Anomalies and Cash Flows*

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ABSTRACT

I examine whether market anomalies reflect rational risk compensation or mispricing by analyzing their cash flow patterns. I document a fundamental dichotomy: accounting anomalies exhibit cyclical cash flows consistent with risk-based pricing, whereas non-accounting anomalies display countercyclical patterns indicative of mispricing. This distinction arises from differences in information transmission. Accounting anomalies rely on clearly defined information from financial statements, whereas non-accounting anomalies depend on information that diffuses gradually. Building on Hong and Stein's (1999) framework of gradual information diffusion, I show how these differences in information transmission generate distinct return patterns. The model predicts that slowly diffusing information leads to short-term overreaction and long-term correction. Further analysis through the lens of price-fundamental gaps reveals that non-accounting anomalies exhibit stronger differences between resolution and build-up anomalies, particularly in their cash-flow cyclicality and bond risk exposure, which serves as a measure of cyclicality. These findings suggest that a unified theory of market anomalies must account for both rational risk compensation and behavioral biases, with their relative importance depending on the nature of the underlying information.

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I. Introduction

The debate over whether market anomalies reflect rational risk compensation or mispricing remains a cornerstone question in asset pricing. Under risk-based explanations, anomalies generate abnormal returns because they expose investors to systematic risks not captured by traditional models such as the CAPM, necessitating additional compensation for bearing such risks. In contrast, mispricing-based explanations attribute these excess returns to deviations of prices from assets' fundamental values, driven by irrational investor behavior or market frictions.

Because anomaly returns reflect changes in the expected discounted future cash flows, studying the cash flow patterns of anomalies provides direct evidence of their underlying mechanism. Lochstoer and Tetlock (2020) make an important contribution by highlighting the role of cash flows in understanding anomaly returns. Building on their insights, I explore whether their findings extend to a broader set of anomalies beyond the five they examine, which represent only a small subset of the more than 300 documented anomalies in the literature (Harvey, Liu, and Zhu, 2016). My analysis reveals that both anomalies and placebos exhibit similar cash-flow-driven patterns under their methodology, suggesting that their framework provides limited additional guidance on the economic sources of anomalies. These findings motivate my alternative approach of examining realized cash flows directly.

This paper documents a fundamental dichotomy in market anomalies. Accounting anomalies exhibit procyclical cash flows consistent with rational risk compensation, whereas non-accounting anomalies display countercyclical patterns suggestive of mispricing. Accounting anomalies rely on well-defined, readily available information disclosed through financial statements, allowing for immediate integration into prices. In contrast, non-accounting anomalies depend on information that diffuses gradually into prices, making it more difficult for investors to evaluate cash flow implications in real time. For example, while a signal such as short-term reversal is easy to calculate, it remains challenging for investors to understand its implications for future cash flows and determine how much of this information has been incorporated into the price.

I develop a theoretical framework to explain how different information transmission mechanisms

generate distinct return patterns. Extending Hong and Stein's (1999) model of gradual information diffusion, I introduce two types of information: immediately observable information that all market participants see simultaneously and information that diffuses gradually across the market. This extension captures the key distinction between accounting and non-accounting signals. The model shows that when information about future cash flows diffuses gradually, predictable return patterns emerge even with zero expected returns. Specifically, prices initially overreact to slowly diffusing information, resulting in positive short-term returns in non-accounting anomalies. As the true cash-flow implications become clear over time, prices correct, leading to negative long-term returns. This endogenous pattern of short-term overreaction and long-term correction provides a theoretical basis for why non-accounting anomalies reflect mispricing rather than risk compensation.

My empirical analysis begins by tracking firms in both accounting and non-accounting anomalies. The methodology is as follows: for each month t from 1973 to 2020, I form quintile portfolios by sorting firms based on their characteristics and buying (selling) the quintile with the highest (lowest) expected return performance. I then track the log annual cash-flow growth of these portfolios for up to three years. An anomaly's cash-flow growth is calculated as the difference between its long and short portfolio growth rates. This tracking approach provides insights into anomalies through firm-level cash-flow fundamentals (e.g., Cohen, Polk, and Vuolteenaho, 2009). While short-term cash flows can be noisy due to idiosyncratic factors (e.g., Babenko, Boguth, and Tserlukevich, 2016) and dividend policy stickiness (e.g., DeAngelo and DeAngelo, 2000; Benartzi, Michaely, and Thaler, 1997; Leary and Michaely, 2011), examining growth over multiple years reveals more reliable patterns.

The results show striking differences between accounting and non-accounting anomalies. Accounting anomalies systematically buy firms with slower cash-flow growth and sell those with faster growth. In contrast, non-accounting anomalies buy firms with faster cash-flow growth and sell those with slower growth. These patterns persist across different economic conditions. Over the full sample period, accounting anomalies show consistently negative cash-flow growth (-2.4%, -2.0%, and -1.7% in years one through three), while non-accounting anomalies show positive growth in the first two years (4.8% and 2.1%) before turning slightly negative (-0.5%) in year three. The contrast

is particularly pronounced during recessions: non-accounting anomalies deliver faster cash-flow growth in recessions than in expansions during the first two years. This countercyclical pattern suggests lower fundamental risk, which contradicts with their high average returns under risk-based explanations.

In my second approach, I directly track the cash flows of accounting and non-accounting anomaly portfolios from 1973 to 2022, rather than tracking individual firms. While the portfolios are rebalanced monthly, I measure annual cash-flow growth as the ratio of dividends received in the most recent 12 months to those received in the preceding 12 months. This portfolio-level analysis reveals different patterns in how anomaly cash flows respond to economic conditions. During recessions, accounting anomalies show near-zero cash-flow growth, consistent with their exposure to systematic risk. In contrast, non-accounting anomalies maintain positive cash-flow growth during recessions, suggesting countercyclical behavior. During expansions, both categories exhibit robust cash-flow growth.

My third approach examines the cyclical properties of anomaly cash flows via the Cochrane and Piazzesi (CP) bond factor, following Koijen, Lustig, and Van Nieuwerburgh (2017). The CP factor, known to forecast future economic activity, serves as a measure of cyclicality. A positive loading indicates procyclical cash flows and thus greater risk exposure. The analysis reveals a complex temporal pattern. Over a one-year horizon, the CP factor negatively predicts cash-flow growth for both types of anomalies. However, over a three-year horizon, the relations diverge: accounting anomaly cash-flow growth becomes positively related to the CP factor, indicating procyclical behavior, whereas non-accounting anomaly cash-flow growth maintains its negative relation. This long-term procyclicality of accounting anomaly cash flows aligns with the patterns observed in the tracking-firm portfolios and further supports their risk-based interpretation.

In my fourth approach, I adopt the methodology of Binsbergen, Boons, Opp, and Tamoni (2023), classifying anomalies into resolution anomalies, which resolve mispricing, and build-up anomalies, which exacerbate mispricing. Binsbergen et al. (2023) estimate the gap between price and fundamental value for anomalies. Following this approach provides key insights by directly linking abnormal returns to mispricing gaps. Among the 90 accounting anomalies, 74 are classified

as resolution anomalies and 14 as build-up anomalies. For the 84 non-accounting anomalies, 58 are resolution anomalies and 26 are build-up anomalies. I then examine the metrics derived from the previous three empirical designs.

Empirically, I find that within accounting anomalies, the differences between resolution and build-up anomalies are generally statistically insignificant. In contrast, within non-accounting anomalies, the differences between the two classifications are statistically significant. Specifically, non-accounting build-up anomalies tend to exhibit higher cash-flow growth during recessions than the other three types of anomalies do. The four categories of anomalies show interesting patterns in terms of bond risk factor loading. The accounting resolution anomalies have negative loadings in the first two years and then positive in the third year; the accounting build-up anmalies have positive loadings since year one, and the loading increases from year one to year two. The non-accounting resolution anomalies have lower negative loadings on bond risk in the first two years and then much higher in the third year. Non-accounting build-up anomalies have higher negative loadings on bond risk compared to resolution anomalies and then lower in the third year. The results show that accounting resolution, accounting build-up, and non-accounting build-up anomalies have more procyclical cash-flow growth in the longer term, while non-accounting resolution anomalies have more countercyclical cash-flow growth in the longer term. The results show that non-accounting resolution and build-up anomalies indeed have different cash flow mechanisms. Over three years, however, the cash flows of non-accounting build-up anomalies exhibit lower negative loadings on bond risk than resolution anomalies. This pattern suggests that the counter-bond risk phenomenon in non-accounting anomalies is concentrated in build-up anomalies in the short term but shifts to resolution anomalies over the long term. These findings are consistent with the hypothesis that non-accounting anomalies' abnormal returns reflect a combination of overreaction and sluggish correction.

This paper contributes to the cross-sectional asset pricing literature by examining how cash flows explain cross-sectional returns. The existing literature has explored this relation through two main approaches related to cash flows. The first stream of research analyzes cash flows indirectly through various economic channels. Santos and Veronesi (2005) explain size and value anomalies

through the relation between labor income and dividends. Cohen, Polk, and Vuolteenaho (2003) decompose the book-to-market ratio to reveal the role of expected cash-flow growth. Campbell and Vuolteenaho (2004) and Campbell, Polk, and Vuolteenaho (2010) employ intertemporal asset pricing theory to examine the cash-flow risk of size and value stocks.

The second stream of literature directly analyzes the cash flows of anomaly portfolios. Bansal, Dittmar, and Lundblad (2005) demonstrate that cash flows carry consumption risk that can explain value, momentum, and size anomalies. Lettau and Wachter (2007) explain the value anomaly through the timing of cash flows, while Hansen, Heaton, and Li (2008) link long-run risk with cash flows to explain the value premium. More recent work by Mao and Wei (2016) shows that cash-flow news uncertainty explains investment-related anomalies through the investment effect. Koijen et al. (2017) document that high book-to-market stocks' cash flows are more sensitive to business cycles than are low book-to-market stocks. Lochstoer and Tetlock (2020) examine how discount-rate and cash-flow news components drive anomaly returns, while Gormsen and Lazarus (2023) show that cash-flow duration can explain multiple factor premiums including value, profitability, investment, low-risk, and payout factors.

This paper differs from previous research in several important dimensions. First, I directly examine the cash flows of anomalies, allowing for fundamental insights into their underlying mechanisms. Second, by avoiding the VAR framework, this paper circumvents the challenge of selecting appropriate state variables. Third, the comprehensive analysis of a large number of anomalies within a unified framework enables broader conclusions about anomalies. In addition to examining cash flows, this paper reveals how the dynamics of expected cash flows generate abnormal returns. While previous studies typically use cash flows to measure systematic risk, as in Lettau and Wachter (2007) who assume that high cash flow covariation indicates greater stochastic discount factor sensitivity, I demonstrate that within the same economy, anomalies can arise from both mispricing and risk compensation.

My empirical findings reconcile competing theories by demonstrating that different anomalies require different explanations within the same economy. The contrasting cash-flow patterns between accounting and non-accounting anomalies support a dual framework for understanding market

anomalies. Accounting anomalies exhibit procyclical cash flows consistent with risk-based models, supporting explanations such as Gormsen and Lazarus's 2023 duration-based explanation, in which firms with shorter durations experience slower cash-flow growth. Conversely, non-accounting anomalies display countercyclical patterns that point to mispricing, supporting behavioral explanations such as Huang, Jiang, Tu, and Zhou (2015), who link cross-sectional returns to investors' biased beliefs about future cash flows.

This dichotomy challenges several existing theories of anomalies. Da, Liu, and Schaumburg (2014) argue that anomalies arise from investor inattention to continuously arriving information, leading to initial underreaction. However, the evidence suggests the opposite. Investors tend to overreact to price changes driven by slowly diffusing information. The findings also challenge theories that downplay the role of cash flows, such as De Long, Shleifer, Summers, and Waldmann (1990), in which mispricing arises solely from noise traders. Such explanations struggle to reconcile the distinct cash-flow patterns observed in accounting and non-accounting anomalies.

Recent work by Bowles, Reed, Ringgenberg, and Thornock (2024) provides complementary evidence supporting this dual framework, particularly for accounting anomalies. They show that abnormal returns for accounting anomalies are concentrated in the first month following information releases. I extend their findings by explaining these rapid price adjustments through the lens of cash flows. Together, we offer a more comprehensive understanding. Accounting anomalies exhibit both rapid price adjustments around information releases and procyclical cash-flow patterns, consistent with efficient processing of clearly defined accounting information.

However, the focus of Bowles et al. (2024) on accounting anomalies leaves unanswered questions concerning how prices adjust to less structured information. By examining both accounting and non-accounting anomalies, I show that the speed and efficiency of price adjustment depend crucially on the nature of the underlying information. When information is clearly defined in financial statements, prices adjust quickly to reflect fundamental risks. In contrast, when information diffuses gradually, as in non-accounting anomalies, prices display patterns of overreaction and correction, reflected in countercyclical cash flows. This dual framework, rapid risk-based pricing for accounting information versus gradual mispricing cycles for non-accounting signals, provides a uni-

fied framework for understanding the diverse patterns in the "anomaly zoo" described by Cochrane (2011).

II. Model

I construct an asset pricing model to illustrate how information diffusion speeds affect return predictability. This model integrates two types of information within the framework established by Hong and Stein (1999), which features two types of boundedly rational investors. All market participants immediately access accounting information, whereas non-accounting information diffuses gradually among newswatchers. Newswatchers observe private diffusing information but fail to extract other newswatchers' information from prices, leading to underreaction when only newswatchers are present. Trend-chasers do not directly observe this private information but are aware that newswatchers possess it. They exploit this underreaction through trend-following strategies, eventually leadiingg to overreaction. In this section, I first develop the model formally and then present simulation evidence.

A. Price formation with instant information only

At time t, newswatchers trade a risky asset that pays a liquidating dividend P_T at a future time T. Newswatchers determine their asset demands based on a static-optimization approach, assuming that they buy and hold until T. The value of P_T is given by $P_T = D_0 + \sum_{t=1}^{T} \zeta_t + \sum_{t=1}^{T} \epsilon_t$, in which ζ_t and ϵ_t are independent, mean-zero, and normally distributed random variables with volatility σ_ζ and σ_ϵ. The key distinction is that ζ_t is observed by all market participants, who also know that it is widely observed. As a result, ζ_t is fully reflected in the price at time t. In contrast, ϵ_t represents shock information that diffuses gradually among newswatchers. Newswatchers base their decisions solely on their information sets, without considering current or past prices.

Newswatchers have exponential utility with risk aversion parameter γ and aim to solve the

optimization problem

$$\max_{q_t} E\left[-\gamma e^{-\gamma W_T} \mid s_t\right] \tag{1}$$

$$s.t.$$

$$W_T = W_t - P_t q_t + P_T q_t, \tag{2}$$

where W_T is the investors' wealth at time T, q_t represents the number of assets traded, and s_t is the signal that aggregate investors receive. When there is only instant information in the market, s_t is equivalent to $\sum_{t=1}^{T} \zeta_t$.

Given this optimization problem, when information arrives only through instant signals, I can derive the following result. The proof is provided in the appendix.

Proposition 1 (Return predictability with accounting information)**.** *Suppose that all market participants simultaneously observe the information signal ζ_t about the terminal dividend P_T at time t. Then the equilibrium prices do not exhibit predictability.*

In this scenario, trend-chasers recognize that newswatchers do not underreact. Consequently, they refrain from engaging in trend-chasing behavior.

B. Price formation with instant and diffusing information among newswatchers

I set up the process of information diffusion following Hong and Stein (1999). Assume that there are z groups of newswatchers that are identical except for the the timing at which each receives information. At time t, the diffusion of information regarding the shock ϵ_{t+z-1} begins, with one of the z groups receiving $\frac{1}{z}\epsilon_{t+z-1}$. At time $t+1$, a second group obtains $\frac{1}{z}\epsilon_{t+z-1}$. This diffusion process continues until time $t+z-1$. By then, each group has received its portion of ϵ_{t+z-1}, rendering the information completely public. In this context, s_t is equivalent to $\sum_{t=1}^{t} \epsilon_t + \sum_{t=1}^{t} \zeta_t + \frac{1}{z}\sum_{i=1}^{z-1}(z-i)\epsilon_{t+i}$.

The expected utility of the newswatchers with signal s_t can be written as:

$$E\left[-\gamma e^{-\gamma W_T} \mid s_t\right] = -\gamma e^{-\gamma\left\{E[W_t|s_t]-\frac{\gamma}{2}var[W_t|s_t]\right\}} \tag{3}$$

$$= -\gamma e^{-\gamma\left\{W_t - P_t q_t + E(P_T|s_t)q_t - \frac{1}{2}\gamma\sigma^2(s_t)q_t^2\right\}}. \tag{4}$$

Maximizing (3) leads to

$$E(P_T|s_t) - P_t - \gamma q_t \sigma^2(s_t) = 0 \tag{5}$$

In this economy, newswacthers are the only source of supply variation. From these assumptions, I derive the equilibrium price.

Lemma 1 (Equilibrium price with newswatchers)**.** *In a market with only newswatchers where information arrives through both instant signals ζ_t and gradually diffusing signals ϵ_t, the equilibrium price at time t is*

$$P_t = D_0 + \sum_{t=1}^{t} \epsilon_t + \sum_{t=1}^{t} \zeta_t + \frac{1}{z}\sum_{i=1}^{z-1}(z-i)\epsilon_{t+i} - \gamma\sigma^2(s_t)Q,$$

where ϵ_t represents gradually diffusing information, ζ_t represents immediately observed information, z is the number of newswatcher groups, γ is the risk aversion parameter, and Q is the asset supply.

C. Price formation with instant and diffusing information, and newswatchers and trend-chasers

I then introduce trend-chasers into the market. These traders operate with a finite horizon j and a new generation enters the market each period t. Trend-chasers look for price patterns, but they focus specifically on the component of price changes that excludes instant information. This component, denoted as $\Delta P_{\epsilon,t-1}$, reflects price movements exclusive of the effects of instant information ζ_{t-1}. The total price change can be decomposed as $\Delta P_{t-1} = \Delta P_{\epsilon,t-1} + \zeta_{t-1}$.

The order flow from generation t trend-chasers, F_t, is expressed as:

$$F_t = \phi \Delta P_{\epsilon,t-1}, \tag{6}$$

where ϕ represents the intensity of trend-chasing. Assume that the order flow from the newswatchers, S_t, is the only source of supply variation. Note that, at any time t, there are j generations of momentum traders in the market. The equilibrium price can be determined by solving for the optimal trend-chasing intensity ϕ.

Lemma 2 (Equilibrium price with newswatchers and trend-chasers)**.** *In a market with both instant and gradually diffusing information, an equilibrium exists with ϕ that satisfies the following:*

$$\phi = cov(P_{t+j} - P_t, \Delta P_{\epsilon,t-1}) / \{\gamma var(P_{t+j} - P_t) var(\Delta P_{\epsilon,t-1})\}. \tag{7}$$

With the setups, I can draw the following conclusion.

Proposition 2. *Given a shock ϵ_{t+z-1} that diffuses among newswatchers at time t, and a shock ζ_t that is observed by every investor at time t:*
(i) There is initial overreaction to ϵ_{t+z-1}.
(ii) The price will eventually converges to the fundamental value.

D. Simulation evidence

Figure 1 displays price dynamics in response to a one standard deviation shock (7.42%) to the terminal cash flow. This shock is calibrated to match the historical annual dividend growth volatility from 1973 to 2023. I set both the information diffusing horizon (z) and trend-chasing horizon (j) to 12 periods, the risk aversion parameter (γ) to 3, and the trend-chasing intensity (ϕ) to 0.2705, which represents the mean value from 100,000 simulations using these parameters.

The left panel shows the immediate price adjustment when information arrives following accounting disclosure at $t = 12$. The right panel contrasts two scenarios of non-accounting information diffusion beginning at $t = 1$. The green line depicts price formation when only newswatchers are present, illustrating the gradual incorporation of information into the price over 12 periods. The orange line introduces trend-chasers to this scenario, showing an initial price overreaction and a sluggish correction. Eventually the price converges to the fundamental value of 1.0742.

Figure 2 presents simulation evidence illustrating how instant accounting information and diffusing non-accounting information influence portfolio returns. I simulate an economy with 500 stocks over 480 periods. The parameters are the same as before. Information diffusion and trend-chasing horizons ($z = j = 12$), risk aversion ($\gamma = 3$), volatility of gradual information shocks ($\sigma_\epsilon = 2$), volatility of immediate information shocks ($\sigma_\zeta = 1$). The initial price D_0 is set as 30. If a stock's price falls to zero or below, it remains at zero for all subsequent periods.

To examine return predictability patterns, I conduct two portfolio analyses. First, to study short-term overreaction, I form zero-cost portfolios based on recent performance. Within a randomly selected 18-period window (between periods 12 and 432), I sort stocks into quintiles based on their past six-period returns. The strategy buys the highest-return quintile and sells the lowest-return quintile, rebalancing monthly to maintain the six-period sorting criterion.

The second strategy examines long-term correction by forming portfolios based on returns from a more distant window. Specifically, I randomly select a 30-period window between periods 12 and 432. At each period t, I sort stocks into quintiles based on their cumulative returns over the window $t - 18$ to $t - 12$. I then form a zero-cost portfolio by taking long positions in the highest-return quintile and short positions in the lowest-return quintile. The portfolio is rebalanced monthly by applying the same sorting procedure using updated historical return windows ($t - 17$ to $t - 13$ for the next period, and so on). I track the performance of this strategy over the subsequent 12 periods.

