Which Expectation?

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Abstract

We test a theory of two-expectations in asset pricing: investors separately form subjective beliefs on the cash flow *level* and cash flow *growth* when valuing assets. Biases in the two beliefs create distinct mispricing. Using 123 anomalies and analysts' earnings forecast term structure data, we find strong evidence for the separability of the two beliefs and quantify their importance for the cross-section of anomalies: (1) Forecast errors in the cash flow level and cash flow growth are uncorrelated. (2) Anomaly portfolios typically capture biases in one belief or the other, but not both. (3) Anomalies with large (small) alphas often have the two biases amplifying (offsetting) each other. (4) Anomalies that capture the growth bias earn more persistent alphas and exhibit stronger factor momentum, but these alphas decline more in recent periods. (5) The first two principal components of anomaly returns are essentially a growth bias factor and a level bias factor. (6) The two biases explain about 50% of the cross-sectional variation in the anomalies' deviation from the CAPM. (7) The alpha decay in recent periods coincides with analysts' improved forecast accuracy.

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Introduction

Consider the Gordon Growth Model (GGM):

$$P_0 = \frac{\mathbb{E}^s[\tilde{CF}_1]}{r - \mathbb{E}^s[\tilde{g}]}, \tag{1}$$

where P_0 is the price at time 0; $\mathbb{E}^s[.]$ is a subjective expectation operator; r is the discount rate; $\tilde{CF}_1$ is the random cash flow in the next period. $\tilde{g}$ is the average cash flow growth rate starting from the next period. The GGM asks investors to form *two* subjective forecasts: the next-period cash flow *level* and the subsequent cash flow *growth*. We teach this equation to students in Introduction to Finance, but what if investors actually use this formula to value firms?

Motivated by this question, we test a model of two-expectations for asset pricing. Although we conduct many tests using over 100 anomaly signals, our central message is simple. Recent studies such as Engelberg et al. (2018) and Kozak et al. (2018) find that most stock market anomalies are linked to biased beliefs. We add to their conclusion that (1) there are two ways in which beliefs can be biased and (2) the two types of biases have different asset pricing implications.

Why do we care about which expectation? In a review article, Brunnermeier et al. (2021) advocate for studying "empirically grounded models of subjective beliefs." Our paper presents an attempt in this direction by pointing out the need to model, not one, but two subjective beliefs. Existing literature often treats biased belief, or even less specific, sentiment, as a catch-all explanation for mispricing. As the field progresses, readers ask for more and more details about why and how beliefs are distorted.[1] The question we raise, "which expectation?" multiplies *all* these questions by two, plus the additional interaction questions, "how do the biases in the two expectations interact?" Letting there be two

[1] See Bordalo et al. (2019); Bouchaud et al. (2019); Cassella and Gulen (2018); Da and Warachka (2011) and others.

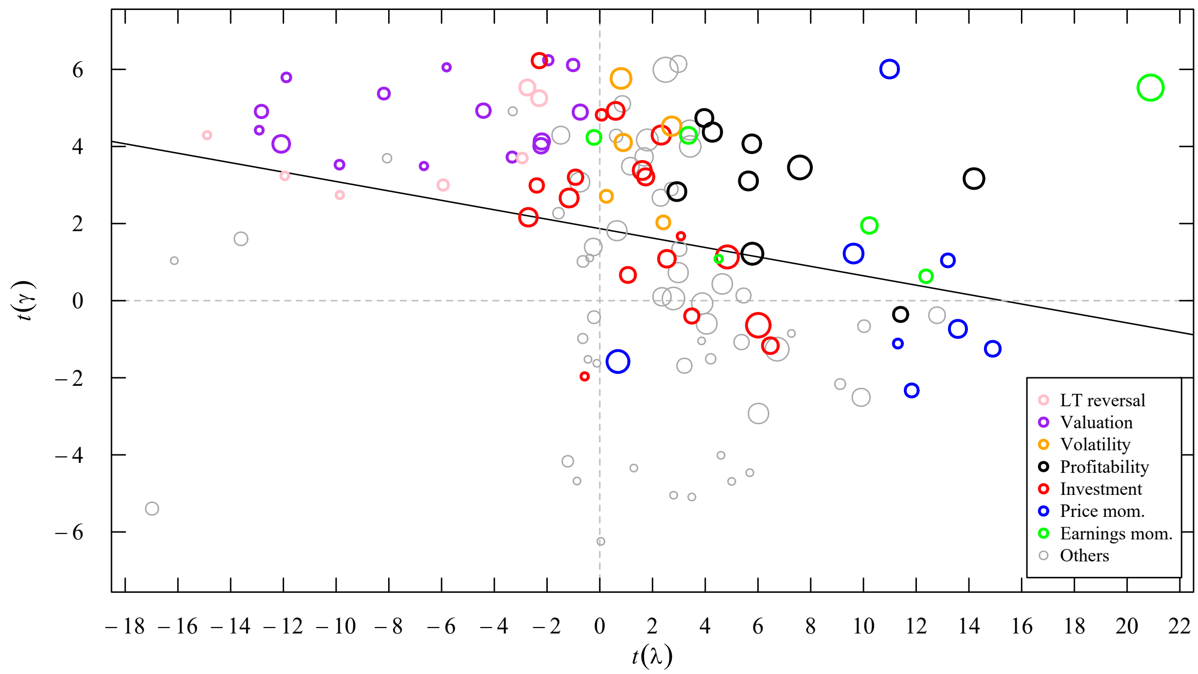

Figure 1: **Level Bias, Growth Bias and Anomalies.** This figure plots the locations of 123 anomalies in the level-growth-bias space. The circle size increases with the average alpha of the group. The data behind this figure is in Table 3. The slopped solid line is the best fitted line of $t(\gamma)$ on $t(\lambda)$: $y = 1.87 - 0.12x$. The R^2 of the fit is 7.0%

expectations moves against our desire to have a parsimonious model, but we show in this paper that perhaps the gain in clarity from adding this extra degree of freedom is worth the sacrifice.

Figure 1 plots 123 HML-style factor portfolios on the level-growth bias space. At the end of each month, we form two-by-three portfolios based on firm size and an anomaly variable following Fama and French (1993) and compute the high-minus-low ex post level bias (λ_t) and growth bias (γ_t). Then we compute the time-series averages of λ_t and γ_t and then their t-values for each factor. A high $t(\lambda)$ means that the factor consistently buys (sells) stocks whose next quarterly earnings exceed (fall short of) the current consensus forecasts. A high $t(\gamma)$ means that the factor consistently buys (sells) stocks whose realized growth for the next two fiscal years consistently exceed (fall short of) the current consensus growth forecasts. To facilitate the analysis, we group anomalies into 23 categories.[2] The color-coded circles

[2]We download the anomaly variables from Chen and Zimmermann (2022). We combine some of their

are factors that belong to the more well-known categories. The size of the circle increases with the t-value of the CAPM alpha of the factor. The data behind the figure is reported in Table A.3 in the Appendix.

Several patterns emerge in Figure 1. First, there is large heterogeneity in how different factors are associated with the two biases, indicated by the large dispersion of the circles. Second, factors that belong to the same category (with the same color) tend to cluster, suggesting that factors of with a similar style line up with the same bias. Third, the best-fitted line of $t(\gamma)$ on $t(\lambda)$ slopes downward. This means that the factors typically do not capture both types of biases. Fourth, the circles generally increase in size from left to right and from bottom to top. Fifth, the vast majority of the circles are located in the first, second and third quadrants, while the fourth quadrant is almost entirely empty.

These patterns in Figure 1 summarizes our central message that the level and growth biases are distinct and they line up with different anomalies. For instance, momentum-type factors tend to capture level bias, while value-type factors capture growth bias. Certain factors that have large alphas, such as the profitability factors, often capture both biases.

Does the separation of the two expectations matter for factor premiums? We find that anomalies associated with the level bias earn larger immediate alphas while those associated with growth bias earn more persistent alpha. The growth-bias anomalies also exhibit stronger factor momentum, suggesting a sluggish correction of growth expectations. Finally, we growth-bias anomalies have bigger decays in the recent periods.

Links with the literature. Our paper relates to three strands of literature: (i) the cross-section of stock returns and mispricing (Bordalo, Gennaioli, Porta, and Shleifer, 2019; Bouchaud, Krüger, Landier, and Thesmar, 2019; Da and Warachka, 2011; Daniel, Hirshleifer, and Sun, 2020; Engelberg, McLean, and Pontiff, 2018, 2020; Hou, Xue, and Zhang, 2015; Kozak, Nagel, and Santosh, 2018; La Porta, 1996; Lakonishok, Shleifer, and Vishny,

categories such as "investment" and "investment alt."

1994; Stambaugh and Yuan, 2016; van Binsbergen, Boons, Opp, and Tamoni, 2021; van Binsbergen, Han, and Lopez-Lira, 2020). (*ii*) general subjective belief formation (Afrouzi, Kwon, Landier, Ma, and Thesmar, 2020; Coibion and Gorodnichenko, 2012, 2015), Afrouzi et al. (2020); Barberis et al. (2015, 2018); Bordalo et al. (2022) and (*iii*) meta-research in asset pricing (Chen and Zimmermann, 2022; Green, Hand, and Zhang, 2017; Harvey, Liu, and Zhu, 2016; Hou, Xue, and Zhang, 2020).

Most related to our paper is Daniel et al. (2020). They propose a factor model motivated by the different behavioral biases investors display at the short and long horizons, but do not tie the biases to beliefs. Kozak et al. (2018) show that most anomalies line up with sentiment proxied by analysts' forecast errors but do not separate the two expectations. Similarly, Engelberg et al. (2018) find that most anomalies are more pronounced during earnings announcements and days with corporate news. They conclude that biased beliefs likely drive many anomaly returns but do discuss which expectation is biased.

1 Validation

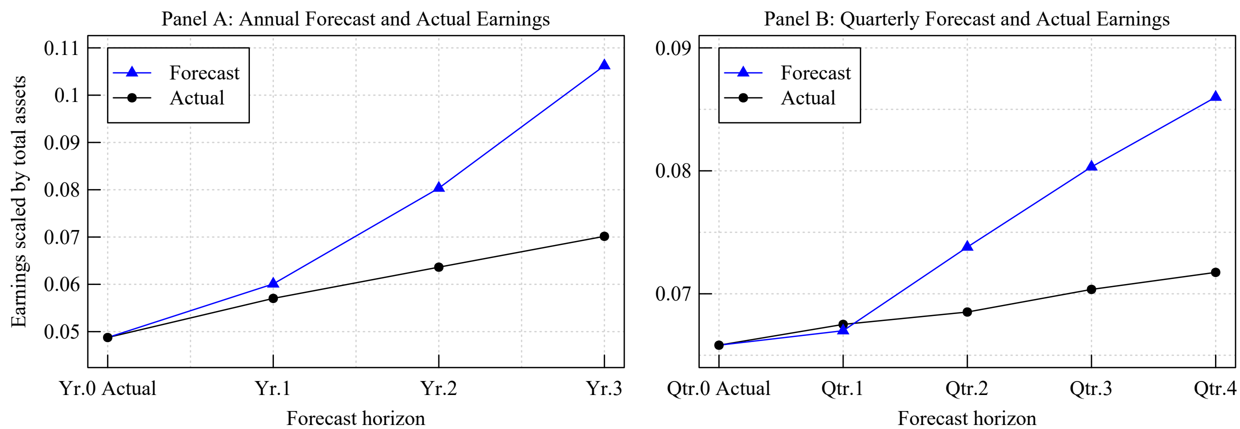

Figure 2: **Unconditional Forecast and Actual Earnings Term Structure.** This figure plots the unconditional average earnings forecasts over different horizons and the corresponding actual earnings. We scale all earnings by lagged total assets. We annualize the quarterly earnings by multiplying them by four. The sample includes stock-month observations with available forecast and actual earnings data over all the different plotted horizons. To avoid overweighting firms with better data availability within a fiscal year or quarter, we only use the July sample in Panel A, and the January, April, July and October sample in Panel B. We first compute the averages by years and then average across all the years to avoid overweighting periods with more observations.

Figure 2 plots the average earnings forecasts with the corresponding actual earnings over different horizons. Panel A uses annual earnings and Panel B uses quarterly earnings data. The distinction between near-term forecast and longer-horizon forecasts is apparent even in these unconditional averages. The forecast bias at the imminent horizon is small. However, as we move from the imminent horizons (Yr.1 and Qtr.1) to two-period ahead (Yr.2 and Qtr.2), there appears to be a jump in the forecast bias. This bias increases almost linearly with forecast horizon from the next period onward. This pattern, a kink at how forecast horizon affects bias, is consistent with our level-growth framework that the longer-horizon forecasts are governed by a seperate growth forecast. We now more formally validate our theory.

1.1 The level and slope of the forecast term structure: Results from principal component analysis

If the level-growth framework is a good description of reality, we should observe that the total variation in analysts' forecast term structure is largely explained by just two principal components (PC): a level PC and a slope PC.

[Table 1 here]

Table 1 Panel A shows the results for the principal component analysis using analysts' annual and quarterly consensus (mean) earnings forecast term structure. The left panel shows the results using annual forecasts and the right panel uses quarterly forecasts. The level–slope structure is apparent in both panels. The first PCs in both panels load evenly on forecasts at all horizons. The second PCs load negatively on the near-term forecasts and positively on the longer-term forecasts. The bottom row shows the cumulative proportion explained by the PCs. For the annual forecasts, the first two PCs explain 99% of the variation. For the quarterly forecasts, the first two PCs explain 95% of the variation. The third PC in both panels corresponds to the curvature. The fourth PC in the right panel appears to correspond to a seasonality factor.

Panel B shows the PCA results for the forecast *revisions*. The results are largely the same as those in Panel A. The first PC is a level shift, and the second PC is a rotation. Figure 3 visualizes the PC loadings on forecast revisions at different horizons. These results suggest that the typical forecast term structure movements are parallel shifts and rotations. To the best of our knowledge, we are the first to show that analysts' forecasts exhibit such a strong level-slope structure, and their revisions a shift-rotation structure.

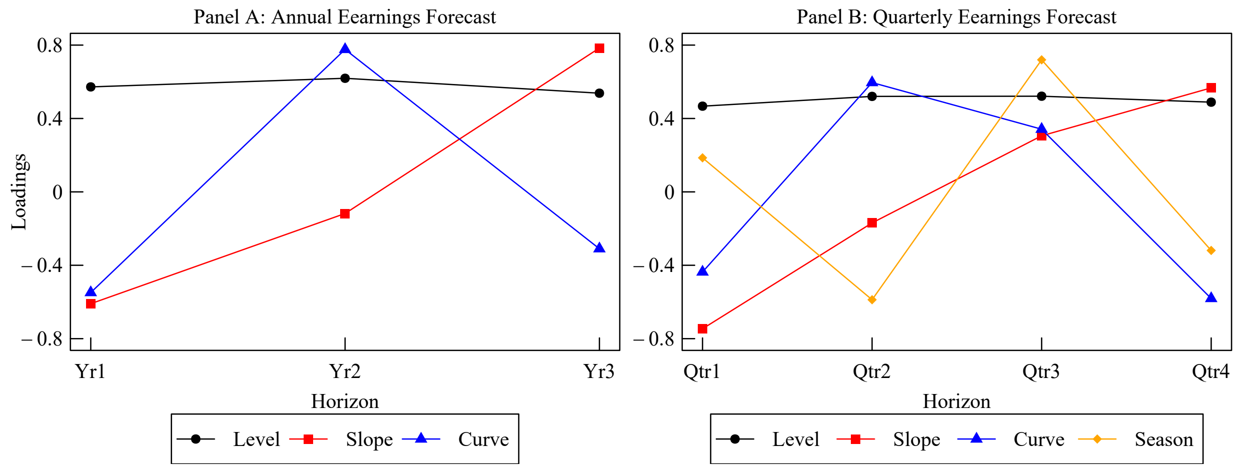

Figure 3: **Principal Component analysis on analysts' annual and quarterly earnings forecast revisions.** The sample includes stock-month observations that have non-missing data on the monthly change in consensus earnings forecasts at the three annual or four quarterly horizons. These values correspond to those in Panel B of Table 1.

