Anomalies on a Schedule: Month-End Liquidity Demand and the Factor Zoo

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Abstract

The first principal component of daily factor returns earns 83% of its mean in a six-day window ending four days before month-end, when institutions raising cash sell their most dispensable stocks, those far below 52-week highs. Across 153 factors over 1963–2025, 47% of the average premium accrues in that window, and exposure to dispensable stocks explains 72% of cross-sectional variation in factor returns inside it against 1.0% outside. Part of what the literature counts as distinct premia is one payment for supplying month-end liquidity. When settlement shortened to T+1 in 2024, the window moved one day closer to month-end. Much of the factor zoo earns its premium on a schedule set by the demand for cash.

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1 Introduction

Hundreds of characteristics predict the cross-section of stock returns, and a large literature seeks to reduce this zoo to a small number of common components or a low-dimensional stochastic discount factor. We show that part of this common structure has a specific economic origin: a large share of the average factor's premium accrues during a few trading days late each month, when institutions raise cash, and a factor's return during those days depends on whether it holds the stocks institutions sell. The first principal component of daily factor returns earns 83% of its mean inside that window.

Across the 153 characteristic-sorted factors in the Jensen, Kelly, and Pedersen (2023) library (2023, JKP) over 1963–2025, 47% of the average factor's premium accrues during a six-trading-day window that ends four trading days before month-end, which we call the PreTOM window. That window covers only about 29% of a typical month's trading days. The concentration is not uniform across factors. Some earn large positive average returns during these six days while others earn negative returns. The paper explains this pattern, traces it to institutional demand for cash, and shows that part of what the literature counts as distinct premia is a single payment for supplying liquidity at month-end.

The liquidity demand comes from institutions that must raise cash before month-end. Recurring obligations such as pension payrolls lead them to sell securities for settled cash, generating temporary price pressure (Etula et al., 2020), and when they sell, they part first with dispensable stocks, salient underperformers trading far below their 52-week highs, which offer tax-loss benefits and pay little in dividends (Nathan, Suominen, and Tasa, 2026).[1] A factor's dispensability exposure, the long-minus-short gap in the dispensability of its holdings, explains 72% of the cross-sectional variation in average PreTOM returns across 152 factors, excluding the 52-week-high characteristic itself. Outside the window the same exposure explains 1.0%. Factors short dispensable stocks earn positive PreTOM returns, and factors long them earn negative returns. Because, as we show, most factors in the zoo are short dispensable stocks, the average factor collects the liquidity-demand premium rather than paying it.

[1] Nathan, Suominen, and Tasa (2026) introduce dispensability and show that month-end selling of dispensable stocks generates most of the momentum premium through its short leg. Distance below the 52-week high is closely related to momentum (George and Hwang, 2004). Sections 3.4, 3.5, and 6.2 show that our results are not momentum in disguise.

Settlement mechanics allow a direct test of the cash-need interpretation. In 2024 the settlement cycle was shortened from two days to one, moving the last sale that settles before month-end one day closer to it. Following the change, price pressure on dispensable stocks shifts one trading day toward month-end. Factor returns shift with it, and the shift is largest for the factors and ETFs with the greatest dispensability exposure.

A natural concern is that this concentration is a relic of the early sample, when anomaly returns were large. Average anomaly premia have indeed fallen from 35 basis points per month in 1963–1993 to 23 in 1994–2025, and to 10 since 2010, consistent with the post-publication decay documented by McLean and Pontiff (2016). Yet the PreTOM share of the average premium has risen across the same periods, from 45% to 49% to 55%, and a PreTOM trading day now earns about 3.1 times as much as a rest-of-month trading day, up from 2.0 times in the early sample. Since 2010, over half of what the zoo delivers accrues inside the window.

Dispensability exposure organizes the zoo. It is economically meaningful in 134 of the 152 factors we study, and because it prices the cross-section inside the window and almost nowhere outside it, the factors remain distinct premia that share a single seasonal payment. The common component that earns 83% of its mean inside the window is itself aligned with dispensability exposure. The 18 factors with little exposure are concentrated in the q-theory-related investment, growth, and accruals characteristics of Hou, Xue, and Zhang (2015).

The intensity of month-end price pressure varies substantially across months. We measure its realized price impact with a monthly liquidity-demand shock, defined as the PreTOM return spread between the least- and most-dispensable stock deciles. Larger shocks should benefit factors that are short dispensable stocks and hurt factors that are long them. In panel regressions with factor and month fixed effects, factor returns load on the shock in proportion to their dispensability exposure, and the interaction explains 18.5% of the remaining factor-month variation in PreTOM returns. Outside the window, the interaction is statistically insignificant.

We provide further evidence linking the PreTOM return patterns to selling pressure from month-end liquidity demand. Complementing Nathan, Suominen, and Tasa (2026), we show that dispensable stocks underperform during PreTOM and experience elevated net seller-initiated trading, including within fixed factor legs. The price concession is larger when seller-initiated trading is tilted toward dispensable stocks and market volatility is elevated; mutual-fund outflows widen it further in these states.

The mechanism also explains relationships among prominent factors that have puzzled the literature. Momentum and quality portfolios are predominantly short dispensable stocks while value portfolios are predominantly long them, so momentum and quality earn positive PreTOM returns and value earns negative ones, and accounting for the daily return component aligned with dispensability exposure reduces the negative momentum-value correlation of Asness, Moskowitz, and Pedersen (2013) by 39%. The paper also develops further implications that follow from the mechanism we uncover: part of value's apparent underperformance, a calendar-based component of the factor-momentum effect of Ehsani and Linnainmaa (2022), and a reinterpretation of the idiosyncratic-volatility puzzle of Stambaugh, Yu, and Yuan (2015).

Our findings are consistent with theories in which demand for immediacy creates temporary price pressure (Grossman and Miller, 1988) that anticipation need not eliminate: capital moves slowly (Duffie, 2010), and when the timing of future selling is known but its magnitude is uncertain, liquidity suppliers do not fully position in advance (Vayanos and Woolley, 2013). Month-end liquidity demand has exactly this structure, predictable in timing but uncertain in magnitude. Consistent with this, Etula et al. (2020) show that their month-end return predictability persists rather than being competed away. Exploiting it requires standing ready to supply liquidity precisely when the demand for cash is aggregate and risk is most expensive to bear, so the concession compensates liquidity suppliers for bearing that risk rather than representing an unexploited arbitrage. Our own evidence supports this reading, because the concession is largest exactly when market uncertainty is elevated (Section 4.3).[2]

Our work relates to four strands of the literature. First, we contribute to research on the common structure of the factor zoo (Cochrane, 2011; Harvey, Liu, and Zhu, 2016; McLean and Pontiff, 2016; Freyberger, Neuhierl, and Weber, 2020; 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 a common cross-sectional dimension that organizes factor returns during a known liquidity-demand

[2]Other settings in which anticipated transactions and flows affect returns are described by Lou, Yan, and Zhang (2013) and Dong, Kang, and Peress (2025).

window. It affects 134 of the 152 factors, showing that monthly anomaly returns partly reflect heterogeneous exposure to a recurring, signed month-end demand shock.

Second, we contribute to the literature on calendar-time return patterns (Ariel, 1987; Ogden, 1990; Heston and Sadka, 2008; Keloharju, Linnainmaa, and Nyberg, 2016). Keloharju, Linnainmaa, and Nyberg (2016) conclude that factor seasonalities reflect many distinct return premia with weak cross-sectional correlations. At the intra-month frequency, we instead find a strong common structure: exposure to a single stock characteristic explains 72% of the cross-sectional variation in average factor returns during PreTOM and is linked to a specific institutional mechanism. The long-horizon Heston and Sadka (2008) seasonality factor is among the few factors with little exposure to this mechanism, suggesting that annual and intra-month cycles are distinct phenomena.

Third, we contribute to the demand-based asset-pricing literature (Coval and Stafford, 2007; Lou, 2012; Koijen and Yogo, 2019; Gabaix and Koijen, 2021). We identify a recurring cross-sectional demand shock that propagates through anomaly portfolios through the stocks they hold. Closest to our work are Hartzmark and Solomon (2025), Etula et al. (2020), and Nathan, Suominen, and Tasa (2026), who document predictable price pressure arising from dividends, month-end cash needs, and liquidity-driven trading. We show how such pressure propagates throughout the factor zoo. Unlike persistent-flow and broad noise-trader-demand explanations (Dong, Kang, and Peress, 2025; Huang, Song, and Xiang, 2025), the component we identify is tied to a six-day settlement-timed window, and its incidence across factors is predicted by their portfolio holdings.

Fourth, our findings connect to both the q-factor framework (Hou, Xue, and Zhang, 2015) and the mispricing-factor framework (Stambaugh, Yu, and Yuan, 2012; Stambaugh and Yuan, 2017). Both emphasize investment, profitability, accruals, issuance, and related corporate-policy characteristics. These characteristics are disproportionately represented among the small group of factors with little exposure to month-end liquidity demand. The evidence therefore distinguishes a broad, calendar-bound liquidity-demand component from a smaller set of return patterns associated with longer-horizon corporate policies and longer-horizon seasonality.

The remainder of the paper is organized as follows. Section 2 describes the data and empirical design. Section 3 shows that exposure to dispensable stocks organizes the cross-section of factor returns, reorganizes the zoo along this axis, separates dispensability from momentum and from mechanical factor-library overlap, and replicates the pattern in two independently constructed factor libraries. Section 4 analyzes the realized month-end liquidity-demand shock and its relation to factor returns. Section 5 studies the T+1 settlement reform and validates the resulting timing shift in ETF portfolios. Section 6 investigates selling pressure on dispensable stocks within factor portfolios. Section 7 reinterprets a broader set of canonical anomalies and relates our findings to the factor-momentum results of Ehsani and Linnainmaa (2022). Section 8 concludes.

2 Data and Empirical Design

2.1 Factor Returns

We build decile-sorted long–short factor portfolios from the 153 monthly firm characteristics of Jensen, Kelly, and Pedersen (2023), from WRDS. Each characteristic is a stock-level number observed at each month-end, and defines one factor portfolio, which we index by f. Each month, for each factor f, we sort stocks into deciles by the characteristic's previous month-end value, using NYSE breakpoints, and hold the portfolios fixed through the month.[3] The daily factor return on trading day t is

$$R_{f,t} \;=\; s_f \left(R_{D10,f,t} \;-\; R_{D1,f,t}\right), \tag{1}$$

where $R_{D10,f,t}$ and $R_{D1,f,t}$ are the value-weighted returns on factor f's highest-characteristic decile ($D10$) and lowest-characteristic decile ($D1$), and $s_f \in \{-1, +1\}$ orients the factor in the direction its original study reports as the anomaly premium, taken from the Factor Details file of Jensen, Kelly, and Pedersen (2023). For momentum, whose premium is long past winners, $s_f = +1$; for low-beta, whose premium is long low-beta stocks, $s_f = -1$. Unless otherwise stated, every factor therefore enters in its intended anomaly direction, so a positive $R_{f,t}$ is the premium as the anomaly was originally defined. Concentration tests use absolute returns, $|R_{f,t}|$, and do not depend on the sign.

[3] NYSE breakpoints, following Fama and French (1993), compute the decile cutoffs from NYSE-listed stocks only and then apply those cutoffs to the full NYSE/AMEX/NASDAQ universe. This keeps the many small AMEX and NASDAQ stocks from crowding into the extreme deciles, which would otherwise be dominated by microcaps.

The decile portfolios are value-weighted by each stock's prior-day market capitalization. The NYSE breakpoints and value-weighting follow the anomaly-replication approach of Hou, Xue, and Zhang (2020), who emphasize this specification to keep microcaps from dominating the extreme deciles. The sample spans February 1963 through December 2025, covering 755 calendar months and 15,834 trading days. The JKP characteristics differ in their start dates, because some require accounting or market data items available only later in the sample. Cross-sectional tests therefore include each factor over its available history, with one observation per factor.

Analyses with stricter data requirements use correspondingly smaller samples; each table's notes state the restriction imposed and the resulting factor count. One restriction applies throughout and is worth fixing here: tests involving dispensability exclude the 52-week-high factor that defines the measure, leaving 152 of the 153 characteristics as tested factors. Tables that condition on common daily coverage across factors, such as Table 11, likewise count only the trading days on which every included factor trades.

Section 3.7 replicates the PreTOM–Rest asymmetry in the Chen and Zimmermann (2022) and Hou, Xue, and Zhang (2020) libraries, using the factor returns those libraries provide. The same pattern appears in Jensen, Kelly, and Pedersen's own published low/high tercile portfolios (Internet Appendix Section IA.20).

Throughout the paper, i indexes stocks, f factor portfolios, m months, t trading days, and e ETFs. Internet Appendix Table IA.1 collects the main variable definitions.

2.2 Trading Day Index

Let τ denote the last trading day of month m. Days before month-end are denoted $\tau-i$ ($\tau-1, \tau-2, \ldots$), and days after month-end are denoted $\tau+i$ ($\tau+1, \tau+2, \ldots$). *PreTOM* is the six-trading-day window $[\tau-9, \tau-4]$. We also refer to PreTOM as the "cash-demand window," because institutions raise cash before month-end during these days. *Rest* denotes all trading days outside PreTOM. The PreTOM window is not chosen using factor returns: its boundaries are pinned down by the aggregate market return path, the only consecutive run of trading-day positions with negative average market excess returns (Figure 2), a pattern first documented by Etula et al. (2020). Section 3.2 compares it with randomly placed six-day windows.

Post denotes the seven-trading-day window $[\tau{-}3, \tau{+}3]$ around month-end, comprising the three trading days before month-end, month-end itself, and the first three trading days afterward. Post is not disjoint from Rest. Specifications that require three disjoint windows, such as Table 11, redefine Rest to exclude the Post days and state this modification explicitly. We reserve τ for event-time indexing and use T for settlement notation, where $T{+}1$ and $T{+}2$, for example, denote settlement one or two business days after the trade date.

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.[4] We use the May 2024 transition for our difference-in-differences analysis in Section 5. We expect faster settlement to shift the price pressure generated by month-end liquidity demand one trading day closer to month-end, from $\tau{-}4$ to $\tau{-}3$.

2.4 Market Uncertainty, Order Flow, and Fund Flows

In Section 4.3, we relate the monthly PreTOM liquidity-demand shock $\mathrm{LDS}_m^{\mathrm{PreTOM}}$ which we define as the return spread between the least- and most-dispensable stock deciles (Section 4.1), to seller-initiated order flow and to the state of the market entering the window. We measure that state with the VIX index of option-implied volatility, using its level at the *prior* month-end, VIX_{m-1}. We predetermine it in this way so that it is not simultaneous with the PreTOM concession it helps explain.

We measure an order-flow-based proxy for selling pressure using the WRDS Intraday Indicators data, which classify TAQ trades as buyer- or seller-initiated following Lee and Ready (1991). For stock i on day t, define

$$\mathrm{NetSell}_{i,t} = \frac{\mathrm{SellVol}_{i,t} - \mathrm{BuyVol}_{i,t}}{\mathrm{SellVol}_{i,t} + \mathrm{BuyVol}_{i,t}}, \tag{2}$$

where buyer- and seller-initiated volumes are measured in dollars. This variable measures the direction of trading pressure. It does not identify the trader behind each trade. In

[4] 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).

Section 4.3 we aggregate this stock-day measure to a monthly net-seller-pressure variable, NSP_m, used in Table 7.

