# Anomalies and Cash Flows<sup>∗</sup>

### Yi Zhou†

#### ABSTRACT

I analyze the cash flows of 174 anomalies, categorized into accounting and non-accounting, to explore the reasons behind their abnormal returns. Tracking their cash flow growth at both the firm and anomaly levels reveals distinct patterns: accounting anomalies show procyclical growth, aligning with risk-based models. In contrast, non-accounting anomalies exhibit countercyclical growth and thus provide a hedge against economic downturns. This study bridges various anomaly theories within the cross-sectional asset pricing literature by empirically demonstrating that different anomalies can exhibit either risky or risk-hedging cash flows. The distinct cash flow growth patterns observed between the two groups of anomalies underscore the necessity for separate theoretical frameworks to fully explain the two categories of anomalies.

<sup>∗</sup> I thank Scott Cederburg, Richard Sias, Mitch Towner, and seminar participants at the University of Arizona for helpful comments and suggestions. Any errors remain my own.

<sup>†</sup>Zhou is from the Department of Finance at the Eller College of Management, University of Arizona, Tucson, AZ 85721, yizh@arizona.edu.

# I. Introduction

Anomaly strategies buy and sell stocks based on certain firm characteristics. These strategies earn positive abnormal returns relative to the Capital Asset Pricing Model. [1](#page-1-0) Despite many years of study, financial economists disagree about whether anomalies exist due to risk or mispricing, a cornerstone of cross-sectional asset pricing literature. Under risk-based models, anomalies earn high returns because the representative agent requests compe[nsation for the risk not considered in the CAPM \(e.g.,](#page-27-0)Daniel, Mota, Rottke, and Santos, [2020;](#page-27-0) [Schneider, Wagner, and Zechner,](#page-28-0) [2020\)](#page-28-0). Nevertheless, under mispricing models, anomalies earn high returns because irrational investors drive the prices of firms deviating from the values of those firms (e.g., [Stambaugh, Yu, and Yuan,](#page-28-1) [2012](#page-28-1); Binsbergen, Boons, Opp, and Tamoni, [2023\)](#page-27-1).

Considering that a portfolio's return is the change in expected discounted future cash flows, and anomalies are no exception, a natural way to tackle the question is through anomalies' cash flow behaviors (e.g., [Lettau and Wachter,](#page-28-2) [2007](#page-28-2); [Hansen, Heaton, and Li](#page-28-3), [2008](#page-28-3)). However, the popular vector autoregression (VAR) return decomposition frame-work [\(Campbell,](#page-27-2) [1991](#page-27-2)[\) has limited ability in examining anomaly cash flows.](#page-28-4) Lochstoer and Tetlock [\(2020\)](#page-28-4) decompose the returns of five anomalies into cash flow and discount rate components, as in [Campbell](#page-27-2) [\(1991\)](#page-27-2), and underscore that their empirical findings provide guidance for asset pricing theories seeking to explain cross-sectional abnormal returns. However, an analysis using only five anomalies is limited for drawing broad conclusions or identifying common patterns, given that more than 300 anomalies exist in the factor zoo [\(Harvey, Liu, and Zhu,](#page-28-5) [2016](#page-28-5); [Cochrane 2011\)](#page-27-3). Additionally, after applying their methodology to placebo portfolios, I find that anomalies resemble placebos under the framework: anomaly and placebo returns are similarly driven by cash flow components. The common patterns between anomalies and placebos undermine the anomaly

<span id="page-1-0"></span><sup>1</sup>See, for example, [Fama and French](#page-27-4) [\(1992](#page-27-4)) for the evidence on value premium, [Jegadeesh and Titman](#page-28-6) [\(1993\)](#page-28-6) for buying recent winners and selling recent losers, and [Cooper, Gulen, and Schill](#page-27-5) [\(2008\)](#page-27-5) for asset investment effects.

return decomposition methodology's effectiveness in guiding anomaly theories.

To address the limitation of [Lochstoer and Tetlock](#page-28-4) [\(2020](#page-28-4)), I first expand the number of anomalies from five to 174, including 90 accounting and 84 non-accounting anomalies. To assess anomaly cash flow shocks, [Lochstoer and Tetlock](#page-28-4) [\(2020](#page-28-4)) utilize the VAR framework in [Campbell](#page-27-2) [\(1991](#page-27-2)) in an indirect manner. That is, [Lochstoer and Tetlock](#page-28-4) [\(2020\)](#page-28-4) estimate firm-level cash flow shocks and subsequently aggregate these shocks to the anomaly level. In contrast, my approach follows [Campbell](#page-27-2) [\(1991](#page-27-2)) closely and directly estimates anomalylevel shocks from the cash flows of the anomalies themselves. I find that results heavily depend on state variable selection. Given a portfolio return, I select two of ten state variables, resulting in 45 combinations. The results from these combinations yield mixed conclusions: in 20 out of 45 combinations, accounting anomaly returns are found to be more or equally driven by cash flow shocks than non-accounting anomaly returns, while in the remaining 25 combinations, accounting anomaly returns are less driven by cash flow shocks than non-accounting anomaly returns.

Recognizing the limitations and instabilities associated with both the indirect and direct applications of the VAR return decomposition framework, I seek alternative approaches to analyzing anomaly cash flows.[2](#page-2-0) In my first approach, I track firms in both accounting and non-accounting anomalies. For each month t from 1973 to 2020, I sort firms based on characteristic  $X_{t-1}$  into quintiles and buy (sell) the quintile with the highest (lowest) expected return performance. Following the formation of these quintile portfolios, I track their log annual cash flow growth for up to three years. I calculate the annual cash flow growth anomaly by subtracting the growth of the short side from the growth of the long side. Tracking firms provides insights into anomalies at the firm level through cash flow fundamentals [\(Cohen, Polk, and Vuolteenaho,](#page-27-6) [2009](#page-27-6)). Additionally, over short periods, cash flow fundamentals can be contaminated by idiosyncratic noise [\(Babenko, Boguth, and Tserlukevich](#page-27-7), [2016](#page-27-7)) , the stickiness of dividends, and delays

<span id="page-2-0"></span><sup>&</sup>lt;sup>2</sup>I examine dividend growth at the base cash flows. The conclusions in the paper also hold for payout (the sum of dividends and repurchases), as elaborated in the appendix.

in changing dividends [\(DeAngelo and DeAngelo](#page-27-8), [2000](#page-27-8); [Benartzi, Michaely, and Thaler](#page-27-9), [Benartzi et al.](#page-27-9); [Leary and Michaely](#page-28-7), [2011\)](#page-28-7). Hence, examining these phenomena over a longer period allows for a more accurate and reliable understanding of anomaly cash flow behaviors.

I observe notable disparities in the cash flow growth of the two types of anomalies. Accounting anomalies buy firms with slower cash flow growth and sell firms with faster cash flow growth, while non-accounting anomalies buy firms with faster cash flow growth and sell firms with slower cash flow growth. To reveal the relation between anomalies and the macroeconomy, I assess the tracking-firm cash flow growth during full, recession, and expansion periods. Across the full period, the tracking-firm cash flow growth of accounting anomalies, on average, is negative in all three years  $(-2.4\%$  for year one,  $-2.0\%$  for year two, and  $-1.7\%$  for year three), whereas the tracking-firm cash flow growth of non-accounting anomalies on average is positive in the first two years (4.8% for year one and 2.1% for year two) and slightly negative in the third year  $(-0.5\%)$ . This pattern persists in both recession and expansion periods. The tracking-firm portfolios of accounting anomalies show negative cash flow growths in the three years after formation in both recessions and expansions. The tracking-firm portfolios of non-accounting anomalies show positive cash flow growth during both recessions and expansions. In the first two years, the growth of non-accounting anomaly cash flows during the recessions is faster than the growth during the expansions. The observation suggests that non-accounting anomalies offer faster cash flow growth when the investors are likely to need them most.