Panel (a) of Figure 2 shows the payoff trajectories of quintile-based zero-cost portfolios formed based on recent past returns. The left plot displays the median (50th percentile) and two boundary percentiles (95th and 5th) for the aggregated payoff distribution. The right plot disaggregates the trajectories into winner and loser quintiles, demonstrating divergence on the long and short sides. Over the 12-month period, the results indicate short-term trend-chasing behavior, with winner portfolios continuing to rise and loser portfolios declining. This trend leads to positive returns for the zero-cost portfolio, reflecting short-term overreaction. Panel (b) of Figure 2 reveals the subsequent correction through portfolios formed on more distant past returns. The left plot displays the distribution of portfolio payoffs, showing a clear downward trend in the zero-cost

strategy. The right plot breaks down this correction into winner and loser quintiles. This pattern, in contrast to that in Panel (a), shows that past winners experience price decreases, whereas past losers see price recoveries. This reversal aligns with the model's prediction that prices eventually converge to fundamental values.

These simulation results demonstrate how different information diffusion speeds create distinct price patterns through the interaction between newswatchers and trend-chasers. When information arrives instantly, prices adjust efficiently. In contrast, when information diffuses gradually, newswatchers' inability to aggregate information leads to initial price underreaction. Trend-chasers exploit this underreaction through their trading strategies, resulting in short-term price overreaction. As information eventually becomes fully revealed to all market participants, prices converge to fundamental values, generating the long-term reversal pattern.

III. Data and Variable Definitions

I start my analysis by describing the data sources and explaining how I construct anomalies and annual cash-flow growth series. I use the 174 continuous firm-level characteristics constructed by Chen and Zimmermann (2022) to construct anomaly portfolios.[1] I classify an anomaly as an accounting anomaly if it is constructed based on a characteristic directly containing information from 10-K or 10-Q filings; otherwise, an anomaly is classified as a non-accounting anomaly. Among the 174 anomalies, 90 are accounting anomalies, and 84 are non-accounting anomalies. Additionally, I obtain stock data from the Center for Research on Securities Prices (CRSP) and macroeconomy data from the Federal Reserve Bank of St. Louis.

A. Tracking-firm portfolios

For every month from 1973 to 2022, I sort firms into quintiles based on the focal firm characteristic using the New York Stock Exchange (NYSE) breakpoints. Then I buy (sell) the quintile with

[1]The Chen and Zimmermann (2022) firm-level characteristic data are available at `https://www.openassetpricing.com/data/`. I use the August 2023 release version. I thank Andrew Chen and Tom Zimmerman for making the data available.

the highest (lowest) expected return performance. Within the quintile, firms are value-weighted. I follow the firms in each monthly quintile portfolio for three years. I call these portfolios tracking-firm portfolios because I aim to examine anomaly features through the fundamentals of firms in this anomaly. The dividends of a tracking-firm portfolio in a month are the sum of the dividends received from firms in the portfolio in the month. I calculate the dividends paid out by a firm in the month as multiplying the lagged market equity by the gap between return (ret) and ex-dividend return (retx).

B. Tracking-anomaly portfolios

To track the cash flows of anomalies, I use monthly rebalanced portfolios. I sort firms into quintiles based on the focal firm characteristics using the NYSE breakpoints and rebalance every month from 1973 to 2022. I calculate the cash-flow growth of the first and fifth quintiles following Koijen and Van Nieuwerburgh (2011). I calculate the log annual dividend growth on the long side (L) and the short side (S) at the end of month t as follows:

$$\begin{aligned} \Delta d_t^L &= log(\sum_{k=0}^{11} D_{t-k}^L) - log(\sum_{k=12}^{24} D_{t-k}^L) \text{ and} \\ \Delta d_t^S &= log(\sum_{k=0}^{11} D_{t-k}^S) - log(\sum_{k=12}^{24} D_{t-k}^S), \end{aligned} \tag{8}$$

where D_t is the dollar value dividend in month t. I convert the cash-flow growth to real term by subtracting the log change in Consumer Price Index for All Urban Consumers from the U.S. Bureau of Labor Statistics. The cash-flow growth of an anomaly is calculated as the cash-flow growth of its long side minus the cash-flow growth of its short side $\Delta d_t^L - \Delta d_t^S$.

C. Bond factors

I follow Cochrane and Piazzesi (2005) to construct bond factors, which I call CP factors. The CP factor is a linear combination of two- to five-year treasury yields. I use monthly zero-coupon yield

data provided by Liu and Wu (2021) to construct log returns on bonds.[2] The linear combination is the fitted value of the following regression:

$$\bar{r}^e_{2,3,4,5} = c + y^1_t + y^2_t + y^3_t + y^4_t + y^5_t + \epsilon_t, \tag{9}$$

where $\bar{r}^e_{2,3,4,5}$ is the average one-year excess return on bonds with two to five years of maturities, y^1_t is the one-year yield, and y^n_t is the n-year forward rate (n = 2, 3, 4, and 5).

IV. Empirical Evidence

A. Tracking the cash-flow growth of firms in anomalies

In this section, I focus on the fundamentals of anomaly cash flows through tracking-firm portfolios from 1973 to 2020. I track the annual cash-flow growth of each portfolio for up to three years postformation without rebalancing. For each anomaly, I calculate the average log annual cash-flow growth across all months for each of the three years after formation. I report these averages in Table I, which is organized into three vertical panels that represent the ends of one, two, and three years postformation, respectively. Panels A, B, and C display these averages for the entire sample, during recessions, and during expansions, with recession and expansion periods defined according to the National Bureau of Economic Research (NBER) business cycle dating table.

Throughout the full sample, firms on the long side of accounting anomalies typically exhibit slower cash-flow growth than their short side counterparts over the three-year period. This disparity in growth rates results in the observed negative cash-flow growth of accounting anomalies, with average tracking-firm cash-flow growths of −2.4%, −2.0%, and −1.5% at the end of the first, second, and third years, respectively. In contrast, the long side of non-accounting anomalies generally shows faster cash-flow growth than on the short side in the initial two years postformation. The difference between the long and short sides decreases as the horizon lengthens. Within non-accounting anomalies, the average tracking-firm cash-flow growths are 5.0%, 1.9%, and −0.6% for

[2] I appreciate Jing Wu and Yan Liu for making the data available. The data can be found at `https://sites.google.com/view/jingcynthiawu/yield-data?authuser=0`.

the first, second, and third years after formation, respectively.

During recessions and expansions, accounting and non-accounting anomalies show distinct patterns in cash-flow growth. As detailed in Panels B and C, accounting anomalies show similar cash-flow growth rates in both recession and expansion periods. In the three years following the formation, firms in accounting anomalies consistently present negative cash-flow growth. Conversely, firms in non-accounting anomalies tend to show countercyclical cash-flow growth. Panel B shows that one year after formation in a recession month, non-accounting anomalies' tracking-firm cash-flow growth is 12.5%; in two years, the growth is 3.4%; and in three years, the growth is −3.0%. Panel C shows that, after the formation in an expansion month, non-accounting anomalies' tracking-firm cash-flow growth is positive in the first two years, at 4.0% and 1.9%, which are slower than the growth in the first two years after formation in a recession month.

Figure 3 uses box-and-whisker plots to visually describe the distributions of mean tracking-firm cash-flow growth for accounting and non-accounting anomalies, measured over one to three years postformation. The plot's box spans the interquartile range (25th to 75th percentiles), with the median represented by an orange line, whereas the whiskers stretch from the 10th to the 90th percentiles. The plots, arranged horizontally, depict the distributions for long-short anomalies, and separately for long and short sides. Vertically, they display these distributions for results measured one, two, and three years after formation.

In the top row's left subfigure, firms in a majority of accounting anomalies tend to have negative cash-flow growth one year after formation, while the majority of non-accounting anomalies have positive tracking-firm cash-flow growth. For accounting anomalies, the short side's box is positioned above that of the long side, whereas for non-accounting anomalies, the pattern is reversed with the long side's box being greater. The subsequent subfigures reveal a convergence of both anomaly types' distributions toward zero, showing that the differences between accounting and non-accounting anomalies decreases over time, as indicated in Table I.

To evaluate whether the observed difference between accounting and non-accounting is statistically significant, I conduct a binomial test. If accounting and non-accounting anomalies are not different in tracking-firm cash-flow growth, the two types of anomalies should be thoroughly

intermixed when ranked by tracking-firm cash-flow growth. Accordingly, the null hypothesis of the binomial test is that, among the 87 anomalies with above-median values, the proportion of accounting and non-accounting anomalies is 90-87, i.e., the ratio of accounting and non-accounting anomalies. I apply the test to anomalies, their long sides, and their short sides separately.

The results, presented in three distinct panels within Table II, show statistically significant differences in tracking-firm cash-flow growth between accounting and non-accounting anomalies. By the end of the first year after formation, the 87 anomalies with above-median values include 35 accounting anomalies and 52 non-accounting anomalies, and the below-median group includes 55 accounting and 32 non-accounting anomalies. The p-value is 0.041. By the end of the second year, the above-median group includes 30 accounting anomalies and 57 non-accounting anomalies, and the below-median group includes 60 accounting anomalies and 27 non-accounting anomalies. The p-value is 0.002. By the end of the third year, the pattern persisted. The above-median group includes 36 accounting anomalies and 51 non-accounting anomalies, and the below-median group includes 54 accounting and 33 non-accounting anomalies, resulting in a p-value of 0.068. Over the span of three years, these results consistently demonstrate that, at the firm level, accounting anomalies tend to exhibit significantly slower cash-flow growth anomalies than non-accounting anomalies. Panels B and C extend this analysis to different business cycles, revealing that the observed disparities are also significant in the first two years postformation, regardless of whether the anomalies were formed during recession or expansion periods. For a detailed breakdown of the tracking-firm cash-flow growth for each anomaly, refer to Table III.

B. Anomaly cash-flow growth and business cycles

In this section, I examine the log annual cash-flow growth of anomalies using monthly rebalanced portfolios. Using monthly rebalanced portfolios allows me to examine anomaly cash-flow growth more directly and at the aggregate level. For the long- or short-side portfolio of an anomaly, the annual cash-flow growth is the sum of the dividends received in the past 12 months divided by the sum of the dividends received in the preceding 12 months. The monthly dividends of the portfolio are calculated as described in Section III. I then examine the mean and standard deviation of

anomalies' log annual cash-flow growth during recessions and expansions.

Figure 5a shows the distributions of the mean (first row) and standard deviation (second row) of accounting and non-accounting anomalies' cash-flow growth during recessions. The top left figure shows that, for accounting anomalies during recession, the distribution of the mean of cash-flow growth surrounds zero. For non-accounting anomalies, the main body of the distribution is above zero. The findings suggest that accounting anomalies tend to deliver slower cash-flow growth than non-accounting anomalies when investors' marginal utility is high. The second figure in the row shows that this observation holds for the long sides of accounting and non-accounting anomalies. The left box-and-whisker plot in the third figure shows that the main body of the distribution on the short side of accounting anomalies is below the zero line. The right plot in the third figure shows that non-accounting anomalies tend to sell portfolios with stronger negative cash-flow growth during recession periods. The findings suggest that, for non-accounting anomalies, positive cash-flow growth at the long-short level is the result of both long- and short-side portfolios. The figures in the second row show that, during recession periods, the long-short, long-side, and short-side portfolios of accounting anomalies generally have less volatile cash-flow growth than those of non-accounting anomalies.

Figure 5b depicts the distributions of the mean (first row) and standard deviation (second row) of accounting and non-accounting anomalies' cash-flow growth during expansions. The top left subfigure shows that the boxes of both accounting and non-accounting anomalies are above zero, indicating that both types of anomalies tend to earn increasing cash flow during expansion periods. The second and third figures in the same row show that the box of the long side of either type of anomaly is higher than the box of its short side. Additionally, within each figure, the boxes of the two categories largely overlap. The subfigures in the second row show that, similar to what is observed in Figure 5a, the box of accounting anomalies is lower than the box of non-accounting anomalies. The observations suggest that the differences between accounting and non-accounting anomalies arise mainly from cash-flow growth during recession periods.

C. *Anomaly cash-flow growth and bond market risk*

In this section, I relate accounting and non-accounting anomalies' cash-flow behaviors to bond market risk. Bonds and equities are crucial investment vehicles in the market. An anomaly that shows fast (slow) cash-flow growth in times of high (low) bond returns exposes its holder to bond market risk. The positive abnormal returns of such an anomaly could be compensation for the associated risk due to its comovement with the bond market. Conversely, an anomaly exhibiting fast (slow) cash-flow growth during periods of low (high) bond returns could hedge against bond market risk. This hedging characteristic challenges risk-based explanations for anomalies' positive abnormal returns. Additionally, Cochrane and Piazzesi (2005) show that their bond factor predicts returns on bonds and macroeconomic uncertainty. Hence, examining the relation between anomaly cash flows and bond market risk provides a link between anomalies and macroeconomic uncertainty.

Following the approach of Koijen et al. (2017), I employ a predictive regression to investigate this relation:

$$\Delta d_{a,t+k} = c_{a,t} + \beta_a CP_t + \epsilon_{a,t}, \tag{10}$$

where Δd_{t+k} is portfolio a's k-month-leading (k=12, 24, 36) log real annual cash-flow growth at month t, CP_t denotes the CP factor, and β_a denotes the metric for measuring the bond market risk. If the cash-flow growth of an anomaly is positively precited by the bond factor, i.e., a positive β_a, the cash flow of this anomaly is exposed to the time-varying bond market risk. If the cash-flow growth of an anomaly is negatively predicted by the bond factor, i.e., a negative β_a, the cash flow of this anomaly hedges the time-varying bond market risk.

Cochrane and Piazzesi (2005) demonstrate that their bond factor effectively forecasts returns on bonds and fluctuations in macroeconomic uncertainty. In this context, if the cash-flow growth of an anomaly is positively predicted by the bond factor, indicated by a positive β_a, it suggests that the anomaly's cash flow is exposed to the bond market risk. Conversely, if the cash-flow growth of an anomaly is negatively predicted by the bond factor, as shown by a negative β_a, it implies that the anomaly's cash flow serves as a hedge against the time-varying risks associated with the bond

market.

Table IV presents how the CP bond factor predicts future cash-flow growth of accounting and non-accounting anomalies. The first two rows show that, with cash-flow growth in one year as the dependent variable, the mean of β_a is -0.31 for accounting anomalies and -0.58 for non-accounting anomalies. The two negative values indicate that over a short one-year horizon, the cash-flow growth rates of both types of anomalies do not comove with the bond market risk in the same direction. Additionally, the long sides of accounting anomalies and non-accounting anomalies have similar β_a values of 0.27 and 0.25, respectively. However, the short side of accounting anomalies shows a weaker loading on past CP factors, 0.58, than that of non-accounting anomalies, 0.82. The middle two rows show that, with cash-flow growth in two years serving as the dependent variable, the mean of β_a is -0.07 for accounting anomalies and -0.69 for non-accounting anomalies. The coefficient -0.07, while still negative, is weaker than the previous value of -0.31. Finally, the last two rows show that, when the cash-flow growth in three years serves as the dependent variable, the mean of β_a is 0.45 for accounting anomalies and -0.59 for non-accounting anomalies. The findings suggest that as the horizon extends, the cash-flow growth of accounting anomalies increasingly correlates positively with the bond factor, suggesting greater exposure to bond market risk in the long term. In contrast, non-accounting anomalies maintain a stable negative loading on past CP factors, consistently acting as a hedge against bond market risk.

Figure 7 illustrates the distributions of β_a in predicting leading-three-year annual cash-flow growth. The left panel of the figure reveals that a majority of accounting anomalies are characterized by positive β_a, whereas most non-accounting anomalies show negative β_a. The middle panel focuses on the long side of these anomalies, showing that the primary beta range for accounting anomalies is marginally greater than that of non-accounting anomalies. The right panel indicates that, on the short side, the distribution of β_a for accounting anomalies is lower than that for non-accounting anomalies. These observations imply that accounting anomalies generally show positive exposure to bond market risk, while non-accounting anomalies are more likely to have negative exposure.

To examine whether the observed difference is significant, I employ a binomial test that is similar to the one used in examining tracking-firm cash-flow growth differences. If the leading-

three-year cash-flow growth of accounting and non-accounting anomalies are similarly exposed to bond market risk, I expect to see that the two types of anomalies' β_a distribute evenly. I set the hypotheses as follows: among the 87 anomalies with above-median β_a, the proportion of accounting and non-accounting anomalies is 90 to 87. I apply the test to the 174 anomalies, their long sides, and their short sides.

Table V summarizes the testing results. The left panel shows that, out of 87 anomalies with bond factor betas above the median, 56 are accounting anomalies and 31 are non-accounting anomalies; out of 87 anomalies with bond factors below the median, 34 are accounting anomalies and 53 are non-accounting anomalies. The p-value is 0.018. The middle panel shows the test results for the long-side portfolios. Out of the 87 anomalies with above-median β_a, 54 are accounting anomalies and 33 are non-accounting anomalies; out of the 87 anomalies with below-median β_a, 36 are accounting anomalies and 51 are non-accounting anomalies. The p-value is 0.054. The right panel shows the test results for the short sides and the opposite results from long sides. Out of 87 anomalies with above-median β_a, 34 are accounting anomalies and 53 are non-accounting anomalies; out of 87 anomalies with below-median β_a, 56 are accounting anomalies, and 31 are non-accounting anomalies. The p-value is 0.023. The three binomial tests show that accounting and non-accounting anomalies' future cash-flow growth is exposed to the bond market in significantly different directions, with the phenomenon being more prominent on the short side.

D. Resolution and build-up anomalies

While prior studies often interpret positive (negative) alphas as evidence of underpricing (overpricing) that subsequently corrects, Binsbergen et al. (2023) demonstrate that abnormal returns can alternatively indicate that prices are pushed further from their fundamental values. Adopting their methodology, I classify anomalies into resolution anomalies, which correct mispricing, and build-up anomalies, which exacerbate it. This classification is particularly valuable, as it directly ties abnormal returns to mispricing gaps by estimating the deviation between the market price and fundamental value, while shedding light on the roles of accounting and non-accounting information in driving these dynamics.

Following Binsbergen et al. (2023), I compute the price wedge as the negative logarithm of the ratio of the fundamental price $\tilde{P}_t$ to the market price P_t:

$$PW_t = -\log\left(\frac{\tilde{P}_t}{P_t}\right). \tag{11}$$

To estimate the fundamental price, I use SDFs, m_t, derived from the class of exponentially affine multifactor models as in Binsbergen et al. (2023). The SDF is expressed as:

$$\frac{m_{t+J}}{m_t} = e^{-\sum_{s=1}^{J} r_{f,t+s} - \frac{\Gamma'\Sigma\Gamma}{2}J - \Gamma'\cdot\left(\sum_{s=1}^{J}\left(r_{t+s} - r_{f,t+s}\right) - \mu\right)}, \tag{12}$$

where $r_{f,t}$ represents the continuously compounded monthly risk-free short rate, r_t is the continuously coumpounded monthly anomaly return, Γ is the risk price for the market, Σ denotes the covariance between anomaly returns and risk prices of the market, and μ is the mean excess anomaly return. The projection horizon J is set to 180 months. The fundamental price $\tilde{P}_t$ is calculated by taking the unconditional average across $N - J + 1$ portfolio cohorts, as follows:

$$\tilde{P}_t = \hat{E}\left[\sum_{s=1}^{J}\frac{m_{t+s}}{m_t}D_{t+s} + \frac{m_{t+J}}{m_t}P_{t+J}\right] \tag{13}$$

$$= \frac{1}{N-J+1}\sum_{t=0}^{N-J}\left[\sum_{s=1}^{J}\left(\frac{m_{t+s}}{m_t}D_{t+s}\right) + \frac{m_{t+J}}{m_t}P_t\right]. \tag{14}$$

Figure 8 illustrates the relation between alphas and price wedges for the long and short sides of accounting and non-accounting anomalies. Resolution anomalies are positioned in quadrants II and IV, whereas build-up anomalies occupy quadrants I and III. Among the 90 accounting anomalies, 74 are classified as resolution anomalies, and 14 as build-up anomalies. For the 84 non-accounting anomalies, 58 are resolution anomalies and 26 are build-up anomalies.

The figure reveals distinct distribution patterns between the two categories of anomalies. Accounting anomalies (orange points) exhibit a more concentrated distribution, with long positions clustering in quadrant I and short positions in quadrant IV. In contrast, non-accounting anomalies (blue points) are more dispersed across all four quadrants, reflecting greater heterogeneity in their

pricing and return dynamics. These patterns highlight fundamental differences in how accounting and non-accounting anomalies are related to mispricing and correction.

Next, I analyze the metrics derived from the previous three empirical designs. Within accounting anomalies, the differences between resolution and build-up anomalies are generally found to be statistically insignificant. In contrast, within non-accounting anomalies, the differences are statistically significant, suggesting stronger distinctions in cash-flow behaviors between resolution and build-up classifications. Table VII presents the cash-flow behaviors associated with resolution and build-up anomalies, separately for accounting and non-accounting anomalies. This table provides detailed insights into how these two classifications differ in their cash-flow dynamics, highlighting variations in economic implications between accounting and non-accounting anomalies.

Panel A shows the average of tracking-firm cash-flow growth over three years, separating anomalies into accounting and non-accounting categories and further classifying them into resolution and build-up anomalies within each category. For accounting anomalies, the differences in cash-flow growth between resolution and build-up classifications are minimal and statistically insignificant across all three years. For instance, in year one, the difference is -0.010 with a t-statistic of -0.325, indicating no meaningful deviation between the two classifications. This lack of significance suggests that accounting anomalies do not exhibit substantial differences in tracking-firm cash flows between resolution and build-up classifications over time.

In contrast, non-accounting anomalies display larger and statistically significant differences in cash-flow growth between resolution and build-up classifications. In year one, the difference is -0.087 with a t-statistic of -2.316, highlighting a noticeable gap in cash-flow growth for resolution anomalies compared with build-up anomalies. This pattern persists in subsequent years, with increasingly negative differences (-0.117 in year two and -0.135 in year three), accompanied by t-statistics of -2.717 and -2.936, respectively. These results indicate that non-accounting anomalies are associated with meaningful adjustments in tracking-firm cash flows, particularly for resolution anomalies.

