# The Liquidity-Demand Component of the Factor Zoo

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**Abstract**

The factor zoo contains a large, recurring month-end liquidity-demand component. Across the 153-factor library of Jensen, Kelly, and Pedersen (2023) over six decades (1963–2025), a factor's short-minus-long exposure to asset dispensability, proxied by distance from the 52-week high, accounts for 63% of the cross-section of mean factor returns during the six trading days ending four trading days before month-end (PreTOM), but only 2.3% outside that window. We trace this to predictable cash demand: investors who need cash sell the holdings least costly to liquidate—stocks with embedded losses, low foregone income, or salient underperformance. Selling pressure maps into factor returns: factors short dispensable stocks rise in PreTOM, while factors long them fall. The relation replicates in two independent anomaly libraries, appears in stock-level returns and seller-initiated order flow, and is larger when intermediary balance-sheet stress is high. The May 2024 move to T+1 settlement provides a signed timing test: the pattern shifts from four to three trading days before month-end, with sign and magnitude predicted by pre-reform dispensability exposure. Net of this component, the zoo splits in two: a transient month-end price-pressure component, and a smaller persistent set of 16 factors, 15 of them tied to investment, accruals, profitability, and related $q$-theory variables. The decomposition also recasts canonical anomalies. Because what matters is which leg holds dispensable stocks, the same shock lifts momentum and quality while depressing value, accounting for the negative value–momentum correlation and part of value's apparent weakness. It also gives a calendar interpretation of the idiosyncratic-volatility puzzle, where the primitive is a stock's candidacy for liquidation, not its volatility.

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# 1 Introduction

The factor zoo contains a large, recurring month-end liquidity-demand component. Over six decades, from 1963 to 2025, 76.5% of the 153 factors in Jensen, Kelly, and Pedersen (2023) have larger absolute daily returns in the pre-turn-of-the-month (PreTOM) window, the six trading days ending four trading days before month-end, than during the rest of the month (Rest).

We show that this concentration reflects predictable cash demand. Investors facing end-of-month cash needs sell the holdings least costly to liquidate—stocks with embedded losses, low foregone income, or salient underperformance.[1] Nathan, Suominen, and Tasa (2026) call this stock-level liquidation characteristic asset dispensability. This selling pressure maps directly into factor returns: factors short dispensable stocks earn positive returns in PreTOM; factors long them earn negative returns. Within PreTOM, exposure to stocks far below their 52-week highs, our proxy for asset dispensability, accounts for 63% of the cross-sectional variation in mean factor returns; outside PreTOM, the same exposure accounts for 2.3% (Figure 1).[2] The same cross-sectional asymmetry appears in two independent factor catalogs.[3]

Once we account for this liquidity-demand component, the zoo is much smaller and more economically grounded. Of the 152 tested factors (we exclude the 52-week-high proxy itself), 16 remain significant after removing the component and requiring significance outside PreTOM. They are concentrated in investment, accruals, profitability, and closely related characteristics—those emphasized by $q$-theory (Hou, Xue, and Zhang, 2015) and featured in mispricing-factor models (Stambaugh and Yuan, 2017). Anomaly returns thus combine a recurring month-end liquidity-demand component with a smaller persistent component tied to standard economic characteristics.

To take the idea of asset dispensability to factor returns, we proceed in two steps. First, we estimate each factor's PreTOM loading without using any stock characteristic. Second, we ask which stock characteristic, aggregated to the factor level as short-leg minus long-leg

[1] Etula et al. (2020) document the month-end cash-raising pattern in aggregate volume and stock returns.

[2] George and Hwang (2004) show that distance from the 52-week high acts as a salient reference point in equity markets.

[3] The catalogs are Chen and Zimmermann (2021), containing 179 decile-sorted factors, and Hou, Xue, and Zhang (2020), containing 199 factors (185 with both top- and bottom-decile portfolio returns).

exposure, best matches those loadings. The answer is distance from the 52-week high. This choice is economically natural: stocks far below their recent highs are salient underperformers and are more likely to carry embedded losses and low foregone income (they pay little in dividends, so selling them forfeits little income), making them attractive candidates for liquidation, as shown by Nathan, Suominen, and Tasa (2026). We therefore use distance from the 52-week high as our empirical proxy for asset dispensability. The resulting factor-level exposure is stable across decades and sets the sign of the PreTOM component.

The month-end liquidity-demand mechanism that maps dispensability into factor returns has three ingredients and rests on Grossman and Miller (1988)'s demand for immediacy. First, cash demand is predictable in timing but stochastic in magnitude. Second, investors meet it by selling the holdings with the lowest liquidation cost. Third, liquidity suppliers absorb the resulting order imbalance only at a price concession when risk-bearing capacity is limited. Duffie (2010)'s slow-moving-capital framework explains why anticipation does not eliminate this concession, as with the price pressure documented around other anticipated events.[4] A factor portfolio loads on this price pressure mechanically through its holdings: if it is short the stocks being sold, its long–short return rises in the cash-demand window; if it is long them, its return falls. Etula et al. (2020) document this cash demand at the aggregate level; Nathan, Suominen, and Tasa (2026) show it accounts for the PreTOM concentration of the momentum premium. We extend the mechanism to the cross-section of factor portfolios.

We measure the realized monthly liquidity-demand shock as the PreTOM return spread between the least- and most-dispensable deciles of stocks. A positive shock means dispensable stocks underperformed during the window. In a panel of factor-months with factor and month fixed effects, factor returns load on this liquidity-demand shock in proportion to their dispensability exposure, and the interaction explains 18% of within-factor PreTOM variation. The same specification outside the PreTOM cash-demand window is statistically indistinguishable from zero. Factors with strong dispensability exposure partially reverse these PreTOM premia in the trading days following the window; factors orthogonal to dispensability show no comparable reversal.

Two further results directly support the dispensability mechanism. First, dispensable

[4]Lou, Yan, and Zhang (2013) show that anticipated, repeated supply shocks—Treasury auctions—move prices predictably even though they are fully foreseen, and Dong, Kang, and Peress (2025) show that persistent, predictable capital flows have price impact and forecast factor returns; in both, slow-moving arbitrage capital leaves an anticipated order imbalance only partly absorbed.

stocks underperform the market during PreTOM and face elevated net seller-initiated trading in TAQ, directly linking the return pattern to selling pressure. Second, the 2024 move to T+1 settlement shifts the predicted cross-sectional pattern by one trading day; the shift is strongest among high-dispensability factors and ETFs, and only 4 of 1,000 placebo reform dates produce the equivalent shift.[5]

The mechanism also recasts several canonical anomalies. Momentum and quality rise before month-end because their short legs contain dispensable stocks, consistent with Nathan, Suominen, and Tasa (2026); value falls because its long leg contains many of them. The same logic helps explain the negative value–momentum correlation, part of value's apparent weakness, and a calendar-based component of factor momentum (complementing Ehsani and Linnainmaa (2022)). It also gives a calendar interpretation of the idiosyncratic-volatility puzzle of Stambaugh, Yu, and Yuan (2015). In the arbitrage-asymmetry view, high idiosyncratic volatility makes overpriced stocks hard to short, so mispricing persists. In our evidence, the cash-demand-window concession falls first on dispensable stocks, and idiosyncratic volatility mainly amplifies that concession when it coincides with dispensability. Outside the cash-demand window, the Stambaugh and Yuan (2017) MGMT composite recovers its usual explanatory power, while the PERF composite, whose power is concentrated inside the window, does not. Monthly anomaly tests therefore conflate a persistent mispricing component with a recurring liquidity-demand concession.

The PreTOM relation is not simply momentum under another name, nor is it an artifact of factor construction. Distance from the 52-week high is related to momentum (George and Hwang, 2004), but factor-level dispensability exposure remains significant in horse races that control for momentum. The cross-sectional return relation also replicates in the Chen–Zimmermann and Hou–Xue–Zhang anomaly libraries, survives controls for liquidity, shorting costs, beliefs, and mispricing-factor benchmarks, and remains after residualizing stock-level dispensability on standard return and risk characteristics. The cleanest test holds factor membership fixed. Within each factor's short leg, we sort stocks only on dispensability; the most-dispensable sub-quintile underperforms the least-dispensable sub-quintile by a pooled 12.3 basis points per day in PreTOM relative to the rest of the month, with an individually

[5] The reform is mandated by SEC (2023). Nathan, Suominen, and Tasa (2026) document the corresponding stock-level shift.

significant differential in 139 of 152 factors.[6] The pattern therefore comes from which stocks are sold in the cash-demand window, not from exposure to momentum or from covariance among factor portfolios.

Our work relates to four literatures. First, to work reducing the dimensionality of the factor zoo (Cochrane, 2011; Harvey, Liu, and Zhu, 2016; McLean and Pontiff, 2016; Hou, Xue, and Zhang, 2020; Kozak, Nagel, and Santosh, 2020; Kelly, Pruitt, and Su, 2019; Lettau and Pelger, 2020; Bryzgalova, Huang, and Julliard, 2023; Feng, Giglio, and Xiu, 2020): we identify an economically interpretable dimension whose premium is calendar-dependent rather than estimating latent factors statistically.

Second, to the calendar-time return literature (Ariel, 1987; Ogden, 1990; Heston and Sadka, 2008; Etula et al., 2020; Nathan, Suominen, and Tasa, 2026). Keloharju, Linnainmaa, and Nyberg (2016) document return seasonalities in factors and anomalies at the annual calendar-month frequency and conclude that they aggregate from many distinct factor premiums with low cross-sectional correlations.[7] We document a sub-monthly cycle of opposite structure: a single cross-sectional factor absorbs 63% of factor return variation in PreTOM and is governed by an identified institutional mechanism. The Heston and Sadka (2008) same-calendar-month factor passes our filter, confirming that the annual and intra-monthly cycles are empirically separable.

Third, to demand-based asset pricing (Coval and Stafford, 2007; Lou, 2012; Koijen and Yogo, 2019; Gabaix and Koijen, 2021): we locate a recurring cross-sectional demand shock that anomaly portfolios load on through portfolio overlap. The closest prior is Hartzmark and Solomon (2025), who document market-wide predictable price pressure; we identify the cross-sectional analog that maps onto the factor zoo. Dong, Kang, and Peress (2025) document a complementary time-series channel from persistent flows. Fourth, to the $q$-factor framework (Hou, Xue, and Zhang, 2015) and the mispricing-factor framework (Stambaugh, Yu, and Yuan, 2012; Stambaugh and Yuan, 2017): the factors that pass the institutional filter are those that production-based asset pricing predicts should carry compensation.

Monthly anomaly returns combine two components: a transient month-end price-pressure component generated by predictable cash demand, and a persistent component tied to invest-

[6] The 52-week-high characteristic itself is excluded from this test, leaving 152 of the 153 factors.

[7] Keloharju, Linnainmaa, and Nyberg (2021) discriminate risk- versus mispricing-based explanations for the annual cycle; our channel is predictable liquidity demand, distinct from both.

ment, accruals, profitability, and related characteristics. Most anomalies are not spurious; their monthly returns simply bundle the two.

The empirical design has four steps. First, factor returns line up with dispensability exposure only in the cash-demand window. Second, the realized monthly price concession on dispensable stocks moves factor returns in proportion to that exposure. Third, seller-initiated order flow shows extra selling pressure on dispensable stocks in the same window. Fourth, the T+1 settlement reform shifts the pattern one trading day closer to month-end with the sign predicted by pre-reform exposure.

The rest of the paper documents the cross-sectional structure of factor returns, measures the realized liquidity-demand shock and tests its predictions across the T+1 settlement reform and stock-, trade-, and ETF-level evidence, characterizes the factors with little exposure to the liquidity-demand component, and revisits canonical factors through the dispensability mechanism.

# 2 Data and Empirical Design

## 2.1 Factor Returns

We build decile-sorted long–short portfolios from the 153 firm characteristics of Jensen, Kelly, and Pedersen (2023), downloaded from WRDS. For each characteristic $f$ and trading day $t$, we sort stocks into deciles on NYSE breakpoints using the value of $f$ at the previous month-end, and define the long–short return as

$$R_{f,t} \;=\; R_{D10,f,t} \;-\; R_{D1,f,t}, \tag{1}$$

where $R_{D10,f,t}$ and $R_{D1,f,t}$ are the value-weighted returns on the top (D10) and bottom (D1) decile portfolios formed on characteristic $f$ at the previous month-end. We apply no per-factor sign flip: $D10$ is the high-characteristic decile, so factors whose original literature predicts the low side as the long leg (e.g., low-beta) appear with $R_{f,t} < 0$ in expectation. This convention has two implications for what follows. Headline concentration tests use the absolute value of factor returns, $|R_{f,t}|$, and are therefore invariant to factor sign. Cross-sectional regressions of mean PreTOM returns on $d_f$ use the $D10-D1$ convention for all 153 factors, so the sign of the estimated slope reflects the data rather than a researcher choice of sign convention.

Portfolios are value-weighted (VW) by daily-lagged market capitalization, following Hou, Xue, and Zhang (2020). The sample spans February 1963 through December 2025, covering 755 calendar months and 15,834 trading days. The Chen and Zimmermann (2021) and Hou, Xue, and Zhang (2020) replications in Section 9.2 use the factor returns provided by those libraries. Appendix IA.28 reports construction robustness: the PreTOM-versus-Rest asymmetry is unchanged under Jensen, Kelly, and Pedersen (2023)'s own published low/high tercile portfolios and under both external libraries.

## 2.2 Trading Day Index

We index trading days relative to month-end with $\tau$. The last trading day of month $m$ is $\tau = 0$; $\tau = -1$ is the preceding trading day, $\tau = -2$ the day before that, and so on. Positive values refer to trading days after month-end, with $\tau = 1$ the first trading day of the next month. *PreTOM* is the six-day window $\tau = -9, \dots, -4$, inclusive; for compactness, we also write this window as $[\tau{-}9, \tau{-}4]$. *Rest* includes all trading days outside PreTOM. When used, *Post* denotes the seven-day window $[\tau{-}3, \tau{+}3]$ around month-end: the three trading days before month-end ($\tau{-}3, \tau{-}2, \tau{-}1$), the last trading day ($\tau = 0$), and the three trading days after ($\tau{+}1, \tau{+}2, \tau{+}3$). We reserve $\tau$ for this event-time index and use $T$ only for settlement, where T+1 and T+2 refer to trade date plus one or two business days.

## 2.3 Settlement Reform

U.S. equity settlement shortened from T+3 to T+2 on September 5, 2017, and from T+2 to T+1 on May 28, 2024.[8] We use the May 2024 transition for the difference-in-differences analysis in Section 5, which directionally shifts the settlement-driven selling window toward month-end and provides a one-day shift prediction for which factors should be most affected.

We use $i$ to index stocks, $m$ months, $f$ factors, and $e$ ETFs. The main objects are $\delta_{i,m}$, stock-level dispensability; $d_f$, a factor's short-minus-long exposure to dispensability; $\text{LDS}_m$, the realized monthly liquidity-demand shock; and $d_e$, ETF holdings-weighted dispensability. Internet Appendix Table IA.1 collects the variable definitions.

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

# 3 The Common Month-End Component

Anomaly returns concentrate before month-end. We first estimate each factor's PreTOM loading without using any stock characteristic, then identify the stock characteristic that best matches that loading. The answer carries the stock-level notion of dispensability of Nathan, Suominen, and Tasa (2026) into the factor-zoo setting, and we document the calendar asymmetry it implies.