In my second approach to analyzing anomaly cash flows, I directly track accounting and non-accounting anomaly cash flows. As mentioned earlier, these anomalies are rebalanced monthly. The annual cash flow growth of a quintile portfolio is defined as the sum of dividends received in the most recent 12 months divided by the sum of dividends received in the preceding 12 months. To relate with the macroeconomy, I assess the cash flows of accounting and non-accounting anomalies across economic cycles. During recessions, accounting anomaly cash flow growth is close to zero, whereas non-accounting anomaly cash flow growth is positive. During expansions, cash flows of both categories grow robustly.

My third approach to analyzing anomaly cash flows is from the perspective of bond market risk. Specifically, I adopt the approach by [Koijen, Lustig, and Van Nieuwerburgh](#page-28-8) [\(2017\)](#page-28-8), Lustig, and Van Nieuwerburgh (2017), that is, examining the predictive power of Cochrane-Piazzessi (CP) bond factor [\(Cochrane and Piazzesi,](#page-27-10) [2005\)](#page-27-10) on the growth of anomaly cash flows. The CP bond factor is known to forecast future economic activity, as suggested by [Koijen et al.](#page-28-8) [\(2017\)](#page-28-8). A positive loading on the CP factor indicates a strong procyclicality, implying higher risk in anomaly cash flows. I find that the CP factor negatively predicts the cash flow growth of both accounting and non-accounting anomalies over one year. However, over a three-year horizon, the CP factor positively predicts the cash flow growth of accounting anomalies, while it continues to negatively predicts that of the non-accounting anomalies. This finding indicates that, in the long term, accounting anomaly cash flow growth is more procyclical, aligning with the patterns observed in tracking-firm portfolios.

This study bridges various anomaly theories within the cross-sectional asset pricing literature by empirically demonstrating that different anomalies can exhibit either risky or risk-hedging cash flows. The distinct cash flow growth patterns observed between the two groups of anomalies underscore the necessity for separate theoretical frameworks to fully explain the two categories of anomalies. The cash flow growth pattern observed in accounting anomalies support risk-based models. For instance, [Gormsen and Lazarus](#page-28-9) [\(2023\)](#page-28-9) provide a duration-based explanation for anomalies, noting that firms with shorter duration (long side firms) typically experience slower cash flow growth. Nevertheless, such explanations are difficult to reconcile the countercyclical cash flow growths of nonaccounting anomalies. Therefore, a comprehensive understanding of anomaly cash flows requires considering both risk-based and alternative explanations to accurately capture <span id="page-5-1"></span>the nuanced dynamics present in different types of anomalies.

# II. 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](#page-27-11) [\(2022\)](#page-27-11) to construct anomaly portfolios.[3](#page-5-0) I classify an anomaly as accounting anomaly if it is constructed based on a characteristic directly containing information from 10-K or 10-Q filings; otherwise, an anomaly is a non-accounting anomaly. Out of the 174 anomalies, 90 are accounting anomalies and 84 are non-accounting. Additionally, I obtain stock data from the Center for Research on Securities Prices (CRSP). I obtain macroeconomy data from the Federal Reserve Bank of St. Louis website.

### A. Tracking-firm portfolios

For every month from 1973 to 2017, 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 the highest (lowest) expected return performance. Within the quintile, firms are value-weighted. I follow the firms in each monthly quintile portfolios for three years. I call these quintile portfolios tracking-firm portfolios because I aim to examine the anomaly features from the angle of the fundamentals of firm-level cash flows. The dividends of a tracking-firm portfolio in a month are the sum of the dividends perceived from firms in the portfolio in the month. I calculate the dividends paid out by a firm in the month as the product of the lagged market equity and the gap between return including (ret) and excluding dividens (retx).

<span id="page-5-0"></span><sup>3</sup>The [Chen and Zimmermann](#page-27-11) [\(2022](#page-27-11)) 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.

### B. Tracking-anomaly portfolios

For 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 2020. I first calculate the value-weighted monthly returns and ex-dividend returns for the long sides and short sides of anomalies. Missing delisting returns and delisting exdividend returns are set to -30% if the delisting code is between 400 and 600 or zero for all others. In the delisting month, I set the return (ex-dividend return) equal to the delisting return (delisting ex-dividend return). Then I assume investing \$1 at the beginning of sample periods in the long-side portfolio and another \$1 in the short-side portfolio. The dividends received in the month at the portfolio level are the lagged exclude-dividend price multiplied by the difference between the cumulative return and the cumulative return on capital. 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:

$$
\Delta d_t^L = \log(\sum_{k=0}^{11} D_{t-k}^L) - \log(\sum_{k=12}^{24} D_{t-k}^L) \text{ and}
$$
  

$$
\Delta d_t^S = \log(\sum_{k=0}^{11} D_{t-k}^S) - \log(\sum_{k=12}^{24} D_{t-k}^S),
$$
 (1)

where  $D_t$  is the dollar value dividend at month t. The cash flow growth of the anomaly is calculated as the cash flow growth on the long side minus that on the short side  $\Delta d_t^L - \Delta d_t^S$ . 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.

#### C. Bond factors

I follow [Cochrane and Piazzesi](#page-27-10) [\(2005](#page-27-10)) 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](#page-28-10) [\(2021](#page-28-10)) [4](#page-7-0) to construct log returns on bonds  $r_t^n$ , where *n* indicates the maturity of 1, 2, 3, 4, or 5 years. The linear combination is the fitted value of the following regression:

$$
\bar{r}_{2,3,4,5}^e = c + y_t^1 + y_t^2 + y_t^3 + y_t^4 + y_t^5 + \epsilon_t,\tag{2}
$$

where  $\bar{r}_{2,3,4,5}^e$  is the average one-year excess return on bonds with 2 to 5 years of maturities,  $y_t^1$  is the one-year yield, and  $y_t^n$  is the *n*-year forward rate.

## III. Anomaly Cash Flows

### A. Tracking cash flow growth of firms

In this section, I examine the cash flow growth of anomalies using buy-and-hold portfolios. Using buy-and-hold portfolios gives me two advantages. First, it allows me to examine the anomaly features from the angle of the fundamentals of firm-level cash flows [\(Cohen et al.,](#page-27-6) [2009\)](#page-27-6). Second, over a short horizon, the cash flow behavior can be contaminated by idiosyncratic noise; over a long horizon, I can gather more reliable information about cash flow behaviors. For each long-short anomaly portfolio, and its long and short side, I calculate the mean and the standard deviation of the buy-and-hold log annual cash flow growth over the 1-year, 2-year, and 3-year horizons across the formation months.