We measure mutual-fund flow pressure by aggregating daily fund-level net flows of U.S. equity mutual funds, scaled by assets under management, summing over the PreTOM days of month m, and flipping the sign so that positive values denote outflows; daily flows are winsorized at the 1st and 99th percentiles before aggregation.

In some tests we control for the average daily CRSP value-weighted market return over the PreTOM window and the average daily change in VIX over the same window. We define the crisis-period control as an indicator equal to one in the four most acute crisis months in our sample, the Lehman collapse during September–October 2008 and the COVID crash in February–March 2020. The summary table also includes d_f, factor f's short-minus-long dispensability tilt, defined as the average difference in dispensability (distance below the 52-week high) between its two legs; its formal construction is in Section 3.1. Table 1 reports summary statistics and sample coverage for these variables.

3 The Common Month-End Component and the Dispensability Axis

Factor returns concentrate in the PreTOM window. We measure the concentration on a balanced sample of 141 factors, those whose return series begin by December 1964 and extend through 2025, so that factor composition stays fixed across the subperiods compared below. These factors earn an average of 29 basis points per month. Of this premium, 13 basis points accrue during the six PreTOM days, which account for only about 29% of the trading days in a typical month; averaged across factors, the PreTOM share of the monthly premium is 47%. A PreTOM trading day therefore earns about 2.2 times as much as a rest-of-month day (Table 2).

The concentration is broad rather than driven by a handful of factors. For each factor, we compare its absolute average daily long–short return in PreTOM with that in the rest of the month. Of the 153 JKP factors, 113, or 73.9%, have the larger absolute return in PreTOM. The pattern appears across all 14 JKP themes.[5]

[5] Jensen, Kelly, and Pedersen (2023) group the 153 characteristics into 14 themes (such as Momentum,

Nor is the result a generic feature of selecting any six trading days. Randomly placed six-day windows reproduce neither the prevalence of larger factor returns nor the unusually wide cross-sectional dispersion observed in PreTOM. Section 3.2 and Internet Appendix Table IA.2 report the placebo tests.

The concentration has not weakened as anomaly premia have declined. Average anomaly returns fall from 35 basis points per month in 1963–1993 to 23 basis points in 1994–2025, consistent with the post-publication decay documented by McLean and Pontiff (2016) and Jensen, Kelly, and Pedersen (2023). Yet the PreTOM share rises from 45% to 49%, while the number of factors with a larger absolute daily return in PreTOM remains nearly unchanged, at 112 of 153 in the first half and 107 in the second (Internet Appendix Table IA.12). Since 2010, the average anomaly premium falls further to 10 basis points per month, but 55% is still earned in PreTOM. The month-end concentration has therefore become, if anything, more pronounced as anomaly premia have decayed.

None of the evidence above uses a stock characteristic. The concentration of factor returns in a common month-end window is established before any characteristic enters the analysis. We next ask which stock characteristic organizes the cross-section of PreTOM returns. Section 6.2 later traces the concentration to dispensable stocks within factor legs, connecting our results also to evidence that anomaly returns arise disproportionately from the short side (Stambaugh, Yu, and Yuan, 2012; Stambaugh and Yuan, 2017).

3.1 How Dispensability and Other Characteristics Explain PreTOM Returns

Distance below the 52-week high is the best characteristic to explain the cross-section of mean PreTOM factor returns $\bar{R}_f^{\text{PreTOM}}$ over the full sample. Aggregating this characteristic across each factor's long and short legs gives us a factor-level dispensability exposure. Following Nathan, Suominen, and Tasa (2026), we interpret stocks trading far below their 52-week highs as "dispensable": natural liquidation candidates because they are salient underperformers, often embed losses whose realization carries tax benefits, and tend to pay low dividends. We treat distance below the 52-week high as a proxy for dispensability rather than the latent

Value, Profitability, Investment, and Low Risk) by hierarchically clustering factors on their return correlations; we use these groupings throughout.

trait itself. Internet Appendix Table IA.43 profiles the stocks the measure identifies.

To identify the characteristic that best organizes PreTOM factor returns, we build a factor-level exposure for every characteristic in the JKP library—aggregating the standardized characteristic across each factor's long and short legs, as described below—and rank the candidates by the resulting cross-sectional R^2. For each candidate characteristic c and stock i, we standardize the stock's month-end characteristic value $c_{i,m}$ within month m,

$$z^c_{i,m} = z_m(c_{i,m}), \tag{3}$$

where $z_m(\cdot)$ subtracts the month-m cross-sectional mean and divides by the cross-sectional standard deviation. Thus, $z^c_{i,m}$ measures stock i's characteristic value relative to other stocks that month. For factor f, let $\bar{z}^c_{1,f,m}$ and $\bar{z}^c_{10,f,m}$ denote the market-capitalization-weighted averages of $z^c_{i,m}$ among the stocks in its $D1$ and $D10$ legs.[6] We define factor f's *characteristic exposure* to c, denoted CE^c_f, as its average intended-signed $D1$-minus-$D10$ difference,

$$\mathrm{CE}^c_f \;=\; \frac{1}{M_f}\sum_{m=1}^{M_f} s_f\left(\bar{z}^c_{1,f,m} \;-\; \bar{z}^c_{10,f,m}\right), \tag{4}$$

where M_f is the number of months for which factor f is available. The sign s_f is the same as in equation (1), so characteristic exposure and factor returns share a common orientation: a positive CE^c_f means that the anomaly is short stocks with high values of characteristic c relative to the stocks in its long leg. We then estimate the cross-factor regression

$$\bar{R}^{\mathrm{PreTOM}}_f \;=\; \alpha^c + \beta^c\,\mathrm{CE}^c_f + \varepsilon^c_f, \tag{5}$$

where each observation is a factor and $\bar{R}^{\mathrm{PreTOM}}_f$ is factor f's average daily PreTOM return. We estimate equation (5) separately for each candidate characteristic c and rank the characteristics by the resulting R^2. In each such regression, we exclude the factor formed on the candidate characteristic, so no characteristic receives mechanical credit for explaining its own factor; Internet Appendix Section IA.9 reports the full ranking.

Distance below the 52-week high has the greatest explanatory power over the full sample (Table 3). Its factor-level exposure explains 72% of the cross-sectional variation in PreTOM

[6]The weight is the stock's market capitalization at month-end m, contemporaneous with the characteristic.

returns, compared with 47% for the next-ranked characteristic, the bid–ask high–low spread (Panel A). No single characteristic is uniquely correct, because liquidation candidacy is a latent trait with several correlates. We interpret distance below the 52-week high as a parsimonious proxy for that trait rather than the trait itself, and adopt it as our baseline because it is the strongest single full-sample predictor and has the most direct economic connection to which stocks investors are willing to liquidate (George and Hwang, 2004; Nathan, Suominen, and Tasa, 2026).[7]

Two features establish that distance below the 52-week high captures a genuine liquidation-candidacy trait rather than relabeling a correlated characteristic. The exposure retains 39% of its PreTOM explanatory power ($t = +6.75$) after residualizing stock-level dispensability on reversal, prior returns, market beta, idiosyncratic volatility, and quality (Section 3.5), and the gap between the returns of the least- and most-dispensable stocks *within* a factor's leg widens in PreTOM, holding factor membership constant (Section 6.2).

We construct the dispensability proxy directly from the JKP 52-week-high variable. JKP report the ratio of the current price to the trailing 52-week high; we define dispensability as the proportional distance from that high, standardized within each month:

$$\delta_{i,m} \;=\; z_m\!\left(\frac{\max_{s\in\mathcal{T}_m} P_{i,s} \;-\; P_{i,m}}{\max_{s\in\mathcal{T}_m} P_{i,s}}\right), \tag{6}$$

where $P_{i,m}$ is stock i's month-end closing price, $\mathcal{T}_m$ is the trailing 252-trading-day window, and $z_m(\cdot)$ standardizes the measure across stocks in month m. Higher $\delta_{i,m}$ therefore indicates that a stock is farther below its 52-week high and more dispensable. We observe $\delta_{i,m}$ at the end of month m and use it to explain returns in month $m+1$.

We call $\delta_{i,m}$ the stock-level dispensability score. Factor f's dispensability exposure is the

[7] Quality and mispricing composites fit comparably well in recent decades. This is what one would expect if the stocks trading far below their highs have also become more fundamentally distressed over time, so that measures of fundamental weakness increasingly pick out the same liquidation candidates; a joint test finds both distance from the high and quality contributing in the modern sample (Internet Appendix Table IA.41). A composite that adds quality nonetheless buys little. It raises the modern-period fit only modestly, leaves the sign, the mechanism, and the PreTOM–Rest asymmetry unchanged, and fits worse over the full sample. We therefore retain the single parsimonious proxy and treat the growing role of quality as a robustness result rather than a respecification (Internet Appendix Section IA.22).

average intended-signed difference between the scores of its two legs,

$$d_f \;=\; \frac{1}{M_f}\sum_{m=1}^{M_f} s_f\left(\bar{\delta}_{1,f,m} \;-\; \bar{\delta}_{10,f,m}\right), \tag{7}$$

where $\bar{\delta}_{1,f,m}$ and $\bar{\delta}_{10,f,m}$ are the value-weighted average dispensability scores in factor f's $D1$ and $D10$ legs, and s_f orients the difference in the anomaly's intended direction, as in equation (1). Thus d_f is the factor's net short exposure to dispensable stocks. A positive d_f means that the factor is short more-dispensable stocks than it is long, so month-end selling of those stocks raises its return; a negative d_f means that the factor is long them, so the same selling lowers its return.[8]

3.2 Calendar Asymmetry

Before testing where dispensability exposure prices returns, we fix what the window is and where it comes from. The PreTOM window is defined from the aggregate market return path, not from the factor cross-section. It is the only contiguous set of within-month trading-day positions for which the average CRSP market excess return is negative on every day: returns turn negative at $\tau-9$, remain negative through $\tau-4$, and recover at $\tau-3$, averaging -4 basis points per day over the window (Figure 2; Etula et al., 2020). The cross-sectional pattern is also stable across the six days. Correlations between the vectors of average factor returns at different PreTOM positions average 0.55, compared with 0.15 among Rest positions (Figure IA.1), so the concentration reflects a recurring six-day pattern rather than a single-date spike. Randomly placed six-day windows reproduce neither the fit nor the dispersion. Rerunning the full 153-characteristic search on random placements yields a maximum R^2 of 0.34 on average and 0.58 at the 99th percentile, placing the actual value deep in the tail ($p = 0.001$; Internet Appendix Table IA.20), and the variance across factors of mean daily returns is 3.88 times larger inside the window than outside it, a dispersion ratio that exceeds

[8] The dispensability exposure is not a new object; it is the 52-week-high exposure from the characteristic search. JKP record the characteristic as the ratio of price to the 52-week high, while dispensability is the distance below the high. Flipping the variable this way only flips the sign of its within-month z-score, so d_f is CE_f^c for the 52-week-high characteristic with the sign reversed, chosen so that a positive d_f means the factor is short dispensable stocks. The R^2 and t-statistics do not depend on the sign, so the top row of Panel A in Table 3 and the d_f regressions that follow report the same relationship.

99.7% of 10,000 random placements ($p = 0.003$; Internet Appendix Table IA.2).

Having constructed d_f, we test whether its relation to factor returns is confined to the PreTOM window. For each window $w \in \{\text{PreTOM}, \text{Rest}, \text{Post}\}$, let $\bar{R}_f^w$ denote factor f's average daily long–short return in that window. We estimate

$$\bar{R}_f^w \;=\; \alpha^w + \beta^w d_f + \varepsilon_f^w, \qquad w \in \{\text{PreTOM}, \text{Rest}, \text{Post}\}, \tag{8}$$

separately for each window, with one observation per factor. The slope β^w measures how factor returns vary with dispensability exposure in window w. The regressions include 152 factors, excluding the 52-week-high factor used to construct d_f. Inference uses a month-block bootstrap that recomputes both returns and exposures in each draw.[9]

The temporary-pressure hypothesis predicts a different sign in each window. A factor with high dispensability exposure is short the stocks that face month-end selling, so in PreTOM that selling depresses those stocks and the factor earns a positive return. The more strongly a factor is short dispensable stocks, the larger that return, so β^{PreTOM} is large and positive. Outside the pre-turn window there is no concentrated cash demand, so dispensability exposure should not move returns systematically and β^{Rest} is near zero. In Post the sign flips. To the extent the pressure is due to liquidity demand rather than news, the stocks depressed during PreTOM recover at least partly once cash demand subsides, so the exposure that earned positive returns before the turn earns negative returns after it and β^{Post} is negative. A permanent risk premium would instead produce a positive slope in every window, so the positive, zero, negative pattern is the distinctive signature of transitory price pressure.

Panel B of Table 3 shows this calendar asymmetry and Figure 1 plots the two main windows side by side. The estimated slopes trace the predicted signature in full: $\beta^{\text{PreTOM}} = +5.05$ basis points per day per unit of exposure ($t = +4.06$), $\beta^{\text{Rest}} = +0.34$ ($t = +0.40$), and $\beta^{\text{Post}} = -1.69$ ($t = -1.54$; Post covers the seven trading days $[\tau-3, \tau+3]$ around month-end). Dispensability exposure explains 72% of the cross-sectional variation in PreTOM

[9] 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. Each bootstrap uses $B = 5{,}000$ draws, with calendar months sampled with replacement.

returns but only 1.0% in Rest. Because factor portfolios are held fixed within the month, the sharp PreTOM–Rest contrast cannot arise from changes in portfolio composition. The negative Post slope is consistent with partial reversal after month-end; Internet Appendix Section IA.10 shows that the reversal concentrates in the factors with large absolute exposure, while low-exposure factors exhibit continuation.

The PreTOM component is large enough to appear even in standard full-month returns. When we run the same cross-sectional regression on full-month average daily returns, d_f still explains 30% of the cross-section ($\beta = +1.74$, $t = +2.42$). Monthly anomaly returns therefore inherit a substantial part of the PreTOM liquidity-demand structure, even though the relation is concentrated inside the PreTOM window.

Alternative calendar stories imply different timing. Window dressing (Lakonishok et al., 1991) points to quarter-ends, tax-loss harvesting to December, and foregone dividend income (Hartzmark and Solomon, 2025) to dividend-yield characteristics, none of which matches a monthly pattern organized by distance below the 52-week high; Nathan, Suominen, and Tasa (2026) address each alternative at the stock level.

3.3 Robustness of the Cross-Sectional Fit

This subsection tests the cross-sectional fit against the objections most likely to explain it away. Inference throughout uses the month-block bootstrap-t on the slope of equation (5).

The first objection is that dispensability is momentum in disguise, because momentum losers are the archetypal dispensable stocks. Dropping the seven momentum-theme factors leaves the asymmetry intact. The overlap runs deeper than factor deletion can address, however, so we return to it three times: Section 3.4 runs the direct horse races, Section 3.5 residualizes on the momentum characteristics themselves, and the within-leg sub-sort of Section 6.2 holds factor membership fixed and varies only dispensability.