Panel B shows the average anomaly-level cash-flow growth within the four categories: accounting-resolution, accounting-build-up, non-accounting-resolution, and non-accounting-build-up anoma-

lies. These results are presented for the full sample and under two distinct economic conditions: expansion and recession. Within accounting anomalies, resolution anomalies generally exhibit higher portfolio-level cash-flow growth than build-up anomalies across all economic conditions, with gaps of 0.012, 0.011, and 0.026 under the three conditions. However, these differences are not statistically significant. In contrast, within non-accounting anomalies, resolution anomalies display lower cash-flow growth than build-up anomalies. The differences are -0.019, -0.003, and -0.136, with the gap being statistically signficant and notably wider during recessions.

Panel C shows the average of bond factor betas for each of the four categories. Within accounting anomalies, the beta of resolution anomalies becomes closer to zero over the three-year horizon, whereas the beta of build-up anomalies becomes more positive. The gap in year three is -1.044 and is statistically significant. As Koijen et al. (2017) suggest, CP is strongly and positively associated with future economic activity. The gap shows that accounting build-up anomalies are procyclical. In the case of non-accounting anomalies, the bond factor beta of resolution anomalies beomes more negative while the bond factor beta of build-up anomalies becomes less negative. In year two, the difference is positive, 1.055. In year three, the difference becomes negative at -0.725.

Overall, the findings in this section reveal that, over a longer horizon, accounting anomalies expose investors to greater procyclical risk than non-accounting anomalies. This difference in risk exposure stems from their distinct cash-flow growth patterns and their loadings on past bond factors. With cash-flow growth positively predicted by bond factors, accounting anomalies exhibit more sensitive cash-flow growth to bond market risk. This sensitivity to bond market risk could reflect a sensitivity to uncertainty in the macroeconomy. In contrast, non-accounting anomalies consistently exhibit negative exposure to bond market risk. This pattern suggests that these anomalies are less impacted by macroeconomic uncertainties that affect the bond market, potentially providing investors with a hedge against macroeconomic fluctuations. This divergence in risk exposure between accounting and non-accounting anomalies highlights the need for distinct explanations for each category, especially when considering investment horizons.

V. VAR Return Decomposition

In this section, I evaluate the applicability of the vector autoregression (VAR) return decomposition framework for identifying anomalies' cash-flow patterns. I begin by assessing the indirect return decomposition method of Lochstoer and Tetlock (2020). However, this approach proves inadequate, primarily because it yields indistinguishable results for both anomalies and placebo portfolios, failing to offer clear insights into the unique drivers of anomaly returns.

A. Indirect anomaly return decomposition

Lochstoer and Tetlock's (2020) methodology is characterized as indirect because it does not directly estimate the cash-flow and discount-rate components from the unexpected returns of anomalies. Their process begins by decomposing each individual firm's return into cash-flow and discount rate components and then cumulate these components to the anomaly level. In this subsection, I apply their approach to the 174 anomalies, and extend the analysis to placebo portfolios, offering a thorough exploration of the method's properties.

Following Lochstoer and Tetlock (2020), I start with firm-level returns:

$$\begin{aligned} r_{i,t+1} - E_t[r_{i,t+1}] &= (r^{agg}_t - E_t[r^{agg}_{t+1}]) + (r^{fs}_{i,t+1} - E_t[r^{fs}_{i,t+1}]) \\ &\approx (CF^{agg}_{t+1} - DR^{agg}_{t+1}) + (CF^{fs}_{i,t+1} - DR^{fs}_{i,t+1}), \end{aligned} \tag{15}$$

where r^{agg}_{t+1} is the market-level aggregate return, $r^{fs}_{i,t+1}$ is the firm-specific return, CF^{agg}_{t+1} ($CF^{fs}_{i,t+1}$) is the aggregate-level (firm-specific) cash-flow shock component, and DR^{agg}_t ($DR^{fs}_{i,t}$) is the aggregate-level (firm-specific) discount-rate shock component. To estimate the aggregate-level return components, I use a time-series VAR system:

$$Z^{agg}_{t+1} = \mu^{agg} + A^{agg} Z^{agg}_t + \epsilon^{agg}_{t+1}, \tag{16}$$

where Z^{agg}_t denotes a vector containing the value-weighted aggregate log return and a vector of aggregate characteristics at time t: $[r^{agg}_t; X^{agg}_t]$.

At time $t+1$, I sum the expected discount rate change effects from all future periods to obtain the aggregate discount-rate shocks:

$$\begin{aligned} DR_{t+1}^{agg} &= E_{t+1}\sum_{j=2}^{\infty}\kappa^{j-1}r_{t+j}^{agg} - E_t\sum_{j=2}^{\infty}\kappa^{j-1}r_{t+j}^{agg} \\ &= e_1'\kappa A^{agg}(I-\kappa A^{agg})^{-1}\epsilon_{t+1}^{agg}. \end{aligned} \tag{17}$$

Here, A^{agg} is the coefficient matrix from equation (16), κ is the loglinear constant, e_1' a vector whose first element is one and other elements are zeros, and ϵ_{t+1} is the residual vector from equation (16). The unexpected changes in the expected return and state variables are incorporated into ϵ_{t+1}^{agg}. Since shocks to log stock returns are composed of shocks to expectations of cash-flows and discount rates, I can obtain cash-flow shocks (CF_{t+1}^{agg}) by subtracting discount-rate shocks from shocks to log stock returns:

$$\begin{aligned} CF_{t+1}^{agg} &= r_{t+1}^{agg} - E_t[r_{t+1}^{agg}] + DR_{t+1}^{agg} \\ &= e_1'\epsilon_{t+1}^{agg} + e_1'\kappa A^{agg}(I-\kappa A^{agg})^{-1}\epsilon_{t+1}^{agg}. \end{aligned} \tag{18}$$

I use a separate cross-sectional weighted least squares system with firm-specific characteristics:

$$Z_{i,t+1}^{fs} = \mu^{fs} + A^{fs}Z_{i,t}^{fs} + \epsilon_{i,t+1}^{fs}, \tag{19}$$

where $Z_{i,t}^{fs}$ denotes a vector containing the firm-specific variables $[r_{i,t}^{fs}; X_{i,t}^{fs}]$. In this vector, $r_{i,t}^{fs}$ indicates firm i's log annual return demeaned by log market return, and $X_{i,t}^{fs}$ denotes a vector of firm characteristics demeaned by value-weighted characteristics. I estimate firm-specific cash-flow and discount-rate components as in equations (18) and (17) except that I use firm-specific A^{fs} and $\epsilon_{i,t+1}^{fs}$.

As firm-level return components are available, I follow Lochstoer and Tetlock (2020) and construct the components of anomaly unexpected returns as the weighted average of the underlying firms' return components. The cash-flow (discount-rate) shocks of the long or short side are the weighted average of the cash-flow (discount-rate) shocks of firms in the portfolio. The cash-flow

(discount-rate) shocks of an anomaly portfolio, $CF_{a,t+1}$ ($DR_{a,t+1}$), are computed as the difference between the long-side cash-flow (discount-rate) shocks and the short-side cash-flow (discount-rate) shocks:

$$\begin{aligned} CF_{a,t+1} &= \sum_{l=1}^{L} CF_{l,t+1} W_l - \sum_{s=1}^{S} CF_{s,t+1} W_s \text{ and} \\ DR_{a,t+1} &= \sum_{l=1}^{L} DR_{l,t+1} W_l - \sum_{s=1}^{S} DR_{s,t+1} W_s, \end{aligned} \tag{20}$$

where a denotes the anomaly under consideration and W_l (W_s) denotes stock l's (s's) weight in the long (short) side of the portfolio.

To explore whether anomaly returns are driven by cash-flow shocks or discount-rate shocks under the framework, I expand the variance of unexpected log real returns:

$$\begin{aligned} var(r_{a,t+1} - E_t[r_{a,t+1}]) &= var(CF_{a,t+1} - DR_{a,t+1}) \\ &= var(CF_{a,t+1}) + Var(DR_{a,t+1}) - 2Cov(CF_{a,t+1}, DR_{a,t+1}). \end{aligned} \tag{21}$$

The contributions to anomaly a's return variation from cash-flow shocks and discount-rate shocks are defined as

$$\begin{aligned} var(CF) &= \frac{var(CF_{a,t+1})}{var(CF_{a,t+1}) + var(DR_{a,t+1}) - 2cov(CF_{a,t+1}, DR_{a,t+1})} \times 100\% \text{ and} \\ var(DR) &= \frac{var(DR_{a,t+1})}{var(CF_{a,t+1}) + var(DR_{a,t+1}) - 2cov(CF_{a,t+1}, DR_{a,t+1})} \times 100\%. \end{aligned} \tag{22}$$

To complete the component reporting, the covariances between cash-flow shocks and discount-rate shocks are reported in the form of negative covariances multiplied by two:

$$cov(CF, DR) = \frac{-2 \times cov(CF_{a,t+1}, DR_{a,t+1})}{var(CF_{a,t+1}) + var(DR_{a,t+1}) - 2cov(CF_{a,t+1}, DR_{a,t+1})} \times 100\%. \tag{23}$$

Regards to the predictors X_t in the VARs, I use the five characteristics in Lochstoer and Tetlock (2020) to predict returns. They are value, profitability, investment, size, and six-month momentum.

Corresponding to anomalies, I build two sets of random long-short portfolios as placebos. In the

first set, a long-short placebo's long side and short side consist of non-overlapping randomly picked firms. I call them random placebos. Additionally, inspired by studies that reveal that anomalies capture cross-sectional correlations (e.g., Daniel and Titman, 1997; Daniel, Mota, Rottke, and Santos, 2020; and Clarke, 2022), I construct a second set of placebos that I call high-correlation placebos. Such a placebo's long (short) side involves nonrepeating firms that tend to have high monthly return correlations in the previous year. I describe the detailed construction steps in the appendix.

Figure 9 provides a detailed comparison of the return decomposition for anomalies and placebos. Panel (a) describes the distributions of the cash-flow and discount-rate shock proportions for the 174 anomalies and 10,000 random placebos. The y-axis shows the frequency of these occurrences, while the x-axis shows the share of returns attributable to cash-flow or discount-rate shocks. Anomaly return components are represented in blue, contrasting with the red used for placebos. The left subfigure in Panel (a) shows that, under the indirect return decomposition framework, both anomalies and random placebos are driven primarily by cash-flow shocks. This similarity is highlighted by a considerable overlap in their distributions, indicating that the framework leads to analogous outcomes for both groups. The right subfigure aligns with this observation, showing that the role of discount-rate shocks in driving return variation is comparably weak for both anomalies and placebos.

Panel (b) shows how cash-flow and discount-rate shocks contribute to the variation in returns of anomalies and high-correlation placebos and confirms the overriding influence of cash-flow shocks under the indirect VAR framework. Under this framework, most return variation in anomaly and high-correlation placebo returns are driven by cash-flow shocks. I conducted a Kolmogorov-Smirnov test on the distributions illustrated in the left plot of Panel (b), resulting in a p-value of 0.004. However, applying a Kolmogorov–Smirnov test to the samples of return variation from discount-rate shocks in the right plot of the same panel yields a p-value of 0.251, indicating that I cannot reject the null that discount-rate shocks in anomaly and placebo unexpected returns come from the same underlying distribution. The striking overlap in the distributions is even more pronounced here than in Panel (a), underscoring the challenge in differentiating anomalies from placebos under

this indirect return decomposition framework. This resemblance suggests that the indirect VAR framework may not effectively discriminate between genuine anomalies and placebo effects.

VI. Conclusion

To date, the existing literature tends to study anomalies through a single mechanism. Tracking cash flows of 174 anomalies at the firm and portfolio levels, I show that a complete theory aiming to explain cross-sectional anomalies needs to account for both risk-based and mispricing-based mechanisms. Accounting anomalies, based on clearly defined financial statement information, exhibit procyclical cash flows consistent with the rational risk compensation explanation. In contrast, non-accounting anomalies, which depend on gradually diffusing information, display countercyclical patterns consistent with mispricing-based explanations.

These findings underscore Hayek's 1945 fundamental insight that market prices aggregate dispersed information. The dichotomy between accounting and non-accounting anomalies reveals how the nature of information affects this aggregation process. When information is clearly defined in financial statements, prices efficiently incorporate fundamental risks. However, when information must diffuse gradually through the market, the aggregation process becomes more complex, leading to systematic patterns of overreaction and correction. The resolution-buildup dimension provides additional insights into these mechanisms.

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Table I

Descriptive Statistics of Tracking-firm Cash-Flow Growth

For every month between 1973 and 2020, I sort stocks into value-weighted quintile portfolios based on the focal characteristic. The quintile portfolios are determined by the NYSE breakpoints. I track the quintile portfolio's log annual cash-flow growth for three years after its formation without rebalancing. The cash-flow growth of a long-short portfolio is calculated by deducting its short side's log annual cash-flow growth from its long side's log annual cash-flow growth. Then I average these cash-flow growth rates across formation months. Panel A reports the mean of average cash-flow growth within accounting and non-accounting anomalies for the whole sample. Panel B reports the mean of average cash-flow growth if the formation month is during recessions. In addition, Panel C reports the mean of average cash-flow growth if the formation month is during expansions. The recession and expansion months are defined as in the NBER business cycle dating table.

	Year One			Year Two			Year Three		
	Long-Short	Long	Short	Long-Short	Long	Short	Long-Short	Long	Short
				Panel A: Cash Flow Growth					
Accounting	-0.024	0.005	0.028	-0.020	0.009	0.029	-0.015	0.016	0.031
Non-Accounting	0.050	0.043	-0.007	0.019	0.030	0.011	-0.006	0.023	0.028
				Panel B: Cash Flow Growth in Recessions					
Accounting	-0.026	-0.112	-0.086	-0.015	-0.016	-0.001	-0.008	0.078	0.086
Non-Accounting	0.125	-0.068	-0.194	0.034	-0.001	-0.036	-0.030	0.070	0.100
				Panel C: Cash Flow Growth in Expansions					
Accounting	-0.023	0.022	0.045	-0.020	0.012	0.033	-0.016	0.007	0.023
Non-Accounting	0.040	0.059	0.019	0.017	0.033	0.017	-0.002	0.017	0.018

Table II

Tracking-Firm Cash-Flow Growth of Anomalies: Accounting vs. Non-Accounting

For every month between 1973 and 2020, I sort stocks into value-weighted quintile portfolios based on the focal characteristic. The quintile portfolios are determined by NYSE breakpoints. I track the quintile portfolio's log annual cash-flow growth for three years after its formation without rebalancing. The cash-flow growth of a long-short portfolio is calculated by deducting the log annual cash-flow growth on the short side from that on the long side. Then I calculate the average of these cash-flow growth rates across formation months within each anomaly. I compare these tracking-firm cash-flow growth averages between accounting and non-accounting anomalies for the full sample, recession periods, and expansion periods. To achieve the goal, I design a binomial test. The null hypothesis is that accounting and non-accounting anomalies are equally likely to have above-median tracking-firm cash-flow growth. The p-values are reported.

	Long-Short			Long Side			Short side		
	Accounting Above/Below	Non-Accounting Above/Below	p-value	Accounting Above/Below	Non-Accounting Above/Below	p-value	Accounting Above/Below	Non-Accounting Above/Below	p-value
Panel A: Full periods									
Year One	35/55	52/32	0.041	30/60	57/27	0.002	54/36	33/51	0.054
Year Two	30/60	57/27	0.002	32/58	55/29	0.007	56/34	31/53	0.018
Year Three	36/54	51/33	0.068	37/53	50/34	0.087	49/41	38/46	0.453
Panel B: Recessions									
Year One	35/55	52/32	0.041	38/52	49/35	0.135	53/37	34/50	0.107
Year Two	34/56	53/31	0.024	44/46	43/41	0.831	58/32	29/55	0.005
Year Three	48/42	39/45	0.592	48/42	39/45	0.592	39/51	48/36	0.200
Panel C: Expansions									
Year One	34/56	53/31	0.024	31/59	56/28	0.004	52/38	35/49	0.163
Year Two	30/60	57/27	0.002	33/57	54/30	0.013	55/35	32/52	0.032
Year Three	38/52	49/35	0.135	43/47	44/40	0.670	49/41	38/46	0.453

Table III

Tracking-Firm Cash-Flow Growth in Three Years after Formation

For every month between 1973 and 2020, I sort stocks into value-weighted quintile portfolios based on the focal characteristic. The quintile portfolios are determined by the NYSE breakpoints. I track the quintile portfolio's log annual cash-flow growth for three years after its formation without rebalancing. Then I calculate the mean of these cash-flow growth rates across formation months. The table shows the calculated mean for each anomaly: long-short (LS), long side (L), and short side (S).

		Year One			Year Two			Year Three		
Acronym	Type	LS	L	S	LS	L	S	LS	L	S
AbnormalAccruals	Acc	0.002	0.017	0.015	0.015	0.022	0.007	-0.006	0.023	0.028
Accruals	Acc	-0.016	0.023	0.039	-0.014	0.006	0.020	-0.021	0.009	0.030
Activism1	Non-Acc	-0.002	0.036	0.038	0.074	0.066	-0.008	0.042	0.025	-0.017
AM	Acc	-0.097	-0.025	0.072	-0.036	0.016	0.052	-0.019	0.029	0.048
AnalystRevision	Non-Acc	0.125	0.066	-0.059	0.089	0.059	-0.029	0.014	0.023	0.009
AnnouncementReturn	Non-Acc	0.058	0.062	0.004	0.024	0.042	0.018	0.027	0.033	0.006
AssetGrowth	Acc	-0.085	-0.011	0.075	-0.051	-0.015	0.035	-0.040	0.012	0.052
BetaLiquidityPS	Non-Acc	0.004	0.030	0.026	0.009	0.029	0.020	0.001	0.029	0.028
BetaTailRisk	Non-Acc	0.088	0.099	0.010	0.090	0.094	0.005	0.072	0.080	0.008
betaVIX	Non-Acc	-0.005	0.027	0.031	0.018	0.037	0.018	-0.025	0.018	0.043
BM	Acc	-0.046	0.011	0.057	-0.030	0.019	0.049	-0.013	0.028	0.042
BMdec	Acc	-0.070	-0.010	0.060	-0.030	0.018	0.048	-0.023	0.024	0.047
BookLeverage	Acc	0.020	0.057	0.038	0.007	0.033	0.027	0.010	0.035	0.025
BPEBM	Acc	0.015	0.008	-0.007	0.007	0.017	0.010	-0.000	0.015	0.015
Cash	Acc	0.045	0.067	0.022	0.023	0.038	0.015	0.027	0.042	0.015
CashProd	Acc	-0.086	-0.012	0.074	-0.059	-0.003	0.056	-0.033	0.004	0.037
CBOperProf	Acc	0.019	0.043	0.024	0.016	0.029	0.013	0.004	0.031	0.027
CF	Acc	-0.185	-0.072	0.113	-0.078	-0.019	0.059	-0.083	-0.018	0.065
cfp	Acc	-0.073	-0.060	0.013	-0.066	-0.014	0.051	-0.039	-0.008	0.031
ChangeInRecommendation	Non-Acc	0.007	0.055	0.048	0.017	0.037	0.020	-0.011	0.034	0.045
ChAssetTurnover	Acc	0.046	0.040	-0.005	-0.008	0.014	0.021	-0.015	0.015	0.030
ChEQ	Acc	-0.091	-0.009	0.082	-0.065	-0.015	0.049	-0.048	0.010	0.058
ChInv	Acc	-0.028	0.010	0.038	-0.044	-0.009	0.035	-0.022	0.009	0.031
ChInvIA	Acc	-0.023	0.025	0.048	-0.019	0.012	0.031	-0.014	0.021	0.035
ChNNCOA	Acc	0.041	0.044	0.003	0.009	0.018	0.009	-0.005	0.021	0.026
ChNWC	Acc	0.019	0.035	0.016	-0.012	0.001	0.013	-0.012	0.027	0.039
ChTax	Acc	0.128	0.083	-0.045	0.053	0.045	-0.008	0.023	0.026	0.003
CompEquIss	Acc	-0.030	0.029	0.060	0.032	0.052	0.020	0.018	0.052	0.034
CompositeDebtIssuance	Acc	-0.003	0.031	0.035	-0.012	0.023	0.035	-0.028	0.014	0.042
CoskewACX	Non-Acc	0.010	0.018	0.008	0.028	0.025	-0.002	-0.008	0.019	0.027
CPVolSpread	Non-Acc	-0.014	0.010	0.024	0.011	0.008	-0.003	-0.001	0.015	0.015
dVolCall	Non-Acc	-0.015	0.010	0.026	-0.002	0.023	0.024	-0.014	0.025	0.039
dVolPut	Non-Acc	0.015	0.019	0.004	0.006	0.025	0.020	0.017	0.038	0.021
dCPVolSpread	Non-Acc	-0.006	0.012	0.018	0.000	-0.003	-0.003	0.003	0.029	0.026
CustomerMomentum	Non-Acc	0.027	0.031	0.004	0.020	0.021	0.001	-0.000	0.013	0.013
DelBreadth	Non-Acc	0.113	0.089	-0.025	0.073	0.058	-0.015	0.028	0.036	0.008
DelCOA	Acc	-0.043	0.010	0.053	-0.033	0.007	0.040	-0.014	0.015	0.029
DelCOL	Acc	-0.043	0.009	0.052	-0.022	0.010	0.031	-0.004	0.029	0.034
DelEqu	Acc	-0.083	0.000	0.083	-0.068	-0.020	0.048	-0.050	0.010	0.060
DelFINL	Acc	0.009	0.023	0.014	0.002	0.021	0.019	-0.015	0.019	0.034
DelLTI	Acc	-0.021	0.015	0.036	-0.027	0.004	0.031	-0.018	0.018	0.036
DelNetFin	Acc	0.049	0.063	0.014	0.021	0.035	0.014	0.005	0.032	0.027
dNoa	Acc	-0.043	0.006	0.049	-0.033	0.003	0.036	-0.040	0.017	0.057
DolVol	Non-Acc	-0.012	0.023	0.035	-0.021	0.001	0.022	-0.003	0.019	0.022
EarningsConsistency	Acc	0.057	0.062	0.005	-0.021	0.015	0.036	0.044	0.049	0.004
EarningsForecastDisparity	Non-Acc	0.125	0.059	-0.066	0.076	0.040	-0.037	0.003	0.024	0.021
EarningsStreak	Acc	0.162	0.054	-0.108	0.061	0.045	-0.016	0.048	0.024	-0.024
EarningsSurprise	Acc	0.055	0.052	-0.003	0.033	0.036	0.003	0.006	0.022	0.015
EarnSupBig	Acc	0.038	0.018	-0.021	0.035	0.021	-0.014	-0.019	0.005	0.024
EBM	Acc	-0.064	-0.023	0.041	-0.031	-0.008	0.023	-0.027	-0.008	0.018
EntMult	Acc	-0.102	-0.030	0.072	-0.076	-0.008	0.068	-0.056	0.004	0.059