## 3.1 Factor Returns Concentrate in PreTOM

For each factor, we compute the average daily long–short return separately in PreTOM, from $\tau = -9$ through $\tau = -4$, and in the remaining trading days. Of the 153 JKP factors, 117, or 76.5%, earn a larger absolute daily long–short return in PreTOM than in the rest of the month. The concentration is broad across the 14 JKP themes,[9] is mainly a short-leg phenomenon, and is stable across subperiods (Internet Appendix Table IA.7).[10]

## 3.2 Estimating Each Factor's PreTOM Loading

To measure each factor's PreTOM concentration without imposing structure, for each factor $f$ we run a daily time-series regression of the factor's long–short return on a PreTOM dummy. The slope $\lambda_f$ is the average daily PreTOM return spread of factor $f$ relative to Rest:

$$R_{f,t} \;=\; \alpha_f + \lambda_f \cdot \mathbf{1}[\mathrm{PreTOM}_t] + \varepsilon_{f,t}. \tag{2}$$

The 153 estimated $\lambda_f$ range from $+10.5$ to $-9.1$ basis points per day.[11]

[9] Jensen, Kelly, and Pedersen (2023) group the 153 characteristics into 14 themes (such as Momentum, Value, Profitability, Investment, and Low Risk) by hierarchically clustering factors on their return correlations; we use these groupings throughout.

[10] The theme-level, leg-level, and subperiod splits are in Internet Appendix Table IA.6. The PreTOM concentration appears in 109 of 153 factors in 1963–1993 and 113 of 153 factors in 1994–2025. Investment is the main exception, with only 4% of its return earned in PreTOM.

[11] Internet Appendix Table IA.34 reports $\lambda_f$ for all 153 factors, ranked, with the PreTOM and Rest components.

### 3.3 The Stock Characteristic Behind the PreTOM Component

The cross-section of factor returns during the cash-demand window is summarized model-free either by the loading $\lambda_f$ or by the mean PreTOM long–short return $\bar{R}_f^{\text{PreTOM}}$. The two differ only by each factor's Rest-window average, which is nearly orthogonal to dispensability across factors (Section 3.5), so they order factors near-identically. We work with $\bar{R}_f^{\text{PreTOM}}$, the object the headline decomposition uses, and ask which stock characteristic, aggregated to the factor level, best matches its cross-section.

For each candidate characteristic $c$ in the JKP library, we construct a factor-level exposure $d_f^c$ as the time-averaged value-weighted difference in $c$ between the factor's bottom (D1) and top (D10) deciles—its short and long legs, since $R_{f,t} = D10 - D1$,

$$d_f^c \;=\; \frac{1}{M}\sum_{m=1}^{M}\left(\bar{c}_{\text{D1},f,m} \;-\; \bar{c}_{\text{D10},f,m}\right), \tag{3}$$

where $\bar{c}_{\text{D1},f,m}$ and $\bar{c}_{\text{D10},f,m}$ are the value-weighted averages of $c$ in factor $f$'s D1 and D10 deciles in month $m$. We then run the cross-factor regression

$$\bar{R}_f^{\text{PreTOM}} \;=\; \alpha^c + \beta^c\, d_f^c + \varepsilon_f^c \tag{4}$$

one characteristic at a time, and rank characteristics by the resulting $R^2$.

Distance from the 52-week high has the highest correlation with mean PreTOM returns. Its factor-level exposure accounts for 62% of their cross-section, ahead of the Piotroski F-score at 48% (Panel A of Table 1; full ranking in Internet Appendix Table IA.34). The next-best characteristics are mainly quality, low-risk, and profitability variables; value, accruals, and investment variables do not rank near the top.

We therefore adopt distance from the 52-week high as our baseline measure of stock-level dispensability. Among the candidate characteristics it is the one most aligned with the empirically estimated PreTOM cross-section, and stocks far below their recent highs are natural candidates for liquidation when investors need cash (George and Hwang, 2004; Nathan, Suominen, and Tasa, 2026). Several quality, profitability, and low-risk characteristics load on the same component and rank close behind, more so in the later subsample; the within-leg sub-sorts and order-flow evidence reported below show that distance from the 52-week high is the cleanest proxy for the calendar-priced dispensability component.

The characteristic search is a measurement step, not the source of the economic hypothesis. The hypothesis comes from the stock-level dispensability mechanism in Nathan, Suominen, and Tasa (2026): when investors need cash, they sell the holdings with the lowest liquidation cost. Distance from the 52-week high is a natural proxy because it captures salient underperformance and is related to embedded losses and low foregone income. The search asks whether this economically motivated proxy is also the best empirical counterpart of the structure-free month-end component in the factor zoo.

### 3.4 Measuring Stock-Level Dispensability

We measure dispensability at the stock-month level using distance from the 52-week high, the proxy selected in Section 3.3.

For each stock $i$ at the end of month $m$, define its price-to-high ratio as

$$h_{i,m} \;=\; \frac{P_{i,m}}{\max_{\tau \in \mathcal{T}_m} P_{i,\tau}}, \tag{5}$$

where $P_{i,m}$ is the month-end closing price and $\mathcal{T}_m$ is the trailing 252-trading-day window. A stock at its 52-week high has $h_{i,m} = 1$; a stock far below its high has a low value of $h_{i,m}$.[12]

We convert this ratio into a monthly dispensability score by standardizing it across stocks and reversing the sign:

$$\delta_{i,m} \;=\; -\, z_m(h_{i,m}), \tag{6}$$

where $z_m(\cdot)$ subtracts the month-$m$ cross-sectional mean and divides by the month-$m$ cross-sectional standard deviation. High values of $\delta_{i,m}$ therefore identify stocks that are far below their 52-week highs relative to other stocks in the same month. The score is observed at the end of month $m$ and used for returns in month $m+1$.

We then aggregate stock-level dispensability to the factor level. For factor $f$, let $\bar{\delta}_{\mathrm{D1},f,m}$ and $\bar{\delta}_{\mathrm{D10},f,m}$ denote the value-weighted average dispensability scores of the bottom and top

[12]The trailing 252 trading days correspond to approximately 12 calendar months. In implementation we use JKP's *prc_highprc_252d* characteristic.

characteristic deciles used to form month-$m$ returns. Define

$$d_f \;=\; \frac{1}{M}\sum_{m=1}^{M}\left(\bar{\delta}_{\mathrm{D1},f,m} \;-\; \bar{\delta}_{\mathrm{D10},f,m}\right). \tag{7}$$

Thus $d_f$ is the factor's average short-minus-long exposure to dispensable stocks under the common D10−D1 return convention. We refer to $d_f$ as the factor's *dispensability exposure.*

**Sign convention.** A high value of $d_f$ means that factor $f$ is short more-dispensable stocks than it is long. If month-end liquidity demand pushes dispensable stocks down, high-$d_f$ factors earn positive PreTOM returns and low-$d_f$ factors earn negative PreTOM returns.

## 3.5 Calendar Asymmetry and Reversal

Dispensability exposure $d_f$ organizes the cross-section of PreTOM factor returns. For each factor $f$, recall that $\bar{R}_f^{\mathrm{PreTOM}}$ is its average daily long–short return in PreTOM, and let $\bar{R}_f^{\mathrm{Rest}}$ denote its average in the rest of the month. We estimate two cross-sectional regressions over the 152 factors (excluding the 52-week-high characteristic itself, the self-loading factor whose $d_f$-component coincides with its own characteristic by construction):

$$\bar{R}_f^{\mathrm{PreTOM}} = \alpha^{\mathrm{PreTOM}} + \beta^{\mathrm{PreTOM}} \cdot d_f + \varepsilon_f^{\mathrm{PreTOM}}, \tag{8}$$

$$\bar{R}_f^{\mathrm{Rest}} = \alpha^{\mathrm{Rest}} + \beta^{\mathrm{Rest}} \cdot d_f + \varepsilon_f^{\mathrm{Rest}}, \tag{9}$$

with month-block bootstrap inference ($B = 5{,}000$ draws, calendar months sampled with replacement; both $\bar{R}_f$ and $d_f$ recomputed within each draw).[13]

Across the 152 factors, dispensability exposure $d_f$ accounts for 63% of the cross-factor variation in PreTOM daily returns and only 2.3% outside the window (Panel A of Table 1, Figure 1). Because the factor portfolios are fixed within the month, the PreTOM–Rest contrast cannot be attributed to portfolio overlap alone. We develop this argument further in Section 9.2.

Run on the full-month average daily return, the same regression yields $\beta = +2.11$

[13] We bootstrap because the 152 factors are not independent observations: they share stocks and load on common themes, so their returns are cross-sectionally correlated. Resampling whole calendar months preserves this dependence, whereas standard errors that treat the factors as independent would overstate the precision of the slope.

($t_{\text{boot}} = +2.71$, $R^2 = 29\%$). That is, the PreTOM component is large enough that the full-month cross-section inherits its structure. Distance from the 52-week high is not meant to be orthogonal to standard characteristics. A useful proxy for dispensability should partly overlap with past returns, risk, and quality, because these variables help identify stocks that are natural candidates for sale. The relevant question is whether those characteristics exhaust the calendar-priced component, and they do not. After residualizing stock-level dispensability on reversal, prior 11-month return, market beta, idiosyncratic volatility, and QMJ-safety, the reconstructed factor loading still accounts for 36% of the PreTOM cross-section and only 2% of the Rest cross-section (Internet Appendix Table IA.14). The 52-week-high measure therefore contains liquidation-related variation beyond standard factor characteristics.

The calendar pattern is not sensitive to the exact six-day window. Re-estimating the cross-sectional regression over every six-day window in the trading month, the $R^2$ remains high for windows beginning in the second half of the month, ranging from 0.56 to 0.68, and dropping to 0.11 or below outside that region (Figure 2). This pattern is consistent with selling pressure building over a trading week rather than appearing on a single day. The timing also matches the aggregate return pattern: PreTOM is the only consecutive stretch of trading days in the month in which the CRSP market return is uniformly negative, averaging $-4$ basis points per day before recovering at $\tau-3$ (Internet Appendix Figure IA.2).[14]

The timing of the cross-section matches the timing of liquidity demand. Regressing factor returns on the dispensability exposure separately by calendar window (Panel B of Table 1), this exposure accounts for 63% of the cross-section in PreTOM, 2.3% in Rest, and has the opposite sign in the Post window $[\tau-3, \tau+3]$, consistent with factor return reversal. The same stocks that are temporarily sold before month-end partially recover afterward.

The reversal is concentrated where the mechanism predicts. Sorting factors by the absolute value of their dispensability exposure, high-exposure factors show a negative Post-on-PreTOM relation: factors that earn the most from dispensability pressure in PreTOM give back a substantial share of that return in the following seven trading days. Low-exposure factors do not show the same pattern. They behave more like ordinary anomaly portfolios, with continuation rather than reversal (Internet Appendix Table IA.9).

[14]The cross-factor return pattern is also more stable within PreTOM than elsewhere. Pairwise correlations of factor-return vectors across trading-day positions average 0.51 within PreTOM, compared with 0.13 within Rest (Figure IA.1).

Dispensability does not describe all factor returns. It identifies a transient component that appears in the cash-demand window and partly reverses afterward, and the factors with little exposure to this component are therefore the natural candidates for the persistent component we study later.

# 4 The Realized Liquidity-Demand Shock

## 4.1 Measuring the Liquidity Shock

Month-end liquidity demand is predictable in timing but not in magnitude. Institutions face recurring cash needs, rebalancing demands, and settlement constraints around month-end, but the latent demand behind these trades is not directly observed and need not come from a single source. What we observe is its equilibrium price impact.

We measure that price impact with the PreTOM return spread between least- and most-dispensable stocks:

$$\mathrm{LDS}_m^{\mathrm{PreTOM}} \equiv \bar{R}_{\mathrm{D10},m}^{\mathrm{PreTOM}} - \bar{R}_{\mathrm{D1},m}^{\mathrm{PreTOM}}, \tag{10}$$

where D1 is the decile of stocks farthest from the 52-week high and D10 is the decile nearest the high. A positive value of $\mathrm{LDS}_m^{\mathrm{PreTOM}}$ means that dispensable stocks underperform least-dispensable stocks during PreTOM. The same construction gives $\mathrm{LDS}_m^{\mathrm{Rest}}$ and $\mathrm{LDS}_m^{\mathrm{Post}}$. Unconditionally, $\mathrm{LDS}_m$ is positive in PreTOM (+6.82 bps/day, $t = +3.05$), close to zero in a mid-month placebo window $[\tau-15, \tau-10]$ ($-0.36$ bps/day, $t = -0.15$), and negative in the post-window $[\tau-3, \tau+3]$ ($-6.34$ bps/day, $t = -2.96$).[15]

$\mathrm{LDS}_m$ is not a flow measure. It is the realized price concession on dispensable stocks. We therefore interpret it as a Grossman–Miller price-pressure shock, not as a Pástor and Stambaugh (2003) liquidity-risk factor. Investors demand immediacy, liquidity suppliers absorb the imbalance at a concession, and the concession is larger when risk-bearing capacity is scarce. Duffie (2010) supplies the property our setting requires: the concession persists even when the shock is anticipated and repeated, because intermediation capacity is limited and end-investor capital is slow to move.

[15] Window-mean estimates and standard errors are reported in Internet Appendix Table IA.3.

## 4.2 What Predicts the Magnitude of the Shock?

Table 2 asks when the price concession on dispensable stocks is large. We relate $\text{LDS}_m^{\text{PreTOM}}$ to three classes of variables: intermediary balance-sheet stress, direct selling pressure, and aggregate market conditions.

The results are consistent with the price-pressure interpretation. Intermediary stress predicts $\text{LDS}_m^{\text{PreTOM}}$ across specifications. In the TAQ sample, the seller-initiated trading imbalance between dispensable and least-dispensable stocks also predicts the shock, directly linking the return spread to selling pressure. Mutual-fund flows have little explanatory power on their own, but their effect strengthens when intermediary balance sheets are strained. This is the Grossman–Miller logic: selling pressure has the largest price impact when immediacy provision is costly. Standard traded-liquidity and Amihud measures lose explanatory power once intermediary stress is included. The broad macro stress proxies—changes in VIX and the crisis dummy—enter with negative partial coefficients, but this reflects their collinearity with intermediary stress and the market return, which already absorb the stress channel with the predicted sign; conditional on those, the macro proxies carry little independent information.

The same specifications do not explain mid-month returns and show partial reversal in the post-window (Internet Appendix Tables IA.50 and IA.51). The evidence is therefore concentrated in the cash-demand window and its immediate aftermath. The price concession is the common component of the factor zoo: factors covary with it in proportion to their dispensability exposure $d_f$.

## 4.3 The Liquidity Shock as a Common Component

If $\text{LDS}_m^{\text{PreTOM}}$ is a common monthly shock, factor returns should load on it in proportion to their predetermined dispensability exposure. We test this in a factor–month panel with factor and month fixed effects:

$$R_{f,m}^{\text{PreTOM}} \;=\; \alpha_f \;+\; \tau_m \;+\; \beta \left(d_f \times \text{LDS}_m^{\text{PreTOM}}\right) \;+\; \varepsilon_{f,m}, \tag{11}$$

indexed by factor $f$ and month $m$, with two-way clustered standard errors. Month fixed effects absorb aggregate shocks, including the level of $\text{LDS}_m^{\text{PreTOM}}$ itself. The interaction asks whether, in months when the shock is large, factor returns move according to their ex ante exposure to dispensable stocks.

