1.64	No signal
age	Other	+0.28	+1.1	−0.1	+0.51	−0.15	+0.17	No signal
opex_at	Other	+0.24	+2.3	+0.6	+1.26	+0.94	+1.53	No signal
cash_at	Other	+0.24	+0.3	+1.7	+0.13	+0.95	+0.87	No signal
eq_dur	Other	+0.17	+0.4	−1.8	+0.20	−1.53	−1.22	No signal
corr_1260d	Other	+0.09	−2.2	+1.8	−1.33	+1.08	+0.14	No signal
aliq_at	Other	+0.09	−0.5	+0.5	−0.33	+0.14	−0.05	No signal
capex_abn	Other	+0.05	−2.5	−1.2	−2.20	−1.60	−2.47	Liquidity-demand
tangibility	Other	+0.00	+0.8	+0.1	+0.60	+0.46	+0.71	No signal
ni_ar1	Other	−0.01	−0.8	+1.0	−0.85	+1.25	+0.61	No signal
rd5_at	Other	−0.02	+3.2	−0.0	+1.88	−0.49	+0.53	No signal
rd_sale	Other	−0.02	+1.9	−1.0	+1.11	−1.23	−0.47	No signal
pi_nix	Other	−0.02	+1.8	+0.2	+1.50	+0.61	+1.33	No signal
coskew_21d	Other	−0.04	−0.7	−0.1	−0.60	−0.28	−0.64	No signal
earnings_variability	Other	−0.16	−0.2	−1.0	−0.31	−0.88	−0.98	No signal
dolvol_var_126d	Other	−0.34	+1.8	−1.0	+1.53	−0.64	+0.24	No signal
turnover_var_126d	Other	−0.36	+1.0	−0.9	+0.87	−0.64	−0.09	No signal
ival_me	Other	−0.37	−1.3	+1.7	−0.73	+1.65	+1.00	No signal

Table IA.28 continued

Factor	Theme	d_f	Pre (bps)	Rest (bps)	t_{Pre}	t_{Rest}	t_{Full}	Category
aliq_mat	Other	−0.40	−2.9	+2.2	−1.78	+2.25	+0.97	Opposite-signed
ocfq_saleq_std	Other	−0.42	−5.1	−0.2	−2.85	−0.34	−1.87	No signal
ni_ivol	Other	−0.46	−1.6	−0.5	−0.81	−0.20	−0.62	No signal
turnover_126d	Other	−0.47	+0.5	+1.7	+0.16	+0.87	+0.81	No signal
rd_me	Other	−0.61	+0.2	+1.8	+0.11	+1.63	+1.44	No signal
betabab_1260d	Other	−0.63	−6.1	+2.3	−1.95	+1.07	−0.26	No signal
bev_mev	Other	−0.70	−3.4	+1.1	−1.60	+1.08	+0.01	No signal
niq_be_chg1	Profit Growth	+0.21	+3.7	+0.7	+2.96	+0.80	+2.43	Liquidity-demand
ni_inc8q	Profit Growth	+0.19	+3.7	+1.3	+1.92	−1.03	+0.95	No signal
niq_at_chg1	Profit Growth	+0.16	+3.4	−0.1	+2.51	−0.24	+1.18	No signal
saleq_su	Profit Growth	+0.13	+2.1	+0.2	+1.55	+0.30	+1.13	No signal
ocf_at_chg1	Profit Growth	+0.10	+2.1	+1.2	+1.78	+1.44	+2.25	No signal
qmj	Profitability	+1.21	+7.5	+0.9	+3.38	+0.20	+2.22	Liquidity-demand
mispricing_perf	Profitability	+1.13	+9.5	+2.3	+4.10	+1.50	+3.59	Liquidity-demand
niq_at	Profitability	+0.83	+6.1	+1.6	+3.45	+1.20	+2.87	Liquidity-demand
ni_be	Profitability	+0.83	+6.0	+0.9	+2.92	+0.82	+2.32	Liquidity-demand
ebit_bev	Profitability	+0.80	+6.5	+1.7	+3.50	+1.23	+2.96	Liquidity-demand
niq_be	Profitability	+0.71	+6.6	+1.5	+3.50	+1.25	+2.98	Liquidity-demand
ni_me	Profitability	+0.70	+6.0	+2.3	+2.99	+1.50	+2.86	Liquidity-demand
qmj_prof	Profitability	+0.68	+6.9	+1.7	+3.99	+1.23	+3.42	Liquidity-demand
ebit_sale	Profitability	+0.68	+5.6	+0.5	+2.86	+0.30	+1.85	No signal
ope_bel1	Profitability	+0.58	+5.4	+1.5	+2.77	+1.24	+2.66	Liquidity-demand
op_at	Profitability	+0.51	+6.6	+1.1	+3.34	+0.92	+2.79	Liquidity-demand

Table IA.28 continued

Factor	Theme	d_f	Pre (bps)	Rest (bps)	t_{Pre}	t_{Rest}	t_{Full}	Category
op_atl1	Profitability	+0.51	+5.9	+1.1	+3.05	+0.87	+2.53	Liquidity-demand
ope_be	Profitability	+0.50	+6.2	+2.0	+3.00	+1.53	+2.99	Liquidity-demand
fcf_me	Profitability	+0.43	+2.2	+2.9	+1.52	+2.67	+3.02	Residual
cop_at	Profitability	+0.35	+6.4	+2.5	+3.79	+2.35	+4.24	Residual
gp_at	Profitability	+0.34	+5.3	+0.1	+2.94	+0.06	+1.82	No signal
cop_atl1	Profitability	+0.33	+6.1	+2.2	+3.63	+1.97	+3.81	Residual
gp_atl1	Profitability	+0.31	+4.7	−0.6	+2.54	−0.73	+0.86	No signal
niq_su	Profitability	+0.14	+3.2	+0.3	+2.87	+0.35	+1.87	No signal
ebitda_mev	Profitability	+0.07	+3.1	+3.2	+1.58	+2.82	+3.23	Residual
ocf_me	Profitability	−0.02	+1.8	+3.9	+1.13	+3.29	+3.47	Residual
qmj_safety	Quality	+1.68	+6.2	−0.4	+3.14	−0.41	+1.44	No signal
z_score	Quality	+0.68	+3.8	−1.2	+2.20	−1.03	+0.30	No signal
f_score	Quality	+0.30	+2.5	+1.4	+1.68	+1.23	+1.91	No signal
qmj_growth	Quality	+0.23	+4.5	+0.3	+3.15	+0.31	+2.05	Liquidity-demand
mispricing_mgmt	Quality	+0.15	+3.2	+3.3	+2.21	+3.47	+4.29	Residual
kz_index	Quality	−0.57	−1.2	−0.0	−0.82	+0.64	+0.11	No signal
o_score	Quality	−1.26	−5.7	−1.2	−3.29	−0.71	−2.40	Liquidity-demand
ret_1_0	ST Reversal	+0.49	+3.3	−1.6	+1.39	−0.78	+0.02	No signal
seas_1_1na	Seasonality	+0.85	+7.5	+1.6	+2.62	+1.06	+2.34	Liquidity-demand
seas_2_5na	Seasonality	+0.28	+2.1	−1.3	+1.11	−1.19	−0.50	No signal
seas_1_1an	Seasonality	+0.16	+3.6	+0.5	+2.03	+0.18	+1.20	No signal
seas_6_10na	Seasonality	+0.14	−3.5	−1.6	−2.13	−1.50	−2.41	Liquidity-demand
seas_2_5an	Seasonality	+0.09	+2.3	+2.0	+1.44	+2.03	+2.54	Residual

Table IA.28 continued

Factor	Theme	d_f	Pre (bps)	Rest (bps)	t_{Pre}	t_{Rest}	t_{Full}	Category
seas_11_15na	Seasonality	+0.07	−1.2	−0.8	−0.92	−1.03	−1.33	No signal
seas_6_10an	Seasonality	+0.06	+3.6	+3.3	+2.55	+3.56	+4.34	Residual
seas_16_20na	Seasonality	+0.04	−2.3	+0.3	−1.57	+0.12	−0.78	No signal
seas_11_15an	Seasonality	+0.03	+3.9	+1.5	+2.73	+1.73	+3.04	Liquidity-demand
seas_16_20an	Seasonality	+0.01	+2.4	+3.0	+1.59	+2.63	+3.05	Residual
at_me	Size	−0.36	−3.5	+2.1	−1.64	+1.62	+0.39	No signal
at_be	Size	−0.47	−1.5	+1.2	−0.82	+1.04	+0.43	No signal
prc_highprc_252d	Value	+1.44	+8.7	−1.8	+2.69	−0.87	+0.75	No signal
prc	Value	+1.23	+7.6	−0.1	+3.49	−0.05	+1.71	No signal
ocf_at	Value	+0.67	+6.3	+2.4	+3.73	+2.08	+3.85	Residual
sale_bev	Value	+0.47	+4.9	+2.8	+2.97	+2.87	+4.19	Residual
eqnpo_me	Value	+0.22	+4.9	+2.8	+2.68	+2.37	+3.34	Residual
eqpo_me	Value	−0.11	+1.3	+1.2	+0.64	+0.95	+1.15	No signal
div12m_me	Value	−0.11	+1.6	−0.2	+0.76	+0.02	+0.48	No signal
sale_me	Value	−0.58	−1.7	+3.3	−1.02	+2.84	+1.91	Opposite-signed
be_me	Value	−0.68	−2.9	+2.9	−1.20	+2.01	+1.06	Opposite-signed

IA.15 The Persistent Component: Triple Intersection of Identification Methods

The headline residual-zoo identification (Section 7.1) intersects three complementary tests at $|t| > 3$ under month-block bootstrap inference. Each test makes different assumptions and has different power properties; the intersection identifies factors robust to the methodological choice.

Table IA.29: The Persistent Factor Cohort

Method	Survivors at $\|t\| > 3$
A: Rest-window $\|t_{\text{Rest}}\| > 3$ (bootstrap)	23
B: Partialling-out $\|t_{\hat{\alpha}}\| > 3$ (bootstrap)	41
C: Full-month $\|t_{\text{full}}\| > 3$ (bootstrap)	49
A ∩ B	16
A ∩ C	22
B ∩ C	23
Triple intersection (A ∩ B ∩ C)	16
of which q-theory or q-related	15

Notes: Method A applies the bootstrap $|t| > 3$ threshold to factors' average daily Rest-window long-short return. Method B applies it to the partialled-out alpha $\hat{\alpha}_f = T^{-1} \sum_m [R^{\text{full}}_{f,m} - d_f \cdot b_{D,m}]$ where $b_{D,m}$ is the cross-sectional slope from monthly regressions of PreTOM returns on d_f. Method C applies it to the full-month average daily long-short return without dispensability conditioning. Each method uses month-block bootstrap with $B = 5{,}000$ draws on the 1963–2025 monthly factor panel (152 factors, prc_highprc_252d excluded as the self-loading factor). The triple intersection identifies factors that survive every method, i.e., are robust to the operationalization of the residual-significance test.

Table IA.30: Identity of the 16 Persistent Factors

Factor code	Description	Theme	Class	t_{Rest}	t_{full}	d_f
dsale_dinv	ΔSales − ΔInventory	Accruals	Strict q	+3.76	+4.65	+0.083
oaccruals_at	Operating accruals to assets	Accruals	Strict q	-4.35	-5.19	-0.016
oaccruals_ni	Operating accruals to net income	Accruals	Strict q	-3.89	-4.60	-0.094
netis_at	Net total (equity+debt) issuance to assets	Debt Issuance	q-related	-4.47	-4.81	-0.207
cowc_gr1a	Working-capital growth	Investment	Strict q	-3.62	-5.63	-0.140
inv_gr1a	Inventory growth	Investment	Strict q	-4.06	-4.35	-0.066
lnoa_gr1a	Long-term net operating assets growth	Investment	Strict q	-3.68	-3.77	-0.016
ncoa_gr1a	Non-current operating assets growth	Investment	Strict q	-3.36	-3.62	+0.036
nfna_gr1a	Net financial assets growth	Investment	Strict q	+3.40	+4.22	+0.079
nncoa_gr1a	Net non-current operating assets growth	Investment	Strict q	-3.56	-3.91	+0.000
noa_at	Net operating assets to assets	Investment	Strict q	-4.10	-5.57	-0.130
noa_gr1a	Net operating assets growth	Investment	Strict q	-4.23	-5.16	-0.054
ocf_me	Operating cash flow to market equity	Profitability	Strict q	+4.14	+4.36	+0.104
mispricing_mgmt	Stambaugh–Yuan MGMT composite	Quality	q-related	+3.85	+5.09	+0.203
seas_6_10an	Same-calendar-month seasonality (6–10y)	Seasonality	Seasonal	+3.68	+4.86	-0.009
sale_bev	Sales to book enterprise value	Value	q-related	+3.74	+4.48	-0.017

Notes: The persistent factors from Table 7. t_{Rest} is the t-statistic outside PreTOM after removing the d_f component; t_{full} is the unconditional full-month t; d_f is the dispensability exposure.