1.2 Correlations among growth forecasts at different horizons

Our second validation test examines the correlation between *growth* forecasts at different horizons. If the cash flow level and growth forecasts are separately formed, we should expect that the growth forecasts within the longer horizon bucket to be highly correlated because they are derived from the same forecasting parameter. In contrast, short-term growth forecasts should be much less correlated with the longer-horizon growth forecasts.

Panel C of Table 1 shows the correlation matrix between the growth forecast in year 1, the forward growth forecast in year 2, and the forward growth forecast in year 3. We see that the correlations between year 2 and year 3 forecasts is indeed quite high, at 0.66, while the correlations between year 1 and year 2 forecasts are much lower, at only 0.23. This result means that the growth forecasts for year 2 and year 3 often align while the year 1 growth forecast is distinct.

1.3 Growth forecasts and the cross-section of stock returns

Our third validation test moves from the expectation space to the return space, to examine the relation between growth forecasts and average stock returns. Existing results by such as La Porta (1996) and Bordalo et al. (2019) show that analysts' growth forecasts negatively predict subsequent stock returns. If the first period forecast and subsequent growth forecasts are formed separately as the cash flow level and growth, we should expect that only growth forecasts beyond the first period negatively predict stock returns.

Table **??** shows the monthly value-weighted CAPM alpha (and t-values) for portfolios formed on growth and forward growth forecast deciles. We sort stocks by year 1 growth forecast, year 2 forward growth forecast, and year 3 forward growth forecast. We omit the results for deciles three, four, seven and eight to conserve space. Our results are not driven by small stocks as we exclude micro caps and low-price stocks, and our stocks are all followed by analysts. The next section describes our sample construction in detail.

Consistent with our theory, we find that only forward growth forecasts at year 2 and year 3 significantly and negatively predict abnormal returns. Stocks with the highest forward growth forecasts at the second and third year horizon earn a negative CAPM alpha of -0.67% and -0.58% per month, with t-values of -3.21 and -2.63. The High$-$Low long-short portfolios earn significantly negative CAPM alphas of -0.74 and -0.62, with t-values of -0.34 and -2.62. In contrast, the first row shows that the near-term growth forecast slightly positively predict subsequent CAPM abnormal returns. The last column uses the Fama and French (2015)–Carhart (1997) six-factor model as the benchmark model. The abnormal return of Yr.2 long-short portfolio remains significant even after controlling for the additional factors, while the abnormal return from the Yr.3 strategy is subsumed. These results are consistent with Da and Warachka (2011) who show that the disparity between long- and short-horizon growth forecasts significantly predict stock returns. The results in Table **??** suggest that the first-period growth forecast has a bias structure that differ from the biases in the longer-horizon growth forecasts.

In this section, we motivate our two-expectation theory with psychologically and economically grounded arguments. Then we validate the theory in three different ways. The next section describes our sample and methodology for studying the cross-section of anomalies.

We do not take a stance on why this level-growth structure occurs, but offer some potential explanations here. First, analysts may face different incentives for forecasting earnings over different horizons. Second, the short-term cash flow level may be more carefully managed by firms. Third, agents may form expectations on the cash flow level and growth in fundamentally different ways. While we do not aim to differentiate between these alternative explanations, we believe understanding the relative importance of these mechanisms is an important topic for future research. Instead, we focus on understanding the implications of this level-growth structure.

1.4 An illustrative Model

We provide an illustrative model in Appendix A. Our theory imposes a strong restriction on the possible relation between firm characteristics and the term structure of forecast errors. This restriction allows for a powerful test to distinguish whether a firm characteristic captures biases in the cash flow level or cash flow growth. We implement the model's prediction in Table A.1, which can be helpful for more theoretically minded readers to clarify the intuition. We also discuss some limitations of analysts' long-term growth forecasts and the benefits of using the slope of the forecast term structure as a measure growth forecast.

2 Data and Methodology

2.1 Data

We use data from three standard sources: (1) stock market data from CRSP, (2) firms' financial information from Compustat and (3) analysts' consensus forecast and actual earnings from IBES. We download data on 203 anomaly variables from Chen and Zimmermann's (2022) website.[3]

Our stock-month sample includes common stocks (share code = 10 or 11) traded in NASDAQ, AMEX or NYSE (exchange code = 1, 2, or 3) with positive book value of equity, lagged total assets above \$10 million, share price above \$5, and that are above the 20$^{\text{th}}$ NYSE-size percentile in the previous month. The sample period is from July 1985 to June 2019. The starting time is constrained by the IBES data on forecast and actual earnings.[4]

We require the anomaly variables to be continuous, available throughout the sample period, and available for at least 500 stocks in the average month in the sample period. These filters enable us to study a comprehensive set of variables in a consistent statistical framework. We construct standard HML-style factors using each of the variables and compute pairwise correlations of these factor returns. If two factors are over 95% correlated, we keep only the one with more stock-level non-missing observations. We end up with 123 anomaly variables. A detailed list of these variables in the Appendix. The variables are signed to forecast a positive abnormal return.[5] Consistent with prior research, the average and median absolute correlation between the factors are modest, at 0.26 and 0.20, respectively.

[3] https://www.openassetpricing.com

[4] The IBES earnings forecast summary becomes consistently available for a large cross-section in 1985. The IBES actual earnings is available up to June 2022. One of our key variables — ex post growth surprise — requires earnings realization for three-year ahead forecasts. The availability of the realized values restricts out last monthly three-year ahead earnings forecast observation to be in May 2019.

[5] We flip the signs of Beta, BetaFP and BetaTailRisk to be consistent with the "low-risk anomaly." We also manually add a short-term reversal signal, which is the lagged-one-month stock return multiplied by negative one.

2.2 Level Surprise, growth surprise, and anomaly profits

For ease of discussion, we work with surprises in our empirical implementation to align the signs across different tests (i.e. a factor that captures positive surprise should also earn positive abnormal returns). We define the ex post level surprise and growth surprise as:

$$\begin{aligned} LSurp_{i,t} &\equiv \frac{CF_{i,t}^{1Q} - \mathbb{E}^s[\tilde{CF}_{i,t}^{1Q}]}{K_{i,t-1}} \times 4, \\ GSurp_{i,t} &\equiv \frac{(CF_{i,t}^{3Y} - CF_{i,t}^{1Y}) - (\mathbb{E}^s[\tilde{CF}_{i,t}^{3Y}] - \mathbb{E}^s[\tilde{CF}_{i,t}^{1Y}])}{K_{i,t-1}} \times \frac{1}{2}. \end{aligned} \tag{2}$$

$LSurp_{i,t}$ is the familiar earnings surprise — the difference between firm i's actual next-quarter earnings ($CF_{i,t}^{1Q}$) and analysts' consensus (mean) forecast of this earnings measured at time t ($\mathbb{E}^s[\tilde{CF}_{i,t}^{1Q}]$), scaled by the firm's total assets available in the previous month $K_{i,t-1}$.[6] Note that $CF_{i,t}^{1Q}$ is an ex post realized value that is unknown at time t while $\mathbb{E}^s[\tilde{CF}_{i,t}^{1Q}]$ is the consensus forecast available at time t.

$GSurp_{i,t}$ is the ex post cash flow growth surprise, which is equal to firm i's actual earnings growth from one-year to three-years ahead ($CF_{i,t}^{3Y} - CF_{i,t}^{1Y}$) minus the difference between the consensus three-year-ahead and one-year-ahead earnings forecasts at time t, ($\mathbb{E}^s[\tilde{CF}_{i,t}^{3Y}] - \mathbb{E}^s[\tilde{CF}_{i,t}^{1Y}]$), scaled by lagged total assets. Using the cash flow differences to measure growth, rather than using growth rate, helps avoid the noise introduced by small denominators and accommodate firms with negative earnings. We annualize $LSurp_{i,t}$ and $GSurp_{i,t}$ by multiplying them by four and one-half, respectively. The choice of denominator matters (see the model in Appendix A).

We use the monthly CAPM alphas of the anomaly portfolios to measure the strength of the anomalies. The portfolio construction procedure follows the HML-style two-by-three sort in Fama and French (1993). We first split the our sample each month into the big and small

[6] We follow the literature and assume the financial variables in annual reports are available seven months after the fiscal year ends.

groups using the NYSE 50^{th} percentile market value of equity (ME).[7] We then sort stocks into high, medium and low using the 70^{th} and the 30^{th} percentiles of the corresponding firm characteristic of our NYSE sample. We compute the monthly value-weighted average returns for the six resulting portfolios. The factor return is the difference between the average of the two high portfolios and the average of the two low portfolios. We rebalance the portfolios monthly to capture the potentially short-lived alphas of some anomalies. The alphas are the intercepts of the time-series regressions of the long-short returns on the market return in excess of the risk-free interest rate.[8] The standard errors are Newey-West adjusted with 12 lags to account for serial correlations of the residuals.

2.3 Relating anomalies to the level and growth biases

We define a "factor surprise" analogously to factor premium. We first measure the ex post cash flow level surprise and growth surprise for each anomaly portfolio each month. This procedure is identical to constructing the HML-style factor returns, but only replacing returns by the ex post level or growth surprises. If a factor has a positive level (growth) surprise spread in a month, it means that the stocks in the long portfolio this month on average *will* receive positive level (growth) surprise in the future. We then compute the time-series average of the level and growth spreads for each factor as the factor surprises. We expect that if a factor earns a positive premium at least in part due to expectations biases, it should on average have a positive level factor surprise and/or positive growth factor surprise.

Table 2 reports the summary statistics of our sample. The first two rows show the distribution of stock-month level and growth surprises. The total number of observations for the two surprises are around 670,000 and 341,000. Data on growth surprises are less avail-

[7] To mitigate the impact of micro cap stocks, as discussed in the data section, we remove stocks that are below the 20^{th} ME percentile after sorting by size, so the small portfolio includes firms with ME between the 20^{th} to the 50^{th} NYSE percentiles. We perform the other sorting using this all-but-micro sample.

[8] We acquire market return and risk-free rate of return from Kenneth French's website.

able because many stock-months do not have three-year ahead earnings forecasts available. Consistent existing findings that most firms beat earnings forecasts and analysts' forecast have optimism bias at the long horizon, the average and median $LSurp$ are slightly positive at 0.01% and 0.07% of total assets, while the $GSurp$ are typically negative, with an average and median value of -1.52% and -0.34% of total assets.

[Table 2 here]

The second panel shows the distribution of the factor-level average surprise spread and the associated time-series t-values.[9] We see that the factors on average line up with the direction of both types of surprises. The average level surprise (λ) is 0.06 percent of total assets and the average growth surprise (γ) is 0.46. Yet, the average factor is not significantly exposed to either of the two surprises, as indicated by the average t-values being only at 1.39 and 1.70.

The last panel shows the correlations between the main variables. Contrary to intuition may suggest, the level and growth surprises are essentially uncorrelated, with a correlation coefficient of just 0.04. The correlation between the CAPM α and λ is 0.23 and that between α and γ is 0.44. These high correlations indicate that the two expectation biases, despite being distinct from each other, are both important determinants of the cross-section of anomaly alphas. Importantly, the last cell shows that the correlation between λ and γ is strongly negative, which means that in our sample, if a factor captures one type of bias, it is *less* likely to also capture the other type of bias. This negative correlation reinforces our point that the two biases are distinct.

[9] Unless noted otherwise, we Newey-West adjust all time-series standard errors with 12 lags (one year).

3 Empirical Results

3.1 Which expectation?

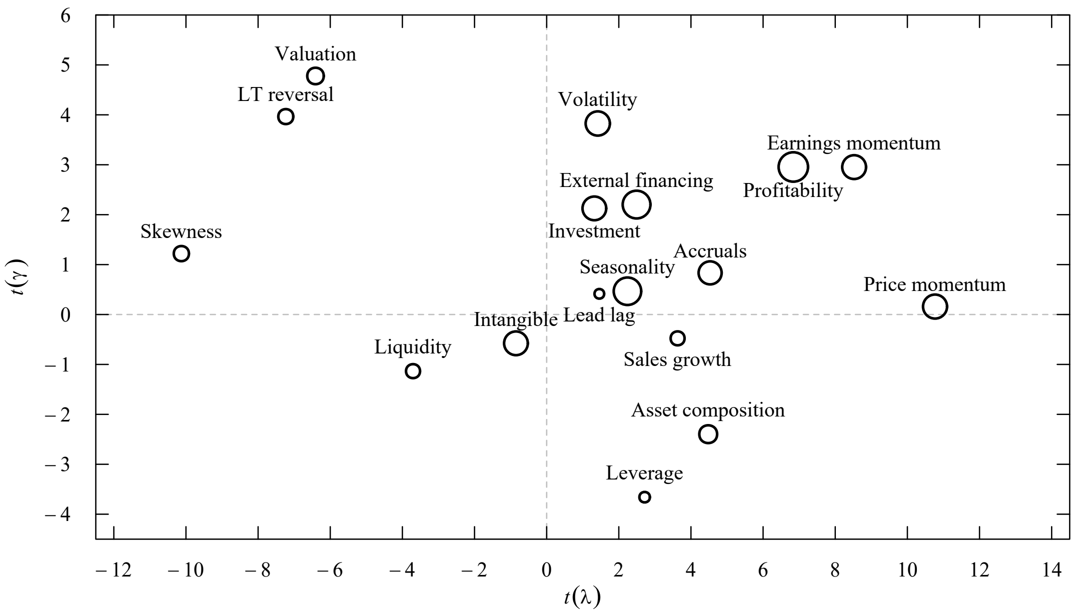

Figure 4: **Level Bias, Growth Bias and Anomalies.** This figure plots the locations of 17 anomaly groups in the level-growth-bias space. The circle size increases with the average alpha of the group. The data behind this figure is in Table 3.

Figure 4 plots the average $t(\gamma)$ against $t(\lambda)$ for 17 categories that contain at least three anomalies. The size of the circle increases with the average t-values of the CAPM alpha of the group. The underlying data is in Table 3.

After aggregating by anomaly groups, Figure 4 continues to show a large dispersion. Specifically, factors in some categories, such as those about price momentum, strongly capture level surprises but do not capture growth surprises, as indicated by their large $t(\lambda)$ and small $t(\gamma)$ values. On the opposite side of the graph, the top left corner, the valuation and long-term reversal factors strongly predict growth surprise, but their negative average $t(\lambda)$ values reveal that these factor portfolios net long stocks that tend to miss quarterly earnings forecasts.

Several anomaly categories are located in the first quadrant and are significantly associated with at least one bias: price momentum, earnings momentum, profitability, accruals, external financing, investment, volatility, and seasonality. These anomalies are associated with both level and growth biases in the "right" direction, and with no exceptions, all these categories earn statistically significant alphas on average as shown in Table 3.

Valuation and long-term reversal strategies earn small alphas in our sample. Yet, their low alphas do not seem particularly puzzling based on their locations in the level-growth bias space. The opposing signs of λ and γ for these anomalies mean that although they can profit from investors' biased growth expectations, they suffer from being on the wrong side of the level bias. Such interaction between biases would have been missed if one discusses just one type without the other. This interaction also leads to deeper economic insights: the lack of alpha from a strategy does not necessarily imply the lack of expectation error. Insignificant alphas can result from large but offsetting biases, whatever the underlying mechanism may be.[10]

Table 3 reports the average λ, γ and α for all 23 anomaly categories (Panel A) and an overall summary (Panel B). Columns 1, 2 and 3 in Panel A displays the averages of the factor-level estimates by categories. Columns 4, 5 and 6 shows the average t-values. The last column shows the number of characteristics included in the category. The bottom row shows the averages across all categories.

[Table 3 here]

Panel B summarizes the associations between the anomalies and the two biases. Among the 123 factors studied, 60 capture significant level surprise (with a $t(\lambda) > 1.96$), 64 capture significant growth surprise (with a $t(\gamma) > 1.96$). 98 anomalies significantly capture at least one bias, with 19 capturing both, and 18 neither. The anomalies that capture both biases earn the largest alphas. Those that are capture only one bias earn lower alphas. The

[10] The negative sign on λ is consistent with Doukas et al. (2002) who find value firms are more likely to miss earnings forecasts and as a result argue that the value premium cannot be due to expectation errors.

anomalies that are unrelated to either bias earn the lowest alphas. To account for multiple testing, in Panel C, we raise the cutoff of the t-value to 3, following the suggestion by Harvey et al. (2016). The general pattern remains largely unaffected. These results confirm that biased beliefs are common drivers behind many anomalies. Furthermore, level and growth biases are about equally common among anomalies.

