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

Hanjun Kim*
David Eccles School of Business
University of Utah

This Draft: March, 2026

[PRELIMINARY: PLEASE DO NOT CITE OR DISTRIBUTE]

Abstract

Does real-time information guarantee fresh signals? This paper identifies a "Staleness Trap" in market anomalies: while signals are highly persistent, their associated returns decay much faster than the underlying signals. Consequently, even when utilizing the freshest data, standard portfolio methodologies mechanically accumulate aged, stale constituents. Using a novel Signal Age metric, I show that these aged continuers trap one-third of portfolio capital with negligible returns, whereas fresh entrants drive half of the aggregate premium. In contrast, aged constituents in accounting anomalies continue to yield stable returns, revealing a fundamental dichotomy between market and accounting anomalies. I provide evidence that this structural divergence stems from their underlying economic mechanisms. Rather than capturing slow information diffusion, market anomalies proxy for transient risk states and limits to arbitrage that demand short-lived compensation.

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

JEL Classification: G11, G12, G14

*Email: hanjun.kim@eccles.utah.edu.

Disclosure Statement

Research Support: This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Conflict of Interest: The author, Hanjun Kim, declares no financial relationships or other potential conflicts of interest that could inappropriately influence or bias the findings, interpretations, or conclusions of this study.

Data Access and Responsibility: As the sole author, I had full access to all the data in the study and take responsibility for the integrity of the data and the accuracy of the data analysis.

1 Introduction

The identification of cross-sectional stock return predictors has been a cornerstone of empirical asset pricing over the past several decades. The literature has documented hundreds of predictive characteristics, commonly referred to as the "anomaly zoo" (Cochrane, 2011; Harvey, Liu, & Zhu, 2016; Hou, Xue, & Zhang, 2020). To evaluate these predictors, empirical studies rely on standard portfolio methodologies, which typically involve sorting stocks into deciles based on a specific characteristic. A critical, yet often implicit, assumption underlying this approach is that the sorting variables (i.e., signals) accurately reflect the most current and actionable information available to market participants. However, recent literature challenges this assumption by highlighting a *staleness problem* in empirical research. Notably, Bowles, Reed, Ringgenberg, & Thornock (2024) and Bowles, Reed, Ringgenberg, & Thornock (2026) show that conventional methodologies suffer from this problem because they rely on stale accounting data. This staleness is driven not only by exogenous reporting lags but also by the standard empirical convention of lagging accounting variables (often by four to six months) to ensure public availability. By precisely aligning portfolio formation with actual information release dates, they demonstrate that the true anomaly premium is concentrated around the release of fresh information.

While the staleness problem is increasingly understood and addressed in the context of accounting anomalies tied to discrete information release dates, the empirical asset pricing literature encompasses another vast set of predictors: market anomalies. Unlike accounting anomalies, market anomalies such as momentum (Jegadeesh & Titman, 1993), idiosyncratic volatility (Ang, Hodrick, Xing, & Zhang, 2006), and short-term reversal (Lehmann, 1990) rely on trading data that updates continuously.[1] This continuous nature allows investors to construct anomaly portfolios using the most recent information available at any given moment, theoretically circumventing the exogenous reporting lags and conventional delays associated with accounting variables. Consequently, standard empirical practices generally operate under the assumption that these high-frequency sorting variables provide a timely reflection of a stock's active mispricing or current risk state. This struc-

[1] While market variables do not update in strict continuous time mathematically, the widespread availability of high-frequency Trade and Quote (TAQ) data allows them to be measured at the millisecond level. For empirical and implementational purposes, this near-instantaneous updating effectively eliminates the exogenous reporting lags characteristic of accounting variables, justifying the use of the term continuous in this context.

tural distinction between accounting and market anomalies naturally raises an empirical question: does the use of real-time data inherently guarantee that the resulting cross-sectional signal is fresh, thereby insulating market anomalies from the staleness problem? In other words, the continuous availability of data may not necessarily imply that the economic information captured by the signal is fresh.

This paper addresses this question by documenting a "Staleness Trap" in market anomalies. I demonstrate that while continuous market data bypasses the *exogenous* staleness of discrete reporting lags, it is inherently subject to *endogenous* staleness. This endogenous staleness is defined by a persistence mismatch: the predictive power of a market signal is short-lived, but the cross-sectional rank of that signal is highly persistent. While market data updates continuously, the underlying signals often exhibit strong, state-like stickiness (Keloharju, Linnainmaa, & Nyberg, 2021). Once a stock enters an extreme anomaly decile, it tends to remain there for an extended period.[2] Although this initial activation captures a fresh risk state demanding high expected returns, the persistent nature of the signal keeps the stock mechanically pinned in that portfolio long after arbitrageurs have corrected the mispricing or the risk state has dissipated. Because the expected return of the stock decays much faster than the underlying signal itself, anomaly portfolios mechanically accumulate decayed positions, thereby falling into the staleness trap.

At the portfolio level, this staleness trap manifests as an inefficient allocation of capital. Standard decile sorting methodologies do not differentiate between a stock that newly triggered a signal today and a stale continuer that has remained in the same extreme leg for several months or even years. Because these aged constituents are mechanically retained even after their predictive power has vanished, portfolio capital is inefficiently distributed. Rather than dynamically allocating weight to fresh risk states, a substantial fraction of the investable capital becomes tied up in decayed positions. Ultimately, this structural friction dilutes the aggregate anomaly premium, as the high returns generated by fresh entrants are offset by the disproportionate capital weight assigned to stale continuers.

[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 & Titman, 1993), a stock that experiences a large idiosyncratic price shock will mechanically remain in the extreme winner decile for several months, as the historical shock is retained within the rolling 11-month formation window. 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 remains persistent.

To empirically investigate the lifecycle of anomaly signals and quantify the impact of endogenous staleness, I construct a novel stock-level state variable called "Signal Age." Utilizing the Open Source Asset Pricing (OSAP) database provided by A. Y. Chen & Zimmermann (2022), I analyze 91 accounting and 55 market anomalies over the 1960 to 2024 sample period. Signal Age recursively tracks the number of consecutive months a stock has persisted in the extreme long or short leg of a specific anomaly portfolio. This metric allows me to disentangle extreme portfolios into three mutually exclusive groups: "Fresh" entrants (stocks in the extreme decile for exactly one month), "Middle" continuers (two to six months), and "Stale" continuers (more than six months). [3]

My empirical analysis begins by examining the composition of standard anomaly portfolios. I find that extreme portfolios are predominantly populated by aged constituents; the conditional probability of a stock remaining in an extreme market anomaly leg from one month to the next exceeds 72%. When decomposing the aggregate anomaly premium, I find a significant mismatch between capital allocation and profit generation for market anomalies. Stale constituents account for approximately 33% of the portfolio market capitalization but produce only 8% of the total returns. In contrast, fresh constituents occupy 37% of the investable capital while generating 50% of the profits. This disproportionate contribution provides direct evidence of the staleness trap, demonstrating that standard sorting methodologies allocate substantial capital to older, persistent constituents whose expected returns have largely dissipated.

While the additive decomposition illustrates the mechanical misallocation of capital within standard portfolios, it does not perfectly isolate the predictive power of constituents at different stages of their lifecycle. To evaluate the pure premium of each age group, I construct independent portfolios formed exclusively of constituents from the same age bucket. By rescaling the constituent weights within each age group to sum to unity, this approach controls for the asymmetric capital distribution. It measures the precise long-short return an investor would earn by trading only fresh constituents versus holding only stale constituents. This analysis reveals a rapid and monotonic decline in the performance of market anomalies as constituents age. A value-weighted long-short portfolio formed exclusively of fresh constituents yields a return of 0.89% per month, whereas

[3]The definition of the Fresh bucket strictly isolates the initial signal activation. The six-month threshold distinguishing Middle from Stale constituents is not arbitrary; it is grounded in both the statistical decay properties of the sorting variables and standard economic horizons. A detailed discussion of these cutoff choices and their empirical rationale is provided in Section 3.

the premium for stale continuers drops by roughly half to 0.31%. Importantly, I show that this rapid decay is not driven by time-varying exposures to standard systematic risk factors. After adjusting for the Fama & French (2015) five factors augmented with the momentum factor (Carhart, 1997), the value-weighted alpha of fresh market signals remains highly significant at 0.75% per month, monotonically declining to 0.15% for stale signals. Conversely, accounting-based anomalies exhibit no such performance degradation; their unadjusted returns and risk-adjusted alphas remain stable or increase during stale periods. This dichotomy aligns with theories of gradual information diffusion and post-earnings-announcement drift (Bernard & Thomas, 1989; Hirshleifer, Lim, & Teoh, 2009), confirming that the staleness trap is uniquely detrimental to continuous market signals.

To uncover the economic forces driving this dichotomy, I conceptually distinguish between two dimensions of newness: the expectational dimension (signal surprise) and the temporal dimension (signal freshness). Using the information arbitrage framework of Bowles et al. (2026), I sort fresh entrants into terciles based on the magnitude of their expectational surprise. For accounting anomalies, the premium is primarily driven by high-surprise entrants, corroborating the view that predictable fundamental updates are efficiently priced ex-ante by arbitrageurs. For market anomalies, however, expectational surprise does not dictate the premium. Fresh market signals earn returns exceeding 1.1% per month even when their entry is predictable from historical data. This implies that market anomalies are not arbitraged away prior to realization, suggesting they proxy for transient risk constraints or localized limits to arbitrage (Shleifer & Vishny, 1997; Pástor & Stambaugh, 2003). Investors demand compensation for bearing a specific risk state exactly when it is active; once the state ages and dissipates, the compensation vanishes.

I further test this limits-to-arbitrage interpretation by conditioning anomaly performance on aggregate macroeconomic states. If the freshness premium merely reflects investor overreaction during periods of high sentiment (Daniel, Hirshleifer, & Subrahmanyam, 1998), it should be concentrated in up markets and vanish during downturns (Cooper, Gutierrez, & Hameed, 2004). However, I find that the freshness premium for market anomalies remains statistically significant even following 36-month down markets, while the return to holding stale market signals drops near zero. Stock-level regressions reinforce this finding, showing that the freshness premium is significantly amplified during periods of high aggregate market volatility (VIX), consistent with the pricing of liquidity provision (Nagel, 2012). When funding liquidity tightens, the cost of bearing localized risk states

increases, driving up the required premium for fresh market signals.

From a practical standpoint, the rapid decay of market signals alters the calculus of transaction cost mitigation. A standard prescription for managing high-turnover anomalies is to delay trades or hold onto existing positions, effectively tolerating stale signals to reduce turnover frictions (Novy-Marx & Velikov, 2016). However, because the expected return of continuous market anomalies decays faster than the signal itself, the conventional practice of holding onto aged signals degrades net performance. Using high-frequency Trade and Quote (TAQ) data to estimate effective bid-ask spreads, I show that the gross premium of fresh market signals is sufficient to offset trading frictions, yielding a statistically significant net return of 0.58% per month. In contrast, the net return of holding stale market signals becomes statistically indistinguishable from zero.