IA.16 The Persistent Component: Comparison Across Identification Strategies

The headline residual-zoo identification (Section 7.1) uses the partialling-out approach: factors with bootstrap $|t_{\hat{\alpha}_f}| > 3$, where $\hat{\alpha}_f$ is the full-month return after subtracting the dispensability-attributable component $d_f \cdot b_{D,m}$. The complementary check uses Rest-window returns directly. The two procedures answer slightly different questions: the alpha-based test asks "what is the factor's full-month return after accounting for dispensability exposure?"; the Rest-window test asks "what is the factor's return on days *outside* the dispensability window?" Both converge on the same q-theory residual.

P.1. Method 2 variants and permutation inference

Table IA.31: Residual Zoo: Survivor Counts Under Two Identification Strategies

	Both	α-based only	Rest-based only	Neither
$\lvert t\rvert > 3$ threshold	18	22	7	105
α-based total: 40; Rest-based total: 25				

Notes: α-based survivors: factors with $|t_{\alpha_f}| > 3$ where $\hat{\alpha}_f = T^{-1}\sum_m [R_{f,m} - d_f \cdot b_{D,m}]$, and $b_{D,m}$ is the month-m cross-sectional OLS slope of PreTOM returns on d_f across the 152 non-self-loading factors. $R_{f,m}$ is the full-month average daily long-short return. Inference: month-block bootstrap with $B = 5{,}000$ draws. Rest-based survivors: factors with $|t_{\text{Rest},f}| > 3$ on the 15-day Rest window (direct test on Rest returns). Sample: 1963–2025.

Table IA.32: Method 2 Variants and Permutation Inference

	Real d_f		Shuffle persistent factor count (90% interval)		
Variant	Persistent factors	q-share	5th pctile	50th pctile	95th pctile
Monthly M2 ∩ M1 ∩ M3 (baseline)	15	86.7%	19	21	22
Daily M2 ∩ M1 ∩ M3	11	72.7%	12	15	17
Monthly M2 ∩ M1 ∩ M3, Rest\Post	1	100%	4	4	5
Daily M2 ∩ M1 ∩ M3, Rest\Post	4	75.0%	4	4	5

Notes: M1 = Rest-window significance ($|t| > 3$). M2-monthly residualizes monthly factor returns on the month-m cross-sectional slope on d_f; M2-daily residualizes daily returns on the day-t cross-sectional slope on d_f, then sums to monthly. M3 = full-month significance ($|t| > 3$). Rest\Post excludes the $[\tau-3, \tau+3]$ window from Rest. q-share = fraction of persistent factors classified in Investment, Accruals, Profitability, or Quality-mispricing themes in JKP. Shuffle distribution from 50 permutations of d_f across the 152 factors, re-running the full Method 2 procedure each iteration. The real persistent factor count sits below the shuffle 5th percentile in three of four variants and equals the 5th percentile in the fourth. Baseline persistent factor identities (monthly ∩ Rest) listed in Table IA.29; the single Rest\Post-monthly persistent factor is *noa_at*; the four Rest\Post-daily persistent factors are *mispricing_mgmt*, *netis_at*, *noa_at*, and *ocf_at*.

IA.17 T+1 DiD Bootstrap: Robustness to Pre-Reform Start

The headline T+1 DiD bootstrap in Table IA.42 uses 1963 as the pre-reform start. We confirm robustness to this choice by re-running the bootstrap with pre-reform starts of 1980, 2000, 2010, and 2017-09 (the T+2 settlement era). Across the five windows, anchor $\hat{b}$ varies by less than 10% (range +29.0 to +32.0) and bootstrap t varies by less than 0.13 (range +1.72 to +1.84). Power is bound by the fixed 19-month post-reform sample, not by pre-reform length.

IA.18 Pre/Post-1990 Subperiod Robustness

The cross-sectional dispensability premium in PreTOM is stable across a 1990 cut: $b_D = +6.29$ ($t = +8.32$) before 1990 versus $b_D = +5.23$ ($t = +8.11$) after, with R^2 attenuating from 0.68 to 0.50. Within-theme correlations between d_f and PreTOM returns are similarly stable across most JKP themes. One exception is the accruals theme, where the within-theme correlation flips from +0.89 to −0.16, consistent with the well-documented post-publication attenuation of the accruals anomaly (Green, Hand, and Soliman, 2011). The Rest-window structural break documented in §9.2 of the main paper occurs around 2003, not 1990, and reflects evolving post-PreTOM dynamics (decimalization, factor-premium compression) rather than the institutional-intermediation transition the 1990 cut would isolate.

Panel A. Cross-sectional slope

	PreTOM			Rest		
Period	$\hat{b}_D$	t	R^2	$\hat{b}_D$	t	R^2
1963–1990	+6.288	+8.32	0.677	+1.149	+1.47	0.075
1990–2025	+5.227	+8.11	0.502	+0.162	+0.28	0.002

Panel B. Within-theme decomposition

		1963–1990			1990–2025		
Theme	k	$\overline{d_f}$	$\overline{R^{Pre}}$	ρ	$\overline{d_f}$	$\overline{R^{Pre}}$	ρ
Momentum	7	+1.23	+6.79	+0.84	+1.11	+5.82	+0.70
Profitability	21	+0.35	+4.01	+0.82	+0.37	+5.64	+0.67
Value	9	+0.42	+3.03	+0.93	+0.34	+3.31	+0.80
Profit Growth	5	+0.31	+3.93	+0.89	+0.15	+2.78	+0.93
Quality	7	+0.07	+1.06	+0.98	+0.07	+2.36	+0.92
Seasonality	10	+0.18	+1.41	+0.79	+0.18	+1.95	+0.63
Accruals	8	−0.03	−1.64	+0.89	+0.03	+0.85	−0.16
Investment	27	−0.02	−1.90	+0.84	+0.02	+0.19	+0.59
Other	27	−0.07	−0.77	+0.69	−0.10	−0.37	+0.20
Debt Issuance	8	−0.18	−2.68	+0.75	−0.08	−1.51	+0.61
Low Risk	20	−0.37	−3.09	+0.84	−0.35	−2.64	+0.84

IA.19 Cross-Factor Horse Race: Candidate Construction

This appendix documents the construction of the eight candidate predictors used in the cross-factor horse race (Section 7.2, Table 8). Each candidate is summarized by a single per-factor scalar that we regress against the dispensability loading d_f and the average daily long-short return $\bar{R}_f$ in PreTOM and Rest. All candidates are cross-sectionally standardized (mean 0, standard deviation 1) within the regression so that coefficients are comparable across rows.

S.1. Mechanical-overlap and risk-loading candidates

UMD overlap. For each factor f we compute the value-weighted holdings overlap between f's deciles and the Jegadeesh and Titman (1993) 12–2 momentum sort. Overlap is defined as the time-average market-cap-weighted correlation between the indicator vector of stocks in f's extreme decile and the indicator vector of stocks in UMD's matching extreme decile. Construction uses portfolio composition rather than realized returns, so the test does not condition on the dependent variable. Sample: 1963–2025 monthly holdings.

Market beta (d_f^{β}). The factor-level market-beta loading is the time-averaged D10−D1 difference of stock-level 60-month rolling market beta (JKP `beta_60m`) within each factor's NYSE-breakpoint deciles. Sample: 1963–2025.

S.2. Liquidity- and friction-based candidates

Pastor-Stambaugh aggregate liquidity (β_f^L). For each factor we estimate a monthly time-series regression of the long-short return on the Pástor and Stambaugh (2003) non-traded liquidity-innovation series (eq. 8 in the original paper), controlling for the Fama-French three factors with Newey-West HAC standard errors at four lags:

$$R_{f,m}^{LS} = a_f + b_f^{\text{Mkt}}\text{MktRF}_m + b_f^{\text{SMB}}\text{SMB}_m + b_f^{\text{HML}}\text{HML}_m + \beta_f^L \text{LIQ}_m + \varepsilon_{f,m}.$$

β_f^L is the FF3-controlled slope. Sample: 1962–2024 (PS liquidity-data window).

Amihud illiquidity (β_f^A). The factor-level Amihud loading is the time-averaged D1−D10 difference of stock-level six-month rolling Amihud illiquidity (JKP `ami_126d`) within each factor's NYSE-breakpoint deciles. Sample: 1980–2024 (Amihud panel-availability window).

Shorting cost (SIRIO). We follow Drechsler and Drechsler (2021) in proxying shorting cost by the ratio of short interest to institutional ownership. SIRIO is computed at the stock-month level from Compustat short interest and 13F institutional holdings, then aggregated to the factor level as the time-averaged value-weighted D1−D10 difference within each factor's NYSE-breakpoint deciles. Sample: 2003–2025 (matched window for both the SIRIO panel and the corresponding $\bar{R}_f$ in the horse-race regression).

S.3. Belief- and sentiment-based candidates

Subjective Belief Factor (β_f^{SBF}). The SBF series is the realized one-quarter-ahead state variable s_{t+1} from Cui, De la O, and Myers (2025), sampled quarterly 1982Q4–2022Q2 and provided directly by the authors. We forward-fill the quarterly series to daily ($\mathrm{SBF}_d = s_{Q(d)}$ for days d in realization quarter Q) and estimate per-factor daily time-series regressions with FF3 controls and Newey-West HAC standard errors at 60 lags:

$$r_{f,d} = a_f + b_f^{\mathrm{Mkt}}\mathrm{MktRF}_d + b_f^{\mathrm{SMB}}\mathrm{SMB}_d + b_f^{\mathrm{HML}}\mathrm{HML}_d + \beta_f^{\mathrm{SBF}}\mathrm{SBF}_d + \varepsilon_{f,d}.$$

β_f^{SBF} is the SBF loading per factor. Sample: 1982Q4–2022Q2.

MGMT and PERF mispricing factors. We follow Stambaugh and Yuan (2017) (Section IA.12) and use their MGMT and PERF composites, each constructed as an average of percentile ranks across constituent anomaly signals. The factor-level loadings MGMT_f and PERF_f are the time-averaged value-weighted D1−D10 differences of stock-level MGMT and PERF scores within each factor's NYSE-breakpoint deciles. Sample: 1963–2025.

S.4. Sample-matching for the horse-race regression

For each candidate, both the dependent variable $\bar{R}_f$ and the candidate X_f are recomputed on a sample window matched to the candidate's data availability: 1980–2024 for Amihud, 2003–2025 for SIRIO, 1982Q4–2022Q2 for SBF, and 1963–2025 for the remaining five candidates. Matched-sample d_f-alone R^2 values appear in column 3 of Table 8; the ΔR^2 column reports the joint-minus-d_f-alone difference, which isolates each candidate's incremental cross-sectional content beyond what dispensability captures on the same sample.

IA.20 Per-Factor PreTOM Coefficient

The per-factor PreTOM dummy regression (paper equation 6) yields one $\hat{\lambda}_f$ per factor. Table IA.34 ranks all 153 JKP factors from most positive (factors that earn most of their returns in the PreTOM window) to most negative (factors actively suppressed by the window). Pre and Rest columns are the average daily long–short return in each window (bps/day); $\hat{\lambda}_f$ = Pre − Rest.