The panel estimates support this prediction. Across 152 factors and 755 months (113,907 factor-months) from 1963 to 2025 (the 52-week-high characteristic that defines $d_f$ is excluded throughout), the interaction coefficient is 0.511 with $t = 16.04$, explaining 18% of within-factor PreTOM variation (Table 3, Panel A). The same specification on Rest returns yields a coefficient that is economically small and statistically indistinguishable from zero ($\beta = 0.016$, $t = 0.65$). The same monthly shock moves anomaly portfolios in proportion to their predetermined dispensability exposure. As a falsification, replacing $\text{LDS}_m^{\text{PreTOM}}$ with $\text{LDS}_m^{\text{Post}}$ produces a coefficient indistinguishable from zero ($\beta = 0.002$, $t = 0.05$).

A mechanical-overlap concern arises because LDS is built from stock returns, and factor portfolios hold subsets of those stocks. We address this by rebuilding the shock after excluding stocks that appear in the extreme legs of all factors in the same JKP theme. This exclusion changes the shock substantially for several themes: the correlation with the full-universe LDS ranges from 0.41 to 0.97 across themes, with a mean of 0.77. The panel coefficient remains close to the matched baseline, 0.450 versus 0.514, and the Rest estimate remains small and statistically insignificant ($\beta = 0.022$, $t = 0.72$; Table 3, Panel B). The result is therefore unlikely to be driven by the same stocks entering both the factor return and the shock construction within a theme. Internet Appendix Table IA.4 reports the Full-LDS Rest placebo ($\beta = -0.003$, $t = -0.12$) alongside the same row under the theme-wide exclusion.

# 5 The T+1 Settlement Reform

The SEC's May 28, 2024 transition from T+2 to T+1 equity settlement (SEC, 2023) shifts settlement-related month-end selling by one trading day. Prior to the reform, open-end mutual funds faced a structural mismatch: fund redemptions settled on T+1 while equity sales settled on T+2. To meet month-end cash demands on time, funds had to sell equities one day earlier than their redemption settlement required, four trading days before month-end under T+2. The May 2024 reform eliminated this mismatch by aligning equity settlement with fund redemption settlement at T+1, removing the need for precautionary pre-selling at $\tau{-}4$ and shifting it to $\tau{-}3$. The factor-zoo setting yields a cross-sectional implication of this shift that the time-series test in Nathan, Suominen, and Tasa (2026) does not impose: the reform-induced shift should scale linearly with each factor's dispensability exposure $d_f$ and be absent in factors orthogonal to dispensability.

The logic is mechanical. Under T+2, investors who need settled cash by month-end must sell by $\tau-4$; under T+1, they can sell by $\tau-3$. The price pressure should therefore move one trading day later. For factors short dispensable stocks, the long–short return should move from $\tau-4$ to $\tau-3$; for factors long dispensable stocks, the sign of the shift flips.

For each factor $f$, define the signed factor return $R_{f,t} \equiv R^{D10}_{f,t} - R^{D1}_{f,t}$. Using the T+2 era from September 5, 2017 through April 30, 2024 and the T+1 era from June 1, 2024 through December 31, 2025, with May 2024 dropped, we estimate

$$\begin{aligned} R_{f,t} \; &= \alpha_f + b_{f,\tau-4}\,\mathbf{1}_{[\tau-4],t} + b_{f,\tau-3}\,\mathbf{1}_{[\tau-3],t} + c_f\,\mathrm{T1Reform}_t \\ &\qquad + \pi_{f,\tau-4}\,\mathbf{1}_{[\tau-4],t}\,\mathrm{T1Reform}_t + \pi_{f,\tau-3}\,\mathbf{1}_{[\tau-3],t}\,\mathrm{T1Reform}_t + \varepsilon_{f,t}, \end{aligned} \tag{12}$$

where $\mathrm{T1Reform}_t$ indicates dates from June 1, 2024 onward and the omitted reference category is the early-month window $[\tau+5, \tau+8]$. The per-factor DiD of interest is

$$\Delta_f \;\equiv\; \pi_{f,\tau-3} - \pi_{f,\tau-4}. \tag{13}$$

Under T+1, settlement-driven selling shifts from $\tau-4$ to $\tau-3$. For a factor with $d_f > 0$, the short leg holds dispensable stocks: pre-reform $\tau-4$ selling depressed D1 and thus elevated $R_f = D10 - D1$ at $\tau-4$; post-reform, the elevation moves from $\tau-4$ to $\tau-3$, giving $\Delta_f > 0$. For $d_f < 0$ the long leg holds dispensable stocks and the prediction flips: $\Delta_f < 0$. The cross-sectional implication is that $\Delta_f$ should scale linearly with signed $d_f$.

The cross-sectional DiD test yields a one-sided randomization $p$-value of 0.004: only 4 of 1,000 placebo windows produce a slope as large as the actual May 2024 slope of $b = +47.9$ basis points per unit of $d_f$ (precision-weighted), placing the realized slope at the 99.6th percentile of a placebo distribution of 1,000 pseudo-reform dates drawn from 1990 to 2015 (Figure 3, Table 4). Each placebo imposes the same 80-month pre-period and 19-month post-period and re-estimates the signed cross-sectional DiD.

The choice of weighting matters and we report both specifications explicitly. The unweighted OLS slope is +33.4 bps per unit of $d_f$, with a placebo $p$-value of 0.067; the precision-weighted WLS slope is +47.9 bps, with a placebo $p$-value of 0.004. The dependent variable $\Delta_f = \pi_{f,\tau-3} - \pi_{f,\tau-4}$ is an estimated DiD coefficient, and its precision varies substantially across factors. We report WLS because of this heterogeneous precision; we weight by the inverse of the analytical variance of $\Delta_f$ from equation (12), the standard remedy for cross-sectional regressions with estimated dependent variables (Lewis and Linzer, 2005). We also report OLS, capped-weight WLS, winsorized-weight WLS, theme-equal regression, and leave-one-theme-out slopes (Internet Appendix Table IA.12). The estimates remain positive across these specifications, so the sign of the settlement shift does not depend on a small number of high-precision factors.

The estimates are positive under all three inference procedures. JKP theme-clustered analytical standard errors yield $p = 0.007$ for WLS, and month-block bootstrap inference yields $p = 0.076$ for WLS and $p = 0.107$ for OLS. The placebo distribution is the primary inference because the reform is a single calendar event and the post-reform sample is short. Internet Appendix Table IA.11 reports all three.

Influence diagnostics show that no single factor drives the WLS estimate. Appendix Table IA.12 reports weighting and influence diagnostics using an alternative cell-mean-dispersion precision measure; these checks produce slopes in the same direction and range as the main WLS specification, with leave-one-factor-out slopes positive across all 152 exclusions and slope changes bounded by roughly $\pm 7$ bps. The most influential single factor is the Ohlson O-score, a measure of financial distress. Leave-one-theme-out slopes and Cook's-distance diagnostics are reported in Internet Appendix Table IA.12.

The mechanism predicts the sign of $\Delta_f$ for each canonical factor from its $d_f$. UMD ($d_f > 0$): predicted positive, observed +188 bps. QMJ ($d_f > 0$): predicted positive, observed +93 bps. Book-to-market ($d_f < 0$): predicted negative, observed −87 bps (Panel C of Table 4). The signs agree with the prediction for all three canonical factors, and the magnitudes increase with $|d_f|$. The largest coefficient change occurs at the predicted day, $\tau-4$, consistent with the relaxation of the old settlement boundary pressure. The $\tau-3$ coefficients have the predicted signs but smaller magnitudes, indicating that the reform removes the old settlement constraint more than it creates a new one-day trading cluster.

# 6 Selling Pressure on Dispensable Stocks

We validate the mechanism through four channels at higher statistical power than the factor-level cross-section: stock-level returns, trade-level selling pressure, the within-short-leg sub-sort, and the cross-section of ETFs.

## 6.1 Stock-Level Returns

To check that the PreTOM dispensability return spread is present in individual stock returns and not only in our factor portfolios, we run a two-stage Fama-MacBeth regression of market-adjusted stock returns on dispensability quintiles, controlling for the three Fama-French firm characteristics (lagged 60-month market beta, log market capitalization, and book-to-market). The relationship is monotone increasing across dispensability quintiles, apart from a mild Q3–Q4 non-monotonicity. The Q5−Q1 PreTOM-minus-Rest spread is −6.14 bps/day ($t = -3.55$) under VW with FF3 controls (Internet Appendix Table IA.52). The estimate is stable across specifications: without controls, the spread is −7.91 ($t = -3.65$); equal-weighted versions deliver −7.11 (no controls) to −7.16 (with FF3 controls, $t = -5.56$); adding momentum, reversal, investment, profitability, and idiosyncratic volatility leaves the VW spread at −5.30 ($t = -3.46$). Specification details and the full regression equations are in the stock-level Fama–MacBeth section of the Internet Appendix (Table IA.52).

## 6.2 Net Selling at Month-End (TAQ)

We test whether net seller-initiated flow in TAQ scales with the continuous dispensability characteristic during PreTOM. If month-end selling pressure is driven by stock-level dispensability, the flow-dispensability slope should steepen in PreTOM relative to the rest of the month.

We use the WRDS Intraday Indicators dataset, which classifies every TAQ trade as buyer- or seller-initiated via Lee and Ready (1991). The outcome variable, NetSell, is the difference between seller- and buyer-initiated dollar volume, scaled by total dollar volume; we report coefficients in percentage points of this flow share.[16] Restricting to stocks above the NYSE

[16]Lee-Ready classification identifies the side initiating each trade, not the trader's identity. The test therefore measures the directional balance of trading pressure rather than institutional flow specifically.

median market capitalization, the stock-day panel covers 2003–2022 with approximately 17.8 million observations. We estimate

$$\text{NetSell}_{i,t} \;=\; \alpha_i + \lambda_t + \beta\,\delta_{i,m-1} + \gamma\left(\delta_{i,m-1} \times \text{PreTOM}_t\right) + u_{i,t}, \tag{14}$$

where $\delta_{i,m-1}$ is stock $i$'s dispensability lagged one month (defined in Section 3.4 as the negated within-month $z$-score of distance from the 52-week high, a continuous measure), $\text{PreTOM}_t \in \{0, 1\}$ indicates PreTOM days, and $\alpha_i, \lambda_t$ are stock and day fixed effects. The day fixed effect absorbs any market-wide PreTOM shift in net order flow; the coefficient of interest, $\gamma$, isolates the *cross-sectional* steepening of the dispensability–selling-pressure relationship inside PreTOM.

The interaction is positive and significant: the cross-sectional slope between dispensability and net seller-initiated flow steepens during PreTOM relative to the rest of the month ($\hat{\gamma} = +1.46$ pp per unit of $\delta$, $t = +3.89$; Table 5, column 1). The cross-section that shows the PreTOM return spread also shows the PreTOM order-flow tilt.

The quintile specification gives the same result. Replacing $\delta$ with an indicator for the top dispensability quintile (Q5) and interacting it with PreTOM yields $\hat{\gamma}_{Q5} = +1.99$ pp ($t = +2.73$; Table 5, column 3): the most-dispensable stocks experience an additional roughly two percentage points of net seller-initiated dollar volume share during the six PreTOM days, on top of the persistent baseline absorbed by the stock fixed effect.

## 6.3 Within-Short-Leg Dispensability Sub-Sort

The mechanism operates within factor legs, not only across factor names. This is the most direct answer to the concern that $d_f$ merely proxies for overlap with the standalone 52-week-high factor, or for mechanical covariance among factor portfolios: it holds factor-leg membership fixed and varies only stock-level dispensability. Within each strong-fit factor's short leg, we sort stocks again by dispensability. A factor-level explanation predicts no difference within the short leg; a stock-level dispensability mechanism predicts that the most-dispensable stocks should underperform specifically in PreTOM.

We work with six factors with strong PreTOM concentration: twelve-month price momentum (D1, losers), gross profitability (D1, low), operating profitability (D1, low), the

Ohlson O-score (D10, high distress), earnings-to-price (D1, low),[17] and QMJ (D1, junk). For each factor we restrict to the short-leg decile and sub-sort within that decile by within-month $z$-score of the dispensability score $\delta_{i,m}$ into five within-leg quintiles, and compute the Q5−Q1 spread (most-dispensable minus least-dispensable).

Across the six factors, the within-leg PreTOM spread ranges from −9.5 to −13.9 basis points per day, with per-factor $t$-statistics between −1.8 and −3.1 (Table 6). The pooled spread is −11.4 basis points per day (date-clustered $t = -3.05$), while the Rest-window spread is an order of magnitude smaller (−1.2, $t = -0.46$). The within-leg spread is thus concentrated in PreTOM even within a fixed anomaly leg.

Extending the within-leg sub-sort to the full library of 152 factors gives a pooled PreTOM-minus-Rest DiD of −12.3 bps/day (factor-clustered $t = -52.3$).[18] The within-leg differential is individually significant at $|t| > 2$ in 139 of 152 factors (91%), so the pattern is broad across the library, not concentrated in a small set of factors. The economically meaningful statistics are the −12.3 bps/day differential and the 139/152 factor count, not the mechanically large pooled $t$.

This isolates the dispensability characteristic from any factor-level covariance structure: stocks within a single factor's short leg share the factor characteristic and any covariance pattern attributable to that factor membership, yet sorting by stock-level dispensability still produces a sizable PreTOM differential. The result is the stock-level analog of Daniel and Titman (1997)'s finding that characteristics retain predictive power after controlling for factor loadings: the dispensability primitive operates at the stock level, not as covariance with any single dominant factor.

Distance from the 52-week high is one of several possible empirical proxies for dispensability. Among eight alternative proxies, only distance from the 52-week high produces a within-leg spread concentrated in PreTOM. We test the five empirically strongest alternatives

[17] We classify earnings-to-price as a profitability characteristic following JKP, not as a value factor: in our sample, low E/P stocks are systematically further from their 52-week highs than high E/P stocks ($d_f = +0.16$), consistent with low E/P signaling weak earnings rather than high valuation multiples. Book-to-market and sales-to-price, the genuine value factors in JKP's taxonomy, have $d_f < 0$, and their long legs (D10, value) contain the dispensable stocks; we discuss them separately in the Internet Appendix, "Additional Canonical-Anomaly Implications."

[18] Factor-clustering treats the 152 factor-level differentials as the clusters; the per-factor DiDs are highly precise because each is an average over millions of within-leg stock-days, so the cross-cluster aggregation produces a large pooled $t$. Adding a second clustering dimension on date (two-way clustering) yields a similarly large pooled $t$, since the dispensability sort works similarly across factors on the same days.

from the Section 3.3 cross-sectional search (F-score, QMJ, the Stambaugh–Yuan PERF mispricing composite, 21-day realized volatility, and the 21-day Hou–Xue–Zhang idiosyncratic volatility) plus three further characteristics emphasized in the related literature as proxies for stock quality, profitability, and idiosyncratic risk (QMJ-safety, operating profitability, and the 21-day CAPM idiosyncratic volatility). Most alternatives produce comparable $Q5 - Q1$ spreads in PreTOM and Rest, so the PreTOM-minus-Rest differential—the calendar-priced component—is small or zero. The differential is −7.85 bps/day ($t = -11.7$) for distance from the 52-week high, −2.48 ($t = -2.9$) for operating profitability, and +3.10 ($t = +2.7$) for 21-day realized volatility (sign reversed because high realized volatility marks dispensable rather than least-dispensable stocks); all remaining alternatives have $|t| < 2$. The −7.85 differential for the 52-week-high proxy here is estimated on the matched eight-proxy horse-race sample and is therefore smaller than—and not directly comparable to—the −12.3 full-library pooled estimate reported above, which aggregates the within-leg sub-sort across all 152 factors. The full horse-race tables, including the data-selected top-five alternatives and the literature-named set, are in Internet Appendix Table IA.40.