(*continued on next page*)

Table III (*continued*)

		Panel A: Mean								
		Year 1			Year 2			Year 3		
Acronym	Type	LS	L	S	LS	L	S	LS	L	S
EP	Acc	-0.048	-0.010	0.039	-0.084	-0.016	0.068	-0.043	0.004	0.047
EquityDuration	Acc	-0.047	0.004	0.051	-0.048	0.002	0.050	-0.032	0.019	0.050
ExclExp	Non-Acc	0.006	0.040	0.034	0.005	0.032	0.027	0.004	0.025	0.021
FEPS	Non-Acc	0.245	0.056	-0.189	0.030	0.019	-0.011	-0.066	0.009	0.074
fgr5yrLag	Non-Acc	-0.168	-0.011	0.158	-0.155	-0.018	0.137	-0.129	0.000	0.130
FirmAgeMom	Non-Acc	0.129	0.152	0.024	0.192	0.157	-0.034	0.060	0.055	-0.005
ForecastDispersion	Non-Acc	0.188	0.073	-0.115	0.064	0.044	-0.019	0.001	0.035	0.034
Frontier	Acc	-0.257	-0.168	0.089	-0.110	-0.040	0.070	-0.055	-0.003	0.053
GP	Acc	0.030	0.046	0.016	0.035	0.039	0.004	0.034	0.042	0.007
GrAdExp	Acc	-0.061	-0.007	0.054	-0.060	-0.011	0.049	-0.009	0.022	0.031
grcapx	Acc	-0.008	0.037	0.045	-0.013	0.022	0.035	-0.018	0.024	0.042
grcapx3y	Acc	-0.028	0.024	0.052	-0.013	0.025	0.038	-0.001	0.032	0.033
Herf	Non-Acc	0.011	0.031	0.020	0.005	0.016	0.011	0.013	0.020	0.008
HerfBE	Non-Acc	0.007	0.031	0.024	0.005	0.019	0.013	0.006	0.020	0.014
hire	Non-Acc	-0.077	-0.013	0.065	-0.065	-0.010	0.054	-0.029	0.023	0.052
IdioVol3F	Non-Acc	0.153	0.039	-0.114	0.015	0.015	-0.000	-0.031	0.012	0.044
IdioVolAHT	Non-Acc	0.229	0.039	-0.190	-0.015	0.016	0.032	-0.052	0.013	0.064
Illiquidity	Non-Acc	-0.021	0.008	0.030	-0.011	0.009	0.020	0.002	0.024	0.022
IndMom	Non-Acc	0.044	0.057	0.013	0.050	0.042	-0.008	-0.004	0.023	0.027
IndRetBig	Non-Acc	0.023	0.010	-0.012	0.018	0.019	0.001	0.015	0.017	0.003
IntanBM	Acc	-0.247	-0.161	0.085	-0.080	-0.022	0.058	-0.034	0.014	0.048
IntanCFP	Acc	-0.216	-0.111	0.105	-0.105	-0.028	0.077	-0.069	-0.005	0.064
IntanEP	Acc	-0.182	-0.084	0.098	-0.122	-0.048	0.074	-0.073	0.000	0.074
IntanSP	Acc	-0.229	-0.150	0.079	-0.080	-0.007	0.073	-0.013	0.045	0.058
IntMom	Non-Acc	0.106	0.066	-0.039	0.096	0.073	-0.023	-0.002	0.035	0.037
Investment	Acc	0.020	0.031	0.010	-0.001	0.015	0.015	0.012	0.035	0.023
InvestPPEInv	Acc	-0.055	-0.008	0.047	-0.039	-0.020	0.019	-0.029	0.008	0.037
InvGrowth	Acc	-0.065	-0.020	0.046	-0.037	-0.010	0.027	-0.034	0.008	0.042
iomom_cust	Non-Acc	-0.004	0.027	0.031	0.029	0.028	-0.000	-0.020	0.016	0.036
iomom_supp	Non-Acc	0.007	0.048	0.041	0.013	0.031	0.018	-0.003	0.028	0.032
Leverage	Acc	-0.088	-0.013	0.075	-0.035	0.018	0.053	-0.022	0.030	0.052
LRreversal	Non-Acc	-0.120	-0.023	0.096	0.009	0.060	0.051	-0.016	0.023	0.039
MaxRet	Non-Acc	0.062	0.030	-0.032	0.003	0.008	0.004	-0.049	0.006	0.055
MeanRankRevGrowth	Acc	-0.043	0.018	0.061	-0.058	0.002	0.060	-0.078	-0.012	0.066
Mom12m	Non-Acc	0.197	0.077	-0.120	0.152	0.084	-0.068	0.012	0.052	0.040
Mom12mOffSeason	Non-Acc	0.167	0.089	-0.078	0.133	0.084	-0.048	0.037	0.056	0.019
Mom6m	Non-Acc	0.149	0.071	-0.078	0.090	0.065	-0.025	0.034	0.049	0.015
Mom6mJunk	Non-Acc	0.232	0.031	-0.202	0.113	0.086	-0.027	0.028	0.058	0.030
MomOffSeason	Non-Acc	-0.130	-0.027	0.104	-0.053	0.018	0.071	-0.055	0.006	0.061
MomOffSeason06YrPlus	Non-Acc	-0.054	0.024	0.078	-0.054	0.018	0.072	-0.042	0.019	0.061
MomOffSeason16YrPlus	Non-Acc	-0.005	0.025	0.030	0.008	0.023	0.015	-0.027	0.006	0.033
MomSeason	Non-Acc	0.017	0.050	0.033	0.005	0.037	0.032	0.009	0.033	0.025
MomSeason06YrPlus	Non-Acc	0.011	0.046	0.035	0.016	0.039	0.023	0.000	0.029	0.029
MomSeason11YrPlus	Non-Acc	0.003	0.038	0.034	0.001	0.027	0.026	-0.001	0.030	0.030
MomSeason16YrPlus	Non-Acc	0.003	0.031	0.029	0.002	0.019	0.017	0.005	0.017	0.012
MomSeasonShort	Non-Acc	0.037	0.047	0.010	0.038	0.045	0.007	-0.005	0.029	0.034
NetDebtFinance	Acc	0.023	0.030	0.007	0.020	0.025	0.005	-0.000	0.026	0.026
NetDebtPrice	Acc	0.096	-0.022	-0.118	-0.022	-0.025	-0.003	-0.007	-0.001	0.006
NetEquityFinance	Acc	-0.067	0.025	0.091	-0.062	0.012	0.074	-0.063	0.020	0.083
NetPayoutYield	Acc	-0.115	-0.027	0.087	-0.069	-0.012	0.057	-0.074	0.001	0.075
NOA	Acc	0.009	0.045	0.037	-0.023	0.027	0.050	-0.014	0.029	0.043
OPLeverage	Acc	-0.006	0.030	0.036	0.010	0.030	0.020	0.012	0.036	0.024
OptionVolume1	Non-Acc	-0.007	0.050	0.057	-0.027	0.011	0.038	-0.017	0.017	0.034
OrderBacklog	Acc	-0.007	0.031	0.039	-0.002	0.040	0.042	-0.021	0.013	0.035
OrderBacklogChg	Acc	0.058	0.072	0.014	0.004	0.016	0.012	0.007	0.019	0.012
OrgCap	Acc	0.001	0.026	0.026	0.008	0.009	0.001	0.020	0.016	-0.004
PayoutYield	Acc	-0.183	0.006	0.189	-0.095	0.010	0.105	-0.060	0.019	0.079
PctAcc	Acc	-0.008	-0.006	0.002	-0.007	-0.003	0.004	-0.005	0.024	0.029
PctTotAcc	Acc	-0.086	-0.023	0.063	-0.119	-0.033	0.087	-0.039	0.023	0.062
PriceDelayRsq	Non-Acc	0.005	0.042	0.037	-0.023	0.001	0.024	-0.016	0.018	0.034
PS	Acc	0.229	-0.137	-0.365	0.123	-0.019	-0.142	0.064	0.030	-0.033
RD	Acc	-0.091	-0.032	0.059	-0.036	-0.003	0.033	-0.032	0.006	0.038

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Table III (*continued*)

		Panel A: Mean								
		Year 1			Year 2			Year 3		
Acronym	Type	LS	L	S	LS	L	S	LS	L	S
RDcap	Acc	0.055	-0.085	-0.140	-0.026	-0.046	-0.020	-0.008	-0.001	0.006
RDS	Acc	-0.038	0.002	0.040	-0.010	0.015	0.026	-0.013	0.005	0.018
RealizedVol	Non-Acc	0.136	0.035	-0.100	-0.017	0.006	0.023	-0.049	0.005	0.054
ResidualMomentum	Non-Acc	0.027	0.039	0.012	0.055	0.043	-0.012	0.010	0.028	0.018
retConglomerate	Non-Acc	0.004	0.043	0.039	0.031	0.036	0.005	0.010	0.013	0.003
ReturnSkew	Non-Acc	0.003	0.035	0.032	0.010	0.018	0.009	-0.005	0.015	0.019
ReturnSkew3F	Non-Acc	-0.005	0.031	0.037	0.003	0.017	0.015	-0.002	0.016	0.017
REV6	Non-Acc	0.209	0.101	-0.108	0.073	0.058	-0.015	0.044	0.036	-0.008
RevenueSurprise	Acc	0.034	0.054	0.020	0.046	0.044	-0.002	-0.003	0.013	0.016
RIVolSpread	Non-Acc	0.034	0.050	0.015	-0.035	-0.011	0.024	-0.026	0.014	0.040
roaq	Acc	0.148	0.065	-0.082	0.070	0.052	-0.018	0.013	0.038	0.024
sfe	Non-Acc	0.148	0.045	-0.103	0.011	0.033	0.021	0.008	0.038	0.030
ShareIss1Y	Acc	-0.046	0.015	0.061	-0.031	0.013	0.044	-0.037	0.007	0.045
ShareIss5Y	Acc	-0.080	-0.009	0.071	-0.062	-0.011	0.051	-0.045	-0.002	0.043
SmileSlope	Non-Acc	-0.004	0.016	0.020	0.009	0.005	-0.004	-0.003	0.020	0.023
std_turn	Non-Acc	0.234	-0.005	-0.239	0.029	-0.011	-0.040	-0.043	0.003	0.046
tang	Acc	-0.022	0.017	0.039	-0.022	0.007	0.029	-0.019	0.007	0.027
Tax	Acc	0.006	0.011	0.004	-0.010	0.008	0.018	0.026	0.016	-0.010
TotalAccruals	Acc	-0.081	-0.014	0.067	-0.053	-0.004	0.049	-0.024	0.020	0.044
TrendFactor	Non-Acc	0.017	0.019	0.002	0.025	0.030	0.005	-0.010	0.025	0.035
VolSD	Non-Acc	0.015	0.035	0.020	-0.010	0.010	0.020	-0.005	0.016	0.021
XFIN	Acc	-0.006	0.024	0.031	0.013	0.019	0.007	0.005	0.029	0.024
zerotrade	Non-Acc	0.025	0.038	0.013	-0.043	0.005	0.048	-0.053	0.001	0.054
zerotradeAlt1	Non-Acc	0.035	0.045	0.010	-0.015	0.011	0.025	-0.050	0.006	0.056
zerotradeAlt12	Non-Acc	0.005	0.029	0.024	-0.057	0.004	0.060	-0.062	0.003	0.065
Activism2	Non-Acc	-0.014	0.019	0.033	0.038	0.079	0.041	0.049	0.091	0.043
AdExp	Acc	-0.145	-0.075	0.070	-0.047	0.005	0.052	-0.039	0.016	0.055
AgeIPO	Non-Acc	-0.118	0.479	0.597	0.045	0.128	0.083	-0.050	0.046	0.096
AnalystValue	Non-Acc	0.008	0.052	0.044	-0.036	0.020	0.055	-0.030	0.007	0.037
AOP	Non-Acc	-0.097	-0.018	0.079	-0.065	-0.011	0.054	-0.021	0.012	0.032
Beta	Non-Acc	0.058	0.078	0.020	0.066	0.077	0.011	0.072	0.084	0.012
BetaFP	Non-Acc	-0.022	-0.003	0.019	0.028	0.034	0.006	0.030	0.042	0.012
BidAskSpread	Non-Acc	-0.086	-0.051	0.035	0.010	0.024	0.014	0.039	0.052	0.013
BrandInvest	Acc	0.014	0.051	0.037	-0.042	-0.010	0.032	-0.060	-0.027	0.033
Coskewness	Non-Acc	0.007	0.027	0.020	0.004	0.026	0.022	-0.009	0.018	0.026
DelDRC	Acc	0.288	0.219	-0.069	0.049	0.137	0.087	-0.007	0.051	0.058
FirmAge	Non-Acc	0.199	0.214	0.015	0.027	0.037	0.009	0.011	0.021	0.010
FR	Acc	-0.007	-0.013	-0.006	-0.016	-0.008	0.008	-0.023	-0.015	0.008
GrLTNOA	Acc	-0.036	0.010	0.046	-0.014	0.017	0.031	-0.009	0.017	0.026
GrSaleToGrInv	Acc	-0.004	0.018	0.023	-0.009	0.007	0.016	0.005	0.030	0.024
GrSaleToGrOverhead	Acc	0.010	0.025	0.015	-0.020	0.003	0.022	-0.027	0.011	0.038
HerfAsset	Non-Acc	0.012	0.034	0.023	0.004	0.019	0.014	0.008	0.021	0.012
High52	Non-Acc	0.400	0.087	-0.314	0.129	0.045	-0.084	-0.004	0.031	0.035
MomOffSeason11YrPlus	Non-Acc	-0.024	0.032	0.056	-0.015	0.015	0.030	0.002	0.031	0.029
MRreversal	Non-Acc	-0.097	-0.014	0.083	-0.036	0.013	0.049	-0.011	0.022	0.033
NumEarnIncrease	Acc	0.049	0.072	0.024	0.019	0.039	0.021	0.002	0.028	0.026
OperProf	Acc	0.052	0.035	-0.017	0.022	0.019	-0.003	-0.006	0.020	0.026
OperProfRD	Acc	0.054	0.049	-0.006	0.029	0.030	0.001	0.029	0.036	0.007
OptionVolume2	Non-Acc	-0.065	-0.015	0.050	-0.010	0.004	0.014	-0.004	0.012	0.016
PredictedFE	Acc	-0.108	-0.005	0.103	-0.087	-0.005	0.082	-0.081	-0.002	0.079
PriceDelaySlope	Non-Acc	0.007	0.046	0.039	-0.013	0.010	0.023	-0.022	0.005	0.027
PriceDelayTstat	Non-Acc	-0.005	0.035	0.040	0.005	0.029	0.024	-0.006	0.021	0.027
ProbInformedTrading	Non-Acc	0.848	0.038	-0.810	0.314	0.030	-0.284	0.111	0.057	-0.084
realestate	Acc	-0.002	0.048	0.050	0.030	0.058	0.028	0.044	0.058	0.014
RoE	Acc	0.100	0.050	-0.051	0.012	0.022	0.011	-0.018	0.029	0.047
ShortInterest	Non-Acc	0.001	0.025	0.024	-0.033	0.002	0.036	-0.033	0.009	0.042
skew1	Non-Acc	0.064	0.073	0.008	0.064	0.058	-0.006	0.005	0.019	0.014
SP	Acc	-0.179	-0.106	0.073	-0.060	-0.013	0.047	-0.025	0.018	0.043
VarCF	Acc	0.073	0.054	-0.018	0.027	0.036	0.009	-0.006	0.034	0.040
VolMkt	Non-Acc	0.121	0.046	-0.074	0.001	0.017	0.016	-0.046	0.016	0.063
VolumeTrend	Non-Acc	0.044	0.053	0.009	-0.010	0.015	0.025	-0.027	0.020	0.047

Table IV

Means of Bond Factor Betas

The table presents the mean values of bond factor betas within accounting and non-accounting anomalies. The betas are obtained through the following predictive regression: $\Delta d_{i,t+k} = c_{i,t} + \beta CP_t + \epsilon_{i,t+k}$, in which $\Delta\ d_{i,t+k}$ is portfolio i's log real annual dividend growth at month $t+k$ (k=12, 24, 36), and CP_t is the bond factor at month t. I employ the regression to the long- and short-side portfolios and anomalies over the annual cash-flow growth in one to three years. The annual cash-flow growth is the sum of the dividends received by the long(short) portfolio in the most recent 12 months. The long-short anomaly cash-flow growth is the difference between the log dividend growth of the long side and the log dividend growth of the short side. The sample period covers 1973 to 2022.

		Long-Short	Long Side	Short Side
Year One	Accounting	-0.31	0.27	0.58
	Non-Accounting	-0.58	0.25	0.82
Year Two	Accounting	-0.07	1.27	1.34
	Non-Accounting	-0.69	1.17	1.86
Year Three	Accounting	0.45	1.55	1.10
	Non-Accounting	-0.59	1.51	2.09

Table V

Bond Factor Risk: Accounting vs Non-Accounting

The table compares accounting and non-accounting anomalies in terms of exposure to bond market risk. The horizon used is three years. The p-values are computed using binomial tests, considering the null hypothesis that accounting and non-accounting anomalies are equally likely to have above-median bond factor coefficients. The sample period covers 1973 to 2022.

	Long-Short			Long Side			Short side		
	Accounting Above/Below	Non-Accounting Above/Below	p-value	Accounting Above/Below	Non-Accounting Above/Below	p-value	Accounting Above/Below	Non-Accounting Above/Below	p-value
Dividends	56/34	31/53	0.018	54/36	33/51	0.054	34/56	53/31	0.023

Table VI

Bond Factor Risk by Anomalies

The table shows the coefficients, t-statistics, and R^2 from a test of the following predictive regression: $\Delta d_{i,t+36} = c_{i,t} + \beta CP_t + \epsilon_{i,t+k}$, in which $\Delta\ d_{i,t+36}$ is portfolio i's log real annual dividend growth at month $t+36$, CP_t the bond factor at month t. I employ the regression to the long- and short-side portfolios and anomalies over the one-year, two-year, and three-year horizons. The annual dividends are the sum of the dividends received by the long(short) portfolio in the most recent 12 months. The long-short anomaly dividend growth is the difference between the log dividend growth of the long side and the log dividend growth of the short side. The sample period covers 1973 to 2022.