I report the summary statistics about the mean and standard deviation of buy-andhold cash flow growth by category in Table [I.](#page-29-0) The first three columns of the table report the averages of the means within accounting anomalies and non-accounting anomalies over the three horizons. The averages of the mean of accounting anomaly buy-and-hold cash flow growth in the three years are negative,  $-2.6\%$  for year 1,  $-2.0\%$  for year 2, and  $-1.6\%$ for year 3, respectively. As a comparison, the averages of the mean of non-accounting

<span id="page-7-0"></span><sup>&</sup>lt;sup>4</sup>I appreciate Professor Wu and Professor Liu for making the data available. The data can be found at <https://sites.google.com/view/jingcynthiawu/yield-data?authuser=0>.

anomaly cash flow growth are positive in the first two years, 4.9% for year 1, and 2.1% for year 2, and is negative in the third year, -0.4%. Comparing the second column and the third column, I find that the difference at the long-short anomaly level comes from both the long side and the short side. Within the same category of anomalies, the long side of accounting (non-accounting) anomalies has slower (faster) firm-level cash flow growth than the short side of accounting (non-accounting) anomalies over the three horizons. In year 1, the averaged mean of cash flow growth on the long side of accounting anomalies is approximately one-fifth (0.006/0.029) of that on the short side; in year 2, about one-third  $(0.010/0.030)$ ; in year 3, about half  $(0.018/0.034)$ . As to the non-accounting anomalies, the averaged mean of cash flow growth on the long side, in year 1, is approximately nine times (0.044/0.005) the absolute value of that on the short side; in year 2, approximately three times  $(0.031/0.010)$ ; in year 3, approximately the same  $(0.025/0.029)$ . Across the two categories, the long (short) side of accounting anomalies has slower (faster) firm-level cash flow growth than the long (short) side of non-accounting anomalies over the three horizons. The findings suggest that accounting anomalies tend to buy firms with slower cash flow growth and sell firms with faster cash flow growth, whereas non-accounting anomalies tend to sell firms with faster cash flow growth and buy firms with faster cash flow growth.

For each anomaly, I also calculate the standard deviation of the buy-and-hold cash flow growth over the three horizons. I report the averages of the standard deviations within accounting anomalies and non-accounting anomalies in the last three columns of Table [I.](#page-29-0) The third-to-last column shows that, in year 1, the average of standard deviation of nonaccounting anomalies is  $24\%$  (0.257/0.208-1) higher than that of accounting anomalies; in year 2, 14% (0.224/0.196-1); in year 3, 13% (0.212/0.188). The last two columns show that the difference mainly arises from the short sides of anomalies. The average of standard deviation on the short side of non-accounting anomalies exceeds that of accounting anomalies by  $35\%$   $(0.214/0.158-1)$ ; in year 2,  $26\%$   $(0.187/0.149-1)$ ; in year 3,

18% (0.174/0.147-1). In contrast, the long sides of two categories, over the three horizons, are close in average standard deviation. Non-accounting anomalies tend to have more volatile cash flow growth than accounting anomalies. Nevertheless, the difference at the second moment is smaller than that at the first moment.

Figure [1](#page-44-0) visually describes the distributions of average buy-and-hold cash flow growth for accounting and non-accounting anomalies in box-and-whisker plots. The box represents the interquartile range, encapsulating the 25th to 75th percentiles, with the median depicted by the orange line within the box. The whiskers extend to the 10th and 90th percentiles. From left to right, the figures show the distributions of the mean of buy-andhold cash flow growth for long-short anomalies, the long sides, and the short sides. From top to bottom, the three rows show the distributions at the 1-year, 2-year, and 3-year horizons.

The left subfigure on the top line shows that, in year 1, the majority of accounting anomalies have a negative mean of cash flow growth, while the majority of non-accounting anomalies have a positive mean of cash flow growth. Within the same category, for accounting anomalies, the box on the short side is higher than the box on the long side. For non-accounting anomalies, the opposite occurs: the long-side box is higher than the short-side box. The second and third subfigures in the first column show that both categories of anomalies' distributions concentrate around zero over time. The observation explains the decreasing differences between accounting and non-accounting anomalies in Table [I.](#page-29-0)

To evaluate whether the observed difference between accounting and non-accounting is statistically significant, I perform a binomial test. The test has the null hypothesis that, out of all 174 anomalies, accounting and non-accounting anomalies are equally likely to have a mean of firm-level cash flow growth above the median. I apply the test to the pooled long-short anomalies, pooled long sides, and pooled short sides. I report the results for the three pools in the first three columns, middle three columns, and last three columns in Table [II.](#page-30-0) The table shows that the observed difference in the mean of firmlevel cash flow growth between accounting and non-accounting anomalies is statistically significant.

The first row in the left panel shows that, in year 1, of the 87 anomalies in the abovemedian group, 33 are accounting anomalies and 54 are non-accounting anomalies; of the 87 anomalies in the below-median group, 57 are accounting anomalies and 30 are nonaccounting anomalies. The p-value of the binomial test is 0.031, indicating that the null is rejected at the 0.05 level. The second row of the same panel shows that, in year 2, of the 87 anomalies in the above-median group, 29 are accounting anomalies and 58 nonaccounting anomalies; of the 87 anomalies in the below-median group, 61 are accounting anomalies and 26 are non-accounting anomalies. The p-value is 0.002, indicating that the null is rejected at the 0.05 level. The third row in the same panel shows that, in year 3, of the 87 anomalies in the above-median group, 35 are accounting anomalies and 52 are non-accounting anomalies; of the 87 anomalies in the below-median group, 55 are accounting anomalies and 32 are non-accounting anomalies. The p-value is 0.086, indicating that the null is rejected at the 0.10 level. This panel shows that, over the three years, accounting anomalies as a group tend to have significantly slower firm-level cash flow growth than non-accounting anomalies.

The center panel shows that the binomial test results for the long side of the anomalies are consistent with those on the long-short of the anomalies. The first to third rows in the center panel show that, over the three horizons, the long sides of accounting anomalies tend to have fewer observations that are below median than above, while non-accounting anomalies have more counts above the median than below. The p-values for the first two years are 0.010 and 0.018, indicating that the difference in the first two years are statistically significant at the 0.05 level. The right panel shows that the short sides of the anomalies are opposite to the long-short anomalies and the long sides. The first to third rows in the panel show that the short sides of accounting anomalies have more observations that are above the median than those below, while the short sides of nonaccounting anomalies have fewer observations that are below median than those above. For reference, Table [III](#page-31-0) presents the buy-and-hold cash flow growth over the 1-year, 2-year, and 3-year horizons for each anomaly.

### B. Anomaly cash flow growth and business cycles

In this section, I examine the quarterly 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. In this section particularly, I examine the cash flow growth of accounting and non-accounting anomalies during business cycles. For the long- or short-side portfolio of an anomaly, the quarterly cash flows are the sum of the dividends received in the three months in the quarter. The monthly dividends of the portfolio are calculated as described in Section [II.](#page-5-1) I calculate the seasonally adjusted quarterly dividend growth for the long side and short side of each anomaly, and use the difference between the two as the growth of the long-short portfolio. I classify the quarters in the sample period into two groups based on the National Bureau of Economic Research Business Cycle Dating table. If the table shows a quarter with a value of one, I classify it as a recession quarter, otherwise an expansion quarter. Then, I examine the mean and standard deviation of quarterly cash flow growth for each anomaly during recession periods and during expansion periods.