3.2 Level and growth biases in the principal component portfolios

We next quantify the importance of the two biases for the average return of anomaly portfolios. We do so in two ways. We discuss the first way in this subsection and the second in the next.

We extract the principal component portfolios from the anomaly returns. If the two biases are important, we should see that the first few principal components line up with them. This methodology is identical to the Table 4 in Kozak et al. (2018) (KNS) except now we have two forecast biases (λ and γ) while they have one bias δ, which is a version of our level bias but using market value of equity as the scaling variable. We base our choice of total assets as the scaling variable on the model in Appendix A.

Table 4 shows the first ten principal component portfolios and their characteristics. These portfolios are linear combinations of the original factor portfolios, ordered by the amount of total return variation they explain. We are interested in whether the level-growth bias are captured by *different* major principal components. If so, we can conclude that (1) the "sentiment demand" caused by the two biases are important common determinants of anomaly returns and (2) there are two kinds of "sentiments," one about the level and one about the growth.

The first and second columns in Table 4 report the λ and γ for the PC portfolios. They are the original portfolios' biases rotated into the PC space.[11] We see that the first PC

[11]They correspond to the β in the Table 4 in Kozak et al. (2018). All PC portfolios are normalized to

portfolio has a large and positive γ, at 10.4, and a slightly negative λ at -0.82. The second PC portfolio has a large and positive λ at 2.54 but a small and negative γ at -0.42.

The third and fourth columns assess the statistical significance of the two biases in the PC portfolios. The large $t(\gamma)$ in the first PC and $t(\lambda)$ in the second PC show that the first two PC portfolios *separately* capture the the level and growth biases. The fifth and sixth columns report the the total bias accounted for by each PC, computed as $\frac{\lambda_i}{\lambda'\lambda}$ and $\frac{\gamma_i}{\gamma'\gamma}$. We see that the first PC accounts for 80.26% of total growth bias and only 7.57% of the total level bias. The second PC accounts for 71.73% of the total level bias but only 0.13% of the total level bias. Thus, it would be approximately correct to state that within the comprehensive set of anomalies we study, the first PC is a growth bias factor while the second PC is a level bias factor. The first two PCs explain 38.7% and 19.8% of the total variation, or a combined amount of 58.5%. The variation explained by the third PC sharply decline to just 6.2%.

The columns $t(\alpha)$ and $t(\beta)$ report the t-values of the CAPM alpha and market beta. Not surprisingly, the first two PCs earn significant CAPM alphas, with t-values of 1.99 and 2.51. More interesting is the fact that the market betas of the first two PCs are both strongly negative. This is consistent with one of KNS's untested predictions that systematic mispricing should line up with systematic risk — it is difficult for arbitrageurs to eliminate the two bias-induced mispricing because doing so requires them to be net short the market or use derivatives to hedge the negative exposure, which is costly or for many institutions, not allowed.

Other PCs have little relation with the two biases. However, some of them have large values of $t(\alpha)$. The sources of their abnormal return can stem from other types of mispricing, risk- or other preference-based mechanism, but we do not explore this direction.

Our results regarding the principal component portfolios confirm that the two biases are indeed different and are both important.

have positive CAPM α for the each of interpretation.

3.3 The cross-section of alpha and alpha persistence

Alpha. A more direct way to assess the importance of the two biases is to examine to what extent λ and γ explain the cross-sectional variations in alphas. The alphas of the 123 factor portfolios are quite disperse. Existing interpretations of this dispersion include data mining, learning from academic publications, and small-stock bias in some earlier studies. Our test can quantify the importance of biased beliefs in explaining the alpha dispersion in our relatively recent sample period.

The first panel in Table 5 shows the results from simple OLS of CAPM alpha on λ and γ. In the panel on the right, we report the simple t-values and the t-values (in parentheses) using bootstrapped standard errors.[12] The first column indicates the horizon of the alphas. The first row, for example, uses the alpha in the first month of portfolio formation as the dependent variable. The coefficients of interest are β_λ and β_γ. We see that these two coefficients are 0.31 and 0.12 in the first row. The standard deviations of λ and γ are 0.27 and 0.95 as shown in Table 2. These numbers mean that a one-standard deviation increase of λ and γ relative to other anomalies in our sample are associated with 8.37 and 11.4 basis points increase in the monthly CAPM alpha. The (bootstrapped) t-values for β_λ and β_γ are high, at 6.15 (5.61) and 8.58 (7.38). The last column reports the adjusted-R^2 from the simple OLS. The R^2 in the first row is which range from 40.8%. This high R^2 is consistent with the results from the PCA in the last subsection.

Alpha persistence. We have so far motivated and validated the existence of the two different biases, empirically shown their separability and both important in explaining the cross-sectional variation of alphas. This whole exercise, however, is practically useful only if the two biases have different implications along some dimensions. In the remainder of this subsection, we show that growth bias is a major determinant of the persistence of mispricing.

[12] We use bootstrapping method to account for the correlation among anomalies and non-normality of returns. In the bootstrapping, we resample 123 observations with replacement with the number of trials equal to 5,000. Changing the number of trials do not affect the results.

In Table 5 starting from the second row, we report the OLS regression results using the alphas over different horizons as the dependent variables. We first estimate the monthly alpha in each month after portfolio formation, ranging from 1 to 25 months ahead. Then we sum the alphas over a horizon, such as from one to six, seven to twelve and so on, to compute the "cumulative alphas." We then regress these cumulative alphas on λ and γ. If a bias generates persistent alpha, we should see that its slope coefficient remains large and significant at long horizons. In rows two to six, we see that β_γ remain large and highly statistically significant during the two years after portfolio formation. In the first six months, β_γ is 0.81. From month 19 to 24, β_γ only decline slightly to 0.61. The t-value also only declines slightly from 11.59 (9.23) to 9.29 (8.23). In contrast, β_λ is only statistically significant in the first year of portfolio formation, with $\beta_\lambda = 1.88$ and 0.61 in the first and second six months. The R^2 of these regressions are very high, ranging from 43% to 55%, suggesting that the explanatory power of the biases extend beyond short-term return predictability.

[Table 5 here]

An alternative way to characterize persistence is that given the size of the initial alpha, how persistent this alpha is. The bottom panel tests the effects of the two biases on alpha persistence with this interpretation. We add into the regression the initial alpha of the factor, which is the alpha in the first month of portfolio formation. Then we shift the horizon of the dependent variables forward by one month. The results show that, after controlling for the initial alpha, level bias and growth bias significantly explain higher alphas in the second to sixth months, as indicated by the significant β_λ and β_γ for the $[2, 7]$ horizon. This means that compared to other anomalies that earn similar alphas without capturing expectation biases, those that do earn higher abnormal returns in the subsequent six months.

When we move beyond the first six months, however, the sign of β_λ becomes negative, and then significantly negative beyond the one-year horizon. In contrast, β_γ remains large and significantly positive. These results confirm the results in the first panel and show that

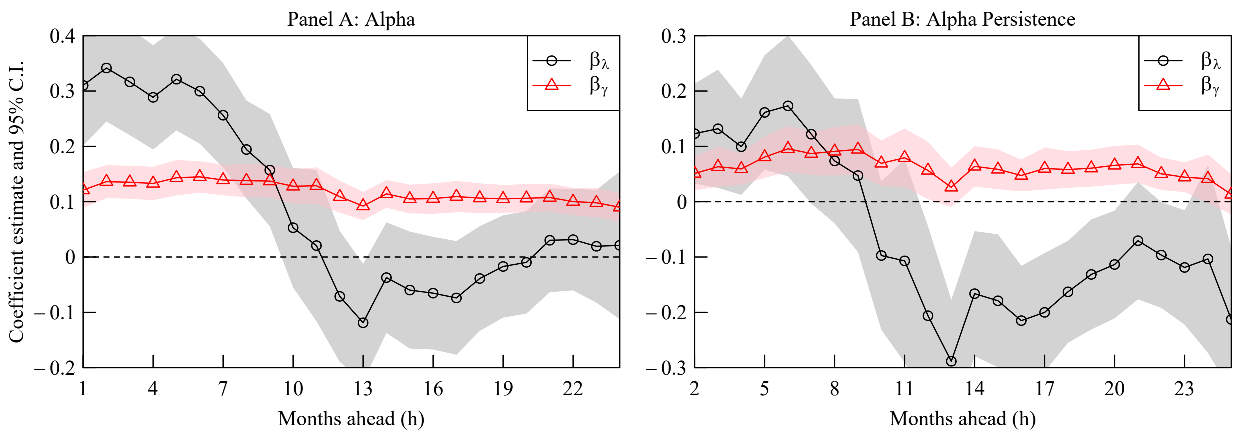

Figure 5: **Level, Growth and the Magnitude and Persistence of Alphas.** This table shows the Bootstrap average OLS regression coefficients (β_λ and β_γ) from: $\alpha_{h,i} = \beta_0 + \beta_\lambda \lambda_i + \beta_\gamma \gamma_i + \beta_{\alpha_1} \alpha_{1,i} + \epsilon_i$. h indexes for the number of months since the characteristic becomes publicly available. i indexes for characteristic. The regression for Panel A omits the regressor α_1. The $+/-$ 1.96 standard error bounds are obtained from 5,000 bootstrap trials that resample with replacement.

growth forecast bias is associated with highly persistent mispricing.

Figure 5 provides a visualization of these results using monthly alpha at different horizons as the dependent variables. Panel A shows the regression slopes β_λ and β_γ in the specification that only include λ and γ. Panel B shows the results for the specification that includes α_1 as an independent variable. The conclusions we have from Table 5 that anomaly portfolios that capture growth bias earn persistent alpha is illustrated quite clearly by the red lines that are persistently and significantly above zero over a two-year horizon.

PC persistence. An alternative way to test whether growth bias explains persistent differences in factor return is to examine the persistence of the importance of the "growth bias" principal component portfolios. We have shown in the last subsection that the first PC extracted from the *first-month* return of factor portfolios is essentially a growth bias PC, and the second one is the level bias PC. If growth bias matters for longer-horizon return variations, we should expect that (1) the first PC extracted from portfolio returns at different months since portfolio formation to be very similar and (2) the fraction of the total variation which the first PC explains should remain high even for returns many months after portfolio

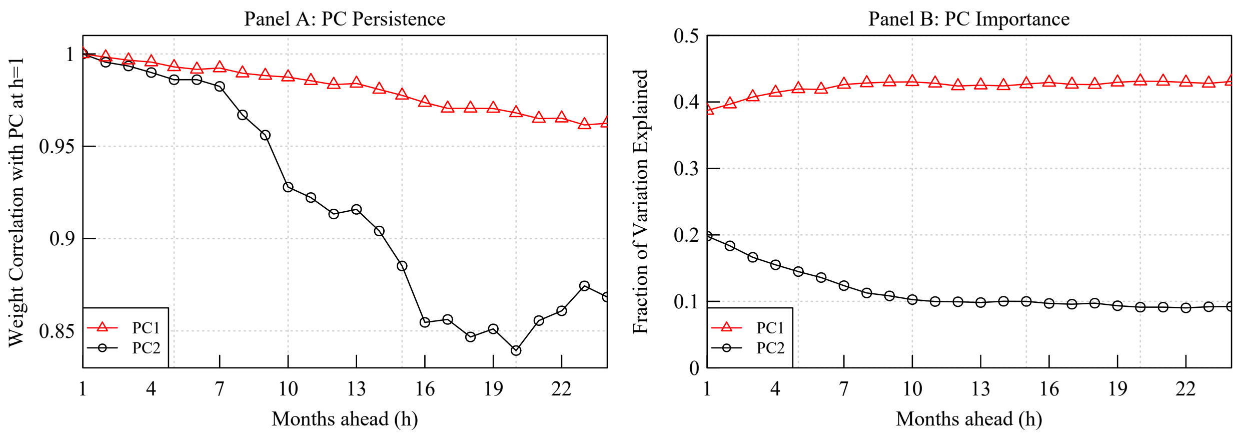

Figure 6: **Principal Component Portfolios Persistence and Importance.** Panel A plots the correlations between the weights of the PCs extracted from anomaly portfolio returns in month 1 and month h since portfolio formation. A high value means the PC for the month-h returns is similar to the PC for the first-month return. Panel B plots the fraction of month-h return variation explained by the first and second PCs extracted from month-h returns.

formation.

Figure 6 plots the persistence and the importance of the first and second principal components as a function of the number of months since the anomaly portfolio formation. Panel A shows the correlation in the weight vectors of the first-month PCs and those of the month-h PCs. A value close to 1 means that the PC extracted from month-h return variation is similar to that extracted from the first-month return variation. Indeed, we see that PC1, the growth bias PC, remains very similar much in the subsequent two years. The correlation between the first-month PC1 and month-h PC1 stays above 95% even at $h = 24$. In contrast, PC2 appears to change its identity sharply between month 7 and month 16. The month-24 PC2 only correlates with the first-month PC2 at about 87%. Panel B shows the fraction of total month-h return variation explained by their first two PCs. We see that the PC1 across all h explain about 40% of the total return variation, while the fraction explained by PC2 declines quickly from around 20% initially to 10% in the tenth month.

3.4 Factor Momentum and Persistent Mispricing

Ehsani and Linnainmaa (2022) show that most factors exhibit momentum and this factor momentum gives rise to individual stock momentum. To the extent that factor momentum may represent continuous price correction, an interesting question is whether the type of expectation bias matters. We answer this question using a two-step regression similar to that in the previous subsection. We first estimate the first-order autoregressive coefficient (ρ) for each of the 123 factor returns. Then we regress ρ on λ and γ:

$$\begin{aligned} R_{i,t} &= a_i + \rho_i R_{i,t-1} + \eta_{i,t}, \\ \rho_i &= \delta_0 + \delta_\lambda \lambda_i + \delta_\gamma \gamma_i + \epsilon_i. \end{aligned} \tag{3}$$

The coefficients of interest are δ_1 and δ_2, which capture the incremental factor momentum associated with the increase the in the two spreads.

Table 6 shows the results from the second regression. First, we see that factors exhibit strong momentum, as indicated by the highly significant δ_0 estimate. Second, δ_λ is negative and δ_γ is significantly positive, suggesting that factor momentum is more pronounced if the factor captures growth forecast error.

In terms of the economic magnitude, the unconditional average ρ is 6.87%, which means that a one percent increase in the factor return last month predicts a 6.87 bps increase in expected factor return this month. A one-standard-deviation increase in γ is associated with (0.95×1.99=)1.91 bps increase (27.8% of the unconditional mean) in the factor momentum effect. In contrast, a one standard deviation increase in λ is associated with a decrease of $(0.27\times -3.84=)-1.04$ bps decrease in the factor momentum.

Figure 7 plots the 123 anomaly portfolios in the $t(\rho)$-$t(\gamma)$ space. We see a clear upward-sloping association between $t(\rho)$ and $t(\gamma)$, suggesting that the factors that reliably capture growth forecast bias more consistently exhibit momentum.

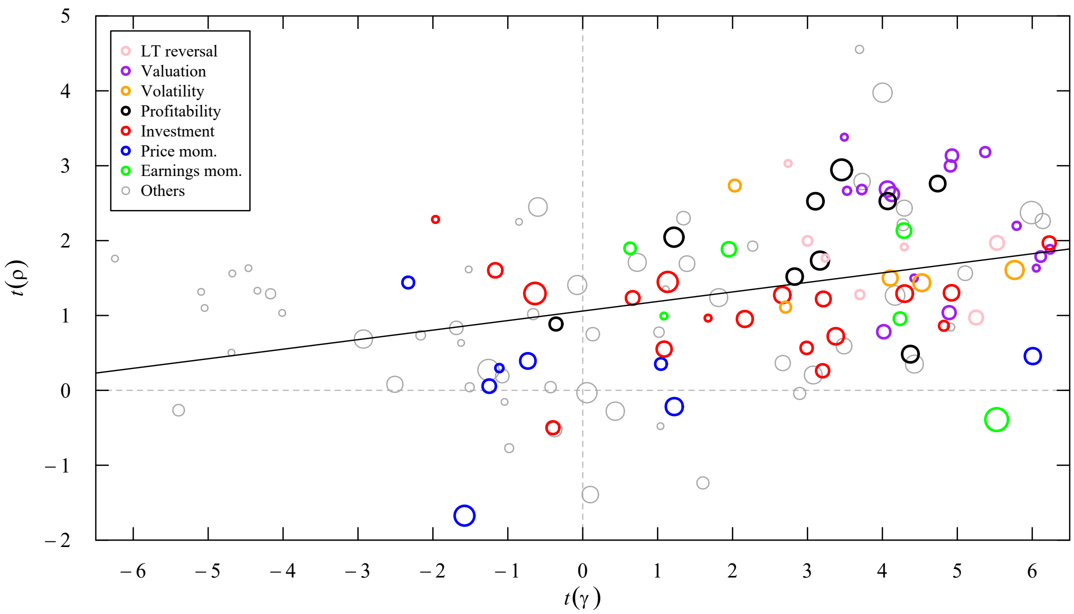

Figure 7: **Factor Momentum and Growth Bias.** This figure plots the locations of 123 anomalies in the $t(\rho)$-$t(\gamma)$ space. ρ is estimated for each anomaly with the regressions $R_{i,t} = a_i + \rho_i R_{i,t-1} + \eta_{i,t}$, where $R_{i,t}$ is the return of factor i in month t. The slopped solid line is the best fitted line of $t(\rho)$ on $t(\gamma)$: $y = 1.06 + 0.13x$. The R^2 of the fit is 13.0%.

