Fresh Data, Stale Positions: The Staleness Trap in Market Anomalies

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Abstract

I identify a "Staleness Trap" in market anomalies: while signals are highly persistent, their associated return opportunities decay much faster than the underlying signals. Consequently, even when using the freshest data, standard portfolio methodologies mechanically accumulate stale positions whose economically relevant premiums have largely dissipated. I develop a measure of Signal Age and show that these stale continuers absorb one-third of portfolio capital while generating negligible returns, whereas fresh entrants drive roughly half of the aggregate premium. In accounting anomalies, by contrast, stale continuers remain profitable. A market anomaly position follows a within-portfolio lifecycle: it earns its strongest return in the month it enters, and the premium is larger among stocks that are costly to absorb, decays more slowly where the absorbing capital arrives slowly, and rises when risk-bearing capacity tightens. None of these absorption signatures appears in accounting anomalies. In market anomalies, what becomes stale is not the information but the position itself.

Keywords: Asset Pricing Anomalies, Limits to Arbitrage, Information Economics, Return Predictability

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1 Introduction

The identification of cross-sectional stock return predictors has long been a central enterprise in empirical asset pricing. The literature has documented hundreds of predictive characteristics (Harvey et al., 2016; Hou et al., 2020), a "zoo of new factors" in the words of Cochrane (2011). Empirical studies typically evaluate these predictors by sorting stocks into portfolios based on the current level of a characteristic. An implicit but important assumption underlying this practice is that sorting on the current signal level is a good proxy for sorting on the current return opportunity. Recent work challenges this assumption in the context of accounting anomalies. In particular, Bowles et al. (2024) and Bowles et al. (2026) show that conventional implementations rely on stale accounting information because disclosure is discrete and standard empirical conventions further delay portfolio formation by several months. When portfolios are instead aligned with actual information release dates, much of the measured premium is concentrated around the arrival of fresh accounting information.

At first glance, market anomalies appear insulated from this problem. Unlike accounting anomalies, market anomalies such as momentum (Jegadeesh and Titman, 1993), idiosyncratic volatility (Ang et al., 2006), and short-term reversal (Lehmann, 1990) are constructed from trading data that update continuously.[1] Because these signals can be formed using the most recent available data, they appear largely immune to the informational staleness created by discrete reporting lags and conventional implementation delays. This raises a broader question: do real-time data necessarily guarantee economically fresh positions? More generally, staleness need not be understood narrowly as the use of old information. Positions can become economically stale when they remain in the portfolio after the return opportunities they were meant to capture have materially weakened. In accounting anomalies, that misalignment arises because implementation relies on information that is already old. In market anomalies, however, a similar misalignment can arise even when the underlying data are fully current.

I show that this misalignment takes a distinct form in market anomalies, which I call a "Staleness Trap." Although continuous market data eliminate the informational delays that arise in accounting

[1] Market variables do not update in literally continuous time, but prices, returns, and trading variables are observed at much higher frequency than accounting disclosures. For empirical and implementation purposes, market signals are therefore not subject to the exogenous reporting lags that characterize accounting variables.

settings, they do not prevent portfolios from becoming economically stale. The source of the problem is a persistence mismatch: the cross-sectional rank of a market signal remains highly persistent even as the associated return opportunity decays much more quickly. Once a stock enters an extreme anomaly leg, it often remains there for an extended period because many market-based characteristics are mechanically or statistically persistent.[2] As a result, standard level-based portfolio rules continue to hold stocks whose extreme ranking remains intact even after their economically relevant premiums have largely dissipated. What becomes stale in market anomalies is therefore not the raw information itself, but the portfolio position generated by a persistent sorting rule.

At the portfolio level, this staleness trap changes how capital is allocated across positions of different ages. Standard decile methodologies do not distinguish between a stock that has just entered an extreme portfolio and a stale continuer that has remained in the same leg for many months. Yet these positions are not economically equivalent. Because aged constituents are retained even after their return opportunities have largely faded, portfolio capital remains assigned to stale positions. This composition lowers aggregate anomaly returns: the profits generated by fresh entrants are diluted by the disproportionate capital weight assigned to aged continuers. Standard portfolio construction therefore retains stale exposure rather than reallocating toward economically fresh positions.

To empirically investigate the within-portfolio lifecycle of positions induced by anomaly signals, I construct a stock-level measure called "Signal Age," defined as the number of consecutive months a stock remains in the same long or short leg of an anomaly portfolio. Using the comprehensive Open Source Asset Pricing (OSAP) dataset from Chen and Zimmermann (2022), which compiles a wide range of anomaly signals from 1960 to 2024, I examine 91 accounting anomalies and 55 market anomalies. I classify positions inside the current extreme-leg portfolio into three age groups: Fresh (entered in the current month), Middle-aged (held for 2–6 consecutive months), and Stale (held for more than 6 months).[3]

[2]This rank persistence often arises mechanically from signal construction or statistically from the autoregressive nature of trading variables. For instance, in the case of price momentum (Jegadeesh and Titman, 1993), a stock that experiences a large idiosyncratic price shock will mechanically remain in the extreme winner decile for several months, because the shock stays inside the rolling twelve-month formation window until it drops out. Similarly, variables based on trading frictions, such as idiosyncratic volatility or illiquidity, naturally cluster over time. Consequently, despite continuous high-frequency price updates, the cross-sectional rank of these stocks can remain persistent.

[3]The six-month boundary follows the rank-autocorrelation profile of the sorting variables, which flattens after

The empirical evidence shows that currently formed extreme portfolios in market anomalies contain a large mass of aged positions. Once a stock enters the top or bottom decile of a market anomaly, it remains there in the following month with probability 72.5% on the long leg and 64.3% on the short leg. This persistence generates an imbalance between capital allocation and profit generation. On average, stale continuers absorb roughly one-third of total portfolio capital but contribute only about 8% of aggregate anomaly returns. By contrast, fresh entrants account for only 37% of portfolio capital while generating roughly half of total profits. This disproportionate contribution summarizes the staleness trap: standard sorting methodologies allocate meaningful capital to aged continuers whose economically relevant premiums have largely dissipated.

The return evidence shows that this capital-allocation imbalance reflects a within-portfolio position lifecycle. To isolate the incremental return associated with each age group, I move beyond additive decompositions and construct standalone age-specific portfolios. In value-weighted market anomalies, fresh positions earn 0.89% per month, compared with 0.31% for stale positions; after controlling for the Fama–French five factors and momentum, the corresponding alphas are 0.75% and 0.15%, respectively. Event-time evidence points in the same direction: market positions earn their highest returns near activation and weaken as they continue to reside in the same extreme leg. Accounting anomalies exhibit a different within-portfolio lifecycle. Fresh accounting positions are not the main source of value-weighted profitability; middle-aged and stale positions continue to yield statistically significant returns over subsequent months. This contrast is consistent with gradual information diffusion in accounting anomalies, while suggesting that profitability in market anomalies is more concentrated near position activation.

This within-portfolio perspective is conceptually distinct from related work that decomposes firm characteristics into persistent and transitory components. Baba-Yara et al. (2024) compare portfolios sorted on a characteristic at different historical dates and show that the persistent component of a signal carries substantial pricing information. Their analysis varies the date at which the sort is formed. My analysis instead holds the formation date fixed at t and asks how profitability is distributed within the current extreme-leg portfolio across positions that differ in how long they have already resided there. The two perspectives are therefore complementary; the related

roughly six months, and standard medium-term holding conventions in the momentum literature. Section 3 details the choice.

literature section discusses how they relate to one another in detail.

I then use several diagnostics to discipline the economic interpretation of the market freshness premium. First, I distinguish between *expectational newness*, which captures how surprising a signal change is relative to its own history, and *temporal newness*, which captures how recently a stock entered an extreme portfolio. For accounting anomalies, the two dimensions are tightly linked: high-surprise fresh entrants earn the strongest returns, consistent with discrete information arrivals driving subsequent price adjustment. For market anomalies, predictable fresh entrants continue to earn large returns, indicating that temporal position age contains return information beyond expectational surprise. Second, observable stock characteristics do not account for the large return gap between fresh and middle-aged market positions. Third, the fresh market premium remains large across aggregate market states, is amplified among stocks that are costly to absorb rather than among stocks with weak investor attention, and decays more slowly in event time exactly where trading is thin and capital arrives slowly. Fourth, the premium rises in periods of greater aggregate stress. Together, these results point to a constrained-absorption interpretation in which newly activated market positions earn larger premia where and when the capital that absorbs them is more limited. In every one of these diagnostics the accounting side serves as a placebo in which the same signature is absent.

The within-portfolio lifecycle pattern also has asset-pricing and implementation implications. Post-publication attenuation in market anomalies is concentrated more heavily in stale constituents, so the remaining predictive content after publication is relatively more tied to newly activated positions. Fresh market portfolios also add more to the maximum Sharpe ratio of standard factor models than middle-aged or stale market portfolios, indicating that freshness identifies the component of market-anomaly profitability that contributes most to the mean-variance frontier. On the implementation side, trading activity evolves over the position lifecycle, and position age matters directly for net returns. Fresh market positions are more expensive to trade, but their higher gross returns are sufficient to survive effective-spread transaction cost adjustments, leaving a net return of approximately 0.58% per month. Stale market positions, by contrast, generate net returns that are statistically indistinguishable from zero. Thus, retaining aged market positions to reduce turnover may lower trading costs while preserving the part of the portfolio where expected profits have largely disappeared.

The remainder of the paper proceeds as follows. Section 2 reviews the related literature. Section 3 describes the data and sample construction and the construction of Signal Age. Section 4 presents the core evidence on portfolio persistence, age-sorted profitability, and the contrast between market and accounting anomalies. Section 5 examines economic interpretations of the market-specific freshness premium, including event-time patterns, surprise, market states, where the premium is amplified and how quickly it is absorbed, and aggregate stress. Section 6 discusses asset-pricing and implementation implications, including post-publication attenuation, mean-variance contribution, trading activity over the position lifecycle, and transaction-cost-adjusted profitability. Section 7 concludes.

2 Related Literature

This paper contributes first to the literature on signal timing and information freshness in anomalies. Bowles et al. (2024) and Bowles et al. (2026) show that conventional accounting-anomaly implementations often rely on stale information because disclosure is discrete and empirical portfolio formation lags public release dates. Their central point is that informational freshness matters for measured returns. My paper complements and extends this insight by showing that a distinct problem remains even when the underlying data update continuously. While this literature emphasizes informational staleness arising from delayed disclosure, I show that market anomalies remain vulnerable to position staleness because standard portfolio rules continue to hold positions long after the associated return opportunities have largely faded. In this sense, real-time data do not by themselves guarantee economically fresh positions. More broadly, the paper also relates to recent work comparing accounting and market anomalies through their underlying economic dynamics, including Zhou (2025). Relative to that literature, my contribution is to provide a portfolio-lifecycle perspective: profitability in market anomalies is concentrated near signal entry and weakens with continued portfolio residence, whereas accounting anomalies remain profitable over much longer horizons.

Second, this paper contributes to the literature on anomaly attenuation, portfolio implementation, and the dynamics of expected returns. McLean and Pontiff (2016) show that anomaly returns decline after publication, Chordia et al. (2014) link the broader attenuation to rising liquidity and

trading activity, and Chen and Velikov (2023) show that, net of trading costs and publication effects, the average anomaly earns close to nothing in the modern era. Ehsani and Linnainmaa (2022) and Ehsani et al. (2025) show that factor premia themselves have exploitable time-series dynamics: factor returns are positively autocorrelated, and scaling factor exposure to this predictability yields more mean-variance-efficient factors. My results speak to a related but distinct question: how profitability is distributed across the lifecycle of positions within an anomaly portfolio. Rather than treating all extreme-ranked stocks symmetrically, I show that much of the profitability of market anomalies is concentrated among fresh entrants, while aged continuers absorb capital with little incremental return. In this sense, temporal freshness is an implementation dimension of anomaly portfolios.

A closely related strand of work decomposes firm characteristics into persistent and transitory components and examines which component is more strongly priced. Baba-Yara et al. (2024) compare portfolios sorted on characteristics such as size, book-to-market, profitability, and investment at different historical dates, and show that much of the pricing information in these signals is carried by their persistent component. Their analysis varies the date at which the sort is formed, contrasting portfolios based on current characteristic values with those formed several months or years earlier and subsequently held. My analysis varies a conceptually distinct dimension: holding the sort date fixed at t, I ask how profitability is distributed *within* the resulting portfolio across positions that differ in how long they have already been occupying the extreme decile. The two constructions are not equivalent. A portfolio based on a twelve-month-old ranking is dominated by stocks that were extreme in the past but may no longer be, whereas my stale bucket comprises stocks that remain extreme today *and* have been so for at least six consecutive months. The resulting evidence is therefore complementary to, rather than a substitute for, the characteristic-level persistence decomposition. For accounting anomalies, both perspectives highlight the pricing importance of persistence. For market anomalies, however, a lifecycle decomposition reveals that most of the remaining profitability is concentrated near portfolio entry—a margin that characteristic-level persistence exercises are not designed to detect. Even if a predictor contains a priced persistent component, it does not follow that continued residence in the extreme leg of the *portfolio* it generates remains equally profitable over time.

Finally, this paper relates to the literature on limits to arbitrage, constrained capital, and

trading frictions. Models of slow-moving capital and intermediary constraints emphasize that prices may adjust gradually when risk-bearing capacity is limited (Shleifer and Vishny, 1997; Gromb and Vayanos, 2010; Duffie, 2010), and empirical work ties aggregate liquidity and the returns to liquidity provision to that capacity (Pástor and Stambaugh, 2003; Nagel, 2012). Rather than attempting to decompose the precise structural friction, I use reduced-form evidence to show that fresh market premia are larger among stocks whose newly activated positions are harder to absorb, decay more slowly where the capital that absorbs them arrives more slowly, and rise when aggregate risk-bearing capacity is tighter. The evidence from aggregate stress states and transaction-cost-adjusted returns aligns with this constrained-absorption interpretation. In this sense, the paper connects the anomaly-implementation literature to broader work on constrained risk-bearing and trading frictions, showing that standard portfolio construction can retain aged positions even as the associated compensation weakens. It also complements work such as Novy-Marx and Velikov (2016) by showing that turnover is not only a cost to be minimized; in market anomalies, reducing turnover by holding aged positions may preserve the least profitable portion of the strategy.

3 Data and Methodology

In this section, I describe the data sources, sample selection criteria, and the empirical framework used to measure signal persistence and construct the "Signal Age" metric.

3.1 Data Sources and Sample Selection

The primary dataset for anomaly signals is drawn from the Open Source Asset Pricing (OSAP) database provided by Chen and Zimmermann (2022). This comprehensive library allows for a standardized comparison across a wide range of predictors by providing code and data to reproduce hundreds of anomaly signals. I merge these signals with monthly stock return and market capitalization data obtained from the Center for Research in Security Prices (CRSP). The sample period spans from January 1960 to December 2024.

Following standard literature conventions (e.g., Fama and French, 1993; Hou et al., 2015), I apply several filters to ensure the investability of the sample and to mitigate the influence of microstructure noise. I restrict the analysis to common stocks (CRSP Share Codes 10 and 11)

listed on the NYSE, AMEX, and NASDAQ (Exchange Codes 1, 2, and 3). To avoid results driven by illiquid micro-cap stocks, I exclude firms with a closing price below \$5 at the end of the portfolio formation month. Furthermore, to support portfolio sorting based on NYSE breakpoints, I require a minimum of 100 NYSE stocks to be available in any given month to calculate valid cross-sectional deciles. Finally, to maintain diversification within the sorted portfolios, I require each extreme portfolio leg to contain a minimum of 10 constituent stocks.

3.2 Signal Construction and Classification

A first step in using the OSAP database is to align the direction of diverse anomalies. Raw predictors often vary in their relationship with expected returns; for instance, high asset growth typically predicts lower returns, whereas high momentum predicts higher returns. To address this, I use the signed metadata provided by Chen and Zimmermann (2022) to align all signals so that a higher rank consistently implies a higher expected return (the long leg) and a lower rank implies a lower expected return (the short leg). Specifically, let $S^{raw}_{i,s,t}$ denote the raw value of signal s for stock i at month t. The aligned signal $S_{i,s,t}$ is calculated as the product of the raw signal and its sign direction suggested by the original literature.

To avoid ambiguous portfolio assignments caused by heavily tied ranks, I restrict the sample to continuous variables. Using the metadata classifications provided by OSAP, I then categorize the eligible predictors into two groups based on the nature of the underlying information. The first group, *Market Anomalies*, consists of signals derived from the PRICE and TRADING categories. These signals, such as Momentum, Idiosyncratic Volatility, and Short-Term Reversal, rely on market data that are updated at high frequency. The second group, *Accounting Anomalies*, consists of signals from the ACCOUNTING category, such as Accruals and Asset Growth. These signals are governed by discrete information release dates and empirical reporting lags, providing a comparison group for the high-frequency nature of market anomalies. Applying these criteria yields a final dataset comprising 55 market anomalies and 91 accounting anomalies. Appendix Table A1 lists the individual signals assigned to each group.

3.3 The "Signal Age" Metric

To disentangle the impact of fresh information from the mechanical persistence of cross-sectional ranks, I introduce a stock-level state variable, *Signal Age* ($\tau_{i,s,t}$), which measures the exact duration a stock has resided in an extreme portfolio leg. For each anomaly s in month t, I first sort stocks into deciles based on the aligned signal $S_{i,s,t}$ using NYSE breakpoints. Let $Leg_{i,s,t} \in \{Long, Short, None\}$ denote the portfolio assignment of stock i, where the Long leg corresponds to the top decile (D_{10}) and the Short leg to the bottom decile (D_1).

The Signal Age $\tau_{i,s,t}$ is defined recursively. For a stock currently in the Long leg (i.e., $i \in D_{10,t}$), the age is set to one if the stock was not in the Long leg in the previous month (an Entrant). If the stock was already in the Long leg in the previous month (a Continuer), its age increments by one. Formally:

$$\tau_{i,s,t}^{Long} = \begin{cases} 1 & \text{if } i \in D_{10,t} \text{ and } i \notin D_{10,t-1} \\ \tau_{i,s,t-1}^{Long} + 1 & \text{if } i \in D_{10,t} \text{ and } i \in D_{10,t-1} \end{cases} \tag{1}$$

An equivalent definition applies to the Short leg. If a stock falls outside the extreme deciles in month t, its age counter is reset to zero. Throughout, the subscript t indexes the portfolio holding month: $S_{i,s,t}$ denotes the signal used to form the month-t portfolio and is measured with information available through the end of month $t-1$. A stock's decile membership and Signal Age in month t therefore reflect only information available at formation, and the associated returns are realized over month t. Portfolio formation uses no contemporaneous return information.

Based on the empirical distribution of signal duration, I classify portfolio constituents into three mutually exclusive buckets. *Fresh* stocks ($\tau = 1$) represent recent entrants that have just crossed the extreme decile threshold. *Middle* stocks ($2 \leq \tau \leq 6$) capture intermediate continuers that have remained in the extreme decile for up to half a year. Finally, *Stale* stocks ($\tau > 6$) represent positions that have persisted in the extreme leg for more than six months.

The six-month boundary distinguishing Middle from Stale constituents is based on both statistical properties and economic conventions. Statistically, the rank autocorrelations in Figure 2 show that the autocorrelation of the underlying sorting variables declines most during the first six months before settling into a persistent, slow-moving tail. Economically, a six-month horizon aligns with standard medium-term holding periods in the asset pricing literature (e.g., Jegadeesh

and Titman, 1993) and allows at least one to two subsequent quarterly earnings cycles to elapse. This classification scheme provides a framework to examine how return predictability evolves across different stages of the portfolio lifecycle.

4 The Staleness Trap: Within-Portfolio Evidence

This section establishes the main empirical fact. The analysis is not about the calendar-time decay of an anomaly after academic discovery. It is about the within-portfolio lifecycle of stock-signal-leg positions generated by standard anomaly strategies. A standard decile portfolio does not distinguish a position that has just entered an extreme leg from a position that has remained in the same leg for many months. Signal Age measures this portfolio residence. I first show that continuing positions are quantitatively important, then decompose standard portfolio returns by position age, and finally show that the age profile survives standard risk adjustment.

4.1 Portfolio Persistence and Signal-Age Composition

To establish the baseline performance and introduce the composition of the anomaly portfolios, this section presents the summary statistics and the empirical distribution of signal age. Table 1 reports the summary statistics of value-weighted and equal-weighted returns, alongside the average signal age of the portfolios, computed separately for market and accounting anomalies. The signal age at the firm level represents the consecutive number of months a stock has resided in the extreme long or short leg. To construct the portfolio-level age, I calculate both the equal-weighted average age of the constituent firms and the value-weighted average age based on their lagged market capitalization.[4]

[INSERT TABLE 1 HERE]

Consistent with prior literature, both anomaly classifications yield positive average returns.

[4] Although Table 1 reports both value-weighted and equal-weighted summary statistics, the subsequent analysis focuses on value-weighted portfolios. Equal-weighted returns are more sensitive to small and micro-cap stocks and are less closely tied to investable capital allocation. The corresponding equal-weighted results are qualitatively similar and do not alter the main conclusions, but value-weighted evidence is emphasized throughout for economic interpretability and implementability.

Turning to signal duration, the equal-weighted average signal age for constituents in market and accounting anomalies is 12.7 and 16.3 months, respectively. This cross-sectional average signal age reflects the steady-state distribution of existing signals at a given point in time. Because it is calculated by averaging across all constituents currently present in the portfolio, it captures the cross-sectional composition of the strategy. When evaluated on a value-weighted basis, the average signal age for accounting anomalies rises to 25.3 months. This divergence between equal- and value-weighted metrics indicates that within accounting anomalies, a disproportionate share of total market capitalization is concentrated in large firms with stale constituents, further motivating the need to decompose portfolio performance by age.

A central premise of the staleness mechanism is that standard sorting methodologies accumulate aged constituents. To visualize this composition, Figure 1 plots the cross-sectional distribution of signal age for both market and accounting anomaly groups. To prevent specific anomalies or time periods with a broader cross-section of available stocks from dominating the distribution, I use a signal-month equal-weighting approach. Specifically, I first calculate the proportion of stocks in each age bin, ranging from one month to an aggregated bin for twelve months or longer, within each specific anomaly and month. I then average these within-portfolio proportions across all available months and signals for each respective category.

[INSERT FIGURE 1 HERE]

The empirical distribution presented in Figure 1 illustrates the lifecycle of anomaly signals and shows differences between the two classifications. Focusing first on the left side of the distribution, market anomalies exhibit a large inflow of new entrants, with fresh stocks (age of exactly one month) comprising 36.6% of the portfolio. In contrast, fresh constituents account for only 11.6% of accounting anomalies.

However, moving to the right side of the distribution, both groups display a heavy right tail with a significant mass in the aggregated twelve-plus months category. This accumulation is largest in accounting anomalies, where 34.9% of the portfolio consists of stocks that have remained in the same extreme decile for over a year. While market anomalies experience a higher inflow of fresh entrants, they still maintain a 23.1% mass in this oldest age bucket.