Figure ?? shows the distributions of the mean (first row) and standard deviation (second row) of cash flow growth of accounting and non-accounting anomalies during recession periods. 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 non-accounting anomalies tend to deliver faster cash flow growth than accounting anomalies when the representative investor's 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 zero. The distribution also overlaps with the distribution of the long side in the second figure, explaining the surrounding zero distribution at the long-short portfolio level. The right plot in the third figure shows that non-accounting anomalies tend to sell portfolios with more 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 ?? depicts the distributions of the mean (first row) and standard deviation (second row) of cash flow growth on accounting and non-accounting anomalies during expansion periods. 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 ??, the box of accounting anomalies is lower than the box of non-accounting anomalies. The observations suggest that the differences between accounting and nonaccounting anomalies mainly arise from cash flow growth during recession periods.

### C. Anomaly cash flow growth and bond factors

In this section, I relate accounting and non-accounting annual cash flow growth to the bond market risk. I consider the following predictive regression:

$$
\Delta d_{a,t+k} = c_{a,t} + \beta_a C P_t + \epsilon_{a,t},\tag{3}
$$

where  $\Delta d_{t+k}$  is portfolio a's k-month-leading (k=12, 24, 36) log real annual cash flow growth at month t,  $CP_t$  denotes the bond factor, and  $\beta_a$  denotes the metric for measuring the bond market risk. A larger  $\beta_a$  suggests greater exposure to the time-series bond market risk.

Table [IV](#page-37-0) summarizes the averages of betas within accounting and non-accounting anomalies over the three forecast horizons. The first column shows that, within accounting anomalies, the averages of the bond factor betas over the three horizons are -0.31, -0.07, and 0.45. The bond factor negatively predicts accounting anomaly cash flow growth in the near future but positively predicts it in the distant future. Within non-accounting anomalies, the averages of bond factor betas over the three horizons are -0.58, -0.69, and -0.59. The values indicate that the bond factor negatively predicts the cash flow growth of non-accounting anomalies consistently over the three horizons. The second column reports the mean bond factor betas on the long sides for accounting and non-accounting anomalies, respectively. The gap between these two anomalies are computed to be 0.02 in year 1, 0.10 in year 2, and 0.04 in year 3. Each of the gaps is lower than 10% of the average beta within accounting or non-accounting anomalies over that prediction horizon. The third column shows that on the short side, the gaps between accounting and non-accounting anomalies become wider over years. In year 1, the average of betas of non-accounting anomalies is  $40\%$  (0.82/0.58-1) greater than that of accounting anomalies; in year 2, 39% (1.86/1.34-1) greater; in year 3, 90% (2.09/1.10-1) greater. Additionally, comparing the second and third columns, I find that the betas on the short sides change from larger than the betas on the long side (0.58 and 0.27) to smaller than the betas on the short side (1.10 and 1.55).

Figure [5](#page-47-0) depicts the distributions of the bond factor betas for the portfolios in year 3. The left subfigure shows that the majority of accounting anomalies have positive bond factor betas while the majority of non-accounting anomalies have negative bond factor betas. The second figure shows that, on the long side, the main body of betas of accounting anomalies is slightly higher than that of non-accounting anomalies. The right subfigure shows that, on the short side, the distribution of betas of accounting anomalies is lower than that of non-accounting anomalies. The findings suggest that accounting anomalies tend to have positive exposure to the bond market risk while non-accounting anomalies tend to have negative exposure to the bond market risk.

To examine whether the observed difference is significant, I employ a similar binomial test used in examining firm-level cash flows to the mean of bond factor betas. The null hypothesis is that, out of all 174 anomalies, an accounting anomaly and a non-accounting anomaly are equally likely to have a bond factor beta that is above the median. I perform the test on pooled long-short anomaly portfolios, pooled long-side portfolios, and pooled short-side portfolios.

Table [V](#page-38-0) 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 0.010, indicating the null is rejected at 0.05 level. Out of 87 anomalies with bond factors below the median, 34 are accounting anomalies and 53 are non-accounting anomalies. The p-value is 0.010, indicating that the null is rejected at the 0.05 level. The center panel shows the test results on the long-side portfolios. Out of 87 anomalies with betas above the median, 54 are accounting anomalies and 33 are non-accounting anomalies; out of 87 anomalies with betas below the median, 36 are accounting anomalies and 51 are nonaccounting anomalies. The p-value is 0.031. The right panel shows the test results for the short-side portfolios, which show the opposite results from the anomalies and on long sides. Out of 87 anomalies with betas above the median, 34 are accounting anomalies and 53 are non-accounting anomalies; out of 87 anomalies with betas below the median, 56 are accounting anomalies and 31 are non-accounting anomalies.

Overall, the results in this section show that accounting anomalies expose investors to greater bond market risk than non-accounting anomalies.

# IV. VAR Return Decomposition

In this section, I show that the vector-autoregression return decomposition framework is [not suitable for solving the problem. First, I demonstrate that](#page-28-4) Lochstoer and Tetlock [\(2020](#page-28-4)) do not comprehensively address the question what drives anomaly returns. This limitation arises from the tendency of their methodology to deliver same results for anomalies and placebos. Second, I apply the [Campbell](#page-27-2) [\(1991](#page-27-2)) methodology for the aggregate market to anomaly portfolios. I find that the conclusion delivered by this methodology changes with the choices of state variables.

#### A. Indirect anomaly return decomposition

Lochstoer and Tetlock [\(2020\)](#page-28-4) devolop an empirical method based on [Campbell](#page-27-2) [\(1991\)](#page-27-2) to decompose anomaly unexpected returns into cash flow shocks and discount rate shocks. [Lochstoer and Tetlock](#page-28-4) [\(2020](#page-28-4)) examine whether cash flow shocks or discount rate shocks drive five widely accepted anomalies' returns. The findings of these discount rate and cash flow decompositions should guide the speficifcations of anomaly theories. However, five is a small number for making broad conclusions and identifying systematic patterns across ano[malies, considering that the factor zoo contains more than 300 anomalies \(](#page-28-5)Harvey et al. [\(2016\)](#page-28-5)).

In this study, I first apply [Lochstoer and Tetlock'](#page-28-4)s [\(2020](#page-28-4)) methodology to the 174 anomalies that I studies. Then I apply their methodology to two types of placebos, which I call randome placebos and high correlation placebos. I find that the common patterns that [Lochstoer and Tetlock](#page-28-4) [\(2020\)](#page-28-4) conclude through the five anomalies in the

174 anomal[ies as well as the two types of placebos. Next, I briefly introduce the](#page-28-4) Lochstoer and Tetlock [\(2020](#page-28-4)) methodlogy and then show the results.

The methodology has two major steps. The first step is to decompose firm returns using a log-linear return decomposition method similar to [Campbell](#page-27-2) [\(1991](#page-27-2)). The second step is to construct anomaly return decomposition using firm-level CF shocks and DR shocks as components.