The remainder of this paper is organized as follows. Section 2 reviews the related literature. Section 3 describes the data sources, the construction of the anomaly library, and the Signal Age methodology. Section 4 presents the core portfolio-level evidence, including the decomposition of the anomaly premium, standalone age-based returns, and robustness to systematic risk factors. Section 5 investigates the economic origins of the freshness premium by evaluating expectational surprise, testing alternative behavioral explanations based on macroeconomic states, and analyzing stock-level responses to aggregate risk constraints and trading activity. Section 6 assesses the practical implementation of the strategy and the impact of transaction costs. Section 7 concludes.

2 Related Literature

This paper contributes to three main strands of literature in empirical asset pricing: the timing of information and data freshness, the replication and design of cross-sectional anomalies, and the economic origins of the anomaly zoo regarding limits to arbitrage.

First, this paper extends the emerging literature on information timing and data freshness in asset pricing (McLean & Pontiff, 2016; Engelberg, McLean, & Pontiff, 2018; Bowles et al., 2024). While Bowles et al. (2024) and Bowles et al. (2026) highlight how exogenous reporting lags mask the true predictability and surprise-driven nature of accounting anomalies, I complement their findings by demonstrating that continuous market anomalies suffer from endogenous staleness even in the absence of reporting delays. Furthermore, this paper contributes to the contemporaneous

debate regarding the fundamental dichotomy between accounting and market anomalies. Zhou (2025) evaluates this divide through the macroeconomic lens of realized cash flows, arguing that the long-term countercyclicality of continuous anomalies points to behavioral mispricing driven by slow information diffusion. By utilizing the Signal Age metric, I offer a contrasting microstructure perspective. I demonstrate that the premiums of market anomalies are heavily concentrated in their initial, fresh stages. Rather than slowly diffusing cognitive errors, these high-frequency patterns suggest that market anomalies represent rapidly decaying, transient risk states where investors demand short-lived compensation.

Second, this study contributes to the literature on the replication, implementation, and lifecycle of the anomaly zoo (Harvey et al., 2016; Hou et al., 2020; A. Y. Chen & Zimmermann, 2022). While McLean & Pontiff (2016) argue that market learning reduces anomaly returns, A. Y. Chen & Velikov (2023) show that most predictors become unprofitable once we account for transaction costs and modern market efficiency. My results show that signal freshness is a key survival factor: while persistent signals fade as the market becomes more efficient, fresh signals remain profitable even in highly competitive environments. Fama & French (2007) demonstrate that the value and size premiums are largely driven by the migration of stocks across portfolio boundaries. I generalize this migration effect across the entire cross-section of 146 anomalies, showing that the transition into an extreme state is the primary engine of return predictability for market variables. Additionally, while prior literature has attempted to proxy for the lifecycle of specific characteristics—such as using trading volume to identify early- versus late-stage momentum (Lee & Swaminathan, 2000)—these indirect measures are often subject to ongoing empirical debate (T.-Y. Chen, Chou, Hsieh, & Rhee, 2021). By introducing Signal Age as a direct, mechanical metric, I resolve this measurement ambiguity and isolate signal staleness as an inherent drag on portfolio performance.

Finally, this paper adds to the literature on limits to arbitrage, time-varying risk constraints, and transaction costs (Shleifer & Vishny, 1997; Pástor & Stambaugh, 2003; Stambaugh & Yuan, 2017; Novy-Marx & Velikov, 2016). The Staleness Trap documented in this paper serves as a methodological manifestation of the slow-moving capital frictions theorized by Duffie (2010).[4] My

[4]While Duffie focuses on the slow physical movement of arbitrage capital into profitable states, I document a "slow movement' of portfolio weights out of decayed states. Standard age-agnostic methodologies effectively act as inattentive investors, failing to purge stale signals even after the underlying risk-bearing premium has been absorbed by the market.

stock-level evidence reinforces that market anomalies behave as transient risk states, as their freshness premium expands during periods of high aggregate volatility (Nagel, 2012). Furthermore, by demonstrating that the fresh premium survives transaction costs while the stale premium does not, this paper refines the conventional wisdom on turnover mitigation (Novy-Marx & Velikov, 2016), showing that mechanically holding aged market signals is a mathematically suboptimal response to trading frictions.

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 A. Y. Chen & 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 & French, 1993; Hou, Xue, & Zhang, 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 ensure robust 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 guarantee adequate diversification within the sorted portfolios, I mandate that each extreme portfolio leg contains a minimum of 10 constituent stocks.

3.2 Signal Construction and Classification

A critical step in utilizing the OSAP database is ensuring directional consistency across 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 utilize the signed metadata provided by A. Y. Chen & 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 $S_{i,s,t}^{raw}$ 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 ensure robust decile sorting and avoid ambiguous portfolio assignments caused by heavily tied ranks, I restrict the sample exclusively to continuous variables. Using the metadata classifications provided by OSAP, I then categorize the eligible predictors into two distinct 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 continuous market data that is continuously updated. 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, serving as a natural control group to contrast with the high-frequency nature of market anomalies. Applying these criteria yields a final dataset comprising 55 market anomalies and 91 accounting anomalies.

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 strictly reset to zero.

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, strictly isolating the immediate activation of the signal. *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 legacy positions that have persisted in the extreme leg for more than six months.

The six-month boundary distinguishing Middle from Stale constituents is grounded in both statistical properties and economic conventions. Statistically, as demonstrated by the rank autocorrelations in Figure 2, the underlying sorting variables experience their most pronounced decay 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 & Titman, 1993) and ensures that at least one to two subsequent quarterly earnings cycles have elapsed, rendering the original information conceptually aged. Consequently, this classification scheme provides a structured framework to empirically investigate how the predictive power of anomaly signals evolves across different stages of their lifecycle.

4 The Staleness Trap: Portfolio-Level Evidence

4.1 Signal Age Distribution and Portfolio Composition

To establish the baseline performance and introduce the structural 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.

[INSERT TABLE 1 HERE]

Consistent with prior literature, both anomaly classifications yield positive average returns, confirming the baseline predictive power of these signals in the cross-section of stock returns. 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. Notably, when evaluated on a value-weighted basis, the average signal age for accounting anomalies rises substantially 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 highly stale constituents, further motivating the need to decompose portfolio performance by age.

A central premise of the endogenous staleness mechanism is that standard sorting methodologies mechanically 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 employ 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 reveals clear structural differences between the two classifications. Focusing first on the left side of the distribution, market anomalies exhibit a substantial 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 most prominent 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 substantial 23.1% mass in this oldest age bucket.

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

4.2 The State-Like Persistence of Anomaly Signals

To formally quantify the structural 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 the anomaly behaves as a slow-moving state variable, mechanically 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), largely driven by the low frequency of corporate earnings reports. Notably, while market anomalies show lower initial autocorrelation coefficients and a relatively faster decay rate than their accounting counterparts, their persistence remains substantial 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 strictly from the extreme deciles. Therefore, my second approach directly 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 that exact same leg in month $t-1$.

Table 2 reports these conditional portfolio transition probabilities. The persistence within the extreme deciles is substantial, corroborating 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 highly stable portfolio composition month over month.

Crucially, 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 identified mispriced assets reacting to recent shocks. Instead, they are aged continuers carried over from the prior month. This substantial month-over-month overlap confirms that extreme portfolios are predominantly populated by stocks pinned in a persistent state, rather than dynamic fresh entrants.

Collectively, 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 are predominantly populated by highly persistent constituents. This robust state-like behavior sets the empirical stage for decomposing the portfolio returns to isolate the performance of fresh news from the drag of aged constituents.

[INSERT TABLE 2 HERE]

4.3 Decomposing the Premium: Evidence of the Staleness Trap

Building on the evidence of rank persistence, I next examine how this structural stickiness impacts the aggregate anomaly premium. Before conducting the decomposition, I classify portfolio constituents into three mutually exclusive buckets based on their signal age: *Fresh* (stocks in the extreme decile for exactly one month), *Middle* (stocks persisting for two to six months), and *Stale* (stocks persisting for more than six months). To evaluate the performance of these groups, I follow a two-step averaging procedure akin to Fama & 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 portfolio 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 3 reports the results of this return decomposition and reveals a fundamental difference between accounting anomalies and market anomalies. For accounting anomalies, fundamental variables are updated at discrete, low-frequency intervals. Consequently, once a stock enters an extreme portfolio, it mechanically retains its rank for several months. More importantly, the returns associated with these fundamental updates do not realize instantaneously; rather, they accrue gradually over time due to limited investor attention and post-earnings-announcement drift. The empirical results reflect this dynamic: the Fresh bucket accounts for only 9.3% of the portfolio capital and 18.9% of the profits. a large portion of both capital (90.7%) and profits (81.1%) are concentrated

in the Middle and Stale buckets. This demonstrates that for discrete accounting signals, the slow diffusion of information aligns with the low-frequency nature of the data, meaning that holding aged constituents is inherently consistent with the strategy's profitability.

In distinct contrast, market anomalies exhibit a clear difference between capital allocation and profit generation. 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 mechanically allocate a substantial portion of capital into aged, persistent positions whose predictive power has largely dissipated, thereby diluting the efficiency of the aggregate portfolio.

[INSERT TABLE 3 HERE]

4.4 Standalone Performance and the Decay of Market Signals

While the additive decomposition illustrates capital misallocation within standard portfolios, it does not perfectly isolate the predictive power of constituents at different stages of their lifecycle. Mathematically, the additive contribution of an age bucket is a function of its relative capital weight within the aggregate portfolio. If the distribution of signal age is asymmetric between the long and short legs—for instance, if the long leg contains predominantly aged constituents while the short leg is heavily populated by fresh entrants—the additive decomposition may distort the true long-short spread of a specific age group. To address this, I construct standalone value-weighted and equal-weighted portfolios for each age bucket. This approach rescales the constituent weights within each bucket to sum to 100% independently for both the long and short legs. This methodological distinction isolates the pure predictive premium of the constituents, addressing the practical question of how an anomaly strategy exclusively trading fresh entrants would perform compared to one strictly holding aged positions.

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 aligns with standard empirical protocols designed to ensure that estimated premiums are not spuriously driven by sparsely populated outliers (Hou et al., 2020).

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, Carlson, Fisher, & Simutin, 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 & Siegel, 2001).[5]

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 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 4 presents these standalone returns and highlights a structural divergence in how signal decay affects the two anomaly classifications. For market anomalies, there is a rapid deterioration in performance as the constituent ages. A value-weighted long-short portfolio formed exclusively of fresh market constituents yields a return of 0.89% per month ($t = 8.92$). However, as the constituents age, the return drops significantly to 0.39% ($t = 6.75$) for the Middle bucket, and remains at 0.31% ($t = 5.14$) for the Stale bucket. This decay pattern is equally evident in equal-weighted returns, where the fresh portfolio earns 1.24% per month compared to 0.34% for the stale portfolio.

[5]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.

Conversely, accounting anomalies do not exhibit this performance degradation. The standalone value-weighted return for fresh accounting constituents is 0.13% per month, increasing to 0.28% in the Middle bucket before returning to 0.21% for the Stale bucket. More notably, when evaluating equal-weighted returns, the fresh accounting portfolio yields a statistically insignificant -0.09% ($t = 1.08$). Instead, the highest equal-weighted returns are generated by the Middle (0.33%, $t = 8.04$) and Stale (0.34%, $t = 7.73$) buckets.