The TAQ version gives similar evidence in order flow at a tighter level of conditioning. The within-leg test restricts attention to short legs that are already dispensable on average, then sub-sorts on residual dispensability within each leg. This conditioning compresses the spread relative to the full-panel estimate in Table 5: the unconditional Q5-vs-non-Q5 PreTOM differential is +1.99 pp (Table 5, column 3), while the within-already-short-leg Q5−Q1 PreTOM-vs-Rest differential is +0.38 pp ($t = +4.08$, pooled across the six factors with factor-clustered SE). Both estimates pick up the same flow tilt at different levels of conditioning; the gap reflects the compressed within-leg variation in dispensability, not a different phenomenon. The same within-leg sub-sort that produces lower returns also produces directional order flow toward the most-dispensable side.

## 6.4 Cross-ETF Evidence

The same exposure predicts returns and the T+1 timing shift in real-money ETF holdings, providing a portfolio-level validation in tradable vehicles. For each ETF we compute holdings-weighted dispensability $d_e$, the portfolio weight on stocks far below their 52-week highs. Across 541 U.S. equity broad, style, factor, and cap-based ETFs, those with higher

$d_e$ earn lower PreTOM returns (FF3-controlled slope $-10.59$ bps/day, $t = -2.03$), with no comparable Rest relation; and across the 416 ETFs spanning the settlement reform, high-$d_e$ baskets exhibit the same $\tau-4$-to-$\tau-3$ shift as factor portfolios (DiD +36.9, $t = +2.22$). Appendix IA.11 reports the specifications, the cross-section and timing-shift scatters (Figure IA.3), and the full results (Table IA.26).

# 7 What Remains After Month-End Liquidity Demand?

Removing the liquidity-demand component does not destroy the factor zoo; it splits the zoo into two parts. This is the paper's second contribution. Once the recurring monthly cycle is taken out, many factor premia shrink or are absorbed into the liquidity-demand component, leaving a smaller persistent set concentrated in investment, accruals, profitability, and related variables from the Stambaugh and Yuan (2017) mispricing decomposition.

The result is a decomposition, not a rejection of anomaly returns: the transient liquidity-demand component concentrates in PreTOM, while the persistent component resides in those economic characteristics and earns its premium across the month.

Figure 5 summarizes the filtering.

## 7.1 The Persistent Component of the Factor Zoo

We identify persistent factors using three tests. A factor must remain significant outside PreTOM, remain significant after removing the part of its return explained by dispensability exposure, and remain significant at the full-month frequency. Each test uses the $|t| > 3$ threshold of Harvey, Liu, and Zhu (2016) with month-block bootstrap inference ($B = 5{,}000$).[19]

The three tests impose different requirements. The Rest test requires returns to remain significant outside the liquidity-demand window. The liquidity-adjusted test asks whether the factor remains significant after removing the part of its return explained by dispensability

[19] Formally: (1) *Rest-window:* $|t_{\text{Rest}}| > 3$ on returns outside the PreTOM window. (2) *Liquidity-adjusted return:* for each factor define $\alpha_{f,m} \equiv R^{\text{full}}_{f,m} - d_f \cdot b_{D,m}$, where $b_{D,m}$ is the month-$m$ cross-sectional slope of *PreTOM* factor returns on $d_f$ (the slope that absorbs the liquidity-demand component); require $|t_\alpha| > 3$ on $\hat{\alpha}_f$. (3) *Full-month:* $|t| > 3$ on raw full-month returns without dispensability conditioning.

exposure. The full-month test requires the anomaly to remain significant under the standard monthly criterion. The intersection is therefore stringent.

The 16-factor persistent set is the intersection of three filters: significant Rest returns, significant liquidity-adjusted return, and significant full-month returns. Of the 152 JKP anomalies, 23 pass the Rest test, 41 pass the liquidity-adjusted test, and 49 pass the full-month test. The triple intersection contains 16 factors (Internet Appendix Table IA.29). Twelve are strict $q$-theory variables: eight NOA or investment-growth factors, three accruals measures, and one profitability factor. Three more are $q$-related: the Stambaugh and Yuan (2017) MGMT composite, book-to-sales, and net equity-plus-debt issuance. The remaining persistent factor is the Heston and Sadka (2008) same-calendar-month seasonality factor, an annual seasonal pattern outside the monthly liquidity cycle. Strict $q$ plus $q$-related accounts for 15 of the 16 persistent factors (94%).

Two separate properties of the cross-section bear on the cohort. The first is that the dispensability adjustment does nontrivial filtering: with $d_f$ randomly shuffled across the 152 factors and the full procedure re-run 50 times, the median shuffle yields 21 persistent factors versus 16 under the real $d_f$, and the real count sits below the 5th percentile of the shuffle distribution. The second is that the $q$-theory composition does not depend on this filtering. Across shuffles, all 16 baseline factors appear in the median iteration, and the median shuffle cohort is already $q$-concentrated, with a strict-$q$-plus-$q$-related share of 75%; the true $d_f$ filter raises this to 94%. The $q$-theory concentration is therefore a structural property of the cross-section rather than a product of any specific $d_f$ arrangement, and the dispensability filter does real additional work—sharpening the share by 19 points and trimming roughly six marginal factors whose Rest-window significance reflects residual PreTOM exposure.

The eliminated factors include intermediate-horizon momentum constructions and free cash flow yield, whose full-month returns are largely absorbed by linear exposure to $d_f$ ($t_\alpha = +0.32$ and $-0.33$ for the raw and FF3-residual momentum constructions, $+0.90$ for FCF yield). These premia are absorbed by the liquidity-demand component: their full-month return is well-explained by the liquidity-demand channel, and they fail the residualized-alpha test even though they clear the full-month test.

Under the primary filter, 16 of 152 anomalies remain significant as independent persistent factors. The liquidity-exposed anomalies are not necessarily false anomalies; their monthly returns are sufficiently aligned with the recurring liquidity-demand component that they fail the persistent-component filter. The persistent component concentrates in the $q$-theory core identified by Hou, Xue, and Zhang (2015): investment, accruals, and profitability variables account for 12 of the 16 persistent factors, and the Stambaugh and Yuan (2017) MGMT composite aggregates these same variables. After filtering for liquidity-demand effects, the persistent factors concentrate in a small set of investment, accruals, and profitability variables, the same variables that $q$-theory (Hou, Xue, and Zhang, 2015) and the mispricing-factor framework of Stambaugh and Yuan (2017) emphasize as candidate sources of expected return. The $q$-theory dominance also rationalizes the credit-rating concentration documented by Avramov et al. (2013): their four $q$-theory anomalies (asset growth, accruals, capital investments, net issuance) are absorbed by MGMT, while the two non-$q$ anomalies in their study (price momentum and idiosyncratic volatility) retain a credit-conditional premium consistent with a separate distress-momentum channel (Avramov et al., 2007).

#### 7.1.1 Specification Sensitivity

The persistent factor count depends on whether the Method 1 significance test is run on Rest or on its strictly disjoint subset Rest \ Post, which additionally excludes the Post window. The primary specification uses Rest and yields 16 persistent factors. As a sensitivity check we re-run the triple-intersection bootstrap on Rest \ Post, keeping the same PreTOM-only partialling (Table 7). The stricter cut narrows the cohort from 16 to 7, but the $q$-theory concentration is essentially preserved: 15 of the 16 are $q$-theory or $q$-related; 86% of the 7 are. The residual remains concentrated in $q$-theory and mispricing variables under either specification. The conclusion is therefore not that all persistent anomalies are $q$-theory factors; the persistent component is concentrated in investment, accruals, profitability, and closely related variables.

#### 7.1.2 Robustness to Filter Frequency and Rest-Window Definition

The headline filter operates at monthly frequency, residualizing factor returns on the month-$m$ cross-sectional slope on $d_f$. Because $d_f$ has 63% cross-sectional explanatory power in PreTOM and 2.3% in Rest, monthly residualization averages over a frequency mismatch and may under-extract the dispensability component. We re-run the procedure at daily frequency: each trading day, regress the 152 factor returns on $d_f$ and subtract the loaded component; sum the residuals to monthly returns; apply the same significance threshold. The daily-frequency variant yields 11 persistent factors versus a shuffle 5th percentile of 12, a contrast directionally consistent with the monthly result. The smaller baseline count reflects tighter residualization at the frequency where $d_f$ operates; the persistent cohort remains concentrated in $q$-theory variables (72.7%), with the three non-$q$-theory persistent factors being two payout/asset-scaled characteristics that are $q$-theory-adjacent (`eqnpo_me`, `sale_bev`) and one calendar-seasonality factor (`seas_6_10an`) that also appears in the monthly cohort. This daily-frequency cohort corroborates the monthly-frequency baseline; the monthly baseline remains the primary specification.

A second robustness check redefines Rest to exclude the Post window $[\tau-3, \tau+3]$, isolating days outside both PreTOM and its post-reversal aftermath. Under this restriction the persistent factor count tightens to a single factor at monthly frequency—`noa_at`, the canonical net-operating-assets investment characteristic (Hirshleifer et al., 2004)—and to four at daily frequency: `noa_at`, `netis_at`, `ocf_at`, and the Stambaugh and Yuan (2017) MGMT composite. All four are $q$-theory or mispricing-management variables. The drop is consistent with the mechanism: Post contains the reversal documented in Section 3.5, which is itself part of the dispensability cycle. Including Post in Rest captures the full post-PreTOM dynamics; excluding it isolates factors whose returns are independent of the monthly cycle. The $q$-theory factors that remain significant under this restriction form the most restrictive persistent set. We adopt Rest (PreTOM's binary complement) as the primary definition because it accommodates the full mechanism, and report Rest\Post as a sensitivity boundary.

#### 7.1.3 Properties of the Persistent Cohort

The 16 persistent factors share two properties (Table IA.53): low dispensability exposure and within-month return continuation.

First, the persistent factors have low dispensability exposure: the liquidity-demand component identified in Sections 3.4–3.5 and the persistent cohort are distinct findings. The typical persistent factor has a $|d_f|$ roughly one-quarter as large as the typical factor in the universe (mean $|d_f| = 0.078$ for the 16 persistent factors versus 0.318 for the 143-factor universe of tested factors with both PreTOM and Post window statistics available), and the most dispensability-exposed persistent factor ($|d_f| = 0.207$) is still well inside what counts as a weak loading at the universe level (max $|d_f| = 1.751$). None of the persistent factors falls in the third of factors most exposed to dispensability. A one-sided Mann–Whitney test comparing the $|d_f|$ distribution of the 16 persistent factors against the 143-factor universe, with the alternative that persistent factor $|d_f|$ values tend to be smaller, rejects equality at $p = 0.0017$.

Second, the persistent factors exhibit within-month return continuation rather than reversal. Regressing each persistent factor's Post-window return on its PreTOM return yields a positive slope of $\hat{\beta} = +0.73$ ($t = +8.24$, $R^2 = 0.83$): the higher a persistent factor's PreTOM return, the higher its Post return. Each persistent factor's PreTOM and Post returns share the same sign without exception. The eliminated zoo's high-$|d_f|$ tercile shows the opposite ($\hat{\beta} = -0.50$, $t = -4.53$, $R^2 = 0.31$). This continuation in the persistent factors contrasts with the high-$|d_f|$ reversal documented in Section 3.5: transient pricing (high $|d_f|$) reverses, while persistent pricing ($q$-theory cohort) continues.

The same permutation placebo introduced in Section 7.1 (shuffling $d_f$ across factors) yields an average of 15.8 of the 16 baseline persistent factors in the intersection, with the Post-on-PreTOM continuation slope averaging +0.71 (range +0.67 to +0.74) and positive in every draw. The continuation is therefore a property of factors passing Methods 1 and 3, not of factors passing the $d_f$ partial-out specifically; we treat it as a feature of the cohort rather than as a mechanism that selected it. The low dispensability exposure documented above is by contrast a genuinely $d_f$-conditional fact: under the permutation null, the shuffled exposure has zero mean by construction, so the rank-based separation between persistent factors and the eliminated set is a property of the true $d_f$ vector.

## 7.2 Cross-Factor Horse Races

We test whether some other cross-sectional characteristic absorbs $d_f$ in the PreTOM regression. We add candidates one at a time to

$$\bar{R}_f^{\text{Pre}} = a + b_D\, d_f + b_X\, X_f + u_f \tag{15}$$

across 152 factors with month-block bootstrap inference. The eight candidates are factor-level loadings on UMD, market beta, the Pástor–Stambaugh aggregate liquidity factor, Amihud illiquidity, the SIRIO shorting-cost proxy, the Subjective Belief Factor (SBF), and the

MGMT and PERF mispricing factors of Stambaugh and Yuan.[20]

Inference is month-block bootstrap with $B = 5{,}000$ draws, resampling calendar months with replacement and recomputing both $\bar{R}_f$ and $d_f$ inside each draw on the candidate's matched sample window.[21]

The coefficient on $d_f$ remains positive and statistically significant in all eight joint regressions, with bootstrap $t$ between +2.6 and +4.2 (Table 8).

**Six statistically insignificant cases.** Of the eight candidates, six enter the joint regression with $|t_{\text{boot}}| < 2$: UMD ($t = +0.23$), market beta (+0.78), PS liquidity (+0.32), Amihud (−0.06), SIRIO (+0.43), and SBF (−1.65).[22] All six correlate with $d_f$ in the cross-section, and all six predict $\bar{R}_f^{\text{Pre}}$ univariately. None adds anything once $d_f$ is in the regression: their univariate predictive power runs through their correlation with $d_f$.

**MGMT and PERF.** MGMT and PERF are the only candidates that retain incremental explanatory power alongside $d_f$ under bootstrap inference. With $d_f$ included, MGMT enters PreTOM at $t_{\text{boot}} = -2.99$ and PERF at $t_{\text{boot}} = -2.15$; the joint $R^2$ rises to 0.70, compared with 0.62 for $d_f$ alone.[23] $d_f$ itself is not displaced: it remains at $t_{\text{boot}} = +3.72$ alongside MGMT and +3.22 alongside PERF. In Rest, $d_f$'s coefficient is indistinguishable from zero, while MGMT alone accounts for 32% of cross-factor variation ($t_{\text{boot}} = -3.82$).

This pattern describes what remains after accounting for the liquidity-demand component. MGMT and PERF aggregate $q$-theory and accounting variables: net stock issuance, accruals, asset growth, profitability, and distress. These are the same variables that remain

[20]Citations: Pástor and Stambaugh, 2003 (PS liquidity); Drechsler and Drechsler, 2021 (SIRIO); Cui, De la O, and Myers, 2025 (SBF); Stambaugh and Yuan, 2017 (MGMT/PERF). We thank Sean Myers for sharing the SBF data series. Construction details for all eight are in Internet Appendix S.

[21]Each candidate is run on a sample window matched to its data availability: 1980–2024 for Amihud, 2003–2025 for SIRIO, 1982Q4–2022Q2 for SBF, and 1963–2025 for the others. Both $\bar{R}_f$ and $X_f$ are recomputed on the candidate's window so the comparison is sample-consistent. Because both $\bar{R}_f$ and $d_f$ are recomputed on the candidate's window, each column is internally consistent, but $R^2$ levels are not strictly comparable across candidates with different sample windows.

