Which Expectation?*

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Abstract

We test a theory of two expectations in asset pricing: investors separately form beliefs on cash flow level and cash flow growth when valuing assets. Using 123 anomalies and analysts' earnings term structure forecasts, we find strong evidence for the separability of the two beliefs. Forecast errors in cash flow level and cash flow growth are uncorrelated. Anomaly portfolios typically manifest biases in one belief or the other but not both. Anomalies with large (small) alphas often have the two biases amplifying (offsetting) each other. The first two principal components of anomaly returns are essentially a growth bias factor and a level bias factor. The two biases explain about 50% of the anomaly portfolios' cross-sectional deviation from the CAPM. Level bias generates large initial alpha and growth bias generates persistent alpha. We also provide an explanation for the recent alpha decay with analysts' improved forecast accuracy.

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1 Introduction

Gordon's classic growth model (GGM) shows that the price of an asset is theoretically determined by its expected cash flow level and expected cash flow growth. Therefore, to explain mispricing from the perspective of the GGM, investors must have biased beliefs about cash flow level or cash flow growth or both. And yet, existing studies on investors' belief and asset pricing often do not distinguish between the two variables but treat biased belief, or sentiment, as one catch-all explanation for mispricing. In this paper, we broaden the scope of the literature by jointly studying the two theoretically motivated expectation biases based on the GGM. There are four sets of major findings in this paper.

First, we find strong evidence for the separability of the two beliefs. Using data on analysts' earnings term structure forecast, we find that forecast errors in cash flow level and cash flow growth are uncorrelated. We then study 123 representative anomalies and measure the average amounts of level and growth biases captured by each anomaly. We find that the anomalies are typically associated with either level bias or growth bias, but not both. Furthermore, we conduct a principal component analysis (PCA) on the long-short anomaly portfolio returns and find that the first principal component (PC) is essentially a growth bias factor, and the second PC is a level bias factor, further confirming the orthogonality of the two beliefs.

Second, we quantify the importance of the two expectation biases for the cross-section of anomaly returns. We find that the first and second PCs (which separately capture the growth and level biases) jointly explain 58.5% of the total variation of the 123 long-short anomaly portfolio returns, with 38.7% explained by the first PC and 19.8% explained by the second PC. We alternatively assess the importance of the two biases by regressing the anomaly portfolios' CAPM alphas on the level and growth biases captured by each portfolio. This regression produces an R-sqaured of about 50%, implying that the two biases explain about half of the anomaly portfolios' average return deviations from the CAPM.

Third, we study the asset pricing implications of the two biases. We highlight the importance of accounting for both biases by noting that anomalies with large (small) alphas typically have the two biases amplifying (offsetting) each other. For example, the profitability factors, which earn some of the largest alphas in our sample, benefit from disproportionally holding stocks that will exceed both analysts' cash flow level forecasts and growth forecasts. In contrast, the value factors, which earn relatively small alphas in our sample, benefit from holding stocks that will exceed the growth forecasts but are hurt by holding stocks that will likely miss the level forecasts. Furthermore, the two biases are associated with alphas of different natures. Anomalies associated with level bias earn large but transient alphas. Anomalies associated with growth bias earn more persistent alphas and exhibit stronger factor momentum. Finally, we demonstrate the practical relevance of our framework by proposing trading strategies that exploit conditional biases across different horizons.

Fourth, we examine how the biases and anomaly alphas have evolved over time. We find that analysts' forecasts have become more accurate in recent periods, and the alpha decay of the anomaly portfolios coincides with this forecast accuracy improvement. Cross-sectionally, anomalies that have lost more of their abilities to capture expectation biases have experienced larger alpha decays. Anomalies associated with growth bias have experienced a larger decay than anomalies associated with level bias.

Our paper primarily contributes to the literature on the cross-section of stock returns, anomalies, analysts' forecasts, and market efficiency. Some related work La Porta (1996), Da and Warachka (2011), Stambaugh and Yuan (2016), Harvey et al. (2016), McLean and Pontiff (2016), Green et al. (2017), Engelberg et al. (2018), Kozak et al. (2018), Bouchaud et al. (2019), Bordalo et al. (2019), Daniel et al. (2020), Engelberg et al. (2020), Chen and Zimmermann (2022), van Binsbergen et al. (2022), Lochstoer and Muir (2022), among others. Our paper is closely related to Daniel et al. (2020) who propose a factor model motivated by the different behavioral biases investors display at the short and long horizons, respectively. Unlike our analysis, they do not connect their factors to the biases in 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. Engelberg et al. (2018) find that most anomalies are an order of magnitude stronger during earnings announcements and days with corporate news. They conclude that biased beliefs likely drive many anomaly returns but do not explicitly identify sources of the expectation biases.