Overall, this cross-sectional distribution shows that extreme anomaly portfolios are not composed solely of newly selected stocks. Instead, they represent a mixture of recent entrants and stale positions that have persisted for extended periods. The coexistence of fresh and stale constituents within the same portfolio motivates the performance decomposition in the subsequent sections.

To quantify the staleness of anomaly portfolios, I examine the time-series persistence of the underlying signals. If extreme portfolios primarily capture the arrival of fresh information, the underlying sorting variables should exhibit rapid mean reversion as prices quickly incorporate the news. Conversely, high persistence indicates that extreme portfolio membership remains persistent over time, retaining capital in aged positions.

I evaluate signal persistence using two complementary approaches. First, I estimate the autocorrelation structure of the cross-sectional signal ranks. To standardize the diverse scales and distributions of different predictors, I convert the raw signal value for each firm into a continuous cross-sectional percentile rank (ranging from 0 to 1) in each month. For each individual anomaly, I then compute the pooled Pearson correlation between a stock's current percentile rank in month t and its lagged rank at 1-, 3-, 6-, and 12-month horizons across the entire sample period. This procedure yields a distinct set of autocorrelation coefficients for each of the 146 anomalies. Finally, Figure 2 plots the cross-sectional average of these autocorrelation coefficients within the market and accounting classifications.

[INSERT FIGURE 2 HERE]

As expected, accounting anomalies exhibit high persistence with slow decay over the 12-month horizon (declining from 0.94 at the 1-month lag to 0.47 at the 12-month lag), consistent with the low frequency of corporate earnings reports. While market anomalies show lower initial autocorrelation coefficients and a relatively faster decay rate than their accounting counterparts, their persistence remains large even at longer horizons (0.69 at the 1-month lag and 0.46 at the 12-month lag). This indicates that despite being derived from continuous data, market variables do not revert to their cross-sectional mean immediately.

While rank autocorrelations provide a continuous measure of persistence across the entire cross-section, the investable anomaly premium is derived from the extreme deciles. Therefore, my second

approach measures the stability of the extreme portfolios by estimating transition probabilities. Specifically, I calculate the conditional probability that a stock remains in the extreme long (or short) leg in month t, given that it was in the same leg in month $t-1$.

Panel C of Table 1 reports these conditional portfolio transition probabilities. The persistence within the extreme deciles is large, consistent with the autocorrelation results. For accounting anomalies, the conditional probability of a stock remaining in the extreme portfolio is 90.3% for the long leg and 90.6% for the short leg. This implies a stable portfolio composition month over month.

The transition probabilities for market anomalies also reveal a persistent portfolio structure. Although market anomalies are updated with high-frequency data and theoretically possess a higher capacity for turnover, the conditional probability of remaining in the extreme leg is 72.5% for the long leg and 64.3% for the short leg. This means that, on average, roughly two-thirds of the constituents in a market anomaly portfolio are not newly entering positions. Instead, they are aged continuers carried over from the prior month. This month-over-month overlap shows that extreme portfolios contain many persistent positions rather than only dynamic fresh entrants.

The rank autocorrelation and portfolio transition metrics reinforce the findings from the signal age distribution. The extreme portfolios for both discrete accounting anomalies and continuous market anomalies contain persistent constituents. This state-like behavior sets the empirical stage for decomposing portfolio returns to isolate the performance of newly activated exposure from the returns of aged constituents.

4.2 Decomposing Standard Portfolio Profits

Building on the evidence of rank persistence, I next examine how this persistence affects the aggregate anomaly premium. Portfolio constituents are grouped into the Fresh, Middle, and Stale buckets defined in Section 3. To evaluate the performance of these groups, I follow a two-step averaging procedure akin to Fama and MacBeth (1973). First, for each anomaly in a given month, the total value-weighted long-short return is additively partitioned into the contributions of the three age buckets based on their lagged market capitalization weights. I then compute the cross-sectional average of these return contributions, as well as their respective *Capital Share* (the proportion of total market capitalization allocated to a bucket) and *Profit Share* (the proportion of the total port-

folio return generated by that bucket), across all anomalies within the same classification (Market or Accounting). Second, I calculate the time-series averages of these monthly cross-sectional means. Statistical significance of the time-series averages is assessed using Newey-West standard errors with six lags.

Table 2 reports the results of this return decomposition and shows a difference between accounting anomalies and market anomalies. For accounting anomalies, fundamental variables are updated at discrete, low-frequency intervals. Once a stock enters an extreme portfolio, it can therefore retain its rank for several months. The empirical results show that returns are not concentrated only at initial entry: the Fresh bucket accounts for only 9.3% of the portfolio capital and 18.9% of the profits, while a large portion of both capital (90.7%) and profits (81.1%) are concentrated in the Middle and Stale buckets. This pattern is consistent with the view that, for discrete accounting signals, low-frequency information and gradual price adjustment make continuing constituents an important part of the strategy's profitability.

For market anomalies, the relation between capital allocation and profit generation is different. Despite being derived from continuous trading data, stale constituents occupy 32.9% of the portfolio's market capitalization while producing only 8.4% of the total returns. Meanwhile, fresh entrants are profitable: they command 37.5% of the investable capital but drive half of the aggregate profits (50.5%). This disproportionate contribution provides empirical evidence of the staleness trap in market anomalies. Standard sorting methodologies allocate a large portion of capital into aged, persistent positions whose realized contribution is weak relative to their capital share, thereby lowering the return contribution of the aggregate portfolio.

[INSERT TABLE 2 HERE]

4.3 Standalone Profitability over Position Age

While the decomposition in Table 2 is informative about where the returns of the standard anomaly portfolio are actually realized across the signal-age distribution, it does not by itself isolate the conditional premium associated with a given stage of the signal lifecycle. By construction, an age bucket's additive contribution reflects two distinct forces: the return spread generated by the

positions in that bucket and the amount of capital that the conventional sorting rule allocates to those positions within the parent portfolio. This distinction is especially important in the present setting because the staleness trap operates through both return weakening and capital retention. Aged positions may continue to absorb substantial portfolio weight even after their predictive content has weakened, so a small contribution may reflect low conditional profitability, an unfavorable weight structure, or both. To separate these two forces more cleanly, I construct standalone value-weighted portfolios for each age bucket. Within each bucket, the long and short legs are rescaled independently to sum to 100%, so the resulting returns more directly capture the profitability of trading positions at a given stage of the signal lifecycle.[5]

A practical challenge in constructing these granular sub-portfolios is signal sparsity. For certain anomalies, specific age buckets may occasionally lack a sufficient number of constituents to form a well-diversified long-short portfolio. To provide a conservative estimate and mitigate the influence of idiosyncratic noise, I impose a minimum investability requirement: a standalone portfolio must contain at least ten constituent stocks in total, with both the long and short legs populated. This threshold guards against premiums estimated from a handful of names, in the spirit of the prescriptions of Hou et al. (2020) against results driven by the thinnest segments of the cross-section.

If a sub-portfolio fails to meet this threshold in a given month, I assume the strategy cannot be implemented and assign a zero excess return, equivalent to holding the risk-free asset. Incorporating these zero-return months into the time-series yields the unconditional expected return of the strategy. This approach explicitly accounts for the opportunity cost of uninvested capital and avoids the overconditioning bias that can arise from selectively evaluating performance only during periods with ex-post active signals (Boguth et al., 2011). Furthermore, evaluating the strategy unconditionally scales the conditional anomaly premium by its empirical frequency of occurrence, providing a consistent measure of the strategy's long-term economic value (Ferson and Siegel, 2001).[6]

Consistent with the decomposition analysis, the aggregate standalone performance is evaluated using a two-step averaging procedure. First, in each month, I compute the cross-sectional average

[5]This distinction is also important for interpretation. Following the logic of Berk (2000), the age-sorted results in this paper should not be read as within-group rejection tests of standard asset-pricing models. Rather, the decomposition is a portfolio-attribution exercise, and the standalone portfolios measure the returns to separately formed age-specific strategies.

[6]Estimating the conditional expected return by simply excluding these uninvestable months yields qualitatively identical results. I proceed with the unconditional framework throughout the analysis to establish a conservative baseline.

of the standalone long-short returns, as well as the portfolio characteristics, across all anomalies within a given classification. Second, I calculate the time-series average of these monthly cross-sectional means, with statistical significance assessed using Newey-West standard errors with six lags.

Table 3 presents these standalone returns and shows how profitability evolves over the signal lifecycle across the two anomaly classifications. For market anomalies, performance declines as constituents age. A value-weighted long-short portfolio formed exclusively from fresh market constituents yields a return of 0.89% per month ($t = 8.92$). As constituents age, the return falls to 0.39% ($t = 6.75$) for the Middle bucket and remains lower at 0.31% ($t = 5.14$) for the Stale bucket. This pattern indicates that the profitability of market anomalies is concentrated among newly refreshed positions, while older constituents retain weaker standalone return spreads.

Conversely, accounting anomalies do not exhibit the same pattern of performance deterioration. The standalone value-weighted return for fresh accounting constituents is 0.13% per month, rises to 0.28% ($t = 6.28$) in the Middle bucket, and remains economically similar at 0.21% ($t = 4.40$) in the Stale bucket. Thus, unlike market anomalies, the return spread in accounting anomalies does not decline with signal age. The fresh bucket is the lower-return segment, which is consistent with the view that accounting-based predictability does not rely disproportionately on newly refreshed constituents.

The size distribution indicates that fresh market constituents are not concentrated in the micro-cap tail. As highlighted by Fama and French (2008), micro-caps account for roughly 60% of the cross-section of stocks but represent only 3% of the total market capitalization. I therefore follow the methodological prescriptions of Hou et al. (2020) by using NYSE breakpoints, imposing a \$5 price filter, and focusing primarily on value-weighted returns. The empirical size distribution of the portfolios points in the same direction. Hou et al. (2020) define micro-caps as stocks falling below the 20th percentile of NYSE market equity.[7] In contrast to this threshold, Table 3 reports that the median market capitalization of the fresh market portfolio is \$884 million. These magnitudes indicate that the returns to fresh market constituents are not confined to the most illiquid micro-cap

[7]To provide historical context, the average 20th percentile cutoff of NYSE market capitalization steadily increases over the sample period, ranging from \$34.9 million in the 1960s to \$505.2 million in the 2000s, and reaching \$869.8 million in the 2020s. The full-sample average cutoff is \$322.9 million. The fresh market portfolio's median capitalization of \$884 million is above this full-sample micro-cap threshold.

segment of the market.

These findings highlight a difference between accounting and market anomalies. For accounting anomalies, the persistence of Middle and Stale returns is consistent with the literature on limited attention and post-announcement drift, in which fundamental information is incorporated into prices over a longer horizon (Hirshleifer et al., 2009). In this sense, aging is not inherently detrimental for accounting-based strategies. In contrast, market anomalies exhibit profitability that is more concentrated near signal entry and weakens with continued portfolio residence. As a result, failing to condition on signal age in market anomalies retains aged constituents whose economically relevant premiums have largely dissipated, thereby reducing overall portfolio performance.

[INSERT TABLE 3 HERE]

4.4 Risk-Adjusted Profitability by Position Age

Having established the standalone return pattern, I next estimate standard factor-adjusted alphas. This exercise separates the age-performance pattern from differences in exposure to established systematic risk factors.

I estimate time-series regressions of the age-sorted standalone portfolio returns constructed in the previous section on the Fama and French (2015) five-factor model augmented with the Carhart (1997) momentum factor (UMD). I first calculate the cross-sectional mean of the standalone long-short returns across all anomalies within a given classification in each month. This collapses the panel data into a single aggregate time-series of monthly returns for each age bucket. Specifically, for the value-weighted aggregate long-short portfolios across the Fresh, Middle, and Stale buckets, I estimate the following time-series regression model:

$$R_{p,t} = \alpha_p + \beta_{1,p} MKT_t + \beta_{2,p} SMB_t + \beta_{3,p} HML_t + \beta_{4,p} RMW_t + \beta_{5,p} CMA_t + \beta_{6,p} UMD_t + \epsilon_{p,t} \quad (2)$$

where $R_{p,t}$ represents the cross-sectionally averaged monthly return of the long-short portfolios for a specific age bucket p (Fresh, Middle, or Stale) at time t. Table 4 reports the estimated alphas

(α_p) and factor loadings, with statistical significance evaluated using Newey-West standard errors with six lags.

Panel A of Table 4 shows that the age-related decline in market-anomaly profitability is not explained by standard factor loadings. For value-weighted portfolios, the risk-adjusted alpha of fresh market positions is 0.75% per month ($t = 7.42$). As the signal ages, this alpha declines monotonically to 0.26% in the Middle bucket and 0.15% in the Stale bucket. Thus, the abnormal return associated with market signals weakens as positions become older even after controlling for standard risk factors.

In contrast, Panel B shows that accounting anomalies do not exhibit the same immediate weakening after risk adjustment. The value-weighted alpha for fresh accounting signals is 0.04% ($t = 0.66$), while the Middle bucket yields a larger alpha of 0.23% ($t = 7.68$), and the Stale bucket continues to generate a positive and significant alpha of 0.08% ($t = 3.27$). These results mirror the raw return patterns and reinforce the contrast between the two anomaly classes. For accounting anomalies, profitability remains distributed over a longer signal lifecycle, whereas for market anomalies, abnormal performance is more concentrated in the earliest stage of portfolio residence.

[INSERT TABLE 4 HERE]

An important concern is that the Fresh market premium could mechanically reflect more extreme signal ranks or larger recent rank changes rather than position age itself. Appendix Table A5 addresses this concern using anomaly-age-bucket panel regressions that control for both the average signal rank level and the average signal rank change of the constituents in each age bucket. The controls are informative, but they do not subsume the freshness effect. In the fully controlled specifications, the coefficient on $Fresh \times Market$ remains positive at 0.18% ($t = 3.44$) for additive contributions and 0.50% ($t = 1.74$) for standalone returns.[8] Thus, the Fresh market pattern is not simply a proxy for signal extremity or recent rank movement.

[8]The standalone coefficient is larger but less precisely estimated because it isolates age-specific long-short returns after rescaling each bucket independently. This removes the capital-share smoothing embedded in the parent portfolio contribution and therefore produces a noisier, but more direct, estimate of the age-conditioned return spread. The contribution specification is more precise because it retains the weighting structure of the standard anomaly portfolio.

Appendix Table A7 provides a complementary anomaly-breadth check. I exclude each Market anomaly one at a time and recompute both the contribution decomposition and the standalone value-weighted return object. The main comparison is Fresh versus Stale. The standalone Fresh–Stale spread remains positive and statistically significant in all 55 exclusions. The contribution Fresh–Stale spread is similarly robust: it remains positive and significant in every exclusion, with estimates ranging from 0.13% to 0.20% per month. Thus, the contrast between newly activated and stale market positions is not driven by a single anomaly.

A related microstructure concern is that the Fresh market result could mechanically reflect short-term reversal or bid-ask bounce. Appendix Table A7 addresses this concern by excluding the short-term reversal signal, `STreversal`, and recomputing the main market-age results. After excluding `STreversal`, the contribution Fresh–Stale difference is 0.187% per month with a t-statistic of 4.70, and the standalone Fresh–Stale difference is 0.656% per month with a t-statistic of 4.22. Both are close to the corresponding full-sample estimates of 0.171% and 0.575%. The Market Fresh pattern is therefore not a single-signal short-term-reversal artifact. Appendix Table A8 addresses the same family of concerns from a different direction by separating each age bucket into its long and short legs. If short-sale frictions generated the Fresh market premium, the premium would have to come from the short leg, and newly activated short positions would have to earn lower returns than aged ones. The opposite holds. In the standalone object, the long leg falls from 2.74% per month in the Fresh bucket to 0.93% in the Stale bucket, while the short leg falls from 1.85% to 0.62%. Because the short leg is held short, its own age gradient works against the Fresh–Stale spread rather than producing it, and the entire spread gradient comes from the long side. The additive contributions in Panel B give the same answer.

Having established that the Fresh market premium is not a mechanical artifact of signal extremity, recent rank movement, a single dominant anomaly, short-term reversal, or the short side of the trade, I turn to its economic interpretation.

5 Economic Interpretation: Within-Portfolio Position Staleness

This section evaluates which economic interpretations are most consistent with the rapid age-related weakening of market-anomaly profitability documented in the preceding analysis. The object is the

within-portfolio position, not the anomaly's calendar age after discovery. The goal is to discipline how the freshness premium should be interpreted.

I organize the evidence around a simple economic sequence. When a market signal newly assigns a stock to an extreme long or short leg, a standard anomaly investor opens a new position. If arbitrage capital absorbs these positions gradually, the return premium should be highest near activation and should decline as the position ages. This interpretation follows the slow-moving capital and limits-to-arbitrage logic in Duffie (2010), Shleifer and Vishny (1997), and Gromb and Vayanos (2010), with direct episodic evidence in Mitchell et al. (2007): when forced liquidations pushed convertible bonds and merger targets below fundamental value, it took several months for new capital to arrive and close the dislocations.[9] Throughout the section, I use constrained absorption as a broad description of this idea: newly activated positions may face delayed price adjustment, limited risk-bearing capacity, or gradual trading demand.

The section proceeds in four steps. First, event-time paths and the accounting contrast ask whether the evidence looks like a position lifecycle rather than a static composition effect. Second, surprise and aggregate market states ask whether temporal position age contains return information beyond expectational surprise and favorable return environments. Third, stock-level friction tests and event-time decay tests ask where the premium is larger and how quickly it is absorbed. Fourth, aggregate-stress tests ask when absorption capacity matters.

5.1 Event-Time Returns after Position Activation

The constrained-absorption interpretation has a simple event-time implication. Fresh market positions should earn high returns near entry, and those returns should decline as arbitrage capital, trading activity, and prices adjust. Figure 3 tests this prediction by forming age-bucket portfolios at horizon 1 and holding the formation portfolio fixed through horizon 12. This is an unconditional formation-cohort path: it does not require a stock to remain in the same anomaly leg at future horizons.

[9]The S&P 500 index-deletion evidence in Duffie (2010) illustrates this pattern at the individual-stock level: deleted stocks drop sharply, by roughly 14% between the announcement and effective dates, and the decline is reversed completely within about 60 days after the effective date as additional capital arrives. The diagnostics in this section ask whether the same slow-adjustment logic operates at the level of newly activated anomaly positions.

[INSERT FIGURE 3 HERE]

The market-anomaly path is front-loaded. In the value-weighted Market Fresh path, the return is 0.89% at horizon 1, falls to 0.19% at horizon 2, stays near 0.20% through horizon 6, and is statistically insignificant at 0.05% by horizon 12. Because the formation cohort is held fixed, an interpretation in which Freshness is merely a static characteristic of the constituent stocks predicts a flat path. The observed path instead declines immediately after activation: the newly opened position is most profitable near entry, and the opportunity weakens as the position ages.

Appendix Figure A1 reports complementary survivor paths that condition on a Fresh entrant remaining in the same signal and same long or short leg at future horizons. Those paths are useful for understanding continuing positions, but they are necessarily conditional on survival. The unconditional path in Figure 3 is therefore the paper's primary lifecycle evidence.

Stock characteristics tell a consistent story. Table 5 reports market capitalization, price, realized volatility, dollar volume, and effective spreads for Fresh, Middle, and Stale portfolios. Fresh and Middle market stocks are similar in average market capitalization ($2,742 versus $2,767 million) and dollar volume, and differ only marginally in realized volatility (47.5% versus 45.8% annualized), yet their standalone returns in Table 3 differ substantially, at 0.89% versus 0.39% per month. Fresh stocks also have slightly higher effective spreads, but differences of this magnitude are too small to account for the return gap. The somewhat higher volatility and spreads instead indicate that newly activated positions can be marginally more difficult to bear or trade.

[INSERT TABLE 5 HERE]

Risk-adjusted portfolio statistics point in the same direction. Appendix Table A6 shows that the value-weighted Market Fresh portfolio has an annualized Sharpe ratio of 1.63 gross of transaction costs, compared with 0.92 for Middle and 0.72 for Stale. This matters because arbitrageurs evaluate opportunities using risk-adjusted returns, not average returns alone.

5.2 Why Accounting Continuers Are Different

The accounting results provide the main contrast. In market anomalies, continued portfolio residence often means that a position remains in the portfolio after the return opportunity has been partly absorbed. Accounting continuation has different economic content. Accounting variables update discretely, often summarize persistent fundamental states, and are processed through quarterly or annual information events rather than a continuously updating trading signal. A stock that remains in an accounting anomaly leg may therefore continue to reflect a return-relevant fundamental state, rather than an old signal whose original payoff should already have disappeared.

This interpretation requires distinguishing two clocks. The release-date analysis in Bowles et al. (2024) times returns around the public release of accounting information and shows that release-date returns are concentrated soon after the information event. My analysis asks a different question: conditional on a stock currently occupying an extreme anomaly leg, how is next-month profitability distributed across positions with different portfolio residence ages? In other words, Bowles et al. (2024) time the information event, whereas Signal Age times the portfolio position. A continuing accounting position in my classification is therefore not a claim that the same accounting news released many months earlier remains unprocessed. It is a current portfolio position that has continued to satisfy the extreme-leg condition, potentially because of persistent fundamentals, repeated quarterly or annual updates, and gradual processing of accounting information.

This distinction is visible in the empirical results, not only in the interpretation. In the contribution decomposition, the Fresh accounting bucket accounts for only 9.3% of portfolio capital and 18.9% of profits, while the Middle and Stale buckets jointly account for 90.7% of capital and 81.1% of profits. The standalone evidence is similar: Table 3 shows that the value-weighted Fresh accounting portfolio earns 0.13% per month, while the Middle and Stale portfolios earn 0.28% and 0.21%, respectively. The risk-adjusted evidence in Table 4 points in the same direction. The Fresh accounting alpha is small and statistically insignificant at 0.04%, whereas the Middle and Stale alphas are positive and significant at 0.23% and 0.08%. Thus, accounting continuation is not a low-return residual state analogous to stale market exposure. It is where much of the accounting-anomaly profitability remains.

The event-time evidence provides a second way to see the same contrast. The Market Fresh

path described above falls after formation, but accounting formation cohorts do not display the same decline. As shown in Figure 3, the Fresh accounting path remains close to its initial level across the event window, earning roughly 0.14% at horizon 1 and similar magnitudes at horizons 6 and 12, and the Middle and Stale accounting cohorts also remain positive throughout. The point is not that accounting returns never decay after information releases. Rather, portfolio residence age is less tightly linked to a single payoff window for accounting signals because the underlying fundamentals are persistent and the information environment evolves through discrete updates.

Appendix Table A3 provides a robustness check on this accounting-clock issue. When Signal Age is redefined using lower-frequency portfolio formation, the accounting continuation pattern continues to hold. Under quarterly rebalancing, value-weighted accounting returns are similar across Fresh, Middle, and Stale buckets, at 0.27%, 0.22%, and 0.22% per month. Under annual rebalancing, the Fresh accounting bucket earns 0.18% per month, while the Middle and Stale buckets each earn 0.22%. These results do not imply that accounting information is stale in the release-date sense. They instead show that, when accounting positions continue to satisfy the extreme-leg condition, they retain predictive content under alternative portfolio clocks. The market side of the same table behaves differently, as the paper's interpretation requires. The market Fresh–Stale difference remains positive under both clocks and is 0.36% per month under annual rebalancing. It is smaller and less precisely estimated under quarterly rebalancing, at 0.22% per month, because a quarterly Fresh bucket admits positions that have already resided in the extreme leg for as long as three months and therefore blends the monthly Fresh and Middle groups.