4 Biases Decay and Alpha Decay

People learn. In this section, we briefly explore how expectation biases have evolved over time and whether their changes have affected anomaly returns. Existing studies show that most anomalies perform poorly after 2002. We hypothesize that this decay in their performance may be due to increased forecast accuracy.

Table 7 shows the factor-level average statistics in the pre- and post-2002 sample. The first two columns show that the average factor in our sample earns a CAPM alpha of 0.36 percent per month and the average t-value is 5.53. The post-2002 CAPM alpha, however, averages at only 0.07% and the average t-value is 2.80. The average monthly Sharpe Ratio also decreases from 0.26 to 0.10. The panel on the right shows the average level and growth biases captured by the factors in the two subperiods. The average factor captures 0.11 level bias in the earlier sample but this number becomes zero in the later period. This decline also appears for the growth bias. The average $t(\gamma)$ increases in the later sample period, suggesting that the average factor can still profit from betting against the growth bias.

Table 8 links the bias decay and alpha decay for factors. We sort anomaly portfolios into quintiles by the magnitude of decay in λ and γ. The first panel shows that, for the anomalies whose ability to capture level bias decline the most in the post-2002 period, the alpha decay is 0.18% and the decay in monthly Sharpe Ratio is 4.16. The alpha decay is much smaller for anomalies to do not experience a λ decay. The difference in alpha and Sharpe ratio decay between the high and low λ decay quintiles are 0.18 and 3.47. The t-values from these two differences are 2.34 and 1.56. The second panel shows the same pattern for γ decay, except the results now are more statistically significant. The difference in alpha decays between the high and low γ decay groups are 0.33 and 6.00, with t-values of 4.86 and 2.74. These results suggest that the change in expectation biases are likely responsible for the change in the factors' performance.

Table 9 shows the stock level statistics. The first two rows compare the average surprise and surprise dispersion in the two periods. The numbers are yearly averages of monthly averages. We see that a typical stock in a typical year before 2002 misses earnings forecasts, indicated by the negative $LSurp$. This number changes to positive in the later period. The typical growth surprise is deeply negative in the pre-2002 sample, while this magnitude is reduced by half in the recent sample. The last two columns show that the dispersion in the level and growth surprises have also declined in the recent periods. These results suggest that analysts' level and growth forecasts have both become less overly optimistic. The typical level forecast even has become overly pessimistic. The dispersion of the surprise has declined by about one-third, suggesting the forecasts have become more accurate.

5 Alternative Interpretations

We discuss two alternative interpretations for our results. First, the relations we find between anomalies and the two biases may reflect in-sample cash flow shocks rather than ex ante expectation errors. Second, the results could be due to analysts' misaligned incentives that distort prices, rather than investors genuinely form biased beliefs.

The first issue mirrors the joint hypothesis problem in tests of market efficiency—one must take a stance on what the correct model of expectations is to test whether systematic biases exist. Our preferred interpretation depends on ex post realizations being good proxies for the ex ante rational expectations, but this needs not be the case. For example, Hou and van Dijk (2019) show that the disappearance of the size effect in recent data is likely due to large firms consistently receiving positive profitability shocks. Following their description, we can restate our results as: cash flow level shocks and growth shocks are two important determinants of anomaly returns, but these shocks may not repeat in the future.

Yet, we find the "cash flow shocks" interpretation less appealing because the hedged portfolios are well diversified. It is hard to argue why cash flow shocks are so often and so significantly positive for one group of firms and strongly negative for another by firm characteristics. Beliefs, on the other hand, have been shown to be subject to various biases for reasons such as inattention, informational frictions, overconfidence and extrapolation. These biases often correlate with firm characteristics such as valuation ratios, past performance, cash flow volatility and information environment. Thus it is conceivable that many characteristics within these common themes can serve as noisy proxies for the biases.

The second issue relates to whether analysts' forecasts can indeed represent investors' forecasts. It is well-known that analysts' forecasts, especially those at longer horizons, are overly optimistic on average. Researchers sometimes attribute this overoptimism to incentive misalignment. For example, analysts may want to curry favor to the management to gain access to better information or generate investment banking business. Investors' beliefs, which would be otherwise unbiased, may be distorted by analysts' misleading forecasts.

We do not take a stance on how much of the biased beliefs are from the agency problem and how much of the biases is from nature. We believe this is an important and general question that deserves separate investigation. Similarly, we do not discuss the potential mechanism that drive the two types of biases. We focus on, and only on, showing the sharp distinction between cash flow level and growth biases, as well as their effects on asset prices.

6 Conclusion

We show that investors appear to form beliefs about cash flow level and cash flow growth separately. Anomaly returns exhibit different properties depending on which bias the variable associates with. Our results suggest that when modeling subjective beliefs, one may need to have two processes, one for cash flow level and one for cash flow growth. Future research on the interactions between the two expectations can be fruitful.

Table 1: Validating the Theory: Principal Component Analysis and Correlations

Panel A shows loadings (eigenvectors) of the Principal Components of the analysts' monthly consensus earnings forecasts at different annual and quarterly horizons. Panel B shows the loadings of the change in earnings forecasts at different horizons. The PCA is conducted using firm-month level observations for which forecasts or forecast revisions are available at all applicable horizons. Panel C shows the correlation matrix of growth and forward growth forecasts over the three annual horizons (i.e., from year zero to one, from one to two, from two to three). Growth forecasts from year n to year n+1 equal to the consensus earnings forecast for year n+1 minus that for year n. Earnings forecasts and growth forecasts are all scaled by lagged total assets. We cross-sectionally winsorize the variables each month at the second and ninety-eighth percentiles.

Panel A: Principal Component Analysis on the Forecast Term Structure

Annual Forecast				Quarterly Forecast				
Horizon	PC1	PC2	PC3	Horizon	PC1	PC2	PC3	PC4
Yr.1	0.57	−0.64	−0.51	Qtr.1	0.50	−0.67	−0.47	−0.30
Yr.2	0.61	−0.09	0.79	Qtr.2	0.50	−0.29	0.57	0.58
Yr.3	0.55	0.76	−0.34	Qtr.3	0.50	0.38	0.42	−0.65
				Qtr.4	0.50	0.57	−0.53	0.38
Cum. Prop	88.0%	99.0%	100.0%		90.7%	95.0%	98.0%	100.0%

Panel B: Principal Component Analysis on the Forecast Term Structure Revision

Annual Forecast Revision				Quarterly Forecast Revision				
Horizon	PC1	PC2	PC3	Horizon	PC1	PC2	PC3	PC4
Yr.1	0.57	−0.61	−0.55	Qtr1	0.47	−0.75	−0.44	−0.19
Yr.2	0.62	−0.12	0.78	Qtr2	0.52	−0.17	0.60	0.59
Yr.3	0.54	0.78	−0.31	Qtr3	0.52	0.31	0.34	−0.72
				Qtr4	0.49	0.57	−0.58	0.32
Cum. Prop	70.1%	90.1%	100.0%		74.2%	87.1%	94.7%	100.0%

Panel C: Correlation between Growth Forecasts and Forward Growth Forecasts

	Yr.0 to 1	Yr.1 to 2	Yr.2 to 3
Yr.0 to 1	1	0.23	0.09
Yr.1 to 2	0.23	1	0.66
Yr.2 to 3	0.09	0.66	1

Table 2: Descriptive Statistics

This table reports the summary statistics for the main variables in our study. $LSurp$ and $GSurp$ are the ex post level surprise and growth surprise defined in Eq.(2). α is the value-weighted monthly CAPM alpha of the anomaly long-short portfolio. λ and γ are the average level and growth surprise spread of the anomaly portfolios. $t(.)$ are the t-values associated with the estimate. Section 2.2 and 2.3 describes these variables in detail. The last row displays the Spearman rank correlation coefficients between the variables.

	Count	Mean	SD	Min	p25	p50	p75	Max
$LSurp(\%)$	671,978	0.01	2.65	−32.40	−0.38	0.07	0.74	17.83
$GSurp(\%)$	341,344	−1.52	5.72	−103.17	−1.91	−0.34	0.32	20.20
$LSurp$ spread (λ)	123	0.06	0.27	−0.67	−0.05	0.05	0.17	0.85
$t(\lambda)$	123	1.39	6.67	−16.98	−1.19	1.74	4.62	20.89
$\|t(\lambda)\|$	123	5.03						
$GSurp$ spread (γ)	123	0.46	0.95	−2.42	−0.08	0.34	1.01	2.55
$t(\gamma)$	123	1.70	3.08	−6.24	−0.62	2.27	4.20	6.24
$\|t(\gamma)\|$	123	3.01						

	$(LSurp, GSurp)$	(α, λ)	(α, γ)	(λ, γ)
Correlation	0.04	0.23	0.44	−0.37

Table 3: Level Bias, Growth Bias and Anomalies

This table shows the average λ, γ and α and the average corresponding t-values by anomaly categories (Panel A). Panel B and C provide a summary of how the anomalies are associated with level and growth surprises overall. An anomaly is about level or growth bias if the t-values of λ and γ are greater than 1.96 or 3. The detail list of the anomalies, their categorization and the individual estimates are in Table A.3 in the Appendix.

Panel A: Results by Anomaly Type

Category	λ	γ	α	$t(\lambda)$	$t(\gamma)$	$t(\alpha)$	N
Investment	0.04	0.28	0.21	1.32	2.13	2.33	18
Valuation	−0.28	1.69	0.23	−6.41	4.78	1.23	15
Profitability	0.28	0.87	0.42	6.84	2.96	3.20	9
External financing	0.08	0.61	0.30	2.49	2.20	2.95	9
Price momentum	0.54	0.05	0.38	10.77	0.16	2.38	8
Seasonality	0.03	0.07	0.28	2.24	0.47	2.91	8
LT reversal	−0.28	0.95	0.17	−7.23	3.96	1.00	7
Earnings momentum	0.29	0.61	0.22	8.52	2.95	2.35	6
Volatility	0.07	1.35	0.42	1.42	3.83	2.41	5
Sales growth	0.10	−0.05	0.07	3.63	−0.48	0.84	5
Accruals	0.13	0.27	0.19	4.53	0.83	2.23	4
Liquidity	−0.11	−0.14	0.14	−3.71	−1.13	0.85	4
Asset composition	0.20	−1.13	0.14	4.48	−2.40	1.43	4
Leverage	0.13	−1.09	0.02	2.72	−3.66	0.31	4
Intangible	−0.09	−0.15	0.24	−0.85	−0.58	2.34	3
Skewness	−0.15	0.12	0.08	−10.13	1.22	1.02	3
Lead lag	0.06	0.09	0.03	1.46	0.41	0.18	3
Volume	0.06	1.71	0.44	1.33	4.64	3.35	2
Composite accounting	0.04	0.21	0.09	1.10	0.52	0.85	2
Short sale	0.09	0.89	0.45	2.50	5.99	5.67	1
Ownership	0.62	−0.07	0.25	12.79	−0.38	2.47	1
Industry concentration	0.12	−0.86	−0.03	4.60	−4.01	−0.23	1
Age	0.05	−0.57	−0.19	1.29	−4.34	−2.53	1
Average	0.09	0.25	0.20	1.99	0.87	1.72	

Panel B: Overall Summary using $t > 1.96$ as cutoff

	Level	Level only	Growth	Growth only	Either	Both	Neither	All
Count	60	41	64	45	105	19	18	123
α	0.26	0.20	0.30	0.25	0.26	0.41	0.08	0.23
$t(\alpha)$	2.46	2.09	2.19	1.73	2.15	3.26	0.75	1.94

Panel C: Overall Summary using $t > 3$ as cutoff

	Level	Level only	Growth	Growth only	Either	Both	Neither	All
Count	47	36	54	43	90	11	33	123
α	0.26	0.19	0.31	0.27	0.26	0.47	0.14	0.23
$t(\alpha)$	2.37	2.01	2.25	1.92	2.15	3.53	1.38	1.94

Table 4: Bias in Principal Component Portfolios

This table uses principal component portfolios based on 123 HML-style long-short anomaly strategies. λ and γ are the average level and growth bias spreads for the Principal Component portfolios. $t(\alpha)$ and $t(\beta)$ are the t-values of the CAPM alpha and beta of the Principal Component portfolios. All t-values are computed using Newey-West adjusted standard errors with 12 lags. % $\lambda'\lambda$, % $\gamma'\gamma$, % Var. show how much of the variation in level bias, growth bias and total return variation are accounted for by the Principal Component.

PC	λ	γ	$t(\lambda)$	$t(\gamma)$	% $\lambda'\lambda$	% $\gamma'\gamma$	$t(\alpha)$	$t(\beta)$	% Var.
1	−0.82	10.40	−3.52	5.05	7.57	80.26	1.99	−4.84	38.7
2	2.54	−0.42	15.25	−0.66	71.73	0.13	2.51	−3.72	19.8
3	0.01	−0.18	0.08	−0.26	0.00	0.02	0.66	1.26	6.2
4	0.40	2.27	4.68	4.48	1.79	3.83	0.60	2.73	3.5
5	0.40	1.58	5.37	3.52	1.81	1.86	2.83	0.88	2.9
6	0.08	0.61	1.11	1.92	0.07	0.28	2.29	−1.90	2.4
7	0.17	0.72	4.20	3.23	0.32	0.38	2.78	−0.26	2.1
8	0.62	0.25	7.28	1.10	4.26	0.05	5.83	0.57	1.8
9	−0.07	−1.09	−1.25	−3.57	0.06	0.87	3.47	−1.07	1.5
10	−0.03	1.08	−0.50	2.72	0.01	0.87	0.24	1.10	1.2

Table 5: Level, Growth and the Magnitude and Persistence of Alphas

This table reports the results from OLS estimates from regressing the 123 anomaly portfolios' alphas on λ, γ and initial alphas: $\sum_h \alpha_{h,i} = \beta_0 + \beta_\lambda \lambda_i + \beta_\gamma \gamma_i + \beta_{\alpha_1} \alpha_{1,i} + \epsilon_i$. The dependent variable is the sum of the monthly value-weighted CAPM alphas over the horizon h. i indexes for anomaly portfolios. The first panel excludes the regressor α_1. The left panel shows the OLS estimates. The right panel reports the t-values and the bootstrapped t-values (in parentheses). The last column reports the adjusted-R^2. The bootstrapping procedure resamples 5,000 times with replacement.