We organize our paper as follows. We motivate the two-expectation framework in Section 2. Section 3 describes the data and validates the framework. Section 4 describes our methodology for measuring the biases captured by anomalies. Section 5 presents the empirical results on the relation between anomalies and the two biases. Section 6 connects the changes in anomaly profits over time to the changes in expectation biases. Section 7 discusses some alternative interpretations. Section 8 concludes the paper.

2 Why Multiple Expectations?

Consider the Gordon Growth Model (GGM):

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

where P_0 is the price at time 0; $\mathbb{E}[.]$ is an expectation operator, not necessarily rational; r is the discount rate; $\tilde{\pi}_1$ is the random cash flow in the next period; $\tilde{g}$ is the cash flow growth rate starting from the next period. The GGM asks investors to form two cash flow expectations: 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?

The idea of distinguishing between the level and growth expectations dates back at least to Barberis, Shleifer, and Vishny (1998) when they discussed their model's failure to explain investors' underreaction to quarterly earnings surprises toward the end of their paper:

> "To explain this evidence [of underreaction to earnings surprises], our model needs to be extended. One possible way to extend the model is to allow investors to estimate the level and the growth rate of earnings separately. Indeed, in reality, investors might use annual earnings numbers over five to seven years to estimate the growth rate but higher frequency quarterly earnings announcements (perhaps combined with other information) to estimate earnings level." (Barberis, Shleifer, and Vishny, 1998, p.332)

We take this idea seriously and test it from different angles in our paper. Figure 1 provides a graphical summary of some of our main findings (details will be provided in later sections). The figure 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) for each factor. 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 one to three years consistently exceeds (falls short of) the current consensus growth forecasts. To facilitate the analysis, we group anomalies into 23 categories.[1] The color-coded circles 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 B.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 with similar styles 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

[1] We download the anomaly variables from Chen and Zimmermann (2022). We combine some of their categories, such as "investment" and "investment alt."

bottom to top, suggesting that the factors benefit from holding stocks that exceed analysts' level and growth forecasts. Fifth, the vast majority of the circles are located in the first, second, and third quadrants, while the fourth quadrant is almost empty. These patterns in Figure 1 set forth our central messages that the level and growth biases are distinct, they line up with different anomalies, and they are both important for factor premiums.

3 Data and Validation

3.1 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 anomaly variables from Chen and Zimmermann's (2022) website.[2] 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 values of equity, lagged total assets above \$10 million, share price above \$5, and that are above the 20^{th} NYSE-size percentile in the previous month. The sample period is from July 1985 to June 2019. The starting time and ending time are constrained by the IBES data on forecast and actual earnings.

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 is in Table B.4 of the Online Appendix. The

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

variables are signed to forecast a positive abnormal return.[3] Consistent with prior research, the average and median absolute correlation between the factors are modest, at 0.26 and 0.20, respectively.

3.2 The level and slope

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 forecasts 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 periods 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 in the slope of how forecast horizon affects bias, is consistent with our level-growth framework that the longer-horizon forecasts are governed by a separate growth forecasting process. We now more formally validate our theory.

If the level-growth framework is a good description of how analysts form forecasts in 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. This is indeed the case.

Panel A of Table 1 shows the results from the PCA using analysts' annual and quarterly consensus (mean) earnings forecast term structure at the firm-month level. 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. Figure 3 provides a visualization of the PCA results. The first PCs in both panels load evenly on forecasts at all horizons (the

[3]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.

solid black line). The second PCs load negatively on the near-term forecasts and positively on the longer-term forecasts, and this association between the loadings and horizon is close to linear (the red line). The bottom row of Panel A shows the cumulative proportion of variance explained by the PCs. For the annual forecasts, the first two PCs explain 99.0% 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 blue line). The fourth PC in the right panel appears to correspond to a seasonality factor (the orange line).