This distinction also disciplines how the absorption diagnostics later in the section should behave. A continuing accounting position is a repeatedly refreshed exposure to a persistent fundamental state rather than a one-time dislocation awaiting arbitrage capital. The two families also differ in what position entry time-stamps. A market signal is itself a price and trading outcome: a stock enters the extreme leg because its recent price or trading behavior has just changed, so market entry coincides with the dislocation that has to be absorbed. An accounting signal moves when reported fundamentals cross a ranking threshold, an event mechanically decoupled from contemporaneous price pressure. Compensation for absorbing dislocations should therefore appear at market entry specifically. There is no concentrated entry event to absorb on the accounting side, so absorption costs and the speed of capital arrival should not govern accounting returns. The

remaining subsections report exactly this pattern.

The same distinction motivates the surprise-sorted evidence in the next subsection. If accounting profitability is tied to information events, then fresh accounting entrants should earn returns primarily when the underlying signal change is difficult to forecast. By contrast, if market freshness reflects a portfolio-position lifecycle, predictable market entrants can still earn large returns when they are newly activated. This contrast is informative because the issue is not persistence itself, but the mismatch between position persistence and opportunity persistence.

5.3 Freshness vs. Surprise: Two Dimensions of Newness

Bowles et al. (2026) show that anomaly signals derived from financial statements are themselves predictable and that investors can earn returns before the signals are formally observed. Their evidence makes forecastability a natural dimension to examine when interpreting accounting-signal returns, and it connects to a broader account in which anomaly returns follow the arrival of information: Engelberg et al. (2018) find that anomaly returns are 50 percent larger on corporate news days and six times larger on earnings announcement days, consistent with biased expectations that are partly corrected when news arrives. If part of an accounting signal can be anticipated before it is released, then returns around fresh signal realizations should differ depending on how predictable the underlying signal change was. I therefore separate two dimensions of newness: the expectational dimension, represented by the magnitude of the signal surprise, and the temporal dimension, represented by signal freshness.

To empirically decouple surprise from freshness, I focus strictly on the "Fresh" bucket, which consists of stocks that have just entered the extreme decile in the current month. I measure the expectational surprise as the directional change in a stock's cross-sectional signal rank from the previous month to the current month. I then sort these fresh entrants into terciles: Low Surprise (stocks that gradually drifted into the extreme decile and were highly predictable), Mid Surprise, and High Surprise (stocks that experienced a sudden, unpredictable jump). I aggregate these sub-portfolio returns using a two-step procedure. First, I compute the cross-sectional mean of the standalone long-short returns for each surprise tercile across all anomalies within a given classification in each month. Second, I calculate the time-series average of these monthly cross-sectional means, assessing statistical significance using Newey-West standard errors with six lags.

[INSERT TABLE 6 HERE]

Table 6 reports the returns of these fresh entrants conditional on their surprise magnitude, showing different patterns across the two anomaly groups. For accounting anomalies, the results are consistent with the predictability channel emphasized by Bowles et al. (2026). The returns of fresh accounting constituents are monotonic in the magnitude of the surprise. The Low Surprise tercile generates a statistically significant, negative value-weighted long-short return of -0.35% ($t = -3.45$). In contrast, the High Surprise tercile earns a significant 0.44% per month ($t = 6.25$).

This pattern is consistent with the view that hard-to-predict accounting updates contain more unanticipated information at realization. In the accounting sample, the return to newly activated positions is concentrated among high-surprise entrants, while low-surprise entrants do not earn a positive premium. This evidence indicates that expectational newness is especially important for accounting signals. It is also compatible with the portfolio-age evidence: an unanticipated accounting update can initiate a price-adjustment process that unfolds over several months when investor attention is limited (Hirshleifer et al., 2009). Thus, for accounting anomalies, surprise is a key margin for the initial premium, while temporal freshness is less decisive because post-announcement drift unfolds over a longer horizon.

The market-anomaly results point in a different direction. For fresh market constituents, expectational surprise does not dictate the realization of returns. The Low Surprise entrants, which are stocks that were highly predicted to enter the extreme decile, earn a value-weighted return of 1.09% per month ($t = 7.73$). This performance is higher than the 0.85% ($t = 7.33$) earned by the High Surprise entrants.

This finding indicates that the profitability of fresh market signals does not primarily arise from unexpected information arrivals. If the premium were mainly driven by the correction of return surprises, predictable fresh entrants would not continue to earn such large returns. Instead, the evidence suggests that temporal freshness captures an economically distinct source of compensation that is concentrated near signal entry. In other words, for market anomalies, the relevant margin is not whether the signal is surprising, but whether the position is newly activated in the portfolio lifecycle. What is priced is therefore the newly opened position rather than the information that opened it. This is precisely the object to which the slow-moving capital logic of Duffie (2010)

applies, and the remaining tests examine the fresh market premium through that lens.

5.4 Freshness across Aggregate Market States

The preceding results show that fresh market profitability is not primarily a correction for unexpected signal changes. A distinct behavioral possibility is that the premium reflects overreaction or sentiment-driven mispricing concentrated in favorable market environments. Under this interpretation, fresh market profitability should be strongest after rising aggregate markets and should weaken after broad market downturns. I test this prediction using aggregate market-state splits in the spirit of Cooper et al. (2004).

I measure the aggregate market state using the cumulative return on the CRSP value-weighted index, including dividends, over the 6, 12, and 36 months prior to the portfolio formation month. For each horizon $h \in \{6, 12, 36\}$, I define an UP market state if the lagged cumulative market return from month $t - h$ to $t - 1$ is non-negative, and a DOWN market state otherwise. I then construct a continuous aggregate time series for each age bucket by calculating the cross-sectional mean of the standalone long-short returns across all anomalies within a classification in each month. To estimate state-specific average returns while preserving the continuous time-series structure, I regress the resulting aggregate return series on UP and DOWN indicators without an intercept and compute Newey–West standard errors with six lags.

[INSERT TABLE 7 HERE]

Table 7 presents the value-weighted long-short returns of the age portfolios conditioned on the 6, 12, and 36 month market states. Focusing on the longest horizon, fresh market constituents earn 0.90% per month after UP markets and 0.81% per month after DOWN markets. Both estimates are statistically significant, and the age profile remains steep in both states. By contrast, stale market constituents earn 0.32% per month after UP markets and an insignificant 0.21% after DOWN markets. Thus, the fresh market premium survives outside bull-market environments. It remains economically large after prolonged market declines, where an optimistic-sentiment interpretation would predict the premium to weaken most.

Accounting anomalies display a different pattern. Fresh accounting constituents earn 0.12% per month after UP markets and 0.23% after DOWN markets, neither of which resembles the large fresh-market premium. These state splits reinforce the main distinction in the paper: temporal freshness is especially important for market anomalies, while accounting-anomaly profitability is less concentrated in the initial month of portfolio entry. The persistence of the fresh market premium after broad downturns narrows the interpretation of the effect. It points away from a simple bullish-sentiment story and motivates tests of whether the premium is linked to the cost of absorbing newly activated positions and to tighter risk-bearing conditions.

5.5 Where Absorption Is Costly: Stock-Level Evidence

The market-state results address whether fresh market profitability is confined to favorable aggregate return environments. I next ask which stock-level conditions are associated with larger returns to newly activated market positions. The organizing hypothesis makes a specific prediction about where these returns should be concentrated. If the premium compensates the absorption of newly activated positions, it should be larger among stocks for which absorbing a new position is more expensive, and it should not depend on investor attention as such. I therefore examine two families of conditioning variables, each constructed to isolate one margin. Market capitalization and dollar trading volume measure the cost of building a position of meaningful size: in live institutional execution data, realized trading costs rise steeply as capitalization and volume fall (Frazzini et al., 2018). Analyst coverage and institutional ownership measure how closely a stock is followed. Both are strongly related to size and trading activity, so, following the residual-coverage design of Hong et al. (2000), who residualize coverage on firm size and find momentum profits roughly sixty percent larger in the least covered third, I residualize each within month on size and dollar volume. The attention proxies therefore measure how widely a stock is followed among stocks of similar tradability. If the premium compensates absorption, the cost margin should amplify it; if it reflects gradual diffusion of information to inattentive investors, thin coverage and thin ownership should.

The stock-level tests draw on cross-sectional variation across stocks, while the aggregate-stress tests that follow draw on time-series variation across periods. If newly activated positions are harder to absorb, both margins should show a positive signature. The timing required is modest. Absorption may be delayed relative to instantaneous pricing, yet still complete faster than the

persistence of the signal rank itself. In that case, premia are concentrated near activation even though standard sorting rules continue to retain the position.

The sample consists of stock-months that appear in the extreme leg of at least one anomaly portfolio. This restriction keeps the analysis focused on the intensive margin of anomaly exposure: among stocks that are already anomaly-active, does the return associated with newly activated signals differ across economic environments? I summarize each stock's anomaly exposure using signed signal-count measures in the spirit of Engelberg et al. (2018). Let $s_{a,i,t} = 1$ if stock i is in the long leg of anomaly a in month t, $s_{a,i,t} = -1$ if it is in the short leg, and $s_{a,i,t} = 0$ otherwise. Let $Fresh_{a,i,t}$ indicate that this extreme-leg position has signal age equal to one month. I define

$$NetFresh_{i,t}^{Mkt} = \sum_{a \in \mathcal{M}} s_{a,i,t} Fresh_{a,i,t}, \tag{3}$$

$$NetFresh_{i,t}^{Acct} = \sum_{a \in \mathcal{A}} s_{a,i,t} Fresh_{a,i,t}, \tag{4}$$

$$NetTotal_{i,t} = \sum_{a \in \mathcal{M} \cup \mathcal{A}} s_{a,i,t}, \tag{5}$$

Here, $\mathcal{M}$ and $\mathcal{A}$ denote the market and accounting anomaly sets. Thus, the market-freshness score is the net number of newly activated market-anomaly signals for stock i, while $NetTotal_{i,t}$ controls for the stock's overall signed anomaly score. The coefficient on $NetFresh_{i,t}^{Mkt}$ therefore isolates the temporal recency of market-anomaly positions rather than the mere fact that a stock has many extreme anomaly signals.

I estimate a single specification and vary the conditioning variable across columns:

$$\begin{aligned} R_{i,t} = {} & \beta_1 NetFresh_{i,t}^{Mkt} + \beta_2 \big(NetFresh_{i,t}^{Mkt} \times Z_{i,t-1}\big) \\ & + \beta_3 NetFresh_{i,t}^{Acct} + \beta_4 \big(NetFresh_{i,t}^{Acct} \times Z_{i,t-1}\big) + \beta_5 NetTotal_{i,t} \\ & + \theta Z_{i,t-1} + \gamma X_{i,t-1} + \mu_i + \delta_t + \epsilon_{i,t}. \end{aligned} \tag{6}$$

Here, $Z_{i,t-1}$ denotes one of the four conditioning indicators: the two attention proxies (low analyst coverage, low institutional ownership) and the two absorption-cost markers (small size, low dollar volume). The dependent variable is the monthly stock return in percent. $X_{i,t-1}$ includes lagged size, 12 month momentum, 1 month short-term reversal, and lagged dollar volume. The model

includes firm fixed effects, μ_i, and date fixed effects, δ_t, and standard errors are double clustered by firm and month.

I use two attention proxies and two absorption-cost markers. First, analyst coverage is measured using I/B/E/S $NUMEST$ from the U.S. summary statistics file and linked to CRSP through the WRDS I/B/E/S–CRSP link. Within each I/B/E/S ticker-month, I keep the latest summary date. After merging to the stock-month panel, firms without I/B/E/S coverage are assigned $NUMEST = 0$, and the coverage variable is $\log(1 + NUMEST_{i,t-1})$. Second, institutional ownership is constructed from Thomson 13F holdings. I aggregate institutional shares by CUSIP and report date, link CUSIPs to CRSP $PERMNO$ through the CRSP name history, divide institutional shares by CRSP shares outstanding, cap the resulting ownership ratio at one, and forward-fill quarterly reports to monthly observations for at most five months. At an actual 13F report month, a CRSP common stock with no reported institutional holdings is assigned zero institutional ownership rather than treated as missing. Because analyst coverage and institutional ownership are strongly related to firm size and trading activity, I residualize each variable within month on lagged size and lagged dollar volume, and define low coverage and low institutional ownership as bottom-tercile residual indicators. The two absorption-cost markers use the same lagged size and dollar-volume variables that enter the regressions as controls. Small indicates membership in the bottom tercile of lagged market capitalization within each month, and Low Volume indicates membership in the bottom tercile of lagged dollar volume within each month. Because size and dollar volume also enter every specification as continuous controls, their level effects on returns are already absorbed. The interaction coefficient therefore measures how the return to a newly activated market signal differs in the least liquid third of the cross-section relative to the rest, holding the direct effects of size and volume fixed.

[INSERT TABLE 8 HERE]

Table 8 reports the results. Two features stand out. First, the baseline market-freshness coefficient is positive and statistically significant in every column. In the absorption-marker columns the baseline group contains the larger and more liquid two thirds of the cross-section, and one additional net fresh market signal is still associated with roughly 5 to 7 basis points of additional

next-month return in that group. The fresh market premium is therefore present throughout the cross-section rather than confined to any subgroup.

Second, the premium is strongly amplified where absorption is costly. The interaction between market freshness and Low Volume is 0.3432, and the interaction with Small is 0.2818, both significant at the 1 percent level. Among thinly traded stocks, one additional net fresh market signal is associated with about 34 basis points of additional next-month return beyond the baseline effect. The attention proxies behave differently. The interaction with low analyst coverage is -0.0138 with a standard error of 0.0161, and the interaction with low institutional ownership is 0.0242 with a standard error of 0.0195. Both are economically small and statistically indistinguishable from zero: holding tradability fixed, being less followed adds nothing. A diffusion account predicts amplification precisely along these margins, and the data show none, while both direct measures of the cost of absorbing a new position amplify the premium strongly.

The accounting side sharpens the contrast. Limited attention demonstrably impedes the processing of earnings information (Hirshleifer et al., 2009), and accounting signals are the canonical hard-to-process information, so if the fresh premium reflected the slow diffusion of hard-to-process information, fresh accounting entrants should earn the most where attention is thin. Instead, the accounting-freshness main effects are negative in every column, and the accounting interactions are negative or zero throughout, including -0.3277 for Low IO, -0.2390 for Small, and -0.0752 for Low Volume. Absorption frictions amplify the return content of newly activated market positions specifically, consistent with the two-clock interpretation developed earlier in this section.

5.6 How Fast the Premium Is Absorbed: Event-Time Decay by Liquidity

The cross-sectional evidence shows where the fresh market premium is larger. The absorption hypothesis has a second implication that concerns time rather than levels. Duffie (2010) emphasizes that the amplitude of a price concession and the duration of its reversal are distinct dimensions of a slow-moving capital episode, and that both depend on how quickly capital arrives. The address describes the search model of Duffie et al. (2007) as one in which the size of the immediate price reaction and the half-life of its reversal both decrease in the mean rate at which investors locate suitable counterparties. The previous subsection tested the level margin of this prediction. This subsection isolates the time margin. Applied to newly activated positions, the implication is that

the fresh market premium should decay more slowly where the capital that competes it away arrives more slowly. Where capital arrives quickly, the same premium should disappear almost immediately.

I test this implication by returning to the unconditional formation-cohort design behind Figure 3 and splitting the Fresh cohort by the liquidity of its constituents at formation. For each signal and month, I form the Fresh long-short portfolio at horizon one, divide its constituents into within-month terciles of lagged average daily dollar volume, and hold each tercile portfolio fixed with its formation weights through horizon twelve. Average daily dollar volume is the prior month's dollar trading volume divided by the number of trading days in that month, with NASDAQ volume adjusted for interdealer double counting following Gao and Ritter (2010).[10]

[INSERT FIGURE 4 HERE]

Figure 4 reports the paths. In the most liquid tercile, the Fresh market cohort earns 0.410% in the formation month, with a Newey-West t-statistic of 4.86, and the compensation attached to the newly opened position is exhausted in that single month. The horizon-two return is -0.019%, and no horizon beyond the first is statistically significant. The sorting rule operates on a much slower schedule. Panel C of Table 1 shows that a stock in an extreme market leg remains there the following month with probability 72.5% for the long leg, so the standard portfolio typically retains these positions for many months after the single month in which they pay. This mismatch between the speed of absorption and the speed of the sorting rule is the staleness trap observed in event time, and it arises in the segment of the market where absorption is fastest. The remaining terciles measure how the decay speed varies with the arrival rate of capital. The middle tercile remains significant at ten of twelve horizons. The least liquid tercile earns 0.547% at formation and is still earning 0.091% with a t-statistic of 2.13 a year later, so absorption there takes more than a year to complete. The formation-month levels differ only moderately across terciles. What separates the terciles is not how much a fresh position earns at activation but how quickly that compensation is

[10]The liquidity split requires merging trading-volume data, which removes about five percent of stock-months. On the matched sample the aggregate Fresh market cohort path is nearly identical to the path in Figure 3, with returns of 0.879% at horizon one, 0.221% at horizon three, and 0.202% at horizon six. The sample restriction therefore does not affect the object being split.

competed away.

The tercile paths also explain the shape of the aggregate path in Figure 3. The sharp decline over the first two horizons comes from liquid names, and the persistent tail comes from illiquid names. The two components carry very different amounts of capital. The most liquid tercile holds roughly three quarters of the value-weighted portfolio capital and about four fifths of the Fresh cohort's formation capital, while the least liquid tercile holds roughly six percent of the Fresh cohort's capital. Among illiquid names an aged position does retain compensation, which is exactly what slow capital arrival requires. This persistence does not rescue the standard portfolio. The positions involved hold little capital and sit in the segment of the market where trading is most expensive. Because value weighting concentrates capital in liquid names, the staleness trap documented in the portfolio evidence is sharpest precisely among liquid names, where the return opportunity dies fastest while standard sorting rules continue to hold the position for months.

The accounting side again serves as the placebo. Panel (b) of Figure 4 shows no entry concentration in any liquidity tercile. The formation month is the weakest month of the path in all three terciles, and the least liquid tercile earns -0.325% at formation, an estimate close to the low-surprise fresh accounting return in Table 6. Beyond the formation month the three accounting paths fluctuate between roughly 0.1% and 0.3% for the full year with no liquidity ordering, and the most liquid tercile remains profitable deep into the year, earning 0.305% at horizon six. The speed of capital arrival governs nothing on the accounting side. This is what the two-clock interpretation requires. A continuing accounting position reflects a persistent fundamental state rather than a one-time dislocation, so there is no concentrated entry event for arriving capital to absorb.

5.7 When Absorption Is Costly: Aggregate Stress

The stock-level and event-time evidence identify where the fresh market premium is larger and how quickly it is absorbed. I now ask when. Specifically, I ask whether the same market-freshness premium varies with aggregate conditions that affect risk bearing. Models of limits to arbitrage and slow-moving capital imply that prices may adjust gradually when arbitrage capital is scarce or costly to deploy (Shleifer and Vishny, 1997; Gromb and Vayanos, 2010; Duffie, 2010). Related evidence on liquidity provision and intermediary asset pricing motivates using aggregate liquidity, funding, and intermediary-capital proxies to capture variation in risk-bearing capacity (He et al.,

2017; Adrian et al., 2014). Under this view, newly activated market positions should command larger premia when aggregate funding liquidity and intermediary balance-sheet conditions are more strained.

I estimate the aggregate-stress specification

$$\begin{aligned} R_{i,t} = {} & \alpha_1 NetFresh_{i,t}^{Mkt} + \alpha_2\big(NetFresh_{i,t}^{Mkt} \times Stress_t\big) \\ & + \alpha_3 NetFresh_{i,t}^{Acct} + \alpha_4\big(NetFresh_{i,t}^{Acct} \times Stress_t\big) + \alpha_5 NetTotal_{i,t} \\ & + \gamma X_{i,t-1} + \mu_i + \delta_t + \epsilon_{i,t}. \end{aligned} \tag{7}$$

The main effect of $Stress_t$ is absorbed by the date fixed effects. All stress proxies are standardized to have mean zero and unit variance, so the interaction coefficients measure the change in the marginal return associated with one additional net fresh signal when the stress proxy increases by one standard deviation.

I use five aggregate stress proxies. VIX is the monthly average of the daily CBOE Volatility Index; Nagel (2012) shows that the expected return to supplying liquidity is strongly predictable by the VIX and spikes when liquidity suppliers withdraw during turmoil, which is the aggregate counterpart of the position-level prediction tested here. The TED spread is the monthly average of the FRED $TEDRATE$ series and captures the funding-spread margin that Adrian et al. (2014) use, alongside volatility and the Baa–Aaa spread, to validate broker-dealer leverage as a measure of funding constraints. Pástor–Stambaugh liquidity is the monthly innovation in the WRDS $ff.liq_ps$ file, multiplied by -1 so that higher values indicate lower liquidity and greater stress (Pástor and Stambaugh, 2003). The He–Kelly–Manela intermediary capital measure uses the monthly intermediary capital risk factor from He et al. (2017), sign-aligned so that higher values indicate tighter intermediary-capital conditions. The Adrian–Etula–Muir broker-dealer leverage factor is taken from Adrian et al. (2014); the quarterly series is mapped to quarter-end months and forward-filled to monthly observations, then sign-aligned so that higher values indicate greater stress.[11] This sign convention makes all five coefficients directly comparable: positive interactions mean

[11] The He–Kelly–Manela data are downloaded from Asaf Manela's data page, `https://asaf.manela.org/data/`. The Adrian–Etula–Muir broker-dealer leverage data are downloaded from Tyler Muir's data page, `https://sites.google.com/site/tylersmuir/home/data-and-code`. Pairwise correlations among the standardized stress proxies range from -0.05 to 0.47 in the prepared stress-factor panel, with the largest correlation between VIX and TED. I therefore interpret the proxies as related but not redundant measures of aggregate stress, rather than as five independent structural channels.

that the fresh-market premium is larger in more stressed aggregate states. I estimate each proxy in a separate interaction specification, treating the variables as alternative observable measures of aggregate stress rather than as mutually exclusive channels.

[INSERT TABLE 9 HERE]

Table 9 shows that the market-freshness premium varies with aggregate stress. Column (1) first reports the baseline no-interaction specification. The coefficient on $NetFresh^{Mkt}$ is 0.1897, while the coefficient on $NetFresh^{Acct}$ is -0.1808. Thus, one additional net fresh market signal is associated with an approximately 19 basis point higher monthly return, whereas the fresh accounting score has the opposite sign, consistent with the portfolio-level contrast documented earlier.

Columns (2)–(6) then interact the fresh scores with the aggregate stress proxies one at a time. The interaction between $NetFresh^{Mkt}$ and the stress proxy is positive for all five measures: 0.0484 for VIX, 0.0283 for TED, 0.0405 for Pástor–Stambaugh liquidity stress, 0.0572 for He–Kelly–Manela intermediary capital stress, and 0.0339 for Adrian–Etula–Muir broker-dealer leverage stress. Each coefficient is statistically significant. Economically, the estimates imply that the return associated with one additional net fresh market signal rises by about 3 to 6 basis points per month when the corresponding stress proxy increases by one standard deviation.