The methodology starts with the framework of variance decomposition for stock re-turns from [Campbell](#page-27-2) [\(1991](#page-27-2)), who shows that unexpected real stock returns,  $r_{i,t+1}$  –  $E_t[r_{i,t+1}]$ , can be decomposed into CF shocks,  $CF_{i,t+1}$ , and DR shocks,  $DR_{i,t+1}$ :

$$
r_{i,t+1} - E_t[r_{i,t+1}] \approx CF_{i,t+1} - DR_{i,t+1},\tag{4}
$$

where

<span id="page-16-0"></span>
$$
CF_{i,t+1} = (E_{t+1} - E_t) \sum_{j=1}^{\infty} \kappa^{j-1} \Delta d_{i,t+j},
$$
\n(5)

and

$$
DR_{i,t+1} = (E_{t+1} - E_t) \sum_{j=2}^{\infty} \kappa^{j-1} r_{i,t+j}.
$$
 (6)

In equation [\(22\)](#page-22-0),  $r_{i,t+1}$  is firm is realized log return for year t, and  $E_t[r_{i,t+1}]$  is the conditional expected log return of firm  $i$  for the following period at time  $t$ . In equation [\(5\)](#page-16-0),  $\Delta d_{i,t+j}$  denotes the log dividend growth of firm i for year  $t+j$ , and  $\kappa$  is a constant slightly smaller than one. In equation (3),  $r_{i,t+j}$  denotes the log real return on stock i for the  $(t+j)th$  period.

Following LT, I incorporate the firm-level stock return decomposition methodology by [Vuolteenaho](#page-28-11) [\(2002](#page-28-11)) to capture the dynamics of anomaly returns. More specifically, I assume that at time t, firm i's expected log return for term  $t + 1$ ,  $E_t[r_{i,t+1}]$ , is linear in the previous period's aggregate and market-adjusted characteristics. In this framework, aggregate characteristics are value-weighted averages of firm-level characteristics. Marketadjusted firm characteristics are firm characteristics reduced by their value-weighted averages. I describe the assumption as

$$
E_t[r_{i,t+1}] = \delta_0 + \delta'_1 X_{it}^{ma} + \delta'_2 X_t^{agg},
$$
\n(7)

where  $X_{i,t}^{ma}$  denotes the vector of firm i's market-adjusted

characteristics at time t, and  $X_t^{agg}$  denotes the vector of aggregate characteristics at time  $t$ . I use the same five characteristics used by LT: value (book-to-market ratio,  $lnBM$ ), profitability (gross profit,  $lnProt$ ), investment (change in assets,  $lnInv$ ), size (change in market value,  $d5.lnME$ ), and momentum (six-month return,  $lnMom6$ ). More details about the five characteristics are described in the data section. Accordingly,  $\delta_1$ denotes the vector of coefficients between expectation of log returns and firm-level marketadjusted characteristics, while  $\delta_2$  denotes the vector of coefficients between expectation of log returns and aggregate characteristics.

Following LT, I use a time-series VAR system to capture the dynamics of returns at the aggregate level and a panel VAR system to explore cross section information. The time-series VAR generates the coefficient matrix,  $A<sup>agg</sup>$ , necessary to estimate the aggregate CF and DR shocks:

$$
Z_{t+1} = \mu^{agg} + A^{agg} Z_t + \epsilon_{t+1}^{agg}, \tag{8}
$$

where  $Z_t$  denotes a vector containing the value-weighted aggregate log return and aggregate characteristics at time t:  $[r_t^{agg}]$  $_{t}^{agg}$ ;  $X_{t}^{agg}$  $_{t}^{agg}$ .

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

$$
DR_{t+1}^{agg} = E_{t+1} \sum_{j=2}^{\infty} \kappa^{j-1} r_{t+j}^{agg} - E_t \sum_{j=2}^{\infty} \kappa^{j-1} r_{t+j}^{agg}
$$
  
=  $e'_1 \kappa A^{agg} (I - \kappa A^{agg})^{-1} \epsilon_{t+1}^{agg}$ . (9)

Here,  $e_1'$  $\frac{1}{1}$  is a vector whose first element is one and other elements are zeros. The unexpected change in the expected return and state variables are incorporated in  $\epsilon_{t+1}^{agg}$ . The structure of  $e_1'$ 1 allows me to obtain the unexpected change in the expected return.

Since shocks to log stock returns are composed of shocks to expectations of CFs and DRs, I can obtain CF shocks  $(CF_{t+1}^{agg})$  by subtracting DR shocks from shocks to log stock returns:

$$
CF_{t+1}^{agg} = r_{t+1}^{agg} - E_t[r_{t+1}^{agg}] + DR_{t+1}^{agg}
$$
  
=  $e'_1(I + \kappa A^{agg}(I - \kappa A^{agg})^{-1})\epsilon_{t+1}^{agg}$ . (10)

The second VAR is a cross-sectional weighted least squares system with firms' marketadjusted characteristics. In this system, each year has the same weight. Similar to the first VAR, I estimate the coefficient matrix,  $A^{ma}$ :

$$
Z_{i,t+1} = \mu^{ma} + A^{ma} Z_{i,t} + \epsilon_{i,t+1},\tag{11}
$$

where  $Z_{i,t} = [r_{it}^{ma}; X_{it}^{ma}]$  denotes a vector containing market-adjusted variables. In the vector,  $r_{it}^{ma}$  indicates log stock returns demeaned by the market return, and  $X_{it}^{ma}$  denotes market-adjusted characteristics. I estimate firm i's market-adjusted DR shocks at period  $t+1$ :

$$
DR_{i,t+1}^{ma} = e_1' \kappa A^{ma} (I - \kappa A^{ma})^{-1} \epsilon_{i,t+1}.
$$
\n(12)

Similar to how I obtain CF shocks at the aggregate level, I subtract market-adjusted DR

shocks from shocks to expected log returns to obtain CF shocks at the firm-level,  $CF_{i,t+1}^{ma}$ :

$$
CF_{i,t+1}^{ma} = r_{i,t+1}^{ma} - E_t[r_{i,t+1}^{ma}] + DR_{i,t+1}^{ma}
$$
  
=  $e'_1(I + \kappa A^{ma}(I - \kappa A^{ma})^{-1})\epsilon_{i,t+1}.$  (13)

The four component shocks combine to obtain firm-level CF shocks,  $CF_{i,t}$ , and DR shocks,  $DR_{i,t}$ :

$$
DR_{i,t} = DR_t^{agg} + DR_{it}^{ma}
$$
\n
$$
\tag{14}
$$

and

$$
CF_{i,t} = CF_t^{agg} + CF_{it}^{ma}.
$$
\n
$$
(15)
$$

As firm-level return decomposition information is available, I follow LT and construct the components of anomaly return variance as the weighted average of underlying firms' decomposition components. The DR (CF) shocks of the long or short side of the portfolio are the weighted average of the DR (CF) shocks of firms contained in that portfolio. Assuming the portfolio is value-weighted, the weights are the firm's market capitalization standardized by sum of the market capital value of all the firms in that portfolio. Assuming the portfolio is equal-weighted, the weights are the reciprocal of the firm counts in that year. The DR (CF) shocks of an anomaly portfolio,  $CF_{a,t+1}$   $(DR_{a,t+1})$ , is computed as the difference between the long-side DR (CF) shocks and the short-side DR (CF) shocks:

$$
CF_{a,t+1} = \sum_{l=1}^{L} CF_{l,t+1}W_l - \sum_{s=1}^{S} CF_{s,t+1}W_s
$$
\n(16)

and

$$
DR_{a,t+1} = \sum_{l=1}^{L} DR_{l,t+1}W_l - \sum_{s=1}^{S} DR_{s,t+1}W_s
$$
\n(17)