Panel B of Table 1 shows the PCA results for the actual earnings term structure that is matched with the forecast term structure data studied in Panel A. We see that the actual earnings term structure can also be largely summarized by the first two principal components, suggesting that a two-factor model of the earnings process is a good approximation of reality. The level-slope pattern remains apparent from the PC loadings but less clearly so than the pattern in analysts' forecasts. In particular, the loadings of the first actual earnings PCs are less equal across horizons, and the loadings of the second PCs are less linearly associated with horizon. In addition, the first two PCs account for a smaller fraction of total variance for actual earnings (96.9% for annual earnings and 92.6% for quarterly earnings) than for earnings forecasts. These results in Panels A and B suggest that analysts indeed use a level-growth foresting framework, which is a reasonably accurate approximation of reality, to generate forecasts.

Our next 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 the growth forecasts within the longer horizon bucket to be highly correlated among themselves because they are derived from the same forecasting function. In contrast, short-term growth forecasts implied by the next-period level forecast 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 one

$(F[\pi_1]-\pi_0)$, the forward growth forecast in year two $(F[\pi_2]-F[\pi_1])$, and the forward growth forecast in year three $(F[\pi_3]-F[\pi_2])$. We see that the correlation between year two and year three forecasts is indeed quite high, at 0.66, while the correlations between year one and year two forecasts are much lower, at only 0.23. We also examine this correlation structure using panel regressions and find a similar pattern. We present the regression results in Table 2. In particular, we find that the year one growth forecast only weakly explains year two and year three forward growth forecasts with tiny coefficients and R^2s of around 1.2%. However, the year two forward growth forecast strongly explains the year three forward growth forecast, with a coefficient of 0.7 and an R^2 of 25.2%. These results strongly suggest that year two and year three often align while the year one growth forecast is distinct.

Our third validation test moves from the expectation space to the return space and examines the relation between growth forecasts and average stock returns. Existing studies, such as La Porta (1996) and Bordalo et al. (2019), show that analysts' long-term 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 3 shows the monthly value-weighted CAPM alpha and t-values for portfolios formed on growth and forward growth forecast quintiles. We sort stocks by year one growth forecast, year two forward growth forecast, and year three forward growth forecast each month into quintiles. The forecasts are scaled by market value of equity.[4] 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.

Consistent with our level-growth characterization of the forecast term structure, in Panel A, we find that only forward growth forecasts at year two and year three negatively predict abnormal returns. Stocks with the highest forward growth forecasts at year two and year 3

[4] In Appendix B.2, we show that when predicting returns, market value of equity is the correct scaler. The intuition is that for an optimistic forecast to predict a low subsequent return, the optimism needs to account for a significant fraction of the current market value of the stock.

earn a negative CAPM alpha of −0.38% and −0.26% per month, with t-values of −2.43 and −1.58. The H−L long-short portfolios earn negative CAPM alphas of −0.46 and −0.26, with t-values of −2.18 and −1.39. In contrast, the first row shows that the year one growth forecast positively predicts CAPM alpha. In Panel B, we use the Fama and French (2015)–Carhart (1997) six-factor model as the benchmark model. The abnormal return of the year two long-short portfolio remains negative at −0.27% (with a t-value of −1.69) even after controlling for the additional factors, while the abnormal return from the year three portfolio is fully subsumed.[5] The results in Table 3 suggest that the first-period growth forecast has a bias structure that differs from the biases in the longer-horizon growth forecasts.

In this section, we validate in the data that analysts appear to form their forecast term structure with a level and a growth expectation. However, we do not take a strong stand 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 (e.g., Da and Warachka, 2011; Ke and Yu, 2006). Second, the short-term cash flow level may be more carefully managed by firms (e.g., Richardson et al., 2004). 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. In this paper, we instead focus on understanding the implications of this level-growth structure.

3.3 An illustrative model

We provide an illustrative model in Appendix A.1. Our level-growth forecasting framework 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 distin-

[5] The asset pricing results here seem weak because the forecasts themselves are very noisy proxies for forecast errors. In a later section, we use a machine learning-based measure by van Binsbergen et al. (2022) to further demonstrate the asset pricing implications of our framework.

guish whether a firm characteristic captures biases in the cash flow level or cash flow growth. We test the model's prediction in Table B.1 and Table B.2 with two well-known characteristics, book-to-market equity and past twelve-month return, to exemplify our conceptual framework. Those results are helpful for readers to gain intuition.