A potential concern when interpreting the returns of fresh market constituents is whether this premium is an artifact driven by illiquid micro-cap stocks. As highlighted by Fama & French (2008), micro-caps account for roughly 60% of the cross-section of stocks but represent only 3% of the total market capitalization. To mitigate this micro-cap bias, the research design adheres to the methodological prescriptions of Hou et al. (2020) by utilizing NYSE breakpoints, imposing a $5 price filter, and focusing primarily on value-weighted returns. Furthermore, the empirical size distribution of the portfolios does not support the micro-cap hypothesis. Hou et al. (2020) define micro-caps as stocks falling below the 20th percentile of NYSE market equity.[6] In contrast to this threshold, Table 4 demonstrates that the median market capitalization of the fresh market portfolio is $884 million. These magnitudes confirm that the returns to fresh market constituents are predominantly generated by investable, small-to-mid-cap (SMID) equities, indicating that the observed premium reflects economic fundamentals rather than microstructure frictions.

These findings highlight a fundamental difference between accounting and market anomalies. For accounting anomalies, fundamental information diffuses slowly into prices due to investor inattention and post-announcement drift. Because these returns materialize gradually, retaining aged constituents allows investors to capture the delayed premium. Thus, staleness is a natural and profitable feature of these strategies. In contrast, market anomalies reflect transient risk states and temporary limits to arbitrage. Because market participants resolve these frictions quickly, the predictive power is concentrated immediately after the signal is triggered. Therefore, failing to condition on signal age in market anomalies forces investors to hold aged constituents with decayed expected returns, which reduces overall portfolio performance.

[6] 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. Consequently, the fresh market portfolio's median capitalization of $884 million indicates that the typical constituent resides safely above the micro-cap threshold across a large portion of the evaluated timeframe.

[INSERT TABLE 4 HERE]

4.5 Robustness to Systematic Risk Factors

While the standalone portfolios establish a clear deterioration in the raw returns of market anomalies, it is necessary to determine whether this freshness premium is robust to standard asset pricing models. If the high returns of fresh market signals merely reflect an increased exposure to established systematic risk factors, the observed performance decay could be interpreted as a mechanical shift in risk profiles rather than a true deterioration of the underlying anomaly premium.

To address this, I estimate time-series regressions of the age-sorted standalone portfolio returns constructed in the previous section on the Fama & 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 both the value-weighted and equal-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 5 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 5 demonstrates that the rapid decay of market anomalies cannot be explained by standard risk factors. For value-weighted portfolios, the risk-adjusted alpha of fresh market signals is a highly significant 0.75% per month ($t = 7.42$). As the signal ages, this alpha decreases monotonically to 0.26% in the Middle bucket and 0.15% in the Stale bucket. The equal-weighted results exhibit a similarly robust pattern, with the fresh portfolio generating an alpha of 1.16% per month compared to 0.22% for the stale portfolio. This confirms that the staleness trap is not a consequence of time-varying factor exposures; the core predictive power of market signals inherently

deteriorates over time.

In contrast, Panel B confirms that the performance of accounting anomalies does not suffer from immediate decay following risk adjustment. The value-weighted alpha for fresh accounting signals is 0.04% ($t = 0.66$), while the Middle bucket yields a higher alpha of 0.23% ($t = 7.68$). Furthermore, the equal-weighted alpha for fresh accounting signals is even negative (-0.16%), whereas the Middle and Stale buckets generate highly significant alphas of 0.29% and 0.25%, respectively. These findings are consistent with the raw return patterns and support the framework that accounting signals are subject to gradual information diffusion and post-announcement drift, whereas market signals proxy for short-lived, transient states.

[INSERT TABLE 5 HERE]

4.6 Panel Regression Analysis of Signal Age

4.6.1 Controlling for Signal Level and Change

The preceding analyses evaluate the anomaly premium by pooling stocks into aggregate portfolios each month. While this approach establishes the overall magnitude of the staleness trap, it introduces the concern that the results might be driven by a few specific anomalies with large cross-sectional sample sizes. To address this concern and formally test the robustness of the age effect, I transition to a panel regression framework utilizing data at the anomaly, age bucket, and month level. This structure allows each anomaly to be evaluated equally and independently before drawing aggregate inferences.

A related concern is whether the freshness premium merely captures the magnitude of the underlying signal. Fresh entrants might mechanically exhibit more extreme signal ranks or experience larger expectational surprises compared to stale continuers. To verify that the freshness premium represents a distinct temporal dimension rather than just signal intensity, I 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:

$$\begin{aligned} R_{s,p,t} = &\beta_1(Fresh_p \times Market_s) + \beta_2(Middle_p \times Market_s) \\ &+ \beta_3 Fresh_p + \beta_4 Middle_p + \beta_5 Market_s \\ &+ \gamma_1 SignalRankLevel_{s,p,t} + \gamma_2 SignalRankChange_{s,p,t} \\ &+ \mu_s + \eta_p + \delta_t + \epsilon_{s,p,t} \end{aligned} \tag{3}$$

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 6 presents the panel regression estimates. Columns 1 and 3 report the baseline specifications without portfolio characteristic controls. In these baseline models, the interaction term between the fresh age bucket and the market anomaly indicator is positive and statistically significant for both the additive contribution (0.21%, Column 1) and the standalone return (0.56%, Column 3). This confirms that fresh constituents generate a disproportionately large share of the premium in market anomalies compared to stale continuers.

Columns 2 and 4 incorporate the average signal rank level and rank change to account for signal extremity. Column 2 reveals an important dynamic: both the signal rank level (0.064, $p < 0.05$) and the signal rank change (0.245, $p < 0.05$) are positively and significantly associated with the return contribution. This confirms the intuitive premise that signal extremity and momentum do play a structural role in driving portfolio returns.

Crucially, however, the inclusion of these controls does not subsume the freshness premium.

Despite the statistically significant explanatory power of the signal characteristics in Column 2, the $Fresh \times Market$ interaction remains economically robust and statistically significant. In the fully controlled specifications, the coefficient for the decomposition contribution is 0.18% ($t = 3.44$) in Column 2, and the coefficient for the standalone expected return is 0.50% ($t = 1.74$) in Column 4. The persistence of this premium demonstrates that the high expected returns associated with fresh market signals are not simply an artifact of extreme ranks or large characteristic jumps. Rather, the temporal freshness of the signal isolates a unique dimension of return predictability and provides independent predictive power.

[INSERT TABLE 6 HERE]

4.6.2 Post-Publication Decay and Signal Freshness

I next utilize this panel framework to investigate how the staleness trap interacts with the well-documented post-publication decay of anomalies (McLean & Pontiff, 2016). The existing literature demonstrates 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, sophisticated 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:

$$
\begin{aligned}
R_{s,p,t} = \beta_1 (Fresh_p \times Market_s \times PostPub_{s,t}) \\
+ \beta_2 (Middle_p \times Market_s \times PostPub_{s,t}) \\
+ \beta_3 (Fresh_p \times Market_s) + \beta_4 (Middle_p \times Market_s) \\
+ \beta_5 (Fresh_p \times PostPub_{s,t}) + \beta_6 (Middle_p \times PostPub_{s,t}) \\
+ \beta_7 (Market_s \times PostPub_{s,t}) + \beta_8 PostPub_{s,t} \\
+ \beta_9 Fresh_p + \beta_{10} Middle_p + \beta_{11} Market_s \\
+ \gamma_1 SignalRankLevel_{s,p,t} + \gamma_2 SignalRankChange_{s,p,t} \\
+ \mu_s + \eta_p + \delta_t + \epsilon_{s,p,t}
\end{aligned}
\tag{4}
$$

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. Similar to the baseline equation, the main effects (β_9, β_{10}, and β_{11}) are absorbed by the fixed effects.

Table 7 reports the regression estimates and provides evidence on the mechanism underlying the decay of market anomalies. Focusing on the fully controlled standalone returns in Column 4, the interaction between market anomalies and the post-publication indicator ($Market \times PostPub$) yields a significantly negative coefficient of -0.37% ($t = -2.35$). Because the stale bucket serves as the omitted base group, this negative coefficient specifically measures the post-publication decay experienced by the aged constituents of market anomalies. This confirms that the baseline, persistent components of market anomalies experience a significant decline in performance after public dissemination.

The triple interaction term ($Fresh \times Market \times PostPub$) captures how the post-publication effect for fresh market constituents differs from that of the stale base group. The coefficient is economically large and statistically significant at 0.93% ($t = 2.13$). This indicates that the fresh constituents of market anomalies resist the post-publication decay, maintaining a strong relative premium compared to their stale counterparts in the post-publication era. The interaction for the middle bucket ($Middle \times Market \times PostPub$) is positive (0.18%) but lacks statistical significance.

These estimates provide further insight into the nature of post-publication decay. The aggregate decline in market anomaly returns is not a uniform phenomenon; rather, it is primarily concentrated in the stale constituents. Once an anomaly becomes public knowledge, arbitrageurs effectively attenuate the predictability of persistent, aged signals. The concentrated decay in stale constituents is consistent with the repricing dynamics discussed by Pénasse (2022). When investors learn about an anomaly through publication, they buy the affected stocks, causing a one-time price increase. This price jump raises returns today but leaves less profit for the future, effectively drying up the expected premium for persistent signals. In contrast, the premium associated with fresh entrants exhibits resilience against the influx of arbitrage capital. Consequently, in the post-publication environment, the residual predictive power of market anomalies becomes increasingly concentrated in their freshest signals, further reinforcing the staleness trap. The resilience of the freshness premium to public dissemination carries important theoretical implications. If anomaly returns were purely the result of behavioral mispricing, academic publication would provide a blueprint for arbitrageurs to eliminate the premium. The inability of arbitrage capital to compress the fresh return suggests that these signals may instead represent compensation for bearing transient risk or structural limits to arbitrage—a hypothesis formally tested in the following section.

[INSERT TABLE 7 HERE]

5 Economic Origins of the Freshness Premium

The preceding portfolio-level analysis establishes the staleness trap as a persistent feature of continuous market anomalies. Building on this evidence, this section investigates the underlying economic mechanisms driving the rapid decay of these predictability. Specifically, I examine whether the freshness premium of market anomalies is generated by behavioral overreaction to expectational surprises or if it represents compensation for bearing transient risk under limits to arbitrage. To evaluate these competing hypotheses, I first analyze portfolio performance conditional on signal predictability and aggregate macroeconomic states. I then transition to a stock-level framework to cleanly isolate the intensive margin of signal freshness.