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 DR shocks or CF shocks, I examine

the source of unexpected log real return variance:

$$
var{r_{a,t+1} - E_t[r_{a,t+1}]} = var{CF_{a,t+1} - DR_{a,t+1}}
$$
  
=  $var{CF_{a,t+1}} + Var{DR_{a,t+1}} - 2Cov{CF_{a,t+1}, DR_{a,t+1}}.$  (18)

The contribution to anomaly a return movements from CF shocks is defined as

$$
var(CF) = \frac{var\{CF_{a,t+1}\}}{var\{CF_{a,t+1}\} + var\{DR_{a,t+1}\} - 2cov\{CF_{a,t+1}, DR_{a,t+1}\}} \times 100\%.
$$
 (19)

Similarly, the contribution from DR shocks is defined as

$$
var(DR) = \frac{var\{DR_{a,t+1}\}}{var\{CF_{a,t+1}\} + var\{DR_{a,t+1}\} - 2cov\{CF_{a,t+1}, DR_{a,t+1}\}} \times 100\%.
$$
 (20)

To complete the components reporting, the covariances between DR shocks and CF shocks are reported in the form of negative covariances multiplying by two:

$$
cov(CF, DR) = \frac{cov\{CF_{a,t+1}, DR_{a,t+1}\}}{var\{CF_{a,t+1}\} + var\{DR_{a,t+1}\} - 2cov\{CF_{a,t+1}, DR_{a,t+1}\}} \times 100\%.
$$
 (21)

The five firm characteristics for predicting returns are value, profitability, investment, size, and six-month momentum. The value characteristic  $(lnBM)$  is calculated as  $ln(book)$ equity<sub>t</sub>/market equity<sub>t</sub>), 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](#page-27-12) [\(2015](#page-27-12)), I calculate the profitability characteristic (lnProf) as  $ln(1 + \text{earnings before } tax_t/book \text{ equity}_t)$ . Following [Cooper et al.](#page-27-5)  $(2008)$ , 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](#page-28-12) [\(2017\)](#page-28-12), 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.

Corresponding to anomalies, I build two sets of random long-short portfolios in as placebos. In the first set, a long-short placebo's long side and short side consist of nonoverlapping randomly picked firms. I call them random placebos. Inspired by studies that reveal anomalies capture cross-sectional correlations (e.g., [Daniel and Titman,](#page-27-13) [1997](#page-27-13); [Daniel et al.](#page-27-0), [2020](#page-27-0); and [Clarke,](#page-27-14) [2022\)](#page-27-14), I construct a second set I call high-correlation placebos. Such a placebo's long (short) side involves non-repeating firms that have high monthly return correlations in the previous year. I describe detailed construction steps in the appendix.

Figure [6](#page-48-0) compares the anomaly return decomposition with the placebo return decomposition. Panel (a) presents the CF and DR shock variance distributions of value-weighted random placebos along with value-weighted anomalies. The y-axis describes the occurrence frequency of observations and the x-axis indicates the proportion of return from DR or CF shocks. Placebo return decompositions are shown in gray. Anomaly return decompositions are shown in blue. The left subfigure shows that, under the indrect return decomposition framework, returns of both anomalies and random placebos are driven by cash flow shocks. Additionally, there is a big overlap between the two distributions. The right subfigure shows that for both anomalies and random placebos, the contribution of discount rate shocks to return variation is generally low.

Panel (b) presents the cash flow and discount rate shock components' contribution to high correlation placebo returns and anomaly returns. Consistent with the observation from random placebos, most of the variaton in both anomaly returns and high correlation placebo returns is attributable to cash flow shocks. A noticeable difference is that the distributions have more overlap than the subfigures in panel (a).

#### B. Direct anomaly return decomposition

The return decomposition framework is based on a log-linear approximation of returns. The approximation suggests that the unexpected changes in log real stock returns,  $r_{t+1}$  –  $E_t[r_{t+1}]$ , can be decomposed into unexpected changes in expectations about future cash flows (CF shocks), and unexpected changes in expectations about future discount rates (DR shocks):

<span id="page-22-0"></span>
$$
r_{t+1} - E_t[r_{t+1}] \approx CF_{t+1} - DR_{t+1},\tag{22}
$$

where  $CF_{t+1}$  denotes the CF shock in month  $t + 1$  and  $DR_{t+1}$  the DR shock.

To capture the return dynamics of the long/short sides of anomalies, I use a VAR system:

<span id="page-22-1"></span>
$$
Z_{t+1} = \mu + A_m Z_t + \epsilon_{t+1},\tag{23}
$$

where  $Z_t$  denotes a vector containing the value-weighted log real return and two state variables at time t, that is  $[r_t; x_{1,t}, x_{2,t}]$ . The system says that the return of a buy-only or sell-only portfolio  $m$  can be predicted by its lagged return and the two lagged state variables. Note that the log real return is the monthly return of the portfolio of interest, and the two state variables are the portfolio-level value-weighted aggregate characteristics. On month  $t + 1$ , I sum up the unexpected changes in the discount rate from all future periods to obtain DR shocks:

$$
DR_{t+1} = E_{t+1} \sum_{j=2}^{\infty} \kappa^{j-1} r_{t+j} - E_t \sum_{j=2}^{\infty} \kappa^{j-1} r_{t+j}
$$
  
=  $e'_1 \kappa A'_m I - \kappa A_m$ )<sup>-1</sup>  $\epsilon_{t+1}$ . (24)

Here,  $E_{t+1}r_{t+j}$  is the conditional expected log return of portfolio m at month  $t+1$ ,  $A_m$ the coefficient matrix from equation [23,](#page-22-1)  $\kappa$  a constant slightly smaller than one,  $e'_1$  $_1'$  a vector whose first element is one and whose other elements are zeros, and  $\epsilon_{t+1}$  the residual vector from equation [23.](#page-22-1) The unexpected changes in the expected return and state variables are incorporated in  $\epsilon_{t+1}$ . The structure of  $e'_1$ 1 allows me to obtain the unexpected change in the expected return. Since shocks to log stock returns are composed of shocks to expectations about cash flows and discount rates, I can obtain CF shocks  $(CF_{t+1})$  by subtracting DR shocks from shocks to returns:

$$
CF_{t+1} = r_{t+1} - E_t[r_{t+1}] + DR_{t+1}
$$
  
=  $e'_1(I + \kappa A_m(I - \kappa A_m)^{-1})\epsilon_{t+1}.$  (25)

After obtaining the CF (DR) shocks from both the long side and the short side of a long-short anomaly portfolio, I calculate the CF (DR) shocks at the anomaly level as the difference in the CF (DR) shocks between the long side and short sides,

$$
CF_{a,t+1} = CF_{t+1}^L - CF_{t+1}^S, \text{ and}
$$
  

$$
DR_{a,t+1} = DR_{t+1}^L - DR_{t+1}^S.
$$
 (26)

To explore whether anomaly returns are driven by DR shocks or CF shocks, I examine the source of unexpected log real return variance:

$$
var(r_{t+1} - E_t[r_{t+1}]) = cov(r_{t+1} - E_t[r_{t+1}], CF_{t+1} - DR_{t+1})
$$
  
= 
$$
cov(r_{t+1} - E_t[r_{t+1}], CF_{t+1}) - cov(r_{t+1} - E_t[r_{t+1}], DR_{t+1})
$$
 (27)

The percentage of return variation that is attributed to CF shocks is defined as

$$
cov(CF) = \frac{cov(r_{t+1} - E_t[r_{t+1}], CF_{t+1})}{var(r_{t+1} - E_t[r_{t+1}])} \times 100\%.
$$
\n(28)

The percentage of anomaly a's return variation that is attributed to DR shocks is

$$
cov(DR) = \frac{cov(r_{t+1} - E_t[r_{t+1}], DR_{t+1})}{var(r_{t+1} - E_t[r_{t+1}])} \times 100\%.
$$
\n(29)

Note that the sum of  $cov(CF)$  and  $cov(DR)$  equals 100%. Thus, comparing  $cov(CF)$ across portfolios is enought to examine whether the returns are driven more by CF shocks or DR shocks.