4 Methodology

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:

$$\begin{aligned} LSurp_{i,t} &\equiv \frac{\pi_{i,t,1q} - \mathbb{F}_t[\pi_{i,t,1q}]}{K_{i,t-1}} \times 4, \\ GSurp_{i,t} &\equiv \frac{(\pi_{i,t,3y} - \pi_{i,t,1y}) - (\mathbb{F}_t[\pi_{i,t,3y}] - \mathbb{F}_t[\pi_{i,t,1y}])}{K_{i,t-1}} \times \frac{1}{2}, \end{aligned} \tag{2}$$

where $\pi_{i,t,h}$ is the firm's earnings, of which the subscripts, i, t, h, indicate firm, time, and horizon of the earnings, respectively, and $h = 1q, 1y, 3y$ indicates one-quarter-ahead, one-year-ahead and three-year-ahead. $K_{i,t-1}$ is firm i's total assets measured at time $t-1$.

$LSurp_{i,t}$ is the familiar earnings surprise — the difference between firm i's actual next-quarter earnings ($\pi_{i,t,1q}$) and analysts' consensus (mean) forecast of this earnings measured at time t ($\mathbb{F}_t[\pi_{i,t,1q}]$), scaled by the firm's lagged total assets. We follow the literature and assume the financial variables in annual reports are available six months after the fiscal year ends. Note that $\pi_{i,t,1q}$ is an ex post realized value that is unknown at time t while $\mathbb{F}_t[\pi_{i,t,1q}]$ 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 ($\pi_{i,t,3y} - \pi_{i,t,1y}$) minus the difference between the consensus three-year-ahead and one-year-ahead earnings forecasts at time t, ($\mathbb{F}_t[\pi_{i,t,3y}] - \mathbb{F}_t[\pi_{i,t,1y}]$), 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 accommodates 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 using total assets as the denominator matters and we explain why in Appendix A.1.

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 sample each month into the big and small groups using the NYSE 50^{th} percentile market value of equity.[6] 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.[7] The standard errors are Newey-West adjusted with 12 lags to account for serial correlations of the residuals.

We define a "factor surprise" analogously to factor premium. We first measure the ex post 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 a 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 expectation biases, it should on

[6] 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.

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

average have a positive factor level surprise and/or positive factor growth surprise.

Panel A of Table 4 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 available 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.

The second panel shows the distribution of the factor surprise the associated t-values.[8] We see that the factors on average line up with the direction of both types of surprises. The average factor level surprise, which we denote by λ, is 0.06 and the average growth surprise, denoted by 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 what intuition may suggest, the level and growth surprises are essentially uncorrelated, with a correlation coefficient of just 0.04. The correlation between the CAPM alpha 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 at -0.37, 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.

Panel B summarizes the associations between the anomalies and the two biases. Among the 123 factors studied, 60 significantly capture level surprise (with a $t(\lambda) > 1.96$), and 64

[8] Unless noted otherwise, we use the Newey-West standard errors with 12 lags.

significantly capture 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 capture only one bias earn lower alphas. The 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 unaffected.

These results confirm that biased beliefs are common drivers behind many anomalies. Furthermore, level and growth biases are about equally common among anomalies.

5 Empirical Results

5.1 Which expectation?

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. After aggregating the anomalies by group, Figure 4 continues to show a large dispersion in terms of where the anomalies are located in the level-growth bias space. 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 they earn especially large alphas.

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.[9] This interaction between the two expectations leads to some 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. For investors and analysts, when trying to correct expectation biases, it is important to first identify which expectation needs correction.

Table 5 reports the average λ, γ, and α for all 23 anomaly categories (Panel A). Columns 1, 2, and 3 in Panel A display the averages of the factor-level estimates for each category. Columns 4, 5, and 6 show 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.

5.2 Level and growth biases in the principal component anomalies

We next quantify the importance of the two biases in explaining the returns 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 123 long-short 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 that in Table 4 in Kozak, Nagel, and Santosh (2018) except now we have two forecast biases (λ and γ) while they have one bias they call

[9]For example, Doukas et al. (2002) test the error-in-expectation hypothesis for the value premium. Consistent with our results, they find that value stocks do not beat earnings forecasts. However, because they do not consider growth expectations, their rejection of the error-in-expectation hypothesis appears to be premature.

δ, which is a version of our level bias that uses market value of equity as the scaling variable. We base our choice of using total assets as the scaling variable on the model in Appendix A.1.