		Long-Short			Long Side			Short side		
Acronym	Type	β	$t(\beta)$	R^2	β	$t(\beta)$	R^2	β	$t(\beta)$	R^2
AbnormalAccruals	Acc	0.25	0.36	0.1%	1.01	1.50	2.7%	0.77	1.58	1.7%
Accruals	Acc	0.56	0.65	0.7%	1.47	2.72	10.7%	0.91	1.07	2.3%
Activism1	Non-Acc	-2.88	-1.69	12.7%	-0.21	-0.27	0.1%	2.67	1.70	20.4%
Activism2	Non-Acc	1.52	0.97	2.7%	2.14	1.56	8.7%	0.61	1.20	1.5%
AdExp	Acc	-1.23	-2.01	2.3%	1.01	1.23	2.5%	2.24	2.32	10.7%
AgeIPO	Non-Acc	-0.42	-0.68	0.3%	1.16	2.16	4.4%	1.58	2.50	6.2%
AM	Acc	1.81	1.96	4.2%	2.26	2.28	14.0%	0.44	0.73	0.4%
AnalystRevision	Non-Acc	-1.54	-2.23	4.4%	0.59	1.32	1.4%	2.14	4.07	16.6%
AnalystValue	Non-Acc	1.63	1.48	1.5%	2.29	2.04	3.1%	0.66	1.32	4.4%
AnnouncementReturn	Non-Acc	-2.15	-1.22	2.7%	1.70	1.71	4.7%	3.85	2.73	13.9%
AOP	Non-Acc	0.84	0.76	1.3%	1.65	1.61	5.4%	0.81	2.72	8.2%
AssetGrowth	Acc	1.05	0.89	1.8%	1.69	1.68	7.3%	0.64	1.71	3.0%
Beta	Non-Acc	0.77	0.65	0.6%	2.51	2.42	8.1%	1.74	1.63	9.7%
BetaFP	Non-Acc	0.87	0.96	1.0%	1.51	1.38	3.6%	0.64	0.97	1.7%
BetaLiquidityPS	Non-Acc	0.84	1.15	1.1%	2.10	2.66	9.4%	1.26	2.43	6.1%
BetaTailRisk	Non-Acc	0.69	1.03	2.1%	1.56	2.41	16.7%	0.87	2.93	5.2%
betaVIX	Non-Acc	-0.72	-0.75	0.7%	0.80	1.65	3.1%	1.53	2.03	5.2%
BidAskSpread	Non-Acc	-1.86	-1.76	3.0%	-0.24	-0.66	0.3%	1.62	1.60	2.8%
BM	Acc	0.13	0.12	0.0%	0.97	1.28	2.8%	0.84	0.91	1.3%
BMdec	Acc	-1.19	-0.90	0.7%	2.46	1.93	4.8%	3.65	3.18	11.6%
BookLeverage	Acc	1.15	1.40	1.5%	1.33	3.85	4.9%	0.18	0.23	0.1%
BPEBM	Acc	0.94	1.46	1.2%	1.76	3.65	13.6%	0.82	1.25	1.4%
BrandInvest	Acc	1.91	1.58	4.1%	1.91	1.60	9.1%	-0.01	-0.01	0.0%
Cash	Acc	2.10	2.11	4.0%	2.68	3.05	13.0%	0.59	0.84	0.8%
CashProd	Acc	1.17	2.01	2.0%	1.88	3.98	9.9%	0.71	0.98	1.7%
CBOperProf	Acc	0.18	0.25	0.1%	1.19	1.86	3.6%	1.00	1.84	3.6%
CF	Acc	-0.02	-0.04	0.0%	1.04	2.24	3.0%	1.06	2.20	3.6%
cfp	Acc	1.42	1.22	2.2%	1.69	1.85	6.6%	0.27	0.27	0.2%
ChangeInRecommendation	Non-Acc	-0.12	-0.15	0.0%	0.91	1.80	3.2%	1.03	1.43	5.4%
ChAssetTurnover	Acc	0.22	0.18	0.0%	0.78	1.01	1.5%	0.56	0.73	0.4%
ChEQ	Acc	-1.40	-1.26	1.2%	2.17	2.80	6.2%	3.58	5.03	15.3%
ChInv	Acc	-2.68	-0.99	2.0%	2.44	1.11	2.2%	5.12	3.83	25.4%
ChInvIA	Acc	3.08	1.88	3.4%	3.71	2.59	8.2%	0.63	0.40	0.4%
ChNNCOA	Acc	1.17	0.58	0.4%	4.62	3.30	15.1%	3.45	1.99	4.6%
ChNWC	Acc	-1.92	-1.05	1.3%	1.39	1.00	1.7%	3.32	2.25	6.6%
ChTax	Acc	-1.59	-2.16	2.8%	0.33	0.51	0.4%	1.92	2.91	9.5%
CompEquIss	Acc	2.28	1.66	4.8%	1.94	1.62	7.5%	-0.34	-0.63	0.3%
CompositeDebtIssuance	Acc	1.09	1.08	1.5%	1.56	1.78	6.2%	0.46	1.17	0.8%
CoskewACX	Non-Acc	1.10	1.22	1.9%	1.94	2.82	12.5%	0.84	1.00	1.5%
Coskewness	Non-Acc	1.19	1.69	2.6%	2.02	2.47	11.8%	0.84	1.52	2.2%
CPVolSpread	Non-Acc	-0.20	-0.37	0.1%	1.11	1.55	4.9%	1.31	1.83	8.4%
CustomerMomentum	Non-Acc	2.36	2.48	5.7%	2.37	2.59	9.3%	0.01	0.02	0.0%
dCPVolSpread	Non-Acc	1.92	1.96	4.4%	2.34	2.56	14.5%	0.43	0.70	0.4%
DelBreadth	Non-Acc	0.19	0.42	0.2%	1.01	2.64	5.7%	0.82	1.96	9.8%
DelCOA	Acc	-1.74	-2.34	3.0%	1.16	1.26	1.9%	2.90	3.48	10.9%
DelCOL	Acc	-0.73	-0.41	0.3%	1.01	1.37	1.1%	1.74	1.11	1.9%
DelDRC	Acc	-2.20	-1.54	3.7%	1.69	1.75	5.1%	3.89	2.01	14.5%
DelEqu	Acc	-0.73	-1.03	0.8%	0.58	0.81	0.8%	1.30	2.75	6.4%
DelFINL	Acc	1.84	0.91	0.7%	2.51	1.74	3.2%	0.68	0.59	0.2%
DelLTI	Acc	0.08	0.07	0.0%	1.66	1.61	7.0%	1.58	2.70	6.5%
DelNetFin	Acc	-1.63	-1.88	2.8%	0.35	0.97	0.4%	1.98	2.61	6.7%
dNoa	Acc	-0.97	-0.83	1.1%	0.28	0.37	0.2%	1.25	1.35	3.2%

(*continued on next page*)

Table VI (*continued*)

		Long-Short			Long Side			Short side		
Acronym	Type	β	$t(\beta)$	R^2	β	$t(\beta)$	R^2	β	$t(\beta)$	R^2
DolVol	Non-Acc	-0.14	-0.11	0.0%	0.63	0.64	1.1%	0.77	1.26	2.0%
dVolCall	Non-Acc	0.61	0.89	0.7%	2.59	2.92	14.7%	1.98	2.51	10.7%
dVolPut	Non-Acc	-3.61	-2.86	6.9%	0.46	1.23	3.7%	4.07	2.86	9.0%
EarningsConsistency	Acc	-0.33	-0.16	0.1%	0.83	2.00	6.2%	1.16	0.51	1.0%
EarningsForecastDisparity	Non-Acc	-1.20	-0.34	0.1%	2.39	0.80	0.8%	3.59	1.66	1.7%
EarningsStreak	Acc	-1.53	-1.94	2.1%	0.61	2.32	4.5%	2.14	2.67	4.4%
EarningsSurprise	Acc	-0.45	-0.38	0.1%	-0.21	-0.16	0.0%	0.24	0.41	0.1%
EarnSupBig	Acc	-1.57	-1.94	8.3%	-0.36	-1.07	1.3%	1.21	1.77	8.9%
EBM	Acc	0.58	0.46	0.2%	1.65	1.59	2.8%	1.08	1.24	1.2%
EntMult	Acc	2.20	1.91	7.0%	2.27	2.33	14.7%	0.07	0.11	0.0%
EP	Acc	1.34	1.52	3.2%	1.79	2.06	9.2%	0.45	0.70	0.6%
EquityDuration	Acc	0.60	0.87	1.1%	1.47	1.68	7.6%	0.87	2.45	5.0%
ExclExp	Non-Acc	-0.06	-0.10	0.0%	1.06	1.31	4.3%	1.12	2.49	10.5%
FEPS	Non-Acc	1.62	1.68	3.1%	2.36	2.65	15.8%	0.74	0.92	0.9%
fgr5yrLag	Non-Acc	-2.71	-2.78	6.0%	0.26	0.59	0.3%	2.97	3.16	8.4%
FirmAge	Non-Acc	-4.12	-2.94	8.2%	-0.01	-0.02	0.0%	4.11	3.34	10.5%
FirmAgeMom	Non-Acc	0.18	0.37	0.1%	1.03	1.67	4.1%	0.85	2.18	11.8%
ForecastDispersion	Non-Acc	-1.81	-1.20	1.0%	0.37	0.36	0.1%	2.18	2.33	4.7%
FR	Acc	-2.78	-1.76	2.6%	0.96	0.69	0.7%	3.74	3.86	12.3%
Frontier	Acc	2.16	1.41	4.8%	3.06	1.92	10.2%	0.90	2.06	4.0%
GP	Acc	-0.78	-0.59	0.4%	1.35	1.33	2.4%	2.13	2.78	7.8%
GrAdExp	Acc	-1.12	-0.79	0.9%	1.21	1.15	2.1%	2.33	2.67	8.2%
grcapx	Acc	0.13	0.07	0.0%	2.17	1.27	2.8%	2.04	2.55	8.4%
grcapx3y	Acc	-1.21	-0.73	0.3%	0.47	0.49	0.2%	1.68	1.76	1.8%
GrLTNOA	Acc	1.84	1.86	2.8%	1.67	2.00	4.9%	-0.17	-0.22	0.1%
GrSaleToGrInv	Acc	0.86	1.15	1.1%	0.71	0.92	1.7%	-0.15	-0.26	0.1%
GrSaleToGrOverhead	Acc	1.65	0.98	1.7%	1.46	1.01	2.7%	-0.19	-0.38	0.1%
Herf	Non-Acc	0.12	0.11	0.0%	2.93	2.58	9.5%	2.81	2.93	10.8%
HerfAsset	Non-Acc	-2.79	-1.22	2.9%	0.96	0.53	0.8%	3.75	3.34	13.0%
HerfBE	Non-Acc	1.54	1.01	2.7%	2.09	1.57	8.5%	0.55	0.93	1.0%
High52	Non-Acc	2.64	1.28	2.3%	2.51	1.54	3.9%	-0.14	-0.18	0.0%
hire	Non-Acc	-2.11	-2.29	4.8%	0.52	1.52	1.5%	2.63	2.57	7.3%
IdioVol3F	Non-Acc	0.73	0.85	1.0%	0.33	0.60	0.5%	-0.40	-0.57	0.6%
IdioVolAHT	Non-Acc	-1.04	-0.54	0.2%	0.82	0.67	0.5%	1.86	1.78	1.8%
Illiquidity	Non-Acc	-0.10	-0.05	0.0%	1.19	0.87	0.9%	1.29	1.31	1.1%
IndMom	Non-Acc	0.59	0.34	0.1%	1.56	1.50	2.4%	0.97	1.01	0.7%
IndRetBig	Non-Acc	1.63	0.76	0.5%	1.80	1.21	2.0%	0.17	0.13	0.0%
IntanBM	Acc	-2.83	-1.55	4.0%	0.01	0.01	0.0%	2.84	2.12	9.9%
IntanCFP	Acc	-0.83	-0.76	0.6%	0.81	1.27	2.0%	1.64	1.90	3.9%
IntanEP	Acc	-0.02	-0.01	0.0%	0.56	0.58	1.0%	0.58	0.65	0.5%
IntanSP	Acc	-0.99	-0.84	1.3%	1.01	1.68	3.6%	2.00	1.71	8.3%
IntMom	Non-Acc	0.66	0.92	0.8%	1.19	1.78	3.6%	0.53	0.69	1.0%
Investment	Acc	-0.86	-1.28	1.2%	0.67	1.08	1.2%	1.53	2.92	7.2%
InvestPPEInv	Acc	-0.43	-0.34	0.1%	0.59	0.71	0.7%	1.02	1.40	2.2%
InvGrowth	Acc	0.28	0.22	0.0%	1.31	1.78	3.1%	1.03	1.09	1.2%
IO_ShortInterest	Non-Acc	2.19	2.56	7.2%	2.14	3.02	13.8%	-0.05	-0.10	0.0%
iomom_cust	Non-Acc	0.62	0.65	0.3%	2.01	1.66	3.2%	1.38	1.33	3.7%
iomom_supp	Non-Acc	-0.01	-0.01	0.0%	0.32	0.98	0.9%	0.33	0.32	0.1%
Leverage	Acc	1.59	1.47	1.5%	0.18	0.46	0.2%	-1.41	-1.65	1.4%
LRreversal	Non-Acc	0.61	0.83	0.7%	1.52	1.66	7.4%	0.91	1.18	2.1%
MaxRet	Non-Acc	-0.72	-0.64	0.8%	1.18	1.28	3.2%	1.90	1.71	10.5%
MeanRankRevGrowth	Acc	0.90	0.68	2.7%	2.66	3.26	21.4%	1.76	1.94	18.8%
Mom12m	Non-Acc	3.62	2.82	15.2%	3.01	3.16	14.9%	-0.61	-0.84	1.3%
Mom12mOffSeason	Non-Acc	-3.41	-2.04	2.8%	-1.45	-0.95	1.1%	1.96	1.70	2.7%
Mom6m	Non-Acc	-0.96	-1.47	1.8%	0.00	0.00	0.0%	0.96	1.81	3.3%
Mom6mJunk	Non-Acc	-4.25	-2.49	10.3%	-0.43	-1.34	1.3%	3.82	2.26	9.7%
MomOffSeason	Non-Acc	1.07	1.07	1.5%	1.28	1.83	4.6%	0.21	0.23	0.1%
MomOffSeason06YrPlus	Non-Acc	1.33	0.96	1.7%	3.52	4.45	19.2%	2.19	1.40	5.0%
MomOffSeason11YrPlus	Non-Acc	-0.95	-0.82	1.8%	0.48	0.64	0.7%	1.43	2.04	11.0%
MomOffSeason16YrPlus	Non-Acc	-2.06	-0.87	0.5%	2.22	1.12	2.5%	4.27	1.48	2.4%
MomSeason	Non-Acc	0.32	0.22	0.1%	1.06	1.66	2.0%	0.74	0.57	1.1%
MomSeason11YrPlus	Non-Acc	2.46	0.93	1.3%	3.05	1.47	2.7%	0.59	0.40	0.2%
MomSeason16YrPlus	Non-Acc	0.62	0.67	0.4%	1.81	2.00	8.3%	1.19	2.29	5.0%
MomSeasonShort	Non-Acc	-2.42	-2.27	4.3%	0.18	0.53	0.2%	2.61	2.45	5.6%

(*continued on next page*)

Table VI (*continued*)

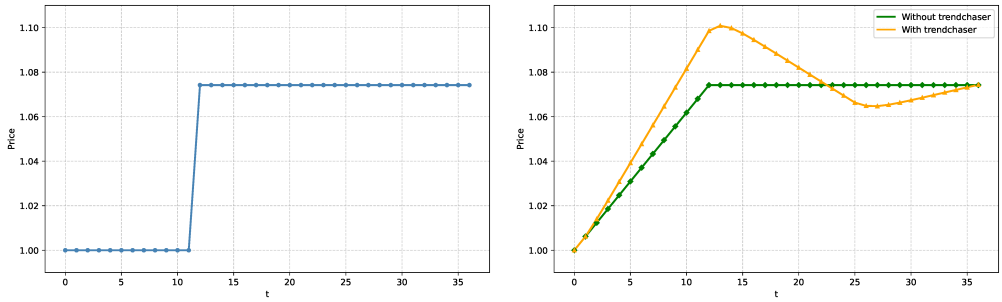
		Long-Short			Long Side			Short side		
Acronym	Type	β	$t(\beta)$	R^2	β	$t(\beta)$	R^2	β	$t(\beta)$	R^2
MRreversal	Non-Acc	-1.41	-1.34	1.7%	-0.15	-0.29	0.1%	1.26	1.82	3.0%
NetDebtFinance	Acc	-2.59	-1.96	3.7%	-0.46	-0.42	0.3%	2.13	2.71	7.3%
NetDebtPrice	Acc	0.05	0.10	0.0%	1.04	2.02	5.6%	0.99	2.54	4.0%
NetEquityFinance	Acc	0.31	0.65	0.2%	1.16	2.76	9.8%	0.86	1.85	2.8%
NetPayoutYield	Acc	0.24	0.24	0.0%	1.45	2.91	3.6%	1.21	1.06	2.3%
NOA	Acc	1.60	2.34	3.0%	2.13	3.46	10.0%	0.53	0.94	0.9%
NumEarnIncrease	Acc	-2.11	-0.89	1.4%	1.46	0.66	0.7%	3.56	2.66	13.3%
OperProf	Acc	-2.50	-1.72	6.1%	0.93	2.16	4.0%	3.43	2.50	13.5%
OperProfRD	Acc	-5.86	-2.01	4.3%	0.35	0.24	0.1%	6.21	1.99	5.5%
OPLeverage	Acc	-1.07	-1.53	1.7%	0.72	1.57	2.6%	1.79	2.58	7.1%
OptionVolume1	Non-Acc	-1.84	-2.27	10.2%	-0.12	-0.28	0.1%	1.72	2.60	12.0%
OptionVolume2	Non-Acc	-1.15	-0.54	0.5%	4.36	2.56	9.6%	5.51	4.71	26.0%
OrderBacklog	Acc	-2.05	-2.79	5.3%	0.15	0.48	0.1%	2.21	2.96	5.7%
OrderBacklogChg	Acc	0.37	0.77	0.5%	1.02	3.02	6.1%	0.65	1.95	3.8%
OrgCap	Acc	-1.08	-1.37	3.0%	0.18	0.38	0.2%	1.27	2.02	6.7%
PayoutYield	Acc	1.95	1.61	5.9%	2.28	2.69	15.3%	0.33	0.39	0.3%
PctAcc	Acc	-2.32	-1.02	1.5%	0.63	0.62	0.4%	2.96	1.94	6.1%
PctTotAcc	Acc	-0.40	-1.05	1.6%	0.66	2.12	4.4%	1.06	2.34	14.2%
PredictedFE	Acc	0.27	0.42	0.1%	0.94	2.76	9.1%	0.67	1.08	0.9%
PriceDelayRsq	Non-Acc	-0.99	-1.49	2.3%	0.76	1.76	3.6%	1.76	2.08	8.2%
PriceDelaySlope	Non-Acc	-0.43	-0.63	0.4%	1.23	2.32	6.0%	1.66	2.43	7.9%
PriceDelayTstat	Non-Acc	-0.74	-1.17	1.5%	0.72	1.54	2.6%	1.47	1.83	8.0%
ProbInformedTrading	Non-Acc	-3.52	-1.36	4.2%	-0.98	-0.48	0.6%	2.54	1.27	6.0%
PS	Acc	-0.81	-0.76	0.4%	0.45	0.63	0.2%	1.26	1.21	2.0%
RD	Acc	-3.26	-0.66	1.0%	4.05	1.23	4.8%	7.31	2.28	7.3%
RDAbility	Acc	-3.02	-2.30	6.2%	0.74	0.72	1.2%	3.76	4.00	17.7%
RDcap	Acc	-0.85	-1.01	0.6%	0.31	0.42	0.2%	1.16	1.07	1.5%
RDS	Acc	1.78	1.89	4.1%	1.92	1.87	5.0%	0.14	0.28	0.2%
realestate	Acc	1.46	2.19	3.0%	1.38	1.98	3.2%	-0.08	-0.17	0.0%
RealizedVol	Non-Acc	1.38	1.68	2.1%	1.47	1.71	3.3%	0.09	0.19	0.0%
ResidualMomentum	Non-Acc	-1.84	-0.94	0.7%	-1.33	-0.71	0.4%	0.51	2.66	5.0%
retConglomerate	Non-Acc	-0.22	-0.23	0.1%	1.09	2.34	5.0%	1.31	1.65	4.1%
ReturnSkew	Non-Acc	6.19	1.88	3.0%	7.68	2.51	5.8%	1.49	0.78	1.8%
ReturnSkew3F	Non-Acc	1.37	1.94	3.8%	1.91	2.24	6.7%	0.53	1.97	7.0%
REV6	Non-Acc	1.79	1.28	3.7%	3.45	2.52	20.1%	1.66	4.46	6.9%
RevenueSurprise	Acc	0.17	0.27	0.0%	1.00	1.68	3.3%	0.84	1.31	2.5%
RIVolSpread	Non-Acc	1.26	1.39	2.0%	1.77	2.01	8.6%	0.51	0.87	0.7%
roaq	Acc	0.92	0.64	0.6%	2.02	1.90	5.9%	1.10	1.17	1.6%
RoE	Acc	0.30	0.51	0.3%	1.14	1.46	5.5%	0.83	2.35	5.0%
sfe	Non-Acc	-2.41	-1.53	1.7%	-0.61	-0.84	0.8%	1.79	1.46	1.8%
ShareIss5Y	Acc	-0.29	-0.15	0.1%	1.25	1.33	3.0%	1.53	1.20	2.9%
ShortInterest	Non-Acc	-0.95	-0.64	0.2%	0.92	1.02	0.6%	1.86	1.98	3.0%
skew1	Non-Acc	-0.13	-0.23	0.0%	1.00	1.47	3.7%	1.13	2.89	9.4%
SmileSlope	Non-Acc	-3.13	-2.43	4.6%	0.38	1.32	1.2%	3.50	3.00	6.9%
SP	Acc	-2.87	-1.88	4.9%	0.49	0.93	1.2%	3.37	2.26	8.5%
std_turn	Non-Acc	-1.17	-0.65	0.6%	3.21	2.33	10.4%	4.38	3.71	15.0%
tang	Acc	-1.68	-0.69	0.9%	0.52	0.53	0.7%	2.20	1.14	2.0%
Tax	Acc	-0.38	-0.37	0.1%	0.46	0.52	0.5%	0.84	1.55	2.1%
TotalAccruals	Acc	0.02	0.04	0.0%	0.75	2.21	3.3%	0.73	1.71	2.9%
TrendFactor	Non-Acc	-0.93	-0.14	0.1%	7.72	2.21	9.3%	8.65	2.07	9.9%
VarCF	Acc	1.52	1.26	1.5%	1.40	1.24	1.5%	-0.12	-0.20	0.0%
VolMkt	Non-Acc	-1.96	-2.67	4.8%	0.43	1.26	1.5%	2.39	3.24	8.4%
VolSD	Non-Acc	-1.56	-1.67	3.2%	0.04	0.07	0.0%	1.61	1.81	5.7%
VolumeTrend	Non-Acc	-0.68	-0.30	0.3%	1.63	1.14	3.4%	2.31	1.55	3.8%
XFIN	Acc	-0.33	-0.36	0.2%	0.75	0.82	1.5%	1.08	1.94	5.4%
zerotrade	Non-Acc	-0.59	-0.70	0.4%	1.17	2.29	10.8%	1.76	1.70	3.8%
zerotradeAlt1	Non-Acc	-0.66	-1.14	0.8%	0.73	1.54	3.3%	1.39	1.75	4.1%
zerotradeAlt12	Non-Acc	-0.12	-0.12	0.0%	0.99	1.11	2.8%	1.11	1.55	4.3%

Table VII

Build-up and Resolution Anomalies

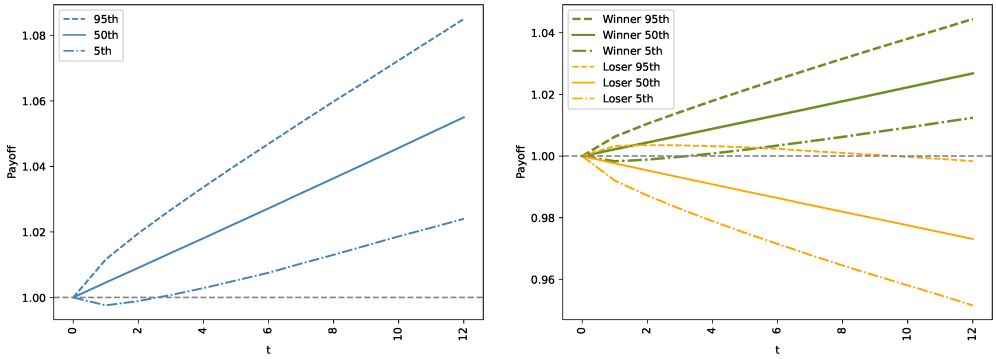
This table compares the cash-flow behaviors of resolution and build-up anomalies within accounting and non-accounting anomalies. Panel A reports tracking-firm anomaly cash-flow growth. Panel B examines anomaly cash-flow growth across full, expansion, and recession periods. Panel C reports the bond factor betas over three years. T-statistics are provided for statistical significance.