Table IA.34: Per-Factor PreTOM Coefficient $\hat{\lambda}_f$, All 153 JKP Factors

Rank	Factor	$\hat{\lambda}_f$ (bps/day)	Pre (bps/day)	Rest (bps/day)
1	prc_highprc_252d	10.47	8.47	-2.00
2	qmj_safety	6.89	5.84	-1.05
3	prc	6.81	6.03	-0.78
4	ret_12_1	6.20	10.25	4.05
5	seas_1_1na	6.07	8.08	2.02
6	ret_9_1	5.60	8.61	3.01
7	qmj	5.60	6.06	0.46
8	mispricing_perf	5.59	8.18	2.59
9	niq_be_chg1	5.22	6.13	0.91
10	ret_1_0	5.15	2.75	-2.40
11	qmj_prof	4.74	5.75	1.01
12	ebit_sale	4.73	4.36	-0.37
13	niq_be	4.65	6.18	1.54
14	niq_at	4.46	5.56	1.09
15	op_at	4.19	5.14	0.95
16	ebit_bev	3.96	5.24	1.27
17	niq_at_chg1	3.96	4.27	0.32
18	zero_trades_252d	3.78	2.67	-1.11
19	zero_trades_21d	3.74	1.64	-2.09
20	zero_trades_126d	3.58	2.26	-1.33
21	op_atl1	3.56	4.56	0.99
22	gp_atl1	3.52	3.55	0.02
23	ni_be	3.52	3.85	0.33
24	sale_emp_gr1	3.48	2.59	-0.89
25	gp_at	3.48	3.82	0.35

Rank	Factor	$\hat{\lambda}_f$	Pre	Rest
26	ope_be	3.30	4.82	1.52
27	ocf_at	3.11	5.09	1.98
28	eq_dur	2.93	0.69	-2.24
29	cop_at	2.91	5.19	2.27
30	ret_60_12	2.90	1.28	-1.61
31	z_score	2.86	2.60	-0.25
32	ope_bel1	2.81	4.05	1.24
33	ret_6_1	2.74	6.05	3.31
34	cop_atl1	2.73	4.86	2.14
35	col_gr1a	2.69	3.43	0.73
36	niq_su	2.67	3.72	1.05
37	qmj_growth	2.67	3.21	0.55
38	sale_gr1	2.62	1.91	-0.72
39	tax_gr1a	2.55	2.76	0.22
40	div12m_me	2.53	1.97	-0.56
41	eqnpo_12m	2.51	3.72	1.22
42	ret_12_7	2.44	6.36	3.92
43	saleq_gr1	2.25	3.40	1.16
44	resff3_6_1	2.19	2.87	0.68
45	rd5_at	2.12	1.89	-0.22
46	ni_inc8q	2.05	1.84	-0.21
47	dolvol_var_126d	2.05	1.42	-0.63
48	seas_2_5na	1.97	0.32	-1.65
49	rd_sale	1.86	1.45	-0.40
50	tangibility	1.81	1.61	-0.21
51	dsale_dsga	1.79	0.95	-0.84
52	f_score	1.63	2.78	1.15
53	eqnpo_me	1.52	4.51	2.98
54	ni_me	1.47	3.87	2.40
55	turnover_var_126d	1.44	1.01	-0.43
56	dgp_dsale	1.39	1.94	0.54
57	lnoa_gr1a	1.34	-1.05	-2.39
58	age	1.32	1.07	-0.26
59	saleq_su	1.30	2.19	0.89

Rank	Factor	$\hat{\lambda}_f$	Pre	Rest
60	seas_11_15an	1.30	3.03	1.72
61	ret_3_1	1.24	3.61	2.37
62	inv_gr1a	0.97	-1.89	-2.85
63	at_gr1	0.86	-0.97	-1.83
64	ami_126d	0.85	0.66	-0.19
65	pi_nix	0.85	1.68	0.83
66	resff3_12_1	0.83	3.99	3.16
67	netis_at	0.79	-2.42	-3.21
68	seas_16_20an	0.73	2.74	2.02
69	seas_1_1an	0.69	2.85	2.17
70	ncoa_gr1a	0.68	-1.50	-2.18
71	seas_6_10an	0.60	3.61	3.01
72	eqpo_me	0.59	1.85	1.26
73	taccruals_ni	0.59	-0.66	-1.25
74	earnings_variability	0.56	-0.41	-0.98
75	rmax5_rvol_21d	0.56	-1.68	-2.24
76	taccruals_at	0.53	-0.49	-1.03
77	mispricing_mgmt	0.53	3.53	3.01
78	be_gr1a	0.51	-0.22	-0.73
79	dbnetis_at	0.50	-0.88	-1.38
80	nncoa_gr1a	0.45	-1.89	-2.34
81	sale_gr3	0.44	0.28	-0.16
82	sale_bev	0.36	3.28	2.92
83	inv_gr1	0.36	-1.84	-2.19
84	market_equity	0.30	0.27	-0.03
85	nfna_gr1a	0.25	2.27	2.02
86	dsale_dinv	0.24	2.62	2.37
87	capx_gr2	0.20	-1.72	-1.93
88	coa_gr1a	0.18	-1.50	-1.68
89	fcf_me	0.14	2.53	2.39
90	at_turnover	0.12	1.37	1.25
91	opex_at	0.07	1.18	1.11
92	capx_gr1	-0.01	-1.84	-1.83
93	oaccruals_ni	-0.14	-2.70	-2.55

Rank	Factor	$\hat{\lambda}_f$	Pre	Rest
94	dsale_drec	-0.24	-0.41	-0.17
95	ocf_at_chg1	-0.24	1.42	1.66
96	ebitda_mev	-0.26	2.45	2.71
97	debt_gr3	-0.30	-0.59	-0.29
98	rskew_21d	-0.36	0.35	0.71
99	noa_gr1a	-0.40	-3.18	-2.77
100	coskew_21d	-0.49	-0.76	-0.26
101	capx_gr3	-0.49	-2.12	-1.62
102	capex_abn	-0.63	-2.15	-1.53
103	fnl_gr1a	-0.67	-1.96	-1.29
104	oaccruals_at	-0.77	-3.83	-3.05
105	sti_gr1a	-0.81	-1.29	-0.48
106	seas_2_5an	-0.87	1.63	2.50
107	seas_11_15na	-0.97	-1.70	-0.73
108	ppeinv_gr1a	-0.99	-2.90	-1.91
109	seas_16_20na	-1.07	-1.89	-0.83
110	eqnetis_at	-1.25	-3.40	-2.15
111	noa_at	-1.34	-3.86	-2.52
112	aliq_at	-1.35	-0.76	0.59
113	cash_at	-1.36	0.42	1.78
114	ocf_me	-1.49	2.01	3.50
115	lti_gr1a	-1.54	-1.60	-0.06
116	iskew_ff3_21d	-1.63	-0.14	1.49
117	ni_ar1	-1.70	-1.13	0.56
118	iskew_capm_21d	-1.71	-0.55	1.16
119	rd_me	-1.74	0.38	2.12
120	dolvol_126d	-1.80	-1.76	0.04
121	iskew_hxz4_21d	-1.87	-0.06	1.81
122	emp_gr1	-1.87	-2.37	-0.50
123	seas_6_10na	-1.98	-3.45	-1.47
124	kz_index	-2.13	-1.66	0.47
125	at_be	-2.19	-1.54	0.65
126	chcsho_12m	-2.26	-4.34	-2.08
127	ncol_gr1a	-2.27	-1.70	0.57

Rank	Factor	$\hat{\lambda}_f$	Pre	Rest
128	turnover_126d	-2.53	-0.87	1.65
129	cowc_gr1a	-2.82	-5.07	-2.25
130	ival_me	-3.12	-1.25	1.87
131	o_score	-3.43	-4.29	-0.85
132	ni_ivol	-3.56	-2.45	1.10
133	corr_1260d	-3.58	-2.61	0.97
134	bev_mev	-3.73	-2.34	1.39
135	netdebt_me	-3.83	-3.12	0.71
136	aliq_mat	-3.90	-1.35	2.54
137	ocfq_saleq_std	-3.93	-3.79	0.14
138	at_me	-3.95	-2.21	1.74
139	bidaskhl_21d	-4.18	-3.55	0.64
140	sale_me	-4.32	-1.53	2.79
141	betadown_252d	-4.99	-2.04	2.95
142	be_me	-5.08	-2.10	2.98
143	debt_me	-5.40	-3.52	1.88
144	rmax1_21d	-5.41	-5.18	0.23
145	rmax5_21d	-5.44	-5.48	-0.04
146	ivol_hxz4_21d	-5.64	-6.70	-1.06
147	ivol_capm_21d	-5.89	-6.74	-0.84
148	beta_dimson_21d	-5.94	-3.84	2.10
149	ivol_ff3_21d	-6.15	-6.67	-0.53
150	ivol_capm_252d	-6.84	-7.15	-0.32
151	rvol_21d	-6.88	-5.99	0.89
152	beta_60m	-8.96	-5.05	3.91
153	betabab_1260d	-9.09	-6.40	2.69

IA.21 Short-Leg vs Long-Leg Decomposition

We decompose each factor's PreTOM premium into the contribution from its short leg (the lower-prc decile) and its long leg (the higher-prc decile), each signed so that "factor wins" is positive ($y_f^{\text{short}} = -\bar{r}_f^{\text{short,Pre}}$ and $y_f^{\text{long}} = +\bar{r}_f^{\text{long,Pre}}$ in daily basis points). Each leg is then regressed on the absolute dispensability gap $|d_f|$ across all 153 factors, with theme-clustered standard errors:

Dependent (bps/day)	$\hat{b}$	t	R^2	Mean
y_f^{short} in PreTOM	**+2.77**	**+10.23**	0.371	+5.97
y_f^{long} in PreTOM	+1.26	+5.26	0.237	−3.64
y_f^{short} in Rest	+0.25	+0.84	0.011	—
y_f^{long} in Rest	−0.43	−0.76	0.032	—

Of the cross-sectional gradient, $69\% = 2.77/(2.77 + 1.26)$ comes from the short leg and 31% from the long leg; both vanish in Rest.

IA.22 Theme-Level PreTOM versus Rest, Daily Long–Short Returns

The bar chart below is the visual companion to Table 1 in the paper.

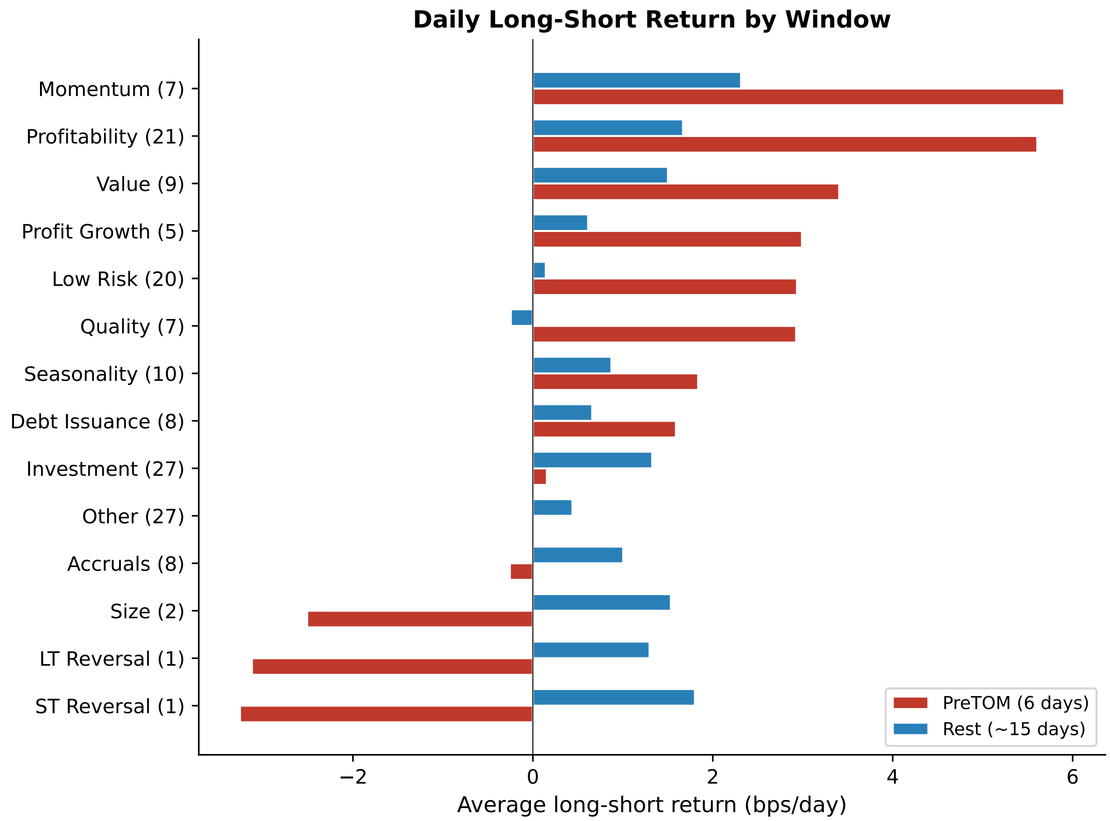

Figure IA.4: Average daily long–short return (bps/day) during the PreTOM window (red) and the rest of the month (blue) for each JKP theme. Returns are raw $D10 - D1$ with no per-factor sign flip, consistent with the convention defined in Section 2.3 of the paper. Number of factors per theme in parentheses. Companion to Table 1.

IA.23 Principal Component Analysis Corroboration

This appendix verifies that the dispensability identification documented in Section 3.5 is consistent with a non-parametric decomposition of the factor return matrix. PCA and the d_f regressions answer different questions: PCA decomposes daily factor-return covariance, while the d_f regressions decompose calendar-window mean returns. We use PCA as corroboration that the dispensability axis is a persistent feature of factor co-movement, complementing the cross-sectional mean-return evidence in the main text.