The accounting interactions again behave differently. Except for VIX, the accounting-freshness interactions are small and statistically insignificant; for VIX, the coefficient is negative. The aggregate-stress loading is therefore concentrated in fresh market signals rather than fresh accounting signals, the same group for which the portfolio-level evidence shows that profitability falls quickly after signal entry. This asymmetry supports the interpretation that newly activated, turnover-intensive market exposures earn larger premia when funding and intermediary conditions make them harder to absorb. The broader stress battery also shows that this state dependence is visible beyond the VIX, appearing in liquidity, funding-spread, intermediary-capital, and broker-dealer leverage measures.

Across the five proxies, the aggregate-stress interactions line up with the stock-level and event-time evidence. Fresh market premia are larger among stocks that are costly to absorb, decay slowly

where capital arrives slowly, and rise in aggregate states where intermediary and funding capacity are tighter. The attention proxies, by contrast, do not support an attention-diffusion account.

5.8 What the Evidence Does and Does Not Establish

Taken together, the evidence describes a position-level lifecycle. The market freshness premium concentrates at signal entry, survives even among predictable Fresh entrants at 1.09% per month, is amplified among stocks that are costly to absorb, is absorbed within a single month among the liquid names that dominate value-weighted portfolios, decays slowly where capital arrives slowly, and is larger in periods when intermediary and funding capacity are tighter. The same diagnostics reinforce the Market–Accounting contrast. Every absorption signature that appears on the market side is absent on the accounting side, where continuation remains profitable over longer horizons because the underlying positions reflect persistent and repeatedly refreshed fundamental states.

The inference here is comparative rather than structural. The tests show where compensation is concentrated and which observable conditions amplify it, while leaving the precise mix of intermediary, funding, and inventory frictions for separate identification. The standard portfolio practice of retaining aged positions therefore continues to absorb capital after the most economically relevant compensation has shifted toward newly activated positions, and that compensation is largest precisely where new positions are costly to absorb and when risk-bearing capacity is tight.

6 Asset-Pricing and Implementation Implications

The preceding section interprets the market staleness trap as a within-portfolio lifecycle pattern. This section uses the lifecycle evidence to study anomaly attenuation, factor design, and implementation. The implementation results also speak to a common prescription in the anomaly-implementation literature: when trading is costly, investors may try to economize on turnover by retaining existing positions longer. I examine four implications: how publication changes where anomaly profitability remains, whether Fresh, Middle, and Stale positions differ in factor-design contribution, how trading activity evolves over the position lifecycle, and how the lifecycle interacts with transaction costs.

6.1 Publication, Learning, and Lifecycle Compression

I first use an anomaly-age-bucket panel framework to investigate how the staleness trap interacts with the well-documented post-publication decay of anomalies (McLean and Pontiff, 2016). The existing literature shows that anomaly returns generally decline after their academic publication due to the influx of arbitrage capital and market learning. However, it remains an open empirical question whether this decay occurs uniformly across the lifecycle of a signal. On the one hand, investors might closely monitor and quickly trade on newly generated signals, leading to a rapid decay of the fresh premium. On the other hand, arbitrage activity might predominantly target established, persistent mispricing, leaving the initial emergence of the signal relatively less affected. To understand these dynamics, I examine how the post-publication effect varies across different signal age buckets.

To formally test this, I introduce a post-publication indicator variable, $PostPub_{s,t}$, which equals one if the current month t is subsequent to the original publication year of anomaly s, and zero otherwise. I estimate the following specification:

$$\begin{aligned} R_{s,p,t} = {} & \beta_1(Fresh_p \times Market_s \times PostPub_{s,t}) \\ & + \beta_2(Middle_p \times Market_s \times PostPub_{s,t}) \\ & + \beta_3(Fresh_p \times Market_s) + \beta_4(Middle_p \times Market_s) \\ & + \beta_5(Fresh_p \times PostPub_{s,t}) + \beta_6(Middle_p \times PostPub_{s,t}) \\ & + \beta_7(Market_s \times PostPub_{s,t}) + \beta_8 PostPub_{s,t} \\ & + \beta_9 Fresh_p + \beta_{10} Middle_p + \beta_{11} Market_s \\ & + \gamma_1 SignalRankLevel_{s,p,t} + \gamma_2 SignalRankChange_{s,p,t} \\ & + \mu_s + \eta_p + \delta_t + \epsilon_{s,p,t} \end{aligned} \tag{8}$$

This model interacts the publication indicator with the age bucket and anomaly classifications. The specification includes all lower-order interaction terms to properly isolate the marginal effects. The main effects (β_9, β_{10}, and β_{11}) are absorbed by the fixed effects.

Table 10 extends the panel framework to examine whether post-publication decay differs across the signal lifecycle. The distinction between the two dependent variables remains useful for inter-

pretation. In the contribution specifications, post-publication effects are reflected in the realized performance of the parent anomaly portfolio and therefore incorporate both changes in age-specific profitability and the capital retained in each age bucket. In the standalone specifications, by contrast, the estimates more directly trace how publication alters the return spread associated with each stage of the signal lifecycle.

Because the specification is fully interacted, Column 4 is easiest to interpret through the implied post-publication effects for each market age bucket. In the fully controlled standalone specification, the implied post-publication effect for stale market positions is -0.37% per month ($t = -2.17$). The corresponding effect for fresh market positions is 0.48% per month ($t = 1.58$). The main comparison is therefore within market anomalies: the Fresh-minus-Stale post-publication differential is 0.85% per month and statistically significant ($t = 2.44$). The Middle-minus-Stale differential is positive but smaller, at 0.14% ($t = 1.06$).

These estimates show that post-publication decay varies across the position lifecycle. The return content of stale market positions weakens after publication, while newly activated positions remain relatively more important. This pattern is consistent with the repricing dynamics in Pénasse (2022), in which investors who learn about an anomaly trade in its direction and compress future returns. In the present setting, that compression should fall hardest on positions that are already known and persistently held. In the post-publication environment, the residual predictive power of market anomalies is therefore more tilted toward newly activated positions. This lifecycle compression is also what the slow-moving capital framework predicts once capital mobility is treated as endogenous. Duffie (2010) observes that as investors learn about a class of opportunities, price impacts shrink and reversals speed up. Publication is such a learning event, and the estimates show that the resulting compression falls on the positions that were already known and persistently held.

The same compression is visible in calendar time without any publication indicator. Appendix Table A9 reports standalone age-bucket returns across subsamples, and the market lifecycle gradient widens steadily as the sample advances. The Fresh–Stale difference is 0.27% per month in the early half of the sample, 0.88% in the late half, and 1.00% over the most recent twenty years. Roughly two thirds of the widening comes from the stale side. Stale market positions earn 0.48% per month in the early half but only 0.13% after 2000 and -0.02% over the last twenty years, while fresh market positions earn 0.75% in the early half and still earn 0.98% per month in that most recent

window. This is the pattern that endogenous capital mobility implies. As more capital learns to pursue a recurring class of opportunities, the slowest component of the premium is competed away first, and what survives is the compensation attached to positions that have only just been opened. The accounting side shows no such ordering. Accounting Fresh returns are negative and statistically insignificant in every recent window, so the market lifecycle gradient has no accounting counterpart even in the most recent sample.

Taken together, the panel and subsample evidence reinforces the paper's empirical message. The freshness premium in market anomalies remains visible after accounting for signal rank level, recent signal movement, and post-publication attenuation, and it is larger in the recent sample than in the early one. Both the publication indicator and calendar time point the same way: once an anomaly is widely known and capital has had time to arrive, the remaining market-anomaly premium is disproportionately located near position activation. The next subsection turns from publication dynamics to the factor-design implication of this same lifecycle pattern.

[INSERT TABLE 10 HERE]

6.2 Mean-Variance Contribution across Position Age

The preceding evidence indicates that freshness is economically relevant not only for interpreting average returns, but also for understanding which component of anomaly profitability remains most relevant to investors once standard benchmark factors are taken into account. Table 4 shows that the lifecycle contrast in anomaly profitability survives standard risk adjustment. The mechanism evidence further shows that fresh market profitability is distinct from expectational surprise, persists across aggregate market states, is amplified among positions that are costly to absorb and decays most slowly where the absorbing capital arrives most slowly, and rises when aggregate risk-bearing conditions are more constrained. The next question is whether freshness also identifies the component of anomaly profitability that contributes most to the mean-variance span of standard benchmark models.

To address this question, I complement the alpha evidence with a factor-model comparison based on the maximum squared Sharpe ratio. The rationale follows Barillas and Shanken (2018), who

show that when the factors are traded, comparing the performance of two candidate factor models is equivalent to comparing the maximum Sharpe ratios attainable with the factors in each model. Building on this result, Barillas et al. (2020) develop formal inference for comparing squared Sharpe ratios across competing traded-factor models. Cooper et al. (2024) use the same logic in evaluating alternative factor constructions. This perspective is useful in the present setting because the paper's claim is that the economically relevant component of anomaly profitability is concentrated near signal activation rather than in aged continuers. The maximum-Sharpe-ratio exercise therefore asks whether the Fresh, Middle, and Stale portfolios add different amounts of incremental mean-variance information once the factor span of a benchmark model is already available.

The exercise also connects to recent evidence that factor premia themselves have exploitable dynamics. Ehsani and Linnainmaa (2022) show that most factors are positively autocorrelated, with the average factor earning 51 basis points per month following a positive year and six basis points following a down year, and Ehsani et al. (2025) show that scaling factor exposure to this predictability yields time-series efficient factors with substantially higher Sharpe ratios, concluding that enhancing existing factors is likely to provide greater benefits than searching for new ones. Signal Age targets a complementary margin: those papers condition on a factor's own past return, while the age decomposition partitions the positions inside the factor at a point in time. Within an anomaly and month, the factor's recent performance is common to all age buckets, so the lifecycle gradient operates inside what factor-level conditioning holds fixed.

Formally, let f_t denote the vector of traded benchmark factors. For any candidate factor set, define the maximum squared Sharpe ratio as

$$\max SR^2(f) \;=\; \mu_f' \Sigma_f^{-1} \mu_f, \tag{9}$$

where $\mu_f = E[f_t]$ is the vector of factor means and $\Sigma_f = \mathrm{Var}(f_t)$ is the factor covariance matrix. If g_t denotes an additional traded factor, then the incremental contribution of augmenting the benchmark model with g_t is

$$\Delta\big(\max SR^2\big) \;=\; \max SR^2(f_t, g_t) - \max SR^2(f_t). \tag{10}$$

A larger value indicates that the added factor expands the attainable mean-variance frontier by more. In the present application, the candidate augmentation factor g_t is the Fresh, Middle, or Stale anomaly factor, constructed separately within the Market and Accounting anomaly groups.

The construction of these factors follows the standalone portfolio methodology used throughout the paper. For each anomaly and month, I first form age-specific standalone long-short portfolios separately for the Fresh, Middle, and Stale buckets using value-weighted long and short legs. If a given anomaly-month does not satisfy the minimum investability requirement, the corresponding age-specific return is set to zero under the unconditional implementation framework. I then average these age-specific long-short returns across all anomalies within a classification group, generating monthly aggregate factor returns for Fresh, Middle, and Stale portfolios separately for Market anomalies and Accounting anomalies. This procedure produces six value-weighted monthly factor series: Market-Fresh, Market-Middle, Market-Stale, Accounting-Fresh, Accounting-Middle, and Accounting-Stale.

I evaluate these factors against three benchmark models. The first benchmark is the Fama and French (1993) three-factor model (FF3). The second augments FF3 with the Carhart (1997) momentum factor (FF3+UMD). The third uses the Fama and French (2015) five-factor model augmented with momentum (FF5+UMD). For each benchmark, I compute the increase in the maximum squared Sharpe ratio when the Fresh, Middle, or Stale factor is added to the benchmark factor span.

Because each comparison in Table 11 augments a traded-factor benchmark with a single additional traded factor, the formal statistical assessment is especially simple. Let g_t denote the added factor and f_t the benchmark factor vector. In the nested traded-factor setting considered by Barillas et al. (2020), testing whether the augmented model improves on the benchmark reduces to testing whether the added factor has zero alpha relative to the benchmark model. Accordingly, for each benchmark specification I estimate the time-series regression

$$g_t = \alpha_g + b_g' f_t + u_t, \tag{11}$$

and test the null hypothesis $H_0 : \alpha_g = 0$. The stars reported next to $\Delta(\max SR^2)$ therefore reflect the statistical significance of the added-factor alpha in this regression. The t-statistics reported in

parentheses are the Newey-West t-statistics for α_g, computed with six lags. In other words, the first line in each row reports the economic magnitude of the model improvement, while the second line reports the formal statistical evidence that the added factor is not redundant relative to the corresponding benchmark model. This is the appropriate significance test in the present setting because the models are nested and the added factor is itself a traded return.

[INSERT TABLE 11 HERE]

Table 11 reports the results. For market anomalies, the improvements are ordered by position age across benchmark specifications. Adding the Fresh factor increases the maximum squared Sharpe ratio by 0.225 relative to FF3, by 0.188 relative to FF3+UMD, and by 0.178 relative to FF5+UMD. The corresponding t-statistics for the added-factor alpha are 9.10, 8.25, and 7.42, respectively. Adding the Middle factor also expands the benchmark factor span, but by smaller amounts: 0.098, 0.063, and 0.048, with t-statistics of 8.46, 7.15, and 5.75. The Stale factor contributes still less, with improvements of 0.072, 0.035, and 0.021 and corresponding t-statistics of 7.27, 5.37, and 3.80. Thus, even after allowing the benchmark model to span standard market, size, value, profitability, investment, and momentum exposures, the mean-variance contribution of market-anomaly profitability declines with position age and remains most concentrated in newly activated positions.

The accounting results provide a useful contrast. For accounting anomalies, the Fresh factor contributes essentially no incremental mean-variance content, with $\Delta(\max SR^2)$ values of only 0.002, 0.003, and 0.001 across the three benchmark models, and corresponding t-statistics of 1.00, 1.38, and 0.66. The Middle factor is the largest accounting component, with improvements of 0.082, 0.121, and 0.093 and t-statistics of 7.82, 8.93, and 7.68. The Stale factor also generates positive improvements of 0.045, 0.041, and 0.015, with corresponding t-statistics of 5.11, 5.13, and 3.27. This pattern mirrors the alpha evidence in Table 4 and reinforces the broader contrast developed throughout the paper: profitability in market anomalies is concentrated near signal entry, whereas accounting anomalies remain economically active over a longer lifecycle, especially among continuing positions.

Taken together, Table 4 and Table 11 provide consistent evidence. Table 4 shows that fresh

market portfolios retain larger abnormal returns than stale portfolios after standard risk adjustment. Table 11 further shows that fresh market portfolios contribute the most to the mean-variance frontier of standard factor models, with Middle and Stale positions contributing progressively less. In this sense, freshness is not only a timing refinement layered on top of an otherwise standard anomaly implementation. Rather, in market anomalies, freshness identifies the component of portfolio positions that contains most of the economically relevant compensation. This age ordering shows that continued portfolio residence is economically meaningful. It is consistent with the paper's broader interpretation that compensation in market anomalies is concentrated near activation and fades as positions age, so that standard portfolio rules retain the least profitable component of the strategy.

6.3 Trading Activity over the Position Lifecycle

Beyond factor design, the lifecycle pattern also has implications for implementation. Before turning to transaction-cost-adjusted returns, I first examine how trading activity evolves over the signal lifecycle. This exercise helps characterize whether fresh and stale positions differ not only in expected returns but also in the timing of trading activity. Using the natural logarithm of monthly trading volume as the dependent variable, I estimate

$$\ln(Volume_{i,t}) = \sum_{c} \sum_{b} \beta_{c,b} Gross_{i,t}^{c,b} + \gamma X_{i,t-1} + \mu_i + \delta_t + \epsilon_{i,t}, \tag{12}$$

where $c \in \{Market, Accounting\}$ and $b \in \{Fresh, Middle, Stale\}$ index anomaly type and age bucket, respectively. $Gross_{i,t}^{c,b}$ is the total number of long and short signals of type c in age bucket b. Because the dependent variable is log-transformed, multiplying the estimated coefficients by 100 provides the approximate percentage change in trading volume per additional signal.

[INSERT TABLE 12 HERE]

Table 12 reports the volume regressions and shows differences between the two anomaly types. The baseline volume reaction to accounting anomalies is larger than that of market anomalies. The fresh accounting bucket is associated with an increase in trading volume (0.0101, t-statistic > 30).

Economically, the activation of an extreme accounting signal is associated with an approximate 1.01% increase in the stock's monthly trading volume. This pattern is consistent with a discrete information-event effect, as fundamental updates can attract investor attention and institutional rebalancing. While the volume decays in the middle and stale periods, it remains significantly positive, consistent with the extended trading activity associated with post-earnings-announcement drift.

For market anomalies, by contrast, the volume dynamics suggest a more gradual adjustment pattern over the signal lifecycle. At entry, the fresh bucket exhibits only a small contemporaneous change in trading volume (0.0004), indicating that market-anomaly activation is not accompanied by the larger trading response observed for fresh accounting signals. Trading activity becomes more visible in the middle bucket (2 to 6 months), where the coefficient increases to 0.0012. This pattern is consistent with a more gradual reallocation of capital into these positions over time rather than an immediate trading response at entry.

As the market constituent ages into the stale bucket (more than 6 months), the coefficient turns negative (-0.0077, absolute t-statistic > 12), indicating a 0.77% decrease in trading volume per stale signal. By this stage, trading activity has receded, while the positions remain retained in the portfolio despite offering little residual premium. Taken together, these lifecycle patterns in trading volume suggest that market-anomaly activation is not accompanied by an immediate increase in broad trading activity at entry. Instead, trading activity appears to adjust more gradually over the signal lifecycle, becoming more visible in the middle stage and receding once positions become stale. Read together with the event-time evidence, the timing is informative. Newly activated market positions earn their largest return in the month of entry, yet that month shows almost no broad trading response, and the trading response becomes visible only over the following months, by which point the return to liquid fresh positions has already been competed away. The capital that absorbs these positions therefore arrives after most of the compensation has been paid. This is the pattern that a slow-moving capital account implies, because the price concession at entry exists precisely when the set of investors available to take the other side is thin.

The trading-volume evidence is informative about the timing of trading activity, but it does not by itself measure the implementation cost of refreshing the portfolio. To evaluate that question, I now turn to turnover-based transaction cost estimates constructed from effective spreads and

realized portfolio rebalancing.

6.4 Transaction Costs and Net Profitability

To measure trading costs, I use WRDS Intraday Indicator Database to obtain the effective bid-ask spread for each stock. The one-way transaction cost for stock i at month t, denoted as $c_{i,t}$, is defined as half of the lagged effective spread. To compute the trading volume required to rebalance the portfolios, I account for the weight drift caused by the stock's realized returns in the prior month. Let $w_{i,t}$ be the target value-weight of stock i in the portfolio at month t. Before rebalancing, the evolved weight of stock i, $\tilde{w}_{i,t}$, is given by:

$$\tilde{w}_{i,t} = \frac{w_{i,t-1}(1 + r_{i,t-1})}{\sum_j w_{j,t-1}(1 + r_{j,t-1})} \tag{13}$$

where $w_{i,t-1}$ is the target weight in the previous month and $r_{i,t-1}$ is the realized return. The required trade amount, or turnover, for stock i to achieve the new target weight is the absolute difference between the target weight and the evolved weight. The aggregate portfolio transaction cost, TC_t, is then calculated as the trade-weighted sum of the individual transaction costs:

$$TC_t = \sum_i |w_{i,t} - \tilde{w}_{i,t}| \times c_{i,t} \tag{14}$$

Finally, the net return of the standalone portfolio is simply the gross return minus this total transaction cost, so that $R_t^{Net} = R_t^{Gross} - TC_t$. I first compute the cross-sectional average of these gross returns, transaction costs, and net returns across all anomalies within a given classification in each month. Second, I calculate the time-series average of these monthly cross-sectional means, with statistical significance assessed using Newey-West standard errors with six lags.

[INSERT TABLE 13 HERE]

Table 13 reports the gross returns, portfolio costs, and net returns for the standalone long-short portfolios across the three age buckets. The results show a different pattern for accounting and market anomalies. For accounting anomalies, transaction cost frictions reduce the returns to

fresh constituents. The fresh accounting portfolio incurs a high trading cost of 0.43% per month, lowering the net long-short return to a statistically significant -0.56% ($t = -4.29$). Conversely, the portfolio of stale accounting constituents incurs a much smaller cost of 0.03% per month and has a positive, though statistically insignificant, net return of 0.06% per month. This pattern suggests that, for discrete fundamental updates, the high-turnover Fresh portfolio is penalized by market microstructure frictions, while continuing accounting positions are less affected by rebalancing costs.

The transaction cost analysis shows a different calculus for market anomalies. Refreshing fresh market constituents is costly: the fresh market portfolio incurs a trading cost of 0.40% per month due to elevated turnover.[12] However, the gross predictive power of these fresh entrants is large enough (0.98% per month) that even after absorbing this trading cost, the fresh market portfolio yields a statistically and economically significant net return of 0.58% per month ($t = 2.37$).

In contrast, the stale market portfolio generates a gross return of only 0.06%, despite benefiting from a low transaction cost of 0.06% per month. Consequently, the net return of holding stale market constituents drops to a statistically insignificant -0.01% ($t = 0.05$). This finding is consistent with the staleness-trap interpretation. Novy-Marx and Velikov (2016) show that introducing a buy-hold spread to retain existing positions is an effective cost-mitigation technique for the broader anomaly zoo. However, the present results highlight a boundary condition. For continuous market anomalies, expected returns weaken much faster than the underlying signal rank. Consequently, the conventional practice of retaining aged positions to save on trading costs can lower net performance. In market anomalies, the economically meaningful premium is concentrated near signal entry rather than during prolonged portfolio residence. As a result, delaying trades or retaining aged positions to reduce turnover may preserve the portion of the strategy where expected profits have already weakened.

Taken together, the implementation evidence is consistent with the broader lifecycle interpretation of the paper. The trading-volume evidence suggests that market-anomaly activation is not matched by an immediate broad trading response at entry, which is consistent with the broader interpretation that fresh positions can be harder to absorb. The transaction-cost calculations

[12]The net-return estimate based on this cost may be conservative. Frazzini et al. (2012) analyze nearly a trillion dollars of live trading data and find that actual institutional trading costs are less than a tenth of those implied by standard academic models. Specifically, they report an average market impact of only 19.8 basis points even for small-cap stocks, which are typically the most expensive to trade. If implementation costs for fresh market signals align with these institutional benchmarks, the operational net premium would be larger than the baseline estimate.

then show that refreshing newly activated positions is expensive in practice. Even so, the gross profitability of fresh market positions is large enough to survive effective-spread transaction cost adjustments. Stale market positions, by contrast, are cheaper to maintain yet generate net returns that are statistically indistinguishable from zero. In market anomalies, turnover reduction achieved by retaining aged positions preserves the lowest-return component of the strategy.