The second objection is that the fit is manufactured by mechanical clustering in the JKP library, whose 153 factors are built from overlapping inputs. If the fit reflected that shared construction, the same structure would appear in PreTOM and Rest, and it does not. The principal-component structure of the daily factor cross-section is almost identical across the two windows, with PC1's variance share at 28% in PreTOM and 28% in Rest. The variance share measures how much of the day-to-day covariance across factors the leading component explains, a feature of the factors' shared construction that is present on every trading day. Factors that load on dispensability do co-move, because they hold overlapping positions in the same beaten-down stocks, but this comovement runs throughout the month. What concentrates in PreTOM is the average return earned along the common component, not its share of daily variance, so equal variance shares across the two windows are the expected result, and they separate the window-invariant construction from the window-specific premium. Yet d_f's cross-sectional R^2 is 72% in PreTOM and only 1.0% in Rest, so shared construction cannot explain a premium that appears in only one part of the month. Internet Appendix Section IA.16 corroborates with further diagnostics (eigenstructure window-invariance, correlation pruning, a multiple-testing bootstrap, and JKP-theme equal weighting).

The third objection is that the measure relabels correlated characteristics. Distance below the 52-week high naturally overlaps with past returns, risk, and quality, which may themselves identify likely liquidation candidates. To assess whether these characteristics account for the result, we residualize stock-level dispensability on reversal, prior 11-month return, market beta, idiosyncratic volatility, and QMJ safety, and reconstruct the factor-level exposure from the residuals. The residualized measure still explains 39% of the cross-sectional variation in PreTOM returns but only 1% in Rest (Internet Appendix Table IA.6). Distance below the 52-week high therefore contains substantial PreTOM-specific information beyond these standard characteristics.

The remaining checks slice the sample. Collapsed to the 14 JKP themes, the exposure explains 86% of the cross-theme PreTOM variation and essentially none of the Rest (bootstrap-t statistics of +3.99 and +0.33; Internet Appendix Table IA.31). The PreTOM–Rest asymmetry holds in every subperiod, with a PreTOM R^2 of 0.45 in 1994–2025 and a Rest fit near zero throughout (Internet Appendix Section IA.22). And excluding stocks priced under \$5 or below the NYSE 20th size percentile leaves the PreTOM fit at 0.63 with the Rest fit again at zero (Internet Appendix Table IA.42).

3.4 Horse Races Against Alternative Exposures

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

$$\bar{R}_f^{\text{PreTOM}} = a + b_D\, d_f + b_X\, X_f + u_f \tag{9}$$

across 152 factors with month-block bootstrap inference. Here $\bar{R}_f^{\text{PreTOM}}$ is factor f's average daily PreTOM return and X_f is its exposure to one candidate variable, built at the factor level from its holdings or from a return loading, as detailed below. If a candidate is a better proxy for dispensability than distance below the 52-week high, its coefficient b_X should absorb the explanatory power and the coefficient b_D should fall toward zero. The first candidate, a mechanical holdings overlap with momentum,[10] addresses the momentum objection of Section 3.3 directly. The remaining seven range from standard risk exposures to prominent proposed explanations for anomaly returns, and each could in principle explain the PreTOM cross-section instead of dispensability: market beta, the Pástor–Stambaugh aggregate liquidity factor (Pástor and Stambaugh, 2003), Amihud illiquidity, the SIRIO shorting-cost proxy (Drechsler and Drechsler, 2021), the Subjective Belief Factor (SBF; Cui, De la O, and Myers, 2025), and the MGMT and PERF mispricing factors of Stambaugh and Yuan (2017). Construction details for all eight are in Internet Appendix Section IA.11.[11] 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.[12]

None of the eight candidates displaces dispensability (Table 4). Its coefficient stays positive and significant in every joint regression, with bootstrap t between +2.5 and +4.2,

[10]The exposure is a mechanical, ex-ante holdings overlap with momentum, not a realized return loading: for each factor we average over months the value-weighted share of its $D1$ leg that lies in the bottom momentum decile (recent losers) minus the value-weighted share of its $D10$ leg in the top momentum decile (recent winners), where momentum is the JKP twelve-minus-one characteristic (`ret_12_1`) sorted into NYSE-breakpoint deciles over 1963–2025.

[11]We thank Sean Myers for sharing the SBF data series.

[12]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.

while each candidate enters insignificantly, with $|t| < 2$ in all eight. Pástor–Stambaugh liquidity, Amihud illiquidity, the subjective-belief exposure, and PERF each predict PreTOM returns on their own, but their univariate power runs through correlation with d_f, and none adds anything once d_f is included. Market beta, MGMT, and the momentum overlap have little univariate power to begin with. The momentum overlap is the sharpest case. Although momentum itself has one of the largest dispensability exposures in the library, mechanical overlap with momentum's legs explains almost none of the cross-section on its own ($R^2 = 2\%$, $t = +0.85$). What prices PreTOM returns is not whether a factor holds recent losers but whether it holds dispensable stocks. Illiquidity behaves like the first group. Amihud illiquidity predicts PreTOM returns on its own, yet entered jointly with d_f the dispensability exposure remains significant while Amihud does not (Table 4), so the result is not a repackaged illiquidity effect.

The two mispricing factors of Stambaugh and Yuan (2017) are no exception in the PreTOM window. MGMT enters at $t = -0.28$ and PERF at $t = -1.48$, and the joint R^2 of 0.72 is the same as the 0.72 that d_f delivers on its own.[13] The dispensability exposure d_f itself stays significant alongside each, at $t = +3.91$ with MGMT and $t = +3.21$ with PERF. Where MGMT is different is *outside* PreTOM. There the d_f coefficient is indistinguishable from zero, while MGMT retains a modest, opposite-signed cross-factor relation to Rest returns (8% of the variation, $t = -2.12$). The key asymmetry is that the liquidity-demand exposure organizes the PreTOM window but has no power outside it. The two objects load on different parts of the calendar rather than on the same one.

The exposure d_f captures the calendar-bound liquidity-demand component, while the MGMT composite captures the lower-frequency q-theory and mispricing component that dominates outside the PreTOM window.

3.5 Dispensability versus Momentum

Distance below the 52-week high is related to momentum (George and Hwang, 2004), so the first question is whether d_f simply repackages momentum exposure. The characteristic search selects distance below the 52-week high ahead of the momentum variables themselves

[13] The d_f-alone R^2 of 0.72 here is estimated on the bootstrap-matched candidate window and is not in general directly comparable to the full-sample fit of $R^2 = 0.72$; for the mispricing factors, whose window is the full 1963–2025 sample, the two coincide (see the note to Table 4).

(Section 3.1, Table 3 Panel A). In the cross-factor horse races (Section 3.4), d_f subsumes trailing-return measures rather than the reverse. The relation also remains after residualizing stock-level dispensability on return and risk characteristics (Internet Appendix Table IA.6). Most directly, the within-short-leg sub-sort of Section 6.2 varies only dispensability.

The same conclusion holds for time-series momentum (TSM; Moskowitz, Ooi, and Pedersen, 2012).[14] Dispensable stocks overlap heavily with time-series-momentum sell signals (82% of the most-dispensable decile has a negative trailing twelve-month return), but the exposure is not subsumed by the signal. Residualizing stock-level dispensability on the TSM sell indicator alone leaves 60% of the PreTOM cross-section explained, and a significant PreTOM-specific component (29%, $t = +5.3$) survives adding the indicator to the full residualization battery (Internet Appendix Table IA.7). More fundamentally, time-series-momentum rebalancing follows no month-end clock, so it cannot generate the PreTOM concentration, the T+1 settlement shift, or the month-end order-flow timing.

3.6 Reorganizing the Zoo Along the Dispensability Axis

Having established that dispensability exposure is a distinct axis rather than momentum in disguise, we use it to reorganize the zoo. Dispensability exposure divides the 152 tested factors into three groups. 94 have significantly positive exposure and are short dispensable stocks, 40 have significantly negative exposure and are long dispensable stocks, and only 18 have exposure statistically indistinguishable from zero, so the month-end liquidity-demand component reaches 134 of the 152 factors. Because the groups are formed from holdings alone, without using returns, the return differences across them reported next are a prediction of the mechanism rather than a consequence of the sort.

The window's effect on each group is economically large and opposite in sign (Table 5). Short-dispensable factors earn +3.67 basis points per day in PreTOM, compared with +1.13 during the rest of the month. Long-dispensable factors earn +0.71 basis points per day outside PreTOM but lose 0.62 during the window. Low-exposure factors are nearly unchanged, at +1.70 basis points per day in PreTOM and +1.52 outside it.

[14] Time-series momentum trades each stock on the sign of its own past return, holding stocks with a positive trailing twelve-month return and shorting those with a negative one. It differs from the cross-sectional momentum used elsewhere in the paper, which ranks stocks against one another rather than against zero. A stock is a time-series-momentum sell when its trailing twelve-month return is negative, and that indicator is what we residualize on.

The 18 low-exposure factors are concentrated in long-horizon seasonality and q-theory–related investment, growth, and accruals characteristics (Hou, Xue, and Zhang, 2015); their identities and exposure estimates are listed in Internet Appendix Table IA.23.

3.7 External Validation

The PreTOM–Rest asymmetry also appears in two independently constructed anomaly libraries: the Chen and Zimmermann (2022) Open Asset Pricing library and the Hou, Xue, and Zhang (2020) Replicating Anomalies catalog. For these external catalogs we avoid our holdings construction and estimate each factor's exposure from returns alone. For each external factor f we take the decile portfolio returns as constructed by the original library, compute the daily long–short return as the top-decile return minus the bottom-decile return, and estimate a return-based exposure to the 52-week-high spread:

$$R_{f,t} \; = \; a_f + b_f^{52H} \, R_t^{52H} + e_{f,t}. \tag{10}$$

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 63.3% of the cross-sectional variation in PreTOM returns (month-block bootstrap $t = +4.23$) versus 1.9% in Rest. Among the 185 Hou–Xue–Zhang anomalies with valid daily decile returns, it accounts for 71.4% in PreTOM ($t = +4.57$) versus 10.3% 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 3.4); the asymmetry replicates regardless. Appendix IA.20 collects these constructions in one table, alongside Jensen, Kelly, and Pedersen (2023)'s own published low/high portfolios.

3.8 The Calendar Timing of the Common Component

The taxonomy above treats factors individually. The same timing appears in portfolios that summarize the zoo. We form three, ordered by their exposure to what the factors share: an equal weighting of all factors, a weighting that tilts toward dispensability, and the leading principal component of daily factor returns. The last is estimated using only days outside the

PreTOM window, so the window plays no role in defining it. Internet Appendix Table IA.27 reports each portfolio's annualized Sharpe ratio computed from all trading days, from the days outside the window, and from the window days alone.

The equal-weighted zoo earns 46% of its mean during the six PreTOM days. The dispensability-weighted portfolio earns 72%, and the leading principal component, estimated entirely from Rest days, earns 83%. Thus, the common component of the factor zoo is itself paid primarily during the six-day cash-demand window.

4 The Realized Liquidity-Demand Shock

The evidence so far establishes a common return component that is concentrated in the PreTOM window. We now ask whether month-to-month variation in that component tracks the realized month-end liquidity concession.

4.1 Measuring the Shock as a Realized Price Concession

Month-end liquidity demand is predictable in timing but not in magnitude. Investors 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 ex-post price impact.

What can be anticipated is the composition of the demand rather than its size. The window is fixed by the settlement calendar, the stocks that will be sold are identifiable from their distance below their 52-week highs, and the funds that will sell them are identifiable from their own recent redemptions, which persist from month to month. The total quantity is a different matter, because one fund's redemptions net against another's subscriptions before anything reaches the market, so the aggregate is close to unforecastable even when its parts are not. And the concession is not a quantity at all. It is the price that the selling commands, which also depends on how much capital is available to absorb it, as we show in Section 4.3. Consistent with this, the payment calendar, aggregate fund flows, and the constrained funds' own flows all fail to forecast the size of the shock out of sample (Internet Appendix Table IA.10).

We measure this price impact with what we call the liquidity-demand shock (LDS), the

PreTOM return spread between the least- and most-dispensable stock deciles,

$$\mathrm{LDS}_m^{\mathrm{PreTOM}} \equiv \bar{R}_{\mathrm{NonDisp},m}^{\mathrm{PreTOM}} - \bar{R}_{\mathrm{Disp},m}^{\mathrm{PreTOM}}, \tag{11}$$

where $\bar{R}_{\mathrm{Disp},m}^{\mathrm{PreTOM}}$ and $\bar{R}_{\mathrm{NonDisp},m}^{\mathrm{PreTOM}}$ are the value-weighted average daily PreTOM returns in month m of the most- and least-dispensable stock deciles. A positive $\mathrm{LDS}_m^{\mathrm{PreTOM}}$ therefore means that dispensable stocks underperform during PreTOM. The shock is the time-series counterpart of the dispensability exposure of Section 3.1. Where d_f records how strongly a factor's holdings tilt toward dispensable stocks, $\mathrm{LDS}_m^{\mathrm{PreTOM}}$ records how hard those stocks are hit in month m, and the next subsection combines the two, asking whether factor returns load on the monthly shock in proportion to their exposure. The deciles are formed at the prior month-end from the raw price-to-high ratio underlying the dispensability score, using NYSE breakpoints.[15] The same construction gives $\mathrm{LDS}_m^{\mathrm{Rest}}$ and $\mathrm{LDS}_m^{\mathrm{Post}}$; because the Post window crosses the month boundary, all seven Post days, $[\tau{-}3, \tau{+}3]$, are assigned to the month ending at τ. The mean spread is positive in PreTOM (+8.93 bps/day, $t = +4.14$), close to zero in the mid-month placebo window $[\tau{-}15, \tau{-}10]$ (+1.67 bps/day, $t = +0.72$), and negative in Post (−4.61 bps/day, $t = -2.23$).[16]

We use "liquidity-demand shock" as shorthand, but LDS is a return-based measure of the realized price concession on dispensable stocks, not independently observed order flow. Because LDS and factor returns are constructed from overlapping stock returns, Section 4.2 rebuilds the PreTOM shock after excluding the extreme-leg holdings of all factors in the same JKP theme and repeats the analysis in Rest (Table 6). Section 6.1 provides complementary order-flow evidence that seller-initiated trading tilts toward dispensable stocks during PreTOM. Economically, LDS captures the concession liquidity suppliers require to absorb a recurring imbalance when risk-bearing capacity is limited.

4.2 The Liquidity Shock as a Common Component

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

[15] In the numbering of that ratio sort, the most-dispensable decile Disp is $D1$ (the stocks farthest below their highs, with the highest $\delta_{i,m}$) and the least-dispensable decile NonDisp is $D10$.

[16] Window-mean estimates and standard errors are reported in Internet Appendix Table IA.8.

and month fixed effects:

$$R_{f,m}^{\text{PreTOM}} \;=\; \alpha_f \;+\; \tau_m \;+\; \beta\left(d_f \times \text{LDS}_m^{\text{PreTOM}}\right) \;+\; \varepsilon_{f,m}, \tag{12}$$

with standard errors two-way clustered by factor and month. Month fixed effects absorb aggregate shocks, including the level of $\text{LDS}_m^{\text{PreTOM}}$ itself. The interaction tests whether, in months when the realized concession is larger, factor returns vary according to their average exposure to dispensable stocks.

The panel estimates support this prediction (Table 6, Panel A). Across the 152 tested factors from 1963 to 2025, the interaction coefficient is 0.505 ($t = 16.71$). Thus, in a month when the concession is one basis point per day larger, a factor with a one-unit-higher d_f earns 0.505 basis points per day more during PreTOM. The interaction accounts for a within R^2 of 18.5%, that is, 18.5% of the PreTOM factor–month variation that remains once factor and month fixed effects are absorbed.[17] The same specification estimated on Rest returns produces an economically small and statistically insignificant coefficient ($\beta = 0.016$, $t = 0.66$). As a placebo, replacing $\text{LDS}_m^{\text{PreTOM}}$ with $\text{LDS}_m^{\text{Post}}$, the same least-minus-most-dispensable return spread measured instead over the seven trading days $[\tau{-}3, \tau{+}3]$ around month-end, also yields a coefficient indistinguishable from zero ($\beta = 0.002$, $t = 0.05$).