[22]SBF is built from quarterly survey forecasts; we verified empirically that its returns do not load asymmetrically on dispensable stocks during PreTOM (mean SBF return differs between PreTOM and Rest days by −0.003, $t = -0.04$), so the calendar conditioning required by the dispensability mechanism is empirically absent.

[23]The $d_f$-alone $R^2$ of 0.62 in this horse race is estimated on the bootstrap-matched candidate window and is not directly comparable to the headline full-sample $d_f$ fit of $R^2 = 0.63$; the levels differ only because of the window and sample used for the candidate predictors (see the note to Table 8).

significant under the dispensability filter (Section 7.1). PERF correlates with $d_f$ at $-0.57$ through its momentum, distress, and profitability components, so its incremental content is partially attenuated once $d_f$ is included. MGMT is cleaner: it captures the investment, financing, and accounting structure that remains when $d_f$ no longer predicts. The horse race and the persistent-cohort composition agree: $d_f$ absorbs the liquidity-demand component of factor returns, while MGMT captures the non-flow $q$-theory structure.

The joint survival of both $d_f$ and MGMT indicates that they capture distinct, calendar-orthogonal dimensions of the cross-section. MGMT reflects low-frequency corporate finance decisions (e.g., asset growth and issuance) that generate a fundamental expected return, which naturally persists throughout the Rest window. In contrast, $d_f$ isolates a high-frequency microstructure friction, selling pressure tied to settlement constraints, which materializes exclusively in the PreTOM window. That $d_f$ remains significant ($t_{\text{boot}} = +3.72$) alongside MGMT in PreTOM indicates that the dispensability mechanism is not a proxy for known $q$-theory fundamentals but a distinct calendar-bound liquidity shock. This is cross-sectional evidence for two distinct dimensions: $d_f$ isolates a calendar-bound liquidity component concentrated in PreTOM, while MGMT captures a lower-frequency $q$-theory/mispricing component that remains important outside the cash-demand window.

# 8 Canonical Anomalies Through the Liquidity-Demand Component

Viewed through the dispensability mechanism, several canonical factor results become different manifestations of the same demand shock. The relevant object is not the factor name but the leg that contains stocks far below their 52-week highs. When month-end cash demand pushes down dispensable stocks, factors short those stocks rise and factors long them fall. Momentum earns a cash-demand-window premium because its short leg contains dispensable losers, consistent with Nathan, Suominen, and Tasa (2026). Quality and low-risk have the same sign of exposure, so selling pressure raises their long–short returns. Value has the opposite exposure: book-to-market is long many of the stocks sold during the cash-demand window, so the same selling pressure suppresses value returns. Figure 6 makes this sign reversal visible.

This mapping turns several separate anomaly facts into one cross-sectional mechanism. The same shock that raises momentum and quality while depressing value helps explain the negative value–momentum correlation and part of value's apparent weakness. It also identifies a calendar-based component of factor momentum, complementing Ehsani and Linnainmaa (2022), and separates the liquidity-demand component from the arbitrage-asymmetry mechanism in Stambaugh, Yu, and Yuan (2015). The contribution is therefore not only that the factor zoo contains a common liquidity-demand component; it is that this component changes how we read some of the most familiar anomalies.

Formally, the mechanism writes each factor's window return as a standard component plus a recurring, calendar-priced dispensability component. Let $g_m \equiv \beta\, \mathrm{LDS}_m^{\mathrm{PreTOM}}$ be the priced liquidity-demand shock, the realized shock $\mathrm{LDS}_m^{\mathrm{PreTOM}}$ of Section 4.3 scaled by the same loading $\beta$ estimated in equation (11). For factor $f$ with dispensability exposure $d_f$, its PreTOM and Rest window returns are

$$r_{f,m}^{\mathrm{PreTOM}} = \alpha_f^{\mathrm{PreTOM}} + d_f\, g_m + \varepsilon_{f,m}^{\mathrm{PreTOM}}, \tag{16}$$

$$r_{f,m}^{\mathrm{Rest}} = \alpha_f^{\mathrm{Rest}} + \varepsilon_{f,m}^{\mathrm{Rest}}, \tag{17}$$

which is the empirical content of equation (11): the priced shock enters only in $P$ and only through $d_f$, with a Rest loading indistinguishable from zero (Section 4.3). This single object—a factor's exposure to dispensable stocks times the cash-demand shock—sets the sign of each factor's PreTOM premium, the value–momentum covariance, and a calendar-anchored piece of factor momentum. We trace each in turn.

## 8.1 One Shock, Opposite Signs: Quality and Value

Quality-minus-junk and book-to-market sit on opposite sides of the dispensability spectrum. QMJ has $d_f = +0.55$, while book-to-market has $d_f = -0.73$. These opposite exposures reflect the construction of the two sorts. QMJ is long quality firms and short junk firms. The short leg contains firms that are typically far from their 52-week highs, so selling pressure on dispensable stocks raises QMJ returns. Book-to-market has the opposite exposure: its long leg disproportionately contains firms trading far below their highs, so the same selling pressure lowers value returns.

QMJ and value are not special cases; their opposite dispensability exposures make the sign of the mechanism visible. The same PreTOM liquidity shock inflates the QMJ premium and suppresses the book-to-market premium.

Figure 6 shows this. The cumulative within-month paths of QMJ and book-to-market diverge inside the PreTOM band: QMJ rises as the dispensable junk leg is sold, while book-to-market falls as the dispensable value leg is sold. Almost the entire QMJ premium accrues in the six PreTOM days: the PreTOM mean is 36 bps/month ($t = +3.52$), compared with 5 bps/month in Rest with a $t$-statistic close to zero. Book-to-market exhibits the opposite pattern: its premium is negative in PreTOM and positive in Rest.

This decomposition also bears on the long-running discussion of the value premium's weakness. Fama and French (2020) report a post-1991 $t$-statistic of 1.06 for HML. In our corresponding book-to-market factor, accounting for the PreTOM component raises the Rest-window $t$-statistic to 2.01. The premium still does not clear the Hou, Xue, and Zhang (2020) $|t| > 3$ bar, but the distance between "alive" and "dead" closes by roughly half. Part of value's apparent weakness therefore reflects the timing of predictable liquidity demand: value's long leg contains precisely the kind of stocks sold during the settlement-window cash-raising period.[24]

## 8.2 Low-Risk and Lottery Anomalies

The low-risk anomaly, summarized by the BAB factor of Frazzini and Pedersen (2014), has a well-known leverage-constraint interpretation: leverage-constrained investors bid up high-beta stocks, depressing their returns relative to low-beta stocks. Our evidence does not replace that explanation. Instead, it shows that the low-risk anomaly also loads on the dispensability dimension. High-beta, high-idiosyncratic-volatility, and high-maximum-daily-return "lottery" stocks are disproportionately far from their 52-week highs and so are among the dispensable holdings investors sell first during cash-demand windows. As a result, part of the low-risk return is earned in the same PreTOM window that inflates momentum and quality.

The pattern is consistent across four standard low-risk sorts. For each factor, $d_f$ is negative, meaning the high-characteristic leg (high beta, high ivol, high lottery exposure)

[24]We refer specifically to book-to-market (*be_me*, $d_f = -0.73$), not the JKP Value theme average, which bundles heterogeneous factors including price-proximity measures that are PreTOM-inflated rather than suppressed.

is the dispensable side. During PreTOM, the high-side decile underperforms by $-6$ to $-9$ bps/day ($t$-statistics between $-2.3$ and $-3.5$), while the low-side decile is essentially flat. The BAB-signed long–short ($D1-D10$) is positive in PreTOM by $+2$ to $+7$ bps/day. In the Post window the high-side decile rebounds sharply ($+9$ to $+13$ bps/day) and the BAB-signed return turns negative. The Post-window reversal in low-risk sorts is the Section 3.5 pattern at the canonical-anomaly level: transient PreTOM premia that reverse, not fundamental compensation that accrues. This liquidity-demand component sits alongside the leverage-constraint mechanism rather than replacing it.

## 8.3 Value–Momentum Correlation

This mechanism also speaks to the familiar negative relation between value and momentum (Asness, Moskowitz, and Pedersen, 2013). Under the decomposition, momentum has $d_M > 0$ because it is short dispensable losers, while value has $d_V < 0$ because its long leg holds many dispensable stocks. Applying equations (16)–(17) to the two factors and taking the cash-demand-window covariance,

$$\mathrm{Cov}\big(r_M^{\mathrm{PreTOM}},\, r_V^{\mathrm{PreTOM}}\big) \;=\; \mathrm{Cov}\big(\varepsilon_M^{\mathrm{PreTOM}},\, \varepsilon_V^{\mathrm{PreTOM}}\big) \;+\; d_M\, d_V\; \mathrm{Var}(g), \tag{18}$$

where the second equality uses orthogonality of the priced shock $g_m$ to the residuals. Because $d_M\, d_V < 0$, the common shock makes the covariance *more negative*; in means, $E[r_M^{\mathrm{PreTOM}} - r_M^{\mathrm{Rest}}] \approx d_M\, E[g] > 0$ and $E[r_V^{\mathrm{PreTOM}} - r_V^{\mathrm{Rest}}] \approx d_V\, E[g] < 0$, so the same shock raises momentum and depresses value.

The data match the sign and are sizable. Removing the daily cross-sectional $d_f$ component—the term $d_f g_m$ in equation (16), neutralized day by day—eliminates 66% of the negative value–momentum covariance, from $-11{,}965$ to $-4{,}090$ (bps$^2$/day), and reduces the correlation from $-0.64$ to $-0.36$ (Table 9). The covariance share exceeds the correlation reduction because neutralization also lowers each leg's return volatility; the covariance statistic isolates the common-shock channel of equation (18) and is the cleaner object. The reduction is similar across calendar windows, indicating that dispensability contributes to the stable covariance relation between the two strategies; the calendar-specific part is its pricing, as liquidity demand raises momentum and depresses value during PreTOM and the pressure partly reverses afterward.

## 8.4 Factor Momentum

Ehsani and Linnainmaa (2022) show that factors with high past returns continue to outperform. Their interpretation is time-varying expected factor premia. The dispensability framework does not replace that interpretation, but it predicts a specific component of factor momentum: because $d_f$ is persistent and PreTOM selling recurs every month, high-$d_f$ factors mechanically accumulate high trailing returns and continue to earn returns in the same calendar window.[25]

The decomposition makes this precise. Summing equation (16) over the trailing year, the cash-window momentum signal $S^{\text{PreTOM}}_{f,m} \equiv \sum_{j=2}^{12} r^{\text{PreTOM}}_{f,m-j}$ contains the term $d_f\,\Lambda^-_m$, where $\Lambda^-_m \equiv \sum_{j=2}^{12} g_{m-j}$ is the trailing sum of priced shocks, while the future cash-window return contains $d_f\,g_m$. A Fama–MacBeth regression of future on trailing cash-window returns has, in each month $m$ and ignoring residual covariance, cross-sectional moments

$$\operatorname{Cov}_f\big(S^{\text{PreTOM}}_{f,m},\, r^{\text{PreTOM}}_{f,m}\big) \approx \Lambda^-_m\, g_m\, \operatorname{Var}_f(d_f), \qquad \operatorname{Var}_f\big(S^{\text{PreTOM}}_{f,m}\big) \approx \big(\Lambda^-_m\big)^2\, \operatorname{Var}_f(d_f),$$

so the month-$m$ cross-sectional slope is approximately $g_m/\Lambda^-_m$; the cross-sectional dispersion of exposure, $\operatorname{Var}_f(d_f)$, cancels. Fama–MacBeth averages these monthly slopes, and the $(\Lambda^-_m)^2$-weighted average that the corresponding pooled factor–month regression estimates has population slope

$$\gamma_{P\to P} \;\approx\; \frac{E[g_m\,\Lambda^-_m]}{E\big[(\Lambda^-_m)^2\big]}. \tag{19}$$

The denominator is a mean of squares and hence positive, so the sign of the slope is set by the numerator,

$$E\big[g_m\,\Lambda^-_m\big] \;=\; K\,\bar{g}^2 \;+\; \sum_{j=2}^{12} \operatorname{Cov}(g_m,\, g_{m-j})\,, \qquad K = 11.$$

The calendar component therefore arises from the recurring positive mean concession $\bar{g} > 0$ even without serial dependence, and persistence in $g_m$ only strengthens it. Because the priced shock is absent in $R$ (equation 17), the same trailing signal does not predict future Rest returns, $\operatorname{Cov}_f(S^{\text{PreTOM}}_{f,m},\, r^{\text{Rest}}_{f,m}) \approx 0$. The mechanism therefore predicts $\gamma_{P\to P} > 0$ and

[25] Factor momentum is not a stock-level characteristic and therefore is not one of the 153 JKP signals analyzed elsewhere in this paper. It is a *meta-factor*, formed by sorting factors on their own trailing returns.

$\gamma_{P\to R} \approx 0$. Equivalently, a factor-momentum portfolio that overweights high-$S$ factors inherits positive dispensability exposure $d_m^{FM} = \sum_f w_{f,m}\, d_f > 0$ and so earns part of its return inside the cash-demand window, $r_m^{FM,P} \approx d_m^{FM}\, g_m$.

To separate factor momentum's calendar-anchored component from any broader persistence, we ask which past-return signal predicts which future-return window. If factor momentum reflects repeated exposure to the dispensability axis, then past PreTOM returns should predict future PreTOM returns specifically, not future Rest returns. If it reflects broader persistence, past Rest returns should predict both future windows symmetrically.

We test this by decomposing the factor-momentum signal by the calendar source of past returns. We build three trailing signals from months $m-12$ through $m-2$ (skip one): the standard compounded full-month return; trailing PreTOM-only returns; and trailing Rest-only returns. For each, we run Fama-MacBeth cross-sectional regressions of next-month average daily return on the signal, separately for PreTOM and Rest targets. We also report a Fama-MacBeth row that uses the per-factor full-sample dispensability exposure $d_f$ as a fixed cross-sectional characteristic rather than as a real-time signal. The $d_f$ row serves as an oracle structural benchmark: it asks how strongly future PreTOM and Rest returns scale with full-sample dispensability exposure, showing what calendar-anchored prediction can deliver under ex-post knowledge of $d_f$. The mechanical prediction is a positive loading on future PreTOM and near-zero on future Rest, which is what we observe.

Factor momentum appears to have two parts. One reflects repeated exposure to the same calendar-priced dispensability axis; another reflects broader persistence outside the liquidity-demand cycle. The first piece appears in the PreTOM-only and $d_f$ rows, which predict future PreTOM returns strongly and future Rest returns weakly or not at all. The second piece appears in the Rest-only row, which predicts the two future windows symmetrically. The second piece is consistent with both the Ehsani and Linnainmaa time-varying-premia channel and the Dong, Kang, and Peress (2025) persistent-flow channel; our test does not distinguish between them. The first piece is the calendar-anchored component identified in this paper.