W.1. Setup

We form a daily long–short return matrix $R \in \mathbb{R}^{T \times F}$ from the JKP universe, where the columns are factor long–short returns ($D10 - D1$, value-weighted, NYSE breakpoints) and the rows are trading days, 1963–2025. We keep factors with at least 95% daily coverage on common dates, yielding $F = 142$ factors (the self-loading `prc_highprc_252d` is excluded along with ten additional factors whose daily series fall below the 95% coverage threshold). The pairwise correlation analysis in Section IA.26 uses the full 152 non-self-loading factors with pairwise-complete observations; the residual-zoo filter in the main paper uses all 152. We then form three sub-samples: full (T = 15,206 days), PreTOM-only (T = 4,350 days corresponding to $\tau-9$ through $\tau-4$ of each month), and Rest-only (T = 10,856 days). Within each sub-sample, factor returns are standardized to unit variance, and the singular-value decomposition of the standardized matrix gives the principal components. The right-singular vectors are the factor loadings on each component. We sign-align each component so that its correlation with d_f across factors is non-negative.

W.2. Correlation PCA recovers dispensability as PC2

The first two principal components of the standardized 142-factor daily return matrix explain 36.1% of total variance, with PC1 explaining 18.62% and PC2 explaining 17.51%. Higher-order components each explain less than 7%.

PC2 loadings correlate strongly with d_f across sub-samples (Table IA.35, Panel A): the correlation is 0.73 in PreTOM-only days, 0.75 in Rest-only days, and 0.74 in the full sample. PC1 loadings are essentially orthogonal to d_f (correlations 0.02 to 0.13); PC1 concentrates on book-to-market and sales-to-price at one end versus asset growth and sales growth at the other, describing the value-versus-investment co-movement documented in the asset-pricing literature.

W.3. Covariance PCA promotes dispensability to PC1

Correlation-matrix PCA standardizes each factor to unit variance before decomposition, while covariance-matrix PCA preserves raw factor volatilities. Because factors with high absolute dispensability exposure are also high-volatility factors (Table IA.36), covariance PCA places greater weight on the dispensability dimension and identifies it as PC1: PC1 explains 27.71% of total variance and its loadings correlate 0.69 with d_f (Table IA.35, Panel B).

W.4. Stability across sub-samples

The PCA structure is essentially identical across PreTOM-only, Rest-only, and full-sample windows under both specifications (Table IA.35). Under correlation PCA, PC2's variance share and its correlation with d_f are stable to within sampling error. Under covariance PCA, PC1's variance share moves by less than one percentage point across the three sub-samples (27.24% in PreTOM, 27.90% in Rest, 27.71% in full), and its correlation with d_f moves by less than two correlation points (0.675, 0.691, 0.687). The factor-loading structure is therefore essentially the same in every calendar window, rather than regime-dependent.

W.5. Tercile reversal table

Table IA.9 reports the Post-on-PreTOM cross-sectional regression within terciles of $|d_f|$, referenced in Section 3.5 of the main paper. The positive slope in the low-$|d_f|$ tercile and the negative slope in the high-$|d_f|$ tercile show that the Post-window reversal strengthens monotonically with the strength of the dispensability loading.

W.6. Implication for the value–momentum correlation

The stable-covariance interpretation has a concrete implication for one of the most studied pairwise relationships in the factor literature. Removing the daily d_f component from each factor's return reduces the unconditional value–momentum correlation from -0.64 to -0.36, a 44% reduction. The reduction is similar inside and outside PreTOM (42% in PreTOM, 45% in Rest), consistent with the covariance-PCA finding that the d_f axis is a stable structural mode. Section 8.3 of the main paper discusses this result in the context of Asness, Moskowitz, and Pedersen (2013).

Table IA.33: T+1 DiD Bootstrap: Robustness to Pre-Reform Start Date

Pre-reform start	$\hat{b}$	Cluster t	R^2	Boot SE	Boot t	Boot 95% CI on R^2	T_{pre}
1963-01 (headline)	+31.638	+4.76	0.131	17.23	+1.84	$(0.005, 0.208)$	735
1980-01	+32.040	+4.78	0.127	17.56	+1.82	$(0.004, 0.204)$	532
2000-01	+31.164	+4.81	0.123	17.33	+1.80	$(0.006, 0.197)$	292
2010-01	+30.021	+4.71	0.119	17.48	+1.72	$(0.003, 0.195)$	172
2017-09 (T+2 era)	+29.047	+4.20	0.124	16.78	+1.73	$(0.004, 0.200)$	80

Notes: Each row is the per-factor T+1 DiD cross-sectional regression $\hat{\delta}_f = a + b \cdot d_f + u_f$ across all 153 factors, with the pre-reform sample running from the listed start date through April 2024. The post-reform window is fixed at 19 months (June 2024 – December 2025; May 2024 dropped as transition). Theme-clustered t uses 14 JKP clusters. Bootstrap t is from $B = 5{,}000$ month-block draws (pre and post months resampled separately; both $\hat{\delta}_f$ and d_f recomputed inside every draw). Anchor $\hat{b}$ varies by less than 10% across windows; bootstrap t varies by less than 0.13. Power is bound by the 19-month post-reform sample, not by the pre-reform length. The 1963-start spec is used as the headline in Table IA.42 because it gives the cleanest d_f estimate and the highest bootstrap t.

Table IA.35: Principal Component Analysis of the Daily Factor-Return Matrix

	Matrix		PC1		PC2	
Sub-sample	Days	Factors	Variance	$\rho(\text{PC1}, d_f)$	Variance	$\rho(\text{PC2}, d_f)$
Panel A: Correlation PCA (per-column standardization before SVD)						
PreTOM-only	4,350	142	18.65%	+0.129	17.49%	+0.728
Rest-only	10,856	142	18.64%	+0.023	17.52%	+0.747
Full sample	15,206	142	18.62%	+0.020	17.51%	+0.744
Panel B: Covariance PCA (demean only, no standardization)						
PreTOM-only	4,350	142	27.24%	+0.675	19.87%	+0.492
Rest-only	10,856	142	27.90%	+0.691	19.47%	+0.485
Full sample	15,206	142	27.71%	+0.687	19.57%	+0.486

Notes: Singular-value decomposition of the daily 142-factor long–short return matrix, applied separately to PreTOM days ($\tau-9$ through $\tau-4$), Rest days, and the full sample, 1963–2025. Panel A standardizes each factor's returns to unit variance within the sub-sample before the SVD (correlation matrix); Panel B demeans only (covariance matrix). Correlation PCA asks whether dispensability is a common pattern after equalizing factor volatilities; covariance PCA asks whether it is an economically large source of total factor-return variation. "Variance" is the share of total variance explained by the corresponding principal component. $\rho(\text{PC}k, d_f)$ is the Pearson correlation between the k-th principal component's factor loadings and the dispensability loading d_f, computed across the 142 factors. PC sign is arbitrary; we align signs so the correlation is non-negative. The 142 factors are those with at least 95% daily coverage on common dates (`prc_highprc_252d` is excluded as the self-loading factor).

W.7. Conclusion

PCA recovers dispensability as an axis of factor co-movement, especially in covariance space, where PC1 explains 27.71% of daily factor-return variance and its loadings correlate 0.69 with d_f. This alignment is stable across PreTOM, Rest, and the full sample. The dispensability dimension is therefore not created mechanically by the PreTOM return premium, but is present across the factor cross-section. What changes across the month is not the existence of the axis, but its expected return: the d_f slope is large and positive in PreTOM, small in Rest, and negative in Post (Section 3.5 of the main paper).

Table IA.36: Daily Factor Volatility by Dispensability Loading

$\lvert d_f \rvert$ tercile	Mean σ_f (bps/day)	N
Low ($\lvert d_f \rvert$ near 0)	77.8	47
Middle	82.6	47
High ($\lvert d_f \rvert$ large)	116.5	48
Cross-factor regression		
$\sigma_f = a + b \cdot d_f$	$b = -0.81$ ($t = -0.17$), $R^2 = 0.000$	$N = 142$
$\sigma_f = a + b \cdot \lvert d_f \rvert$	$b = +49.80$ ($t = +11.30$), $R^2 = 0.477$	$N = 142$

Notes: Per-factor daily return volatility (σ_f = standard deviation of the daily long–short return, bps/day, computed over 1963–2025) for the 144 JKP factors with non-missing d_f. The upper panel reports the mean σ_f by tercile of $|d_f|$. The lower panel reports cross-factor regressions of σ_f on d_f (signed) and on $|d_f|$ (absolute), each estimated by OLS.

IA.24 Stock-Level Fama-MacBeth Specification

This appendix gives the two-stage Fama-MacBeth specification underlying the stock-level results reported in Section 6.1 of the main paper. In the first stage, for each trading day t, we regress stock-level market-adjusted returns on dispensability-quintile dummies and three Fama-French controls (lagged 60-month market beta, log market capitalization, and book-to-market):

$$r_{i,t} - r_t^m \;=\; a_t \;+\; \sum_{q=2}^{5} b_{q,t}\, \mathbf{1}\{Q_{i,m-1} = q\} \;+\; \gamma_t' X_{i,m-1} \;+\; u_{i,t}, \tag{11}$$

$Q_{i,m-1} \in \{1, \ldots, 5\}$ is stock i's NYSE-breakpoint quintile of the dispensability score $D_{i,m-1}$ at month-end $m-1$, with Q_1 (least dispensable, near-52-week-high) omitted. $X_{i,m-1} = (\beta_{i,m-1}, \log ME_{i,m-1}, BM_{i,m-1})$ is the control vector.

The second stage decomposes each daily slope into Rest and PreTOM components:

$$b_{q,t} \;=\; c_0^q + c_1^q\, \mathrm{PreTOM}_t + v_{q,t}, \quad q \in \{2, \ldots, 5\}, \tag{12}$$

with Newey-West standard errors at five lags. $\hat{c}_1^5$ is the Q5−Q1 PreTOM-minus-Rest differential. The quintile coefficients are $\hat{c}_1^2 = -2.09$, $\hat{c}_1^3 = -4.25$, $\hat{c}_1^4 = -3.57$, and $\hat{c}_1^5 = -6.14$ in bps/day, all with $|t| > 2.8$ (Table IA.52 in the main paper). Stocks far from their 52-week highs underperform stocks near them by roughly six basis points per day during the six PreTOM days after controlling for the three Fama-French firm characteristics.

Table IA.37: Stock-Level Fama-MacBeth with Characteristic Controls

	λ_{PreTOM}		λ_{Rest}		Difference	
Specification	coef	t	coef	t	coef	t
Continuous $z(d)$ regressor						
$z(d)$	−3.65	−6.38	−0.81	−1.84	−2.84	−4.19
+ log(ME), log(BM)	−4.44	−7.05	−0.73	−1.59	−3.72	−4.95
+Mom$_{12-1}$, Rev$_1$	−4.73	−6.77	−1.51	−3.13	−3.22	−3.89
+InvGr, GP/A, Ivol	−4.28	−6.46	−1.18	−2.54	−3.10	−3.92
Quintile-dummy regressors (Spec 3 controls)						
Q5 (Disp) dummy	−4.57	−5.84	−1.53	−2.79	−3.04	−3.27
Q1 (Favor) dummy	+1.40	+3.01	+0.32	+1.07	+1.08	+1.98

Notes: Daily cross-sectional Fama-MacBeth regression of excess stock returns (in basis points) on lagged dispensability $z(d)$ plus characteristic controls. For each trading day d:

$$r_{i,d} = \alpha_d + \lambda_d \cdot z(d)_{i,m-1} + \boldsymbol{\gamma}' \mathbf{X}_{i,m-1} + \varepsilon_{i,d}.$$

$z(d)_{i,m-1} = -z(\mathit{prc\_highprc\_252d})_{i,m-1}$, within-month cross-sectionally standardized at the end of the prior month. Controls $\mathbf{X}$ vary by specification: Spec 1 univariate; Spec 2 adds log(ME) and log(BM); Spec 3 adds 12-1 momentum and 1-month reversal; Spec 4 adds investment growth, gross profitability and idiosyncratic volatility (HXZ4-like). Quintile-dummy panel uses the canonical *fmd_q* NYSE-BP quintiles (Q5 = Disp, Q1 = Favor), both included alongside Spec 3 controls. The daily cross-sectional slope λ_d is collected and aggregated separately for PreTOM days ($\tau - 9$ to $\tau - 4$) and Rest-of-month days. Time-series Newey–West HAC standard errors with 6 lags. Sample: JKP universe of common stocks (`shrcd` 10/11), 1963–Dec 2025; ∼3,200 to 3,650 stocks per day, 4,536 PreTOM days and 11,320 Rest days. The PreTOM coefficient is large negative and highly significant across all specifications; the Rest coefficient is small; and the PreTOM–Rest difference is significant at $|t| > 3$ in every spec. The Q5 dummy is significantly negative and the Q1 dummy is significantly positive in PreTOM, both with the predicted sign.