To investigate the properties of the return decomposition framework, I examine the results obtained under 45 different choices of the state variable vector  $Z_t$ . I keep the first element,  $r_t$ , in the vector the same. For the two state variables,  $x_{1,t}$  and  $x_{2,t}$ , I make 45 combinations from a pool of ten 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).

I record the return decomposition results for each combination. For each of the 45 sets, I compare accounting and non-accounting anomalies by the percentages of return variation from CF shocks on long-short anomalies, long sides, and short sides. I apply a binomial test on whether the returns of accounting and non-accounting anomalies are driven by CF shocks of different magnitudes. The null hypothesis is that, out of 174 anomalies, accounting and non-accounting anomalies are equally likely to have abovemedian return variation from CF shocks.

Table [VII](#page-42-0) presents the binomial test results for the 45 combinations. Each row shows the test results from a combination. The combinations are ranked by the count of nonaccounting anomalies with CF shock contribution values above the median. The first row in the left panel shows that, out of 87 anomalies with above-median  $cov(CF)$ , 56 are accounting anomalies and 31 are non-accounting anomalies; out of 87 anomalies with below median  $cov(CF)$ , 34 are accounting anomalies and 53 are non-accounting anomalies. The p-value is 0.10, indicating that the null is rejected at the 0.05 level. This finding indicates that accounting anomalies tend to be driven by CF shocks more than non-accounting anomalies are. In contrast, when AM and rrel are used as state variables (the bottom line), out of 87 anomalies with above-median CF shocks contribution, only 29 are accounting anomalies but 58 are non-accounting anomalies; out of 87 anomalies with below median CF shocks contribution 61 are accounting anomalies and only 26 are non-accounting anomalies. The p-value of the test is 0.002, indicating the null is rejected at the 0.01 level. This finding can be interpreted as that accounting anomaly returns are less driven by CF shocks than non-accounting anomaly returns.

An additional finding is that the interpretations from the long-short anomalies and from the long sides can be different. Considering the goal of a long-short portfolio is to create a wide spread from the long side and the short side, I expect that, compared to non-accounting anomalies, the returns of the long sides of accounting anomalies are also driven more by CF shocks and that the returns of the short sides are driven less by CF shocks. The first row in the left panel shows that accounting anomalies tend to be driven more by CF shocks.

# V. Conclusion

Despite decades of research, financial economists have yet to fully comprehend whether risk or mispricing leads to anomalies. An intuition is that a portfolio's return is the change [in its expected discounted cash flows. Anomalies are no](#page-28-4) exception. Lochstoer and Tetlock [\(2020\)](#page-28-4) propose to investigate the source of anomaly returns for empirical insights to guide model specifations. However, I find the indirect anomaly return decomposition by [Lochstoer and Tetlock](#page-28-4) [\(2020\)](#page-28-4)and direct return decomposition by [Campbell](#page-27-2) [\(1991\)](#page-27-2) insufficient for modeling guidance.

To achieve this goal, I first expand the anomalies examined from five to 174, categorized into accounting and non-accounting. Instead of relying on VAR models to estimate cash flow components, I track the cash flow growth of firms in anomalies and that of anomalies themselves, and explore their variation in recessions and expansions. The findings reveal that accounting anomalies show procyclical growth, aligning with risk-based models. In contrast, non-accounting anomalies show countercyclical growth and thus provide a hedge against economic downturns. This study bridges various anomaly theories within the cross-sectional asset pricing literature by empirically demonstrating that different anomalies can exhibit either risky or risk-hedging cash flows.

# REFERENCES

- <span id="page-27-7"></span>Babenko, Ilona, Oliver Boguth, and Yuri Tserlukevich, 2016, Idiosyncratic cash flows and systematic risk, Journal of Finance 71, 425–456.
- <span id="page-27-9"></span>Benartzi, Shlomo, Roni Michaely, and Richard Thaler, 1997, Do changes in dividends signal the future or the past?, Journal of Finance 52, 1007–1034.
- <span id="page-27-1"></span>Binsbergen, Jules H. van, Martijn Boons, Christian C. Opp, and Andrea Tamoni, 2023, Dynamic asset (mis)pricing: Build-up versus resolution anomalies, Journal of Financial Economics 147, 406–431.
- <span id="page-27-2"></span>Campbell, John Y., 1991, A variance decomposition for stock returns, The Economic Journal 101, 157–179.
- <span id="page-27-11"></span>Chen, Andrew Y., and Tom Zimmermann, 2022, Open source cross-sectional asset pricing, Critical Finance Review 27, 207–264.
- <span id="page-27-14"></span>Clarke, Charles, 2022, The level, slope, and curve factor model for stocks, Journal of Financial Economics 143, 159–187.
- <span id="page-27-3"></span>Cochrane, John H., 2011, Presidential address: Discount rates, Journal of Finance 66, 1047–1108.
- <span id="page-27-10"></span>Cochrane, John H, and Monika Piazzesi, 2005, Bond risk premia, American Economic Review 95, 138–160.
- <span id="page-27-6"></span>Cohen, Randolph B., Christopher Polk, and Tuomo Vuolteenaho, 2009, The price is (almost) right, Journal of Finance 64, 2739–2782.
- <span id="page-27-5"></span>Cooper, Michael J., Huseyin Gulen, and Michael J. Schill, 2008, Asset growth and the cross-section of stock returns, Journal of Finance 63, 1609–1651.
- <span id="page-27-0"></span>Daniel, Kent, Lira Mota, Simon Rottke, and Tano Santos, 2020, The cross-section of risk and returns, Review of Financial Studies 33, 1927–1979.
- <span id="page-27-13"></span>Daniel, Kent, and Sheridan Titman, 1997, Evidence on the characteristics of cross sectional variation in stock returns, The Journal of Finance 52, 1–33.
- <span id="page-27-8"></span>DeAngelo, Harry, and Linda DeAngelo, 2000, Controlong stockholders and the disciplinary role of corporate payout policy: a study of the times mirror compnay, Journal of Financial Economics 56, 153–207.
- <span id="page-27-4"></span>Fama, Eugene F., and Kenneth R. French, 1992, The cross-section of expected stock returns, Journal of Finance 47, 427–465.
- <span id="page-27-12"></span>Fama, Eugene F., and Kenneth R. French, 2015, A five-factor asset pricing model, Journal of Financial Economics 116, 1–22.
- <span id="page-28-12"></span>Gerakos, Joseph, and Juhani T. Linnainmaa, 2017, Decomposing value, Review of Financial Studies .
- <span id="page-28-9"></span>Gormsen, Niels Joachim, and Eben Lazarus, 2023, Duration-driven returns, Journal of Finance 78, 1393–1447.
- <span id="page-28-3"></span>Hansen, Lars Peter, John C. Heaton, and Nan Li, 2008, Consumption strikes back? measuring long-run risk, Journal of Political Economy 116, 260–302.
- <span id="page-28-5"></span>Harvey, Campbell R., Yan Liu, and Heqing Zhu, 2016, ... and the cross-section of expected returns, Review of Financial Studies 29, 5–68.
- <span id="page-28-6"></span>Jegadeesh, Narasimhan, and Sheridan Titman, 1993, Returns to buying winners and selling losers: Implications for stock market efficiency, Journal of Finance 48, 65–91.
- <span id="page-28-8"></span>Koijen, Ralph S. J., Hanno Lustig, and Stijn Van Nieuwerburgh, 2017, The cross-section and time series of stock and bond returns, Journal of Monetary Economics 88, 50–69.
- <span id="page-28-7"></span>Leary, Mark T., and Roni Michaely, 2011, Determinants of dividend smoothing: Empirical evidence, Review of Financial Studies 24, 3197–3249.
- <span id="page-28-2"></span>Lettau, Martin, and Jessica A. Wachter, 2007, Why is long-horizon equity less risky? A duration-based explanation of the value premium, Journal of Finance 62, 55–92.
- <span id="page-28-10"></span>Liu, Yan, and Jing Cynthia Wu, 2021, Reconstructing the yield curve, Journal of Financial Economics 142, 1395–1425.
- <span id="page-28-4"></span>Lochstoer, Lars A., and Paul C. Tetlock, 2020, What drives anomaly returns?, Journal of Finance 75, 1417–1455.
- <span id="page-28-0"></span>Schneider, Paul, Christian Wagner, and Josef Zechner, 2020, Low-risk anomalies?, Journal of Finance 75, 2673–2718.
- <span id="page-28-1"></span>Stambaugh, Robert F., Jianfeng Yu, and Yu Yuan, 2012, The short of it: Investor sentiment and anomalies, Journal of Financial Economics 104, 288–302.
- <span id="page-28-11"></span>Vuolteenaho, Tuomo, 2002, What drives firm-level stock returns?, Journal of Finance 57, 233–264.