5.1 Freshness vs. Surprise: Two Dimensions of Newness

A recent study by Bowles et al. (2026) establishes a framework for understanding anomaly returns through the lens of predictability. They demonstrate that anomaly signals derived from financial statements are inherently predictable, allowing arbitrageurs to trade on these signals before their public release. A direct corollary of their findings is that upon the actual release of the financial information, the observable anomaly premium is primarily driven by expectational surprises, which are instances where the signal was difficult to forecast and thus not preemptively incorporated into prices by investors. Under this information arbitrage framework, predictable fundamental updates are efficiently priced ex-ante and yield no subsequent return upon realization. If a return is predictable from public information, investors should trade it away. The fact that Low Surprise entrants continue to earn high returns suggests that these signals do not reflect easily correctable mistakes. Instead, these returns likely represent the compensation investors require for bearing specific risks that are active only during the initial stage of the signal. While this framework offers a compelling explanation for fundamental anomalies, the structural divergence in the age-based decomposition results suggests that this surprise mechanism may not universally apply to continuous market variables. To formally test this, I propose a conceptual distinction between two dimensions of newness: the expectational dimension, representing the magnitude of the signal surprise, and the temporal dimension, representing the 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 8 HERE]

Table 8 reports the returns of these fresh entrants conditional on their surprise magnitude, revealing a fundamental divergence in the underlying pricing mechanisms. For accounting anomalies, the results provide empirical support for the mechanism proposed 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 drives the premium, yielding a significant 0.44% per month ($t = 6.25$).

This pattern aligns with the view that accounting anomalies represent updates to a firm's fundamental intrinsic value. As Bowles et al. (2026) argue, if a fundamental value update is predictable (Low Surprise), rational investors incorporate this information into prices in advance, eliminating the return upon realization. Consequently, the return is realized primarily when the market makes a prediction error (High Surprise). Furthermore, this explains why accounting anomalies can generate profits even in their stale periods. Although the expectational surprise is the initial trigger, the subsequent price adjustment to fundamental news is often gradual due to limited investor attention. Thus, for accounting anomalies, surprise is the binding constraint for the existence of premium, while freshness is secondary due to the slow decay of post-announcement drift.

In contrast, the results for market anomalies do not support the arbitrage of predictability hypothesis. For fresh market constituents, the 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 substantial 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. Equal-weighted returns similarly remain large across surprise terciles, with Low Surprise market constituents yielding 1.10%.

This finding implies that market anomalies are not driven by expectational information surprises, but rather by transient risk constraints or limits to arbitrage. Market signals, such as idiosyncratic volatility or illiquidity, typically proxy for short-lived frictions or elevated risk states. A key economic insight is that a risk premium cannot be arbitraged away simply because it is predictable. Even if an investor perfectly anticipates that a stock will enter a high-volatility state,

they cannot eliminate the return because the return itself is the required compensation for bearing that specific risk while the state is active.

This mechanism explains the staleness trap observed in market anomalies. Market signals generate returns regardless of whether the signal was a surprise, but only during the immediate activation of the risk state, making temporal freshness the primary binding constraint. Once the initial shock is absorbed or the market adapts to the friction, the premium vanishes rapidly. As the market constituent ages into the stale bucket, the underlying economic constraint relaxes, leaving investors holding a decayed position with no residual compensation.

5.2 Alternative Explanations: Behavioral Overreaction and Market States

To further understand the economic mechanism driving the freshness premium, I examine whether the returns are primarily driven by behavioral overreaction. Cooper et al. (2004) document that cross-sectional momentum profits depend critically on the aggregate state of the market. Grounded in theories of investor overconfidence (e.g., Daniel et al., 1998), they show that aggregate overconfidence is greater following market gains, leading to momentum profits exclusively after UP markets. If the freshness premium of market anomalies is merely a manifestation of investors overreacting to new information due to overconfidence, this premium should be concentrated in UP markets and become insignificant in DOWN markets. Alternatively, if the premium compensates for fundamental risk and limits to arbitrage, it should persist across different macroeconomic states, including prolonged downturns.

To test this hypothesis, I adopt the methodology of Cooper et al. (2004) to condition the portfolio returns on the state of the market. 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 t. Following their definitions, for each horizon $h \in \{6, 12, 36\}$, I identify 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 if the cumulative return is negative. Then, I 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 evaluate the performance of these age portfolios within the macroeconomic states, I create indicator variables for the UP and DOWN markets and regress the resulting aggregate time

series on these indicators without an intercept. This specification allows for the correct estimation of the mean returns and Newey-West standard errors for each state while preserving the continuous time series structure required for autocorrelation adjustments.

[INSERT TABLE 9 HERE]

Table 9 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, for market anomalies, the freshness premium is larger following UP markets, where fresh constituents generate 0.90% ($t = 8.18$) per month compared to 0.32% ($t = 5.28$) for stale constituents. However, contrary to the behavioral overreaction hypothesis, the freshness premium remains statistically and economically significant during DOWN markets. Following 36 months of negative market returns, fresh constituents continue to yield 0.81% ($t = 4.27$). The survival of this premium during prolonged market downturns indicates that the returns to fresh market anomalies are not merely a byproduct of investor overconfidence in bull markets.

Furthermore, the decay in returns, where fresh entrants outperform middle and stale constituents, is consistent across both UP and DOWN states. A notable observation in the DOWN market state is the performance of stale constituents, which drops to a statistically insignificant 0.21% ($t = 0.89$). In environments characterized by heightened risk aversion and depleted liquidity, such as DOWN markets, maintaining stale positions offers no meaningful compensation.

In contrast, the performance of accounting anomalies remains relatively stable regardless of the macroeconomic environment. The long-short return of fresh accounting constituents is 0.12% ($t = 1.63$) in UP markets and 0.23% ($t = 1.10$) in DOWN markets. Collectively, these results resolve the premise of this section. The persistent premium of fresh market constituents across differing macroeconomic environments challenges the sentiment-driven overreaction theory. Instead, it supports the interpretation that market anomalies capture active risk states and limits to arbitrage, which require compensation regardless of the aggregate market trajectory.

5.3 The Marginal Value of Freshness (Stock-Level Evidence)

While the portfolio-level analysis highlights the impact of signal staleness on aggregate anomaly premiums, portfolio sorts inherently compress multidimensional information into binary decile assignments. In reality, a single stock may simultaneously trigger multiple anomaly signals at varying stages of their lifecycles. To rigorously test the mechanisms driving the freshness premium and confirm the robustness of the portfolio results, I transition to a stock-level panel regression framework. This approach allows me to measure the intensive margin of signal freshness while controlling for standard firm-level characteristics.

To cleanly isolate this intensive margin and avoid empirical noise from inactive stocks, I restrict the cross-sectional universe in each month strictly to stocks that appear in the extreme leg of at least one anomaly portfolio. By filtering out stocks with no active signals, this research design ensures that the regressions evaluate the conditional effect of signal age, comparing fresh constituents against stale constituents, rather than the extensive margin of simply possessing an anomaly characteristic versus not having one at all.

To capture the aggregate intensity of a stock's anomaly exposure, I construct signal counting metrics following the methodology of Engelberg et al. (2018). For each stock i in a given month t, I define the overall net anomaly score ($NetTotal_{i,t}$) as the total number of extreme long signals minus the number of extreme short signals across all available predictors. To isolate the temporal dimension, I construct a net fresh anomaly score for both market and accounting anomalies ($NetFresh_{i,t}^{Mkt}$ and $NetFresh_{i,t}^{Acct}$), representing the net count of signals that have just entered the extreme decile in the current month.

To identify the marginal predictive power of signal freshness above and beyond the quantity of extreme anomaly characteristics, I estimate the following panel regression:

$$R_{i,t} = \beta_1 NetFresh_{i,t}^{Mkt} + \beta_2 NetFresh_{i,t}^{Acct} + \beta_3 NetTotal_{i,t} + \gamma X_{i,t-1} + \mu_i + \delta_t + \epsilon_{i,t} \qquad (5)$$

where $R_{i,t}$ is the monthly return of stock i expressed in percentages. $X_{i,t-1}$ is a vector of lagged firm-level control variables including size, 12-month momentum, 1-month short-term reversal, and the natural logarithm of trading volume. The model incorporates firm fixed effects (μ_i) to control

for time-invariant unobserved heterogeneity and date fixed effects (δ_t) to absorb aggregate market shocks. Standard errors are double-clustered by firm and date.

[INSERT TABLE 10 HERE]

Table 10 reports the stock-level return regressions. The results in the second specification provide empirical support for the freshness hypothesis for market anomalies. After controlling for standard firm characteristics and the overall $NetTotal$ score, the coefficient on the market $NetFresh$ score is statistically and economically significant at 0.2018 (t-statistic > 12). Economically, this implies that acquiring one additional fresh market signal is associated with an approximate 20 basis point increase in the stock's expected monthly return, holding all else constant. The returns are driven not solely by the cross-sectional extremeness of the characteristic, but also by the temporal recency of entering that state. This confirms that the portfolio-level freshness premium is a robust stock-level pricing effect.

Conversely, the coefficient for the accounting $NetFresh$ score is significantly negative (-0.1946). This result is consistent with the earlier portfolio decomposition findings. Because fundamental accounting information requires time to be fully incorporated into prices due to limited attention and post-announcement drift, fresh accounting constituents yield negligible or negative marginal returns, leaving the bulk of the profitability to older, persistent positions.

5.4 Aggregate Risk Constraints and Trading Activity

To further examine the economic mechanism behind fresh market anomalies, I test the limits-to-arbitrage hypothesis at the aggregate level. If fresh market anomalies represent compensation for absorbing transient risk or liquidity shocks, the required premium should expand during periods of heightened macroeconomic uncertainty. I proxy for aggregate risk constraints using the CBOE Volatility Index (VIX), centered at its historical mean ($\widetilde{VIX}_t$), and interact it with the stock-level freshness scores:

$$R_{i,t} = \beta_1(NetFresh_{i,t}^{Mkt} \times \widetilde{VIX}_t) + \beta_2(NetFresh_{i,t}^{Acct} \times \widetilde{VIX}_t) + \cdots + \gamma X_{i,t-1} + \mu_i + \delta_t + \epsilon_{i,t} \quad (6)$$

The main effect of the VIX is absorbed by the date fixed effects. Because the historical VIX series is available starting in 1990, the sample size for this interaction specification is reduced.

The third specification in Table 10 supports the risk constraint view. The interaction term between the VIX and the market $NetFresh$ score is significantly positive (0.0067, $t = 2.68$). Economically, a one-unit increase in the VIX above its historical mean amplifies the monthly expected return of a fresh market signal by roughly 0.67 basis points. During periods of elevated market volatility, when arbitrage capital is scarce and aggregate risk aversion is high, the premium associated with entering an extreme market anomaly state increases. This finding provides direct evidence that the freshness premium for market anomalies acts as a reward for liquidity provision and risk-bearing. When macroeconomic uncertainty limits the capacity of arbitrageurs to correct mispricing, the required rate of return for holding stocks with newly activated market frictions must naturally rise.

Finally, to understand the microstructure dynamics of signal staleness, I examine how trading activity evolves over the signal lifecycle. Using the natural logarithm of monthly trading volume as the dependent variable, I run the following regression on the gross count of signals (the sum of long and short signals, denoted as $Gross_{i,t}$) in each age bucket:

$$ln(Volume_{i,t}) = \sum_{c} \sum_{b} \beta_{c,b} Gross_{i,t}^{c,b} + \gamma X_{i,t-1} + \mu_i + \delta_t + \epsilon_{i,t} \tag{7}$$

where $c \in \{Market, Accounting\}$ and $b \in \{Fresh, Middle, Stale\}$. Because the dependent variable is log-transformed, multiplying the estimated coefficients by 100 provides the approximate percentage change in trading volume per additional signal.