Table IA.38: Factor Taxonomy by JKP Theme

Theme	N	Liquidity-demand	Opposite-signed	Market-mechanical	Residual	No signal	Avg d_f
Momentum	7	4	0	0	1	2	+0.58
Profitability (inc.)	**16**	**12**	**0**	**0**	**0**	**4**	**+0.65**
Profitability (CF)	**6**	**0**	**0**	**0**	**6**	**0**	**+0.30**
Investment	27	0	1	0	12	14	+0.13
Value	8	0	2	0	2	4	+0.24
Quality	7	2	0	0	1	4	+0.17
Low Risk	20	0	0	20	0	0	−0.30
Seasonality	10	3	0	0	3	4	+0.17
Debt Issuance	8	1	0	0	3	4	−0.28
Profit Growth	5	1	0	0	0	4	+0.16
Accruals	8	0	0	0	2	6	+0.17
Other	27	1	1	0	0	25	−0.09
Total	149	24	4	20	30	71	

Notes: Classification uses a uniform $|t| > 1.96$ rule on signed long–short returns. *Liquidity-demand*: significant full-month, significant PreTOM, not significant in Rest. *Opposite-signed*: not significant full-month, significant in Rest. *Market-mechanical*: all factors in the JKP Low Risk theme, whose PreTOM concentration reflects aggregate market-beta exposure rather than targeted dispensability selling. *Residual*: significant in Rest, not otherwise classified. *No signal*: not significant in either window. Buckets are mutually exclusive. Profitability is split into income-statement-based (operating profit, net income, earnings) and cash-flow-based (cash operating profitability, free cash flow, operating cash flow, EBITDA/EV); bolded to highlight the dispensability contrast. The cash-flow group includes *ocf_at* (operating cash flow to assets), which JKP assign to the Value theme but we regroup here with cash-flow profitability; this accounts for Profitability totalling 22 here versus 21 in the JKP convention, with Value at 8 versus 9. Avg d_f is the mean dispensability loading (D1−D10) across factors in each theme. Size ($N = 2$), ST Reversal ($N = 1$), and LT Reversal ($N = 1$) are omitted from the table (all four have no residual signal), so the table totals 149; body text counts based on all 153 factors include these four in the no-signal category ($71 + 4 = 75$). This classification uses a permissive $|t| > 1.96$ threshold, so the combined Residual + Opposite-signed count ($30 + 4 = 34$) is broader than the 16-factor persistent component reported in the body text, which applies the Harvey, Liu, and Zhu (2016) $|t| > 3$ threshold to the triple intersection.

Table IA.39: Horse Race Against Three Additional Predictors

	X alone		d_f alone	$d_f + X$ jointly			ΔR^2
Candidate	coef (t_{boot})	R^2	R^2	d_f coef (t_{boot})	X coef (t_{boot})	R^2	from X
Panel A: PreTOM ($\bar{R}_f^{Pre}$)							
ILLIQ	+1.43 (+2.84)	0.15	0.57	+5.49 (+3.03)	−0.02 (−0.06)	0.57	+0.00
SIRIO	+1.62 (+2.06)	0.20	0.56	+5.07 (+3.02)	+0.31 (+0.43)	0.57	+0.01
SBF	−1.81 (−2.79)	0.25	0.53	+4.60 (+2.62)	−0.63 (−1.65)	0.56	+0.02
Panel B: Rest of month ($\bar{R}_f^{Rest}$)							
ILLIQ	+0.32 (+0.91)	0.04	0.03	+0.33 (+0.27)	+0.23 (+0.89)	0.04	+0.01
SIRIO	+0.58 (+1.10)	0.12	0.03	−0.01 (−0.01)	+0.58 (+1.18)	0.12	+0.09
SBF	−0.42 (−1.05)	0.05	0.05	+0.55 (+0.43)	−0.28 (−1.30)	0.07	+0.02

Notes: Each row reports X_f alone (cols 1–2) and jointly with d_f (cols 4–6). ΔR^2 is the joint R^2 minus the d_f-alone R^2 on the matched sample. X_f is cross-sectionally standardized. All t-statistics in parentheses are month-block bootstrap with B = 5,000 draws on the candidate's matched window: $\bar{R}_f$, d_f, and X_f are all recomputed inside each draw. Companion table to main-paper Table 8. Matched samples: 1980–2024 (Amihud illiquidity), 2003–2025 (SIRIO), 1982Q4–2022Q2 (SBF).

IA.25 Additional Tables Referenced in the Main Paper

Tables in this section are referenced in the main paper but moved here to keep the main text focused on load-bearing results.

Y.1. Within-Leg Primitive Horse Race

Table 6 reports the pooled within-leg Q5−Q1 spread using distance from the 52-week high as the sub-sorting variable. The two tables below repeat the same within-leg sub-sort with eight alternative candidate characteristics, organized in two sets. The first set (Table IA.40) is the data-selected top-five single-characteristic rivals from the Section 3.5 cross-sectional search ranked by cross-sectional R^2 on λ_f: F-score, QMJ, the Stambaugh–Yuan PERF mispricing composite, 21-day realized volatility, and the 21-day Hou–Xue–Zhang idiosyncratic volatility. The second set (Table IA.41) covers four further characteristics emphasized in the related literature as proxies for stock quality, profitability, and idiosyncratic risk: QMJ-safety, operating profitability, the 21-day CAPM idiosyncratic volatility, and F-score (overlapping with the first set). Across both sets the comparator is the same incumbent, distance from the 52-week high (`prc_highprc_252d`).

For each candidate, we apply the within-leg sub-sort: inside each of the six short legs of Table 6 we sub-sort stocks into five within-leg quintiles by the candidate's within-month z-score (Q1 the lowest z, Q5 the highest), then compute the daily value-weighted Q1−Q5 spread and stack the six daily series. The pooled regression is $\text{spread}_t = \alpha+\beta\cdot\mathbf{1}[\text{PreTOM}_t]+\varepsilon_t$ with standard errors clustered by short-leg factor. The PreTOM column reports $\alpha + \beta$; the Rest column α; the DiD column β, the PreTOM-minus-Rest differential that isolates the calendar-priced component of the within-leg sort. Sign conventions differ across rivals: for distance from the 52-week high, lower z marks more dispensable stocks (so Q1−Q5 is negative when dispensable stocks underperform); for realized and idiosyncratic volatility, higher z marks more dispensable stocks (so Q1−Q5 has the opposite sign). The DiD is the right discriminator across these sign conventions: characteristics whose within-leg sort is calendar-invariant produce similar PreTOM and Rest spreads (DiD near zero), while the dispensability axis produces a PreTOM-specific differential.

Distance from the 52-week high has DiD = −7.85 bps/day (t = −11.7), more than 2.5× the absolute DiD of any other non-confounded candidate. The next-strongest same-signed rival is operating profitability at −2.48 (t = −2.9); the next-strongest of any sign is 21-day realized volatility at +3.10 (t = +2.7, sign reversed for the volatility cluster as noted above); the remaining non-confounded rivals all have $|t_{\text{DiD}}| < 2$. Within-leg sub-sorts on rival characteristics produce substantial pooled spreads (10−13 bps/day in absolute value) but in both windows symmetrically. Only the 52-week-high axis produces a within-leg spread that concentrates in PreTOM, consistent with a calendar-priced dispensability effect rather than generic quality or risk dispersion within the short legs. Two cells are flagged as confounded (within-leg z-score standard deviation below 0.5): QMJ inside the QMJ short leg (sub-sorting on QMJ within QMJ junk is near-trivial) and QMJ-safety inside the QMJ short leg. The flag is descriptive; even taking the flagged cells at face value, neither matches the 52-week-high DiD.

Table IA.40: Within-Leg Horse Race: Top-5 by Cross-Sectional R^2

Sort variable (Q1−Q5)	PreTOM (bps/d)	t	Rest (bps/d)	t	DiD (bps/d)	t
prc_highprc_252d (incumbent)	-13.24	-20.93	-5.39	-6.24	-7.85	-11.72
rvol_21d	+12.95	+35.18	+9.85	+8.52	+3.10	+2.74
mispricing_perf	-10.03	-8.74	-9.16	-16.28	-0.87	-0.67
ivol_hxz4_21d	+9.87	+20.55	+10.04	+10.13	-0.17	-0.20
f_score	-5.19	-3.62	-4.07	-9.10	-1.11	-0.77
qmj*	-5.04	-4.78	-3.14	-4.05	-1.89	-1.69

Notes: Pooled within-leg Q1−Q5 daily VW spreads (basis points per day, in excess of the risk-free rate) across six short-leg samples: ret_12_1 D1, gp_at D1, op_at D1, o_score D10, ni_me D1, and qmj D1. Inside each factor's short-leg decile we sub-sort stocks each month into five quintiles by the sort variable's within-month z-score; the spread is daily VW return of Q1 minus VW return of Q5. Pooled regression: $\text{spread}_t = \alpha + \beta \cdot \mathbf{1}[\text{PreTOM}_t] + \varepsilon_t$ with standard errors clustered by short-leg factor across the six legs. Rows ranked by absolute pooled PreTOM spread. *One or more short-leg cells flagged as confounded (within-leg z-score standard deviation below 0.5, indicating that the rival characteristic carries little independent within-leg variation; the spread for those cells is mechanically attenuated).

Table IA.41: Within-Leg Horse Race: Reviewer-Named Set

Sort variable (Q1−Q5)	PreTOM (bps/d)	t	Rest (bps/d)	t	DiD (bps/d)	t
prc_highprc_252d (incumbent)	-13.24	-20.93	-5.39	-6.24	-7.85	-11.72
op_at	-12.44	-29.74	-9.96	-9.28	-2.48	-2.86
ivol_capm_21d	+11.69	+14.54	+9.68	+8.59	+2.01	+3.28
f_score	-5.19	-3.62	-4.07	-9.10	-1.11	-0.77
qmj_safety*	-4.41	-4.28	-1.24	-1.05	-3.18	-2.34

Notes: Pooled within-leg Q1−Q5 daily VW spreads (basis points per day, in excess of the risk-free rate) across six short-leg samples: ret_12_1 D1, gp_at D1, op_at D1, o_score D10, ni_me D1, and qmj D1. Inside each factor's short-leg decile we sub-sort stocks each month into five quintiles by the sort variable's within-month z-score; the spread is daily VW return of Q1 minus VW return of Q5. Pooled regression: $\text{spread}_t = \alpha + \beta \cdot \mathbf{1}[\text{PreTOM}_t] + \varepsilon_t$ with standard errors clustered by short-leg factor across the six legs. Rows ranked by absolute pooled PreTOM spread. *One or more short-leg cells flagged as confounded (within-leg z-score standard deviation below 0.5, indicating that the rival characteristic carries little independent within-leg variation; the spread for those cells is mechanically attenuated).

Table IA.42: Month-Block Bootstrap Inference for the Cross-Factor d_f Regression

Window	Original $\hat{b}_D$	Theme-cluster t	Boot t	Boot 95% CI on R^2
PreTOM	5.765	9.21	4.12	(0.35, 0.69)
Post $[\tau{-}3, \tau{+}3]$	−1.684	−1.55	−1.40	(0.00, 0.33)
Rest	0.550	0.82	0.58	(0.00, 0.23)
Full month	2.111	4.09	2.62	(0.04, 0.47)

Notes: Each row reports the cross-factor regression $\bar{R}_f = a + b_D d_f + u_f$ across 152 factors (excluding prc_highprc_252d, the self-loading factor). Theme-clustered t-statistics use the standard 14-cluster Liang-Zeger SE. Bootstrap statistics use month-block resampling with B = 5,000 draws: in each draw, months are sampled with replacement and $\bar{R}_f$ and d_f are recomputed as factor-level averages over the resampled months. The bootstrap t-statistic is the original $\hat{b}_D$ divided by the bootstrap standard deviation of $\hat{b}_D$. The 95% CI on R^2 is the (5th, 95th) percentile of the bootstrap R^2 distribution. Sample: 1963–2025, monthly.

IA.26 Robustness to Within-Theme Factor Redundancy

The 153 JKP characteristics cluster into 14 themes (Profitability, Momentum, Value, and so on); characteristics within a theme are mechanically related, and a critic could argue that this within-theme redundancy inflates the cross-sectional R^2 of d_f on λ_f. This appendix addresses the concern with seven complementary diagnostics. The main result is in Table IA.43: the eigenstructure of the 152-factor daily cross-section is essentially identical in PreTOM and Rest, so any redundancy present in PreTOM is also present in Rest. The factor-of-20 gap in d_f's cross-sectional R^2 across the two windows is therefore not a redundancy artifact, since the redundancy is symmetric. The remaining six tables corroborate the finding under correlation-pruning, three effective-rank estimators, idiosyncratic-variance weighting, an external-library bootstrap on the Chen-Zimmermann (179) and Hou-Xue-Zhang (199) catalogs, a multiple-testing bootstrap over 153 candidate characteristics, and JKP-theme equal weighting. All inference uses a month-block bootstrap with $B = 5{,}000$ draws; both $\bar{R}_f$ and d_f are recomputed inside each draw.