7 Conclusion

This paper studies the within-portfolio position lifecycle of cross-sectional return predictors. Standard empirical asset pricing methods implicitly assume that sorting on the current level of a signal is a good proxy for sorting on the current return opportunity. I show that this assumption is less reliable in market anomalies because signal persistence outlasts return persistence. Even when the underlying trading data are current, standard portfolio rules can retain aged positions whose economically relevant premiums have largely dissipated.

Using Signal Age to decompose currently formed anomaly portfolios, I show that aged market continuers occupy a large fraction of portfolio capital while generating little incremental return. Fresh entrants, by contrast, account for a smaller share of capital but generate roughly half of aggregate market-anomaly profits. Standalone age-specific portfolios and standard factor adjustments point to the same conclusion: market-anomaly profitability is concentrated near position activation and weakens as positions continue to reside in the same extreme leg.

The Market–Accounting contrast is important for this interpretation. Accounting continuers are not stale in the same economic sense as aged market positions. For accounting anomalies, middle-aged and stale positions remain profitable, consistent with discrete fundamental information being processed over longer horizons. For market anomalies, predictable fresh entrants continue to earn large returns, indicating that temporal position age contains return information beyond expectational surprise. Together, the diagnostics locate the market freshness premium in newly activated positions that are difficult to absorb. The premium survives observable stock characteristics and aggregate market states, is amplified among stocks that are costly to absorb rather than among stocks that are less closely followed, decays more slowly in event time where trading is thin and the absorbing capital arrives slowly, and rises when risk-bearing capacity is tight.

The within-portfolio lifecycle pattern also has broader asset-pricing and implementation implications. Post-publication attenuation in market anomalies is concentrated more heavily in stale constituents, so the remaining predictive content after publication is relatively more tied to newly activated positions. Fresh market portfolios provide the largest incremental contribution to the maximum Sharpe ratio of standard factor models, with middle-aged and stale market portfolios adding progressively less. Trading activity also evolves over the position lifecycle. Finally, although fresh market positions are more expensive to trade, their higher gross returns survive effective-spread transaction cost adjustments, while stale market positions generate net returns that are statistically indistinguishable from zero.

Overall, the results show that the continuous updating of market data does not by itself guarantee economically fresh positions. Incorporating Signal Age into portfolio construction helps resolve the mechanical dilution created by aged constituents and provides a more precise way to measure how expected returns evolve across positions inside the current portfolio. More broadly, the paper suggests that future work on anomaly implementation should pay closer attention not only to when data arrive, but also to how long currently held positions remain economically active after entering the portfolio.

References

Adrian, Tobias, Erkko Etula, and Tyler Muir, 2014, Financial intermediaries and the cross-section of asset returns, *Journal of Finance* 69, 2557–2596.

Ang, Andrew, Robert J Hodrick, Yuhang Xing, and Xiaoyan Zhang, 2006, The cross-section of volatility and expected returns, *The journal of finance* 61, 259–299.

Baba-Yara, Fahiz, Martijn Boons, and Andrea Tamoni, 2024, Persistent and transitory components of firm characteristics: Implications for asset pricing, *Journal of Financial Economics* 154, 103808.

Barillas, Francisco, Raymond Kan, Cesare Robotti, and Jay Shanken, 2020, Model comparison with sharpe ratios, *Journal of Financial and Quantitative Analysis* 55, 1840–1874.

Barillas, Francisco, and Jay Shanken, 2018, Comparing asset pricing models, *The Journal of Finance* 73, 715–754.

Berk, Jonathan B, 2000, Sorting out sorts, *The Journal of Finance* 55, 407–427.

Boguth, Oliver, Murray Carlson, Adlai Fisher, and Mikhail Simutin, 2011, Conditional risk and performance evaluation: Volatility timing, overconditioning, and new estimates of momentum alphas, *Journal of Financial Economics* 102, 363–389.

Bowles, Boone, Adam V Reed, Matthew C Ringgenberg, and Jacob R Thornock, 2024, Anomaly time, *The Journal of Finance* 79, 3543–3579.

Bowles, Boone, Adam V Reed, Matthew C Ringgenberg, and Jake Thornock, 2026, Predicting anomalies, *Available at SSRN 4939779* .

Carhart, Mark M, 1997, On persistence in mutual fund performance, *The Journal of finance* 52, 57–82.

Chen, Andrew Y, and Mihail Velikov, 2023, Zeroing in on the expected returns of anomalies, *Journal of Financial and Quantitative Analysis* 58, 968–1004.

Chen, Andrew Y., and Tom Zimmermann, 2022, Open source cross-sectional asset pricing, *Critical Finance Review* 11, 207–264.

Chordia, Tarun, Avanidhar Subrahmanyam, and Qing Tong, 2014, Have capital market anomalies attenuated in the recent era of high liquidity and trading activity?, *Journal of Accounting and Economics* 58, 41–58.

Cochrane, John H, 2011, Presidential address: Discount rates, *The Journal of finance* 66, 1047–1108.

Cooper, Michael, Huseyin Gulen, and Mihai Ion, 2024, The use of asset growth in empirical asset pricing models, *Journal of Financial Economics* 151, 103746.

Cooper, Michael J., Roberto C. Gutierrez, and Allaudeen Hameed, 2004, Market States and Momentum, *The Journal of Finance* 59, 1345–1365.

Duffie, Darrell, 2010, Presidential Address: Asset Price Dynamics with Slow-Moving Capital, *The Journal of Finance* 65, 1237–1267.

Duffie, Darrell, Nicolae Gârleanu, and Lasse Heje Pedersen, 2007, Valuation in Over-the-Counter Markets, *The Review of Financial Studies* 20, 1865–1900.

Ehsani, Sina, Serhiy Kozak, and Juhani T Linnainmaa, 2025, Time-series efficient factors, *Available at SSRN 3555473* .

Ehsani, Sina, and Juhani T Linnainmaa, 2022, Factor momentum and the momentum factor, *Journal of Finance* 77, 1877–1919.

Engelberg, Joseph, R David McLean, and Jeffrey Pontiff, 2018, Anomalies and news, *The Journal of Finance* 73, 1971–2001.

Fama, Eugene F., and Kenneth R. French, 1993, Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics* 33, 3–56.

Fama, Eugene F, and Kenneth R French, 2008, Dissecting anomalies, *The journal of finance* 63, 1653–1678.

Fama, Eugene F, and Kenneth R French, 2015, A five-factor asset pricing model, *Journal of financial economics* 116, 1–22.

Fama, Eugene F, and James D MacBeth, 1973, Risk, return, and equilibrium: Empirical tests, *Journal of political economy* 81, 607–636.

Ferson, Wayne E, and Andrew F Siegel, 2001, The efficient use of conditioning information in portfolios, *The Journal of Finance* 56, 967–982.

Frazzini, Andrea, Ronen Israel, and Tobias J Moskowitz, 2012, Trading costs of asset pricing anomalies, *Fama-Miller Working Paper, Chicago Booth Research Paper* .

Frazzini, Andrea, Ronen Israel, and Tobias J Moskowitz, 2018, Trading costs, *Available at SSRN 3229719* .

Gao, Xiaohui, and Jay R. Ritter, 2010, The marketing of seasoned equity offerings, *Journal of Financial Economics* 97, 33–52.

Gromb, Denis, and Dimitri Vayanos, 2010, Limits of arbitrage: The state of the theory, *Annual Review of Financial Economics* 2, 251–275.

Harvey, Campbell R., Yan Liu, and Heqing Zhu, 2016, ...and the cross-section of expected returns, *Review of Financial Studies* 29, 5–68.

He, Zhiguo, Bryan Kelly, and Asaf Manela, 2017, Intermediary asset pricing: New evidence from many asset classes, *Journal of Financial Economics* 126, 1–35.

Hirshleifer, David, Sonya Seongyeon Lim, and Siew Hong Teoh, 2009, Driven to distraction: Extraneous events and underreaction to earnings news, *The journal of finance* 64, 2289–2325.

Hong, Harrison, Terence Lim, and Jeremy C. Stein, 2000, Bad news travels slowly: Size, analyst coverage, and the profitability of momentum strategies, *Journal of Finance* 55, 265–295.

Hou, Kewei, Chen Xue, and Lu Zhang, 2015, Digesting anomalies: An investment approach, *Review of Financial Studies* 28, 650–705.

Hou, Kewei, Chen Xue, and Lu Zhang, 2020, Replicating anomalies, *Review of Financial Studies* 33, 2019–2133.

Jegadeesh, Narasimhan, and Sheridan Titman, 1993, Returns to buying winners and selling losers: Implications for stock market efficiency, *The Journal of finance* 48, 65–91.

Lehmann, Bruce N, 1990, Fads, martingales, and market efficiency, *The Quarterly Journal of Economics* 105, 1–28.

McLean, R. David, and Jeffrey Pontiff, 2016, Does academic research destroy stock return predictability?, *Journal of Finance* 71, 5–32.

Mitchell, Mark, Lasse Heje Pedersen, and Todd Pulvino, 2007, Slow Moving Capital, *American Economic Review* 97, 215–220.

Nagel, Stefan, 2012, Evaporating Liquidity, *Review of Financial Studies* 25, 2005–2039.

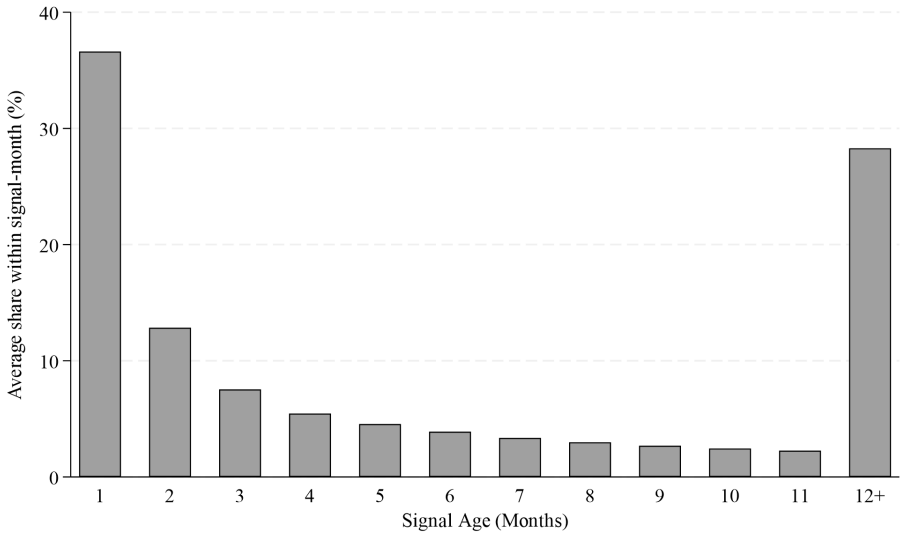
Novy-Marx, Robert, and Mihail Velikov, 2016, A taxonomy of anomalies and their trading costs, *The Review of Financial Studies* 29, 104–147.

Pástor, L'uboš, and Robert F Stambaugh, 2003, Liquidity risk and expected stock returns, *Journal of Political economy* 111, 642–685.

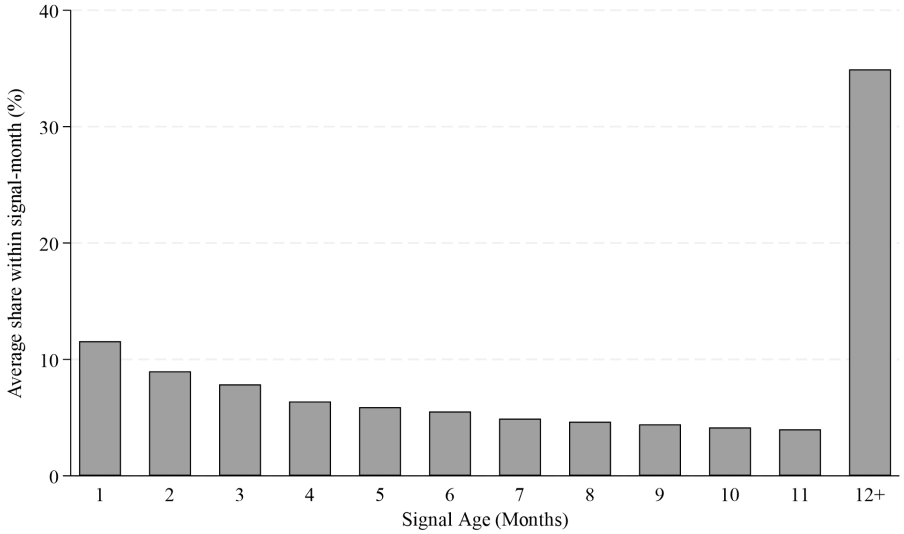
Pénasse, Julien, 2022, Understanding alpha decay, *Management Science* 68, 3966–3973.

Shleifer, Andrei, and Robert W. Vishny, 1997, The limits of arbitrage, *Journal of Finance* 52, 35–55.

Zhou, Yi, 2025, Anomalies and Cash Flows, *SSRN Electronic Journal* .



(a) Market Anomalies



(b) Accounting Anomalies

Figure 1: **Age Distribution of Anomaly Signals**
This figure plots the empirical distribution of signal age for market-based and accounting-based anomalies. Panel (a) reports the distribution for market anomalies, while Panel (b) reports the distribution for accounting anomalies. Signal age is defined as the number of consecutive months a stock has remained in the extreme long or short decile of an anomaly portfolio. The horizontal axis represents the age buckets, ranging from a fresh entrant (1 month) to an aggregated bucket for stale continuers (12 months or more). To prevent anomalies with a larger cross-section of available stocks from mechanically dominating the distribution, the proportion of stocks in each age bucket is first calculated equally within each signal-month, and then averaged across all available months and signals within each respective anomaly group. The sample period spans from 1960 to 2024.

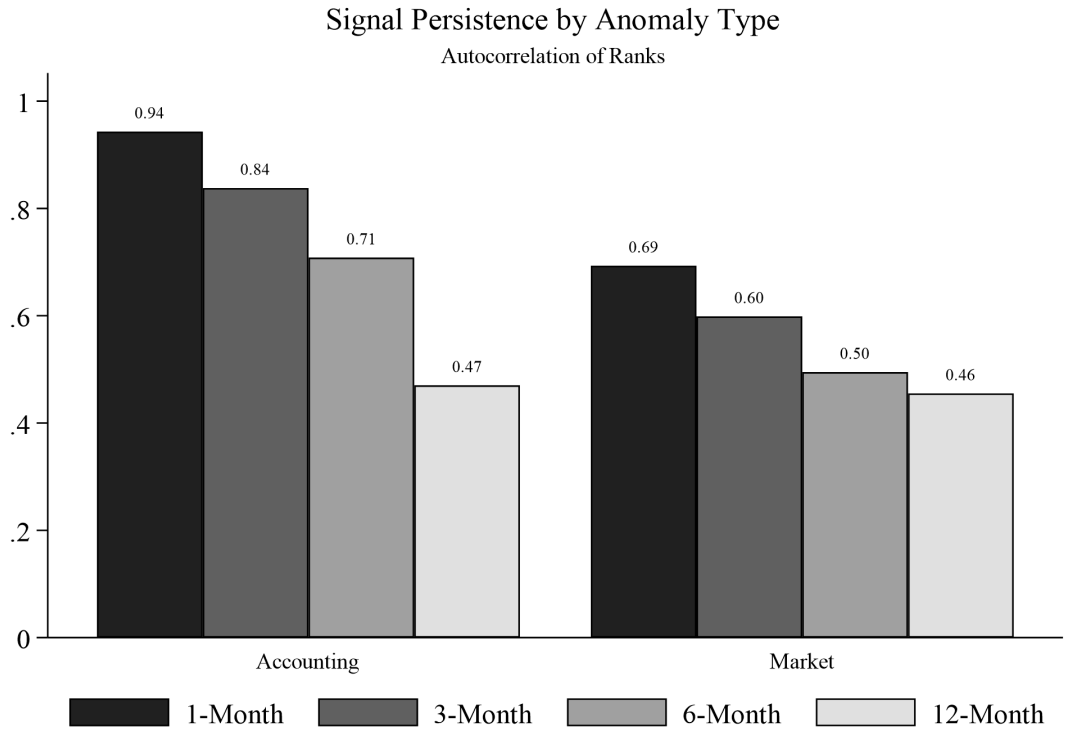
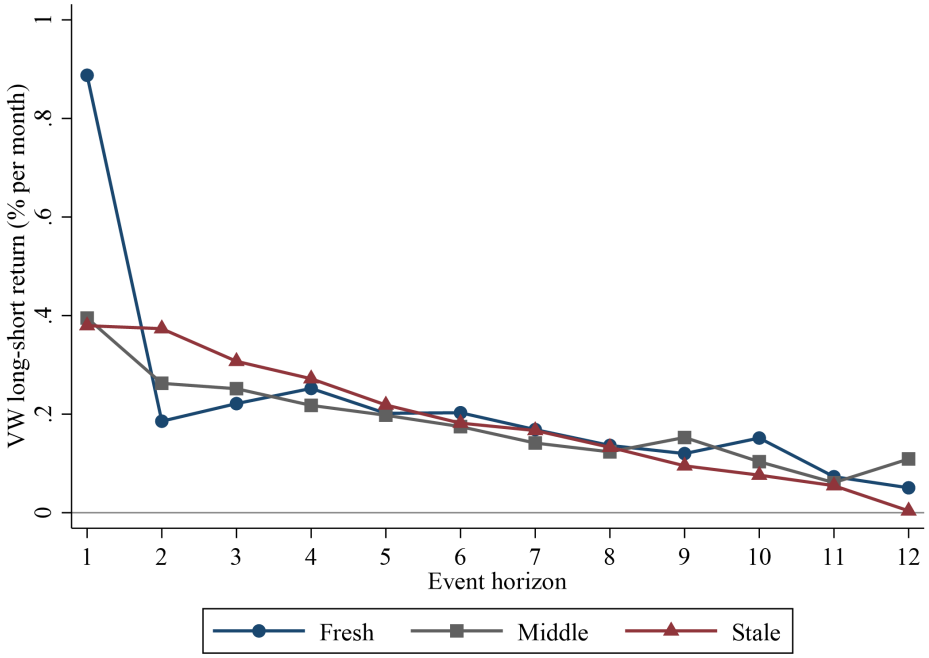
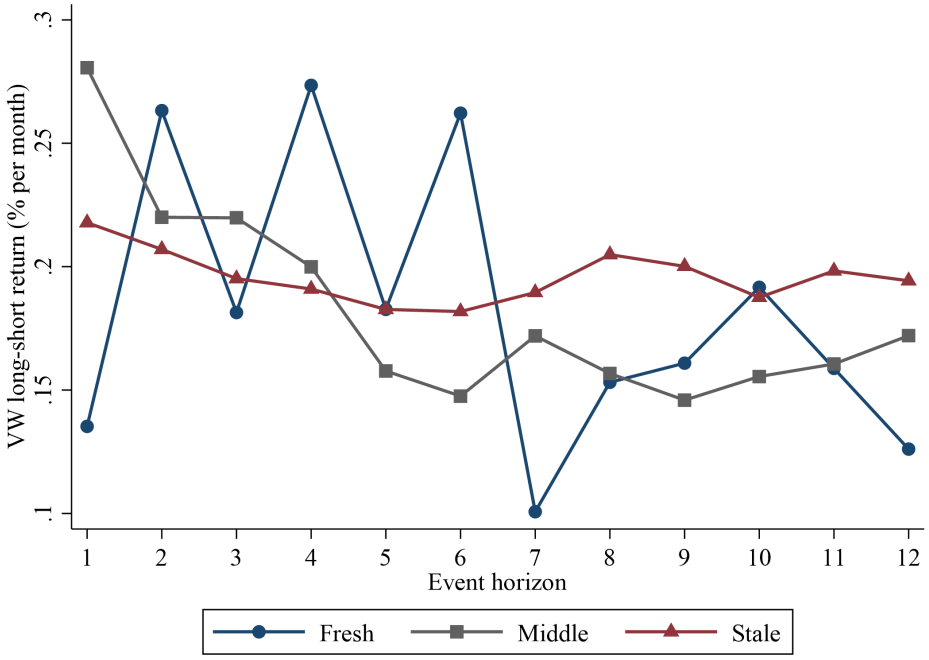


Figure 2: **Signal Persistence by Anomaly Type**
This figure presents the signal persistence for market-based and accounting-based anomalies over different time horizons. Persistence is measured using the rank autocorrelation of the underlying sorting variables. For each anomaly signal, the cross-sectional correlation between a stock's signal rank in month t and its rank in months $t-1$, $t-3$, $t-6$, and $t-12$ is computed. The bars represent the cross-sectional average of these autocorrelation coefficients across all 55 market anomalies and 91 accounting anomalies, respectively.

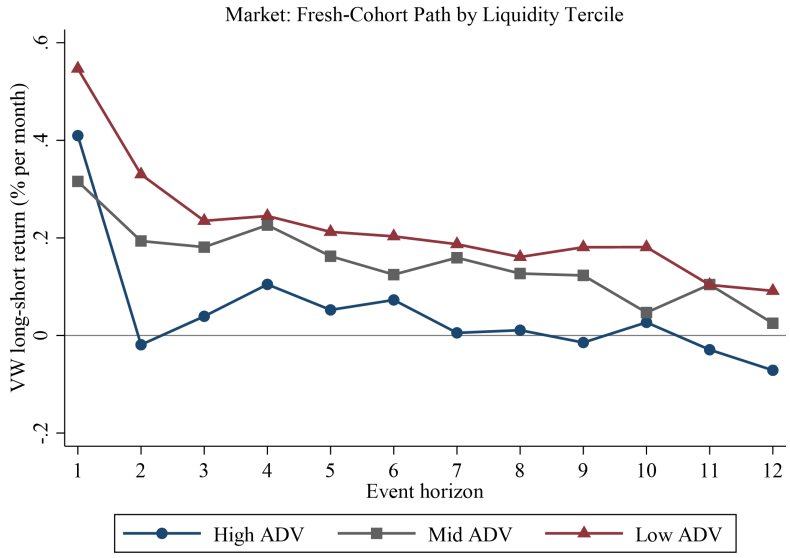


(a) Market Anomalies

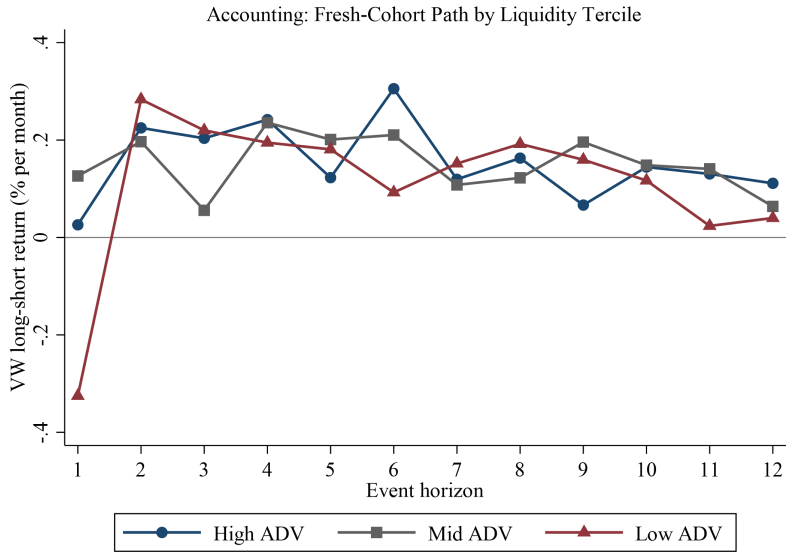


(b) Accounting Anomalies

Figure 3: **Event-Time Returns after Position Activation**
This figure plots value-weighted event-time returns for age-bucket portfolios after formation. At horizon 1, portfolios are formed using the same age-bucket definitions as in the standalone return analysis. The formation portfolio is then held fixed for horizons 2 through 12 without conditioning on future anomaly membership. Panel (a) reports market anomalies and Panel (b) reports accounting anomalies. Returns are monthly long-short returns in percent.