Horizon	β_0	β_λ	β_γ	β_{α_1}	$t(\beta_0)$	$t(\beta_\lambda)$	$t(\beta_\gamma)$	$t(\beta_{\alpha_1})$	$Adj.R^2$
$[1, 1]$	0.16	0.31	0.12		10.79	6.15	8.58		40.8%
					(9.18)	(5.61)	(7.38)		
$[1, 6]$	0.66	1.88	0.81		8.98	7.50	11.59		54.8%
					(7.84)	(7.23)	(9.23)		
$[7, 12]$	0.46	0.61	0.78		6.20	2.40	11.02		49.8%
					(5.40)	(2.05)	(8.82)		
$[13, 18]$	0.42	−0.39	0.63		5.95	−1.74	9.34		47.6%
					(5.83)	(−1.34)	(8.09)		
$[19, 24]$	0.23	0.08	0.61		3.33	0.23	9.29		43.3%
					(3.29)	(0.27)	(8.23)		
$[1, 24]$	1.76	2.17	2.83		6.64	2.33	11.13		50.4%
					(6.08)	(2.14)	(9.02)		
$[2, 7]$	0.07	0.81	0.44	3.25	0.92	3.66	6.30	9.00	72.8%
					(1.01)	(2.78)	(4.20)	(5.76)	
$[8, 13]$	0.08	−0.58	0.42	2.59	0.96	−2.30	5.65	6.59	62.4%
					(0.88)	(−1.51)	(3.26)	(3.70)	
$[14, 19]$	−0.04	−1.05	0.35	2.44	−0.44	−4.38	4.64	6.28	59.8%
					(−0.48)	(−3.63)	(3.49)	(4.43)	
$[20, 25]$	−0.13	−0.72	0.28	2.43	−1.56	−3.16	4.09	6.67	57.0%
					(−1.60)	(−2.29)	(3.06)	(4.55)	
$[2, 25]$	−0.01	−1.54	1.48	10.72	−0.03	−1.79	5.75	7.91	66.9%
					(−0.05)	(−1.33)	(3.65)	(4.73)	

Table 6: Factor Momentum and Biases

This table reports the results from OLS estimates from regressing the 123 anomaly portfolios' first-order autoregressive coefficient ρ on λ, γ. The regression equation is: $\rho_i = \delta_0 + \delta_\lambda \lambda_i + \delta_\gamma \gamma_i + \epsilon_i$. ρ is estimated for each anomaly with the regressions $R_{i,t} = a_i + \rho_i R_{i,t-1} + \eta_{i,t}$, where $R_{i,t}$ is the return of factor i in month t. The left panel shows the coefficient estimates, scaled up by 100. The right panel reports the t-values and the bootstrapped t-values (in parentheses). The last column reports the adjusted-R^2. The bootstrapping procedure resamples 5,000 times with replacement.

Coefficient × 100			t-value			
δ_0	δ_λ	δ_γ	$t(\delta_0)$	$t(\delta_\lambda)$	$t(\delta_\gamma)$	$Adj.R^2$
6.18	−3.84	1.99	10.67	−1.96	3.61	16.7%
			(9.30)	(−1.91)	(3.76)	

Table 7: Level and Growth Bias before and after 2003

This table reports the average level and growth bias spread averaged over the 123 anomaly portfolios. We equally weighted each portfolio to form a portfolio of portfolios. The t-values are Newey-West adjusted with 12 lags. The pre–2003 sample is from 1985:07 to 2002:12. The post–2003 sample is from 2003:01 to 2019:12.

			Average bias spread			
	CAPM alpha		λ		γ	
	Pre	Post	Pre	Post	Pre	Post
Average estimate	0.36	0.07	0.11	0.00	0.66	0.24
Average t-value	5.53	2.80	8.15	0.20	6.20	8.44
Sharpe Ratio	0.26	0.10				

Table 8: Alpha and Sharpe Ratio Decay after 2003

This table reports the alpha and Sharpe Ratio decay for each bias decay quintile. We sort anomalies by their bias decay after 2003, defined as the average spread from 1985:07 to 2002:12 minus the average spread from 2003:01 to 2019:12. Alpha decay and Sharpe Ratio decay are computed analogously. Alpha is the CAPM alpha of the HML-style factor portfolio. Sharpe Ratio is the average divided by the standard deviation of monthly portfolio return (multiplied by 100 for exposition purpose). The t-values of H−L are from a two sample t-tests.

	Level spread decay quintile						
	1(L)	2	3	4	5(H)	H−L	t(H−L)
Alpha decay	0.00	0.12	0.17	0.20	0.18	0.18	2.34
Sharpe Ratio decay	0.68	3.21	7.06	5.31	4.16	3.47	1.56
	Growth spread decay quintile						
	1(L)	2	3	4	5(H)	H−L	t(H−L)
Alpha decay	−0.01	0.04	0.11	0.21	0.32	0.33	4.86
Sharpe Ratio decay	0.74	3.24	3.94	5.64	6.74	6.00	2.74

Table 9: Average Surprise and Surprise Dispersion before and after 2003

This table reports the average and dispersion of level and growth surprise for our monthly stock sample before and after 2003. We report both equally-weighted and value-weighted average, and the standard deviation. We first compute the monthly statistics and then average them over the calendar year. The t-values are from two-sample t-tests using the pre– and post–2003 sample (which have 18 and 17 sample points, respectively).

	EW Average		VW Average		Dispersion	
	LSurp	GSurp	LSurp	GSurp	LSurp	GSurp
Pre (1985 to 2002)	−0.35	−2.26	−0.13	−1.00	2.96	6.43
Post (2003 to 2019)	0.29	−1.08	0.37	−0.55	2.04	3.96
Diff.	0.65	1.18	0.50	0.45	−0.92	−2.47
t(Diff.)	6.43	2.37	5.38	1.26	−4.59	−2.66

A A Model of Level–Growth Expectations

In this section, we provide an illustrative model of two expectations. A representative investor prices a firm. The representative all-equity firm pays out all earnings as dividends at times 1, and 2, and 3 and then liquidates at zero value. The investor prices the firm at time 0 using a present value formula. Then, the correct market value of equity of the firm at time 0 (ME_0) is simply the sum of the three discounted expected cash flows:

$$ME_0 = \delta_1 \mathbb{E}[\tilde{CF_1}] + \delta_2 \mathbb{E}[\tilde{CF_2}] + \delta_3 \mathbb{E}[\tilde{CF_3}], \tag{A.1}$$

where $\tilde{CF_t}$ denotes the random cash flow at time t and $\mathbb{E}[.]$ is the mathematical (rational) expectation operator. δ_t is the discount factor for dividends paid at time t. We let the investor form biased expectations for the next-period cash flow level and subsequent growth using the operator $\mathbb{E}^s[.]$ which take the general forms below:

$$\begin{aligned} \mathbb{E}^s[\tilde{CF_1}] &= \mathbb{E}[\tilde{CF_1}] + \eta, \\ \mathbb{E}^s[\tilde{g}] &= \mathbb{E}[\tilde{g}] + \xi. \end{aligned} \tag{A.2}$$

η and ξ represent the biases in the cash flow level and cash flow growth, regardless of the mechanism. To simplify notation, we use $\bar{x}$ to replace $\mathbb{E}[x]$. Thus the actual valuation of the firm by the investor is:

$$ME_0^A = \delta_1(\bar{CF}_1 + \eta) + \delta_2(\bar{CF}_1 + \eta)(1 + \bar{g} + \xi) + \delta_3(\bar{CF}_1 + \eta)(1 + \bar{g} + \xi)^2. \tag{A.3}$$

We further simplify this equation by dropping the higher order terms $\bar{g}^2$, ξ^2, and $\bar{g}\xi$, so that $(1+\bar{g}+\xi)^2 \approx 1+2\bar{g}+2\xi$. This simplification is equivalent to a first order approximation and does not affect the results but greatly simplify the math. The market value of the firm is then:

$$ME_0^A \approx \delta_1(\bar{CF}_1 + \eta) + \delta_2(\bar{CF}_1 + \eta)(1 + \bar{g} + \xi) + \delta_3(\bar{CF}_1 + \eta)(1 + 2\bar{g} + 2\xi). \qquad \text{(A.4)}$$

The term structure of forecast error—the case of market-to-book: Let K be the total assets. If the firm is all financed by equity, K is also the book-value of equity. Divide both sides by K, so that the left-hand-side becomes the market-to-book equity:

$$\frac{ME_0}{K} = \delta_1\frac{\bar{CF}_1 - \eta}{K} + \delta_2\frac{(\bar{CF}_1 - \eta)(1 + \bar{g} + \xi)}{K} + \delta_3\frac{(\bar{CF}_1 - \eta)(1 + 2\bar{g} + 2\xi)}{K}, \qquad \text{(A.5)}$$

which can be decomposed into a rational component $R(\frac{ME_0}{K})$ and a bias component $B(\frac{ME_0}{K})$:

$$\begin{aligned} R(\frac{ME_0}{K}) &= \delta_1\frac{\bar{CF}_1}{K} + \delta_2\frac{\bar{CF}_1(1+\bar{g})}{K} + \delta_3\frac{\bar{CF}_1(1+2\bar{g})}{K}, \\ B(\frac{ME_0}{K}) &= \delta_1\frac{\eta}{K} + \delta_2\frac{\bar{CF}_1\xi + \eta(1+\bar{g}+\xi)}{K} + \delta_3\frac{2\bar{CF}_1\xi + \eta(1+2\bar{g}+2\xi)}{K}. \end{aligned} \qquad \text{(A.6)}$$

The three terms of $B(.)$ correspond exactly to the (discounted) forecast errors at different horizons scaled by total assets (or book equity). The expressions above show that the biases component of market-to-book can be driven by both level and growth biases, but the two biases would lead to a different forecast error term structure.

Existing evidence suggests that firms with high MB are likely overvalued. If MB primarily captures misvaluation caused by an inflated cash flow level expectation, that is $\eta > 0$ and $\xi \approx 0$, MB should be associated with approximately the same forecast errors over different horizons (i.e. it predicts a flat forecast error term structure) for $\bar{g} \approx 0$ and $\delta_t \approx 1$. If MB captures the errors in the growth forecast ($\eta \approx 0$ and $\xi > 0$), then MB should predict an upward sloping forecast error term structure. Furthermore, the incremental forecast error that MB predicts at subsequent horizons should be approximately equal—that is, the regression coefficient of forecast errors at horizon 1, 2 and 3 on MB should be approximately

0, β, 2β where β is some positive value.

The same reasoning can be generalized to any firm characteristics. Thus, we have a general regression-based method to test whether any firm characteristic x captures cash flow level bias or growth bias.

Proposition 1. ***Firm characteristics, level bias and growth bias.*** *If a firm characteristic x primarily captures biased beliefs about the cash flow level (η), it should predict forecast errors over different horizons with similar magnitude. If x primarily captures biased beliefs about the cash flow growth, it should more strongly predict forecast errors at further horizons.*

We empirically implement this proposition in the left panels of Table A.1 and find that MB mostly captures the growth bias while momentum primarily captures the level bias. We describe this implementation in the next subsection.

B Slow Correction of Growth Forecast Error

The abnormal returns earned by anomalies related to growth bias are highly persistent. This implies that investors correct growth forecast errors only slowly. For the level forecast errors, the correction is faster. In this subsection, we show that this is indeed what is happening in the data. For brevity, we focus on just two most prominent but representative anomalies — value and momentum. As shown in Figure 4, the value-type strategies profit from capturing growth forecast bias while price momentum mostly captures only the level forecast bias. We select the most well-known version of these anomalies, namely, those related to book-to-market equity and the past-11-month stock return.

We focus on the time window around earnings announcements when a large amount of information flows to the market, supposedly correcting the forecast errors. To test the speed of error correction, we compare two quantities: the ex post forecast error predicted by a variable and the forecast revision predicted by the same variable. If error correction is always timely and in full, these two quantities should be approximately equal.

In our theory, the forecast term structure primarily takes two movements: a parallel shift and a rotation. The two movements correspond to a change in the level forecast and a change in the growth forecast. If the level errors correct more quickly than growth errors, we expect that (1) the term structure movement around earnings announcements significantly shifts in parallel, and this shift predicted by the characteristic x should be close to the ex post errors predictable by this x. (2) The movement lacks the rotation required to offset the slope of the ex post forecast error term structure predicted by x.[13]

Table A.1 reports the results of pooled OLS regressions in which the dependent variables are the ex post forecast error and the forecast revision. We measure ex post forecast errors using the difference between the actual earnings in the future and the consensus forecasts in the month before earnings announcements (at $t-1$). We measure forecast revision as the change in the consensus forecast from $t-1$ to $t+1$. Note that the revisions are computed using the forecasts for the same fiscal year, not for the same horizon, because the horizon for these forecasts has just decreased by one period after the announcement. The independent variables are the natural log of book-to-market equity and past-11-month return, which are cross-sectionally standardized to facilitate comparison with results for other variables.

Panel A presents the results using annual forecasts around firms' forth quarter earnings announcements. The first three columns show the relation between firm characteristics and ex post forecast error over the three annual horizons. The first coefficients of -0.04 means that a one standard deviation increase in log(BM) is associated with an average decrease of 0.04 percent of total assets in earnings surprise. Thus, value firms are more likely to report disappointing earnings numbers, consisistent with Doukas et al. (2002). However, the second and third columns show that log(BM) is significantly associated with higher year 2 and year 3 forecast surprise, with coefficients of 0.58 and 1.82. Thus analysts, despite being overly

[13] Please see Appendix A for an illustrative model that details the intuition of this test.

optimistic about value firms for year 1, are overly pessimistic for these firms for year 2 and year 3. The coefficient estimates increase from year 2 to year 3, which is consistent with our earlier conclusion that value-type anomalies are associated with biased growth forecasts.

The "Revision" panel shows how analysts revise their forecasts after earnings announcements. We see that log(BM) significantly predict analysts' forecast revisions. A one-standard-deviation increase in log(BM) is associated with an upward forecast revisions of 0.18 and 0.21 percent of total assets for the subsequent two fiscal years. The point, however, is that such revisions are "too flat" relative to the true ex post forecast error term structure. The revision coefficient for the next-period forecast, 0.18 accounts for (0.18/0.58=)31% of the ex post error predicted. Yet, the Yr.3→2 revision, accounts for only (0.21/1.82=)11.5% of the error predicted ex post. In brief, the steep slope of the forecast error term structure predicted by log(BM) does not match with the almost parallel shift in the forecast term structure. The last two columns are somewhat redundant, but useful for connecting these results with the rest of the paper: the dependent variables are (1) the forecast error in growth, which is simply the difference between the Yr.3 and Yr.2 forecast error, and (2) the revision in growth, which is the difference between the Yr.3 and Yr.2 revisions after the announcements. The point estimates therefore are equal to (up to rounding error) the difference between the coefficients in columns three and two, $1.82 - 0.58 = 1.25$ and in columns five and four $0.21 - 0.18 = 0.02$. The point is to show that the growth revision of 0.02 is economically small and also statistically insignificant, and therefore further highlight the lack of rotation in the forecast term structure movement.

The second Panel presents the results for momentum. We see that $\text{Ret}_{-12,-1}$ is significantly associated with forecast errors in year 1 and year 2, but is uncorrelated with forecast errors in year 3. The results in the "Revision" panel shows that analysts shift the forecast term structure in parallel with some rotation that reflects an upward revision in growth forecast. These results show that, analysts revise the level forecast in the correct direction for momentum stocks, but have the growth forecast revised the wrong way. This finding is novel in that it reveals belief correction and distortion can happen at the same time because they take effect through different estimation parameters. Therefore, a price correction and a price deviation can take place at the same time, and the net effect of information on prices therefore can be ambiguous.

Panel B presents the results using quarterly forecasts and quarterly earnings announcements and the results show the same three patterns: (1) log(BM) predicts disappointing quarterly earnings results, but also predict increasingly favorable surprises at longer horizons, indicating that analysts overestimate value firms' cash flow level but underestimate their growth. (2) log(BM) only predicts a parallel shift without a rotation of the forecast term structure, suggesting that growth forecast error correction is very slow. (3) Past stock return predicts a similar level of forecast error across the four quarterly horizons, and the correction in cash flow level is relatively complete, matching about 50% of the ex post predictable errors.

In this subsection, we use to well-known value and momentum characteristics to demonstrate that the level bias is often corrected relatively quickly while growth bias correction is slow. From these results we can validate again our level-growth framework in that short- and long-horizon cash flow forecasts often move together, as seen from the similar revision coefficients at different horizons. Thus, short- and long-horizon does not well classify the "typical movements" of the forecast term structure dynamic, while the level-growth description seems to do a better job.