Panel A: Tracking-firm cash-flow growth				
		Year one	Year two	Year three
Accounting	Resolution	-0.024	-0.036	-0.048
	Build-up	-0.014	-0.014	-0.014
	difference	-0.010	-0.022	-0.034
	t-stats	-0.325	-0.635	-0.877
Non-Accounting	Resolution	0.020	0.018	0.014
	Build-up	0.108	0.135	0.149
	difference	-0.087	-0.117	-0.135
	t-stat	-2.316	-2.717	-2.936
Panel B: Anomaly-level cash-flow growth				
		Full Sample	Expansion	Recession
Accounting	Resolution	0.023	0.021	0.040
	Build-up	0.011	0.010	0.014
	diff	0.012	0.011	0.026
	t-stat	1.711	1.162	1.215
Non-Accounting	Resolution	0.036	0.032	0.072
	Build-up	0.055	0.035	0.208
	diff	-0.019	-0.003	-0.136
	t-stat	-1.265	-0.189	-2.424
Panel C: Bond factor				
		Year one	Year two	Year three
Accounting	Resolution	-0.721	-0.334	0.021
	Build-up	0.337	0.522	1.054
	diff	-1.056	-0.852	-1.033
	t-stat	-1.423	-1.450	2.718
Non-Accounting	Resolution	-0.449	-0.357	-0.957
	Build-up	-1.049	-1.402	-0.252
	diff	0.600	1.055	-0.725
	t-stat	1.047	1.751	-1.752

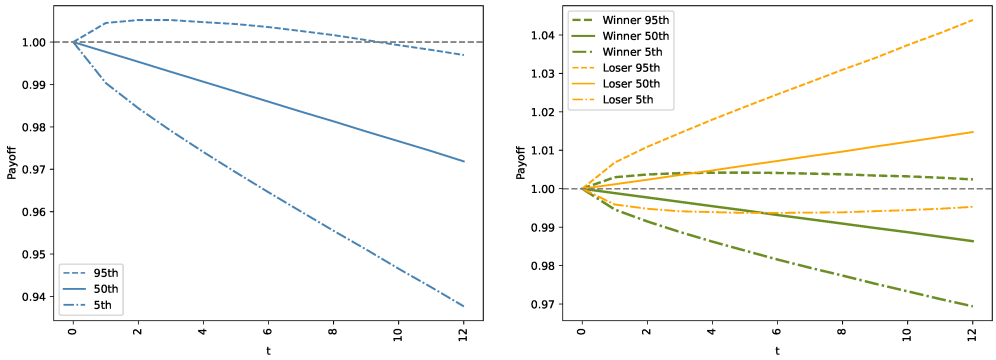


(a) Accounting information **(b)** Non-accounting information

Figure 1. This figure illustrates the price dynamics in response to a one standard deviation shock to the terminal cash flow under three distinct scenarios. The magnitude of the shock (7.42%) is calibrated to match the historical annual standard deviation of dividend growth from 1973 to 2023. The left panel shows immediate price adjustment when information arrives through accounting disclosure at t=12. In the right panel, the green line represents how the same information gradually diffuses from $t = 1$ to $t = 12$ among newswatchers, showing the progressive incorporation of information into prices without the influence of trend chasers; the orange line builds upon the gradual diffusion case, demonstrating how trend-chasing behavior generates an initial overreaction and subsequent sluggish price correction.



(a) Non-accounting anomalies and short-term overreaction



(b) Non-accounting anomalies and long-term correction

Figure 2. Simulation evidence illustrating the mechanism behind non-accounting anomalies through information diffusion. Panel (a) demonstrates short-term overreaction, where winner and loser portfolios diverge, leading to positive returns for zero-cost portfolios. Panel (b) shows long-term correction, with winner and loser portfolios converging, resulting in negative returns for zero-cost portfolios. These results capture the dual dynamics of short-term trend-chasing and long-term price reversal.

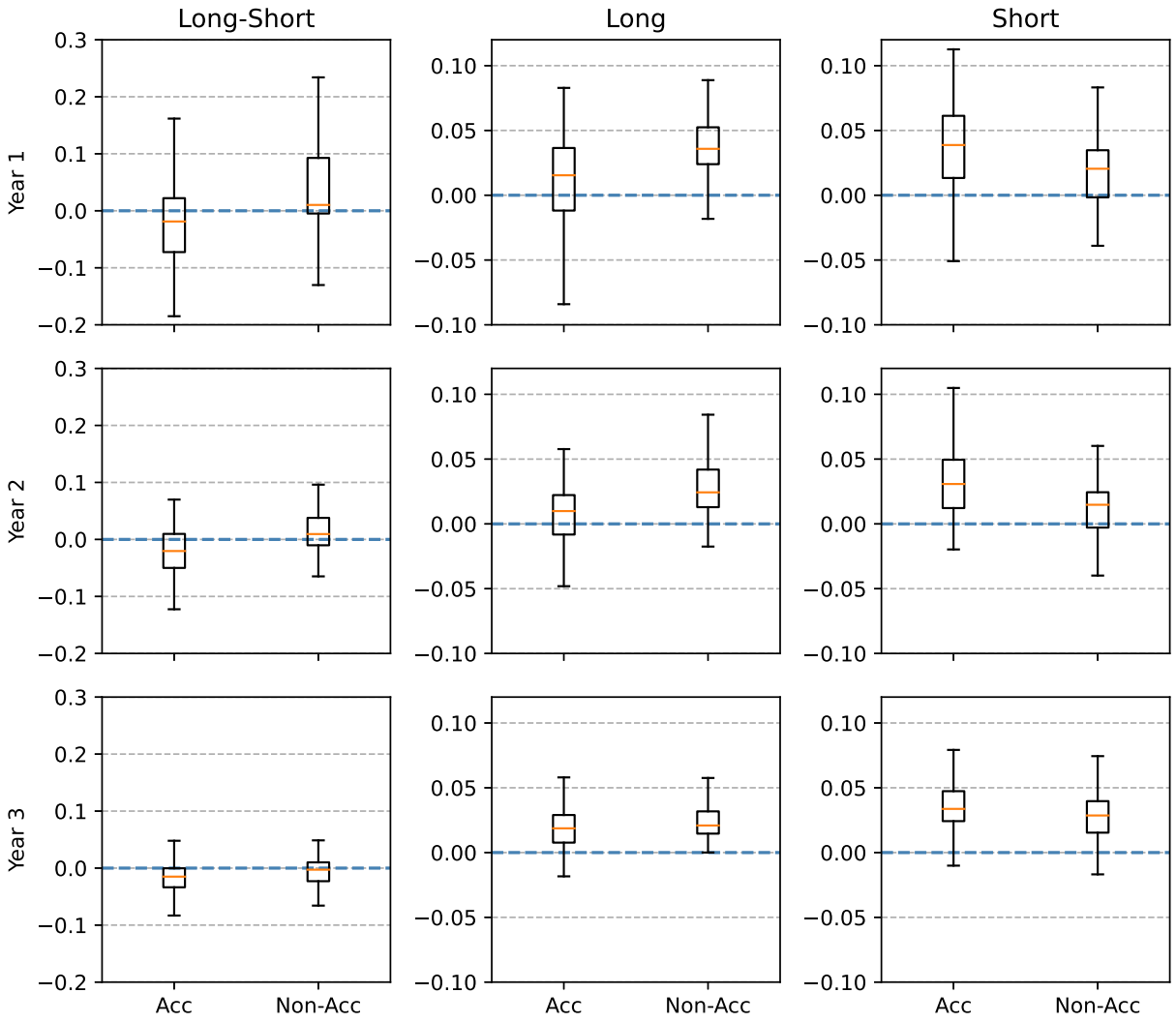


Figure 3. The figures show the distributions of the mean of tracking-firm cash-flow growth across three horizons for accounting and non-accounting anomalies. For every month between 1973 and 2020, I sort stocks into value-weighted quintile portfolios based on the focal characteristic. The quintile portfolios are determined by the NYSE breakpoints. I track the annual cash-flow growth of this portfolio without rebalancing for three years. For each portfolio, I calculate its log annual cash flow growth at the end of the first, second, and third years after formation. The cash-flow growth of a long-short portfolio is calculated by deducting its short side's log annual cash-flow growth from its long side's log annual cash-flow growth. Then, I average this cash-flow growth across formation months. The whiskers show the 10th and 90th percentiles. The orange bars show medians. The boxes show the 25th and 75th percentiles.

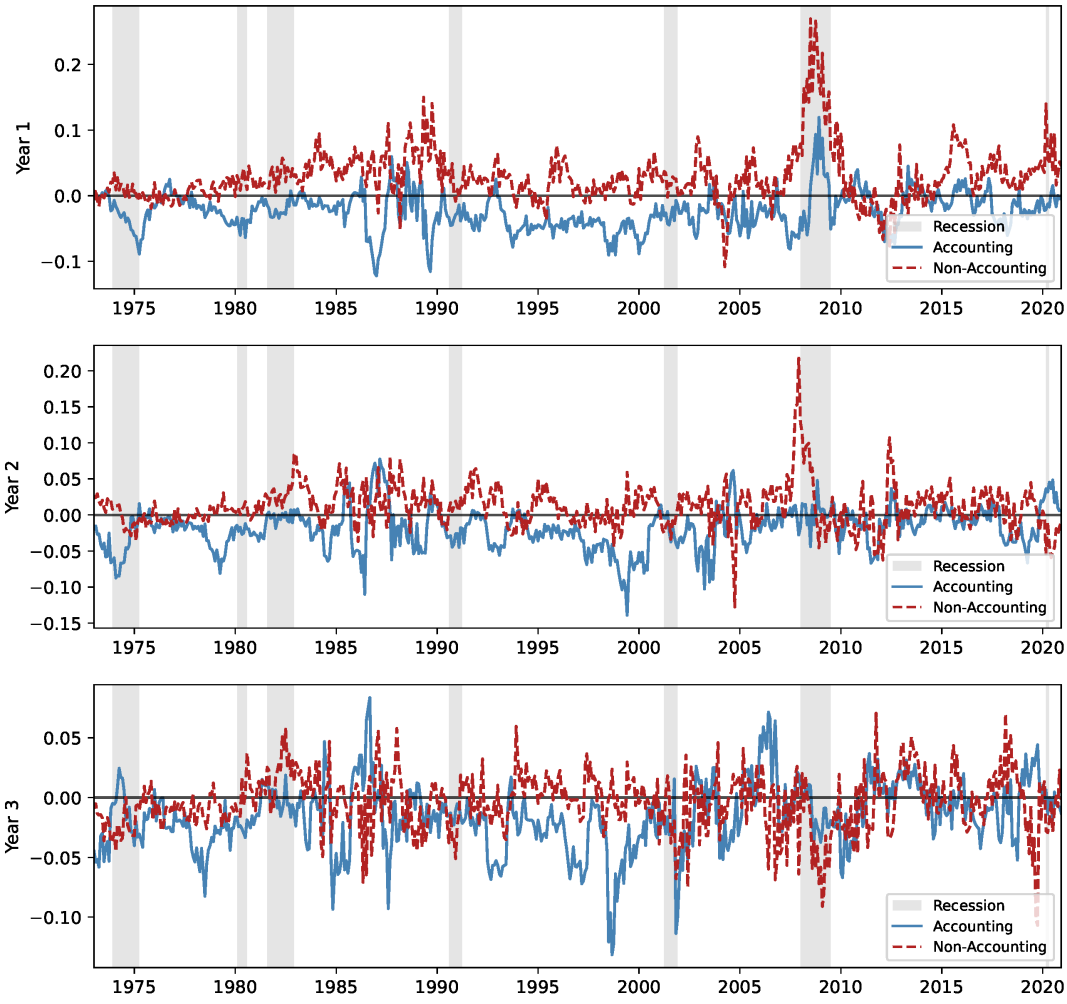
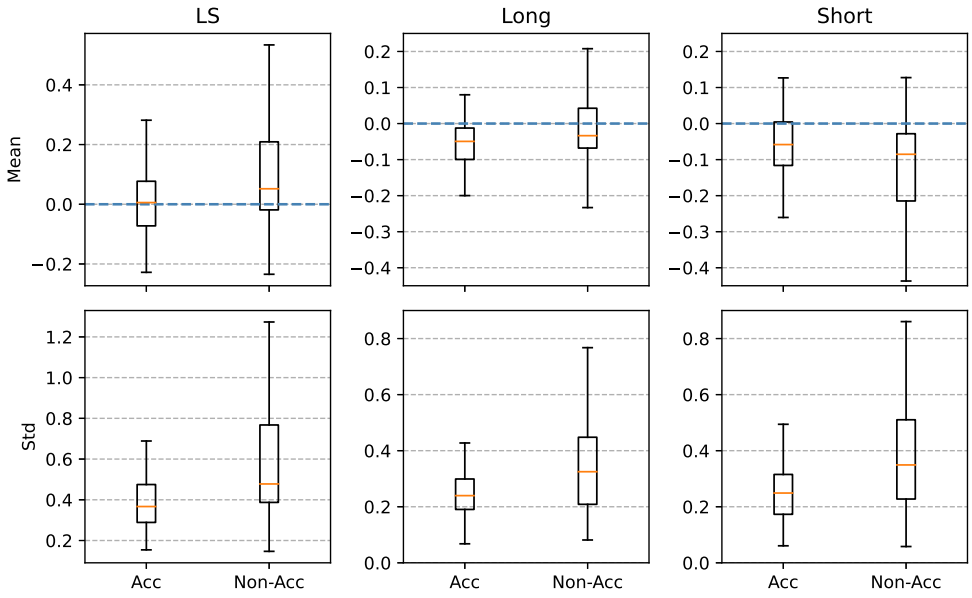
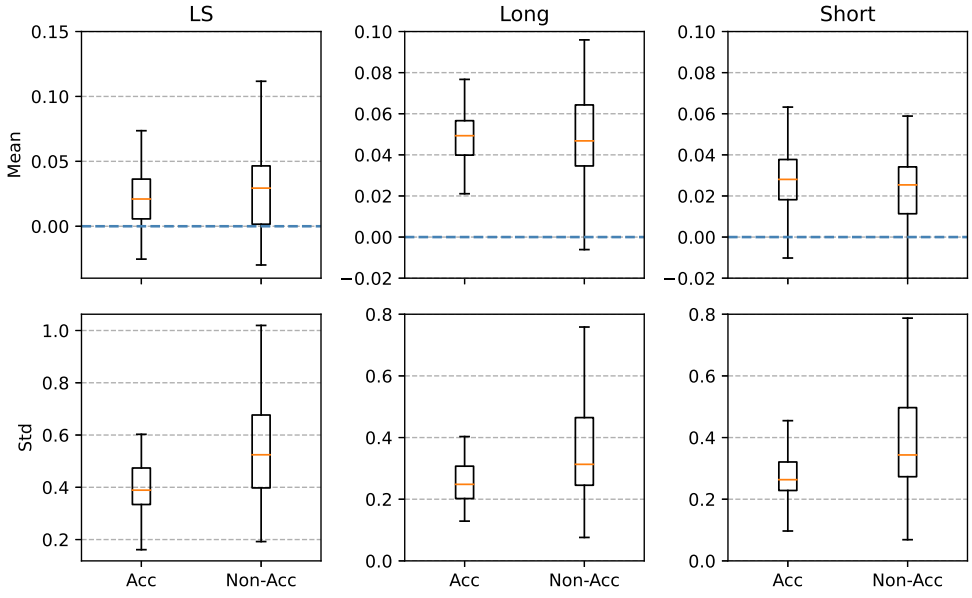


Figure 4. Tracking-firm cash-flow growth of accounting and non-accounting anomalies. For every month between 1973 and 2020, I sort stocks into value-weighted quintile portfolios based on the focal characteristic. The quintile portfolios are determined by the NYSE breakpoints. I track the annual cash-flow growth of this portfolio without rebalancing for three years. For each portfolio, I calculate its log annual cash flow growth at the end of the first, second, and third years after formation. The cash-flow growth of a long-short portfolio is calculated by deducting its short side's log annual cash-flow growth from its long side's log annual cash-flow growth.



(a) Recession



(b) Expansion

Figure 5. Anomaly cash-flow growth within economic cycles. The figures compare the cash-flow growth of accounting and non-accounting anomalies during recession and expansion periods. From 1973 to 2022, I calculate the log annual cash-flow growth for monthly rebalanced anomaly portfolios. I define recession periods as the months with a value of one in the NBER business cycle dating table. The other months are expansion periods. Then, I examine the average and standard deviation of log quarterly cash-flow growth in recession and expansion periods for all portfolios. The cash-flow growth of a long-short portfolio is calculated as the difference in cash flow growth between the long and short sides. Cash flows are constructed from the difference between returns and ex-dividend returns on these portfolios, multiplied by the previous month's ex-dividend price. The whiskers show the 10th and 90th percentiles. The orange bars show medians. The boxes show the 25th and 75th percentiles.

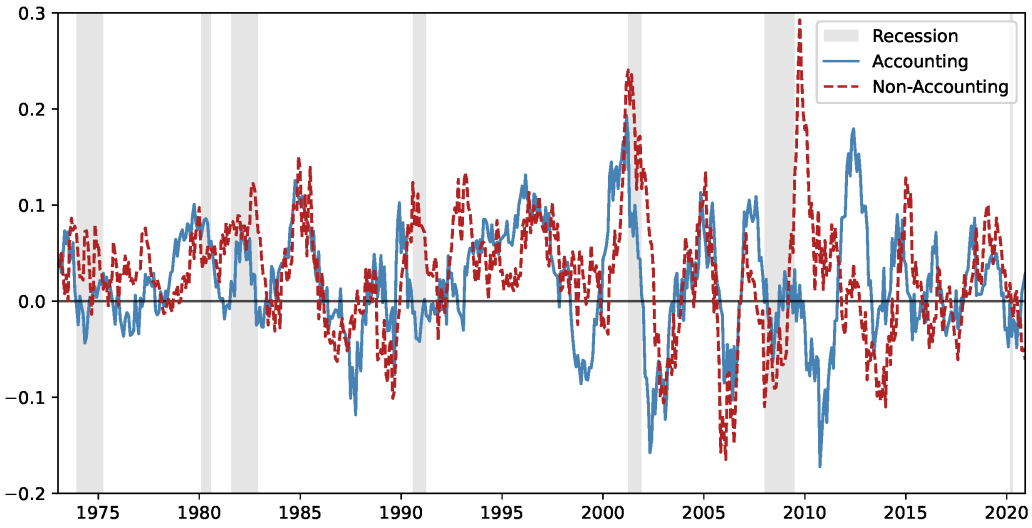


Figure 6. Tracking-anomaly cash-flow growth of accounting and non-accounting anomalies. The figure presents the time series of median cash-flow growth for accounting and non-accounting anomalies. The vertical axis measures the logarithm of annual dividend growth.

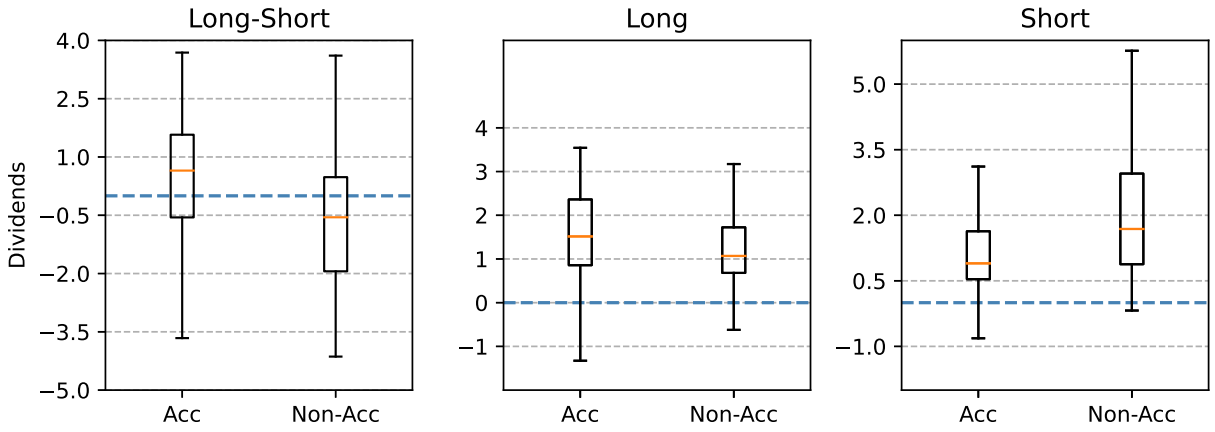


Figure 7. Bond factor beta distributions. The bond factor betas are from a predictive regression. The dependent variable is the 36-month forward log cash flow growth ratio. The independent variables are bond factors. The sample period covers 1973 to 2022. The whiskers show the 10th and 90th percentiles. The orange bars show the medians. The boxes show the 25th and 75th percentiles.