(a) Market Anomalies



(b) Accounting Anomalies

Figure 4: **Event-Time Decay of the Fresh Cohort by Liquidity**
This figure plots value-weighted event-time returns for Fresh formation cohorts split by the liquidity of their constituents at formation, using the formation-cohort design of Figure 3. For each signal and month, the Fresh long-short portfolio is formed at horizon 1, its constituents are divided into within-month terciles of lagged average daily dollar volume, and each tercile portfolio is held fixed with its formation weights through horizon 12. Average daily dollar volume is the prior month's dollar volume per trading day, with NASDAQ volume adjusted for interdealer double counting following Gao and Ritter (2010). Panel (a) reports market anomalies and Panel (b) reports accounting anomalies, and returns are monthly long-short returns in percent. In Panel (a), the most liquid tercile is significant only in the formation month while the least liquid tercile is significant at all twelve horizons. Panel (b) shows no formation-month concentration in any tercile.

Table 1: **Summary Statistics and Extreme-Leg Persistence**
This table reports summary statistics for monthly anomaly returns, constituent signal age, and the persistence of extreme-leg portfolio membership. Panels A and B report value-weighted (VW) and equal-weighted (EW) returns and signal ages for market and accounting anomalies. Signal Age is the number of consecutive months a stock has remained in the same extreme long or short decile of a given anomaly portfolio. Panel C reports the conditional probability that a stock remains in the same extreme long or short leg in month t, conditional on being in that same leg in month $t-1$. The sample includes 55 market anomalies and 91 accounting anomalies constructed from the Open Source Asset Pricing database and spans 1960 to 2024.

Panel A: Market Anomalies

	Count	Mean	SD	p10	p90
Returns (VW, %)	40,009	0.40	5.08	-4.86	5.81
Returns (EW, %)	40,009	0.41	4.40	-3.85	4.82
Signal Age (VW)	40,009	17.08	30.08	1.13	43.59
Signal Age (EW)	40,009	12.69	19.31	1.20	30.79

Panel B: Accounting Anomalies

	Count	Mean	SD	p10	p90
Returns (VW, %)	63,723	0.25	3.92	-4.08	4.54
Returns (EW, %)	63,723	0.36	3.19	-2.83	3.57
Signal Age (VW)	63,723	25.30	29.23	5.60	58.87
Signal Age (EW)	63,723	16.33	14.21	5.71	34.65

Panel C: Extreme-Leg Transition Probabilities

	Long: Prob(Stay)	Short: Prob(Stay)
Market	0.725	0.643
Accounting	0.903	0.906
Total	0.810	0.799

Table 2: **Portfolio Decomposition By Age Bucket**
This table presents the decomposition of the anomaly returns by signal age. For each anomaly and month, stocks in the extreme deciles are classified into three mutually exclusive buckets: Fresh (1 month), Middle (2 to 6 months), and Stale (more than 6 months). The table reports the additive contribution of each age bucket to the total value-weighted Long-Short (LS) portfolio returns. Additionally, it reports the percentage of total profits (Profit%) generated by each bucket and the percentage of total market capitalization (Cap%) allocated to it. The final column reports the difference between the Fresh bucket and the corresponding row bucket. t-statistics, computed using Newey-West standard errors with six lags, are reported in parentheses. The sample period spans from 1960 to 2024.

Panel A: Market Anomalies

	LS Contrib (%)	Profit%	Cap%	Count (N)	Fresh − Bucket (%)
Fresh (1m)	0.20	50.50	37.48	247	–
	(10.88)				
Middle (2-6m)	0.17	41.12	29.59	239	0.04
	(8.66)				(2.27)
Stale (>6m)	0.03	8.38	32.93	270	0.17
	(1.26)				(5.65)

Panel B: Accounting Anomalies

	LS Contrib (%)	Profit%	Cap%	Count (N)	Fresh − Bucket (%)
Fresh (1m)	0.05	18.90	9.31	59	–
	(6.00)				
Middle (2-6m)	0.10	38.34	30.03	177	-0.05
	(6.40)				(-3.75)
Stale (>6m)	0.11	42.76	60.66	291	-0.06
	(3.35)				(-1.96)

Table 3: **Portfolio Returns By Age Bucket**
This table reports the standalone performance of anomaly portfolios constructed exclusively from stocks within specific signal age buckets. To construct these portfolios, for each individual anomaly, month, and extreme portfolio leg (long and short), stocks are grouped into three signal age buckets: Fresh (1 month), Middle (2 to 6 months), and Stale (more than 6 months). Sub-portfolios are then formed at this intersection. Unlike the additive return contributions in Table 2, the weights of the constituent stocks within each sub-portfolio are rescaled to sum to 100%. The table presents the time-series average of the monthly returns for the value-weighted long-short (LS) portfolios across market anomalies (Panel A) and accounting anomalies (Panel B). The table also reports the time-series average and median of the portfolio market capitalization (in millions of dollars) and the number of constituent stocks. The final column reports the difference between the Fresh bucket and the corresponding row bucket. t-statistics, computed using Newey-West standard errors with six lags, are reported in parentheses. The sample period spans from 1960 to 2024.

Panel A: Market Anomalies

	LS Ret (%)	Avg MktCap ($M)	Med MktCap ($M)	Count (N)	Fresh − Bucket (%)
Fresh (1m)	0.89	2,742	884	251	–
	(8.92)				
Middle (2-6m)	0.39	2,767	926	244	0.49
	(6.75)				(4.36)
Stale (>6m)	0.31	5,943	2,269	370	0.57
	(5.14)				(5.47)

Panel B: Accounting Anomalies

	LS Ret (%)	Avg MktCap ($M)	Med MktCap ($M)	Count (N)	Fresh − Bucket (%)
Fresh (1m)	0.13	1,956	384	63	–
	(1.90)				
Middle (2-6m)	0.28	2,470	461	179	-0.14
	(6.28)				(-2.31)
Stale (>6m)	0.21	3,946	919	297	-0.08
	(4.40)				(-1.13)

Table 4: **Risk Adjustment (Fama-French 5-Factor + Momentum)**
This table reports the risk-adjusted performance (alphas) and factor loadings (betas) for the anomaly portfolios conditionally sorted by signal age. For each anomaly and month, stocks are sorted into Fresh (1 month), Middle (2 to 6 months), and Stale (more than 6 months) age buckets. The table presents the time-series regression results of the value-weighted long-short monthly portfolio returns on the Fama-French five factors (MKT, SMB, HML, RMW, CMA) augmented with the momentum factor (UMD). Panel A reports the results for market anomalies, and Panel B reports the results for accounting anomalies. t-statistics, computed using Newey-West standard errors with six lags, are reported in parentheses. The sample period spans from 1960 to 2024.

Panel A: Market Anomalies

	Fresh (1m)	Middle (2-6m)	Stale (>6m)
Alpha	0.75***	0.26***	0.15***
	(7.42)	(5.75)	(3.80)
MKT	-0.01	-0.07***	-0.10***
	(-0.66)	(-5.96)	(-8.16)
SMB	0.12***	0.06**	0.10***
	(4.20)	(2.42)	(4.60)
HML	0.15***	0.13***	0.17***
	(3.68)	(4.35)	(6.47)
RMW	0.07**	0.08***	0.09***
	(2.06)	(2.93)	(4.28)
CMA	0.02	0.10**	0.11***
	(0.25)	(2.24)	(2.76)
UMD	0.13***	0.13***	0.17***
	(7.40)	(10.12)	(12.58)
Adj. R^2	0.14	0.36	0.56

Panel B: Accounting Anomalies

	Fresh (1m)	Middle (2-6m)	Stale (>6m)
Alpha	0.04	0.23***	0.08***
	(0.66)	(7.68)	(3.27)
MKT	-0.00	-0.03***	-0.02***
	(-0.07)	(-3.34)	(-3.12)
SMB	0.03	0.05***	0.03**
	(1.44)	(3.13)	(2.01)
HML	0.18***	0.14***	0.16***
	(5.91)	(7.88)	(10.76)
RMW	0.06*	0.06***	0.11***
	(1.89)	(2.96)	(6.85)
CMA	0.16***	0.16***	0.22***
	(3.04)	(7.20)	(10.71)
UMD	-0.04**	-0.06***	-0.00
	(-2.20)	(-5.92)	(-0.40)
Adj. R^2	0.20	0.52	0.67

Table 5: **Stock Characteristics by Signal Age**
This table reports the characteristics of stocks in Fresh, Middle, and Stale age buckets. For each anomaly and month, stocks in the extreme long and short legs are grouped by signal age using the same classification as in the standalone portfolio analysis. Characteristics are measured before portfolio formation. Market capitalization and dollar volume are in millions of dollars. Realized volatility is computed from lagged daily returns within the prior month and annualized in percent. Effective spread is measured from WRDS Intraday Indicators and is available from 2001 to 2024. The last two columns report Newey–West tests of the difference between Fresh and the corresponding age bucket using six lags.

Panel A: Market Anomalies

	Fresh	Middle	Stale	Fresh − Middle	Fresh − Stale
Avg MktCap ($M)	2,742	2,767	5,943	-22	-3,182
				(-0.36)	(-4.62)
Price ($)	41.40	47.68	120.57	-6.27	-79.13
				(-2.70)	(-5.68)
Realized Vol. (%)	47.46	45.78	41.65	1.70	5.93
				(10.98)	(14.90)
Dollar Volume ($M)	554.78	539.70	923.80	15.79	-364.73
				(0.43)	(-5.73)
Eff. Spread (%)	1.03	0.96	0.96	0.08	0.07
				(9.34)	(4.71)

Panel B: Accounting Anomalies

	Fresh	Middle	Stale	Fresh − Middle	Fresh − Stale
Avg MktCap ($M)	1,956	2,470	3,946	-511	-1,977
				(-6.68)	(-7.88)
Price ($)	25.89	31.03	38.59	-5.18	-12.84
				(-4.85)	(-9.66)
Realized Vol. (%)	51.94	45.38	39.98	6.59	12.14
				(14.03)	(16.94)
Dollar Volume ($M)	358.56	449.99	669.99	-90.97	-308.68
				(-5.53)	(-6.89)
Eff. Spread (%)	1.23	0.97	0.80	0.26	0.43
				(10.47)	(10.49)

Table 6: **Freshness versus Expectational Surprise**
This table investigates whether the premium associated with fresh anomaly signals is driven by expectational surprise. For each anomaly and month, stocks that newly enter the extreme decile (Fresh signals, age = 1) are further sorted into terciles based on the magnitude of their expectational surprise, defined as the change of the signal's rank. The table reports the time-series average of the value-weighted monthly long-short (LS) returns for these surprise-sorted sub-portfolios across market anomalies and accounting anomalies. The table also reports the average and median market capitalization (in millions of dollars), the number of constituent stocks, and the average expectational surprise for each group. t-statistics, computed using Newey-West standard errors with six lags, are reported in parentheses. The sample period spans from 1960 to 2024.

Panel A: Market Anomalies (Fresh Only)

	LS Ret (%)	Avg MktCap ($M)	Med MktCap ($M)	Count (N)	Avg Surp
Low_Surprise	1.09	3,304	1,137	89	0.0751
	(7.73)				
Mid_Surprise	0.74	3,063	1,107	86	0.1937
	(8.30)				
High_Surprise	0.85	2,066	833	94	0.4033
	(7.33)				

Panel B: Accounting Anomalies (Fresh Only)

	LS Ret (%)	Avg MktCap ($M)	Med MktCap ($M)	Count (N)	Avg Surp
Low_Surprise	-0.35	2,227	524	28	0.0378
	(-3.45)				
Mid_Surprise	-0.10	2,494	635	24	0.1545
	(-1.31)				
High_Surprise	0.44	1,666	472	30	0.4359
	(6.25)				

Table 7: **Freshness Premium Across Aggregate Market States**
This table reports the profitability of anomaly portfolios conditionally sorted by signal age across different macroeconomic states. Following Cooper et al. (2004), we define an UP (DOWN) market state if the cumulative return on the CRSP value-weighted index over the 36, 12, or 6 months prior to the portfolio formation is non-negative (negative). The table presents the time-series average of the value-weighted long-short (LS) monthly returns across the Fresh (1 month), Middle (2 to 6 months), and Stale (more than 6 months) age buckets. Panel A reports the results for Market anomalies, and Panel B reports the results for Accounting anomalies. t-statistics, computed using Newey-West standard errors with six lags, are reported in parentheses. The sample period spans from 1960 to 2024.

	36-Month State	**12-Month State**	**6-Month State**
	LS Ret (%)	LS Ret (%)	LS Ret (%)
Panel A: Market Anomalies			
UP Market			
Fresh (1m)	0.90	0.95	0.94
	(8.18)	(7.85)	(7.36)
Middle (2-6m)	0.39	0.39	0.33
	(6.39)	(6.60)	(5.47)
Stale (>6m)	0.32	0.32	0.30
	(5.28)	(5.93)	(5.26)
DOWN Market			
Fresh (1m)	0.81	0.68	0.75
	(4.27)	(4.62)	(5.65)
Middle (2-6m)	0.41	0.41	0.56
	(2.24)	(2.96)	(4.49)
Stale (>6m)	0.21	0.28	0.33
	(0.89)	(1.77)	(2.27)
Panel B: Accounting Anomalies			
UP Market			
Fresh (1m)	0.12	0.07	0.07
	(1.63)	(0.88)	(0.83)
Middle (2-6m)	0.27	0.26	0.23
	(5.52)	(5.53)	(4.91)
Stale (>6m)	0.20	0.16	0.15
	(3.87)	(3.17)	(2.95)
DOWN Market			
Fresh (1m)	0.23	0.34	0.31
	(1.10)	(2.57)	(2.30)
Middle (2-6m)	0.38	0.36	0.42
	(3.52)	(3.60)	(3.98)
Stale (>6m)	0.31	0.38	0.39
	(2.69)	(3.80)	(3.70)

Table 8: **Attention, Absorption Frictions, and Stock-Level Freshness**
This table reports stock-level predictive regressions testing whether the return associated with fresh anomaly exposure varies with attention proxies and with markers of the cost of absorbing newly activated positions. The sample consists of stock-months that appear in the extreme leg of at least one anomaly portfolio, and the dependent variable is the monthly stock return in percent. Net Fresh (Mkt) is the signed count of fresh market-anomaly exposure: the number of market-anomaly signals for which the stock newly enters an extreme long leg minus the number for which it newly enters an extreme short leg. Net Fresh (Acct) is defined analogously for accounting anomalies, and Net Total is the signed count of all active extreme-leg anomaly signals. Low Coverage and Low IO are bottom-tercile indicators of analyst coverage from I/B/E/S and of institutional ownership from Thomson 13F, each residualized within month against size and dollar volume. Small and Low Volume indicate membership in the bottom tercile of lagged market capitalization and of lagged dollar volume within each month. All regressions are unweighted stock-month OLS and include size, momentum, short-term reversal, dollar volume, firm fixed effects, and date fixed effects, with standard errors double clustered by firm and month reported in parentheses. In the interaction rows, Proxy denotes the variable named in the column heading. The attention columns cover fewer stock-months than the absorption-cost columns because analyst coverage and institutional ownership are available only for the subset of firms matched to I/B/E/S and Thomson 13F. The baseline market-freshness coefficient is positive and significant in every column, including in this smaller attention sample.

	Dependent variable: monthly stock return (%)			
	Attention and Monitoring		Absorption Frictions	
	(1)	(2)	(3)	(4)
	Low Coverage	Low IO	Small	Low Volume
Net Fresh (Mkt)	0.1950***	0.1819***	0.0718***	0.0492***
	(0.0197)	(0.0173)	(0.0136)	(0.0152)
Net Fresh (Mkt) × Proxy	-0.0138	0.0242	0.2818***	0.3432***
	(0.0161)	(0.0195)	(0.0188)	(0.0203)
Net Fresh (Acct)	-0.2187***	-0.0833***	-0.0624***	-0.1519***
	(0.0242)	(0.0171)	(0.0167)	(0.0217)
Net Fresh (Acct) × Proxy	-0.0011	-0.3277***	-0.2390***	-0.0752***
	(0.0251)	(0.0307)	(0.0242)	(0.0252)
Net Total	0.0305***	0.0292***	0.0312***	0.0336***
	(0.0044)	(0.0042)	(0.0036)	(0.0036)
Firm Controls	Yes	Yes	Yes	Yes
Firm & Date FEs	Yes	Yes	Yes	Yes
Observations	1,690,070	1,754,503	2,168,414	2,168,414
Adj. R^2	0.1506	0.1522	0.1688	0.1687

Table 9: **Aggregate Stress and Stock-Level Freshness**
This table reports unweighted stock-month predictive regressions for the anomaly-active universe. The dependent variable is the monthly stock return in percent. Column (1) is the no-interaction baseline; columns (2)–(6) interact the fresh market and accounting scores with one standardized stress proxy at a time: VIX, TED, Pástor–Stambaugh liquidity stress (PS), He–Kelly–Manela intermediary capital stress (HKM), and Adrian–Etula–Muir broker-dealer leverage stress (AEM). All regressions include Net Total, size, momentum, short-term reversal, dollar volume, firm fixed effects, and date fixed effects. Standard errors are double clustered by firm and month and reported in parentheses. In the interaction rows, Stress Proxy denotes the standardized variable named in the column heading.

	Dependent variable: monthly stock return (%)					
	No Interaction	Aggregate Stress Proxy				
	(1) Baseline	(2) VIX	(3) TED	(4) PS	(5) HKM	(6) AEM
Net Fresh (Mkt)	0.1897***	0.2003***	0.2109***	0.1916***	0.2007***	0.1965***
	(0.0156)	(0.0205)	(0.0197)	(0.0158)	(0.0174)	(0.0172)
Net Fresh (Mkt) × Stress Proxy		0.0484***	0.0283**	0.0405***	0.0572***	0.0339***
		(0.0182)	(0.0140)	(0.0140)	(0.0126)	(0.0121)
Net Fresh (Acct)	-0.1808***	-0.2390***	-0.2110***	-0.1802***	-0.1683***	-0.1656***
	(0.0191)	(0.0278)	(0.0250)	(0.0195)	(0.0206)	(0.0198)
Net Fresh (Acct) × Stress Proxy		-0.0724***	-0.0055	0.0111	-0.0071	-0.0061
		(0.0254)	(0.0223)	(0.0226)	(0.0184)	(0.0197)
Net Total	0.0326***	0.0250***	0.0261***	0.0320***	0.0283***	0.0290***
	(0.0036)	(0.0052)	(0.0048)	(0.0036)	(0.0038)	(0.0038)
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm & Date FEs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,168,414	1,391,198	1,495,721	2,138,670	1,815,173	1,819,637
Adj. R^2	0.1678	0.1475	0.1494	0.1672	0.1664	0.1694

Table 10: **Post-Publication Decay and Freshness**
This table presents anomaly-level panel regressions evaluating the interaction between freshness and post-publication decay. The dependent variables are the additive contribution return (Contrib) and the standalone return (Stand). Post Pub is an indicator variable equal to one if the current month is subsequent to the original publication year of the respective anomaly. The stale age bucket serves as the omitted base group. Because the specification is fully interacted, age-specific post-publication effects are linear combinations of the reported coefficients. Standard errors are two-way clustered by date and the intersection of anomaly and age bucket, and are reported in parentheses. The sample period spans from 1960 to 2024.

	(1) Contrib	(2) Contrib	(3) Stand	(4) Stand
Post Pub	-0.067	-0.066	-0.004	0.000
	(0.046)	(0.046)	(0.107)	(0.106)
Market × Post Pub	0.007	0.003	-0.365**	-0.371**
	(0.061)	(0.061)	(0.160)	(0.158)
Fresh × Market	0.232***	0.196***	0.262	0.184
	(0.057)	(0.053)	(0.185)	(0.213)
Fresh × Market × Post Pub	-0.071	-0.058	0.907**	0.929**
	(0.094)	(0.094)	(0.445)	(0.437)
Middle × Market	0.150***	0.133***	-0.021	-0.095
	(0.048)	(0.048)	(0.150)	(0.162)
Middle × Market × Post Pub	-0.078	-0.074	0.160	0.180
	(0.075)	(0.075)	(0.161)	(0.160)
Fresh × Post Pub	0.126**	0.126**	-0.060	-0.078
	(0.052)	(0.053)	(0.261)	(0.254)
Middle × Post Pub	0.139***	0.140***	-0.040	-0.037
	(0.050)	(0.050)	(0.084)	(0.084)
Signal Rank (Level)		0.062*		0.296
		(0.032)		(0.193)
Signal Rank (Change)		0.253**		-0.491
		(0.102)		(0.638)
Anomaly FEs	Yes	Yes	Yes	Yes
Age Bucket FEs	Yes	Yes	Yes	Yes
Date FEs	Yes	Yes	Yes	Yes
Observations	311,196	311,196	311,196	311,196

Table 11: **Mean-Variance Contribution of Age-Bucket Portfolios**
This table reports the increase in the maximum squared Sharpe ratio, $\Delta(\max SR^2)$, obtained by augmenting standard benchmark models with age-specific anomaly factors. For each anomaly and month, I first construct value-weighted standalone long-short returns for the Fresh (1 month), Middle (2 to 6 months), and Stale (more than 6 months) age buckets, and then average these returns across anomalies separately for market anomalies and accounting anomalies. The table compares three baseline models: the Fama-French three-factor model (FF3), FF3 augmented with the momentum factor (FF3+UMD), and the Fama-French five-factor model augmented with momentum (FF5+UMD). Panel A reports the results for market anomalies, and Panel B reports the results for accounting anomalies. Following the traded-factor model comparison logic of Barillas and Shanken (2018) and Barillas et al. (2020), statistical significance is assessed using the alpha-based test for the added factor relative to the corresponding benchmark model. t-statistics are reported in parentheses. The sample period spans from 1960 to 2024.

Panel A: Market Anomalies

	FF3	FF3+UMD	FF5+UMD
Fresh	0.225***	0.188***	0.178***
	(9.10)	(8.25)	(7.42)
Middle	0.098***	0.063***	0.048***
	(8.46)	(7.15)	(5.75)
Stale	0.072***	0.035***	0.021***
	(7.27)	(5.37)	(3.80)

Panel B: Accounting Anomalies

	FF3	FF3+UMD	FF5+UMD
Fresh	0.002	0.003	0.001
	(1.00)	(1.38)	(0.66)
Middle	0.082***	0.121***	0.093***
	(7.82)	(8.93)	(7.68)
Stale	0.045***	0.041***	0.015***
	(5.11)	(5.13)	(3.27)

Table 12: **Trading Activity Across Age Bucket**
This table reports the results of panel regressions examining the relationship between signal age and trading activity. To isolate the intensive margin of signal age, the sample universe for these regressions is restricted to stocks that appear in the extreme leg of at least one anomaly in a given month. The dependent variable is the natural logarithm of trading volume. The independent variables of interest are the gross signal scores for market and accounting anomalies. Unlike the net scores used in return regressions, these gross scores are defined as the absolute total count of active signals within a given age bucket for a firm-month, capturing the aggregate magnitude of anomaly activity regardless of the long or short direction. Column (1) evaluates the impact of Gross Fresh signals while controlling for the Gross Total anomaly score. Column (2) explicitly decomposes the total anomaly activity by including the Gross Fresh, Middle, and Stale scores simultaneously. Standard errors are clustered by firm and month and are reported in parentheses. The sample period spans from 1960 to 2024.