The results in Table 11 document the lifecycle of arbitrage activity and highlight structural 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 a substantial 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 reflects the discrete information event effect, as fundamental updates attract immediate 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.

[INSERT TABLE 11 HERE]

For market anomalies, the volume dynamics provide important insight into the staleness trap. When a market anomaly first triggers, the volume increase is positive but relatively muted (0.0004). This subdued initial trading activity aligns with the limits-to-arbitrage framework, suggesting that fresh market states often coincide with localized liquidity constraints or high idiosyncratic risk, making immediate arbitrage costly. Because capital is slow to move into these newly activated states, the mispricing is not instantly corrected, which sustains the freshness premium.

As the constituent ages into the middle bucket (2 to 6 months) and the initial risk or liquidity shock subsides, the trading volume coefficient increases to 0.0012. This increase suggests delayed arbitrage crowding, where capital slowly flows into the anomaly, mechanically compressing the expected return over time. Ultimately, 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. Once the underlying friction is fully resolved, arbitrageurs withdraw from the position. The resulting contraction in liquidity and trading activity leaves stale market constituents mechanically retained in the portfolio with no residual premium.

6 Practical Implementation and Transaction Costs

A natural skepticism regarding the practical profitability of fresh anomaly constituents is that capturing them requires executing trades immediately upon signal formation, inherently leading to high portfolio turnover. A standard prescription in the literature for mitigating these trading frictions, as comprehensively documented by Novy-Marx & Velikov (2016), is to employ transaction cost mitigation techniques such as buy/hold spreads and reduced rebalancing frequencies. Critics might argue, in line with this conventional wisdom, that the staleness trap is not a behavioral oversight but rather a rational response to prohibitive trading frictions. Under this view, investors optimally choose to hold aged constituents because the transaction costs required to constantly refresh the portfolio would subsume the gross alpha. To formally test whether the premium of

fresh constituents survives real-world trading frictions, I incorporate transaction costs into the standalone portfolio returns.

To ensure precision in measuring 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 accurately compute the exact trading volume required to rebalance the portfolios, I account for the mechanical 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:

$$\tilde{w}_{i,t} = \frac{w_{i,t-1}(1 + r_{i,t-1})}{\sum_j w_{j,t-1}(1 + r_{j,t-1})} \tag{8}$$

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 (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:

$$TC_t = \sum_i |w_{i,t} - \tilde{w}_{i,t}| \times c_{i,t} \tag{9}$$

Finally, the net return of the standalone portfolio is simply the gross return minus this total transaction cost ($R_t^{Net} = R_t^{Gross} - TC_t$). 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 12 HERE]

Table 12 reports the gross returns, portfolio costs, and net returns for the standalone long-short portfolios across the three age buckets. The results reveal a distinct dichotomy between accounting and market anomalies. For accounting anomalies, the transaction cost friction substantially penalizes fresh constituents. The fresh accounting portfolio incurs a high trading cost of 0.43% per month, dragging the net long-short return down to a statistically significant negative -0.56%

($t = -4.29$). Conversely, the portfolio of stale accounting constituents incurs a minimal cost of just 0.03% per month, leaving a positive net return. This confirms that for discrete fundamental updates, high turnover is heavily punished by market microstructure frictions, making the strategy of holding persistent, aged constituents an economically rational choice, perfectly in line with the prescriptions of Novy-Marx & Velikov (2016).

Crucially, however, the transaction cost analysis reveals a different calculus for market anomalies. It is true that trading fresh market constituents is expensive. The fresh market portfolio incurs a high trading cost of 0.40% per month due to elevated turnover rates.[7] However, the gross predictive power of these fresh entrants is so substantial (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 provides direct empirical validation of the staleness trap. Novy-Marx & Velikov (2016) convincingly demonstrate that introducing a buy/hold spread to retain existing positions is a highly effective cost mitigation technique for the broader anomaly zoo. However, my results highlight an important boundary condition: for continuous market anomalies, the expected return decays much faster than the underlying signal. Consequently, the conventional practice of retaining aged positions to save on trading costs inadvertently degrades net performance. The exploitable premium is concentrated in the immediate arrival of the information, and this fresh premium is sufficiently large to offset the associated trading frictions.

7 Conclusion

This paper investigates the lifecycle of cross-sectional return predictors, focusing on the temporal dynamics of continuous market anomalies. While empirical asset pricing often assumes that high-

[7] This 0.40% monthly cost likely represents a conservative upper bound. Frazzini, Israel, & Moskowitz (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 the implementation costs for fresh market signals align with these institutional benchmarks, the true operational net premium would be substantially larger.

frequency market variables capture current mispricing or risk, I document a structural persistence mismatch between sorting variables and their return predictability, which I term *endogenous staleness*. Because stock characteristics persist longer than their associated return premiums, standard portfolio formation methods mechanically accumulate aged constituents.

Using a novel Signal Age metric to decompose anomaly portfolios, I demonstrate that stale constituents occupy a substantial fraction of portfolio capital while generating negligible returns. The aggregate anomaly premium is predominantly driven by fresh entrants. When portfolios are reconstructed to isolate these newly activated stocks, the performance of market anomalies improves significantly. Furthermore, this freshness premium is large enough to survive realistic estimates of transaction costs, demonstrating that the conventional practice of retaining aged constituents to reduce turnover inherently degrades net portfolio performance for market anomalies.

Disentangling expectational surprise from temporal freshness reveals a structural dichotomy between accounting anomalies and market anomalies. The premium for accounting anomalies is driven by unpredictable fundamental shocks, consistent with the efficient pricing of new information. In contrast, fresh market constituents yield significant returns even when their entry into the extreme decile is highly predictable. This evidence indicates that market anomalies do not primarily capture slowly diffusing cognitive errors, but rather proxy for transient risk constraints and localized limits to arbitrage.

Additional empirical tests support this interpretation based on risk and market frictions. The freshness premium for market anomalies remains statistically and economically significant during prolonged market downturns, challenging behavioral overreaction theories that predict anomaly profits should be concentrated in high sentiment up markets. Moreover, the premium is amplified during periods of high aggregate volatility. Furthermore, the initial activation of an extreme market state does not generate a significant increase in trading volume, suggesting that severe initial frictions deter immediate arbitrage activity. Together, these findings indicate that fresh market constituents capture episodes of acute liquidity demand and constrained arbitrage capital, where the delayed arrival of trading activity allows the initial premium to persist.

Overall, the results demonstrate that the continuous updating of market data does not guarantee the continued efficacy of a signal. Incorporating signal age into portfolio construction resolves the mechanical dilution caused by aged constituents, providing a more precise measure of the dynamic

nature of cross-sectional risk, trading frictions, and expected returns. Ultimately, while modern markets stream data at the near-instantaneous speed, future research must account for the fact that a fresh timestamp does not guarantee a fresh signal.

References

Ang, A., Hodrick, R. J., Xing, Y., & Zhang, X. (2006). The cross-section of volatility and expected returns. *The journal of finance*, *61*(1), 259–299.

Bernard, V. L., & Thomas, J. K. (1989). Post-earnings-announcement drift: delayed price response or risk premium? *Journal of Accounting research*, *27*, 1–36.

Boguth, O., Carlson, M., Fisher, A., & Simutin, M. (2011). Conditional risk and performance evaluation: Volatility timing, overconditioning, and new estimates of momentum alphas. *Journal of Financial Economics*, *102*(2), 363–389.

Bowles, B., Reed, A. V., Ringgenberg, M. C., & Thornock, J. (2026). Predicting anomalies. *Available at SSRN 4939779*.

Bowles, B., Reed, A. V., Ringgenberg, M. C., & Thornock, J. R. (2024). Anomaly time. *The Journal of Finance*, *79*(5), 3543–3579.

Carhart, M. M. (1997). On persistence in mutual fund performance. *The Journal of finance*, *52*(1), 57–82.

Chen, A. Y., & Velikov, M. (2023). Zeroing in on the expected returns of anomalies. *Journal of Financial and Quantitative Analysis*, *58*(3), 968–1004.

Chen, A. Y., & Zimmermann, T. (2022). Open source cross-sectional asset pricing. *Review of Financial Studies*, *35*(8), 3571–3629.

Chen, T.-Y., Chou, P.-H., Hsieh, C.-H., & Rhee, S. G. (2021). Momentum life cycle, revisited. *Journal of Banking & Finance*, *127*, 106119.

Cochrane, J. H. (2011). Presidential address: Discount rates. *The Journal of finance*, *66*(4), 1047–1108.

Cooper, M. J., Gutierrez, R. C., & Hameed, A. (2004). Market States and Momentum. *The Journal of Finance*, *59*(3), 1345–1365.

Daniel, K., Hirshleifer, D., & Subrahmanyam, A. (1998). Investor psychology and security market under-and overreactions. *the Journal of Finance*, *53*(6), 1839–1885.

Duffie, D. (2010). Presidential Address: Asset Price Dynamics with Slow-Moving Capital. *The Journal of Finance*, *65*(4), 1237–1267.

Engelberg, J., McLean, R. D., & Pontiff, J. (2018). Anomalies and news. *The Journal of Finance*, *73*(5), 1971–2001.

Fama, E. F., & French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, *33*(1), 3–56.

Fama, E. F., & French, K. R. (2007). Migration. *Financial Analysts Journal*, *63*(3), 48–58.

Fama, E. F., & French, K. R. (2008). Dissecting anomalies. *The journal of finance*, *63*(4), 1653–1678.

Fama, E. F., & French, K. R. (2015). A five-factor asset pricing model. *Journal of financial economics*, *116*(1), 1–22.

Fama, E. F., & MacBeth, J. D. (1973). Risk, return, and equilibrium: Empirical tests. *Journal of political economy*, *81*(3), 607–636.

Ferson, W. E., & Siegel, A. F. (2001). The efficient use of conditioning information in portfolios. *The Journal of Finance*, *56*(3), 967–982.

Frazzini, A., Israel, R., & Moskowitz, T. J. (2012). Trading costs of asset pricing anomalies. *Fama-Miller Working Paper, Chicago Booth Research Paper*(14-05).

Harvey, C. R., Liu, Y., & Zhu, H. (2016). ...and the cross-section of expected returns. *Review of Financial Studies*, *29*(1), 5–68.

Hirshleifer, D., Lim, S. S., & Teoh, S. H. (2009). Driven to distraction: Extraneous events and underreaction to earnings news. *The journal of finance*, *64*(5), 2289–2325.

Hou, K., Xue, C., & Zhang, L. (2015). Digesting anomalies: An investment approach. *Review of Financial Studies*, *28*(3), 650–705.

Hou, K., Xue, C., & Zhang, L. (2020). Replicating anomalies. *Review of Financial Studies*, *33*(5), 2019–2133.

Jegadeesh, N., & Titman, S. (1993). Returns to buying winners and selling losers: Implications for stock market efficiency. *The Journal of finance*, *48*(1), 65–91.