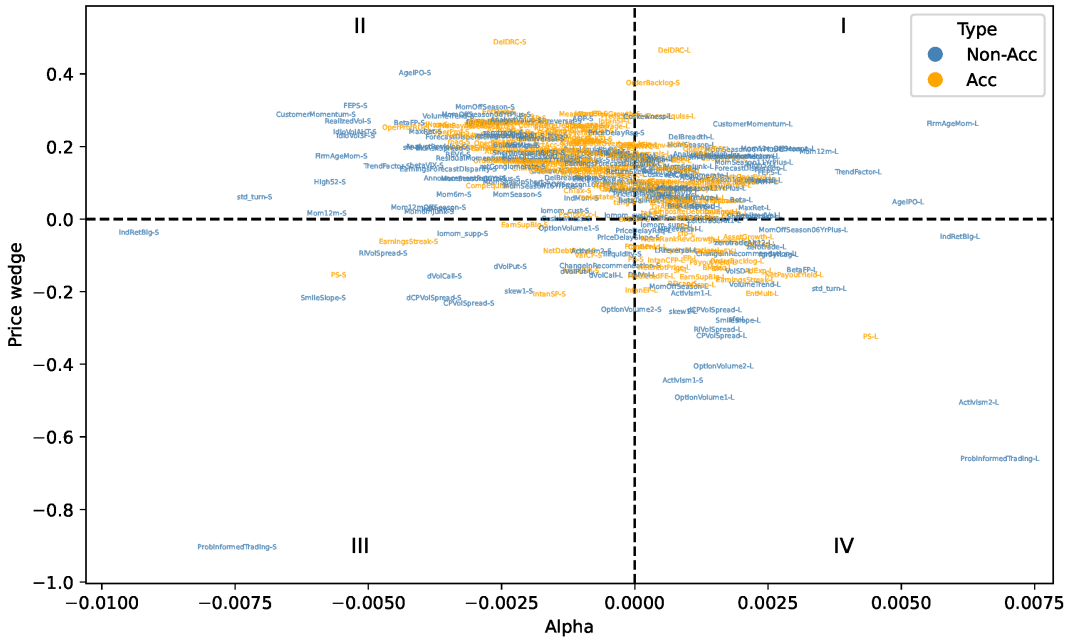
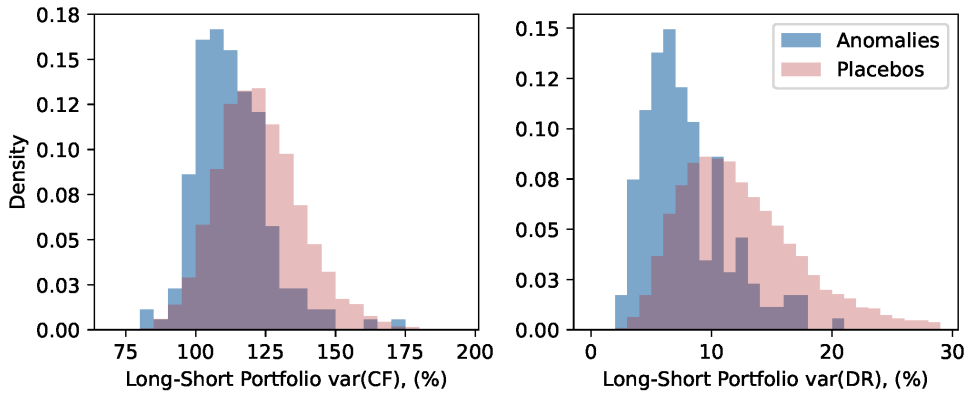
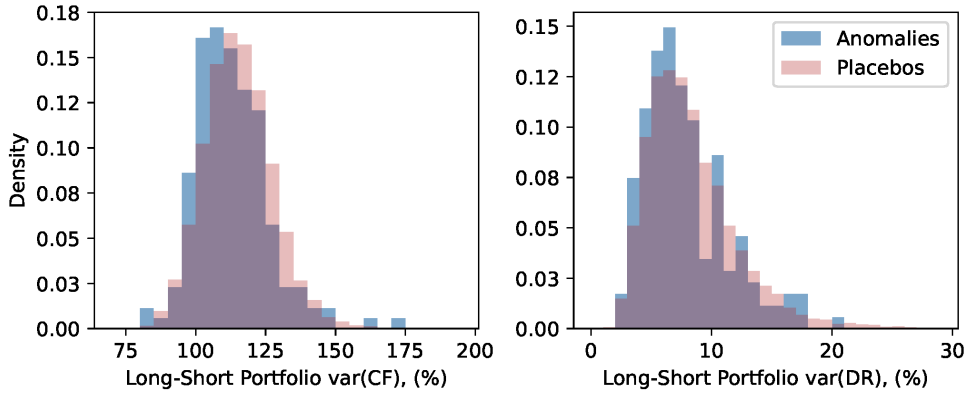


Figure 8. Price wedges, alphas, and accounting and non-accounting anomalies. The figure shows the relation between price wedges and alphas for accounting and non-accounting anomalies. Anomalies in quadrants II and IV are resolution anomalies, whereas anomalies in quadrants I and III are build-up anomalies.



(a) Anomalies and random placebos



(b) Anomalies and high correlation placebos

Figure 9. Indirect return decompositions for anomalies and placebos. The figure displays the distributions of the percentage of anomaly or placebo return variance attributable to cash-flow news and discount-rate news components. In Panel (a), the placebos consist of randomly selected stocks. In Panel (b), the placebos consist of stocks that tend to have higher return correlation in the past year.

Appendix for "Anomalies and Cash Flows"

A. Model appendix

A.1. Proof of Proposition 1

Proof: The investors solve the following optimazation problem:

$$\max_{q_t} E\left[-\gamma e^{-\gamma W_T} \mid s_t\right] \tag{A.1}$$

$$s.t.$$

$$W_T = W_t - P_t q_t + P_T q_t, \tag{A.2}$$

where W_T is the investors' wealth at time T, q_t represents the number of assets traded, and s_t is the signal that aggregate investors receive. When there is only instant information in the market, s_t is equivalent to $\sum_{t=1}^{T} \zeta_t$. Because the shock is mean-zero and normally distributed, the optimization problem is equivalent to

$$\max_{q_t} E\left[-\gamma e^{-\gamma W_{t+1}} \mid s_t\right] \tag{A.3}$$

$$s.t.$$

$$W_{t+1} = W_t - P_t q_t + P_{t+1} q_t, \tag{A.4}$$

$$cov(\Delta P_t, \Delta P_{t-1}) = cov(P_t - P_{t-1}, P_{t-1} - P_{t-2}) \tag{A.5}$$

$$= cov(\zeta_t, \zeta_{t-1}) = 0 \tag{A.6}$$

A.2. Proof of Lemma 2

Proof: By market clearing conditions,

$$S_t + \sum_{i=1}^{j} F_{t+1-i} = Q, \tag{A.7}$$

$$S_t = Q - \sum_{i=1}^{j} F_{t+1-i} = Q - \sum_{i=1}^{j} \phi \Delta P_{\epsilon,t-1}. \tag{A.8}$$

Substituting in equation (6) yields

$$P_t = E(P_{t+1} \mid s_t) - \gamma \sigma^2(s_t) Q \tag{A.9}$$

$$\begin{aligned} &= D_0 + \sum_{t=0}^{t} \epsilon_t + \sum_{t=0}^{t} \zeta_t \\ &\quad + \left\{(z-1)\epsilon_{t+1} + (z-2)\epsilon_{t+2} + \cdots + \epsilon_{t+z-1}\right\}/z \\ &\quad - \gamma \sigma^2(s_t) \left(Q - \sum_{i=1}^{j} \phi \Delta P_{\epsilon,t-i}\right) \end{aligned} \tag{A.10}$$

After normalizing $\gamma\sigma^2(s_t)$ to one and dropping the constant, the price after momentum traders enter is

$$\begin{aligned} P_t =& D_0 + \sum_{t=0}^{t} \epsilon_t + \sum_{t=0}^{t} \zeta_t \\ &+ \{(z-1)\epsilon_{t+1} + (z-2)\epsilon_{t+2} + \cdots + \epsilon_{t+z-1}\}/z \\ &+ \sum_{i=1}^{j} \phi \Delta P_{\epsilon,t-i}. \end{aligned} \tag{A.11}$$

Accordingly,

$$\begin{aligned} \Delta P_t =& P_t - P_{t-1} \qquad (A.12) \\ =& D_0 + \sum_{t=0}^{t} \epsilon_i + \sum_{t=0}^{t} \zeta_i \\ &+ \{(z-1)\epsilon_{t+1} + (z-2)\epsilon_{t+2} + \cdots + \epsilon_{t+z-1}\}/z + \sum_{i=1}^{j} \phi \Delta P_{\epsilon,t-i} \\ &- [D_0 + \sum_{t=0}^{t-1} \epsilon_i + \sum_{t=0}^{t-1} \zeta_i \\ &+ \{(z-1)\epsilon_t + (z-2)\epsilon_{t+1} + \cdots + \epsilon_{t+z-2}\}/z + \sum_{i=0}^{j-1} \phi \Delta P_{\epsilon,t-i}] \qquad (A.13) \\ =& \zeta_t + \frac{\sum_{i=0}^{z} \epsilon_{t+i}}{z} + \phi \Delta P_{\epsilon,t-1} - \phi \Delta P_{\epsilon,t-(j+1)}, \qquad (A.14) \end{aligned}$$

and

$$\Delta P_{\epsilon,t} = \frac{\sum_{i=0}^{z} \epsilon_{t+i}}{z} + \phi \Delta P_{\epsilon,t-1} - \phi \Delta P_{\epsilon,t-(j+1)}. \tag{A.15}$$

At equilibrium, $F_t = q_t$, it follows that

$$\phi \Delta P_{\epsilon,t-1} = \frac{E(P_{t+j} \mid \Delta P_{\epsilon,t-1}) - P_t}{\gamma\sigma^2(P_{t+j} - P_t \mid \Delta P_{\epsilon,t-1})} \tag{A.16}$$

Assume that ΔP_t and $\Delta P'_t$ are covariance-stationary processes. Then, the variance is $E[(\Delta P_t]^2$ and the autocovariance lagged one period is $E[\Delta P_t \Delta P_{t-1}]$. The autocovariance of ΔP_t and $\Delta P_{\epsilon,t-1}$ is

$$\begin{aligned} E[\Delta P_t \Delta P_{\epsilon,t-1}] &= E[(\Delta P'_t + \zeta_t)\Delta P_{\epsilon,t-1}] && (A.17) \\ &= E[\Delta P_{\epsilon,t} \Delta P_{t-1}] + E[\zeta_t \Delta P_{\epsilon,t-1}] && (A.18) \\ &= E[\Delta P_{\epsilon,t} \Delta P_{t-1}] && (A.19) \end{aligned}$$

Rewrite equation (A.16)

$$\phi = \frac{E(P_{t+j} \mid \Delta P_{\epsilon,t-1}) - P_t}{\gamma\sigma^2(P_{t+j} - P_t \mid \Delta P_{\epsilon,t-1})\Delta P_{\epsilon,t-1}} \tag{A.20}$$

$$= \frac{E(P_{t+j} - P_t \mid \Delta P_{\epsilon,t-1})E(P_{\epsilon,t-1})}{\gamma\sigma^2(P_{t+j} - P_t \mid \Delta P_{\epsilon,t-1})\Delta P_{\epsilon,t-1}E(P_{\epsilon,t-1})} \tag{A.21}$$

$$= cov(P_{t+j} - P_t, \Delta P_{\epsilon,t-1})/\{\gamma var(P_{t+j} - P_t)var(\Delta P_{\epsilon,t-1})\}. \tag{A.22}$$

Hong and Stein (1999) have proved that $\mid \phi \mid < 1$ is a necessary condition for a conjectured equilibrium process to be convariance stationary. Therefore, I can use computational algorithm to find the fixed point ϕ that gives the equilibrium.

B. Predictors in VAR return decompositions

B.1. Indirect return decomposition

The value characteristic (*lnBM*) is calculated as *ln(book equity$_t$/market equity$_t$)*, where t indicates year. Book equity is the total shareholder equity, excluding preferred stock equity but adding deferred tax and investment credit. The market capitalization for each stock is calculated as the price multiplied by the number of shares outstanding. For a company with dual-class shares, its market capitalization is the sum of the value of its dual-class shares. The firm's return is a value-weighted average of the returns of the shares of each class. The same rule applies to dividends, turnover, and issuance. Following Fama and French (2015), I calculate the profitability characteristic (*lnProf*) as *ln(1 + earnings before tax$_t$/book equity$_t$)*. Following Cooper, Gulen, and Schill (2008), I calculate the investment (*lnInv*) characteristic as the five-year asset growth average, $\frac{1}{5}\sum_{i=0}^{4} ln(1 + total\ asset_{t-i}/total\ asset_{t-i-1})$. Following Gerakos and Linnainmaa (2018), the size characteristic (*d5.lnME*) is the sum of the five-year changes in size, $\sum_{i=1}^{5}$ *ln(market equity$_{t+1-i}$/market equity$_{t-i}$)*. The six-month momentum (*lnMom6*) is $\sum_{i=0}^{5} ln\ (1+ret_{t+i})$, in which t denotes month.

C. Placebo Construction

C.1. Random placebos

First, I randomly draw 40% of firms each July-to-June year in the sample period. Then, I evenly split the drawn firms into two groups. I build a zero-cost long-short portfolio by buying one of them and shorting the other. I hold the portfolio during the year. I sample 5,000 times for each year and get 5,000 sets of random placebos.

C.2. High-correlation placebos

First, each July-to-June year, I calculate every pair of firms' monthly return correlations. This calculation generates a correlation matrix for firms in the year. As my sample period is 1973 to 2020, I have 47 such matrices. Each of the matrices has N_t dimensions, in which N_t refers to the number of firms in the year.

Then I use a Gaussian copula approach to model random variable dependences. Specifically, for each year, I set up a multivariate normal distribution. The distribution has N_t dimension. Each dimension corresponds to one firm. I use a vector of zeros as the mean vector and the previously-calculated correlation matrix as the covariance matrix. I use the distribution to randomly generate

a vector with N_t elements. Under the setting, the firms/dimensions with high correlations tend to get high or low values in the same draw.

Next, I separate the N_t elements into two groups based on whether the element is negative or positive. I require each group to have at least $25\% \times N_t$ observations. If not, I discard this draw and redo the draw.

If the draw meets the $25\% \times N_t$ threshold, I randomly draw $20\% \times N_t$ observations from each of the two groups. Then I buy the $20\% \times N_t$ observations from the positive group and short the $20\% \times N_t$ observations from the negative group. I hold this portfolio during the following July-to-June year. I repeat the draw for every year and get 47 annual returns. I call this portfolio the high-correlation placebo. I sample 2,000 times for the 1973–2020 period and get 2,000 high-correlation placebos.

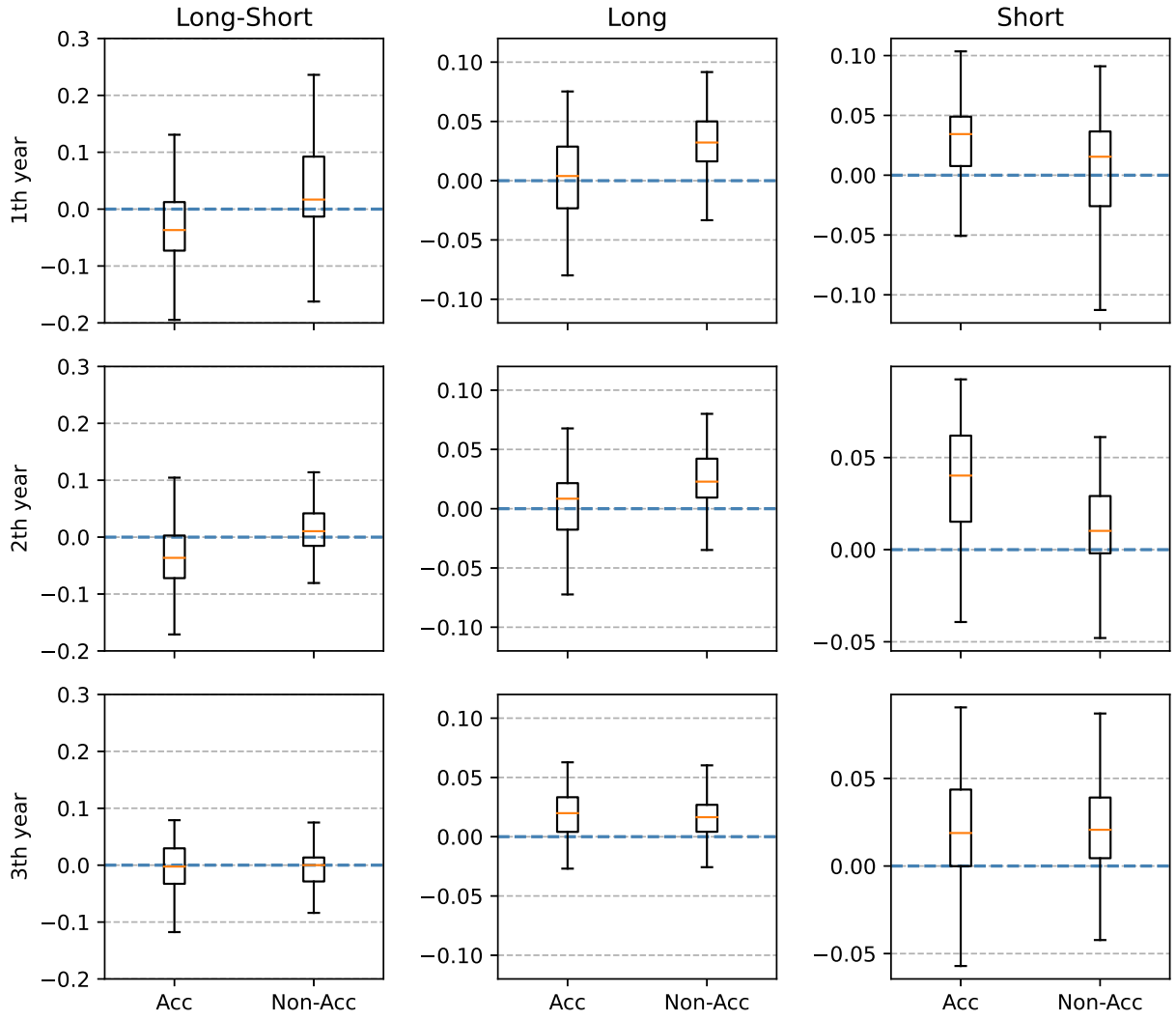


Figure C.1. The figures show the distributions of the means of tacking-firm payout growth across three horizons for accounting and non-accounting anomalies.