Replacing the dependent variable with Post-window factor returns yields a coefficient indistinguishable from zero ($\beta = 0.008$, $t = 0.25$; Table 6, row 3). The factor-level recovery in a given month does not scale with that month's PreTOM concession, even though the dispensability spread itself is negative in the Post window (-4.61 bps/day, $t = -2.23$). Panel C repeats the regression leg by leg, and the dispensable leg shows the same near-zero Post-window interaction, so the null is not an artifact of differencing.

Economically, the estimates reveal a common liquidity-demand component in the factor zoo. During the cash-raising window, factor returns vary systematically with their holdings' exposure to dispensable stocks. To a first approximation, factor f's liquidity-demand component is $\beta\, d_f\, \text{LDS}_m^{\text{PreTOM}}$. The cross-sectional standard deviation of d_f is 0.48, so at the

[17] The fixed effects are not manufacturing this number. Dropping the month fixed effects and entering the level of $\text{LDS}_m^{\text{PreTOM}}$ directly leaves the interaction at 0.505 ($t = 16.72$) with a within R^2 of 17.9%; omitting the level as well gives 0.498 ($t = 15.68$). The interaction $d_f \times \text{LDS}_m^{\text{PreTOM}}$ is close to orthogonal to the month dimension because d_f is nearly mean-zero across factors, so the month fixed effects have little to absorb from it.

average PreTOM shock of 8.9 basis points per day, the estimated coefficient of 0.505 implies that a one-standard-deviation increase in dispensability exposure raises a factor's PreTOM return by approximately 2.2 basis points per day.

A factor that is short dispensable stocks co-moves with $\text{LDS}_m^{\text{PreTOM}}$ because it holds some of the stocks from which LDS is built. Two interpretations are possible. Either LDS measures a market-wide concession that all factors holding dispensable stocks load on, or each factor simply co-moves with the particular stocks it shares with the shock. Theme exclusion distinguishes them. If the shock is common it still moves stocks the factor does not hold and the loading persists; if each factor were only tracking its own holdings, a shock built without them would leave nothing to load on.

We remove each month the union of the D_1 and D_{10} holdings of every factor in the test factor's JKP theme and re-sort the remaining stocks.[18] This is far more conservative than removing only the factor's own two legs.

The rebuilt shocks differ materially from the full-universe LDS, with correlations ranging from 0.43 to 0.98 across themes (mean 0.78; Internet Appendix Table IA.9 reports the by-theme values). Yet the interaction is nearly unchanged (0.424, $t = 11.86$, versus 0.505 on the full-universe shock), and explains 7.7% of the remaining factor–month variation (Table 6, rows 5 and 1). The corresponding Rest estimate stays small and insignificant ($\beta = 0.035$, $t = 1.31$). The loading therefore reflects a common concession that moves dispensable stocks market-wide, not the same stocks mechanically entering both the factor return and the shock construction.

4.3 When Is the Liquidity-Demand Shock Large?

The month-end concession varies in size from month to month, and Section 4.1 argued that this variation cannot be anticipated. This subsection asks what determines the size once it arrives, relating the monthly shock $\text{LDS}_m^{\text{PreTOM}}$ to net seller pressure and to the state of the market entering the window. Continuous state variables are standardized over the estimation

[18] For example, when the test factor is a momentum factor, its short leg, recent losers, overlaps heavily with the most-dispensable stocks (those farthest below their 52-week high) that drive LDS, so a positive loading could be mechanical. The theme exclusion recomputes LDS after dropping every stock that sits in the D_1 or D_{10} leg of any momentum-theme factor that month. The momentum factor is then tested against a shock that contains none of its own holdings.

sample, so coefficients report the change in the concession, in basis points per day, associated with a one-standard-deviation increase in the regressor.

In the TAQ sample, we aggregate the stock-day NetSell measure from Section 2.4 into a monthly spread across the same dispensability deciles used to construct LDS_m:

$$\mathrm{NSP}_m = \overline{\mathrm{NetSell}}^{\mathrm{PreTOM}}_{\mathrm{Disp},m} - \overline{\mathrm{NetSell}}^{\mathrm{PreTOM}}_{\mathrm{NonDisp},m}, \tag{13}$$

where each term is the lagged-market-capitalization-weighted average of $\mathrm{NetSell}_{i,t}$ over the corresponding decile's PreTOM stock-days. A positive NSP_m means that net seller-initiated trading is greater among dispensable stocks than among non-dispensable stocks.

The concession is larger when a given amount of selling meets elevated uncertainty. We interact net seller pressure with VIX_{m-1}, the level of the VIX index at the prior month-end, which measures how costly it is for liquidity suppliers to bear risk entering the window and is predetermined, so the window's own selling cannot move it. We estimate

$$\mathrm{LDS}^{\mathrm{PreTOM}}_m = \alpha + \beta_1\,\mathrm{NSP}_m + \beta_2\,\mathrm{VIX}_{m-1} + \beta_3\left(\mathrm{NSP}_m \times \mathrm{VIX}_{m-1}\right) + \varepsilon_m, \tag{14}$$

with Newey–West standard errors. The interaction β_3 is +36.5 ($t = +3.18$), while the main effect of VIX_{m-1} is near zero, because uncertainty conditions the price impact of selling rather than predicting the concession directly (Table 7). A given amount of dispensable-stock selling produces a larger concession when volatility was already high. Because both regressors are standardized, the magnitude reads directly off the coefficients. At average volatility, a one-standard-deviation increase in net seller pressure raises the concession by +19.4 basis points per day; when VIX_{m-1} sits one standard deviation above its mean, the same increase raises it by +55.9 basis points per day, nearly three times as large. The interaction survives residualizing $\mathrm{LDS}^{\mathrm{PreTOM}}_m$ on the market return ($t = +3.08$) and is absent in the Rest-window placebo ($t = -1.36$; Table 7, columns 2–3). It also survives adding Pástor–Stambaugh liquidity, Amihud illiquidity, and mutual-fund outflows ($t = +3.39$ with all three; Internet Appendix Table IA.11, Panel A).

Mutual-fund redemptions amplify the concession in the same way. Interacting net seller pressure with aggregate fund outflows over the window gives +27.1 basis points per day ($t = +2.70$), so a given amount of selling depresses dispensable stocks further in months when redemptions are heavy. The two amplifiers are distinct rather than one variable in disguise:

entered jointly, the flow interaction is +23.4 (t = +2.98) and the volatility interaction is +3.77 in t-value, and the two conditioning variables correlate only +0.34. The Rest-window placebo is again absent ($t = -1.66$; Internet Appendix Table IA.11, Panel B).

Redemptions are plausibly exogenous to the particular stocks a fund happens to hold, which is why the flow literature uses them to identify price pressure (Coval and Stafford, 2007; Lou, 2012).[19] The amplification is therefore unlikely to run backwards, from the concession to the redemptions.

This is the logic of Grossman and Miller (1988) and Duffie (2010). Liquidity suppliers require a larger concession to bear inventory risk when risk is high, and slow-moving capital does not arrive quickly enough to compete it away. The division of labor between anticipation and compensation is sharp. The timing of the demand is public, the funds that will sell are identifiable in advance from their own flows, and their holdings are disclosed. What remains unknown is the size of the demand and the capacity it will meet, and the concession is the price of bearing exactly that residual. We read the pattern as state dependence consistent with the mechanism rather than as causal identification. The causal weight rests on the T+1 settlement shift, which we turn to in Section 5.

5 The T+1 Settlement Reform

The May 28, 2024 transition from T+2 to T+1 settlement (SEC, 2023) moved the equity-settlement clock forward by one trading day.[20] Before the reform, mutual-fund redemptions settled on T+1 while equity sales settled on T+2. If the PreTOM return patterns reflect selling of dispensable stocks to raise cash, the associated price pressure should shift one trading day later, from $\tau-4$ toward $\tau-3$.

The prediction concerns the holdings that are sold, not the anomaly's sign convention. Selling pressure moves the raw $D10 - D1$ return in opposite directions depending on which leg holds the dispensable stocks, and orienting every factor so that its historical premium is positive would erase that distinction. We therefore run the settlement test on the deciles as

[19] The outflows are nonetheless measured over the same six days as the concession. Using the prior month's outflows instead leaves the interaction positive but insignificant (+14.1, $t = +1.55$).

[20] This settlement reform was particularly impactful for mutual funds' end-of-month liquidity-driven trading as it aligned the settlement practices of mutual funds and stocks, thus eliminating the need of mutual funds to make precautionary equity sales in anticipation of outflows.

sorted, before the orientation s_f is applied. Define the raw factor return as

$$\widetilde{R}_{f,t} \;=\; R_{D10,f,t} - R_{D1,f,t}. \tag{15}$$

We likewise remove the anomaly sign from the exposure measure,

$$\widetilde{d}_f \;=\; \frac{1}{M_f}\sum_{m=1}^{M_f}\left(\bar{\delta}_{1,f,m} - \bar{\delta}_{10,f,m}\right), \tag{16}$$

which is the signed exposure of equation (7) with the anomaly orientation removed, $\widetilde{d}_f = s_f\, d_f$.

The T+2 period runs from September 5, 2017 through April 30, 2024 and the T+1 period from June 1, 2024 through December 31, 2025. We omit May 2024 as the transition month. For each factor, we estimate how its raw $D10 - D1$ return on $\tau{-}4$ and on $\tau{-}3$ changed after the reform, relative to the early-month window $[\tau{+}5, \tau{+}8]$, when settlement-related month-end selling should not operate:

$$\begin{aligned}\widetilde{R}_{f,t} \;&= \alpha_f + \beta_{f,\tau-4}\,\mathbf{1}_{[\tau-4],t} + \beta_{f,\tau-3}\,\mathbf{1}_{[\tau-3],t} + \gamma_f\,\mathrm{T1Reform}_t \\ &\quad + \pi_{f,\tau-4}\,\mathbf{1}_{[\tau-4],t}\,\mathrm{T1Reform}_t + \pi_{f,\tau-3}\,\mathbf{1}_{[\tau-3],t}\,\mathrm{T1Reform}_t + \varepsilon_{f,t},\end{aligned} \tag{17}$$

where $\mathrm{T1Reform}_t$ equals one after the transition and the omitted category is the early-month window. The interaction coefficients $\pi_{f,\tau-4}$ and $\pi_{f,\tau-3}$ measure the post-reform changes at the old and new settlement deadlines, each relative to that baseline. We summarize the timing shift as

$$\Delta_f \;\equiv\; \pi_{f,\tau-3} - \pi_{f,\tau-4}. \tag{18}$$

A positive shift means that, after the reform, the factor's raw return increased more at $\tau{-}3$ than at $\tau{-}4$. The mechanism predicts that the shift rises with the factor's raw dispensability gap:

$$\Delta_f \;=\; a + b\,\widetilde{d}_f + u_f, \qquad b > 0. \tag{19}$$

When $D1$ is the more dispensable leg, moving the selling pressure to $\tau{-}3$ raises $D10 - D1$, producing a positive shift. When $D10$ is more dispensable, the same timing change produces a negative shift.

Because the reform is a single event and the post-reform sample contains only 19 months, we base inference primarily on placebo reform dates. Each placebo reproduces the actual design—an 80-month pre-period, a 19-month post-period, and an omitted transition month—using dates from 1996–2015 so that the placebo windows remain clear of the later settlement reforms.

The data follow this prediction (Figure 3 and Table 8). The precision-weighted slope of the timing shift Δ_f on the raw dispensability gap is +52.2 basis points per exposure unit, $\widetilde{d}_f$. Because the cross-sectional standard deviation of the gap is 0.48, this corresponds to a 25-basis-point larger shift for a one-standard-deviation increase in exposure. Only 9 of the 1,000 placebo reform dates produce a larger slope ($p = 0.010$). The equal-weighted slope is +37.2 basis points ($p = 0.042$). Its decomposition points in the predicted direction on both dates: the exposure slope of the reform effect is −17.3 basis points at the old settlement deadline, $\tau-4$, and +19.9 basis points at the new deadline, $\tau-3$. Each component is only marginally significant on its own ($p = 0.077$ and $p = 0.137$), while their difference is significant ($p = 0.042$). The identifying evidence is therefore the relative shift from the old settlement deadline to the new one, not a separately significant return effect on either date.

The sign prediction is visible in familiar factors. Momentum and quality-minus-junk have positive raw dispensability gaps and shift positively, by +183 and +92 basis points. Book-to-market value has a negative gap and shifts by −91 basis points. Internet Appendix Table IA.13 reports the same shifts averaged within JKP themes.

The positive slope also survives equal weighting, capped and winsorized precision weights, theme-equal estimation, and leave-one-theme-out and leave-one-factor-out tests reported in the Internet Appendix (Tables IA.3 and IA.4).

To conclude, the settlement reform changes when a sale produces usable cash, not the characteristics used to form the factor portfolios. The fact that the cross-sectional return pattern moves one trading day when the settlement deadline moves one trading day is therefore difficult to reconcile with a static characteristic effect or a generic month-end seasonality. It is the timing predicted by cash-motivated selling of dispensable stocks.

5.1 Validation in ETF Portfolios

The portfolios tested so far are our own. The pattern also holds in ETFs, whose holdings we did not choose. If dispensability identifies the stocks sold to raise month-end cash, ETFs that hold more of those stocks should show both the same PreTOM return pattern and the same T+1 timing shift. For each ETF we compute holdings-weighted dispensability d_e, the average dispensability score of its holdings. ETFs with higher d_e hold more stocks far below their 52-week highs.

Across 541 U.S. equity broad, style, factor, and cap-based ETFs, holdings-weighted dispensability predicts lower PreTOM returns (FF3-controlled slope -10.59 bps/day, $t = -2.03$), with no comparable Rest relation.

The settlement evidence also replicates. Among the 416 ETFs spanning the reform, high-d_e baskets exhibit the same $\tau-4$-to-$\tau-3$ shift as factor portfolios (DiD slope +36.9 bps/day per unit of d_e, $t = +2.22$). Details are reported in Internet Appendix IA.7.

6 Selling Pressure Within Factor Portfolios

The T+1 reform identifies the timing mechanism. We now ask whether the trades themselves target the stocks the mechanism predicts. During PreTOM, seller-initiated trading should tilt toward the more-dispensable stocks inside factor portfolios. We test this first by comparing a factor's two legs and then within a single leg. The within-leg design also asks whether the stocks that attract heavier selling suffer the larger PreTOM return concession.

6.1 Seller-Initiated Trading Across Factor Legs

The return evidence implies an order-flow prediction. Within a factor portfolio, seller-initiated trading should tilt toward the leg containing the more-dispensable stocks, and that tilt should strengthen during the PreTOM window. We test this prediction directly using WRDS Intraday Indicators data.