Table 6 shows the results for the first ten principal component portfolios. 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 and growth biases 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 6 report the λ and γ for the PC portfolios. They are the original portfolios' biases rotated into the PC space.[10] We see that the first PC 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 the large $t(\lambda)$ in the second PC show that the first two PC portfolios *separately* capture the level and growth biases. The fifth and sixth columns report 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 the 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 growth 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 declines 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, respectively. More interesting is the fact that the market betas of the first two PCs are

[10] They correspond to the β in Table 4 in Kozak et al. (2018) (KNS). All PC portfolios are signed to have positive CAPM alpha for ease of interpretation.

both significantly negative. This is consistent with one of KNS's 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 even not allowed for many institutions.

Other PCs have little relation with the two biases, as indicated by their small λ and γ values. 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 anomalies confirm that the two biases are indeed different and are both important.

5.3 The cross-section of alpha and alpha persistence

Alpha. Another 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 dispersed. Existing interpretations of this dispersion include data mining, learning from academic publications, and small-stock bias (Harvey et al., 2016; McLean and Pontiff, 2016). Our test quantifies the importance of biased beliefs in explaining the alpha dispersion in our relatively recent sample period.

The first panel in Table 7 shows the results from an OLS of CAPM alpha on λ and γ.

$$\alpha_{h,i} = \beta_0 + \beta_\lambda \lambda_i + \beta_\gamma \gamma_i + \epsilon_i, \tag{3}$$

where $\alpha_{h,i}$ is factor i's alpha over horizon h. In the panel on the right, we report the simple t-values and the t-values using bootstrapped standard errors (in parentheses).[11] The first

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

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 4. These numbers mean that a one-standard-deviation increase of λ and γ relative to other anomalies in our sample are associated with an 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 quite high, at 40.8%, which is consistent with the results from the PCA in the last subsection.

Alpha persistence.[12] In Table 7, 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 remains 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 with longer-horizon alphas are very high, ranging from 43% to 55%, suggesting that the explanatory power of the biases extends beyond short-term return predictability.

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

[12]There is some ambiguity in the term of alpha persistence. Here, alpha persistence means that some signal is persistently predictive of abnormal return. In the next section, we discuss another view of alpha persistence, which is characterized by the autocorrelation of abnormal returns predicted by some signal.

persistence with this characterization. We add to 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 estimates confirm the results in the first panel and show that 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 in the regressions. Panel A shows the regression slopes β_λ and β_γ in the specification that only includes λ and γ. Panel B shows the results for the specification that includes the first-month alpha (α_1) as an independent variable. The conclusion we have from Table 7 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 anomaly. 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 that the first PC explains should remain high even for returns many months after portfolio 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 factor portfolio formation. Panel A shows the correlation between 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 the 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 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 seven and month 16. The month-24 PC2 only correlates with the first-month PC2 at about 87%. Panel B shows the fraction of the total month-h return variation explained by their first two PCs. We see that the PC1 across all h explains 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.

In Online Appendix B.1, we further discuss the slow correction of the growth forecast errors by examining analysts' revisions around earnings announcements.

5.4 Factor momentum and persistent growth bias

Ehsani and Linnainmaa (2022) show that most factors exhibit momentum. To the extent that factor momentum may represent continual price correction, an interesting question is whether the type of expectation bias matters for the strength of factor momentum. 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:

$$
\begin{aligned}
R_{i,t} &= a_i + \rho_i R_{i,t-1} + \eta_{i,t}, \\
\rho_i &= \delta_0 + \delta_\lambda \lambda_i + \delta_\gamma \gamma_i + \epsilon_i,
\end{aligned}
\tag{4}
$$

where $R_{i,t}$ is the long-short factor return for factor i in month t. The coefficients of interest are δ_λ and δ_γ, which measure the incremental autocorrelation associated with the increase in λ and γ.

Table 9 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. This result is consistent with the original evidence in Ehsani and Linnainmaa (2022) that momentum-type factors do not exhibit factor momentum, while value and long-term reversal factors have strong factor momentum.

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 higher 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.