Keloharju, M., Linnainmaa, J. T., & Nyberg, P. (2021). Are return seasonalities due to risk or mispricing? *Journal of Financial Economics*, *139*(1), 138–161.

Lee, C. M., & Swaminathan, B. (2000). Price momentum and trading volume. *the Journal of Finance*, *55*(5), 2017–2069.

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

McLean, R. D., & Pontiff, J. (2016). Does academic research destroy stock return predictability? *Journal of Finance*, *71*(1), 5–32.

Nagel, S. (2012). Evaporating Liquidity. *Review of Financial Studies*, *25*(7), 2005–2039.

Novy-Marx, R., & Velikov, M. (2016). A taxonomy of anomalies and their trading costs. *The Review of Financial Studies*, *29*(1), 104–147.

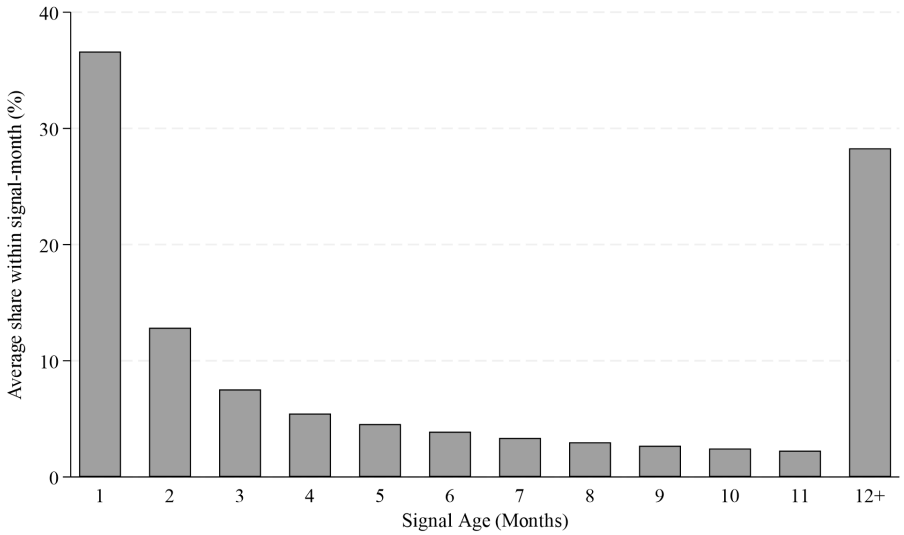
Pástor, L., & Stambaugh, R. F. (2003). Liquidity risk and expected stock returns. *Journal of Political economy*, *111*(3), 642–685.

Pénasse, J. (2022). Understanding alpha decay. *Management Science*, *68*(5), 3966–3973.

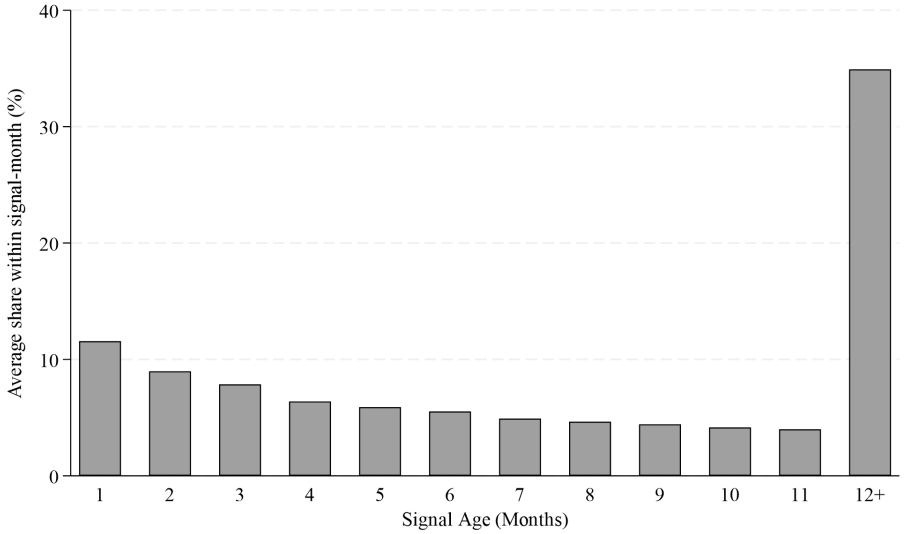
Shleifer, A., & Vishny, R. W. (1997). The limits of arbitrage. *Journal of Finance*, *52*(1), 35–55.

Stambaugh, R. F., & Yuan, Y. (2017). Mispricing factors. *The review of financial studies*, *30*(4), 1270–1315.

Zhou, Y. (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.

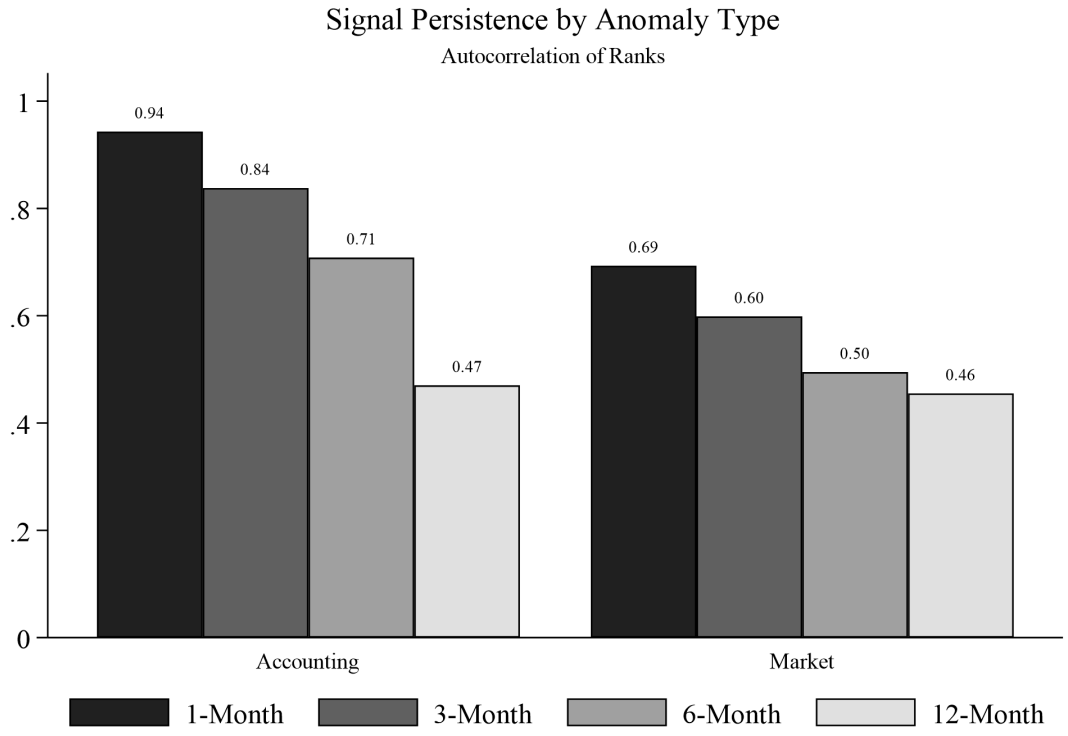


Figure 2: **Signal Persistence by Anomaly Type**
This figure presents the signal persistence for market-based and accounting-based anomalies over different time horizons. Persistence is measured using the rank autocorrelation of the underlying sorting variables. For each anomaly signal, the cross-sectional 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.

Table 1: **Summary Statistics**
This table reports the summary statistics for the monthly portfolio returns and the constituent firm signal age for market-based (Panel A) and accounting-based (Panel B) anomalies. Both value-weighted (VW) and equal-weighted (EW) metrics are presented. Signal age is defined as the number of consecutive months a stock has persisted in the extreme long (top decile) or short (bottom decile) leg of a given anomaly. The sample includes 55 market anomalies and 91 accounting anomalies constructed using the Open Source Asset Pricing (OSAP) database, spanning the period from January 1960 to December 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

Table 2: **Portfolio Transition Probability (Conditional on $t-1$)**
This table reports the time-series transition probabilities of stocks within extreme anomaly portfolios. It presents the conditional probability that a stock remains in the extreme long or extreme short leg in month t, given that it was in the exact same leg in month $t-1$. The probabilities are computed at the stock-level and averaged across all market-based and accounting-based anomalies, respectively. The sample period spans from 1960 to 2024.

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

Table 3: **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. 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 (1m)	0.20	50.50	37.48	247
	(10.88)			
Middle (2-6m)	0.17	41.12	29.59	239
	(8.66)			
Stale (>6m)	0.03	8.38	32.93	270
	(1.26)			

Panel B: Accounting Anomalies

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

Table 4: **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 3, 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 (VW) and equal-weighted (EW) 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. 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 (VW, %)	LS Ret (EW, %)	Avg MktCap ($M)	Med MktCap ($M)	Count (N)
Fresh (1m)	0.89	1.24	2,742	884	251
	(8.92)	(6.47)			
Middle (2-6m)	0.39	0.51	2,767	926	244
	(6.75)	(9.96)			
Stale (>6m)	0.31	0.34	5,943	2,269	370
	(5.14)	(6.19)			

Panel B: Accounting Anomalies

	LS Ret (VW, %)	LS Ret (EW, %)	Avg MktCap ($M)	Med MktCap ($M)	Count (N)
Fresh (1m)	0.13	-0.09	1,956	384	63
	(1.90)	(-1.08)			
Middle (2-6m)	0.28	0.33	2,470	461	179
	(6.28)	(8.04)			
Stale (>6m)	0.21	0.34	3,946	919	297
	(4.40)	(7.73)			

Table 5: **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 (VW) and equal-weighted (EW) Long-Short (LS) 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

	Value-Weighted (VW)			**Equal-Weighted (EW)**		
	Fresh (1m)	Middle (2-6m)	Stale (>6m)	Fresh (1m)	Middle (2-6m)	Stale (>6m)
Alpha	0.75***	0.26***	0.15***	1.16***	0.40***	0.22***
	(7.42)	(5.75)	(3.80)	(5.65)	(10.49)	(6.11)
MKT	-0.01	-0.07***	-0.10***	-0.03*	-0.08***	-0.13***
	(-0.66)	(-5.96)	(-8.16)	(-1.89)	(-8.16)	(-11.06)
SMB	0.12***	0.06**	0.10***	0.08***	0.04*	0.05***
	(4.20)	(2.42)	(4.60)	(2.92)	(1.91)	(2.87)
HML	0.15***	0.13***	0.17***	0.12**	0.12***	0.14***
	(3.68)	(4.35)	(6.47)	(2.34)	(5.27)	(6.28)
RMW	0.07**	0.08***	0.09***	0.09**	0.11***	0.10***
	(2.06)	(2.93)	(4.28)	(2.11)	(4.82)	(4.36)
CMA	0.02	0.10**	0.11***	-0.02	0.07**	0.08**
	(0.25)	(2.24)	(2.76)	(-0.19)	(1.99)	(2.38)
UMD	0.13***	0.13***	0.17***	0.12***	0.11***	0.16***
	(7.40)	(10.12)	(12.58)	(5.44)	(8.97)	(14.11)
Adj. R^2	0.14	0.36	0.56	0.04	0.45	0.64