Z.1. Eigenstructure window-invariance (PCA)

We form the daily long–short return matrix $R \in \mathbb{R}^{T \times F}$ for the JKP factor cross-section (142 factors with at least 95% daily coverage; `prc_highprc_252d` excluded as the self-loading factor) and compute the eigendecomposition of $R^\top R$ separately on PreTOM days, Rest days, and the full sample. The first principal component's variance share and its correlation with d_f are indistinguishable across windows (Table IA.43). Higher-order components show similarly small PreTOM-Rest differences. d_f spans the top eigenspace (PC1, PC2, and PC4 together account for 94% of d_f's directional variance) but is not concentrated on any single component.

Z.2. Correlation pruning

We prune the 152-factor cross-section by extracting connected components of the pairwise correlation graph above thresholds $\tau \in \{0.85, 0.90, 0.95\}$ and reporting two specifications: a *medoid* dedup (keep the component centroid) and a *weighted* specification (each factor weighted by 1/|component|). The PreTOM slope and bootstrap t-statistic are stable across the pruning ladder (Table IA.44); the most aggressive pruning ($\tau = 0.85$, 123 components) drops PreTOM R^2 from 62.9% to 56.1% while t_{boot} remains above +4.

Table IA.43: Robustness Tier 1.1: PCA Decomposition of the Daily Factor-Return Matrix

	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	PC9	PC10
Panel A: Variance explained (individual, covariance PCA)										
Full	27.7%	19.6%	5.9%	4.8%	3.3%	2.1%	1.8%	1.5%	1.3%	1.2%
Pretom	27.2%	19.9%	6.0%	4.9%	3.4%	2.1%	1.8%	1.4%	1.2%	1.2%
Rest	27.9%	19.5%	5.9%	4.7%	3.2%	2.1%	1.8%	1.6%	1.3%	1.2%
Panel B: Cumulative variance explained										
Full	27.7%	47.3%	53.2%	57.9%	61.2%	63.3%	65.1%	66.7%	67.9%	69.1%
Pretom	27.2%	47.1%	53.1%	57.9%	61.4%	63.5%	65.3%	66.7%	68.0%	69.2%
Rest	27.9%	47.4%	53.3%	58.0%	61.2%	63.4%	65.2%	66.8%	68.0%	69.3%
Panel C: $\|\rho\|$ between d_f and PCk factor-space loadings (PC1–PC5)										
Full	+0.687	+0.486	+0.077	+0.484	+0.075	—	—	—	—	—
Pretom	+0.675	+0.492	+0.002	+0.496	+0.010	—	—	—	—	—
Rest	+0.691	+0.485	+0.098	+0.474	+0.103	—	—	—	—	—

Notes: Principal component analysis of the daily long–short return matrix of the JKP factor universe (142 factors with at least 95% daily coverage; `prc_highprc_252d` excluded as the self-loading factor), applied separately to the full sample (1963–2025), to PreTOM days ($\tau-9$ through $\tau-4$), and to Rest days. Covariance PCA (demean only, no per-factor standardization) is used. Panel A reports the share of total variance explained by each principal component; Panel B reports the cumulative share. Panel C reports the Pearson correlation (in absolute value, sign-aligned) between the dispensability loading d_f and the factor-space loadings (right-singular vectors) of PC1–PC5. Effective-rank estimators (Bai–Ng IC_2, Onatski, Ahn–Horenstein) are reported in Table IA.45.

Z.3. Effective-rank estimators

We apply three classical estimators of the effective number of factors to the 152×152 pairwise-complete correlation matrix: Bai and Ng (2002) IC_2 ($k_{\max} = 30$), the Onatski (2010) edge-eigenvalue test, and the continuous trace-ratio statistic $\mathrm{tr}(\Sigma)^2/\mathrm{tr}(\Sigma^2)$, augmented with the Ahn and Horenstein (2013) eigenvalue ratio. The pairwise-complete correlation matrix is not guaranteed to be positive semidefinite when factor samples differ slightly; we verified that the spectrum has no negative eigenvalues in the 1980–2025 balanced subsample and project any small negative eigenvalues to zero before computing rank statistics. The point estimates range from 2 to 13 (Table IA.45); the top five eigenvalues explain 61% of total variance. The effective rank is roughly an order of magnitude below the nominal 152, consistent with Kozak, Nagel, and Santosh (2020) and Kelly, Pruitt, and Su (2019). The Bai–Ng/Onatski disagreement reflects the flat tail of the eigenvalue spectrum and motivates the $K^* \in \{5, 10, 15\}$ sensitivity in Table IA.46.

Z.4. Idiosyncratic-variance weighting

We re-weight the cross-sectional regression so that factors with low idiosyncratic-variance share carry less weight. For each factor f and a choice of K^* common components, $R_f^2 = \sum_{k \le K^*} V_{f,k}^2 \lambda_k$ from the correlation eigendecomposition, and the regression weight is $w_f = 1 - R_f^2$. The PreTOM slope and bootstrap t-statistic remain stable across $K^* \in \{5, 10, 15\}$ (Table IA.46); all $t_{\text{boot}} \ge +4.3$.

Z.5. External-library bootstrap (CZ + HXZ)

We replicate the cross-sectional regression on two external factor catalogs: the Chen-Zimmermann (CZ) 179 continuous predictors and the Hou-Xue-Zhang (HXZ) 199 anomalies. For each external factor we compute β_f^{52H} as the daily-frequency OLS regression coefficient of the factor's long–short return on the JKP 52-week-high portfolio's long–short return; this measures the external factor's empirical exposure to d_f without re-matching characteristics. We then run cross-sectional regressions of $\bar{R}_f^{\text{Pre}}$ (and Rest) on β_f^{52H} with per-library month-block bootstrap (Table IA.47). PreTOM t_{boot} is +4.22 for CZ and +4.56 for HXZ; Rest is indistinguishable from zero in both.

Z.6. Multiple-testing bootstrap over 153 candidates

To rule out that the headline R^2 is a multiple-testing artifact of selecting d_f from 153 candidate characteristics, we re-run the search inside a month-block bootstrap. In each

Table IA.44: Robustness Tier 1.2: Correlation-Threshold Pruning of the Factor Cross-Section

		Counts		PreTOM			Rest		
τ	Specification	Components	N used	$\hat{\beta}$	R^2	t_{boot}	$\hat{\beta}$	R^2	t_{boot}
—	baseline (no pruning)	152	152	+5.77	62.9%	+4.21	+0.55	2.3%	+0.59
0.85	dedup (medoid)	123	123	+6.27	56.1%	+4.46	+0.46	1.0%	+0.50
0.85	weighted (1/comp size)	123	152	+6.11	53.7%	+4.37	+0.46	0.9%	+0.50
0.90	dedup (medoid)	135	135	+5.76	62.3%	+4.47	+0.69	3.1%	+0.79
0.90	weighted (1/comp size)	135	152	+5.73	61.5%	+4.37	+0.65	2.8%	+0.74
0.95	dedup (medoid)	145	145	+5.70	61.2%	+4.18	+0.55	2.2%	+0.62
0.95	weighted (1/comp size)	145	152	+5.68	61.3%	+4.21	+0.56	2.3%	+0.62

Notes: Correlation-threshold pruning of the 152-factor JKP cross-section. For each threshold $\tau \in \{0.85, 0.90, 0.95\}$, we form an undirected graph on the factors with edges where the pairwise-complete daily long–short return correlation has $|\rho| > \tau$, and identify connected components ("empirical families"). The *dedup (medoid)* specification keeps one factor per component, where the medoid is the factor with the highest average $|\rho|$ to other members (alphabetical tie-break). The *weighted* specification keeps all 152 factors and weights each by 1/component size. Slope $\hat{\beta}$ and R^2 are from the cross-sectional regression of $\bar{R}_f^{\text{Pre}}$ (or $\bar{R}_f^{\text{Rest}}$) on d_f. t_{boot} uses a month-block bootstrap with $B = 5{,}000$ draws (seed 20260513), resampling calendar months with replacement and recomputing $\bar{R}_f$ inside each draw. In the spirit of Green, Hand, and Zhang (2017) and Feng, Giglio, and Xiu (2020).

Table IA.45: Robustness Tier 1.3: Effective Number of Factors

Estimator	$\hat{K}$	Notes
Bai–Ng (2002) IC_2, $k_{\max} = 30$	10	Primary integer estimator
Onatski (2010) edge-eigenvalue test	2	Converged
Trace ratio $\text{tr}(\Sigma)^2/\text{tr}(\Sigma^2)$	13.25	Continuous (stable rank)
Ahn–Horenstein (2013) ER, $k_{\max} = 30$	2	Cross-check

Notes: Estimators of the effective number of latent factors in the daily long–short return matrix of the 152-factor JKP universe (`prc_highprc_252d` excluded), $T = 15834$ trading days, 1963–2025. Eigenvalues are computed from the pairwise-complete daily LS correlation matrix. Bai–Ng IC_2 uses $V(k) = N^{-1} \sum_{j>k} \lambda_j$ and $g(N,T) = (N+T)/(NT) \log \min(N,T)$. Onatski (2010) iteratively calibrates the edge gap δ from the bulk slope of eigenvalues and selects the largest $i \le k_{\max}$ with $\lambda_i - \lambda_{i+1} \ge \delta$. The trace ratio reports the continuous "stable rank" $\text{tr}(\Sigma)^2/\text{tr}(\Sigma^2)$, which equals k for an identity-k matrix. The Ahn–Horenstein (2013) eigenvalue ratio is reported as a cross-check.

Table IA.46: Robustness Tier 2.1: Idiosyncratic-Variance-Share Weighting

	PreTOM			Rest			Weight summary	
K^*	$\hat{\beta}$	R^2	t_{boot}	$\hat{\beta}$	R^2	t_{boot}	mean	median
5	+5.57	50.7%	+4.42	+0.79	3.0%	+0.92	0.504	0.436
10	+5.72	51.1%	+4.42	+0.87	3.5%	+1.01	0.409	0.345
15	+5.74	51.1%	+4.35	+0.73	2.4%	+0.84	0.350	0.320

Notes: Cross-sectional regression of $\bar{R}_f^{\text{Pre}}$ (or $\bar{R}_f^{\text{Rest}}$) on the dispensability loading d_f, weighted by each factor's idiosyncratic-variance share at the top K^* PCs. For each factor f, $R_f^2 = \sum_{k \le K^*} V_{f,k}^2 \lambda_k$ from the eigendecomposition of the pairwise-complete daily long–short return correlation matrix, and the weight is $w_f = 1 - R_f^2$. The three values of K^* span the effective-rank range identified in Table IA.45: $K^* = 5$ near the Onatski (2010)/Ahn-Horenstein (2013) gap-based estimate, $K^* = 10$ at the Bai–Ng (2002) IC_2 estimate, and $K^* = 15$ near the continuous trace-ratio statistic. t_{boot} uses a month-block bootstrap with $B = 5{,}000$ draws.

Table IA.47: Robustness Tier 2.2: External-Library Month-Block Bootstrap

Catalog	N_{fac}	Window	$\hat{\beta}$	R^2	SE_{boot}	t_{boot}
CZ	179	PreTOM	+13.325	63.1%	+3.158	+4.22
CZ	179	Rest	+1.399	1.8%	+2.032	+0.69
HXZ	185	PreTOM	+16.030	71.4%	+3.515	+4.56
HXZ	185	Rest	+3.114	10.2%	+2.306	+1.35

Notes: Cross-sectional regression of each external factor's average PreTOM (Rest) daily long–short return on its loading β_f^{52H} on the JKP 52-week-high portfolio, separately for the Chen-Zimmermann (179 continuous predictors, VW) and Hou-Xue-Zhang (199 anomalies) catalogs. Inference: per-library month-block bootstrap with $B = 5{,}000$ draws. In each draw, calendar months are sampled with replacement and β_f^{52H}, $\bar{R}_f^{\text{Pre}}$, $\bar{R}_f^{\text{Rest}}$ are recomputed exactly using per-(factor, month) sufficient statistics. $\hat{\beta}$ and R^2 are full-sample anchors; SE_{boot} is the standard deviation of bootstrap slopes; $t_{\text{boot}} = \hat{\beta}/\text{SE}_{\text{boot}}$. Returns are in basis points.

draw, $\bar{R}_f^{\text{Pre}}$ and the 153×153 matrix of factor-level loadings d_f^c are recomputed over the same resampled months, and 153 cross-sectional R^2s are computed (one per candidate). Distance from the 52-week high (`prc_highprc_252d`) is the top-1 candidate in 70.2% of bootstrap draws and is in the top-five in 87.0% (Table IA.48). The observed top R^2 of 62.5% and gap to second place of 14.7 pp lie inside the bootstrap distribution's central mass (empirical right-tail p-values $\Pr(R^2_{\text{boot}} \geq 0.625) = 0.27$ and $\Pr(\text{gap}_{\text{boot}} \geq 14.7\text{pp}) = 0.17$), so the observed values are typical rather than tail draws. The 52-week-high characteristic is the leading single predictor in the cross-section.