For each factor we fix its D1 and D10 characteristic deciles at the prior month-end, so the legs are predetermined and no within-month information enters. On each trading day we compute each leg's NetSell imbalance (the lagged-market-cap-weighted average of the stock-level $\text{NetSell}_{i,t}$ of Section 2.4). We then compare the two legs. Because the more-dispensable leg differs across factors, D1 for momentum but D10 for book-to-market value, we orient the comparison so that a positive value always means heavier net selling in the more-dispensable leg. If D1 is the more-dispensable leg we compute NetSell_{D1} minus NetSell_{D10}, and otherwise we reverse the subtraction. Equivalently,

$$\text{NSP}_{f,m,w} \;=\; \text{sign}(\widetilde{d}_f)\,\big[\,\overline{\text{NetSell}}^{\,w}_{D1,f,m} - \overline{\text{NetSell}}^{\,w}_{D10,f,m}\,\big], \qquad w \in \{\text{PreTOM}, \text{Rest}\}. \tag{20}$$

Here $\overline{\text{NetSell}}^{\,w}_{D1,f,m}$ is that daily leg imbalance averaged over the days of window w in month m, and likewise for D10. The more-dispensable leg is identified by the raw dispensability gap $\widetilde{d}_f = s_f\, d_f$, not by the intended-signed d_f: a positive gap means D1 is more dispensable, a negative one means D10 is. This factor-specific leg spread differs from the market-wide NSP_m of equation (13), which compares the most- and least-dispensable stock deciles and conditions the time-series tests of Section 4.3.

The more-dispensable leg may attract heavier selling even outside PreTOM. We therefore compare the signed leg spread for the same factor in the same month across PreTOM and Rest. This removes any persistent difference between the factor's two legs and isolates the additional selling tilt during the six-day window. Equivalently, we estimate

$$\text{NSP}_{f,m,w} \;=\; \alpha_{f,m} + \delta\,\mathbf{1}[\,w = \text{PreTOM}\,] + \varepsilon_{f,m,w}, \tag{21}$$

where the factor-by-month fixed effect $\alpha_{f,m}$ absorbs the baseline leg difference. Because each factor-month contributes one PreTOM and one Rest observation, δ is simply the pooled average of $\text{NSP}_{f,m,\text{PreTOM}} - \text{NSP}_{f,m,\text{Rest}}$. A positive δ means that seller-initiated trading tilts more strongly toward the more-dispensable leg during PreTOM. The sample contains 152 factors and 230 months of TAQ coverage from 2003 through 2022. We exclude the 52-week-high factor used to define dispensability and cluster standard errors by month, with two-way clustering by factor and month as an alternative.

Net selling within a factor's portfolio tilts toward its more-dispensable leg, and the tilt strengthens in the PreTOM window, as the mechanism predicts. The pooled difference-in-differences is +8.37 basis points of NetSell share (Table 9), significant under every standard-error choice (month-clustered $t = +2.96$, two-way factor-by-month $t = +2.74$, month-block bootstrap $t = +2.95$), and rising to $t = +5.81$ when the 152 factor means are the unit of observation. The estimate is stable across construction choices, ranging from +7.73 to +9.91

basis points under equal stock weights, predetermined monthly signs, momentum exclusion, and theme-equal weighting.

The tilt should also scale with how far apart the two legs are. When a factor's two legs differ sharply in dispensability, PreTOM selling should tilt strongly toward the more-dispensable leg. When the legs are similar, there should be little differential selling. Consistent with this prediction, the PreTOM-minus-Rest selling tilt rises from an insignificant -0.87 basis points of NetSell share in the lowest-$|d_f|$ tercile, to $+7.31$ in the middle tercile, and $+18.87$ in the highest. The high-minus-low difference is $+19.74$ basis points ($t = +3.01$).

6.2 Within-Short-Leg Dispensability Sub-Sort

The comparison across factor legs still leaves many differences between the two portfolios. We therefore hold factor-leg membership fixed. Within a single factor's short leg, stocks share the same anomaly exposure, and only their dispensability varies. If month-end cash demand is the mechanism, the more-dispensable stocks should underperform their less-dispensable neighbors specifically during PreTOM.

Dispensable stocks may underperform throughout the month because they are fundamentally weaker. The mechanism predicts something stronger, that this within-leg spread becomes substantially larger during PreTOM.

We begin with six representative factors spanning momentum, profitability, distress, earnings, and quality: 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),[21] and QMJ (D1, junk). Panel B of Table 10 repeats the analysis across all 152 factors. For each factor we restrict to the short-leg decile and sub-sort within that decile by the dispensability score $\delta_{i,m}$ into five within-short-leg quintiles, and compute the value-weighted return of the least-dispensable minus the most-dispensable quintile, so a positive spread means the most-dispensable stocks underperform.

The spread widens in PreTOM exactly as predicted. Across the six illustrative factors, the least-minus-most-dispensable spread is $+11.4$ basis points per day in PreTOM (date-

[21] 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 Section 7.1.

clustered $t = +5.28$) and +3.2 in Rest ($t = +2.14$; Table 10 and Figure 4), an incremental PreTOM differential of +8.2 basis points per day. Dispensability matters throughout the month; the return penalty is simply much larger in PreTOM.

Extending the within-short-leg sub-sort to the full library of 152 factors gives a pooled PreTOM-minus-Rest DiD of +11.1 bps/day. The within-short-leg differential is individually significant at $|t| \geq 1.96$ in 129 of 152 factors (85%), so the pattern is broad across the library, not concentrated in a small set of factors.

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 the finding of Daniel and Titman (1997) that characteristics retain predictive power after controlling for factor loadings. The dispensability primitive operates at the stock level. Even within a fixed factor leg, stocks farther from their 52-week highs have the larger PreTOM underperformance.

Among eight alternative proxies tested in the Internet Appendix (Table IA.24), distance below the 52-week high is the only one that produces a strong PreTOM-specific within-short-leg differential.

The within-short-leg sub-sort also produces directionally consistent evidence in order flow. Within each of the six representative short legs, we sort stocks by predetermined dispensability and compute the most-minus-least-dispensable NetSell imbalance. The PreTOM-minus-Rest differential averages +0.23 percentage points (month-clustered $t = +1.67$) and is positive for all six factors. The order-flow evidence is less precise than the return evidence, but it points in the same direction. The stocks that suffer the larger PreTOM return penalty (Table 10) also attract heavier selling during the window.

7 Reinterpreting Canonical Anomalies

The month-end liquidity-demand mechanism provides a common economic interpretation for several canonical anomalies that are usually studied separately. It accounts for why momentum, quality, and value respond with opposite signs, why value and momentum are negatively correlated, why part of value's recent weakness is concentrated before month-end, how a calendar component enters factor momentum, and why the idiosyncratic-volatility puzzle is strongest among the stocks investors are most willing to liquidate.

The organizing principle is simple. When month-end cash demand pushes down dispensable stocks, factors that are short those stocks earn positive returns, while factors that are long them earn negative returns. The subsections below trace several well-known anomalies back to this common mechanism. Related evidence for low-risk factors appears in Internet Appendix Section IA.19.

7.1 Quality-minus-Junk, Value, and the Sign of the Liquidity Shock

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 $d_f = -0.73$.[22] These opposite exposures reflect the construction of the two sorts. Quality-minus-junk (Asness, Frazzini, and Pedersen, 2019) is long profitable, financially strong firms and short financially weak ("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.

Figure 5 shows these opposite responses. 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 37 bps/month ($t = +3.68$), compared with 7 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. In our post-1991 JKP book-to-market series, the full-month t-statistic is +0.49; excluding the PreTOM window raises it to +1.20. Neither clears the Hou, Xue, and Zhang (2020) $|t| > 3$ bar, but the premium is visibly stronger once the six-day window in which value is penalized is set aside. For context, Fama and French (2020) report a post-1991 t-statistic of 1.06 for their annually-rebalanced HML, a differently constructed portfolio. Part

[22] We refer specifically to book-to-market (*be_me*), not the JKP Value theme average, which bundles heterogeneous factors including price-proximity measures that are PreTOM-boosted rather than penalized; the theme's mean d_f is slightly positive (Internet Appendix Table IA.13).

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.

Internet Appendix Section IA.19 shows that the PreTOM dispensability concession also appears within the high-risk legs of low-risk factors after controlling for beta, volatility, prior returns, and lottery characteristics, although the corresponding order-flow evidence is insignificant.

7.2 Value–Momentum Correlation

The value–momentum combination is a cornerstone of multifactor investing because its strong negative correlation makes the two strategies unusually effective diversifiers (Asness, Moskowitz, and Pedersen, 2013). Yet the economic source of that correlation remains unclear. Our evidence points to one structural source. Value and momentum sit on opposite sides of the dispensability axis.

PreTOM is where the dispensability axis is paid, not the only time factor returns move along it. The daily cross-sectional return associated with dispensability exposure has a positive mean during PreTOM and a near-zero mean outside it, but it fluctuates in every window. Because value and momentum load on the axis with opposite signs, those fluctuations move their returns in opposite directions throughout the month.

We measure the importance of this channel by removing the daily return associated with dispensability exposure. Each trading day we regress the cross-section of factor returns on their fixed dispensability exposure d_f, one observation per factor. The estimated slope, $\hat{b}_t$, measures how strongly high-d_f factors outperform low-d_f factors that day. Subtracting each factor's fitted part leaves the neutralized return

$$R^{\perp d}_{f,t} \;=\; R_{f,t} - \hat{b}_t\,(d_f - \bar{d}), \tag{22}$$

which removes the fitted d_f-aligned component while retaining the daily cross-factor average return. The value–momentum correlation falls from -0.65 to -0.39, a 39% reduction, and their covariance falls by 62% (Table 11).[23] The reduction is similar in PreTOM, Rest, and

[23]In levels, the covariance rises from $-11{,}404$ to $-4{,}290$ bps^2/day. The covariance share exceeds the correlation reduction because neutralization also lowers each leg's return volatility.

Post, and the covariance itself is spread across the month roughly in proportion to trading days. PreTOM carries 28% of the total raw covariance while covering 29% of trading days, against 42% for Rest and 30% for Post. The similar reduction across PreTOM, Rest, and Post reflects daily variation along the dispensability axis outside the cash-demand window. It does not imply that month-end liquidity demand causes the comovement on those other days. The exercise is an empirical neutralization rather than an exact variance decomposition. The results nevertheless identify opposite dispensability exposure as a stable and economically large source of the value–momentum hedge.

Value and momentum are the canonical example of a broader correlation structure. Factors with the same sign of d_f tend to comove, while factors with opposite signs tend to move against each other. Gross profitability ($d_f > 0$) and assets-to-market value ($d_f < 0$), in different anomaly themes, correlate at -0.80 over the sample. Pairwise factor correlation lines up with the product $d_f\, d_g$ across the library. Among the 5,110 pairs with opposite dispensability exposure, stronger opposition predicts more negative correlations, with momentum-family factors excluded so the pattern is not driven by the value–momentum pair, and the relation is largely absorbed by the daily d_f-aligned component (Figure 6).

7.3 Factor Momentum

Factor momentum is usually interpreted as persistence in expected factor returns (Ehsani and Linnainmaa, 2022).[24] Our mechanism implies an additional source, repeated exposure to a recurring calendar premium. A factor that is persistently short dispensable stocks tends to earn positive returns during PreTOM. Past PreTOM winners are therefore disproportionately factors with high d_f, and those factors tend to win again in the next PreTOM window. Crucially, this channel does not require the month-end concession itself to be persistent. Past returns reveal which factors repeatedly receive the payment, not how large next month's payment will be. Internet Appendix IA.17 derives this result formally.

This gives a testable calendar prediction. If past returns forecast future returns because they identify which factors repeatedly collect the month-end payment, predictability should be concentrated in the window in which that payment occurs, so past PreTOM returns should forecast future PreTOM returns much more strongly than future Rest returns. If

[24] Factor momentum is not a stock-level characteristic and so is not one of the 153 JKP signals analyzed elsewhere; it is a *meta-factor*, formed by sorting factors on their own trailing returns.

factor momentum also reflects broader persistence in expected factor premia, past Rest returns should forecast future Rest returns as well. The two channels are not mutually exclusive, and the results show that both are present.

We implement this using monthly Fama–MacBeth cross-sectional regressions. At the end of each month we compute four signals for every factor: the standard trailing $m-12$ to $m-2$ return, its PreTOM-only component, its Rest-only component, and the fixed dispensability exposure d_f. We then regress each factor's next-month average daily return on the signal, separately for future PreTOM and future Rest returns, and average the monthly slopes over time. The d_f row is not an investable signal. It is an ex-post benchmark showing what the calendar mechanism predicts if the factor's true dispensability exposure were known. If trailing PreTOM returns partly identify that exposure, they should forecast future PreTOM returns much more strongly than future Rest returns. Internet Appendix Table IA.32 shows exactly that pattern.

The table separates calendar-driven persistence from broader persistence. The fixed dispensability exposure d_f predicts only future PreTOM returns and has essentially no predictive power for future Rest returns. Trailing PreTOM returns behave similarly, forecasting future PreTOM much more strongly than future Rest returns. By contrast, trailing Rest returns predict both windows, consistent with a broader persistence channel unrelated to the recurring month-end payment.

The grid distinguishes the two channels but cannot weigh them, because its slopes come from different signals on different scales. We therefore measure the calendar share with an ex-post return attribution, projecting the standard trailing signal onto the dispensability axis each month by regressing it cross-sectionally on d_f and separating the fitted part from the residual. Because the strategy weights are linear in the signal, running the same zero-cost factor-momentum strategy on each piece gives component returns that add to the total. This attributes about 22% of the realized factor-momentum return, 0.77 of 3.43 basis points per day, to the calendar-aligned component. The attribution is much larger for PreTOM returns (35%) than for Rest returns (12%), consistent with the mechanism operating primarily through the month-end liquidity payment. The full-month estimate is imprecise ($t = +1.62$) but is statistically stronger exactly where the mechanism predicts, accounting for 35% of PreTOM factor momentum ($t = +2.28$).

Factor momentum is therefore not a single phenomenon. About one-fifth of the realized return of the standard factor-momentum strategy is attributable to recurring exposure to the month-end liquidity payment, while the remainder reflects broader persistence in factor returns, consistent with both the Ehsani and Linnainmaa time-varying-premia channel and the Dong, Kang, and Peress (2025) persistent-flow channel, which our test does not distinguish. The calendar-aligned component is concentrated in the PreTOM window, exactly where the mechanism predicts, and there it accounts for about one-third of the realized return.

7.4 A Calendar Component of the Idiosyncratic-Volatility Puzzle

The idiosyncratic-volatility puzzle is one of the best-known anomaly puzzles in asset pricing. Stambaugh, Yu, and Yuan (2015) argue that it reflects limits to arbitrage. Overpriced stocks with high idiosyncratic volatility are difficult to short, which allows overpricing to persist. Our evidence identifies a calendar component of this puzzle.

We revisit their setting using dispensability, replicating their headline result on their own data and reproducing both the idiosyncratic-volatility puzzle and its arbitrage asymmetry (Internet Appendix Section IA.18). Splitting the puzzle by window locates much of it before month-end. Among the most overpriced stocks, the idiosyncratic-volatility spread is -8.5 basis points per trading day during PreTOM against -3.5 outside it. Because PreTOM contains six trading days and the rest of the month roughly fifteen, the window produces about half of the monthly spread. Averaged across mispricing quintiles the spread is negative during PreTOM and positive outside it.

Within the window, that penalty is organized by dispensability rather than by volatility. Idiosyncratic volatility predicts PreTOM returns when entered alone (-1.4 basis points per day per standard deviation, $t = -2.6$), but its coefficient falls to -0.4 ($t = -0.9$) once dispensability is included, while dispensability remains at -1.5 ($t = -3.1$). The unconditional PreTOM relation that appears to be about volatility is largely a relation with dispensability.