Panel B: Accounting Anomalies

	Value-Weighted (VW)			**Equal-Weighted (EW)**		
	Fresh (1m)	Middle (2-6m)	Stale (>6m)	Fresh (1m)	Middle (2-6m)	Stale (>6m)
Alpha	0.04	0.23***	0.08***	-0.16*	0.29***	0.25***
	(0.66)	(7.68)	(3.27)	(-1.80)	(10.91)	(9.95)
MKT	-0.00	-0.03***	-0.02***	-0.03	-0.04***	-0.05***
	(-0.07)	(-3.34)	(-3.12)	(-1.58)	(-7.80)	(-7.66)
SMB	0.03	0.05***	0.03**	-0.05*	0.01	0.01
	(1.44)	(3.13)	(2.01)	(-1.80)	(0.71)	(0.72)
HML	0.18***	0.14***	0.16***	0.12**	0.13***	0.15***
	(5.91)	(7.88)	(10.76)	(2.55)	(9.12)	(11.00)
RMW	0.06*	0.06***	0.11***	0.13***	0.10***	0.12***
	(1.89)	(2.96)	(6.85)	(3.52)	(6.72)	(5.78)
CMA	0.16***	0.16***	0.22***	0.14**	0.12***	0.17***
	(3.04)	(7.20)	(10.71)	(2.25)	(6.26)	(7.45)
UMD	-0.04**	-0.06***	-0.00	-0.03	-0.04***	-0.00
	(-2.20)	(-5.92)	(-0.40)	(-1.47)	(-4.47)	(-0.16)
Adj. R^2	0.20	0.52	0.67	0.12	0.58	0.70

Table 6: **Panel Regressions: Main Effects**
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

Table 7: **Panel Regressions: Post-Publication Effects**
This table presents anomaly-level panel regressions evaluating the interaction between signal 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. 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 8: **Returns by Surprise Group**
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 (VW) and equal-weighted (EW) 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 VW (%)	LS EW (%)	Avg MktCap ($M)	Med MktCap ($M)	Count (N)	Avg Surp
Low_Surprise	1.09	1.10	3,304	1,137	89	0.0751
	(7.73)	(4.40)				
Mid_Surprise	0.74	1.18	3,063	1,107	86	0.1937
	(8.30)	(5.98)				
High_Surprise	0.85	1.17	2,066	833	94	0.4033
	(7.33)	(7.44)				

Panel B: Accounting Anomalies (Fresh Only)

	LS VW (%)	LS EW (%)	Avg MktCap ($M)	Med MktCap ($M)	Count (N)	Avg Surp
Low_Surprise	-0.35	-0.77	2,227	524	28	0.0378
	(-3.45)	(-7.24)				
Mid_Surprise	-0.10	-0.19	2,494	635	24	0.1545
	(-1.31)	(-2.31)				
High_Surprise	0.44	0.38	1,666	472	30	0.4359
	(6.25)	(5.14)				

Table 9: **Returns by Age Bucket Conditional on Market States**
This table reports the profitability of anomaly portfolios conditionally sorted by signal age across different macroeconomic states. Following Cooper, Gutierrez, and Hameed (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 (VW) and equally-weighted (EW) 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 VW (%)	LS EW (%)	LS VW (%)	LS EW (%)	LS VW (%)	LS EW (%)
Panel A: Market Anomalies						
UP Market						
Fresh (1m)	0.90	1.30	0.95	1.42	0.94	1.40
	(8.18)	(6.02)	(7.85)	(5.80)	(7.36)	(5.37)
Middle (2-6m)	0.39	0.51	0.39	0.55	0.33	0.52
	(6.39)	(9.83)	(6.60)	(10.72)	(5.47)	(10.24)
Stale (>6m)	0.32	0.37	0.32	0.40	0.30	0.38
	(5.28)	(6.99)	(5.93)	(7.96)	(5.26)	(7.19)
DOWN Market						
Fresh (1m)	0.81	0.84	0.68	0.67	0.75	0.85
	(4.27)	(4.05)	(4.62)	(5.13)	(5.65)	(7.67)
Middle (2-6m)	0.41	0.46	0.41	0.37	0.56	0.46
	(2.24)	(2.38)	(2.96)	(3.01)	(4.49)	(4.00)
Stale (>6m)	0.21	0.13	0.28	0.17	0.33	0.25
	(0.89)	(0.50)	(1.77)	(1.11)	(2.27)	(1.87)
Panel B: Accounting Anomalies						
UP Market						
Fresh (1m)	0.12	-0.07	0.07	-0.09	0.07	-0.11
	(1.63)	(-0.82)	(0.88)	(-0.95)	(0.83)	(-1.11)
Middle (2-6m)	0.27	0.31	0.26	0.31	0.23	0.29
	(5.52)	(7.16)	(5.53)	(7.06)	(4.91)	(6.81)
Stale (>6m)	0.20	0.32	0.16	0.32	0.15	0.31
	(3.87)	(7.21)	(3.17)	(6.83)	(2.95)	(6.73)
DOWN Market						
Fresh (1m)	0.23	-0.23	0.34	-0.08	0.31	-0.03
	(1.10)	(-0.87)	(2.57)	(-0.49)	(2.30)	(-0.22)
Middle (2-6m)	0.38	0.47	0.36	0.41	0.42	0.43
	(3.52)	(4.09)	(3.60)	(4.76)	(3.98)	(4.91)
Stale (>6m)	0.31	0.47	0.38	0.41	0.39	0.41
	(2.69)	(2.98)	(3.80)	(4.26)	(3.70)	(4.40)

Table 10: **Mechanism Test: Stock-Level Return Predictability**
This table reports the results of stock-level predictive regressions to evaluate the premium of fresh signals while controlling for aggregate anomaly scores and cross-sectional characteristics. 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 one-month-ahead stock return. The primary independent variables of interest is the Net Fresh score for market and accounting anomalies. For each firm-month, the Net Fresh score is defined as the total count of extreme long signals minus the total count of extreme short signals associated with a given stock within the Fresh age bucket. Column (1) includes base controls, Column (2) introduces the net total anomaly score (following Engelberg et al. (2018)), and Column (3) includes interaction terms with the centered CBOE Volatility Index (VIX) to test whether the premium expands during periods of elevated aggregate market stress. Standard errors are clustered by firm and month and are reported in parentheses. The sample period spans from 1960 to 2024 for Columns (1) and (2) and from 1990 to 2024 for Column (3).

	(1) Base Controls	(2) + Net Total	(3) + VIX Interaction
Net Fresh (Mkt)	0.2485***	0.2018***	0.2098***
	(0.0163)	(0.0157)	(0.0207)
Net Fresh (Acct)	-0.1482***	-0.1946***	-0.2531***
	(0.0187)	(0.0191)	(0.0279)
Net Total (All)		0.0461***	0.0404***
		(0.0037)	(0.0054)
Net Fresh (Mkt) × VIX			0.0067***
			(0.0025)
Net Fresh (Acct) × VIX			-0.0099***
			(0.0034)
Controls	Yes	Yes	Yes
Firm & Date FEs	Yes	Yes	Yes
Observations	2,172,989	2,172,989	1,391,311
Adj. R^2	0.1682	0.1687	0.1484

Table 11: **Mechanism Test: Are Fresh Signals Traded?**
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 12: **Gross, Cost, 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 8 and 9. 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

This appendix details the list of anomalies used in my analysis, derived from the universe of 212 signals provided by Open Source Asset Pricing (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 ensure robust portfolio formation and avoid issues related to tied ranks during decile sorting, I restrict the sample exclusively 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
High52	52 week high	George and Hwang	2004
IdioVol3F	Idiosyncratic risk (3 factor)	Ang et al.	2006

Continued on next page

Table A1 – Continued from previous page

Acronym	Long Description	Authors	Year
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
ShortInterest	Short Interest	Dechow et al.	2001
Size	Size	Banz	1981

Continued on next page

Table A1 – Continued from previous page

Acronym	Long Description	Authors	Year
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
ChNNCOA	Change in Net Noncurrent Op Assets	Soliman	2008
ChNWC	Change in Net Working Capital	Soliman	2008

Continued on next page

Table A1 – Continued from previous page

Acronym	Long Description	Authors	Year
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
IntanSP	Intangible return using Sale2P	Daniel and Titman	2006
Investment	Investment to revenue	Titman, Wei and Xie	2004

Continued on next page

Table A1 – Continued from previous page

Acronym	Long Description	Authors	Year
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
SP	Sales-to-price	Barbee, Mukherji and Raines	1996
tang	Tangibility	Hahn and Lee	2009

Continued on next page

Table A1 – Continued from previous page

Acronym	**Long Description**	**Authors**	**Year**
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 Robustness Checks

B.1 Rebalancing Frequencies

One potential concern regarding the analysis of signal age is the inherent difference in the updating frequency of the underlying data. While market-based signals are derived from continuous trading data, fundamental accounting variables are typically updated on a quarterly or annual basis. Although many accounting anomalies incorporate continuous price data that induces monthly variation in cross-sectional rankings, evaluating signal age on a strictly monthly basis could arguably disadvantage accounting anomalies and distort the structural comparison against market signals.

To address this concern and ensure that the "staleness trap" is not an artifact of monthly portfolio formation, I reconstruct the anomaly portfolios using lower-frequency rebalancing schemes. Specifically, I implement a quarterly rebalancing strategy where portfolios are formed at the end of March, June, September, and December, and held for three months. Additionally, following the standard convention of Fama and French (1993), I implement an annual rebalancing strategy where portfolios are formed at the end of June and held for the subsequent twelve months. Under these specifications, Signal Age is redefined in terms of consecutive quarters or years, respectively. Furthermore, to allow a sufficient burn-in period for the proper accumulation of stale signals at these lower frequencies, the sample period for this analysis is restricted to 1980–2024. This adjustment prevents the early years of the sample from being mechanically skewed toward the fresh and middle age buckets.

Table A2 and Table A3 present the portfolio decomposition results under these lower-frequency rebalancing schemes. A primary observation is that the overall additive profitability of both anomaly types declines as the rebalancing frequency decreases, indicating that monthly formation is generally more effective for capturing the aggregate premium. For accounting anomalies under quarterly rebalancing, the capital and profit shares are distributed relatively evenly across the three age buckets, with the Fresh bucket remaining the smallest contributor (27.10% of profits and 21.23% of capital).

When shifting to annual rebalancing, the decomposition results initially appear to show a shift in dynamics: the Fresh bucket for accounting anomalies generates 65.39% of the total profits.

However, this is largely a mechanical artifact of the extended formation window. Because the portfolio is only updated once a year, the Fresh bucket (stocks that entered the extreme decile within the past 12 months) naturally absorbs a substantial 55.63% of the total portfolio capital.