## 8.5 The Idiosyncratic-Volatility Puzzle

The dispensability mechanism gives a calendar interpretation of the idiosyncratic-volatility puzzle of Stambaugh, Yu, and Yuan (2015). In their arbitrage-asymmetry view, idiosyncratic volatility makes shorting overpriced stocks risky, so overpricing persists. In our setting, idiosyncratic volatility is not the primitive: the primitive is whether a stock is a natural candidate for liquidation. We separate the two channels with a stock-day regression that interacts dispensability $D_{i,m}$ and idiosyncratic volatility $V_{i,m}$ with the PreTOM indicator $\mathbf{1}_{P(t)}$,

$$r_{i,t} = a + b_D D_{i,m} + b_V V_{i,m} + b_{DV} D_{i,m} V_{i,m} + \mathbf{1}_{P(t)} \big( c_0 + c_D D_{i,m} + c_V V_{i,m} + c_{DV} D_{i,m} V_{i,m} \big) + u_{i,t}. \quad (20)$$

The cash-demand-window concession loads on dispensability ($c_D < 0$); idiosyncratic volatility alone does not generate the window-specific effect ($c_V \approx 0$); and idiosyncratic volatility amplifies the concession only among dispensable stocks ($c_{DV} < 0$, weakly). Two further tests point the same way: the PreTOM-versus-Rest return gap is monotone in dispensability rather than in idiosyncratic volatility alone, which is not the signature predicted by a pure SYY arbitrage-asymmetry channel, and $\text{LDS}_m^{\text{PreTOM}}$ does not load on lagged Baker–Wurgler sentiment, which further weighs against sentiment-driven mispricing as the calendar-bound channel.

The two mechanisms operate in different parts of the month. The dispensability concession is localized before month-end and tied to forced selling; the SYY channel is persistent and tied to corporate-policy characteristics, and the Stambaugh and Yuan (2017) MGMT composite recovers its explanatory power outside the cash-demand window, while PERF concentrates inside it. Aggregating across the month makes the two look like one anomaly; splitting the month reveals two. SYY explains why mispricing can persist; we explain why a related high-volatility, dispensable-stock return pattern appears predictably before month-end. Full tables are in Internet Appendix Section IA.27.

# 9 Robustness

We organize the robustness evidence around the three threats to our interpretation: that the result is momentum in disguise, that it reflects mechanical overlap in the factor library, or that the six-day window is arbitrary. Each threat has a direct answer, which we collect here with pointers to where each result is shown.

## 9.1 Threat 1: The Result Is Momentum in Disguise

Distance from the 52-week high is also a momentum proxy (George and Hwang, 2004), so $d_f$ could mechanically reflect momentum exposure. Four results rule this out. First, the full-sample characteristic search (Section 3.3, Table 1 Panel A) selects distance from the 52-week high over the momentum characteristics themselves: no momentum-theme variable captures the PreTOM cross-section as well. Second, in the cross-factor horse race (Section 7.2), $d_f$ subsumes trailing returns rather than the reverse. Third, the result remains significant after residualizing stock-level dispensability on standard return and risk characteristics (Internet Appendix Table IA.14). Fourth, and most directly, the within-short-leg sub-sort (Section 6.3) holds factor membership fixed and varies only stock-level dispensability, so it cannot be momentum sorting in another form.

## 9.2 Threat 2: Mechanical Overlap in the Factor Library

A second concern is that the high PreTOM $R^2$ reflects mechanical clustering in the JKP library rather than independent cross-sectional variation. The 153 factors are constructed from overlapping inputs (different profitability measures, return-history horizons, valuation ratios), and any characteristic aligned with a dominant theme could mechanically explain a large share of cross-sectional variation.

The PreTOM/Rest asymmetry rules this out. The principal-component structure of the daily factor cross-section is essentially identical across the two windows: extracting the first principal component separately in each, PC1's variance share is 27% in PreTOM and 28% in Rest, and $d_f$'s correlation with PC1 is 0.68 and 0.69, respectively. The construction-overlap channel measured by PC1 is therefore present in both windows in equal measure. Yet $d_f$'s cross-sectional $R^2$ moves from 63% in PreTOM to 2.3% in Rest. A symmetric redundancy structure cannot generate this asymmetric premium; whatever explains the 63% in PreTOM does so through a calendar-bound channel that the library's shared construction inputs do not capture. Dropping the seven momentum-theme factors leaves the asymmetry intact, and Internet Appendix Section IA.26 corroborates with six further diagnostics (correlation pruning, alternative rank estimators, idiosyncratic-variance weighting, multiple-testing bootstrap, and JKP-theme equal weighting).

The result is also not an artifact of our JKP-characteristic implementation. It reproduces in two anomaly libraries built by other research teams, which cannot share JKP's construction overlap: the Chen and Zimmermann (2021) Open Asset Pricing library and the Hou, Xue, and Zhang (2020) Replicating Anomalies catalog, using their returns as provided and estimating exposure from return time series rather than from our portfolio assignments. The exercise is deliberately conservative. For each external factor $f$ we take the returns as constructed by the original library, compute the daily long–short return as $\mathrm{port10}_t - \mathrm{port01}_t$, and rather than reconstructing $d_f$ from holdings, estimate a return-based exposure to the 52-week-high spread:

$$R_{f,t} \;=\; a_f + b_f^{52H}\, R_t^{52H} + e_{f,t}. \tag{21}$$

The coefficient $b_f^{52H}$ is the external-catalog analog of $d_f$, built entirely from return time series. Regressing each factor's mean PreTOM and Rest returns on $b_f^{52H}$, the pattern reproduces in both catalogs. Among the 179 Chen–Zimmermann predictors, $b_f^{52H}$ accounts for 63.1% of the cross-sectional variation in PreTOM returns (month-block bootstrap $t = +4.22$) versus 1.8% in Rest. Among the 185 Hou–Xue–Zhang anomalies with valid daily decile returns, it accounts for 71.4% in PreTOM ($t = +4.56$) versus 10.2% in Rest. The HXZ Rest residual likely reflects that catalog's emphasis on investment and accruals variables, which carry persistent $q$-theory compensation outside PreTOM (Section 7.1); the asymmetry replicates regardless. Appendix IA.28 collects these constructions in one table, alongside Jensen, Kelly, and Pedersen (2023)'s own published low/high portfolios.

## 9.3 Threat 3: The Window Is Arbitrary

The six-day window could be hand-picked. Three results fix it. First, the rolling-window cross-sectional $R^2$ (Figure 2) peaks at the canonical PreTOM window among all six-day windows in the trading month, so the window is not chosen to maximize fit after the fact. Second, a placebo test on the window itself: defining the cross-factor variance ratio as $\mathrm{Var}_f(\bar{R}_f^{\mathrm{Pre}})/\mathrm{Var}_f(\bar{R}_f^{\mathrm{Rest}})$, the actual PreTOM-versus-Rest ratio is 4.50—mean factor returns are 4.5× more dispersed across factors in PreTOM than in Rest—and exceeds 98.3% of 10,000 random six-day windows ($p = 0.017$; Internet Appendix Table IA.2). Third, and independently of any window choice, the T+1 settlement reform (Section 5) moves the cross-sectional pattern one trading day closer to month-end exactly when settlement mechanics predict; a hand-picked window cannot shift on cue with a regulatory change.

Finally, alternative monthly-frequency mechanisms predict cross-sectional patterns different from what the data show. Window dressing (Lakonishok et al., 1991) predicts quarter-end concentration, but the PreTOM pattern recurs in every month; tax-loss harvesting predicts December concentration, but the pattern is monthly, not annual; and foregone dividend income (Hartzmark and Solomon, 2025) predicts that dividend-yield characteristics organize the cross-section, but $div12m\_me$ ranks well below the top candidates in the agnostic search of Section 3.3. Nathan, Suominen, and Tasa (2026) address each of these alternatives at the stock level.

# 10 Conclusion

This paper separates the factor zoo into two layers. The first is a recurring liquidity-demand layer. It appears during the six trading days ending four trading days before month-end, loads on anomaly portfolios according to their exposure to dispensable stocks, varies with the realized price concession on those stocks, and shifts by one day after the transition from T+2 to T+1 settlement. The second is a smaller persistent layer. It remains significant outside the liquidity-demand window and is concentrated in investment, accruals, profitability, and related $q$-theory and mispricing variables.

The evidence does not imply that the factor zoo is spurious. It implies that monthly anomaly returns pool two different components. One is a transient price-pressure component generated by predictable cash demand and limited immediacy provision. The other is a persistent component associated with standard economic variables. Separating the two clarifies both why many anomalies comove at month-end and why a smaller set remains after accounting for the liquidity-demand component.

For empirical asset pricing, the practical implication is that full-month anomaly tests conflate a persistent premium with a localized, predictable cash-demand concession. Measuring an anomaly's premium outside the cash-demand window, or net of its dispensability exposure, isolates the persistent component and sharpens tests of which characteristics carry compensation.

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Table 1: Dispensability Exposure and Factor Returns

*Panel A: Which stock characteristic matches the structure-free PreTOM loading?*

| Characteristic ($c$) | PreTOM $R^2$ | $\lvert t \rvert$ | 1963–1993 | 1994–2025 |
|---|---|---|---|---|
| **Distance from 52-week high** | **0.62** | **8.18** | **0.62** | **0.42** |
| Piotroski F-score | 0.48 | 5.09 | 0.34 | 0.46 |
| Quality (QMJ composite) | 0.47 | 8.35 | 0.28 | 0.57 |
| Mispricing-performance composite | 0.47 | 7.48 | 0.22 | 0.60 |
| Realized volatility (21-day) | 0.45 | 6.04 | 0.46 | 0.28 |
| Idiosyncratic volatility, HXZ4 (21-day) | 0.45 | 5.76 | 0.45 | 0.26 |
| Idiosyncratic volatility, CAPM (21-day) | 0.44 | 5.85 | 0.43 | 0.26 |
| Operating cash flow / assets | 0.43 | 8.74 | 0.38 | 0.47 |
| Idiosyncratic volatility, FF3 (21-day) | 0.43 | 5.85 | 0.43 | 0.25 |
| Financial safety (QMJ-safety) | 0.43 | 4.99 | 0.31 | 0.47 |

*Panel B: Does the selected exposure correlate with returns only in PreTOM?*

| | PreTOM | | Post $[\tau{-}3, \tau{+}3]$ | | Rest of month | | Full month | |
|---|---|---|---|---|---|---|---|---|
| Predictor | $R^2$ | $t_{\text{boot}}$ | $R^2$ | $t_{\text{boot}}$ | $R^2$ | $t_{\text{boot}}$ | $R^2$ | $t_{\text{boot}}$ |
| Dispensability exposure $d_f$ | 0.63 | +4.21 | 0.13 | −1.42 | 0.023 | +0.59 | 0.29 | +2.71 |

*Notes:* Panel A ranks the 153 JKP characteristics by the cross-factor PreTOM $R^2$ from regressions of mean PreTOM factor returns on the corresponding short-minus-long characteristic exposure, with $|t|$ clustered by JKP theme (the 14 thematic groups into which Jensen, Kelly, and Pedersen (2023) cluster correlated factors, e.g. momentum, value, profitability); the last two columns repeat the $R^2$ within each subperiod. Panel B reports the cross-sectional $R^2$ and month-block bootstrap $t$ ($B = 5{,}000$) from regressions of mean daily long–short returns on the selected dispensability exposure $d_f$ in each intra-month window. Both panels exclude the 52-week-high characteristic itself. VW NYSE-breakpoint $D10 - D1$ long-short returns, 1963–Dec 2025. Full rankings are in Internet Appendix Table IA.34.

Table 2: Determinants of the Monthly Price Concession

*Panel A: Time-series determinants of the liquidity-demand shock during PreTOM ($\text{LDS}_m^{PreTOM}$, bps/day)*

| Predictor | (1) Long-history 1968–2024 | (2) TAQ baseline 2003–2022 | (3) TAQ + interactions 2003–2022 |
|---|---|---|---|
| HKM stress (monthly) | $9.35^{**}$ | | |
| | (2.20) | | |
| HKM stress (daily) | | $33.50^{***}$ | $29.87^{***}$ |
| | | (5.33) | (4.76) |
| Net seller pressure | | $16.07^{***}$ | $15.56^{***}$ |
| | | (3.91) | (3.92) |
| MF outflow | | $-3.81$ | $-6.05$ |
| | | (-0.73) | (-1.24) |
| PS liquidity | $-2.83$ | $-2.52$ | $-3.33$ |
| | (-0.95) | (-0.47) | (-0.63) |
| log Amihud | $-0.54$ | $-7.56$ | $-9.28$ |
| | (-0.20) | (-1.07) | (-1.52) |
| $\Delta$VIX | | $-11.56$ | $-15.10^{**}$ |
| | | (-1.39) | (-2.14) |
| Market return | $-26.40^{***}$ | $-30.22^{***}$ | $-33.66^{***}$ |
| | (-5.79) | (-3.20) | (-3.45) |
| Crisis dummy | $-224.55^{***}$ | $-172.50^{***}$ | $-223.06^{***}$ |
| | (-16.18) | (-4.84) | (-6.27) |
| MF $\times$ HKM | | | $12.50^{***}$ |
| | | | (3.87) |
| MF $\times$ $\Delta$VIX | | | $-5.06^{**}$ |
| | | | (-2.24) |
| Constant | $9.19^{***}$ | 1.75 | $-0.95$ |
| | (4.14) | (0.28) | (-0.18) |
| $N$ | 684 | 230 | 230 |
| Sample | 1968-01–2024-12 | 2003-09–2022-10 | 2003-09–2022-10 |
| $R^2$ | 0.292 | 0.514 | 0.538 |
| Adj. $R^2$ | 0.287 | 0.497 | 0.517 |

*Notes.* Dependent variable is $\text{LDS}_m^{\text{PreTOM}} = \bar{R}_{D10,m}^{\text{PreTOM}} - \bar{R}_{D1,m}^{\text{PreTOM}}$ (bps/day), positive when dispensable stocks underperform. RHS variables are standardized except PS liquidity and the market return, which enter in levels. Column (1) uses 1968–2024; columns (2)–(3) restrict to the TAQ era (2003–2022). Variable definitions are in the data section; window means of $\text{LDS}_m$ are in Internet Appendix Table IA.3. Newey–West standard errors with 12 lags. $^{*},^{**},^{***}$ denote 10%, 5%, 1% significance.

Table 3: Factor Returns and the Monthly Price Concession

| | Test | Factor return window | Shock window | Exclusion | $\beta$ | $t$-stat | $R^2$ | $N$ |
|---|---|---|---|---|---|---|---|---|
| *Panel A: Full sample, 1963–2025* | | | | | | | | |
| (1) | Main test | PreTOM | PreTOM | none | + 0.511 | (+16.04) | 0.181 | 113,907 |
| (2) | Rest comparison | Rest | PreTOM | none | + 0.016 | (+0.65) | 0.000 | 113,907 |
| (3) | Post-window comparison | PreTOM | Post | none | + 0.002 | (+0.05) | 0.000 | 113,907 |
| *Panel B: Matched own-stock-exclusion sample, 1979–2025 (547 months, 152 factors)* | | | | | | | | |
| (4) | Matched baseline | PreTOM | PreTOM | none | + 0.514 | (+15.49) | 0.200 | 83,117 |
| (5) | Theme-excluded shock | PreTOM | PreTOM | JKP theme of $f$ | + 0.450 | (+9.98) | 0.083 | 83,117 |
| (6) | Theme-excluded Rest | Rest | PreTOM | JKP theme of $f$ | + 0.022 | (+0.72) | 0.000 | 83,117 |

*Notes.* Each row estimates a factor–month panel with factor and month fixed effects. The dependent variable is the average daily return of factor $f$ in the window shown in "Factor return window." The regressor is the static $d_f$ (equation 7) interacted with the liquidity-demand shock measured in the window shown in "Shock window." $\text{LDS}_m$ is the return spread between least- and most-dispensable stocks in the indicated window (equation 10). PreTOM is trading days $[\tau-9, \tau-4]$; Rest is all days outside PreTOM; Post is the seven-day window $[\tau-3, \tau+3]$ around month-end. "Exclusion" identifies the stocks removed from the universe used to compute the shock: "none" keeps the full CRSP universe; "JKP theme of $f$" removes the union of $D_1$ and $D_{10}$ holdings across all factors in the same JKP theme as $f$ at the start of month $m$. The theme-wide exclusion lowers the correlation between the theme-excluded LDS and the full-universe LDS to between 0.41 and 0.97 across themes (mean 0.77). Panel B construction requires per-factor monthly decile assignments, available beginning in mid-1979. The 52-week-high characteristic (which defines $d_f$) is excluded throughout. The Full-LDS Rest placebo and the per-month $d_{f,m}$ specification are reported in Internet Appendix Table IA.4. Standard errors are two-way clustered by factor and month.