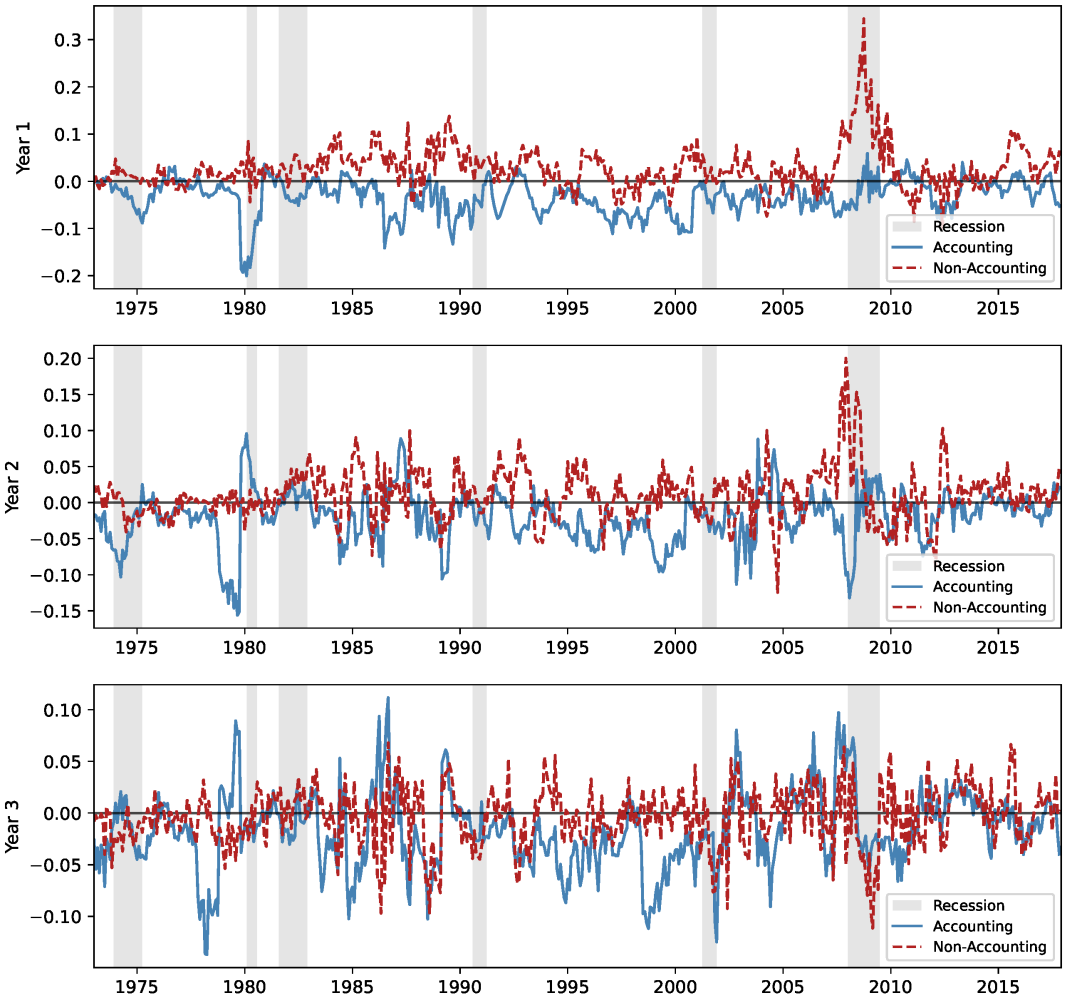
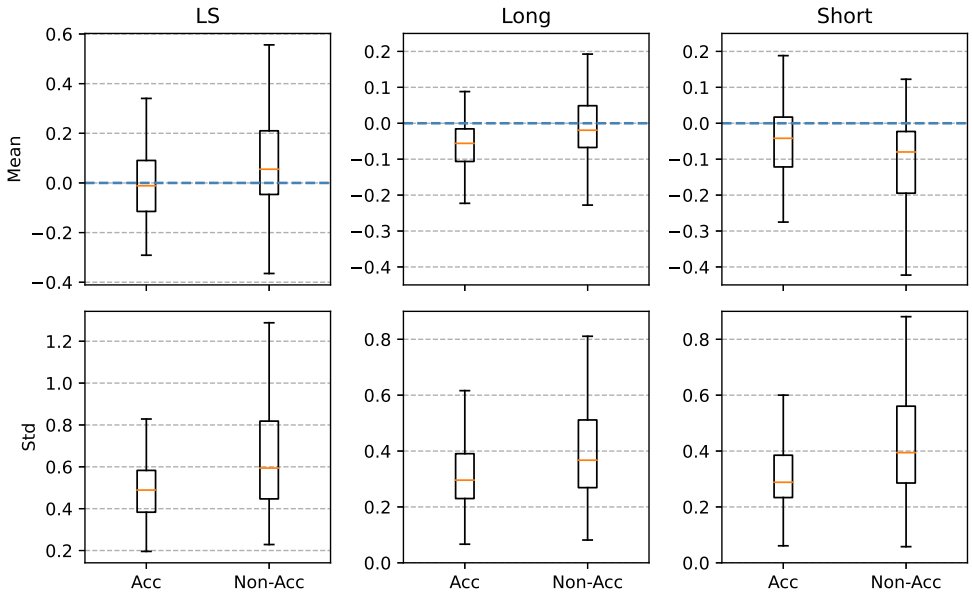
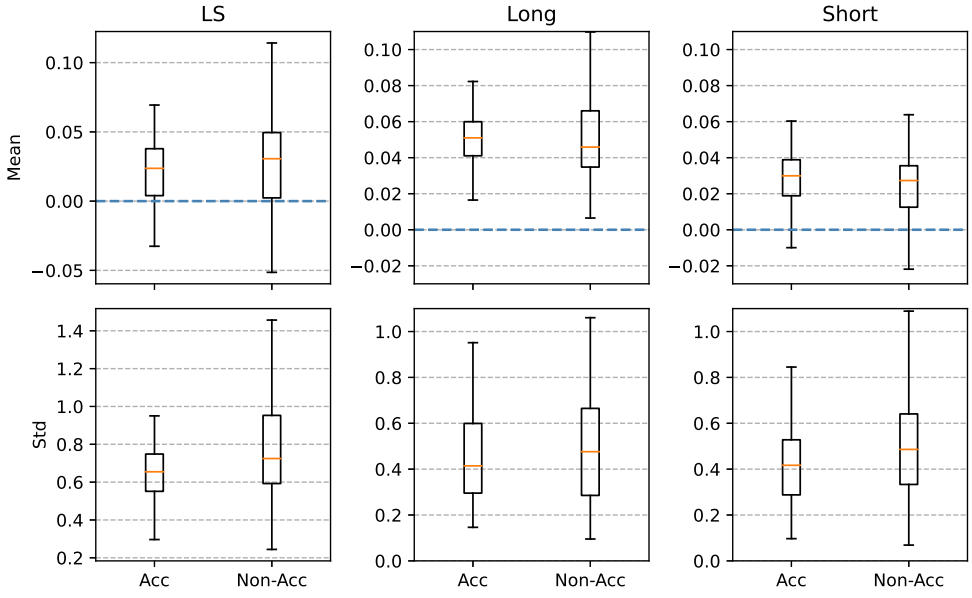


Figure C.2. Tracking-firm total payout growth on accounting and non-accounting anomalies.



(a) Recession



(b) Expansion

Figure C.3. Anomaly total payout growth within economic cycles.

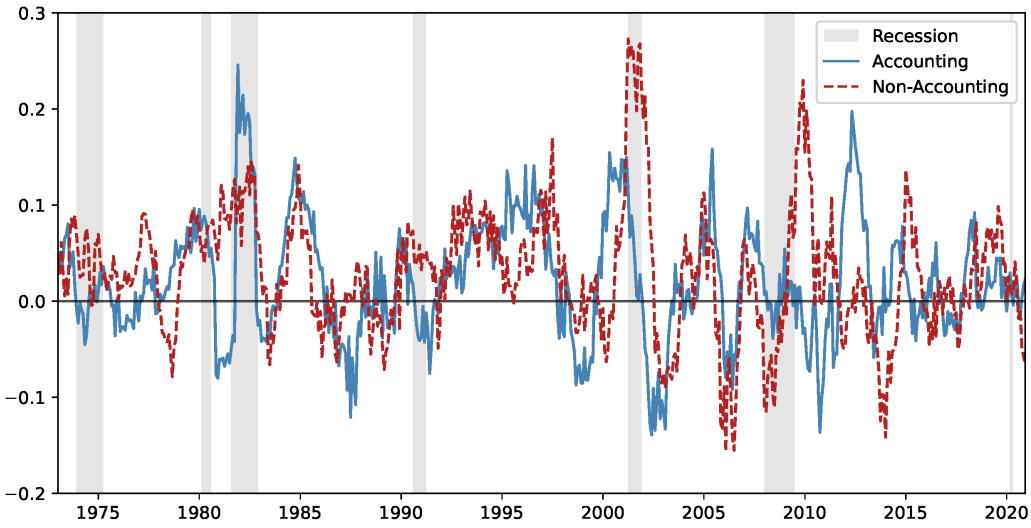


Figure C.4. Tracking-anomaly payout growth on accounting and non-accounting anomalies.

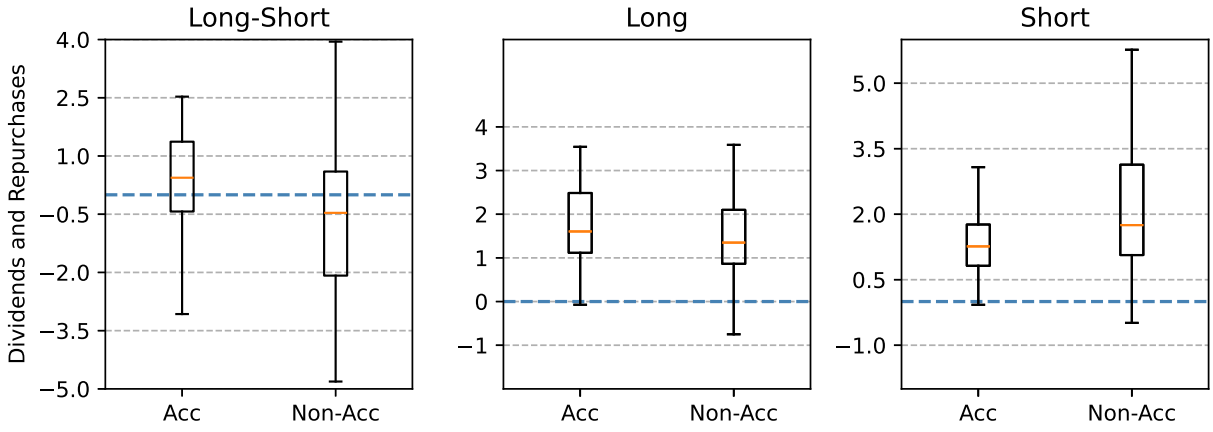


Figure C.5. Bond factor beta distributions. The bond factor betas are from a predictive regression. The dependent variables are 36-month forward log total payout growth ratios. The independent variables are bond factors. The sample period covers 1973 to 2020. The whiskers show the 10th and 90th percentiles. The orange bars show the medians. The boxes show the 25th and 75th percentiles.

Table C.I

Descriptive Statistics of Buy-and-Hold Portfolio Cash Flow Growth

For every month between 1973 and 2020, I sort stocks into value-weighted quintile portfolios based on the focal characteristic. The quintile portfolios are determined by the NYSE breakpoints. I assume holding the portfolios for 3 years. For each portfolio, I calculate its log annual cash flow growth at the end of the 1st year, 2nd year, and 3rd year. The cash flow growth of a long-short portfolio is calculated as the difference in the cash flow growth between the long and the short sides. Then I calculate the mean and standard deviation of these cash flow growth rates across formation months. The table reports the averaged mean and standard deviation of buy-and-hold portfolio cash flow growth for accounting and non-accounting anomalies.

		Year One			Year Two			Year Three		
		Long-Short	Long	Short	Long-Short	Long	Short	Long-Short	Long	Short
Panel A: Cash Flow Growth										
Payout	Accounting	-0.031	-0.003	0.028	-0.019	0.011	0.030	-0.014	0.015	0.029
	Non-Accounting	0.050	0.040	-0.010	0.015	0.026	0.011	0.000	0.021	0.021
Total Cash	Accounting	-0.175	0.544	0.719	0.005	0.023	0.018	-0.026	0.001	0.027
	Non-Accounting	0.008	0.787	0.779	0.004	0.002	-0.002	0.003	0.003	-0.000
Panel B: Cash Flow Growth in Recessions										
Payout	Accounting	-0.043	-0.121	-0.078	0.002	-0.022	-0.024	-0.009	0.084	0.093
	Non-Accounting	0.118	-0.070	-0.188	0.036	-0.025	-0.061	-0.033	0.080	0.113
Total Cash	Accounting	-0.123	0.228	0.351	-0.049	-0.035	0.014	-0.000	0.110	0.110
	Non-Accounting	0.115	0.423	0.307	-0.008	-0.042	-0.034	0.002	0.121	0.118
Panel C: Cash Flow Growth in Expansions										
Payout	Accounting	-0.029	0.015	0.044	-0.022	0.015	0.038	-0.014	0.005	0.019
	Non-Accounting	0.040	0.055	0.015	0.012	0.032	0.020	0.005	0.013	0.008
Total Cash	Accounting	-0.183	0.592	0.776	0.012	0.031	0.019	-0.030	-0.014	0.016
	Non-Accounting	-0.008	0.838	0.845	0.006	0.008	0.002	0.003	-0.013	-0.016

Table C.II

Buy-and-Hold Cash Flow Growth of Anomalies: Accounting vs. Non-Accounting

From every month between 1973 and 2017, I sort stocks into value-weighted quintile portfolios based on the focal characteristic. The quintile portfolios are determined by NYSE breakpoints. I assume holding the portfolios for 3 years. For each portfolio, I calculate its log annual cash flow growth at the end of 1st year, 2nd year, and 3rd year. The dividend growth of a long-short portfolio is calculated as the difference between the long-side dividend growth and the short-side dividend growth. Then I calculate the mean and standard deviation of these cash flow growth across formation months. I caculate the median of pooled accounting and non-accounting anomalies for the mean. Within each pool, I count the number of portfolios above and below the median for accounting and non-accounting anomalies, respectively. I perform binomial tests under the null hypothesis that accounting and non-accounting anomalies are equally likely to have above-median cash flow growth. The p-values are reported.

	Long-Short			Long Side			Short side		
	Accounting Above/Below	Non-Accounting Above/Below	p-value	Accounting Above/Below	Non-Accounting Above/Below	p-value	Accounting Above/Below	Non-Accounting Above/Below	p-value
Panel A: Full periods									
Dividends and Repurchases:									
Year One	35/55	52/32	0.041	30/60	57/27	0.002	54/36	33/51	0.054
Year Two	30/60	57/27	0.002	33/57	54/30	0.013	62/28	25/59	0.000
Year Three	36/54	51/33	0.068	43/47	44/40	0.670	48/42	39/45	0.592
Total Cash:									
Year One	33/57	54/30	0.013	26/64	61/23	0.000	43/47	44/40	0.670
Year Two	46/44	41/43	0.915	48/42	39/45	0.592	53/37	34/50	0.107
Year Three	33/57	54/30	0.013	41/49	46/38	0.393	58/32	29/55	0.005
Panel B: Recessions:									
Dividends and Repurchases									
Year One	34/56	53/31	0.024	39/51	48/36	0.200	54/36	33/51	0.054
Year Two	39/51	48/36	0.200	48/42	39/45	0.592	57/33	30/54	0.010
Year Three	52/38	35/49	0.163	47/43	40/44	0.748	38/52	49/35	0.135
Total Cash:									
Year One	37/53	50/34	0.087	31/59	56/28	0.004	49/41	38/46	0.453
Year Two	39/51	48/36	0.200	45/45	42/42	1.000	48/42	39/45	0.592
Year Three	46/44	41/43	0.915	45/45	42/42	1.000	43/47	44/40	0.670
Panel C: Expansions									
Dividends and Repurchases:									
Year One	32/58	55/29	0.007	28/62	59/25	0.000	53/37	34/50	0.107
Year Two	32/58	55/29	0.007	34/56	53/31	0.024	62/28	25/59	0.000
Year Three	37/53	50/34	0.087	42/48	45/39	0.522	52/38	35/49	0.163
Total Cash:									
Year One	34/56	53/31	0.024	26/64	61/23	0.000	43/47	44/40	0.670
Year Two	48/42	39/45	0.592	49/41	38/46	0.453	53/37	34/50	0.107
Year Three	34/56	53/31	0.024	43/47	44/40	0.670	57/33	30/54	0.010

Table C.III

Bond Factor Risk: Accounting vs Non-Accounting

The table compares accounting and non-accounting anomalies by the counts of above and below the Cochrange and Piazzesi (2005) bond factor median. The horizon used is three years. The p-values are computed using binomial tests, considering the null hypothesis that fundamental and non-fundamental anomalies are equally likely to have above-median bond factor coefficients. The p-values lower than 0.05 are shown in bold.

	Long-Short			Long Side			Short side		
	Accounting Above/Below	Non-Accounting Above/Below	p-value	Accounting Above/Below	Non-Accounting Above/Below	p-value	Accounting Above/Below	Non-Accounting Above/Below	p-value
Payout	54/36	33/51	0.054	50/40	37/47	0.334	37/53	50/34	0.087
Total Cash	44/46	43/41	0.831	44/46	43/41	0.831	46/44	41/43	0.915

Table C.IV

Return Decomposition: Accounting vs Non-Accounting

The table presents binomial tests comparing cash-flow shock contributions to return variation between accounting and non-accounting anomalies. I apply Campbell's (1991) VAR return decomposition to the 174 anomalies, their long sides, and short sides. The state variable vector in VAR consists of monthly log real returns and two additional state variables from ten widely used state variables: TotalAsset-to-Market (AM), Book-to-Market (BM), Momentum (Mom6m), Dividend-Price (DP), Asset-Growth (AssetGrowth), Return-on-Equity (ROE), Size (Size), Profitability (GP), Illiquidity (Illiquidity), and three-month treasury spread (rrel). The cash-flow shock contribution is defined as the covariance between cash-flow shocks and unexpected returns scaled by the variance of unexpected returns. I calculate the median of pooled accounting and non-accounting anomaly cash-flow shock contribution. Within each pool, I count the number of portfolios above and below the median cash-flow shock contribution for accounting and non-accounting anomalies, respectively. I perform binomial tests under the null hypothesis that accounting and non-accounting anomalies are equally likely to have above-median cash-flow shock contribution. The p-values are reported. The state variable combinations are sorted by the number of accounting long-short portfolios with above median cash-flow shocks. The sample period covers 1973 to 2022.

	Long-Short			Long Side			Short side		
	Accounting Above/Below	Non-Accounting Above/Below	p-value	Accounting Above/Below	Non-Accounting Above/Below	p-value	Accounting Above/Below	Non-Accounting Above/Below	p-value
AssetGrowth DP	56/34	31/53	0.010	57/33	30/54	0.005	61/29	26/58	0.000
AssetGrowth GP	54/36	33/51	0.031	47/43	40/44	0.520	51/39	36/48	0.133
RoE DP	54/36	33/51	0.031	55/35	32/52	0.018	60/30	27/57	0.001
BM AssetGrowth	53/37	34/50	0.053	49/41	38/46	0.284	46/44	41/43	0.668
GP DP	53/37	34/50	0.053	52/38	35/49	0.086	57/33	30/54	0.005
RoE AssetGrowth	53/37	34/50	0.053	50/40	37/47	0.198	44/46	43/41	1.000
BM DP	53/37	34/50	0.053	55/35	32/52	0.018	62/28	25/59	0.000
BM GP	51/39	36/48	0.133	47/43	40/44	0.520	56/34	31/53	0.010
Illiquidity Size	51/39	36/48	0.133	51/39	36/48	0.133	49/41	38/46	0.284
Illiquidity DP	51/39	36/48	0.133	55/35	32/52	0.018	56/34	31/53	0.010
RoE GP	49/41	38/46	0.284	42/48	45/39	0.830	50/40	37/47	0.198
Mom6m DP	49/41	38/46	0.284	50/40	37/47	0.198	51/39	36/48	0.133
RoE Illiquidity	48/42	39/45	0.391	42/48	45/39	0.830	46/44	41/43	0.668
AssetGrowth Mom6m	48/42	39/45	0.391	40/50	47/37	0.520	44/46	43/41	1.000
GP Size	48/42	39/45	0.391	39/51	48/36	0.391	48/42	39/45	0.391
AssetGrowth rrel	48/42	39/45	0.391	43/47	44/40	1.000	40/50	47/37	0.520
BM RoE	46/44	41/43	0.668	50/40	37/47	0.198	48/42	39/45	0.391
BM Illiquidity	45/45	42/42	0.830	46/44	41/43	0.668	49/41	38/46	0.284
BM rrel	45/45	42/42	0.830	46/44	41/43	0.668	44/46	43/41	1.000
BM Size	45/45	42/42	0.830	38/52	49/35	0.284	49/41	38/46	0.284

(*continued on next page*)

Table C.IV (*continued*)

	Long-Short			Long Side			Short side		
	Accounting Above/Below	Non-Accounting Above/Below	p-value	Accounting Above/Below	Non-Accounting Above/Below	p-value	Accounting Above/Below	Non-Accounting Above/Below	p-value
AssetGrowth Illiquidity	44/46	43/41	1.000	49/41	38/46	0.284	50/40	37/47	0.198
Mom6m GP	44/46	43/41	1.000	43/47	44/40	1.000	43/47	44/40	1.000
Roe Mom6m	43/47	44/40	1.000	43/47	44/40	1.000	45/45	42/42	0.830
Bm Mom6m	43/47	44/40	1.000	45/45	42/42	0.830	49/41	38/46	0.284
Gp rrel	43/47	44/40	1.000	42/48	45/39	0.830	39/51	48/36	0.391
AssetGrowth Size	43/47	44/40	1.000	39/51	48/36	0.391	44/46	43/41	1.000
DP rrel	42/48	45/39	0.830	46/44	41/43	0.668	47/43	40/44	0.520
GP Illiquidity	41/49	46/38	0.668	38/52	49/35	0.284	45/45	42/42	0.830
Illiquidity rrel	41/49	46/38	0.668	38/52	49/35	0.284	40/50	47/37	0.520
DP Size	39/51	48/36	0.391	45/45	42/42	0.830	45/45	42/42	0.830
RoE Size	39/51	48/36	0.391	35/55	52/32	0.086	41/49	46/38	0.668
Size rrel	39/51	48/36	0.391	36/54	51/33	0.133	40/50	47/37	0.520
Mom6m Illiquidity	39/51	48/36	0.391	41/49	46/38	0.668	41/49	46/38	0.668
AM GP	39/51	48/36	0.391	36/54	51/33	0.133	37/53	50/34	0.198
Mom6m Size	38/52	49/35	0.284	31/59	56/28	0.010	41/49	46/38	0.668
RoE rrel	38/52	49/35	0.284	42/48	45/39	0.830	41/49	46/38	0.668
AM AssetGrowth	37/53	50/34	0.198	35/55	52/32	0.086	32/58	55/29	0.018
AM DP	35/55	52/32	0.086	36/54	51/33	0.133	35/55	52/32	0.086
AM BM	34/56	53/31	0.053	33/57	54/30	0.031	35/55	52/32	0.086
Mom6m rrel	33/57	54/30	0.031	36/54	51/33	0.133	34/56	53/31	0.053
AM RoE	32/58	55/29	0.018	33/57	54/30	0.031	33/57	54/30	0.031
AM Illiquidity	32/58	55/29	0.018	34/56	53/31	0.053	31/59	56/28	0.010
AM Mom6m	32/58	55/29	0.018	34/56	53/31	0.053	36/54	51/33	0.133
AM Size	31/59	56/28	0.010	30/60	57/27	0.005	29/61	58/26	0.002
AM rrel	29/61	58/26	0.002	33/57	54/30	0.031	31/59	56/28	0.010