### <span id="page-29-0"></span>Table <sup>I</sup> Descriptive Statistics of Buy-and-Hold Portfolio Cash Flow Growth

 For every month between <sup>1973</sup> and 2017, <sup>I</sup> sort stocks into value-weighted quintile portfolios based on the focal characteristic. The quintile portfolios are determined by the NYSE breakpoints. <sup>I</sup> assume holding the portfolios for <sup>3</sup> years. For each portfolio, <sup>I</sup> calculate its log annual cash flow growth at the end of the 1st year, 2nd year, and 3rd year. The cash flow growth of <sup>a</sup> long-short portfolio is calculated as the difference in the cash flow growth between the long and the short sides. Then <sup>I</sup> 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.



#### <span id="page-30-0"></span>Table 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. <sup>I</sup> assume holding the portfolios for <sup>3</sup> years. For each portfolio, <sup>I</sup> calculate its log annual cash flow growth at the end of 1st year, 2nd year, and 3rd year. The dividend growth of <sup>a</sup> long-short portfolio is calculated as the difference between the long-side dividend growth and the short-side dividend growth. Then <sup>I</sup> calculate the mean and standard deviation of these cash flow growth across formation months. <sup>I</sup> caculate the median of pooled accounting and non-accounting anomalies for the mean. Withineach 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<br>hypothesis that accounting an accounting anomalies a hypothesis that accounting and non-accounting anomalies are equally likely to have above-median cash flow growth. The p-values are reported.



#### Table III

#### Buy-and-Hold Portfolio Cash Flow Growth across 3 Years

<span id="page-31-0"></span>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 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 dividend growth of a long-short portfolio is calculated as the difference between the long-side dividend growth and the short-tside dividend growth. Then I calculate the mean and standard deviation of these cash flow growth across formation months. The table shows the mean and standard deviation for each anomaly: long-short (LS), long side (L), and short side (S).















#### Table IV

#### Mean of Bond Factor Betas

<span id="page-37-0"></span>The table presents the mean values of bond factor betas within accounting and non-accounting anomalies in three years. The betas are obtained through the following predictive regression:  $\Delta d_{i,t+k} = c_{i,t} + \beta C P_t + \epsilon_{i,t+k}$ , 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  $CP<sub>t</sub>$  the bond factor at month t. I employ the regression to the long- and short-side portfolios, and anomalies over the 1-year, 2-year, and 3-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 2020.



### <span id="page-38-0"></span>Table <sup>V</sup>

### 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 <sup>3</sup> 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 than0.05 are shown in bold.



### Table VI

#### Bond Factor Risk of Monthly-Rebalanced Portfolios

<span id="page-39-0"></span>The table shows the coefficients, t-statistics, and  $R^2$  from a test of the following predictive regression:  $\Delta d_{i,t+36} = c_{i,t} + c_{i,t}$  $\beta C P_t + \epsilon_{i,t+k}$ , 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 1-year, 2-year, and 3-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 2020.







#### <span id="page-42-1"></span><span id="page-42-0"></span>Table VII

#### Return Decomposition: Accounting vs Non-Accounting

 The table presents binomial tests comparing CF shock contribution to return variation between accounting and non-accounting anomalies. <sup>I</sup> apply Campbell (1991) VAR decomposition to long-short anomaly, long side, and short side portfolios. The state variable vector in VAR consists of monthly log real return 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 CF shock contribution is defined as the covariance between CF shocks and unexpected return scaled by the variance of unexpected return. <sup>I</sup> calculate the median of pooled accounting and non-accounting anomaly CF shock contribution. Within each pool, <sup>I</sup> count the number of portfolios above and below the median CF shock contribution for accounting and non-accounting anomalies, respectively. <sup>I</sup> perform binomial tests under the null hypothesis that accounting and non-accounting anomalies are equally likely to have above-median CF shock contribution. The p-values are reported. The state variable combinations are sorted by the count of accounting long-short portfolio with above median CF shocks.







<span id="page-44-0"></span>

Figure 1. The figures show the distributions of the means of buy-and-hold cash flow growth across three horizons for accounting and non-accounting anomalies. In 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 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, 2nd, and 3rd year. The cash flow growth of a long-short portfolio is calculated as the difference in cash flow growth between the long and short sides of buy-and-hold portfolios. Then I calculate the mean of these 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 2. Tracking-firm cash-flow growth on accounting and non-accounting anomalies.



Figure 3. 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 2020, I calculate the seasonality-adjusted log quarterly cash flow growth for monthly rebalanced anomaly portfolios. I define recession periods as the months showing 1 in the NBER business cycle dating table. The other quarters 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 or dividends are constructed from the difference between total 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 4. Tracking-anomaly cash flow growth on accounting and non-accounting anomalies.

<span id="page-47-0"></span>

Figure 5. Bond factor beta distributions. The bond factor betas are from a predictive regression. The dependent variables are 36-month forward log cash flow 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.

<span id="page-48-0"></span>

(b) Anomalies and High Correlation Placebos

Figure 6. Indirect return decompositions for anomalies and placebos.

# Appendix for "Anomalies and Cash Flows"



# A. Appendix A

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



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



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



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



Figure A.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.