We do not explain away the arbitrage asymmetry. The interaction between idiosyncratic volatility and mispricing, which is central to Stambaugh, Yu, and Yuan's account, survives dispensability in both windows, at -0.5 ($t = -3.1$) during PreTOM and -0.8 ($t = -7.1$) outside it. Their mechanism accounts for why overpriced, high-volatility stocks can remain mispriced, while ours accounts for the additional and predictable discount those stocks suffer during the six-day cash-demand window. The shock $\mathrm{LDS}_m^{\mathrm{PreTOM}}$ shows no loading on lagged

Baker and Wurgler (2006) sentiment (Table IA.36), which weighs against a sentiment-driven explanation for the calendar-bound component.

8 Conclusion

We show that a common month-end liquidity-demand mechanism organizes much of the factor zoo. Across 152 characteristic-sorted factors, exposure to dispensable stocks—stocks trading far below their 52-week highs—explains 72% of the cross-sectional variation in returns during the six-day PreTOM window but only 1.0% during the rest of the month. Factor returns also respond to monthly variation in the realized price concession on dispensable stocks in proportion to their exposure. Following the 2024 transition from T+2 to T+1 settlement, this return pressure shifts one trading day closer to month-end, with the direction and magnitude of the shift determined by which factor leg contains the dispensable stocks.

The mechanism extends well beyond the average anomaly. It organizes 134 of the 152 factors we study, leaving only 18 with little exposure to it, and it provides a common economic interpretation for several canonical results, including the value–momentum correlation, part of value's weak performance during PreTOM, a calendar-aligned component of factor momentum, and a calendar component of the idiosyncratic-volatility puzzle. Measured against canonical objects, the same axis accounts for 83% of the mean of the zoo's leading common component, 39% of the value–momentum correlation, and 22% of the realized factor-momentum return. These results do not collapse the factor zoo into a single factor. They show instead that many apparently distinct anomaly returns share a recurring, signed liquidity-demand component whose incidence is determined by the stocks their portfolios hold.

More broadly, expected returns should be understood not only by where they are earned but also by when. Monthly anomaly returns combine payments that arise from different economic mechanisms at different times of the month, and full-month averages hide that decomposition. Part of what the literature has treated as many distinct anomaly premia is a single payment for supplying liquidity on a predictable schedule.

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Table 1: Data and Summary Statistics

Variable	N	Mean	Median	SD	P5	P95
Monthly time series						
Liquidity-demand shock LDS_m (bps/day)						
PreTOM	755	8.9	9.3	66.5	-91.5	113.8
Rest	755	1.5	2.9	46.1	-70.6	63.3
Market excess return (bps/day)						
PreTOM	755	-4.1	1.8	42.7	-71.9	53.0
Rest	755	5.7	7.5	23.9	-34.3	40.6
Net seller pressure NSP_m (% of volume)						
PreTOM	230	0.63	0.27	2.57	-2.72	5.41
Rest	230	0.54	0.33	2.02	-1.48	4.24
MF outflow (bps of assets per day)						
PreTOM	282	0.04	0.10	1.95	-3.04	2.57
Rest	282	-0.39	-0.33	1.31	-2.38	1.44
VIX level (%)						
PreTOM	432	19.3	17.3	7.9	11.5	32.3
Rest	432	19.5	17.6	7.3	11.6	32.2
Cross-section of factors						
Dispensability tilt d_f	152	0.07	0.02	0.48	-0.67	0.94
Absolute dispensability tilt $\lvert d_f \rvert$	152	0.32	0.18	0.37	0.01	1.04
Long–short return, PreTOM (bps/day)	152	2.3	2.2	2.7	-2.2	6.9
Long–short return, Rest (bps/day)	152	1.1	1.2	1.5	-1.7	3.3

Notes: Summary statistics for the paper's main variables; Internet Appendix Table IA.1 collects full definitions. Monthly series span 1963–2025 (755 months), except net seller pressure (2003–2022), mutual-fund (MF) outflows (2000–2023), and VIX (1990–2025); cross-sectional rows have one observation per factor over 1963–2025. The liquidity-demand shock LDS_m is defined in equation 11, the dispensability exposure d_f in equation 7, VIX and MF outflows in Section 2.4, and net seller pressure in equation 13, reported in percent of classified dollar volume (the stock-level imbalance lies in $[-1, 1]$). The market excess return is the daily Fama–French market factor averaged within the indicated window. Each state variable is shown for both the PreTOM window and the remaining days of the month. Per-factor window returns are average daily long–short returns, reported in the intended anomaly direction (Section 2.1); the paper's exposure sorts use the magnitude $|d_f|$.

Table 2: When Are Factor Returns Earned?

Sample	Return (bps/month) Full	PreTOM	Rest	PreTOM share	Pre/Rest day
1963–2025	29	13	15	47%	2.17×
1963–1993	35	16	19	45%	2.04×
1994–2025	23	11	12	49%	2.38×
2010–2025	10	5	4	55%	3.11×

Notes: Factors are oriented in their intended anomaly direction, as in the paper's cross-sectional regressions. Cells are the cumulative return per window per month, in basis points, averaged across the balanced universe of the 141 factors whose long–short series begins by December 1964 and extends into 2025. *Full* is the calendar month, *PreTOM* is $[\tau-9, \tau-4]$, and *Rest* is the remaining same-month days (Full = PreTOM + Rest). *PreTOM share* is PreTOM divided by Full, and *Pre/Rest day* is the PreTOM per-day rate divided by the Rest per-day rate.

Table 3: Dispensability Exposure and Factor Returns

Panel A: Which stock characteristics best explain factor returns during PreTOM?

Characteristic (c)	PreTOM R^2	$\lvert t \rvert$	1963–1993	1994–2025
Distance from 52-week high	**0.72**	**4.05**	**0.68**	**0.45**
Bid-ask spread (high-low, 21-day)	0.47	3.29	0.41	0.21
R&D / market equity	0.44	3.45	0.22	0.45
Mispricing-performance composite	0.43	3.29	0.11	0.60
Quality-minus-junk	0.43	3.46	0.17	0.57
Financial safety (QMJ-safety)	0.42	3.38	0.23	0.49
Market equity (size)	0.41	3.28	0.29	0.43
Idiosyncratic volatility, CAPM (252-day)	0.40	2.86	0.45	0.18
Piotroski F-score	0.40	4.21	0.15	0.50
Idiosyncratic volatility, HXZ4 (21-day)	0.39	2.94	0.44	0.17

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	R^2	t	R^2	t	R^2	t
Dispensability exposure d_f	0.72	+4.06	0.12	−1.54	0.010	+0.40	0.30	+2.42

Notes: Panel A ranks the 153 JKP characteristics by the cross-factor PreTOM R^2 from the regression of mean PreTOM factor returns on the corresponding short-minus-long characteristic exposure CE_f^c, equation (5) (with CE_f^c defined in equation (4)); the last two columns repeat the R^2 within each subperiod. Panel B reports the cross-sectional R^2 for the dispensability exposure d_f in each intra-month window, where τ denotes the last trading day of the month and PreTOM is the window $[\tau-9, \tau-4]$. In Panel A, every regression excludes its own factor (the factor formed on characteristic c loads on CE_f^c mechanically, since CE_f^c is its own $D1-D10$ spread in c), a leave-one-out across the remaining 152 factors; Panel B uses d_f and excludes only the 52-week-high factor that defines it. The t-statistics in both panels are month-block bootstrap ($B = 5{,}000$); we resample whole calendar months with replacement (preserving the cross-factor correlation structure), recompute each factor's mean return, and refit the slope. Both the returns and the exposures are oriented in the intended anomaly direction ($s_f(D10 - D1)$); VW NYSE-breakpoint long-short returns, value-weighted by prior-day market capitalization, 1963–Dec 2025. Definitions, original sources, and construction details for each characteristic are in the Factor Details documentation of Jensen, Kelly, and Pedersen (2023), available at jkpfactors.com. Full rankings of all 153 characteristics are in the replication package.

Table 4: Horse Race Against Standard Factor Exposures

	X alone		d_f alone	$d_f + X$ jointly			Incremental fit
Benchmark X_f	coef (t) (1)	R^2 (2)	R^2 (3)	d_f coef (t) (4)	X coef (t) (5)	R^2 (6)	ΔR^2 (7)
Panel A. PreTOM factor returns							
UMD	+0.41 (+0.85)	0.02	0.72	+4.73 (+4.01)	−0.23 (−0.49)	0.72	+0.01
Market beta	+1.02 (+1.73)	0.13	0.72	+4.55 (+3.98)	+0.09 (+0.16)	0.72	+0.00
PS liquidity	+0.93 (+2.08)	0.11	0.72	+4.53 (+4.11)	+0.13 (+0.37)	0.72	+0.00
MGMT	−0.13 (−0.40)	0.00	0.72	+4.62 (+3.91)	−0.09 (−0.28)	0.72	+0.00
PERF	−1.89 (−3.20)	0.45	0.72	+3.74 (+3.21)	−0.85 (−1.48)	0.78	+0.06
Candidates on matched shorter windows							
Amihud	+1.78 (+3.41)	0.32	0.62	+4.44 (+2.82)	+0.54 (+1.52)	0.64	+0.02
SIRIO	+0.84 (+1.23)	0.07	0.61	+5.11 (+3.22)	−0.18 (−0.26)	0.62	+0.00
SBF	−1.83 (−3.04)	0.33	0.59	+4.18 (+2.60)	−0.80 (−1.92)	0.63	+0.05
Panel B. Rest-of-month factor returns							
UMD	−0.39 (−1.22)	0.06	0.00	+0.28 (+0.35)	−0.43 (−1.38)	0.07	+0.07
Market beta	−0.60 (−1.56)	0.15	0.00	+0.62 (+0.78)	−0.73 (−1.97)	0.19	+0.19
PS liquidity	−0.43 (−1.47)	0.08	0.00	+0.40 (+0.52)	−0.50 (−2.15)	0.09	+0.09
MGMT	−0.45 (−2.12)	0.08	0.00	+0.05 (+0.07)	−0.44 (−2.11)	0.08	+0.08
PERF	−0.09 (−0.24)	0.00	0.00	−0.04 (−0.05)	−0.10 (−0.27)	0.00	+0.00
Candidates on matched shorter windows							
Amihud	+0.53 (+1.47)	0.12	0.03	−0.06 (−0.06)	+0.54 (+2.20)	0.12	+0.08
SIRIO	+0.41 (+0.89)	0.07	0.03	+0.29 (+0.27)	+0.35 (+0.76)	0.08	+0.04
SBF	−0.44 (−1.19)	0.07	0.05	+0.33 (+0.29)	−0.35 (−1.49)	0.08	+0.04

Notes: X_f denotes factor f's exposure to the candidate variable named in the row, entering the regression of equation (9). Each row reports X_f alone (cols 1–2) and jointly with d_f (cols 4–6). The last column reports the joint R^2 minus the d_f-alone R^2 on the matched sample, the incremental fit from adding X_f. 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. The benchmark candidates run on 1963–2025; the additional candidates use their matched windows (1980–2024 for Amihud illiquidity, 2003–2025 for the Drechsler and Drechsler (2021) SIRIO shorting-cost proxy, and 1982Q4–2022Q2 for the Cui, De la O, and Myers (2025) Subjective Belief Factor), so R^2 levels are not strictly comparable across windows.

Table 5: Reorganizing the Factor Zoo: The Dispensability Exposure Taxonomy

Group	N	Avg. daily long–short return (bps)		
		PreTOM	Rest	PreTOM − Rest
	(1)	(2)	(3)	(4)
Short-dispensable ($d_f > 0$)	94	+3.67	+1.13	+2.55
Long-dispensable ($d_f < 0$)	40	−0.62	+0.71	−1.33
Low-exposure ($d_f \approx 0$)	18	+1.70	+1.52	+0.18
Affected ($\lvert t(d_f)\rvert > 1.96$)	134			

Notes: Each of the 152 JKP factors (excluding the 52-week-high characteristic that defines d_f) is classified by the t-statistic of its monthly intended-signed dispensability exposure d_f: short-dispensable ($t > 1.96$), long-dispensable ($t < -1.96$), or low-exposure ($|t| \leq 1.96$). Column 1 reports the number of factors; columns 2–4 report the average daily long–short return (bps) in the PreTOM window, in the rest of the month, and their difference. Returns are oriented in each anomaly's intended direction, $s_f(D10 - D1)$ (Section 2.1).

Table 6: Factor Returns Load on the Liquidity-Demand Shock

	Test	$\beta_{d_f \times \text{LDS}_m}$	t-stat	Within R^2
Panel A: LDS constructed from all eligible stocks, 1963–2025 ($N = 113{,}911$)				
(1)	PreTOM returns on PreTOM LDS	+ 0.505	+16.71	0.185
(2)	Rest-of-month returns on PreTOM LDS	+ 0.016	+0.66	0.000
(3)	Post-window returns on PreTOM LDS	+ 0.008	+0.25	0.000
(4)	PreTOM returns on Post-window LDS	+ 0.002	+0.05	0.000
Panel B: LDS excluding own JKP-theme stocks, 1963–2025 ($N = 113{,}911$)				
(5)	PreTOM returns on PreTOM LDS	+ 0.424	+11.86	0.077
(6)	Rest-of-month returns on PreTOM LDS	+ 0.035	+1.31	0.001
Panel C: Leg-level decomposition, PreTOM and Post windows				
(7)	Dispensable leg, PreTOM returns	+ 0.444	+16.50	0.244
(8)	Dispensable leg, Post returns	+ 0.018	+0.55	0.000
(9)	Non-dispensable (placebo) leg, Post	+ 0.001	+0.10	0.000

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 return window named in the row label (PreTOM is trading days $[\tau-9, \tau-4]$; Rest is all other days; Post is $[\tau-3, \tau+3]$ around month-end). The reported coefficient is on $d_f \times \text{LDS}_m$, where d_f is the factor's static dispensability exposure (equation 7) and LDS_m is the monthly liquidity-demand shock (equation 11), the daily-average return of the least-dispensable stock decile minus the most-dispensable, so positive LDS_m means dispensable stocks underperform; it is constructed in the indicated window. The reported R^2 is the within R^2, computed after absorbing the fixed effects. The 52-week-high factor that defines d_f is excluded from the set of tested factors in every panel, because its own return is the shock (self-loading). Separately, Panel B rebuilds LDS_m itself on a reduced universe, removing the union of D_1 and D_{10} holdings of all factors in the same JKP theme as f and re-sorting the remaining stocks. Panel C decomposes the long–short spread into its two legs and reports each leg in the PreTOM window (row 7) and in the Post window (rows 8 and 9). Each factor's market-adjusted D_1 and D_{10} returns are entered as their signed contribution to the raw $D_{10}-D_1$ long–short spread (the dispensable leg is $-D_1$ when $\widetilde{d}_f > 0$ and $+D_{10}$ when $\widetilde{d}_f < 0$, where $\widetilde{d}_f = s_f\, d_f$ is the raw dispensability gap of equation (16); the placebo is the other leg), so the two contributions sum to the spread. Additional placebos and per-month $d_{f,m}$ specifications are in Internet Appendix Table IA.9. Standard errors are two-way clustered by factor and month.