Table A.1: Forecast Error and Revision around Earnings Announcements

This table shows the results from pooled regressions in which the dependent variables are analysts' earnings forecast error and forecast revision, and the independent variable is the natural logarithm of book-to-market equity or 11-month stock return, which are both lagged by one month and cross-sectionally standardized. The regression equations are of the form:

$$y_{i,t} = \beta_0 + \beta_1 x_{i,t-1} + \mathbf{\Gamma D_t} + \epsilon_{i_t},$$

where $\mathbf{D_t}$ is a full set of time dummies. The y in the "Forecast Bias" panel is the actual earnings, minus the corresponding consensus earnings forecast in the month before an earnings announcement, scaled by lagged total assets. Panel A uses only the annual announcements (those for the forth fiscal quarter) each year. Panel B uses all quarterly earnings announcements. The y in the "Revision" panel is the revision of the n-period forecast as it becomes forecast for the $n-1$ period, scaled by lagged total assets. Revision is computed using the consensus forecast in the month after the earnings announcement minus the consensus in the month before the announcement. The y in the last two columns in Panel A is the growth forecast error before the announcements and the growth forecast revision after the announcement. Growth forecast is the difference between the three-year ahead forecast and the two-year ahead forecast, scaled by lagged total assets. Growth forecast revisions is the change of this forecast as the three-year and two-year ahead forecasts become two-year and one-year ahead. t-values are reported in parentheses. Standard errors are two-way clustered by firm and time.

Panel A: Annual Forecast Error and Revision

	Forecast Error			Revision		F[Growth]	
	Yr.1	Yr.2	Yr.3	Yr.2→1	Yr.3→2	Error	Revision
log(BM)	−0.04	0.58	1.82	0.18	0.21	1.25	0.02
	(−6.19)	(4.47)	(6.27)	(4.70)	(4.08)	(6.99)	(1.17)
N	36,641	36,641	36,641	36,641	36,641	36,641	36,641
Adj.R^2	0.02	0.05	0.09	0.04	0.04	0.07	0.00
$\text{Ret}_{-12,-1}$	0.07	0.50	−0.16	0.20	0.27	−0.66	0.06
	(6.05)	(4.82)	(−0.49)	(5.79)	(5.73)	(−2.51)	(4.69)
N	36,636	36,636	36,636	36,636	36,636	36,636	36,636
Adj.R^2	0.02	0.04	0.05	0.05	0.04	0.05	0.01

Panel B: Quarterly Forecast Error and Revision

	Forecast Error				Revision		
	Qtr.1	Qtr.2	Qtr.3	Qtr.4	Qtr.2→1	Qtr.3→2	Qtr.4→3
log(BM)	−0.20	0.06	0.37	0.68	0.14	0.11	0.08
	(−11.52)	(1.82)	(6.02)	(7.28)	(7.70)	(6.39)	(4.38)
N	175,309	175,309	175,309	175,309	175,309	175,309	175,309
Adj.R^2	0.04	0.03	0.04	0.06	0.03	0.04	0.03
$\text{Ret}_{-12,-1}$	0.30	0.56	0.57	0.43	0.26	0.22	0.21
	(14.46)	(14.43)	(11.33)	(5.94)	(13.47)	(11.75)	(11.21)
N	174,246	174,246	174,246	174,246	174,246	174,246	174,246
Adj.R^2	0.05	0.05	0.05	0.05	0.05	0.05	0.05

C Limitations of Long-term Growth Forecast

The literature commonly uses analysts' long-term growth forecast (LTG), rather than the slope of the earnings forecast term structure measure growth expectation. We detail the three important reasons for why we focus on the forecast term structure in this section.

First, we need precise measures of ex post growth forecast errors. LTG is the defined by the database as the forecasted growth rate over the next "three to five years." Without knowing exactly which year, we cannot measure the bias with reasonable accuracy.

Second, about 8.8% of our sample firms have negative earnings in the previous fiscal year. Among firms with non-missing ex post level surprise and growth surprise about 9.3% have negative earnings. It is unclear how to interpret the LTG of these firms.

Third, the first period forecast appears to be distinct from the forecasts at subsequent periods. It is unclear how much weight LTG has put on the first period growth. Using the forecast term structure, we can separately measure the growth forecast starting from year 1.

Finally, in our auxiliary tests in Table A.1, we need to measure the change in growth forecast for over the same period after earnings announcements. The revision in LTG is over an announcement is driven by two effects (1) the actual growth revision and (2) the change in forecasting period. It is therefore unclear whether a revision is caused by an actual correction in belief or the new forecast horizon included is expected to have a different growth rate.

We are among the first to propose to use the earnings forecast term structure to measure growth expectations. This is an important contribution in adding a new empirical device for future studies.

D Additional Tables

Table A.2: Validating the Theory: Portfolios Formed on Forward Growth Forecasts Table **??** with decile three, four, seven and eight included.

F[G]	(Forward) Growth Forecast Decile									
Horizon	1	2	3	4	5	6	7	8	9	10
Yr.1	−0.42	−0.09	−0.01	0.11	0.16	0.08	0.06	0.07	0.02	−0.09
	(−2.81)	(−1.04)	(−0.10)	(1.29)	(1.93)	(0.91)	(0.64)	(0.89)	(0.18)	(−0.63)
Yr.2	0.06	0.08	0.17	0.16	0.10	0.06	−0.06	−0.10	−0.15	−0.67
	(0.63)	(0.82)	(1.81)	(1.57)	(1.24)	(0.58)	(−0.51)	(−0.78)	(−1.11)	(−3.21)
Yr.3	0.04	0.01	0.21	0.10	0.14	−0.03	0.21	−0.18	−0.12	−0.58
	(0.32)	(0.11)	(2.47)	(1.13)	(1.36)	(−0.32)	(1.94)	(−1.23)	(−0.70)	(−2.63)

Table A.3: Level Bias, Growth Bias, Alpha and 123 CAPM Anomalies

This table presents the λ_1, γ_1 and the CAPM α for the 131 characteristics by categories. This is the data behind Table 3, Figure 4 and Figure **??**.

Panel 1: Investment

No.	Description	λ	γ	α	$t(\lambda)$	$t(\gamma)$	$t(\alpha)$
1	Change in Net Operating Assets	0.16	0.17	0.40	4.84	1.13	4.51
2	Asset Growth	−0.04	0.42	0.34	−1.16	2.66	2.96
3	Growth in Book Equity	−0.08	0.33	0.30	−2.71	2.16	2.83
4	Change in PPE and Inv/Assets	0.08	0.18	0.28	2.54	1.09	2.53
5	Inventory Growth	0.07	0.46	0.26	2.33	4.30	3.05
6	Change in Capex (Three Years)	0.05	0.38	0.26	1.61	3.38	2.97
7	Inventory Growth (Deflated)	0.07	0.40	0.24	1.74	3.21	2.40
8	Change in Net Noncurrent Op Assets	0.15	−0.07	0.24	6.01	−0.64	5.14
9	Change in Capex (Two Years)	0.02	0.55	0.23	0.60	4.92	2.62
10	Change in Equity to Assets	−0.09	0.46	0.23	−2.39	2.99	1.66
11	Employment Growth	−0.08	1.02	0.21	−2.29	6.23	1.90
12	Growth in Advertising Expenses	−0.04	0.54	0.19	−0.92	3.20	1.92
13	Change in Net Financial Assets	0.18	−0.23	0.17	6.47	−1.17	2.27
14	Investment to Revenue	0.11	−0.07	0.15	3.49	−0.40	1.86
15	Change in Current Operating Assets	0.00	0.50	0.15	0.07	4.82	1.06
16	Change in Capital Inv (Ind Adj)	0.03	0.08	0.14	1.07	0.67	2.07
17	Change in Net Working Capital	0.09	0.18	0.03	3.08	1.67	0.47
18	Growth in Long Term Operating Assets	−0.01	−0.25	−0.02	−0.57	−1.96	−0.19

Panel 2: Valuation

No.	Description	λ	γ	α	$t(\lambda)$	$t(\gamma)$	$t(\alpha)$
1	Enterprise Multiple	−0.42	0.75	0.44	−12.08	4.07	2.56
2	Net Payout Yield	−0.10	1.78	0.42	−2.20	4.13	2.17
3	Operating Cash Flows to Price	−0.26	2.08	0.39	−4.41	4.93	1.68
4	Cash Flow to Market	−0.45	2.00	0.33	−12.83	4.91	1.40
5	Sales to Price	−0.32	2.20	0.26	−8.19	5.37	1.10
6	Equity Duration	−0.07	2.05	0.25	−1.01	6.11	1.22
7	Payout Yield	−0.09	0.52	0.24	−2.23	4.02	1.95
8	Analyst Optimism	−0.03	1.19	0.22	−0.74	4.89	1.88
9	Earnings to Price	−0.16	0.78	0.18	−3.32	3.72	0.97
10	Book to Market Using December ME	−0.12	2.55	0.16	−1.95	6.24	0.82
11	Book to Market Using Most Recent ME	−0.52	2.45	0.16	−11.89	5.79	0.70
12	Total Assets to Market	−0.38	2.55	0.13	−5.81	6.05	0.50
13	Efficient Frontier Index	−0.67	2.20	0.11	−12.92	4.42	0.57
14	Enterprise Component Of BM	−0.29	1.30	0.11	−9.87	3.53	0.71
15	Analyst Value	−0.25	0.93	0.04	−6.67	3.49	0.20

Panel 3: Profitability

No.	Description	λ	γ	α	$t(\lambda)$	$t(\gamma)$	$t(\alpha)$
1	Analyst Earnings per Share	0.23	1.82	0.57	3.97	4.74	2.66
2	Cash-Based Operating Profitability	0.33	0.60	0.54	7.59	3.46	4.82
3	Operating Profitability R&D Adjusted	0.30	0.19	0.53	5.79	1.22	4.07
4	Operating Profits / Book Equity	0.09	0.75	0.46	2.93	2.83	2.94
5	Return on Assets (Qtrly)	0.47	0.79	0.43	14.19	3.17	3.59
6	Gross Profits / Total Assets	0.35	1.19	0.39	5.77	4.07	2.86
7	Net Income / Book Equity	0.16	0.93	0.38	5.64	3.11	2.97
8	Taxable Income to Income	0.13	1.62	0.30	4.27	4.37	3.08
9	Change in Taxes	0.51	−0.04	0.17	11.41	−0.36	1.84

Panel 4: External Financing

No.	Description	λ	γ	α	$t(\lambda)$	$t(\gamma)$	$t(\alpha)$
1	Net External Financing	0.08	1.43	0.60	3.43	4.00	4.20
2	Share Issuance (1 Year)	−0.04	1.57	0.41	−1.48	4.29	2.85
3	Net Equity Financing	0.05	1.29	0.39	1.68	3.73	2.99
4	Share Issuance (5 Year)	0.03	0.63	0.28	1.16	3.49	2.77
5	Net Debt Financing	0.10	−0.01	0.25	3.88	−0.07	4.10
6	Change in Financial Liabilities	0.12	−0.10	0.24	4.05	−0.60	3.89
7	Composite Debt Issuance	0.08	0.09	0.23	2.98	0.73	3.65
8	Composite Equity Issuance	0.43	−0.14	0.17	10.02	−0.66	1.39
9	Change in Current Operating Liabilities	−0.12	0.71	0.09	−3.30	4.91	0.68

Panel 5: Seasonality

No.	Description	λ	γ	α	$t(\lambda)$	$t(\gamma)$	$t(\alpha)$
1	Off Season Reversal Years 6 to 10	−0.03	0.49	0.42	−0.76	3.08	3.57
2	Return Seasonality Years 6 to 10	0.04	0.00	0.40	2.79	0.06	4.61
3	Return Seasonality Years 16 to 20	0.01	0.13	0.39	0.65	1.82	3.62
4	Return Seasonality Years 2 to 5	0.06	0.03	0.35	4.65	0.43	3.76
5	Off Season Reversal Years 11 to 15	−0.01	0.20	0.23	−0.25	1.39	2.76
6	Return Seasonality Years 11 to 15	0.04	0.01	0.22	2.36	0.10	3.02
7	Return Seasonality Last Year	0.14	−0.19	0.14	9.12	−2.16	1.03
8	Off Season Reversal Years 16 to 20	−0.02	−0.12	0.08	−0.64	−0.98	0.89

Panel 6: Price Momentum

No.	Description	λ	γ	α	$t(\lambda)$	$t(\gamma)$	$t(\alpha)$
1	Trend Factor	0.04	−0.16	0.62	0.69	−1.58	4.43
2	52 Week High	0.85	1.52	0.53	10.99	6.01	2.88
3	Momentum (12 Month)	0.78	−0.23	0.49	13.58	−0.73	2.67
4	Momentum Based on FF3 Residuals	0.47	0.28	0.40	9.63	1.22	3.26
5	Intermediate Momentum	0.39	−0.59	0.33	11.83	−2.33	1.53
6	Momentum Without The Seasonal Part	0.75	−0.40	0.31	14.90	−1.25	2.01
7	Momentum (6 Month)	0.73	0.26	0.22	13.20	1.04	1.51
8	Industry Momentum	0.28	−0.28	0.14	11.31	−1.11	0.73

Panel 7: Long-term Reversal

No.	Description	λ	γ	α	$t(\lambda)$	$t(\gamma)$	$t(\alpha)$
1	Long-Term EPS Forecast	−0.13	1.23	0.39	−2.30	5.25	2.10
2	Off Season Long-Term Reversal	−0.11	1.24	0.35	−2.75	5.53	2.10
3	Medium-Run Reversal	−0.18	0.64	0.18	−5.94	3.00	1.01
4	Long-Run Reversal	−0.12	0.84	0.14	−2.94	3.70	0.89
5	Intangible Return Using EP	−0.46	0.76	0.10	−11.95	3.24	0.56
6	Intangible Return Using BM	−0.49	1.40	0.05	−14.89	4.29	0.29
7	Intangible Return Using SP	−0.47	0.52	0.01	−9.86	2.74	0.03

Panel 8: Earnings Momentum

No.	Description	λ	γ	α	$t(\lambda)$	$t(\gamma)$	$t(\alpha)$
1	Earnings Announcement Return	0.55	0.42	0.39	20.89	5.53	5.88
2	EPS Forecast Dispersion	0.23	1.73	0.34	3.36	4.29	2.34
3	Predicted Analyst Forecast Error	−0.01	1.01	0.23	−0.22	4.24	1.78
4	Long-vs-Short EPS Forecasts	0.47	0.14	0.17	12.37	0.63	1.45
5	Earnings Surprise	0.32	0.16	0.13	10.23	1.95	2.24
6	Earnings Consistency	0.18	0.20	0.04	4.51	1.08	0.40

Panel 9: Volatility

No.	Description	λ	γ	α	$t(\lambda)$	$t(\gamma)$	$t(\alpha)$
1	Idiosyncratic Risk	0.05	2.15	0.60	0.80	5.77	3.61
2	Frazzini-Pedersen Beta	0.17	1.94	0.58	2.73	4.53	3.14
3	CAPM Beta	0.04	1.82	0.52	0.89	4.10	2.46
4	Tail Risk Beta	0.02	0.55	0.21	0.25	2.71	1.32
5	Cash-Flow to Price Variance	0.08	0.29	0.19	2.41	2.03	1.53

Panel 10: Sales Growth

No.	Description	λ	γ	α	$t(\lambda)$	$t(\gamma)$	$t(\alpha)$
1	Sales Growth Over Inventory Growth	0.08	−0.26	0.15	3.21	−1.69	2.03
2	Change in Asset Turnover	0.18	−0.09	0.15	5.38	−1.07	2.07
3	Revenue Growth Rank	−0.05	0.34	0.12	−1.57	2.27	1.15
4	Revenue Surprise	0.19	−0.10	0.03	7.27	−0.85	0.41
5	Sales Growth Over Overhead Growth	0.11	−0.14	−0.10	3.86	−1.04	−1.48

Panel 11: Liquidity

No.	Description	λ	γ	α	$t(\lambda)$	$t(\gamma)$	$t(\alpha)$
1	Volume Variance	0.24	1.72	0.65	3.41	4.43	3.60
2	Short Term Reversal	−0.61	−0.62	0.21	−16.98	−5.39	1.50
3	Pastor-Stambaugh Liquidity Beta	−0.01	0.16	0.05	−0.38	1.11	0.48
4	Bid-Ask Spread	−0.05	−1.82	−0.34	−0.86	−4.68	−2.18

Panel 12: Leverage

No.	Description	λ	γ	α	$t(\lambda)$	$t(\gamma)$	$t(\alpha)$
1	Operating Leverage	0.12	0.25	0.23	3.02	1.34	2.05
2	Leverage Component of BM	0.24	−1.97	−0.02	5.00	−4.69	−0.13
3	Net Debt to Price	0.00	−1.00	−0.02	0.04	−6.24	−0.14
4	Book Leverage (Annual)	0.17	−1.64	−0.11	2.80	−5.05	−0.54