	(1) Trading Volume	(2) Trading Volume
Gross Fresh (Mkt)	0.0002	0.0004
	(0.0004)	(0.0004)
Gross Fresh (Acct)	0.0090***	0.0101***
	(0.0003)	(0.0003)
Gross Middle (Mkt)		0.0012***
		(0.0004)
Gross Middle (Acct)		0.0020***
		(0.0002)
Gross Stale (Mkt)		-0.0077***
		(0.0006)
Gross Stale (Acct)		0.0028***
		(0.0002)
Gross Total (All)	0.0009***	
	(0.0001)	
Controls	Yes	Yes
Firm & Date FEs	Yes	Yes
Observations	2,171,870	2,171,870
Adj. R^2	0.9517	0.9518

Table 13: **Transaction Costs and Net Returns by Age Bucket**
This table reports the net profitability of anomaly portfolios conditionally sorted by signal age after accounting for trading frictions. Gross monthly returns are adjusted using effective bid-ask spreads estimated from WRDS Intraday Indicator data. Specifically, the net return is calculated by subtracting the estimated one-way transaction costs from the gross portfolio return, as formally defined in Equations 13 and 14. The table presents the gross returns, transaction costs, and net returns for the value-weighted Long-Short (LS) portfolios across the Fresh (1 month), Middle (2 to 6 months), and Stale (more than 6 months) age buckets. The table also reports the time-series average and median of the portfolio market capitalization (in millions of dollars) and the number of constituent stocks. t-statistics, computed using Newey-West standard errors with six lags, are reported in parentheses. The sample period spans from 2001 to 2024.

Panel A: Market Anomalies						
	LS Gross (%)	LS Cost (%)	LS Net (%)	Avg MktCap ($M)	Med MktCap ($M)	Count (N)
Fresh (1m)	0.98	0.40	0.58	6,370	2,037	245
	(3.93)	(12.59)	(2.37)			
Middle (2-6m)	0.18	0.19	-0.02	6,391	2,119	226
	(1.36)	(12.63)	(-0.14)			
Stale (>6m)	0.06	0.06	-0.01	13,852	5,265	373
	(0.46)	(11.60)	(-0.05)			
Panel B: Accounting Anomalies						
	LS Gross (%)	LS Cost (%)	LS Net (%)	Avg MktCap ($M)	Med MktCap ($M)	Count (N)
Fresh (1m)	-0.13	0.43	-0.56	4,568	864	66
	(-1.01)	(12.64)	(-4.29)			
Middle (2-6m)	0.12	0.12	0.00	5,755	1,040	192
	(1.77)	(11.41)	(0.07)			
Stale (>6m)	0.09	0.03	0.06	9,011	2,094	332
	(1.17)	(9.29)	(0.73)			

Appendix:
The Staleness Trap in Market Anomalies

A List of Anomalies and Sample Construction

This appendix documents the sample definition: which anomaly signals enter the Market and Accounting groups, and how the classification follows the underlying data source. The list of anomalies used in my analysis is derived from the 212 signals that the Open Source Asset Pricing release used here classifies as predictors, out of 331 characteristics in total (Chen and Zimmermann, 2022). I categorize these signals into two primary groups based on their underlying data sources. Specifically, Panel A presents Market Anomalies, defined as signals falling under the "price" or "trading" categories. Panel B outlines Accounting Anomalies, which consist of signals classified under the "accounting" category.

To avoid issues related to tied ranks during decile sorting, I restrict the sample to continuous signals. Applying these criteria yields a final set of 146 anomalies, comprising 55 market anomalies and 91 accounting anomalies.

Table A1: List of Anomalies

Acronym	**Long Description**	**Authors**	**Year**
Panel A: Market Anomalies			
AnnouncementReturn	Earnings announcement return	Chan, Jegadeesh and Lakonishok	1996
Beta	CAPM beta	Fama and MacBeth	1973
BetaFP	Frazzini-Pedersen Beta	Frazzini and Pedersen	2014
BetaLiquidityPS	Pastor-Stambaugh liquidity beta	Pastor and Stambaugh	2003
BetaTailRisk	Tail risk beta	Kelly and Jiang	2014
betaVIX	Systematic volatility	Ang et al.	2006
BidAskSpread	Bid-ask spread	Amihud and Mendelson	1986
CoskewACX	Coskewness using daily returns	Ang, Chen and Xing	2006
Coskewness	Coskewness	Harvey and Siddique	2000
DolVol	Past trading volume	Brennan, Chordia, Subra	1998
FirmAgeMom	Firm Age - Momentum	Zhang	2006

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Acronym	Long Description	Authors	Year
High52	52 week high	George and Hwang	2004
IdioVol3F	Idiosyncratic risk (3 factor)	Ang et al.	2006
IdioVolAHT	Idiosyncratic risk (AHT)	Ali, Hwang, and Trombley	2003
Illiquidity	Amihud's illiquidity	Amihud	2002
IndMom	Industry Momentum	Grinblatt and Moskowitz	1999
IndRetBig	Industry return of big firms	Hou	2007
IntMom	Intermediate Momentum	Novy-Marx	2012
LRreversal	Long-run reversal	De Bondt and Thaler	1985
MaxRet	Maximum return over month	Bali, Cakici, and Whitelaw	2011
Mom12m	Momentum (12 month)	Jegadeesh and Titman	1993
Mom12mOffSeason	Momentum without the seasonal part	Heston and Sadka	2008
Mom6m	Momentum (6 month)	Jegadeesh and Titman	1993
Mom6mJunk	Junk Stock Momentum	Avramov et al	2007
MomOffSeason	Off season long-term reversal	Heston and Sadka	2008
MomOffSeason06YrPlus	Off season reversal years 6 to 10	Heston and Sadka	2008
MomOffSeason11YrPlus	Off season reversal years 11 to 15	Heston and Sadka	2008
MomOffSeason16YrPlus	Off season reversal years 16 to 20	Heston and Sadka	2008
MomSeason	Return seasonality years 2 to 5	Heston and Sadka	2008
MomSeason06YrPlus	Return seasonality years 6 to 10	Heston and Sadka	2008
MomSeason11YrPlus	Return seasonality years 11 to 15	Heston and Sadka	2008
MomSeason16YrPlus	Return seasonality years 16 to 20	Heston and Sadka	2008
MomSeasonShort	Return seasonality last year	Heston and Sadka	2008
MRreversal	Medium-run reversal	De Bondt and Thaler	1985
Price	Price	Blume and Husic	1973
PriceDelayRsq	Price delay r square	Hou and Moskowitz	2005
PriceDelaySlope	Price delay coeff	Hou and Moskowitz	2005
PriceDelayTstat	Price delay SE adjusted	Hou and Moskowitz	2005
ProbInformedTrading	Probability of Informed Trading	Easley, Hvidkjaer and O'Hara	2002
RealizedVol	Realized (Total) Volatility	Ang et al.	2006
ResidualMomentum	Momentum based on FF3 residuals	Blitz, Huij and Martens	2011
retConglomerate	Conglomerate return	Cohen and Lou	2012
ReturnSkew	Return skewness	Bali, Engle and Murray	2015
ReturnSkew3F	Idiosyncratic skewness (3F model)	Bali, Engle and Murray	2015

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Acronym	Long Description	Authors	Year
ShortInterest	Short Interest	Dechow et al.	2001
Size	Size	Banz	1981
std_turn	Share turnover volatility	Chordia, Subra, Anshuman	2001
STreversal	Short term reversal	Jegadeesh	1990
TrendFactor	Trend Factor	Han, Zhou, Zhu	2016
VolMkt	Volume to market equity	Haugen and Baker	1996
VolSD	Volume Variance	Chordia, Subra, Anshuman	2001
VolumeTrend	Volume Trend	Haugen and Baker	1996
zerotrade12M	Days with zero trades	Liu	2006
zerotrade1M	Days with zero trades	Liu	2006
zerotrade6M	Days with zero trades	Liu	2006

Panel B: Accounting Anomalies

AbnormalAccruals	Abnormal Accruals	Xie	2001
Accruals	Accruals	Sloan	1996
AdExp	Advertising Expense	Chan, Lakonishok and Sougiannis	2001
AM	Total assets to market	Fama and French	1992
AssetGrowth	Asset growth	Cooper, Gulen and Schill	2008
BM	Book to market, original	Stattman	1980
BMdec	Book to market using December ME	Fama and French	1992
BookLeverage	Book leverage (annual)	Fama and French	1992
BPEBM	Leverage component of BM	Penman, Richardson and Tuna	2007
BrandInvest	Brand capital investment	Belo, Lin and Vitorino	2014
Cash	Cash to assets	Palazzo	2012
CashProd	Cash Productivity	Chandrashekar and Rao	2009
CBOperProf	Cash-based operating profitability	Ball et al.	2016
CF	Cash flow to market	Lakonishok, Shleifer, Vishny	1994
cfp	Operating Cash flows to price	Desai, Rajgopal, Venkatachalam	2004
ChAssetTurnover	Change in Asset Turnover	Soliman	2008
ChEQ	Growth in book equity	Lockwood and Prombutr	2010
ChInv	Inventory Growth	Thomas and Zhang	2002
ChInvIA	Change in capital inv (ind adj)	Abarbanell and Bushee	1998

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Acronym	Long Description	Authors	Year
ChNNCOA	Change in Net Noncurrent Op Assets	Soliman	2008
ChNWC	Change in Net Working Capital	Soliman	2008
ChTax	Change in Taxes	Thomas and Zhang	2011
CompEquIss	Composite equity issuance	Daniel and Titman	2006
CompositeDebtIssuance	Composite debt issuance	Lyandres, Sun and Zhang	2008
DelCOA	Change in current operating assets	Richardson et al.	2005
DelCOL	Change in current operating liabilities	Richardson et al.	2005
DelDRC	Deferred Revenue	Prakash and Sinha	2013
DelEqu	Change in equity to assets	Richardson et al.	2005
DelFINL	Change in financial liabilities	Richardson et al.	2005
DelLTI	Change in long-term investment	Richardson et al.	2005
DelNetFin	Change in net financial assets	Richardson et al.	2005
dNoa	change in net operating assets	Hirshleifer, Hou, Teoh, Zhang	2004
EarningsConsistency	Earnings consistency	Alwathainani	2009
EarningsStreak	Earnings surprise streak	Loh and Warachka	2012
EarningsSurprise	Earnings Surprise	Foster, Olsen and Shevlin	1984
EarnSupBig	Earnings surprise of big firms	Hou	2007
EBM	Enterprise component of BM	Penman, Richardson and Tuna	2007
EntMult	Enterprise Multiple	Loughran and Wellman	2011
EP	Earnings-to-Price Ratio	Basu	1977
EquityDuration	Equity Duration	Dechow, Sloan and Soliman	2004
FR	Pension Funding Status	Franzoni and Marin	2006
Frontier	Efficient frontier index	Nguyen and Swanson	2009
GP	gross profits / total assets	Novy-Marx	2013
GrAdExp	Growth in advertising expenses	Lou	2014
grcapx	Change in capex (two years)	Anderson and Garcia-Feijoo	2006
grcapx3y	Change in capex (three years)	Anderson and Garcia-Feijoo	2006
GrLTNOA	Growth in long term operating assets	Fairfield, Whisenant and Yohn	2003
GrSaleToGrInv	Sales growth over inventory growth	Abarbanell and Bushee	1998
GrSaleToGrOverhead	Sales growth over overhead growth	Abarbanell and Bushee	1998
IntanBM	Intangible return using BM	Daniel and Titman	2006
IntanCFP	Intangible return using CFtoP	Daniel and Titman	2006
IntanEP	Intangible return using EP	Daniel and Titman	2006

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Acronym	Long Description	Authors	Year
IntanSP	Intangible return using Sale2P	Daniel and Titman	2006
Investment	Investment to revenue	Titman, Wei and Xie	2004
InvestPPEInv	change in ppe and inv/assets	Lyandres, Sun and Zhang	2008
InvGrowth	Inventory Growth	Belo and Lin	2012
Leverage	Market leverage	Bhandari	1988
MeanRankRevGrowth	Revenue Growth Rank	Lakonishok, Shleifer, Vishny	1994
NetDebtFinance	Net debt financing	Bradshaw, Richardson, Sloan	2006
NetDebtPrice	Net debt to price	Penman, Richardson and Tuna	2007
NetEquityFinance	Net equity financing	Bradshaw, Richardson, Sloan	2006
NetPayoutYield	Net Payout Yield	Boudoukh et al.	2007
NOA	Net Operating Assets	Hirshleifer et al.	2004
NumEarnIncrease	Earnings streak length	Loh and Warachka	2012
OperProf	operating profits / book equity	Fama and French	2006
OperProfRD	Operating profitability R&D adjusted	Ball et al.	2016
OPLeverage	Operating leverage	Novy-Marx	2011
OrderBacklog	Order backlog	Rajgopal, Shevlin, Venkatachalam	2003
OrderBacklogChg	Change in order backlog	Baik and Ahn	2007
OrgCap	Organizational capital	Eisfeldt and Papanikolaou	2013
PayoutYield	Payout Yield	Boudoukh et al.	2007
PctAcc	Percent Operating Accruals	Hafzalla, Lundholm, Van Winkle	2011
PctTotAcc	Percent Total Accruals	Hafzalla, Lundholm, Van Winkle	2011
PredictedFE	Predicted Analyst forecast error	Frankel and Lee	1998
PS	Piotroski F-score	Piotroski	2000
RD	R&D over market cap	Chan, Lakonishok and Sougiannis	2001
RDAbility	R&D ability	Cohen, Diether and Malloy	2013
RDcap	R&D capital-to-assets	Li	2011
RDS	Real dirty surplus	Landsman et al.	2011
realestate	Real estate holdings	Tuzel	2010
RevenueSurprise	Revenue Surprise	Jegadeesh and Livnat	2006
roaq	Return on assets (qtrly)	Balakrishnan, Bartov and Faurel	2010
RoE	net income / book equity	Haugen and Baker	1996
ShareIss1Y	Share issuance (1 year)	Pontiff and Woodgate	2008
ShareIss5Y	Share issuance (5 year)	Daniel and Titman	2006

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Acronym	Long Description	Authors	Year
SP	Sales-to-price	Barbee, Mukherji and Raines	1996
tang	Tangibility	Hahn and Lee	2009
Tax	Taxable income to income	Lev and Nissim	2004
TotalAccruals	Total accruals	Richardson et al.	2005
VarCF	Cash-flow to price variance	Haugen and Baker	1996
XFIN	Net external financing	Bradshaw, Richardson, Sloan	2006

B Portfolio Construction Robustness

This appendix examines how the main lifecycle patterns behave under alternative portfolio-construction choices, especially the monthly rebalancing clock and the use of decile breakpoints. The first set of tests changes the clock on which portfolios are updated and Signal Age is accumulated. The second set changes the breakpoint used to define the extreme anomaly legs. The goal is not to replace the monthly decile specification, but to ask whether the qualitative Market–Accounting contrast remains visible when the empirical design is made less dependent on the baseline construction choices. To keep the robustness evidence proportional to the main paper, the tables below report the same economic objects as the main analysis in a compact format: contribution to the aggregate strategy, standalone age-bucket returns, and the capital share attached to each age bucket.

B.1 Rebalancing Frequencies

The rebalancing-clock issue is most relevant for accounting anomalies. Market-based signals are derived from continuously updated trading data, whereas fundamental accounting variables are typically updated at quarterly or annual frequencies. Although many accounting anomalies also contain price-scaled components that can move from month to month, a monthly age measure may still record repeated months between fundamental information releases. If so, the stronger performance of continuing accounting positions could partly reflect measurement at too fine a frequency rather than a difference in the lifecycle of accounting and market positions. A related issue is mechanical capital allocation. When a portfolio is rebalanced only quarterly or annually, the Fresh bucket covers the first quarter or year in the extreme leg, so it naturally absorbs more capital than a one-month Fresh bucket in the baseline design.

To evaluate these concerns, I reconstruct the anomaly portfolios using lower-frequency rebalancing schemes. In the quarterly specification, portfolios are formed at the end of March, June, September, and December and held for three months. In the annual specification, following the standard convention of Fama and French (1993), portfolios are formed at the end of June and held for the subsequent twelve months. Signal Age is redefined in units of consecutive quarters or consecutive years, respectively. To allow enough time for stale positions to accumulate under these lower-frequency definitions, the sample period for this analysis is restricted to 1980–2024.

The lower-frequency results should be read in two steps. Table A2 preserves the paper's additive decomposition and shows how the total value-weighted long-short premium is allocated across age buckets under quarterly and annual clocks. This is useful for the contribution question, but it is not a pure return comparison because an age bucket's contribution depends both on its standalone return and on the amount of capital assigned to that bucket. Table A3 therefore provides the cleaner return comparison: it rescales the weights within each age bucket to 100% and asks how an investor would perform when restricted to Fresh, Middle, or Stale positions.

The decomposition evidence shows why this distinction matters. Under quarterly rebalancing, accounting profits and capital are not concentrated in the Fresh bucket: Fresh accounting positions account for 27.10% of profits and 21.23% of capital. Under annual rebalancing, the Fresh accounting bucket generates 65.39% of profits, but it also receives 55.63% of capital because the first-year bucket is mechanically much wider than the one-month Fresh bucket in the baseline analysis. I therefore do not interpret the annual decomposition result as evidence that fresh accounting positions dominate. Rather, it shows that lower-frequency construction changes the capital shares, which is why the standalone age-bucket returns are informative.

The standalone returns support the accounting interpretation in the main text. Under quarterly rebalancing, value-weighted accounting returns are similar across Fresh, Middle, and Stale buckets: 0.27%, 0.22%, and 0.22% per month, respectively. The Fresh–Stale difference is only 0.05% with a Newey–West t-statistic of 1.00. Under annual rebalancing, Fresh accounting positions again do not outperform continuing positions. The Fresh accounting bucket earns 0.18% per month, while the Middle and Stale buckets each earn 0.22% per month. Thus, even when the portfolio clock is made more consistent with the updating frequency of accounting data, the accounting evidence does not resemble the market-anomaly staleness trap. Accounting position age is less tightly linked to a short payoff window, consistent with the main-text interpretation that persistent fundamentals and repeated information updates allow continuing accounting positions to retain return content.

The market results move in the opposite direction. Lower-frequency rebalancing weakens overall profitability, as expected when continuously updated market signals are held for longer intervals, but the age pattern remains visible. Under quarterly rebalancing, the Fresh and Middle market buckets earn 0.28% and 0.29% per month, whereas the Stale bucket falls to 0.06% and is statistically insignificant. Under annual rebalancing, the Fresh market bucket earns 0.19% per month, while the

Middle bucket earns 0.02% and the Stale bucket earns -0.16%. The annual Fresh–Stale difference is 0.36% with a t-statistic of 3.00. The deterioration of old market positions is therefore not simply a byproduct of measuring Signal Age at a monthly frequency.

These results clarify the interpretation of Section 5.2. Lower-frequency clocks do not make accounting Fresh positions look like market Fresh positions, nor do they restore profitability for old market positions. The Market–Accounting contrast therefore appears to reflect a difference in the lifecycle of portfolio positions rather than a mechanical consequence of the monthly rebalancing convention.

Table A2: **Lower-Frequency Contribution Decomposition**
This table reports the additive contribution of each age bucket to total value-weighted long-short returns under quarterly and annual rebalancing. In the quarterly specification, portfolios are formed at the end of March, June, September, and December and held for three months. In the annual specification, portfolios are formed at the end of June and held for the subsequent twelve months. Signal Age is measured in consecutive quarters or consecutive years. The table reports the long-short contribution, the percentage of total profits generated by the bucket, and the percentage of total market capitalization assigned to the bucket. Newey–West t-statistics are reported in parentheses. The sample period is 1980–2024.

Clock	Group	Bucket	LS Contrib (%)	Profit%	Cap%
Quarterly	Market	Fresh (1Q)	0.12	42.63	46.92
			(4.18)		
		Middle (2–3Q)	0.08	29.01	21.94
			(4.26)		
		Stale (≥4Q)	0.08	28.36	31.14
			(2.11)		
	Accounting	Fresh (1Q)	0.06	27.10	21.23
			(3.94)		
		Middle (2–3Q)	0.08	40.83	27.72
			(4.04)		
		Stale (≥4Q)	0.07	32.07	51.05
			(2.08)		
Annual	Market	Fresh (1Y)	0.14	91.32	59.77
			(3.47)		
		Middle (2Y)	0.01	9.05	15.53
			(1.03)		
		Stale (≥3Y)	-0.00	-0.37	24.71
			(-0.02)		
	Accounting	Fresh (1Y)	0.11	65.39	55.63
			(3.66)		
		Middle (2Y)	0.03	19.23	15.92
			(2.48)		
		Stale (≥3Y)	0.03	15.38	28.45
			(1.31)		

Table A3: **Lower-Frequency Standalone Returns**
This table reports standalone value-weighted long-short returns for age-specific portfolios under quarterly and annual rebalancing. Within each anomaly, month, and age bucket, constituent weights are rescaled to sum to 100%, so the entries are pure age-bucket return comparisons rather than additive contributions to the aggregate strategy. The final column reports the Fresh–Stale return difference. Newey–West t-statistics are reported in parentheses. The sample period is 1980–2024.

Clock	Group	Fresh	Middle	Stale	Fresh–Stale
Quarterly	Market	0.28	0.29	0.06	0.22
		(4.70)	(4.27)	(0.48)	(1.78)
	Accounting	0.27	0.22	0.22	0.05
		(4.74)	(3.71)	(3.17)	(1.00)
Annual	Market	0.19	0.02	-0.16	0.36
		(3.37)	(0.30)	(-1.26)	(3.00)
	Accounting	0.18	0.22	0.22	-0.03
		(3.28)	(3.02)	(2.52)	(-0.51)

B.2 Robustness to Quintile Sorting

I next examine whether the baseline results depend on using decile tails. Decile sorts follow common practice in the recent asset-pricing literature (e.g., Hou et al., 2020), but they may place greater weight on noisy observations near the extremes of the cross-sectional signal distribution. To evaluate whether the age pattern depends on this threshold, I reconstruct the portfolios using quintile sorting. A stock enters the extreme portfolio when it moves into the top or bottom quintile, and Signal Age is then measured as the number of consecutive months the stock remains in that extreme quintile leg.