Table 7: State Dependence of the PreTOM Concession on Predetermined Market Uncertainty

Dependent variable: LDS_m^w (bps/day)	PreTOM	PreTOM (resid. mkt)	Rest (placebo)
	(1)	(2)	(3)
Net seller pressure, NSP_m	+19.4	+18.9	-6.4
	(+2.30)	(+2.48)	(-2.54)
VIX_{m-1} (prior month, predetermined)	-11.6	-7.7	-10.9
	(-1.11)	(-0.95)	(-1.70)
$\text{NSP}_m \times \text{VIX}_{m-1}$	+36.5	+31.2	-5.1
	(+3.18)	(+3.08)	(-1.36)
N (months)	230	230	230
R^2	0.203	0.182	0.073

Notes. The table reports equation (14), which regresses the monthly PreTOM concession $\text{LDS}_m^{\text{PreTOM}}$ on net seller pressure, predetermined market uncertainty, and their interaction. VIX_{m-1} is the VIX level at the *prior* month-end (standardized). NSP_m is the market-wide spread of equation (13), the value-weighted PreTOM net-sell spread between the most- and least-dispensable 52-week-high deciles (TAQ, 2003–2022). Column 2 residualizes $\text{LDS}_m^{\text{PreTOM}}$ on the market return; column 3 is a Rest-window placebo. Standard errors are Newey–West(5).

Table 8: T+1 Settlement Reform and Factor-Return Timing

Panel A: Cross-sectional slopes on the raw dispensability gap $\widetilde{d}_f$, and the decomposition of Δ_f

	T+2 settlement		T+1 settlement		Timing shift	
	$b_{\tau-4}$		$b_{\tau-3}$		$b_\Delta = b_{\tau-3} - b_{\tau-4}$	
OLS (unweighted)	−17.3	[0.077]	+19.9	[0.137]	+37.2	[0.042]
WLS (precision-weighted)	−26.0	[0.063]	+26.2	[0.081]	+52.2	[0.010]

Panel B: Canonical factor examples (descriptive)

Factor	sign $\widetilde{d}_f$	Predicted Δ_f	Observed Δ_f (bps)
Momentum (12–1)	+	+	+183
Quality-minus-junk	+	+	+92
Book-to-market	−	−	−91

Notes: Throughout this table $\widetilde{d}_f = s_f\, d_f$ is the raw, pre-anomaly-sign dispensability exposure used in the settlement test. Per-factor DiD $\Delta_f = \pi_{f,\tau-3} - \pi_{f,\tau-4}$ on the raw $R_f = D10 - D1$ (equation 17), 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: cross-sectional regression across the 152 JKP factors (excluding the 52-week-high characteristic), placebo reform-date randomization (1,000 pseudo-reform dates, 1996–2015). Each Panel A column regresses a different dependent variable on $\widetilde{d}_f$ with an intercept: the reform effect under T+2 settlement ($\pi_{f,\tau-4}$), under T+1 settlement ($\pi_{f,\tau-3}$), and their difference (Δ_f). The intercept captures the reform's common timing-shift component. The precision-weighted row uses inverse-variance weights built from Δ_f and applies the same weights to both components, so $b_\Delta = b_{\tau-3} - b_{\tau-4}$ holds exactly in both rows. Bracketed placebo p-values are one-sided in the predicted direction, lower-tail at $\tau - 4$ and upper-tail at $\tau - 3$ and for Δ_f, computed as $p = (k + 1)/(B + 1)$ with k the number of placebo slopes at least as extreme as the actual May 2024 slope. Panel B is descriptive and is not the identifying test; JKP-theme means appear in Internet Appendix Table IA.13. See Figure 3 for the scatter. Long-short ($D10 - D1$) daily returns, VW NYSE-BP deciles.

Table 9: Seller-Initiated Trading Tilts Toward the Dispensable Factor Leg

	NetSell DiD: PreTOM − Rest, bp	t	Positive DiD factors
Panel A: Full-library estimate and robustness			
All factors (factor-month pooled)	+8.37	(+2.96)	101/152
equal-weighted stocks	+9.91	(+3.00)	104/152
predetermined monthly sign	+8.56	(+2.75)	103/152
excluding momentum theme	+8.03	(+2.75)	94/145
Factor-equal (152 factor means)	+8.37	(+5.81)	101/152
Theme-equal (JKP themes)	+7.73	(+2.39)	12/14
Panel B: Heterogeneity by $\|d_f\|$			
High $\|d_f\|$ tercile	+18.87	(+3.02)	43/50
Middle $\|d_f\|$ tercile	+7.31	(+2.66)	35/51
Low $\|d_f\|$ tercile	−0.87	(−0.54)	23/51
High − Low $\|d_f\|$	+19.74	(+3.01)	
Panel C: Six illustrative factors			
Six illustrative factors	+28.64	(+4.18)	6/6

Notes. The dependent variable is the value-weighted NetSell imbalance, the lagged-market-cap-weighted average across stocks of (seller − buyer)/(seller + buyer) classified dollar volume (Lee–Ready). Each factor's characteristic D1/D10 deciles are formed at the prior month-end. For each factor-month-window we difference the two legs and sign the difference by sign($\widetilde{d}_f$), where $\widetilde{d}_f = s_f\, d_f$ is the raw, pre-anomaly-sign dispensability gap of equation (7) ($\widetilde{d}_f > 0$ means D1 is the more-dispensable leg), so a positive value means heavier net selling in the more-dispensable leg. The reported DiD is the PreTOM value minus the Rest value, in basis points of NetSell share, pooled over 152 factors × 230 months (the 52-week-high factor is excluded). The equal-weighted-stocks row recomputes the imbalance weighting stocks equally rather than by lagged market capitalization. The predetermined-monthly-sign row signs each factor-month by whichever leg is the more dispensable at that month's formation date, the prior month-end, rather than by the factor's full-sample sign, so the sign uses no future information. The t-statistics for the factor-month pooled rows are clustered by month; the factor-equal and theme-equal rows use the corresponding factor- or theme-level means as the unit of observation. For the main pooled estimate, alternative inference gives two-way (factor×month) $t = +2.74$ and month-block bootstrap $t = +2.95$. Panel B's High − Low row is the month-clustered difference between the top and bottom $|d_f|$ terciles. The six illustrative factors are the same as in Table 10: momentum, gross and operating profitability, Ohlson O-score, earnings-to-price, and quality-minus-junk.

Table 10: Within-Leg Dispensability: Return Penalties and Seller-Initiated Trading

Panel A: Six representative factors *Positive spread = most-dispensable stocks underperform*

		Pre−Rest (DiD)		PreTOM		Rest of month		PreTOM−Rest
Factor	Leg	bps/day	t	bps/day	t	bps/day	t	NetSell DiD (pp)
Momentum (12-1)	D1	+8.05	+2.37	+9.08	+3.52	+1.03	+0.54	+0.25
Gross profitability	D1	+11.65	+3.45	+11.93	+4.36	+0.28	+0.15	+0.28
Operating profitability	D1	+10.06	+3.10	+13.14	+4.94	+3.09	+1.76	+0.10
Ohlson O-score	D10	+6.56	+2.18	+11.89	+4.81	+5.33	+3.28	+0.39
Earnings-to-price	D1	+8.12	+2.40	+12.52	+4.66	+4.39	+2.38	+0.12
Quality-minus-junk	D1	+4.88	+1.30	+9.98	+3.33	+5.10	+2.48	+0.26
Pooled		+8.22	+3.12	+11.42	+5.28	+3.20	+2.14	+0.23

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

Pooled PreTOM−Rest DiD	+11.06 bps/day
Individually significant ($\lvert t\rvert \geq 1.96$)	129/152
Share significant	85%

Notes: For each representative factor we restrict to its short-leg decile (the short 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. The reported spread is the value-weighted excess return (net of the risk-free rate) of the least-dispensable quintile minus the most-dispensable quintile, in basis points per day, so a positive value means the most-dispensable stocks underperform. Because both quintiles lie in the same leg and window, the risk-free rate, the market, and common factors cancel in the difference. The DiD column reports PreTOM minus Rest. Panel A shows six representative 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. The final column reports the corresponding PreTOM-minus-Rest difference in the most-minus-least-dispensable NetSell imbalance, in percentage points of seller-initiated share, over the 2003–2022 TAQ sample. The pooled estimate is +0.23 percentage points ($t = +1.67$), estimated on factor-month-window cells with standard errors clustered by month. All six factor-level estimates are positive. Per-factor NetSell t-statistics are not reported.

Table 11: Value–Momentum Correlation: Raw vs d_f-Neutralized, by Window

	N_W	ρ_W^{raw}	$\rho_W^{\perp d_f}$	% reduction	share of total cov
Full	15,206	-0.647	-0.392	+39.4%	+100.0%
PreTOM	4,350	-0.647	-0.411	+36.5%	+27.5%
Rest	5,781	-0.677	-0.410	+39.5%	+42.5%
Post	5,075	-0.608	-0.357	+41.2%	+29.9%

Notes: Daily correlation between value (JKP `be_me` long–short) and momentum (JKP `ret_12_1` long–short), 1963–2025, computed for the full month and within three disjoint within-month windows (PreTOM = $\tau-9$ to $\tau-4$, Post = $\tau-3$ to $\tau+3$, Rest = remaining days). Rest here excludes the Post days, a stricter definition than the paper's default Rest (Section 2). The reported correlations are between these two factors only. The N_W column counts only the trading days on which every factor in the neutralization cross-section described below has a return, which is why the full-month N_W falls short of the full-sample trading-day count reported in Section 2. ρ_W^{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 $R_{f,t}^{\perp d} = R_{f,t} - \hat{b}_t(d_f - \bar{d})$ (equation 22), where $\hat{b}_t$ is the same-day cross-sectional slope of returns on d_f; this removes the fitted d_f-aligned component while retaining the daily cross-factor average return. That slope is estimated each day across the 142 factors with at least 95% daily coverage on common dates (`prc_highprc_252d` excluded), which is the only role those factors play here. "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.

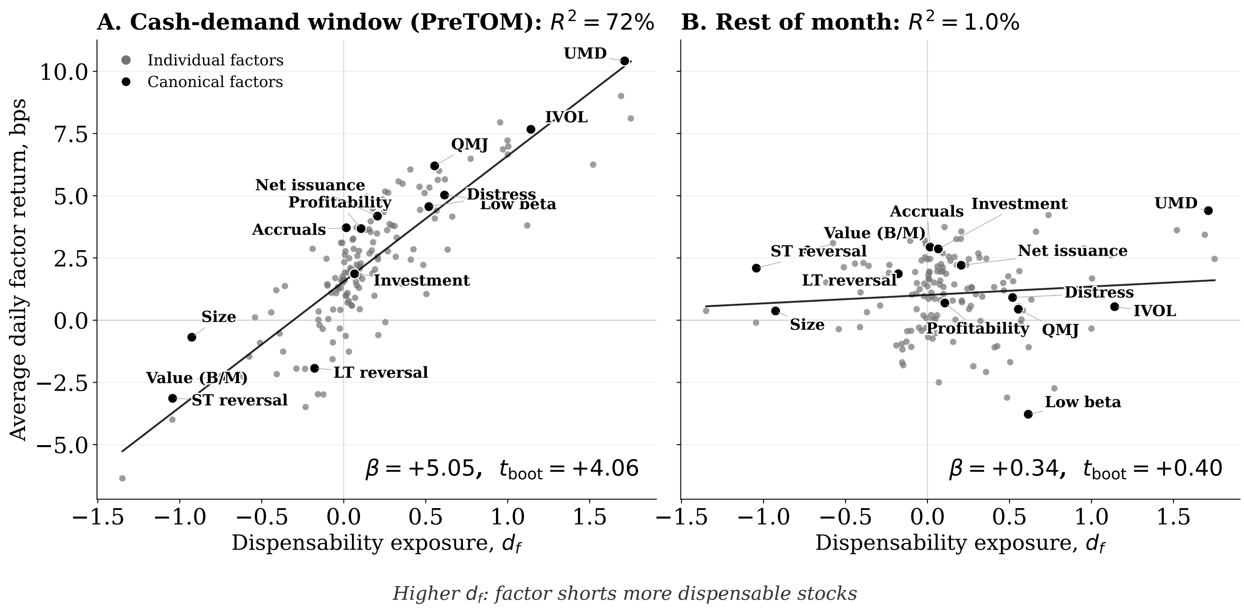

Figure 1: Factor Returns and Dispensability Exposure. Each dot plots a factor's average daily value-weighted return, oriented in the intended anomaly direction ($s_f(D10-D1)$, in basis points), against its intended-signed dispensability exposure d_f, in two windows: Panel A (left) uses returns in the cash-demand (PreTOM) window, Panel B (right) uses returns in the rest of the month. The exposure d_f is the factor's short-leg-minus-long-leg average of stock-level dispensability (each stock's distance below its 52-week high, standardized within the month), so a positive d_f means the factor is short the dispensable stocks and profits when they are sold. Gray dots are the individual factors; black dots mark canonical anomalies (momentum, idiosyncratic volatility, quality, distress, low beta, net issuance, profitability, accruals, investment, size, value, and short- and long-horizon reversal), labeled for orientation. The solid line is the fitted cross-sectional regression in each window. The PreTOM window is the six trading days ending four trading days before month-end. Reported t-statistics are month-block bootstrap (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.

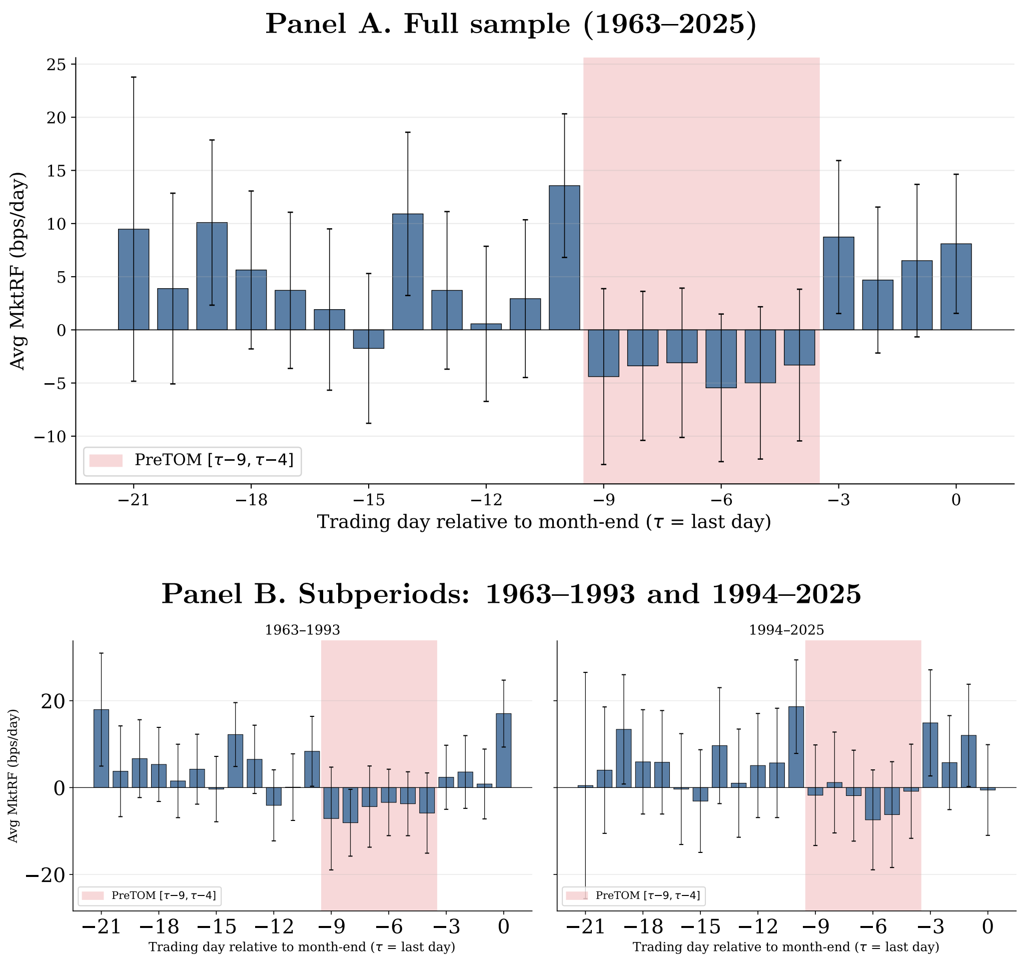

Figure 2: Aggregate market returns around month-end. Both panels plot average daily market excess returns by trading day relative to month-end (τ); the shaded region marks the PreTOM window, $\tau-9$ through $\tau-4$. Panel A pools the full 1963–Dec 2025 sample. Panel B splits the sample at 1994 (matching Table 2) into 1963–1993 and 1994–2025; the average PreTOM market excess return is negative in both halves. Whiskers are 95% confidence intervals.