Panel 13: Asset Composition

No.	Description	λ	γ	α	$t(\lambda)$	$t(\gamma)$	$t(\alpha)$
1	Net Operating Assets	0.17	−0.92	0.33	6.02	−2.93	3.74
2	Real Estate Holdings	0.11	0.61	0.15	2.71	2.90	1.62
3	Cash to Assets	0.29	−1.80	0.06	5.69	−4.46	0.33
4	Tangibility	0.22	−2.42	0.01	3.49	−5.09	0.03

Panel 14: Accruals

No.	Description	λ	γ	α	$t(\lambda)$	$t(\gamma)$	$t(\alpha)$
1	Percent Operating Accruals	0.13	1.42	0.25	2.98	6.14	2.58
2	Accruals	0.16	0.02	0.20	5.45	0.13	2.00
3	Abnormal Accruals	0.25	−0.32	0.20	9.91	−2.51	2.91
4	Total Accruals	−0.01	−0.05	0.10	−0.22	−0.43	1.44

Panel 15: Skewness

No.	Description	λ	γ	α	$t(\lambda)$	$t(\gamma)$	$t(\alpha)$
1	Coskewness	−0.03	0.13	0.12	−0.64	1.02	1.20
2	Return Skewness	−0.20	0.15	0.12	−13.61	1.60	1.64
3	Idiosyncratic Skewness (FF3)	−0.22	0.08	0.01	−16.14	1.04	0.22

Panel 16: Lead Lag

No.	Description	λ	γ	α	$t(\lambda)$	$t(\gamma)$	$t(\alpha)$
1	Price Delay SE Adjusted	0.01	0.77	0.15	0.62	4.28	1.59
2	Price Delay R-Squared	0.16	−0.25	0.11	4.21	−1.51	0.93
3	Price Delay Coefficient	−0.01	−0.23	−0.16	−0.45	−1.52	−1.97

Panel 17: Intangible

No.	Description	λ	γ	α	$t(\lambda)$	$t(\gamma)$	$t(\alpha)$
1	Organizational Capital	0.19	−0.23	0.36	6.73	−1.26	5.11
2	R&D Over Market Cap	−0.10	−1.24	0.23	−1.21	−4.17	1.15
3	Advertising Expense	−0.37	1.02	0.13	−8.07	3.69	0.74

Panel 17: Volume

No.	Description	λ	γ	α	$t(\lambda)$	$t(\gamma)$	$t(\alpha)$
1	Volume Trend	0.07	1.41	0.45	1.80	4.17	4.31
2	Volume to Market Equity	0.06	2.01	0.44	0.86	5.11	2.39

Panel 18: Composite Accounting

No.	Description	λ	γ	α	$t(\lambda)$	$t(\gamma)$	$t(\alpha)$
1	Real Dirty Surplus	0.07	0.57	0.27	2.31	2.67	2.60
2	Pension Funding Status	0.00	−0.15	−0.08	−0.11	−1.62	−0.90

Panel 19: Short Sale, Ownership, Industry Concentration, Age

No.	Description	λ	γ	α	$t(\lambda)$	$t(\gamma)$	$t(\alpha)$
1	Short Interest	0.09	0.89	0.45	2.50	5.99	5.67
2	Breadth of Ownership	0.62	−0.07	0.25	12.79	−0.38	2.47
3	Industry Concentration (Sales)	0.12	−0.86	−0.03	4.60	−4.01	−0.23
4	Firm Age Based on CRSP	0.05	−0.57	−0.19	1.29	−4.34	−2.53

Table A.4: Variables and Reference

This table lists the variable names as in Chen and Zimmermann (2022) and the original papers for the variables. For variable construction, please refer to the signal documentation file available on https://www.openassetpricing.com.

Variable	Description	Reference
dNoa	Change in Net Operating Assets	Hirshleifer (2001)
AssetGrowth	Asset Growth	Cooper et al. (2008)
ChEQ	Growth in Book Equity	Lockwood and Prombutr (2010)
InvestPPEInv	Change in PPE and Inv/Assets	Lyandres et al. (2008)
ChInv	Inventory Growth	Thomas and Zhang (2002)
grcapx3y	Change in Capex (Three Years)	Anderson and Garcia-Feijoo (2006)
InvGrowth	Inventory Growth (Deflated)	Belo and Lin (2012)
ChNNCOA	Change in Net Noncurrent Op Assets	Soliman (2008)
grcapx	Change in Capex (Two Years)	Anderson and Garcia-Feijoo (2006)
DelEqu	Change in Equity to Assets	Richardson et al. (2006)
hire	Employment Growth	Belo et al. (2014)
GrAdExp	Growth in Advertising Expenses	Lou (2014)
DelNetFin	Change in Net Financial Assets	Richardson et al. (2006)
Investment	Investment to Revenue	Titman et al. (2004)
DelCOA	Change in Current Operating Assets	Richardson et al. (2006)
ChInvIA	Change in Capital Inv (Ind Adj)	Abarbanell and Bushee (1998)
ChNWC	Change in Net Working Capital	Soliman (2008)
GrLTNOA	Growth in Long Term Operating Assets	Fairfield et al. (2003)
EntMult	Enterprise Multiple	Loughran and Wellman (2011)
NetPayoutYield	Net Payout Yield	Boudoukh et al. (2007)
cfp	Operating Cash Flows to Price	Desai et al. (2004)
CF	Cash Flow to Market	Lakonishok et al. (1994)
SP	Sales to Price	Barbee Jr et al. (1996)
EquityDuration	Equity Duration	Dechow et al. (2004)
PayoutYield	Payout Yield	Boudoukh et al. (2007)
AOP	Analyst Optimism	Frankel and Lee (1998)
EP	Earnings to Price	Basu (1977)
BMdec	Book to Market Using December ME	Fama and French (2015)
BM	Book to Market Using Most Recent ME	Barr Rosenberg and Lanstein (1998)
AM	Total Assets to Market	Fama and French (1992)
Frontier	Efficient Frontier Index	Nguyen and Swanson (2009)
EBM	Enterprise Component Of BM	Penman et al. (2007)
AnalystValue	Analyst Value	Frankel and Lee (1998)

(Table continues on next page...)

Variable	Description	Reference
FEPS	Analyst Earnings per Share	Cen et al. (2009)
CBOperProf	Cash-Based Operating Profitability	Ball et al. (2016)
OperProfRD	Operating Profitability R&D Adjusted	Ball et al. (2016)
OperProf	Operating Profits / Book Equity	Fama and French (2015)
roaq	Return on Assets (Qtrly)	Balakrishnan et al. (2010)
GP	Gross Profits / Total Assets	Novy-Marx (2013)
RoE	Net Income / Book Equity	Haugen and Baker (1996)
Tax	Taxable Income to Income	Lev and Nissim (2004)
ChTax	Change in Taxes	Thomas and Zhang (2002)
XFIN	Net External Financing	Bradshaw et al. (2006)
ShareIss1Y	Share Issuance (1 Year)	Pontiff and Woodgate (2008)
NetEquityFinance	Net Equity Financing	Bradshaw et al. (2006)
ShareIss5Y	Share Issuance (5 Year)	Daniel and Titman (1997)
NetDebtFinance	Net Debt Financing	Bradshaw et al. (2006)
DelFINL	Change in Financial Liabilities	Richardson et al. (2006)
CompositeDebtIssuance	Composite Debt Issuance	Lyandres et al. (2008)
CompEquIss	Composite Equity Issuance	Daniel and Titman (1997)
DelCOL	Change in Current Operating Liabilities	Richardson et al. (2006)
MomOffSeason06YrPlus	Off Season Reversal Years 6 to 10	Heston and Sadka (2008)
MomSeason06YrPlus	Return Seasonality Years 6 to 10	Heston and Sadka (2008)
MomSeason16YrPlus	Return Seasonality Years 16 to 20	Heston and Sadka (2008)
MomSeason	Return Seasonality Years 2 to 5	Heston and Sadka (2008)
MomOffSeason11YrPlus	Off Season Reversal Years 11 to 15	Heston and Sadka (2008)
MomSeason11YrPlus	Return Seasonality Years 11 to 15	Heston and Sadka (2008)
MomSeasonShort	Return Seasonality Last Year	Heston and Sadka (2008)
MomOffSeason16YrPlus	Off Season Reversal Years 16 to 20	Heston and Sadka (2008)
TrendFactor	Trend Factor	Han et al. (2016)
High52	52 Week High	George and Hwang (2004)
Mom12m	Momentum (12 Month)	Jegadeesh and Titman (1993)
ResidualMomentum	Momentum Based on FF3 Residuals	Blitz et al. (2011)
IntMom	Intermediate Momentum	Novy-Marx (2013)
Mom12mOffSeason	Momentum Without The Seasonal Part	Heston and Sadka (2008)
Mom6m	Momentum (6 Month)	Jegadeesh and Titman (1993)
IndMom	Industry Momentum	Moskowitz and Grinblatt (1999)

(Table continues on next page...)

Variable	Description	Reference
fgr5yrLag	Long-Term EPS Forecast	La Porta (1996)
MomOffSeason	Off Season Long-Term Reversal	Heston and Sadka (2008)
MRreversal	Medium-Run Reversal	De Bondt and Thaler (1985)
LRreversal	Long-Run Reversal	De Bondt and Thaler (1985)
IntanEP	Intangible Return Using EP	Daniel and Titman (1997)
IntanBM	Intangible Return Using BM	Daniel and Titman (1997)
IntanSP	Intangible Return Using SP	Daniel and Titman (1997)
AnnouncementReturn	Earnings Announcement Return	Chan et al. (2001a)
ForecastDispersion	EPS Forecast Dispersion	Diether et al. (2002)
PredictedFE	Predicted Analyst Forecast Error	Frankel and Lee (1998)
EarningsForecastDisparity	Long-vs-Short EPS Forecasts	Da and Warachka (2011)
EarningsSurprise	Earnings Surprise	Foster et al. (1984)
EarningsConsistency	Earnings Consistency	Alwathainani (2009)
IdioRisk	Idiosyncratic Risk	Ang et al. (2006)
BetaFP	Frazzini-Pedersen Beta	Frazzini and Pedersen (2014)
Beta	CAPM Beta	Fama and MacBeth (1973)
BetaTailRisk	Tail Risk Beta	Kelly and Jiang (2014)
VarCF	Cash-Flow to Price Variance	Haugen and Baker (1996)
GrSaleToGrInv	Sales Growth Over Inventory Growth	Ali et al. (2003)
ChAssetTurnover	Change in Asset Turnover	Soliman (2008)
MeanRankRevGrowth	Revenue Growth Rank	Lakonishok et al. (1994)
RevenueSurprise	Revenue Surprise	Jegadeesh and Livnat (2006)
GrSaleToGrOverhead	Sales Growth Over Overhead Growth	Abarbanell and Bushee (1998)
VolSD	Volume Variance	Chordia et al. (2001)
STreversal	Short Term Reversal	Jegadeesh (1990)
BetaLiquidityPS	Pastor-Stambaugh Liquidity Beta	Pástor and Stambaugh (2003)
BidAskSpread	Bid-Ask Spread	Amihud and Mendelson (1986)

(Table continues on next page...)

Variable	Description	Reference
OPLeverage	Operating Leverage	Novy-Marx (2013)
BPEBM	Leverage Component of BM	Penman et al. (2007)
NetDebtPrice	Net Debt to Price	Penman et al. (2007)
BookLeverage	Book Leverage (Annual)	Fama and French (2015)
NOA	Net Operating Assets	Hirshleifer (2001)
realestate	Real Estate Holdings	Tuzel (2010)
Cash	Cash to Assets	Palazzo (2012)
tang	Tangibility	Hahn and Lee (2009)
PctAcc	Percent Operating Accruals	Hafzalla et al. (2011)
Accruals	Accruals	Sloan (1996)
AbnormalAccruals	Abnormal Accruals	Xie (2001)
TotalAccruals	Total Accruals	Richardson et al. (2006)
Coskewness	Coskewness	Harvey and Siddique (2000)
ReturnSkew	Return Skewness	Bali et al. (2016)
ReturnSkew3F	Idiosyncratic Skewness (FF3)	Bali et al. (2016)
PriceDelayTstat	Price Delay SE Adjusted	Hou and Moskowitz (2005)
PriceDelayRsq	Price Delay R-Squared	Hou and Moskowitz (2005)
PriceDelaySlope	Price Delay Coefficient	Hou and Moskowitz (2005)
OrgCap	Organizational Capital	Eisfeldt and Papanikolaou (2013)
RD	R&D Over Market Cap	Chan et al. (2001b)
AdExp	Advertising Expense	Chan et al. (2001b)
VolumeTrend	Volume Trend	Haugen and Baker (1996)
VolMkt	Volume to Market Equity	Haugen and Baker (1996)
RDS	Real Dirty Surplus	Landsman et al. (2011)
FR	Pension Funding Status	Franzoni and Marin (2006)
ShortInterest	Short Interest	Dechow et al. (2001)
DelBreadth	Breadth of Ownership	Chen et al. (2002)
Herf	Industry Concentration (Sales)	Hou and Robinson (2006)
FirmAge	Firm Age Based On CRSP	Barry and Brown (1985)

Table A.5: Alternative Hypothesis: Surprise Relevance and Surprise Dispersion

This table reports the Sharpe Ratio and CAPM alpha of a strategy that averages all 123 anomalies before and after 2003 in the first two columns. In the four columns on the right, we present the Sharpe Ratio and alpha of strategies that trade ex post level and growth surprises. These untradable ex post portfolios follow the same HML–style construction, but use the actual surprises for forecasts made in the previous month.

	Ex post surprise portfolio			
	Level		Growth	
	Pre	Post	Pre	Post
Sharpe Ratio	1.59	1.58	0.55	0.82
CAPM alpha	3.93	3.21	2.19	1.53
	(17.77)	(11.93)	(6.96)	(13.35)

Table A.6: The Term Structure of Forecast Errors and Firm Characteristics

At the end of each month, we sort stocks into quintiles by book-to-market, past return from 12 to 2 months ago, and operating profitability. Then we compute the average ex post forecast surprise at different horizons (one-, two-, three, four-quarters ahead and two- and three-years ahead). Forecast surprise is defined as the actual earnings minus the forecasted earnings scaled by lagged total assets. t-values are computed using Newey-West adjusted standard errors with 12 lags (one year).

	Ex post Surprise at Different Horizons					
BM	Qtr1	Qtr2	Qtr3	Qtr4	Yr2	Yr3
1 (L)	0.18	−0.77	−1.55	−2.23	−2.98	−7.06
2	0.03	−0.53	−0.99	−1.42	−1.78	−3.74
3	0.02	−0.36	−0.71	−0.94	−1.18	−2.33
4	−0.02	−0.34	−0.48	−0.66	−0.78	−1.59
5 (H)	−0.07	−0.25	−0.31	−0.45	−0.51	−1.05
H − L	−0.25	0.52	1.24	1.78	2.48	6.01
t(H − L)	−2.94	3.04	3.86	3.93	4.49	4.50
$\text{Ret}_{-12,-2}$	Qtr1	Qtr2	Qtr3	Qtr4	Yr2	Yr3
1 (L)	−0.48	−1.40	−1.91	−2.34	−2.81	−4.66
2	−0.11	−0.66	−1.01	−1.28	−1.50	−2.76
3	−0.01	−0.39	−0.66	−0.87	−1.09	−2.25
4	0.13	−0.16	−0.46	−0.74	−0.97	−2.40
5 (H)	0.55	0.13	−0.39	−0.99	−1.52	−5.13
H − L	1.03	1.53	1.52	1.35	1.29	−0.46
t(H − L)	6.43	8.02	7.70	4.48	3.21	−0.42
OP	Qtr1	Qtr2	Qtr3	Qtr4	Yr2	Yr3
1 (L)	−0.08	−0.90	−1.58	−2.26	−3.21	−7.67
2	0.02	−0.26	−0.50	−0.70	−0.80	−1.63
3	0.04	−0.28	−0.50	−0.74	−0.85	−1.78
4	0.04	−0.36	−0.63	−0.86	−1.05	−2.17
5 (H)	0.04	−0.60	−1.04	−1.40	−1.68	−3.47
H − L	0.12	0.30	0.54	0.86	1.53	4.20
t(H − L)	2.07	3.22	2.46	2.47	2.73	2.57

Table A.7: The Correlation Structure of Forecasts and Forecast Errors

Panel A: PCA on Ex Post Forecast Errors over the Three Annual Horizons

Horizon	PC1	PC2	PC3
Yr.1	0.51	−0.83	−0.23
Yr.2	0.63	0.17	0.76
Yr.3	0.59	0.54	−0.61
Cum. Prop	70.6%	91.6%	100.0%

Panel B: Explaining Year-3 Forecast Errors and Forecasts with Year-1 and Year-2 Data

	Yr.3 Error		Yr.3 Forecast	
Yr.1 Forecast	1.99	1.27	0.71	0.84
	(20.09)	(17.35)	(28.52)	(54.35)
Yr.2 − Yr.1 Forecast		1.33		1.63
		(49.02)		(57.64)
Constant	−0.03	−0.01	0.06	0.02
	(−19.69)	(−16.68)	(26.96)	(15.23)
N	339,651	339,651	339,651	339,651
Adj.R2	12.9%	52.6%	45.1%	81.5%

References

Abarbanell, Jeffery S, and Brian J Bushee, 1998, Abnormal returns to a fundamental analysis strategy, *Accounting Review* 19–45.