Table A4 combines the contribution and standalone-return evidence under quintile sorting. For market anomalies, the gap between capital allocation and profit generation remains. The Stale bucket absorbs 36.97% of market capitalization but contributes only 8.89% of total profits, while the Fresh and Middle buckets together generate 91.11% of profits with 63.02% of capital. The standalone market age profile is also downward sloping: the value-weighted Fresh market quintile earns 0.59% per month, compared with 0.30% for Middle and 0.24% for Stale. For accounting anomalies, the contribution pattern again differs: Middle and Stale positions jointly account for 83.32% of profits, and standalone returns are much flatter across age buckets. The quintile results therefore address a narrower concern than the rebalancing tests. They show that the main Market–Accounting contrast is not created by the specific use of decile breakpoints or by a small number of extreme tail observations.

Table A4: **Quintile-Sort Robustness**
This table reports contribution and standalone-return evidence when extreme anomaly legs are defined using quintiles rather than deciles. For each anomaly and month, stocks in the extreme quintiles are classified into Fresh (1 month), Middle (2 to 6 months), and Stale (more than 6 months) buckets. The contribution columns report the additive long-short contribution, profit share, and capital share of each bucket. The standalone column rescales weights within each age bucket to sum to 100% and reports the value-weighted long-short return. Newey–West t-statistics for the contribution and standalone return columns are reported in parentheses. The sample period is 1960–2024.

Group	Bucket	LS Contrib (%)	Profit%	Cap%	Standalone LS Ret (%)
Market	Fresh (1m)	0.12	43.78	32.66	0.59
		(9.14)			(7.22)
	Middle (2–6m)	0.13	47.33	30.36	0.30
		(7.85)			(7.29)
	Stale (>6m)	0.02	8.89	36.97	0.24
		(1.02)			(4.67)
Accounting	Fresh (1m)	0.03	16.68	7.61	0.20
		(5.82)			(3.24)
	Middle (2–6m)	0.08	37.70	26.11	0.22
		(7.04)			(6.03)
	Stale (>6m)	0.09	45.62	66.28	0.19
		(3.13)			(4.59)

C Freshness Beyond Signal Level and Rank Changes

This appendix examines whether the Fresh market premium reflects position age itself, rather than stronger signal intensity or larger recent rank movements among newly activated stocks.

C.1 Signal Level and Rank-Change Controls

The preceding analyses evaluate the anomaly premium by pooling stocks into aggregate portfolios each month. I next complement this evidence with a panel regression framework at the anomaly, age bucket, and month level. This structure evaluates the age pattern within anomalies before drawing aggregate inferences.

The panel framework also separates temporal freshness from signal intensity. Fresh entrants may mechanically exhibit more extreme signal ranks or larger recent rank changes than stale continuers. I therefore introduce controls for the average signal rank level and the average signal rank change of the constituents within each portfolio.

I estimate the following panel regression model:

$$\begin{aligned} R_{s,p,t} = {} & \beta_1(Fresh_p \times Market_s) + \beta_2(Middle_p \times Market_s) \\ & + \beta_3 Fresh_p + \beta_4 Middle_p + \beta_5 Market_s \\ & + \gamma_1 SignalRankLevel_{s,p,t} + \gamma_2 SignalRankChange_{s,p,t} \\ & + \mu_s + \eta_p + \delta_t + \epsilon_{s,p,t} \end{aligned} \tag{15}$$

where $R_{s,p,t}$ is the dependent variable, representing either the standalone return or the additive contribution return for anomaly s in age bucket p during month t. The variables $Fresh_p$ and $Middle_p$ are indicator variables for the respective age buckets, with the stale bucket serving as the omitted base group. The variable $Market_s$ is an indicator for market anomalies. The continuous variables $SignalRankLevel_{s,p,t}$ and $SignalRankChange_{s,p,t}$ control for the time-varying portfolio characteristics. The model incorporates anomaly fixed effects μ_s to control for unobserved heterogeneity across different predictors, age bucket fixed effects η_p to account for universal decay patterns, and date fixed effects δ_t to absorb aggregate market shocks. Due to these fixed effects, the main effects for the fresh bucket, the middle bucket, and the market anomaly indicator (β_3, β_4,

and β_5) are absorbed by the estimation. Standard errors are two-way clustered by date and the intersection of anomaly and age bucket.

Table A5 presents the panel regression estimates. Columns 1 and 3 report the baseline specifications without portfolio-characteristic controls. In both cases, the interaction between the fresh age bucket and the market-anomaly indicator is positive and statistically significant, indicating that the fresh-market pattern is visible across anomalies rather than only in aggregate portfolio averages. At the same time, the economic interpretation of the coefficients differs across the two dependent variables. In the contribution specifications, the dependent variable measures the age bucket's realized contribution to the parent anomaly portfolio, so the coefficient reflects both the bucket's conditional profitability and the amount of capital that the conventional sorting rule allocates to it. In the standalone specifications, by contrast, each age bucket is evaluated as an independently rescaled long-short portfolio, so the coefficient more directly captures the return spread associated with that stage of the signal lifecycle.

Columns 2 and 4 add controls for the average signal rank level and the average signal rank change. These controls are economically meaningful: in Column 2, both variables are positively and significantly related to contribution, indicating that signal extremity and recent signal movement do help explain portfolio performance. However, the key result remains unchanged. Even after conditioning on these portfolio characteristics, the coefficient on $Fresh \times Market$ stays positive and statistically significant in both specifications. In the fully controlled regressions, the estimate is 0.18% ($t = 3.44$) when the dependent variable is additive contribution and 0.50% ($t = 1.74$) when it is the standalone return. The larger magnitude in the standalone specification is consistent with the interpretation developed in Section 4.4: once the capital-share mechanics embedded in the parent portfolio are stripped away, the age-conditioned return advantage of fresh market positions becomes more directly visible. Taken together, these results indicate that freshness is not merely a proxy for signal extremity or recent rank movements. Rather, it captures a distinct temporal dimension of return predictability in market anomalies.

Table A5: **Freshness Premium Beyond Signal Level and Rank Change**
This table presents anomaly-level panel regressions evaluating the premium of fresh signals. The sample utilizes a panel at the anomaly, age bucket, and month level. The dependent variables are the additive contribution return (Contrib) and the standalone return (Stand) for each age bucket. The independent variables include interaction terms between age bucket indicators (Fresh, Middle) and the market anomaly indicator. The stale age bucket serves as the omitted base group. Columns (2) and (4) include controls for time-varying portfolio characteristics, specifically the average signal rank level and the average signal rank change. Standard errors are two-way clustered by date and the intersection of anomaly and age bucket, and are reported in parentheses. The sample period spans from 1960 to 2024.

	(1) Contrib	(2) Contrib	(3) Stand	(4) Stand
Fresh × Market	0.210***	0.179***	0.563**	0.497*
	(0.053)	(0.052)	(0.256)	(0.286)
Middle × Market	0.126***	0.111**	0.032	-0.034
	(0.044)	(0.044)	(0.160)	(0.172)
Signal Rank (Level)		0.064**		0.290
		(0.032)		(0.200)
Signal Rank (Change)		0.245**		-0.559
		(0.105)		(0.670)
Anomaly FEs	Yes	Yes	Yes	Yes
Age Bucket FEs	Yes	Yes	Yes	Yes
Date FEs	Yes	Yes	Yes	Yes
Observations	311,196	311,196	311,196	311,196

D Event-Time Robustness and Sharpe Ratios

This appendix provides two complementary diagnostics for the event-time interpretation: a survivor path that conditions on continued same-leg membership, and Sharpe ratios that scale average returns by time-series volatility. The central market-anomaly event-time fact is the attenuation of the original formation-cohort payoff. In the main text, the value-weighted Market Fresh return is 0.89% at horizon 1, falls to 0.19% at horizon 2, remains positive but much smaller at 0.20% at horizon 6, and is statistically insignificant at 0.05% by horizon 12. Thus, the Fresh payoff is not merely a one-month artifact, but the economically relevant return opportunity is front-loaded.

The main text uses an unconditional formation-cohort event path: at horizon one, I identify Fresh, Middle, and Stale portfolios and then follow those formation portfolios forward without requiring the same stocks to remain in the same anomaly leg. That design is closest to the return experience of an investor who forms a portfolio at a given date. The survivor path reported here answers a different question. It conditions on the subset of Fresh entrants that continue to occupy the same signal and the same long or short leg at future horizons. This conditioning makes the survivor path useful for understanding the lifecycle of continuing positions, but it also means that the path should not be interpreted as an unconditional trading strategy.

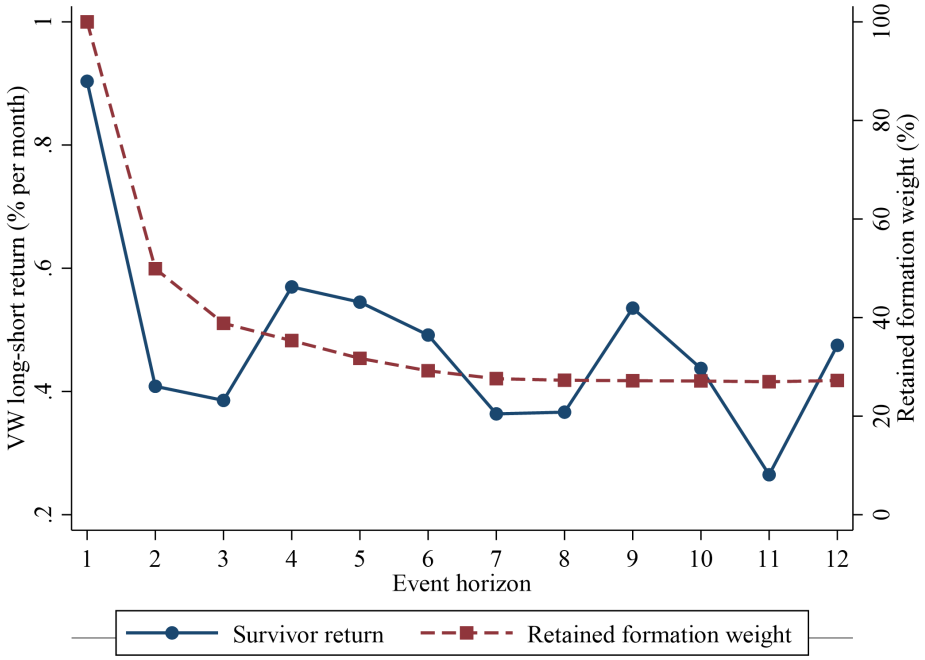
Figure A1 reports the survivor event-time paths. The figure has two components. The return series reports value-weighted long-short returns for the surviving positions at each horizon. The retained-weight series reports the fraction of the original formation weight that remains in the survivor sample. The retained-weight line is important because survival is selective: a stock appears at horizon h only if it has not exited the same anomaly leg before that horizon. For market anomalies, the return series drops immediately from the high activation return to a lower continuation range, and the retained formation weight falls rapidly: roughly one-half remains after one additional month and only about one-quarter remains by horizon twelve. For accounting anomalies, retention is higher, with about four-fifths of formation weight remaining after one additional month and roughly one-half remaining by horizon twelve. These differences are consistent with the main text's characterization of accounting signals as more persistent and tied to lower-frequency information.

The survivor returns should therefore be read together with the retained-weight series. Con-

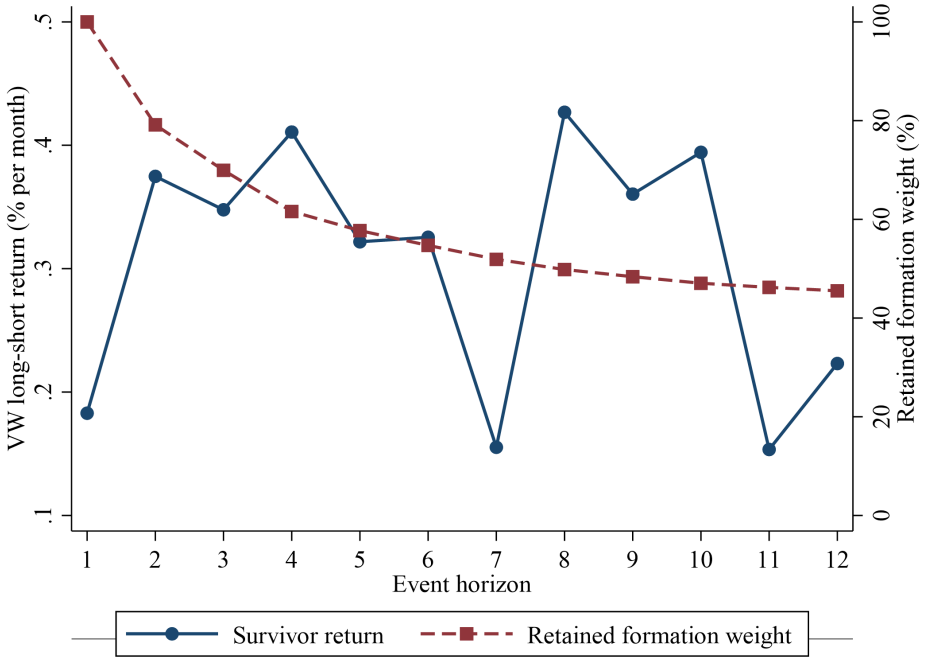
ditional survivors in market anomalies can continue to earn positive returns, but they represent a shrinking and selected subset of the original Fresh cohort. The two paths jointly clarify the interpretation of the market decline. The unconditional path shows that the aggregate payoff to the original Fresh formation portfolio falls after activation. The survivor path shows that later same-leg returns are earned by a much smaller set of positions that continue to satisfy the extreme-leg condition. Together, the evidence indicates that entry is the relevant margin for market anomalies, while continuation is selective and no longer carries the same aggregate economic weight as the initial activation.

Table A6 reports value-weighted Sharpe ratios by age bucket. This diagnostic addresses the arbitrageur-facing concern that average returns alone are not the relevant investment object. In market anomalies, the Fresh bucket has an annualized Sharpe ratio of 1.63, compared with 0.92 for Middle and 0.72 for Stale. The return advantage of Fresh market positions therefore survives when scaled by time-series volatility. The accounting pattern again differs: the Fresh accounting bucket has a much lower Sharpe ratio than the Middle and Stale buckets. This evidence reinforces the main distinction in the paper. For market anomalies, risk-adjusted performance is highest close to position activation. For accounting anomalies, continuing positions retain more of the risk-adjusted return content.

The Sharpe-ratio evidence is descriptive rather than a replacement for the formal maximum-Sharpe-ratio exercise in Table 11. The appendix table evaluates standalone age-bucket portfolios one at a time. Table 11 instead asks how much each age-specific factor expands the mean-variance span of standard benchmark models. The two diagnostics point in the same direction for market anomalies: Fresh positions outperform aged continuers both in average returns and in risk-adjusted performance.



(a) Market Anomalies



(b) Accounting Anomalies

Figure A1: **Survivor Event-Time Paths and Retained Formation Weight**
This figure reports survivor event-time paths for Fresh entrants. A stock remains in the survivor path at horizon h only if it remains in the same signal and the same long or short leg with signal age equal to h. Returns are value-weighted long-short returns in percent. The retained-weight series reports the share of formation weight that remains in the survivor sample at each horizon.

Table A6: **Value-Weighted Sharpe Ratios by Age Bucket**
This table reports average monthly returns, monthly standard deviations, and annualized Sharpe ratios for value-weighted standalone age-bucket portfolios. For each anomaly and month, standalone long-short returns are formed separately for Fresh, Middle, and Stale portfolios and then averaged across anomalies within each classification. Annualized Sharpe ratios are computed as the monthly mean divided by the monthly standard deviation, multiplied by $\sqrt{12}$.

Group	Bucket	Mean (%)	Monthly SD (%)	Ann. Sharpe
Market	Fresh	0.89	1.88	1.63
	Middle	0.39	1.48	0.92
	Stale	0.31	1.49	0.72
Accounting	Fresh	0.13	1.80	0.26
	Middle	0.28	1.11	0.87
	Stale	0.21	1.14	0.65

E Anomaly Breadth and Subperiod Robustness

This appendix reports three breadth and subsample diagnostics for the Market Fresh result: excluding short-term reversal, excluding each Market anomaly one at a time, and splitting the sample across time periods. The first two diagnostics are closely related, so Table A7 combines them in a compact form. Panel A excludes the short-term reversal signal, `STreversal`, and recomputes the Fresh–Stale comparison. Panel B excludes each of the 55 Market anomalies one at a time and summarizes the distribution of Fresh–Stale estimates.

The evidence does not support a short-term-reversal or single-anomaly interpretation. After excluding `STreversal`, the Fresh–Stale spread remains 0.187 percent per month in the contribution object and 0.656 percent per month in the standalone value-weighted return object. The one-signal leave-one-out exercise reaches the same conclusion more broadly. The standalone Fresh–Stale spread remains positive and statistically significant in all 55 exclusions, ranging from 0.385 to 0.656 percent per month. The contribution Fresh–Stale spread is also positive and significant in every exclusion, ranging from 0.134 to 0.199 percent per month. Thus, the Market Fresh result is not mechanically generated by the short-term reversal anomaly or by any single Market predictor.

Table A9 addresses the third concern by reporting value-weighted standalone age-bucket returns across subsamples. The early-half results show that market anomalies are profitable across the lifecycle, but even there Fresh positions outperform Stale positions. The lifecycle pattern becomes more pronounced in the late sample. In the Late Half, Market Fresh earns 1.03 percent per month, compared with 0.28 percent for Middle and 0.15 percent for Stale; the Fresh–Stale difference is 0.88 percent with a t-statistic of 4.59. The result also appears in the post-2000 and last-20-years samples. In the last 20 years, Market Fresh earns 0.98 percent per month, while Market Stale earns a statistically insignificant -0.02 percent, and the Fresh–Stale difference is 1.00 percent with a t-statistic of 3.36.

The accounting results again provide a useful benchmark. Accounting Fresh does not display the same recent-sample strength. In the Late Half, Post-2000, and Last-20-years samples, the accounting Fresh return is negative and statistically weak, while Middle and Stale accounting positions retain more of the profitability. Thus, the subperiod evidence shows that the location of surviving profitability differs across anomaly families. For market anomalies, recent profitability

Table A7: **Market Breadth Checks**
This table reports compact breadth diagnostics for the Market anomaly age-bucket results. Panel A excludes the short-term reversal signal `STreversal` and reports Fresh–Stale difference tests for the contribution decomposition and standalone value-weighted return object. Panel B reports one-signal leave-one-out diagnostics for the same Fresh–Stale comparison. In each leave-one-out iteration, one Market anomaly is excluded and the Market contribution and standalone value-weighted return objects are recomputed. Baseline is the estimate using all 55 Market anomalies. Min, Median, and Max report the distribution of estimates across the 55 leave-one-out samples. Positive reports the number of exclusions for which the difference remains positive. $p < 0.05$ reports the number of exclusions for which the difference is statistically significant at the 5 percent level using Newey–West standard errors with six lags. Differences are monthly percentages.

Panel A: Excluding Short-Term Reversal

Object	Difference	Estimate	t-stat
Contribution	Fresh–Stale	0.187	4.70
Standalone VW	Fresh–Stale	0.656	4.22

Panel B: One-Signal Leave-One-Out

Object	Difference	Baseline	Min LOO	Median LOO	Max LOO	Positive	$p < 0.05$
Contribution	Fresh–Stale	0.171	0.134	0.172	0.199	55/55	55/55
Standalone VW	Fresh–Stale	0.575	0.385	0.577	0.656	55/55	55/55

is concentrated near position activation. For accounting anomalies, the stronger components are continuing positions rather than new entrants.

Overall, the appendix evidence supports the external validity of the main results. The Market Fresh premium is not driven by the short-term reversal signal, is not driven by any single Market anomaly, and is not confined to the early anomaly-sample period. These diagnostics show that the main market lifecycle pattern is broad across signals and sample periods.

Table A8: **Long and Short Leg Decomposition by Age Bucket**
This table separates the value-weighted returns of each age bucket into its long-leg and short-leg components. Panel A reports the standalone object of Table 3, in which constituent weights are rescaled to sum to 100 percent within each age bucket, so the entries are the value-weighted returns of the long and short legs of a separately formed age-specific portfolio. Panel B reports the additive contribution object of Table 2, in which each bucket enters with the capital weight the standard sorting rule assigns to it, so the entries are the bucket's contribution to the return of the parent long leg and parent short leg. In both panels the long-short column equals the long column minus the short column. Because the short leg is held short, a higher short-leg return reduces the long-short return. Newey–West t-statistics with six lags are in parentheses. Returns are monthly percentages. The sample period spans 1960 to 2024.

Panel A: Standalone Value-Weighted Returns				
Group	Bucket	Long	Short	Long–Short
Market	Fresh (1m)	2.74	1.85	0.89
		(11.77)	(8.53)	(8.92)
	Middle (2–6m)	1.33	0.94	0.39
		(7.28)	(4.45)	(6.75)
	Stale (>6m)	0.93	0.62	0.31
		(6.96)	(3.96)	(5.14)
Accounting	Fresh (1m)	3.67	3.54	0.13
		(12.39)	(11.78)	(1.90)
	Middle (2–6m)	1.19	0.91	0.28
		(6.34)	(4.61)	(6.28)
	Stale (>6m)	1.12	0.91	0.21
		(6.51)	(4.72)	(4.40)
Panel B: Additive Contributions to the Parent Portfolio				
Group	Bucket	Long	Short	Long–Short
Market	Fresh (1m)	0.61	0.41	0.20
		(8.55)	(5.44)	(10.88)
	Middle (2–6m)	0.42	0.25	0.17
		(7.39)	(4.03)	(8.66)
	Stale (>6m)	0.36	0.32	0.03
		(6.58)	(4.90)	(1.26)
Accounting	Fresh (1m)	0.18	0.13	0.05
		(6.42)	(4.97)	(6.00)
	Middle (2–6m)	0.35	0.25	0.10
		(5.92)	(4.14)	(6.40)
	Stale (>6m)	0.69	0.58	0.11
		(6.39)	(4.75)	(3.35)

Table A9: **Subperiod Age-Bucket Returns**
This table reports value-weighted standalone age-bucket returns across subsamples. Early Half and Late Half split the full sample into two equal-length periods. Post-2000 uses months from January 2000 onward, and Last 20 Years uses the most recent 240 months in the sample. Returns and Fresh–Stale differences are monthly percentages. t-statistics are computed using Newey–West standard errors with six lags.

Sample	Group	Fresh	Middle	Stale	Fresh–Stale
Early Half	Market	0.75	0.50	0.48	0.27
		(13.65)	(9.86)	(8.32)	(4.07)
	Accounting	0.31	0.35	0.27	0.05
		(4.02)	(6.71)	(4.52)	(0.57)
Late Half	Market	1.03	0.28	0.15	0.88
		(5.41)	(2.75)	(1.43)	(4.59)
	Accounting	-0.04	0.21	0.16	-0.20
		(-0.39)	(2.98)	(2.09)	(-1.86)
Post-2000	Market	1.03	0.24	0.13	0.90
		(4.21)	(1.85)	(1.05)	(3.64)
	Accounting	-0.05	0.19	0.17	-0.22
		(-0.38)	(2.17)	(1.80)	(-1.62)
Last 20 Years	Market	0.98	0.11	-0.02	1.00
		(3.35)	(0.75)	(-0.19)	(3.36)
	Accounting	-0.13	0.07	0.02	-0.16
		(-0.96)	(0.97)	(0.30)	(-1.05)