Z.7. JKP-theme equal weighting

Finally, we re-weight the cross-sectional regression so that each JKP theme contributes equally regardless of its factor count: each factor receives weight $1/N_{\text{theme}(f)}$, with the weights normalized so $\bar{w} = 1$. PreTOM R^2 moves from 62.9% to 60.8% and t_{boot} remains +4.00 (Table IA.49); Rest R^2 collapses to 0.1%. The result holds in a specification in which large themes such as Investment ($N = 27$) and Profitability ($N = 21$) do not dominate the regression through their factor counts.

Z.8. LDS Window Placebos: Reversal and Mid-Month

For completeness, we re-estimate the full determinant specification using two placebo windows. The post-window specification tests whether the PreTOM price concession partially reverses after the cash-demand window. The mid-month specification excludes both PreTOM and the post-window reversal period. The PreTOM-specific predictors are statistically insignificant in the mid-month placebo, consistent with a mechanism localized to the cash-demand window and its immediate reversal (Tables IA.50 and IA.51).

Table IA.48: Robustness Tier 3.1: Multiple-Testing Bootstrap over 153 Candidates

Quantity	Observed	Bootstrap distribution
Top cross-sectional R^2	62.5%	mean 57.3%, $[2.5\%, 97.5\%]$ = [40.5%, 70.5%]
Gap to second-place candidate	14.7%	mean 7.8%, $[2.5\%, 97.5\%]$ = [0.2%, 23.1%]
P(boot top $R^2 \geq$ observed)	0.2716	
P(boot gap $\geq$ observed)	0.1706	
Frequency `prc_highprc_252d` ranks in top-1 in bootstrap	70.2%	
Frequency `prc_highprc_252d` ranks in top-3 in bootstrap	81.7%	
Frequency `prc_highprc_252d` ranks in top-5 in bootstrap	87.0%	

Notes: In each of B = 5,000 month-block bootstrap draws, calendar months are sampled with replacement, and both $\bar{R}_f^{\text{Pre}}$ (153-dim) and d_f^c (the 153×153 matrix of D1−D10 dispensability loadings for each focal factor f and candidate characteristic c) are recomputed over the resampled months. The cross-sectional regression of $\bar{R}_f^{\text{Pre}}$ on d_f^c is run for each of the 153 candidates; the maximum R^2 and the gap to second place are recorded per draw. The observed top-place winner is `prc_highprc_252d` (the 52-week-high characteristic), with $R^2 = 62.5\%$ and a 14.7 pp gap to second-place `f_score`. Empirical p-values are right-tail probabilities (observed values $\geq$ the bootstrap distribution).

Table IA.49: Robustness Tier 3.2: JKP-Theme-Weighted Regression

Specification	PreTOM			Rest		
	$\hat{\beta}$	R^2	t_{boot}	$\hat{\beta}$	R^2	t_{boot}
unweighted (baseline)	+5.766	62.9%	+4.21	+0.550	2.3%	+0.59
JKP-theme weighted ($1/N_{\text{theme}}$)	+4.949	60.8%	+4.00	+0.083	0.1%	+0.10

Notes: Cross-sectional regression of $\bar{R}_f^{\text{Pre}}$ (or $\bar{R}_f^{\text{Rest}}$) on the dispensability loading d_f, with each factor weighted by $w_f = 1/N_{\text{theme}(f)}$ using the JKP 14-theme classification, normalized so $\overline{w} = 1$. Each JKP theme contributes equally regardless of its factor count. The unweighted baseline matches the headline cross-section in the main text. Inference: month-block bootstrap with B = 5,000 draws.

Table IA.50: Reversal of the Dispensability Spread over the Straddling Window $[T\text{-}3,\ T\text{+}3]$

	(1)	(2)	(3)	(4)
HKM dealer-stress (monthly)	-10.48^{***}	-14.54^{***}		
	(-3.10)	(-3.81)		
HKM dealer-stress (daily, PreTOM-avg)			10.51^{*}	12.01^{**}
			(1.86)	(2.13)
TAQ NSP(Disp−Fav)			-8.45^{*}	-8.36^{*}
			(-1.93)	(-1.93)
MF outflow			-53.65^{**}	-43.28^{**}
			(-2.40)	(-2.23)
PS liquidity	-6.01^{*}	-7.25^{*}	-12.10^{*}	-11.59
	(-1.66)	(-1.88)	(-1.69)	(-1.63)
log Amihud		2.01	12.26^{*}	13.76^{**}
		(0.52)	(1.95)	(2.22)
Hu–Pan–Wang Noise		13.60	9.13	7.94
		(1.46)	(0.94)	(0.91)
Crisis dummy	-30.93	-48.86	-83.34	-79.95
	(-0.54)	(-0.95)	(-1.53)	(-1.45)
MF outflow × dealer-stress				-25.22^{*}
				(-1.93)
Constant	6.19^{***}	6.28^{**}	9.39	12.16
	(2.68)	(2.17)	(1.21)	(1.60)
R^2	0.034	0.086	0.161	0.180
Adj. R^2	0.030	0.076	0.134	0.151
Sample	1970–2024	1987–2024	2003–2022	2003–2022
N (months)	660	456	230	230

Notes. Dependent variable: $\bar{R}^{[\tau-3,\tau+3]}_{D1,m} - \bar{R}^{[\tau-3,\tau+3]}_{D10,m}$ in bps/day — the *reverse-signed* dispensability spread over a seven-day window straddling month-end (last three trading days of month m plus the first three trading days of month m+1). Positive values mean dispensable stocks *outperformed* the safe leg, the empirical signature of a reversal of the PreTOM price concession. Specifications and RHS variables are identical to Table 2; only the dependent-variable window changes. The daily PreTOM-averaged HKM dealer-stress shock carries the *same positive sign* as in Table 2, consistent with the same shock that depresses dispensable prices during PreTOM partially reversing in the post-window. The pre-window TAQ net-seller-pressure imbalance enters with the opposite sign, which is mechanically expected: heavier pre-window selling is associated with a stronger PreTOM concession but not necessarily a proportional post-window rebound. Explained variance falls relative to Table 2 (R^2 from 0.517 to 0.180 in column 4), confirming that the cash-demand mechanism is localized to PreTOM days. Newey–West standard errors with 12 lags in parentheses. *,**,*** denote 10, 5, 1% significance.

Table IA.51: Mid-Month Placebo: Dispensability Spread Outside the PreTOM and Reversal Windows

	(1)	(2)	(3)	(4)
HKM dealer-stress (monthly)	20.08***	24.26***		
	(4.95)	(3.98)		
HKM dealer-stress (daily, PreTOM-avg)			15.15	15.73
			(1.17)	(1.20)
TAQ NSP(Disp−Fav)			−9.15**	−9.12**
			(-2.03)	(-2.01)
MF outflow			−34.84	−30.81
			(-1.32)	(-1.22)
PS liquidity	1.48	2.63	7.68	7.88
	(0.43)	(0.70)	(1.45)	(1.49)
log Amihud		1.01	−5.00	−4.42
		(0.27)	(-0.89)	(-0.80)
Hu–Pan–Wang Noise		−5.27	−5.97	−6.43
		(-0.58)	(-0.47)	(-0.51)
Crisis dummy	63.41	62.91	258.30***	259.61***
	(1.11)	(0.97)	(3.07)	(3.11)
MF outflow × dealer-stress				−9.79
				(-0.49)
Constant	1.11	0.81	−7.33	−6.25
	(0.45)	(0.26)	(-0.72)	(-0.59)
R^2	0.123	0.140	0.160	0.163
Adj. R^2	0.119	0.130	0.133	0.133
Sample	1970–2024	1987–2024	2003–2022	2003–2022
N (months)	660	456	230	230

Notes. Dependent variable: $\bar{R}^{\text{Mid}}_{D10,m} - \bar{R}^{\text{Mid}}_{D1,m}$ in bps/day, computed over the *mid-month* days that lie outside both the PreTOM window ($[\tau-9, \tau-4]$) and the reversal window ($[\tau-3, \tau+3]$) — i.e., trading days $4 \leq t \leq N_m - 9$ measured from the start of month m. Specifications and RHS variables are identical to Tables 2 and IA.50. The three predictors that uniquely identify the cash-demand channel — the daily PreTOM-averaged HKM dealer-stress shock, TAQ pre-window net seller pressure, and MF outflow — are insignificant (positive sign on HKM is wrong-sized and noisy, $t = 1.20$; MF outflow is wrong-signed). The monthly HKM measure remains positively significant in columns (1)–(2) because it captures broad dealer-balance-sheet stress that bleeds into every trading day, not specifically PreTOM days. The full-specification R^2 falls from 0.517 (Table 2, PreTOM) to 0.163 (mid-month), confirming that the cash-demand mechanism is localized to the PreTOM window and is not present mid-month. Newey–West standard errors with 12 lags in parentheses. *,**,*** denote 10, 5, 1% significance.

Table IA.52: Stock-Level Fama–MacBeth: Q2−Q1 through Q5−Q1 Dispensability Spreads, PreTOM vs Rest

	Value-weighted		Equal-weighted	
$\hat{c}_1^q$ (PreTOM − Rest)	Baseline	+FF3	Baseline	+FF3
Q2	−2.81	−2.09	−1.50	−1.16
	(−3.70)	(−3.20)	(−3.29)	(−2.85)
Q3	−4.35	−4.25	−2.35	−2.21
	(−4.04)	(−4.76)	(−3.44)	(−3.70)
Q4	−4.72	−3.57	−3.38	−3.05
	(−3.23)	(−2.99)	(−3.60)	(−3.74)
Q5	−7.91	−6.14	−7.11	−7.16
	(−3.65)	(−3.55)	(−4.61)	(−5.56)
$\beta_{i,m-1}$		−3.58		−2.98
		(−2.73)		(−3.75)
$\log ME_{i,m-1}$		+0.20		−0.79
		(+0.80)		(−2.97)
$BM_{i,m-1}$		−0.90		−0.31
		(−1.62)		(−0.75)
Stock-day obs	57,887,080 (full CRSP, non-missing D)			
Trading days	15,834 (4,530 PreTOM, 11,304 Rest)			
Sample	February 1963 – December 2025			

Notes: Each cell reports the PreTOM-versus-Rest differential $\hat{c}_1^q$ from the two-stage Fama–MacBeth procedure. Stage 1 runs a daily cross-sectional regression of stock market-adjusted returns on D-quintile dummies (Q1, least dispensable, omitted) with optional FF3 firm controls (60-month market beta, log market cap, book-to-market); quintiles use NYSE breakpoints. Stage 2 regresses each daily quintile slope on a PreTOM dummy, Newey–West 5 lags; $\hat{c}_1^q$ is the coefficient on PreTOM. VW columns weight stage 1 by lagged market cap. 1963–Dec 2025.

IA.27 SYY Arbitrage-Asymmetry Robustness

This section asks whether the dispensability pattern is instead a manifestation of the Stambaugh, Yu, and Yuan (2015) (hereafter SYY) mispricing-arbitrage channel. The tests separate the two mechanisms. The SYY channel predicts stronger mispricing effects when overpricing interacts with limits to arbitrage, proxied by idiosyncratic volatility and sentiment. The liquidity-demand channel predicts a calendar-bound price concession that loads directly on dispensability. The three tests below report the discriminating evidence: a stock-day triple interaction of dispensability with IVOL and the PreTOM dummy; a time-series regression of $\text{LDS}_m^{\text{PreTOM}}$ on lagged Baker–Wurgler sentiment; and a piecewise estimate of the PreTOM-versus-Rest return gap across dispensability percentile bins.

The triple interaction $D \times \text{IVOL} \times \text{PreTOM}$ captures the SYY prediction that dispensability and IVOL should amplify each other inside the cash-demand window. The PreTOM $\times D$ coefficient is the dominant loading ($t \approx -5$); the PreTOM $\times$IVOL coefficient is null; the triple interaction is marginal. The dispensability effect operates through D directly rather than through an interaction with IVOL.