Table 4: T+1 Settlement Reform and Factor-Return Timing

*Panel A: Theme-level signed timing shifts*

| Theme | $N$ | Mean $\Delta_f$ (bps) |
|---|---|---|
| Investment | 27 | +80.9 |
| Profit Growth | 5 | +66.6 |
| Momentum | 7 | +64.4 |
| Seasonality | 10 | +59.8 |
| Profitability | 21 | +54.5 |
| Accruals | 8 | +53.9 |
| Low Risk | 20 | +39.1 |
| Other | 27 | +20.1 |
| Quality | 7 | +18.2 |
| Value | 9 | −7.3 |
| Debt Issuance | 8 | −35.4 |
| Size | 2 | −64.5 |

*Panel B: The shift increases with dispensability exposure ($\Delta_f = a + b \cdot d_f + u_f$)*

| Specification | $N$ | $b$ | Placebo pctile | Placebo $p$ |
|---|---|---|---|---|
| OLS (unweighted) | 152 | +33.4 | 93.3 | 0.067 |
| WLS (precision-weighted) | 152 | +47.9 | 99.6 | 0.004 |

*Panel C: Canonical-factor sign test*

| Factor | sign $d_f$ | Predicted $\Delta_f$ | Observed $\Delta_f$ (bps) | Match |
|---|---|---|---|---|
| UMD (momentum 12–2) | + | + | +188 | ✓ |
| QMJ (quality) | + | + | +93 | ✓ |
| Book-to-market | − | − | −87 | ✓ |

*Notes:* Per-factor signed DiD $\Delta_f = \pi_{f,\tau-3} - \pi_{f,\tau-4}$ on $R_f = D10 - D1$ (equation 12), with early-month days $[\tau{+}5, \tau{+}8]$ as the no-settlement control. 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. Panel A reports theme-level means of $\Delta_f$ descriptively; themes with fewer than two factors omitted. Panel B: cross-sectional regression across the 152 JKP factors (excluding the 52-week-high characteristic), placebo reform-date randomization (1,000 pseudo-reform dates, 1990–2015); $p$ is the share of placebo slopes exceeding the actual May 2024 slope. See Figure 3 for the scatter. Long-short ($D10 - D1$) daily returns, VW NYSE-BP deciles.

Table 5: Seller-Initiated Trading and Stock-Level Dispensability

| Predictor | (1)<br>Dispensability score | (2)<br>Q5 indicator | (3)<br>Q5 & Q1 indicators |
|---|---|---|---|
| *Main effects* | | | |
| $\beta$ (Disp, continuous) | $+18.3^{***}$ | | |
| | $(+90.1)$ | | |
| $\beta_{Q5}$ (Q5 indicator) | | $+27.8^{***}$ | $+24.3^{***}$ |
| | | $(+74.1)$ | $(+67.3)$ |
| $\beta_{Q1}$ (Q1 indicator) | | | $-19.7^{***}$ |
| | | | $(-53.1)$ |
| *PreTOM interactions* | | | |
| $\gamma$ ($\delta \times$ PreTOM) | $+1.46^{***}$ | | |
| | $(+3.89)$ | | |
| $\gamma_{Q5}$ (Q5 $\times$ PreTOM) | | $+2.50^{***}$ | $+1.99^{***}$ |
| | | $(+3.32)$ | $(+2.73)$ |
| $\gamma_{Q1}$ (Q1 $\times$ PreTOM) | | | $-2.27^{***}$ |
| | | | $(-3.43)$ |
| Stock FE | Yes | Yes | Yes |
| Day FE | Yes | Yes | Yes |
| $N$ (stock-days) | $17.8M$ | $17.8M$ | $17.8M$ |

*Notes:* Stock-day panel regression (equation 14). The dependent variable $\text{NetSell}_{i,t}$ is the difference between seller- and buyer-initiated dollar volume scaled by total dollar volume on day $t$. Column (1) uses $\delta_{i,m-1}$, the within-month $z$-score of dispensability lagged one month; columns (2)–(3) replace it with top (Q5) and bottom (Q1) dispensability-quintile indicators. PreTOM indicates trading days $\tau-9$ through $\tau-4$. Stock and day fixed effects throughout; $t$-statistics in parentheses with stock-clustered SE. The $\gamma$ interaction rows are the objects of interest. Sample: stocks above the NYSE median market capitalization, 2003–2022. $^{*}p<0.10$, $^{**}p<0.05$, $^{***}p<0.01$.

Table 6: Within-Leg Dispensability and Returns

*Panel A: Six strong-fit factors*

| | | PreTOM | | Rest of month | | Pre−Rest | |
|---|---|---|---|---|---|---|---|
| Factor | Leg | bps/day | $t$ | bps/day | $t$ | bps/day | $t$ |
| Momentum (12-1) | D1 | −11.36** | −2.56 | +3.24 | +1.07 | −14.60*** | −2.61 |
| Gross profitability | D1 | −9.87** | −2.19 | +1.23 | +0.42 | −11.10** | −2.02 |
| Operating profitability | D1 | −13.89*** | −3.07 | −1.73 | −0.59 | −12.16** | −2.22 |
| Ohlson O-score | D10 | −11.54*** | −2.59 | −3.85 | −1.41 | −7.69 | −1.48 |
| Earnings-to-price | D1 | −12.22*** | −2.70 | −2.73 | −0.90 | −9.49* | −1.69 |
| Quality-minus-junk | D1 | −9.46* | −1.81 | −3.21 | −0.93 | −6.25 | −0.97 |
| **Pooled** | | **−11.39** | −3.05 | **−1.18** | −0.46 | **−10.21** | −2.26 |

*Panel B: Full-library within-short-leg sort (all 152 factors)*

| | |
|---|---|
| Pooled PreTOM−Rest DiD | **−12.30** bps/day ($t = -52.3$) |
| Individually significant ($\lvert t\rvert \geq 1.96$) | 139/152 |
| Share significant | 91% |

*Notes:* For each strong-fit factor we restrict to its short-leg decile (the embarrassment side: D1 for momentum/profitability/quality, D10 for distress), formed at the prior month-end with NYSE breakpoints, and sub-sort within that decile by the dispensability score $\delta_{i,m}$ into five within-leg quintiles, where high $\delta$ means more dispensable, so Q5 is most dispensable and Q1 is least. The reported spread is Q5−Q1 (most − least dispensable), value-weighted, in basis points per day. Because both quintiles lie in the same leg and window, the market and common factors cancel in the difference. Panel A shows six illustrative strong-fit factors; Panel B reports the pooled result and per-factor significance count across all 152 factors. $t$-statistics use the daily time series of the spread; the pooled row clusters by date. Sample 1963–Dec 2025. $^{*}p$<0.10, $^{**}p$<0.05, $^{***}p$<0.01.

Table 7: The Persistent Component of the Factor Zoo

*Panel A: Filter counts and economic concentration*

| Filter | Count | $q$-related |
|---|---|---|
| Significant full month | 49 | — |
| Significant outside PreTOM | 23 | — |
| Significant after removing $d_f$ exposure | 41 | — |
| **Pass all three filters** | **16** | **15** |

*Panel B: Economic composition of the persistent component*

| Class | Count |
|---|---|
| Strict $q$-theory | 12 |
| Closely $q$-related | 3 |
| Calendar seasonality | 1 |
| **Total persistent factors** | **16** |

*Notes:* A factor belongs to the persistent component if it passes all three filters: significant returns outside PreTOM, significant returns after removing the part explained by dispensability exposure $d_f$, and significant full-month returns ($|t| > 3$ under a month-block bootstrap, $B = 5{,}000$). Panel A reports the count passing each filter and the triple intersection; "$q$-related" counts strict $q$-theory plus closely $q$-related factors. Panel B groups the persistent factors by economic content. The identity of the persistent factors, with $t_{\text{Rest}}$, $t_{\text{full}}$, and $d_f$, is in Internet Appendix Table IA.30.

Table 8: Horse Race Against Standard Factor Exposures

| | $X$ alone | | $d_f$ alone | $d_f + X$ jointly | | | $\Delta R^2$ |
|---|---|---|---|---|---|---|---|
| Candidate | coef ($t_{\text{boot}}$) | $R^2$ | $R^2$ | $d_f$ coef ($t_{\text{boot}}$) | $X$ coef ($t_{\text{boot}}$) | $R^2$ | from $X$ |
| *Panel A: PreTOM* ($\bar{R}_f^{Pre}$) | | | | | | | |
| UMD | +1.64 (+2.62) | 0.22 | 0.62 | +5.02 (+3.91) | +0.13 (+0.23) | 0.62 | +0.00 |
| Market beta | +1.66 (+2.49) | 0.23 | 0.62 | +4.75 (+4.01) | +0.46 (+0.78) | 0.63 | +0.01 |
| PS liquidity | +1.04 (+2.19) | 0.09 | 0.62 | +5.09 (+4.22) | +0.11 (+0.32) | 0.62 | +0.00 |
| MGMT | −1.62 (−4.01) | 0.21 | 0.62 | +4.71 (+3.72) | −1.04 (−2.99) | 0.70 | +0.08 |
| PERF | −2.34 (−3.77) | 0.45 | 0.62 | +3.93 (+3.22) | −1.17 (−2.15) | 0.70 | +0.08 |
| *Panel B: Rest of month* ($\bar{R}_f^{Rest}$) | | | | | | | |
| UMD | +0.01 (+0.02) | 0.00 | 0.00 | +0.30 (+0.34) | −0.08 (−0.22) | 0.01 | +0.00 |
| Market beta | −0.32 (−0.73) | 0.03 | 0.00 | +0.63 (+0.78) | −0.47 (−1.22) | 0.06 | +0.06 |
| PS liquidity | −0.33 (−1.06) | 0.04 | 0.00 | +0.48 (+0.58) | −0.42 (−1.80) | 0.05 | +0.05 |
| MGMT | −1.00 (−3.82) | 0.32 | 0.00 | −0.24 (−0.28) | −1.03 (−4.38) | 0.33 | +0.32 |
| PERF | −0.15 (−0.39) | 0.01 | 0.00 | +0.07 (+0.08) | −0.13 (−0.38) | 0.01 | +0.00 |

*Notes:* Each row reports $X_f$ alone (cols 1–2) and jointly with $d_f$ (cols 4–6). $\Delta R^2$ 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. Three additional candidates (Amihud illiquidity, the Drechsler and Drechsler (2021) SIRIO shorting-cost proxy, and the Cui, De la O, and Myers (2025) Subjective Belief Factor) are reported in Internet Appendix Table IA.39.

Table 9: Value–Momentum Correlation: Raw vs $d_f$-Neutralized, by Window

| | $N_W$ | $\rho_W^{\text{raw}}$ | $\rho_W^{\perp d_f}$ | % reduction | share of total cov |
|---|---|---|---|---|---|
| Full | 15,206 | -0.645 | -0.359 | +44.4% | +100.0% |
| PreTOM | 4,350 | -0.645 | -0.376 | +41.7% | +27.5% |
| Rest | 5,781 | -0.673 | -0.372 | +44.8% | +42.6% |
| Post | 5,075 | -0.609 | -0.331 | +45.6% | +29.8% |

*Notes:* Daily correlation between value (JKP `be_me` long–short) and momentum (JKP `ret_12_1` long–short), 1963–2025, computed within three disjoint within-month windows (PreTOM = $\tau-9$ to $\tau-4$, Post = $\tau-3$ to $\tau+3$, Rest = remaining days). $\rho_W^{\text{raw}}$ is the raw correlation; $\rho_W^{\perp d_f}$ is the correlation after daily cross-sectional $d_f$-neutralization, in which each factor's daily return is replaced by the residual from the same-day cross-sectional regression $R_{f,t} = a_t + b_t d_f + e_{f,t}$ across all 142 factors. "Share of total cov" is $N_W \cdot \text{Cov}_W(V, M)/(N \cdot \text{Cov}_{\text{full}}(V, M))$, the contribution of each window to the unconditional value–momentum covariance.

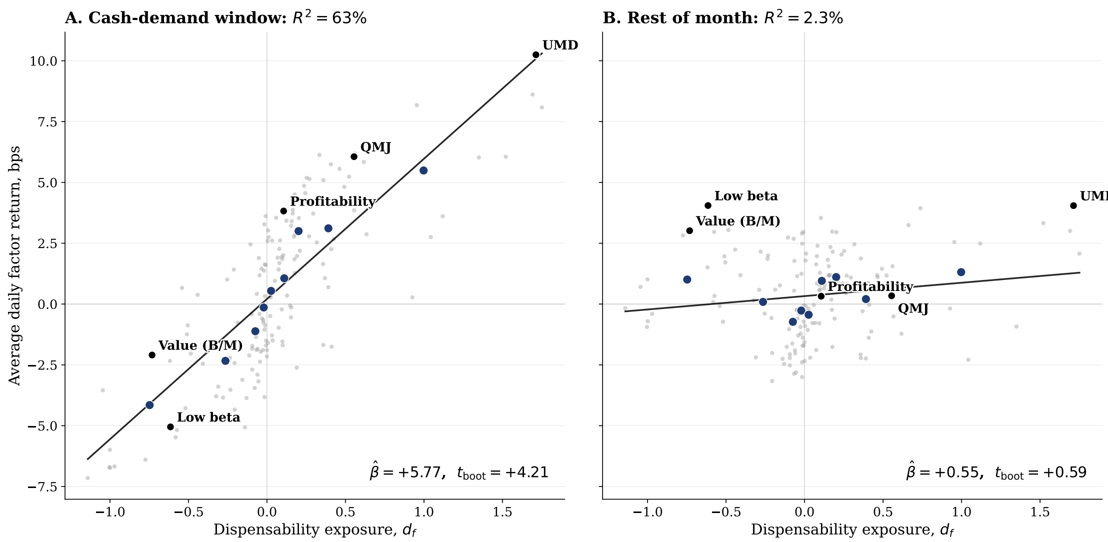


Figure 1: Factor Returns and Dispensability Exposure. Each dot plots a factor's average daily value-weighted $D10 - D1$ return (basis points) against its dispensability exposure $d_f$. The exposure $d_f$ is the factor's short-leg-minus-long-leg average of stock-level dispensability—each stock's distance from its 52-week high, signed so that stocks far from their high (dispensable) load positively—so a positive $d_f$ means the factor is short dispensable stocks, those investors sell first to raise cash. Gray dots are the individual factors; navy dots are equal-count binned means along $d_f$; the five labeled points are canonical anomalies (UMD, QMJ, value, low-beta, profitability) shown for orientation. The cash-demand window (PreTOM) is the six trading days ending four trading days before month-end. $t_{\text{boot}}$ is a month-block bootstrap $t$-statistic ($B = 5{,}000$ draws: the slope divided by its bootstrap standard deviation). The 52-week-high sort is excluded, leaving the 152 tested factors. Sample: 1963–2025.