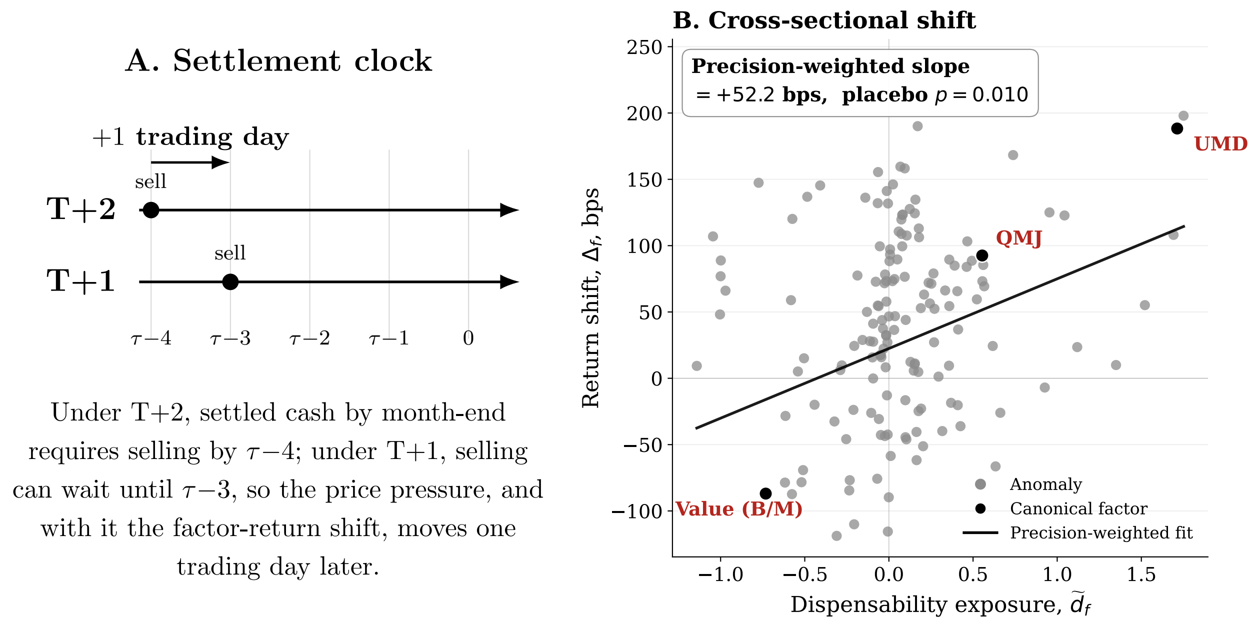

Figure 3: T+1 Settlement Reform and the Cross-Sectional Timing Shift. Each dot is one Jensen, Kelly, and Pedersen (2023) anomaly (the 52-week-high characteristic itself is excluded). The x-axis is the raw dispensability exposure $\widetilde{d}_f$; the y-axis is the per-factor T+1 reform difference-in-differences on the raw factor return, $\Delta_f = \pi_{f,\tau-3} - \pi_{f,\tau-4}$ (equation 18), with $\widetilde{R}_{f,t} = R^{D10}_{f,t} - R^{D1}_{f,t}$ the raw $D10 - D1$ spread. The per-factor regression includes dummies for τ−4, τ−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. UMD, QMJ, and book-to-market are labelled. The solid line is the precision-weighted cross-sectional fit; its slope is +52.2 bps with one-sided placebo $p = 0.010$ against 1,000 pseudo-reform dates drawn from 1996–2015 (Table 8 Panel A). NYSE-BP VW deciles.

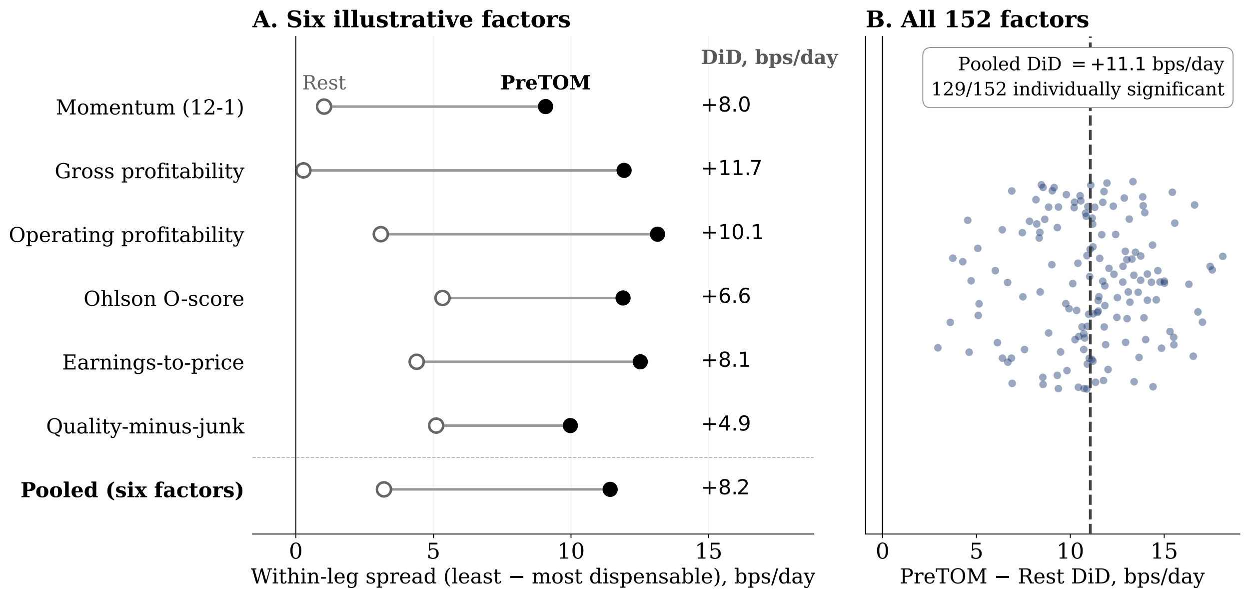

Figure 4: Returns to the least- minus most-dispensable quintiles of stocks within the factors' short legs, during the PreTOM and Rest periods. For each factor, stocks in the short-leg decile (NYSE breakpoints, formed at the prior month-end) are sorted into five quintiles by dispensability $\delta_{i,m}$. The within-short-leg spread is the value-weighted return of the least- minus the most-dispensable quintile, in bps/day; a positive spread means the most-dispensable stocks underperform. Because both quintiles are drawn from the same factor leg, the comparison holds factor membership fixed. Panel A plots the spread in Rest (open circle) and PreTOM (filled circle) for six illustrative factors and their pooled average; the right column reports the PreTOM-minus-Rest DiD. Panel B plots the same DiD for all 152 factors, with dots vertically jittered for visibility and the dashed line at the pooled value. Sample 1963–Dec 2025. Full numbers in Table 10.

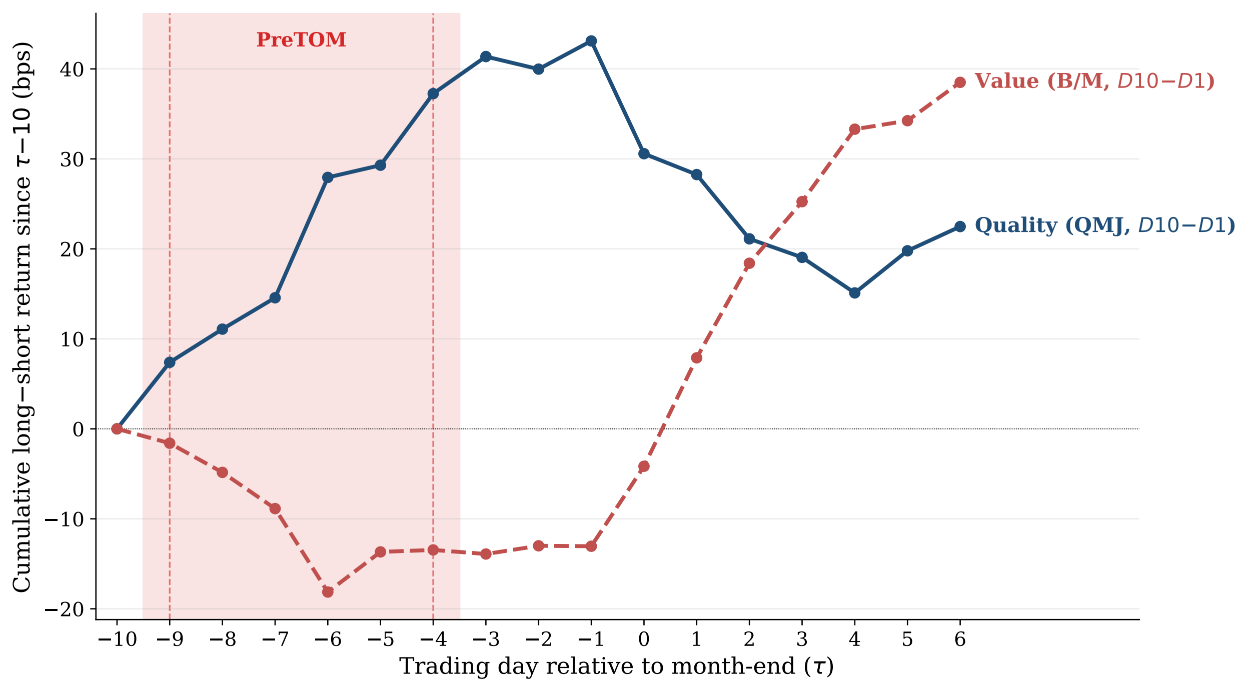

Figure 5: Cumulative Within-Month Long–Short Returns: QMJ and Value. The figure plots the cumulative within-month long–short return ($D10 - D1$) for QMJ (Quality−Junk, blue solid) and Value (book-to-market, red dashed), each normalized to zero at $\tau{-}10$ (just before PreTOM) and accumulated by the average daily long–short return at each subsequent trading-day position. The PreTOM band $[\tau{-}9, \tau{-}4]$ is shaded; days $\tau{+}1$ through $\tau{+}6$ are trading days of the following month. NYSE breakpoints, VW deciles, 1963–Dec 2025.

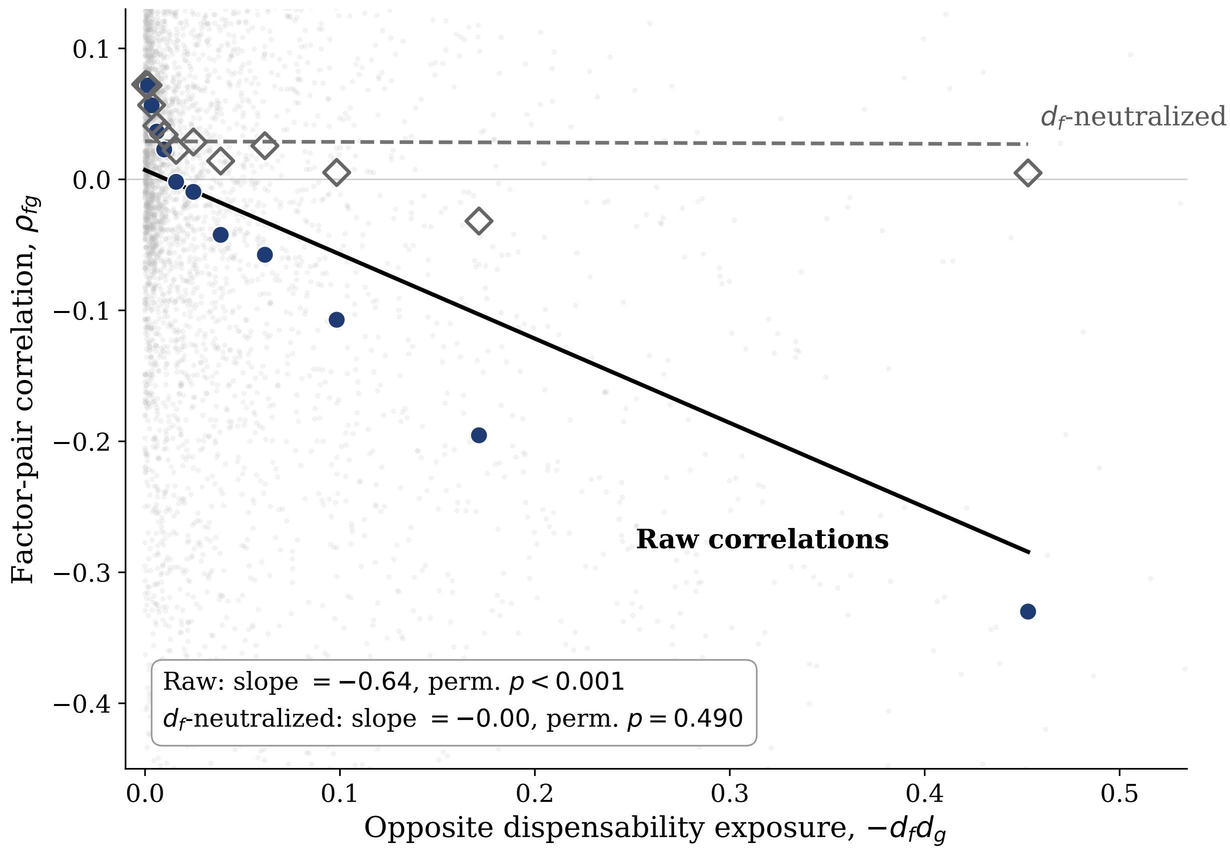

Figure 6: Opposite Dispensability Exposure and Factor-Pair Correlations. The sample is the 5,110 unordered factor pairs with opposite dispensability exposure ($d_f d_g < 0$), excluding momentum-family factors (the Momentum-theme factors together with the residual-momentum characteristics carrying `ret_` or `resff3_` prefixes, a slightly broader exclusion than the seven-factor Momentum theme used in Table 9 and Section 3.3). The exclusion leaves 143 of the 152 tested factors, of which 73 have $d_f > 0$ and 70 have $d_f < 0$, giving 73×70 opposite-side pairs. The horizontal axis is $-d_f d_g$, so larger values mean stronger opposite exposure. Markers are equal-count bin means of the daily long–short return correlation ρ_{fg}; the faint cloud shows the underlying pair-level correlations. Filled circles use raw factor returns; open diamonds use returns after removing each day's cross-sectional component aligned with d_f. The callout reports the OLS slope and a permutation p-value that shuffles d_f labels across factors. NYSE breakpoints, VW deciles, 1963–Dec 2025.