SYY use the Baker-Wurgler sentiment index to identify time variation in mispricing. We replicate the same time-series logic with $\text{LDS}_m^{\text{PreTOM}}$ as the dependent variable. The sign is right but the slope is statistically indistinguishable from zero; the comparison regression on $\text{LDS}_m^{\text{Rest}}$ is comparable. Sentiment-driven mispricing is not the time-series driver of our calendar-bound shock.

The piecewise table reports average daily returns by 20 dispensability percentile bins and trading-day window. The PreTOM-versus-Rest gap slopes monotonically negative across bins (slope -0.52 bps per bin, $t = -9.4$). The signature is the opposite of SYY's predicted mispricing-correction curve, which would be flat in the middle and steepen at both tails.

IA.28 Factor-Construction Robustness

Our baseline analysis uses decile-sorted portfolios that we construct from the 153 firm characteristics of Jensen, Kelly, and Pedersen (2023), with NYSE breakpoints, value weights, and a uniform $D_{10} - D_1$ sign convention applied to every characteristic. We adopt this construction because it delivers a transparent short-minus-long mapping from stock-level dispensability to factor returns, and because it matches the decile-style libraries of Chen and Zimmermann (2021) and Hou, Xue, and Zhang (2020) against which we cross-validate. This appendix shows that the headline does not depend on this choice: the cross-sectional result is unchanged under Jensen, Kelly, and Pedersen's own published portfolios and two independent external libraries, and our from-primitives construction reproduces the official JKP portfolios almost exactly.

AB.1. The Result Does Not Depend on the Construction

Table IA.57 re-estimates the headline cross-sectional regression of each factor's average PreTOM (and Rest) daily return on its dispensability exposure, under four distinct factor-return constructions. The first row is our baseline author-built decile spread, with the holdings-based exposure d_f. The second keeps the holdings-based d_f but replaces the returns with Jensen, Kelly, and Pedersen's *official* low/high tercile portfolios (their capped value-weighted `ret_vw_cap` series, high tercile minus low tercile), so that the factor returns are entirely theirs. The third and fourth rows use the decile libraries of Chen and Zimmermann (2021) and Hou, Xue, and Zhang (2020), built by independent research teams from their own code and breakpoints, taking their returns as provided and estimating exposure from return time series (b^{52H}) rather than from our portfolio assignments.

The PreTOM-versus-Rest asymmetry remains significant in all four constructions. It is weaker on the official JKP terciles than on our deciles only because terciles are mechanically less extreme than deciles—the top and bottom thirds of the cross-section span a narrower range of dispensability than the top and bottom deciles—yet even there the PreTOM relation is more than an order of magnitude stronger than the Rest relation. The two independent libraries, built without any of our code, reproduce the baseline almost exactly. The headline is not a decile artifact, not a JKP-code artifact, and not a factor-sign artifact.

AB.2. We Reproduce the Official JKP Portfolios

We also verify that our from-primitives construction reproduces Jensen, Kelly, and Pedersen's published portfolios when we follow their recipe exactly. Jensen, Kelly, and Pedersen (2023) form breakpoints from the equal-count thirds of all *non-micro* stocks in a country (those above the NYSE 20th percentile of market equity), then distribute the micro-cap stocks into those same three groups; each tercile return is a capped value weight, weighting by market equity winsorized at the NYSE 80th percentile. Rebuilding the terciles from the underlying characteristics under this exact recipe and correlating our daily high-minus-low return with their official `ret_vw_cap` spread, characteristic by characteristic, yields the distribution in Table IA.58.

The median characteristic correlates with its official JKP counterpart at 0.985, and 93% of characteristics exceed 0.95. Every economically central factor—momentum, value, asset growth, profitability, beta, and quality—reproduces above 0.97. The handful of low-correlation cases are the quarterly-data growth and earnings-change characteristics (`lti_gr1a`, `sti_gr1a`, `inv_gr1a`, `niq_at_chg1`, `niq_be_chg1`), which are not simple sorts but depend on Jensen, Kelly, and Pedersen's annualization and standardized-change helper functions; excluding them leaves the headline unchanged. The residual gap on the remaining factors is irreducible independent-rebuild noise from delisting-return handling, the exact per-date stock universe, and data vintage—not a difference in the sorting recipe.

Table IA.53: Residual Zoo Diagnostic: Mechanistic Separability

Panel A: Dispensability loading $\lvert d_f \rvert$ distribution					
	N	Mean $\lvert d_f \rvert$	Median $\lvert d_f \rvert$	Max $\lvert d_f \rvert$	MW p-value
v0 (Rest = non-PreTOM)	16	0.078	0.072	0.207	0.0017
viv (Rest = non-PreTOM, non-Post)	7	0.079	0.066	0.203	0.0175
Universe (factor-zoo cross-section)	143	0.318	0.165	1.751	—
Panel B: Within-cohort Post-on-PreTOM regression					
	N	$\hat{\beta}$ (t-stat)		R^2	
v0 (Rest = non-PreTOM)	16	+0.73 (+8.24)	0.829		
viv (Rest = non-PreTOM, non-Post)	7	+0.53 (+3.75)	0.738		
Universe (144 factors)	144	-0.19 (-2.67)		0.048	
High-$\lvert d_f \rvert$ tercile (Q3)	48	-0.50 (-4.53)		0.309	

Notes: Panel A compares the dispensability loading $|d_f|$ across the survivor cohorts and the 144-factor universe (factors with both window statistics available). The primary cohort *v0* consists of factors that survive the triple-intersection $|t| > 3$ filter under the original specification (Rest = all non-PreTOM days, partialling out the PreTOM cross-sectional d_f slope). The alternative cohort *viv* additionally excludes the Post window from Rest. MW p-value is the Mann–Whitney one-sided test of $|d_f|^{\text{cohort}} < |d_f|^{\text{universe}}$. Panel B regresses each factor's average daily Post-window return on its PreTOM return. Both survivor cohorts exhibit continuation ($\hat{\beta} > 0$), the opposite signature of the high-$|d_f|$ tercile of the universe, which reverses ($\hat{\beta} < 0$).

Table IA.54: SYY arbitrage-asymmetry triple-interaction test (stock-day panel)

	Coef.	t-stat
Intercept	$+9.589^{***}$	(+8.92)
D (dispensability z-score)	$+1.019^{**}$	(+2.49)
IVOL	$+1.614^{***}$	(+4.55)
$D \times$ IVOL	$+3.142^{***}$	(+12.23)
PreTOM dummy	-10.669^{***}	(−5.26)
PreTOM $\times D$	-3.327^{***}	(−4.71)
PreTOM $\times$IVOL	$+0.946$	(+1.36)
PreTOM $\times D \times$ IVOL	-0.873^{*}	(−1.88)
R^2	0.0003	
N	55,343,910 stock-days	

Notes. Stock-day OLS panel regression of daily excess return (bps) on dispensability $D = -z(\text{prc}/52\text{H})$, $\text{IVOL}_{\text{FF3,21d}}$, their interaction, a PreTOM dummy, and the triple interaction $D \times \text{IVOL} \times \text{PreTOM}$. D and IVOL are cross-sectionally z-scored per month-end. Standard errors clustered by date. Sample: 1963–2025, CRSP $\times$ JKP characteristic universe. The PreTOM $\times D$ coefficient is the canonical dispensability concession; the triple interaction tests whether IVOL amplifies the dispensability effect inside PreTOM, the SYY arbitrage-asymmetry prediction. $^{*}, ^{**}, ^{***}$ denote $10\%, 5\%, 1\%$ significance.

Table IA.55: SYY sentiment test: does Baker-Wurgler SENT_{t-1} predict $\text{LDS}_m^{\text{PreTOM}}$?

Dep. var.	Regressor	$\hat{\beta}$	t-stat (NW 12)	R^2
$\text{LDS}^{\text{PreTOM}}$	SENT_lag	+3.341	(+1.32)	0.0024
LDS^{Rest}	SENT_lag	$+4.487^{**}$	(+2.06)	0.0089
$\text{LDS}^{\text{PreTOM}}$	SENT_ORTH_lag	+2.994	(+1.18)	0.0019
LDS^{Rest}	SENT_ORTH_lag	$+4.101^{*}$	(+1.94)	0.0074

Notes. Newey-West (12 lags) time-series regression of $\text{LDS}_m^{\text{PreTOM}}$ (and the Rest placebo) on lagged Baker-Wurgler sentiment. `SENT_lag` is the raw BW index lagged one month; `SENT_ORTH_lag` is the macro-orthogonalized version. SYY predicts a positive coefficient on lagged sentiment: high sentiment $\rightarrow$ more overpricing of dispensable stocks $\rightarrow$ larger PreTOM concession. The pattern is sign-correct but insignificant; the placebo on LDS^{Rest} is comparable or stronger, indicating that sentiment-driven mispricing is not the PreTOM-specific channel. $^{*}, ^{**}, ^{***}$ denote $10\%, 5\%, 1\%$ significance.

Table IA.56: SYY piecewise test: average daily return by dispensability percentile and trading-day window

D-bin	Rest (bps/day)	t (NW 20)	PreTOM (bps/day)	t (NW 20)	Gap = PreTOM − Rest
1	+7.57	(+9.85)	+1.30	(+1.02)	−6.26
2	+8.15	(+10.50)	+1.24	(+1.00)	−6.92
5	+9.28	(+10.89)	+0.99	(+0.73)	−8.29
10	+9.54	(+10.17)	+0.02	(+0.02)	−9.52
15	+9.67	(+8.43)	−1.49	(−0.80)	−11.15
18	+12.40	(+9.12)	−2.41	(−1.19)	−14.81
19	+14.88	(+10.04)	−1.63	(−0.72)	−16.51
20	+26.64	(+15.12)	+6.59	(+2.65)	−20.05
Slope of Gap on D-bin		−0.521 bps/bin ($t = -9.42$)			

Notes. Stocks sorted into 20 percentile bins per month-end on $D = -z(\text{prc}/52\text{H})$; bin 1 contains the least-dispensable stocks (closest to 52-week high) and bin 20 the most dispensable. Cell entries are the time-series mean of the bin's daily equal-weighted CRSP return (bps/day) within PreTOM days vs. Rest days, with Newey-West (20 lag) standard errors. The Gap column reports PreTOM mean minus Rest mean per bin. Only representative bins shown. The full 20-bin curve is in output/syy_piecewise_curve.csv. The negative slope of Gap on D-bin documents that the PreTOM-specific concession strengthens monotonically with dispensability.

Table IA.57: Factor Construction Does Not Drive the Result

Construction	Returns used	Exposure used	PreTOM R^2	Rest R^2
Baseline	Author $D_{10} - D_1$ (JKP chars.)	Holdings d_f	0.629	0.023
Official JKP	Official low/high terciles	Holdings d_f	0.360	0.020
Chen–Zimmermann	As provided	Return-based b^{52H}	0.626	0.018
Hou–Xue–Zhang	As provided	Return-based b^{52H}	0.714	0.102

Notes: Each row reports the cross-sectional R^2 from regressing factors' average daily long-short return on their dispensability exposure, separately for the PreTOM window $[\tau-9, \tau-4]$ and the Rest of the month, under a different factor-return construction. The first two rows use the holdings-based exposure d_f; the external libraries use the return-based analog b^{52H} (Section 9.2). The 52-week-high characteristic that defines d_f is excluded, leaving 152 JKP characteristics; the external libraries use their full factor sets. Official JKP portfolios are the published capped value-weighted low/high terciles from Jensen, Kelly, and Pedersen (2023). The PreTOM relation is more than an order of magnitude stronger than the Rest relation in every construction.

Table IA.58: Replication of Official JKP Portfolios from Primitives

Characteristic	N (days)	Corr. with official
Momentum (12–1)	15,606	0.996
Book-to-market	15,606	0.991
Asset growth	15,606	0.989
Operating profitability	15,606	0.971
Gross profitability	15,606	0.981
Market beta (60m)	15,606	0.998
Quality-minus-junk	15,606	0.990
Median, all 153 characteristics	—	*0.985*
10th percentile	—	*0.960*
Share with corr. > 0.95	—	*93%*
Share with corr. > 0.90	—	*96%*

Notes: Daily time-series correlation between our from-primitives high-minus-low tercile return and Jensen, Kelly, and Pedersen (2023)'s official capped value-weighted (`ret_vw_cap`) spread, by characteristic, over 1963–2025. Our terciles are built using JKP's exact recipe: equal-count thirds of non-micro stocks for breakpoints, with micro caps distributed into the same groups, and capped value weights (market equity winsorized at the NYSE 80th percentile). The top panel lists canonical factors; the bottom panel reports the distribution across all 153 characteristics.

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