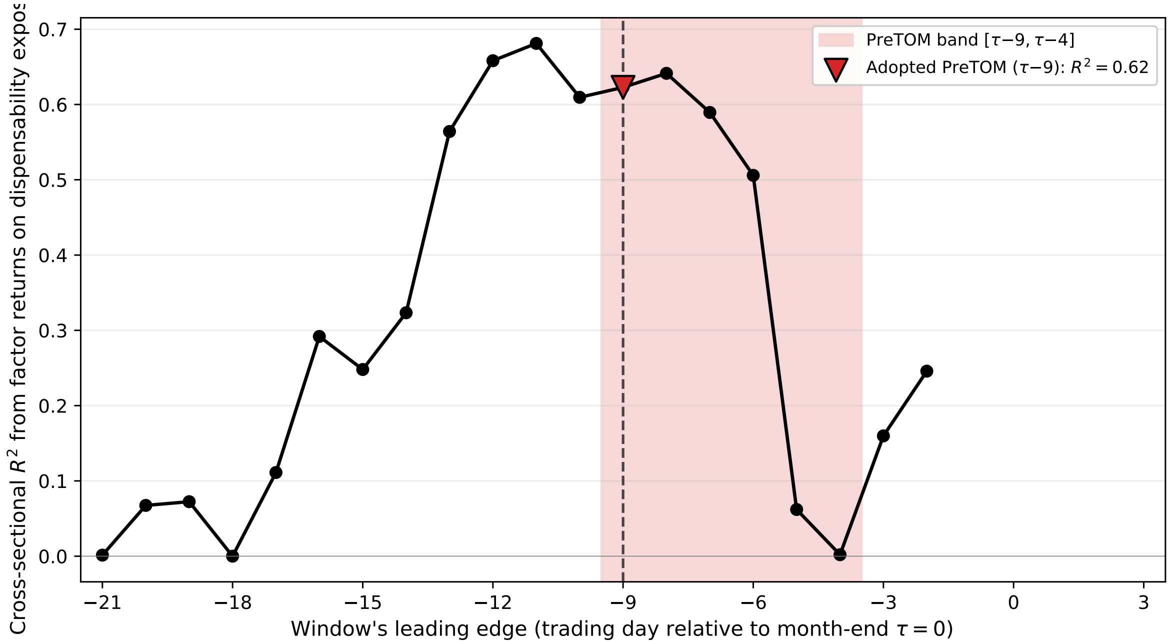


Figure 2: Cross-Sectional Fit by Intra-Month Window. Each point is the cross-sectional $R^2$ from the regression $\bar{R}_f^{\text{window}} = a + b \cdot d_f + u_f$, estimated for every six-day window in the trading month. The $x$-axis is the window's leading edge in trading days relative to month-end ($\tau = 0$); leading edge $\tau{-}9$ corresponds to the canonical PreTOM window $[\tau{-}9, \tau{-}4]$ (red band; triangle marks the adopted window). Sample 1963–Dec 2025. The unconditional market return by intra-month position is in Internet Appendix Figure IA.2.

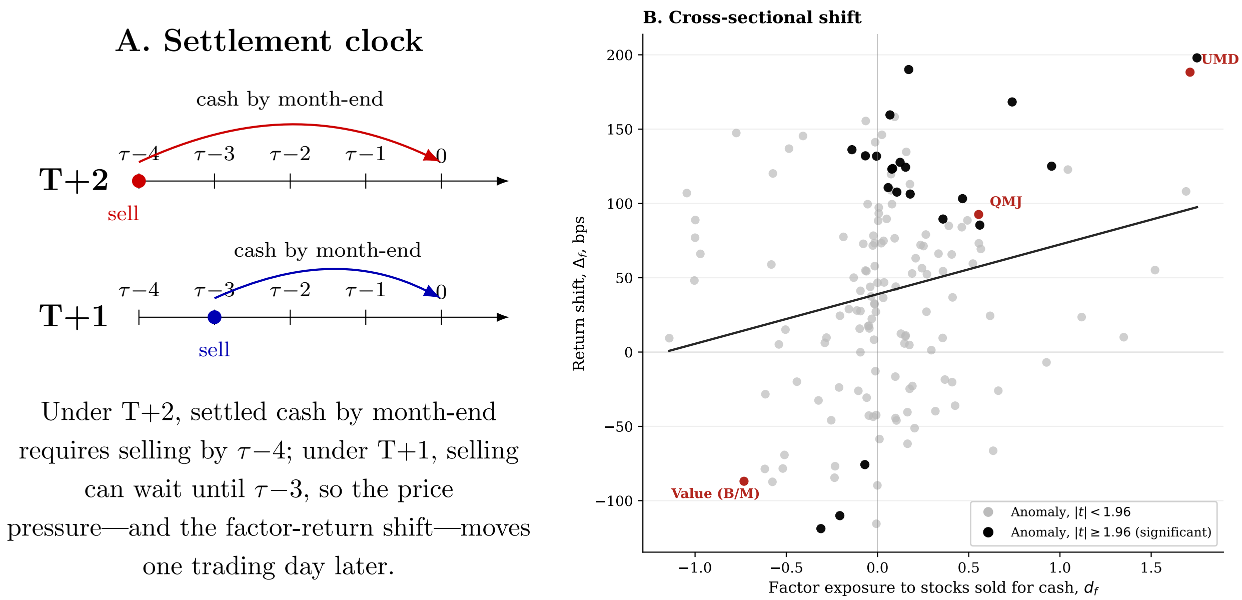


Figure 3: T+1 Settlement Reform and the Cross-Sectional Timing Shift. Each dot is one Jensen, Kelly, and Pedersen (2023) anomaly (the 52-week-high characteristic itself is excluded). The $x$-axis is the dispensability exposure $d_f$; the $y$-axis is the per-factor T+1 reform difference-in-differences on the signed factor return, $\Delta_f = \pi_{f,\tau-3} - \pi_{f,\tau-4}$ (equation 13), with $R_{f,t} = R^{D10}_{f,t} - R^{D1}_{f,t}$. The per-factor regression includes dummies for $\tau-4$, $\tau-3$, Post, and their interactions, with early-month $[\tau+5, \tau+8]$ days as the no-settlement control. Pre-period: T+2 era (September 5, 2017 – April 30, 2024); post-period: T+1 era (June 1, 2024 – December 31, 2025), with May 2024 dropped as a transition month. Anomalies with $|t| \geq 1.96$ are black, the rest light gray; UMD, QMJ, and book-to-market are labelled. The precision-weighted (WLS) placebo slope is +47.9 bps with one-sided $p = 0.004$ against 1,000 pseudo-reform dates drawn from 1990–2015 (Table 4 Panel B). NYSE-BP VW deciles.

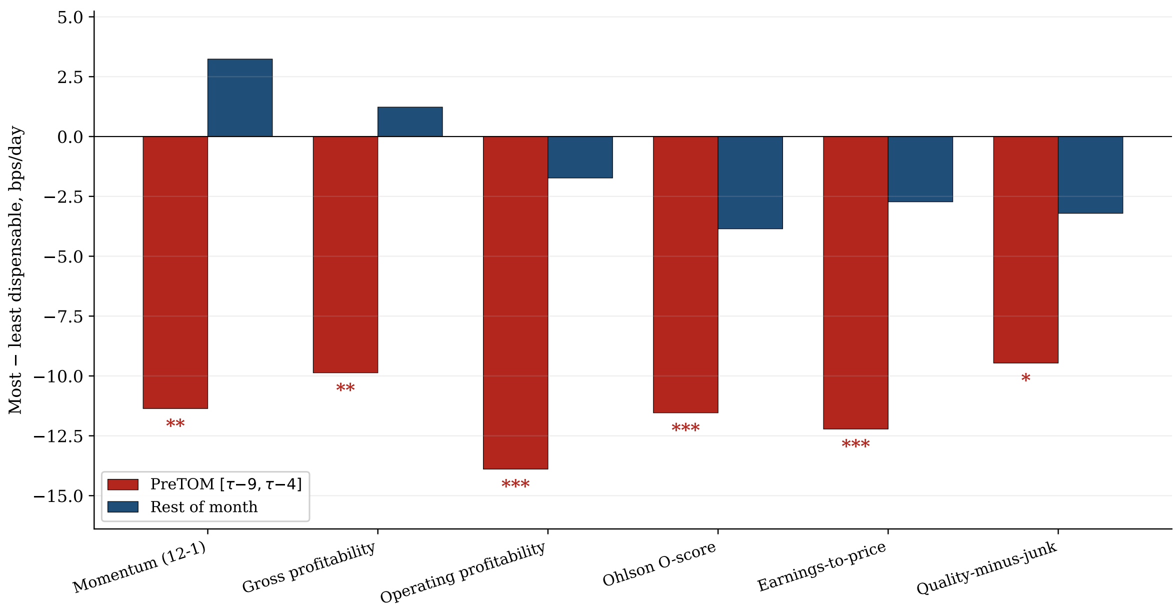


Figure 4: Within-Leg Dispensability Sorts. For each strong-fit factor, stocks in its short-leg decile (NYSE breakpoints, formed at the prior month-end) are sub-sorted by the dispensability score $\delta_{i,m}$ into five within-leg quintiles, where Q5 is most dispensable and Q1 is least. Bars are the value-weighted Q5−Q1 spread (most − least dispensable, bps/day) in PreTOM (red) and in the rest of the month (blue); stars mark PreTOM significance ($^{*}p<0.10$, $^{**}p<0.05$, $^{***}p<0.01$). Because both quintiles lie in the same leg and window, the market cancels in the difference. Sample 1963–Dec 2025. Full numbers in Table 6.

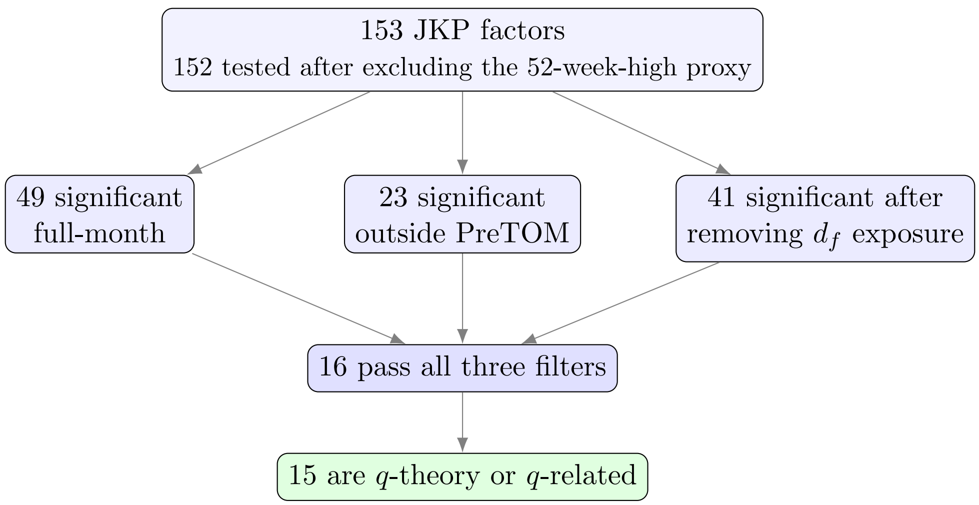


Figure 5: Identifying the Persistent Factor Cohort. Of the 152 Jensen, Kelly, and Pedersen (2023) factors, 49 are significant full-month, 23 are significant outside PreTOM, and 41 are significant after removing each factor's linear exposure to $d_f$; 16 pass all three filters, of which 15 are $q$-theory or $q$-related. Significance uses the $|t| > 3$ threshold of Harvey, Liu, and Zhu (2016) with a month-block bootstrap.

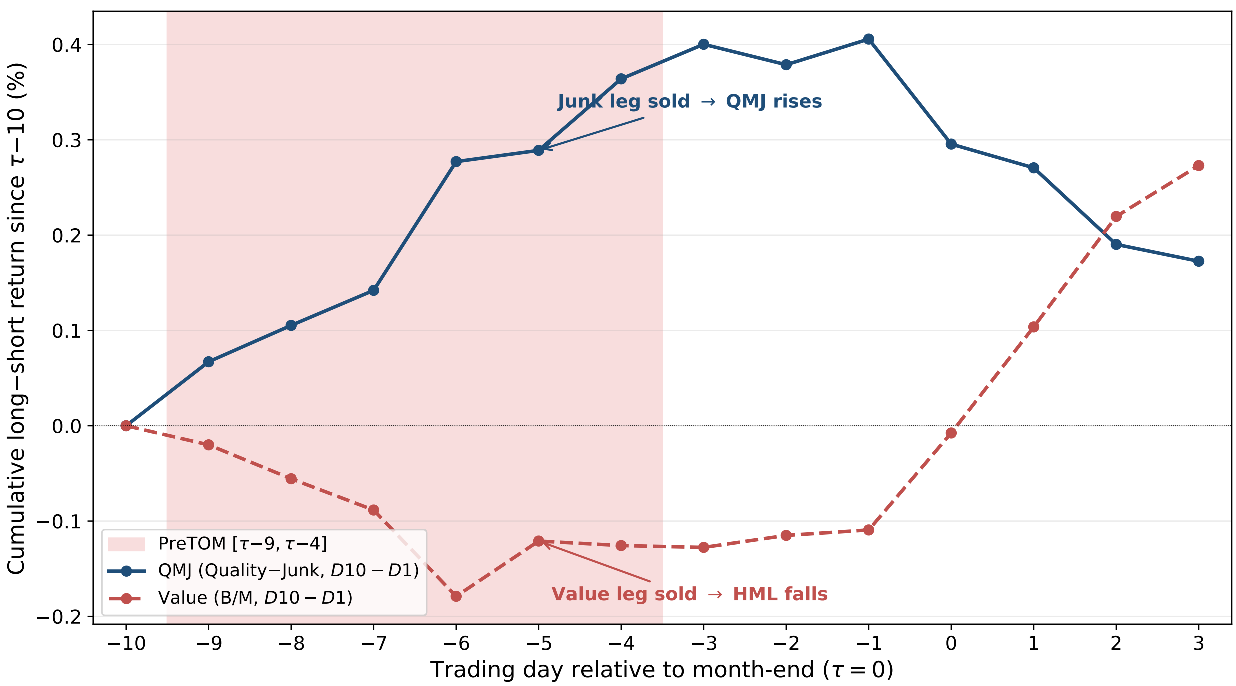


Figure 6: Quality and Value Around Month-End. Cumulative within-month long–short return ($D10 - D1$) for QMJ (Quality−Junk, blue solid) and Value (book-to-market, red dashed), each normalized to zero at $\tau{-}10$ (just before PreTOM) and accumulated by the average daily long–short return at each subsequent trading-day position. The PreTOM band $[\tau{-}9, \tau{-}4]$ is shaded; days $\tau{+}1$ to $\tau{+}3$ are the first three trading days of the following month. NYSE breakpoints, VW deciles, 1963–Dec 2025.