Afrouzi, Hassan, Spencer Yongwook Kwon, Augustin Landier, Yueran Ma, and David Thesmar, 2020, Overreaction in expectations: Evidence and theory, *Available at SSRN* .

Ali, Ashiq, Lee-Seok Hwang, and Mark A Trombley, 2003, Residual-income-based valuation predicts future stock returns: Evidence on mispricing vs. risk explanations, *The Accounting Review* 78, 377–396.

Alwathainani, Abdulaziz M, 2009, Consistency of firms' past financial performance measures and future returns, *The British Accounting Review* 41, 184–196.

Amihud, Yakov, and Haim Mendelson, 1986, Asset pricing and the bid-ask spread, *Journal of financial Economics* 17, 223–249.

Anderson, Christopher W, and Luis Garcia-Feijoo, 2006, Empirical evidence on capital investment, growth options, and security returns, *The Journal of Finance* 61, 171–194.

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

Balakrishnan, Karthik, Eli Bartov, and Lucile Faurel, 2010, Post loss/profit announcement drift, *Journal of Accounting and Economics* 50, 20–41.

Bali, Turan G, Robert F Engle, and Scott Murray, 2016, *Empirical asset pricing: The cross section of stock returns* (John Wiley & Sons).

Ball, Ray, Joseph Gerakos, Juhani T. Linnainmaa, and Valeri Nikolaev, 2016, Accruals, cash flows, and operating profitability in the cross section of stock returns, *Journal of Financial Economics* 121, 28–45.

Barbee Jr, William C, Sandip Mukherji, and Gary A Raines, 1996, Do sales–price and debt–equity explain stock returns better than book–market and firm size?, *Financial Analysts Journal* 52, 56–60.

Barberis, Nicholas, Robin Greenwood, Lawrence Jin, and Andrei Shleifer, 2015, X-capm: An extrapolative capital asset pricing model, *Journal of Financial Economics* 115, 1–24.

Barberis, Nicholas, Robin Greenwood, Lawrence Jin, and Andrei Shleifer, 2018, Extrapolation and bubbles, *Journal of Financial Economics* 129, 203–227.

Barr Rosenberg, Kenneth Reid, and Ronald Lanstein, 1998, Persuasive evidence of market inefficiency, *Streetwise: the Best of the Journal of Portfolio Management* 48.

Barry, Christopher B, and Stephen J Brown, 1985, Differential information and security market equilibrium, *Journal of financial and quantitative analysis* 20, 407–422.

Basu, Sanjoy, 1977, Investment performance of common stocks in relation to their price-earnings ratios: A test of the efficient market hypothesis, *The journal of Finance* 32, 663–682.

Belo, Frederico, and Xiaoji Lin, 2012, The inventory growth spread, *The Review of Financial Studies* 25, 278–313.

Belo, Frederico, Xiaoji Lin, and Santiago Bazdresch, 2014, Labor hiring, investment, and stock return predictability in the cross section, *Journal of Political Economy* 122, 129–177.

Blitz, David, Joop Huij, and Martin Martens, 2011, Residual momentum, *Journal of Empirical Finance* 18, 506–521.

Bordalo, Pedro, Nicola Gennaioli, Rafael LaPorta, and Andrei Shleifer, 2022, Belief overreaction and stock market puzzles .

Bordalo, Pedro, Nicola Gennaioli, Rafael La Porta, and Andrei Shleifer, 2019, Diagnostic expectations and stock returns, *Journal of Finance* 74, 2839–2874.

Bouchaud, Jean-Philippe, Philipp Krüger, Augustin Landier, and David Thesmar, 2019, Sticky expectations and the profitability anomaly, *Journal of Finance* 74, 639–674.

Boudoukh, Jacob, Roni Michaely, Matthew Richardson, and Michael R Roberts, 2007, On the importance of measuring payout yield: Implications for empirical asset pricing, *The Journal of Finance* 62, 877–915.

Bradshaw, Mark T, Scott A Richardson, and Richard G Sloan, 2006, The relation between corporate financing activities, analysts' forecasts and stock returns, *Journal of accounting and economics* 42, 53–85.

Brunnermeier, Markus, Emmanuel Farhi, Ralph S. J. Koijen, Arvind Krishnamurthy, Sydney C. Ludvigson, Hanno Lustig, Stefan Nagel, and Monika Piazzesi, 2021, Review article: Perspectives on the future of asset pricing, *Review of Financial Studies* 34, 2126–2160.

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

Cassella, Stefano, and Huseyin Gulen, 2018, Extrapolation bias and the predictability of stock returns by price-scaled variables, *Review of Financial Studies* 31, 4345–4397.

Cen, Ling, KC John Wei, and Jie Zhang, 2009, The cross-sectional anchoring of forecasted earnings per share and expected stock returns, *Internet access: http://papers. ssrn. com/sol3/papers. cfm* .

Chan, Konan, Louis Chan, Narasimhan Jegadeesh, and Josef Lakonishok, 2001a, Earnings quality and stock returns.

Chan, Louis KC, Josef Lakonishok, and Theodore Sougiannis, 2001b, The stock market valuation of research and development expenditures, *The Journal of finance* 56, 2431–2456.

Chen, Andrew Y., and Tom Zimmermann, 2022, Open source cross sectional asset pricing, *Critical Finance Review* (forthcoming).

Chen, Joseph, Harrison Hong, and Jeremy C Stein, 2002, Breadth of ownership and stock returns, *Journal of financial Economics* 66, 171–205.

Chordia, Tarun, Avanidhar Subrahmanyam, and V Ravi Anshuman, 2001, Trading activity and expected stock returns, *Journal of financial Economics* 59, 3–32.

Coibion, Olivier, and Yuriy Gorodnichenko, 2012, What can survey forecasts tell us about information rigidities?, *Journal of Political Economy* 120, 116–159.

Coibion, Olivier, and Yuriy Gorodnichenko, 2015, Information rigidity and the expectations formation process: A simple framework and new facts, *American Economic Review* 105, 2644–78.

Cooper, Michael J, Huseyin Gulen, and Michael J Schill, 2008, Asset growth and the cross-section of stock returns, *the Journal of Finance* 63, 1609–1651.

Da, Zhi, and Mitch Warachka, 2011, The disparity between long-term and short-term forecasted earnings growth, *Journal of Financial Economics* 100, 424–442.

Daniel, Kent, David Hirshleifer, and Lin Sun, 2020, Short- and long-horizon behavioral factors, *Review of Financial Studies* 33, 1673–1736.

Daniel, Kent, and Sheridan Titman, 1997, Evidence on the characteristics of cross sectional variation in stock returns, *the Journal of Finance* 52, 1–33.

De Bondt, Werner F. M., and Richard Thaler, 1985, Does the stock market overreact?, *Journal of Finance* 40, 793–805.

Dechow, Patricia M, Amy P Hutton, Lisa Meulbroek, and Richard G Sloan, 2001, Short-sellers, fundamental analysis, and stock returns, *Journal of financial Economics* 61, 77–106.

Dechow, Patricia M, Richard G Sloan, and Mark T Soliman, 2004, Implied equity duration: A new measure of equity risk, *Review of Accounting Studies* 9, 197–228.

Desai, Hemang, Shivaram Rajgopal, and Mohan Venkatachalam, 2004, Value-glamour and accruals mispricing: One anomaly or two?, *The Accounting Review* 79, 355–385.

Diether, Karl B., Christopher J. Malloy, and Anna Scherbina, 2002, Differences of opinion and the cross section of stock returns, *Journal of Finance* 57, 2113–2141.

Doukas, John A., Chansog (Francis) Kim, and Christos Pantzalis, 2002, A Test of the Errors-in-Expectations Explanation of the Value/Glamour Stock Returns Performance: Evidence from Analysts' Forecasts, *Journal of Finance* 57, 2143–2165.

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

Eisfeldt, Andrea L, and Dimitris Papanikolaou, 2013, Organization capital and the cross-section of expected returns, *The Journal of Finance* 68, 1365–1406.

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

Engelberg, Joseph, R David McLean, and Jeffrey Pontiff, 2020, Analysts and anomalies, *Journal of Accounting and Economics* 69, 101249.

Fairfield, Patricia M, J Scott Whisenant, and Teri Lombardi Yohn, 2003, Accrued earnings and growth: Implications for future profitability and market mispricing, *The accounting review* 78, 353–371.

Fama, Eugene F., and Kenneth R. French, 1992, The cross-section of expected stock returns, *Journal of Finance* 47, 427–465.

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

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

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

Foster, George, Chris Olsen, and Terry Shevlin, 1984, Earnings releases, anomalies, and the behavior of security returns, *Accounting Review* 574–603.

Frankel, Richard, and Charles MC Lee, 1998, Accounting valuation, market expectation, and cross-sectional stock returns, *Journal of Accounting and economics* 25, 283–319.

Franzoni, Francesco, and Jose M Marin, 2006, Pension plan funding and stock market efficiency, *the Journal of Finance* 61, 921–956.

Frazzini, Andrea, and Lasse Heje Pedersen, 2014, Betting against beta, *Journal of financial economics* 111, 1–25.

George, Thomas J, and Chuan-Yang Hwang, 2004, The 52-week high and momentum investing, *The Journal of Finance* 59, 2145–2176.

Green, Jeremiah, John R.M. Hand, and X. Frank Zhang, 2017, The characteristics that provide independent information about average us monthly stock returns, *Review of Financial Studies* 30, 4389–4436.

Hafzalla, Nader, Russell Lundholm, and E Matthew Van Winkle, 2011, Percent accruals, *The Accounting Review* 86, 209–236.

Hahn, Jaehoon, and Hangyong Lee, 2009, Financial constraints, debt capacity, and the cross-section of stock returns, *The Journal of Finance* 64, 891–921.

Han, Yufeng, Guofu Zhou, and Yingzi Zhu, 2016, A trend factor: Any economic gains from using information over investment horizons?, *Journal of Financial Economics* 122, 352–375.

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

Harvey, Campbell R, and Akhtar Siddique, 2000, Conditional skewness in asset pricing tests, *The Journal of finance* 55, 1263–1295.

Haugen, Robert A, and Nardin L Baker, 1996, Commonality in the determinants of expected stock returns, *Journal of financial economics* 41, 401–439.

Heston, Steven L., and Ronnie Sadka, 2008, Seasonality in the cross-section of stock returns, *Journal of Financial Economics* 87, 418–445.

Hirshleifer, David, 2001, Investor psychology and asset pricing, *Journal of Finance* 56, 1533–1597.

Hou, Kewei, and Tobias J Moskowitz, 2005, Market frictions, price delay, and the cross-section of expected returns, *The Review of Financial Studies* 18, 981–1020.

Hou, Kewei, and David T Robinson, 2006, Industry concentration and average stock returns, *The Journal of Finance* 61, 1927–1956.

Hou, Kewei, and Mathijs A. van Dijk, 2019, Resurrecting the size effect: Firm size, profitability shocks, and expected stock returns, *Review of Financial Studies* 32, 2850–2889.

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

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

Jegadeesh, Narasimhan, 1990, Evidence of predictable behavior of security returns, *Journal of Finance* 45, 881–898.

Jegadeesh, Narasimhan, and Joshua Livnat, 2006, Revenue surprises and stock returns, *Journal of Accounting and Economics* 41, 147–171.

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

Kelly, Bryan, and Hao Jiang, 2014, Tail risk and asset prices, *The Review of Financial Studies* 27, 2841–2871.

Kozak, Serhiy, Stefan Nagel, and Shrihari Santosh, 2018, Interpreting factor models, *Journal of Finance* 73, 1183–1223.

La Porta, Rafael, 1996, Expectations and the cross-section of stock returns, *Journal of Finance* 51, 1715–1742.

Lakonishok, Josef, Andrei Shleifer, and Robert W. Vishny, 1994, Contrarian investment, extrapolation, and risk, *Journal of Finance* 49, 1541–1578.

Landsman, Wayne R, Bruce L Miller, Ken Peasnell, and Shu Yeh, 2011, Do investors understand really dirty surplus?, *The Accounting Review* 86, 237–258.

Lev, Baruch, and Doron Nissim, 2004, Taxable income, future earnings, and equity values, *The accounting review* 79, 1039–1074.

Lockwood, Larry, and Wikrom Prombutr, 2010, Sustainable growth and stock returns, *Journal of Financial Research* 33, 519–538.

Lou, Dong, 2014, Attracting investor attention through advertising, *Review of Financial Studies* 27, 1797–1829.

Loughran, Tim, and Jay W Wellman, 2011, New evidence on the relation between the enterprise multiple and average stock returns, *Journal of Financial and Quantitative Analysis* 46, 1629–1650.

Lyandres, Evgeny, Le Sun, and Lu Zhang, 2008, The new issues puzzle: Testing the investment-based explanation, *The review of financial studies* 21, 2825–2855.

Moskowitz, Tobias J, and Mark Grinblatt, 1999, Do industries explain momentum?, *The Journal of finance* 54, 1249–1290.

Nguyen, Giao X., and Peggy E. Swanson, 2009, Firm characteristics, relative efficiency, and equity returns, *Journal of Financial and Quantitative Analysis* 44, 213–236.

Novy-Marx, Robert, 2013, The other side of value: The gross profitability premium, *Journal of Financial Economics* 108, 1–28.

Palazzo, Berardino, 2012, Cash holdings, risk, and expected returns, *Journal of Financial Economics* 104, 162–185.

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

Penman, Stephen H, Scott A Richardson, and Irem Tuna, 2007, The book-to-price effect in stock returns: accounting for leverage, *Journal of accounting research* 45, 427–467.

Pontiff, Jeffrey, and Artemiza Woodgate, 2008, Share issuance and cross-sectional returns, *The Journal of Finance* 63, 921–945.

Richardson, Scott A, Richard G Sloan, Mark T Soliman, and İrem Tuna, 2006, The implications of accounting distortions and growth for accruals and profitability, *The Accounting Review* 81, 713–743.

Sloan, Richard G, 1996, Do stock prices fully reflect information in accruals and cash flows about future earnings?, *Accounting review* 289–315.

Soliman, Mark T, 2008, The use of dupont analysis by market participants, *The accounting review* 83, 823–853.

Stambaugh, Robert F., and Yu Yuan, 2016, Mispricing factors, *Review of Financial Studies* 30, 1270–1315.

Thomas, Jacob K, and Huai Zhang, 2002, Inventory changes and future returns, *Review of Accounting Studies* 7, 163–187.

Titman, Sheridan, KC John Wei, and Feixue Xie, 2004, Capital investments and stock returns, *Journal of financial and Quantitative Analysis* 39, 677–700.

Tuzel, Selale, 2010, Corporate real estate holdings and the cross-section of stock returns, *The Review of Financial Studies* 23, 2268–2302.

van Binsbergen, Jules H., Martijn Boons, Christian C. Opp, and Andrea Tamoni, 2021, Dynamic asset (mis) pricing: Build-up vs. resolution anomalies, *Available at SSRN* .

van Binsbergen, Jules H., Xiao Han, and Alejandro Lopez-Lira, 2020, Man vs. machine learning: The term structure of earnings expectations and conditional biases, *NBER* working paper.

Xie, Hong, 2001, The mispricing of abnormal accruals, *The accounting review* 76, 357–373.