The standalone portfolio returns (Table A4 and Table A5), which rescale the weights within each bucket to 100%, resolve this mechanical proportionality and reveal the true predictive power of the signals. As shown in the standalone results, trading exclusively on fresh accounting information does not yield a superior premium. Under quarterly rebalancing, the value-weighted returns across Fresh, Middle, and Stale accounting buckets are relatively flat (0.26%, 0.22%, and 0.21%, respectively). Under annual rebalancing, the Fresh accounting bucket yields the lowest standalone return of 0.18% per month, whereas the Stale bucket (signals older than two years) yields a higher return of 0.23%. This confirms that for fundamental signals, older information retains robust predictive power, consistent with theories of gradual information diffusion and post-earnings-announcement drift.

Conversely, the temporal dynamics for market anomalies remain consistent even under inefficient low-frequency sorting. Despite the friction of holding continuous signals for extended periods, the standalone returns for market anomalies still exhibit a pronounced monotonic decay. Under annual rebalancing, the Fresh and Middle market buckets retain some positive premium, but the return for Stale market signals deteriorates to a negative -0.03% per month.

Collectively, these robustness checks confirm that the structural dichotomy between market and accounting anomalies is highly robust to the choice of rebalancing frequency. The rapid decay of expected returns, the staleness trap, is an inherent economic feature of market-based predictors rather than a methodological byproduct of monthly portfolio formation.

Table A2: **Portfolio Decomposition By Age Bucket (Quarterly Rebalancing)**
This table presents the decomposition of the anomaly returns by signal age under a quarterly rebalancing scheme. For each anomaly, stocks are sorted into extreme deciles at the end of each quarter (March, June, September, December) and held for three months. Stocks are classified into three mutually exclusive buckets based on the number of consecutive quarters they have remained in the extreme leg: Fresh (1 quarter), Middle (2 - 3 quarters), and Stale (4 or more quarters). 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. t-statistics, computed using Newey-West standard errors, are reported in parentheses. The sample period spans from 1980 to 2024.

Panel A: Market Anomalies

	LS Contrib (%)	Profit%	Cap%	Count (N)
Fresh (1Q)	0.12	42.63	46.92	341
	(4.18)			
Middle (2-3Q)	0.08	29.01	21.94	201
	(4.26)			
Stale (≥4Q)	0.08	28.36	31.14	335
	(2.11)			

Panel B: Accounting Anomalies

	LS Contrib (%)	Profit%	Cap%	Count (N)
Fresh (1Q)	0.06	27.10	21.23	136
	(3.94)			
Middle (2-3Q)	0.08	40.83	27.72	184
	(4.04)			
Stale (≥4Q)	0.07	32.07	51.05	309
	(2.08)			

Table A3: **Portfolio Decomposition By Age Bucket (Annual Rebalancing)**
This table presents the decomposition of the anomaly returns by signal age under an annual rebalancing scheme. For each anomaly, stocks are sorted into extreme deciles at the end of June each year and held for the subsequent twelve months. Stocks are classified into three mutually exclusive buckets based on the number of consecutive years they have remained in the extreme leg: Fresh (1 year), Middle (2 years), and Stale (3 or more years). 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. t-statistics, computed using Newey-West standard errors, are reported in parentheses. The sample period spans from 1980 to 2024.

Panel A: Market Anomalies

	LS Contrib (%)	Profit%	Cap%	Count (N)
Fresh (1Y)	0.14	91.32	59.77	458
	(3.47)			
Middle (2Y)	0.01	9.05	15.53	142
	(1.03)			
Stale (≥3Y)	-0.00	-0.37	24.71	245
	(-0.02)			

Panel B: Accounting Anomalies

	LS Contrib (%)	Profit%	Cap%	Count (N)
Fresh (1Y)	0.11	65.39	55.63	360
	(3.66)			
Middle (2Y)	0.03	19.23	15.92	112
	(2.48)			
Stale (≥3Y)	0.03	15.38	28.45	149
	(1.31)			

Table A4: **Portfolio Returns By Age Bucket (Quarterly Rebalancing)**
This table reports the standalone performance of anomaly portfolios constructed exclusively from stocks within specific signal age buckets under a quarterly rebalancing scheme. For each anomaly, stocks are sorted into extreme deciles at the end of each quarter (March, June, September, December) and held for three months. Stocks are classified into three mutually exclusive buckets based on the number of consecutive quarters they have remained in the extreme leg: Fresh (1 quarter), Middle (2-3 quarters), and Stale (4 or more quarters). 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 (VW) and equal-weighted (EW) 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. *t*-statistics, computed using Newey-West standard errors, are reported in parentheses. The sample period spans from 1980 to 2024.

Panel A: Market Anomalies

	LS Ret (VW, %)	LS Ret (EW, %)	Avg MktCap ($M)	Med MktCap ($M)	Count (N)
Fresh (1Q)	0.27	0.30	4,327	1,277	354
	(4.60)	(5.50)			
Middle (2-3Q)	0.28	0.21	4,066	1,371	210
	(4.47)	(2.88)			
Stale (≥4Q)	0.15	0.01	7,641	2,872	430
	(1.35)	(0.12)			

Panel B: Accounting Anomalies

	LS Ret (VW, %)	LS Ret (EW, %)	Avg MktCap ($M)	Med MktCap ($M)	Count (N)
Fresh (1Q)	0.26	0.44	4,089	761	140
	(4.47)	(7.08)			
Middle (2-3Q)	0.22	0.40	3,942	742	187
	(3.65)	(7.04)			
Stale (≥4Q)	0.21	0.43	5,387	1,246	312
	(3.22)	(7.09)			

Table A5: **Portfolio Returns By Age Bucket (Annual Rebalancing)**
This table reports the standalone performance of anomaly portfolios constructed exclusively from stocks within specific signal age buckets under an annual rebalancing scheme. For each anomaly, stocks are sorted into extreme deciles at the end of June each year and held for the subsequent twelve months. Stocks are classified into three mutually exclusive buckets based on the number of consecutive years they have remained in the extreme leg: Fresh (1 year), Middle (2 years), and Stale (3 or more years). 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 (VW) and equal-weighted (EW) 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. t-statistics, computed using Newey-West standard errors, are reported in parentheses. The sample period spans from 1980 to 2024.

Panel A: Market Anomalies

	LS Ret (VW, %)	LS Ret (EW, %)	Avg MktCap ($M)	Med MktCap ($M)	Count (N)
Fresh (1Y)	0.19	0.15	4,269	1,237	458
	(3.37)	(2.60)			
Middle (2Y)	0.03	-0.06	4,755	1,582	148
	(0.44)	(-0.77)			
Stale (≥3Y)	-0.03	-0.08	8,275	3,365	284
	(-0.23)	(-0.57)			

Panel B: Accounting Anomalies

	LS Ret (VW, %)	LS Ret (EW, %)	Avg MktCap ($M)	Med MktCap ($M)	Count (N)
Fresh (1Y)	0.18	0.37	3,775	760	360
	(3.28)	(7.39)			
Middle (2Y)	0.23	0.43	4,250	1,027	110
	(3.10)	(6.84)			
Stale (≥3Y)	0.23	0.38	6,700	1,743	157
	(2.93)	(5.62)			

B.2 Robustness to Quintile Sorting

In the main analysis, anomaly portfolios are constructed using decile sorts, following standard conventions in the recent asset pricing literature (e.g., Hou et al. (2020)). While decile sorting provides a sharp contrast between extreme winners and losers, it may be susceptible to the influence of idiosyncratic noise or extreme outliers at the tails of the cross-sectional distribution. To ensure that the documented "Staleness Trap" and the structural dichotomy between market and accounting anomalies are not artifacts of a specific sorting threshold, I reconstruct the portfolios using a quintile sorting methodology. Under this alternative specification, stocks are sorted into five portfolios using the cross-sectional ranking of the anomaly signal. A stock enters the extreme portfolio when it moves into the top or bottom quintile. Signal Age is defined identically to the main analysis, recursively tracking the consecutive months a stock resides in these extreme quintile legs.

Table A6 presents the decomposition of the aggregate anomaly premium under quintile sorting. The core findings remain highly consistent. For market anomalies, standard quintile portfolios continue to mechanically accumulate decayed positions, exhibiting a clear misallocation of capital. The Stale bucket traps approximately 37% of the portfolio's market capitalization but contributes only 8.9% of the total profits. In contrast, Fresh market entrants drive a disproportionate 43.8% of the profits while occupying 32.7% of the investable capital. This confirms that the Staleness Trap is a pervasive feature of continuous market signals, robust to broader portfolio definitions. For accounting anomalies, the premium remains heavily concentrated in the Middle and Stale buckets, which collectively account for over 83% of the total profits, reaffirming the slow diffusion of fundamental information.

Table A7 reports the standalone performance of age-based portfolios using quintile breakpoints. Consistent with the main results, the performance of market anomalies exhibits a pronounced monotonic decay as the signal ages. The value-weighted return for the Fresh market quintile is 0.59% per month ($t = 7.22$), which drops significantly to 0.24% ($t = 4.67$) for the Stale quintile. Conversely, the standalone returns for accounting anomalies show no such decay, maintaining relatively stable value-weighted premiums across the Fresh (0.20%) and Stale (0.19%) buckets. Collectively, these results demonstrate that the rapid decay of market anomalies and the sustained predictability of

accounting anomalies are fundamental economic phenomena, rather than mechanical byproducts of decile segmentation.

Table A6: **Portfolio Decomposition By Age Bucket (Quintile Sorting)**
This table presents the decomposition of the anomaly returns by signal age under a quintile sorting methodology. For each anomaly and month, stocks in the extreme quintiles 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. 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 (1m)	0.12	43.78	32.66	370
	(9.14)			
Middle (2-6m)	0.13	47.33	30.36	404
	(7.85)			
Stale (>6m)	0.02	8.89	36.97	484
	(1.02)			

Panel B: Accounting Anomalies

	LS Contrib (%)	Profit%	Cap%	Count (N)
Fresh (1m)	0.03	16.68	7.61	89
	(5.82)			
Middle (2-6m)	0.08	37.70	26.11	281
	(7.04)			
Stale (>6m)	0.09	45.62	66.28	566
	(3.13)			

Table A7: **Portfolio Returns By Age Bucket (Quintile Sorting)**
This table reports the standalone performance of anomaly portfolios constructed exclusively from stocks within specific signal age buckets under a quintile sorting methodology. 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, 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 (VW) and equal-weighted (EW) 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. 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 (VW, %)	LS Ret (EW, %)	Avg MktCap ($M)	Med MktCap ($M)	Count (N)
Fresh (1m)	0.59	1.10	2,604	636	373
	(7.22)	(5.80)			
Middle (2-6m)	0.30	0.41	2,718	698	407
	(7.29)	(10.49)			
Stale (>6m)	0.24	0.29	5,007	1,451	628
	(4.67)	(5.99)			

Panel B: Accounting Anomalies

	LS Ret (VW, %)	LS Ret (EW, %)	Avg MktCap ($M)	Med MktCap ($M)	Count (N)
Fresh (1m)	0.20	-0.09	2,021	325	92
	(3.24)	(-1.15)			
Middle (2-6m)	0.22	0.28	2,550	408	283
	(6.03)	(8.44)			
Stale (>6m)	0.19	0.28	3,992	766	575
	(4.59)	(7.45)			