5.5 Betting against conditional biases

In this subsection, we demonstrate a practical implication of the level-growth framework for investment. van Binsbergen et al. (2022) construct real-time measures of conditional biases for firms' earnings forecasts at different horizons using a random forest algorithm. They show that a strategy that bets against these biases earns large abnormal returns. In particular, they form portfolios based on the firm's average conditional biases (average BE) across multiple horizons: one-quarter, two-quarter, three-quarter, one-year, and two-year ahead. They sell stocks with a high average BE (overly optimistic) and buy stocks with a low average BE. In our framework, this strategy corresponds to betting against the level bias plus a weighted average of the growth biases at different horizons.

Our framework suggests that expectation bias cannot be fully summarized by one number. The valuation of a firm depends on the entire earnings term structure. To arrive at a correct valuation, investors need to accurately forecast the earnings growth *at each horizon*. Therefore, we expect that the conditional biases in growth forecasts at various horizons should contain independent predictive information for future returns that cannot be captured by the average BE. To test this implication, we obtain the conditional bias measures data from the original authors[13] and construct three additional return predictors

$$\Delta BE_{2Q} = BE_{2Q} - BE_{1Q}, \tag{5}$$

$$\Delta BE_{3Q} = BE_{3Q} - BE_{2Q}, \tag{6}$$

$$\Delta BE_{2Y} = BE_{2Y} - BE_{1Y}, \tag{7}$$

where ΔBE is the conditional growth bias estimate. BE is the conditional bias in the earnings forecast as defined in the original study, which is equal to analysts' consensus earnings forecast minus the random forest benchmark, scaled by market value of equity in the previous month. The subscripts denote the forecast horizon where $1Q, 2Q, 3Q, 1Y, 2Y$ are one-quarter, two-quarter, three-quarter, one-year, and two-year ahead, respectively.

Panel A of Table 8 presents the results from portfolio regressions. The first two rows replicate van Binsbergen et al.'s (2022) results that stocks with high average bias estimates earn large negative alphas. In particular, the high-minus-low portfolio earns a value-weighted Fama-French-Carhart six-factor alpha of -1.13% per month with a t-value of -8.23. The remaining six rows in Panel A report the results for portfolios sorted by the growth bias estimates at the two-quarter (ΔBE_{2Q}), three-quarter (ΔBE_{3Q}), and two-year horizons

[13] We thank Jules van Binsbergen, Xiao Han, and Alejandro Lopez-Lira, for generously sharing the data.

(ΔBE_{2Y}). These strategies indeed earn large and highly significantly negative abnormal returns of -0.86, -0.74 and -1.51 percent per month.

Panel B presents the results from factor spanning tests. The first column shows that the negative return from the long-short portfolio based on average BE can be fully explained by a model that contains the market factor and the three growth bias factors (i.e., the returns on the long-short portfolios formed on ΔBE's). The alpha even turns significantly positive. The loading on the two-year-ahead growth bias factor is large, at 0.78. These results suggest that the predictive power from average BE arises from analysts' predictable biases in growth forecasts. More importantly, columns two, three, and four show that the growth bias factors cannot be fully explained by the average BE factor and growth bias factors for other horizons. The intercepts remain significantly negative at -0.33, -0.55 and -0.58. These results suggest that investors can indeed benefit from treating expectation bias as a high-dimensional object rather than collapsing it into one variable.

6 Bias Decay and Alpha Decay

People learn. Besides, the information environment improves over time. Thus, we conjecture that expectation biases may shrink over time, which in turn shrinks the factor premiums. In this section, we explore how expectation biases have evolved and whether their changes may have affected anomaly returns. Existing studies show that most anomalies perform poorly in recent periods and particularly after 2003 (e.g., Green et al., 2017). We hypothesize that this decay in their performance may be due to increased forecast accuracy.

Table 10 shows the average factor-level statistics in the pre- and post-2003 samples. 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-2003 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 pre-2003 average γ is 0.66 while the post-2003 γ shrinks to 0.24, though still statistically highly significant.

Table 11 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 ($\times$100) 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 and Sharpe Ratio 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 is likely responsible for the change in the factors' performance. Anomalies that primarily capture growth bias appear to be more strongly affected by the bias decay.

Table 12 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 $LSurp$ (-0.35). This number changes to positive (0.29) in the later period. The typical growth surprise is deeply negative (-2.26) in the pre-2002 sample, while this magnitude is reduced by half (to -1.08) in the recent sample. These results suggest that analysts' level and growth forecasts have both become less optimistically biased in the recent sample. The typical level forecast even has become overly pessimistic. The last two columns show that the dispersion in the level and growth surprises have declined in recent periods. The decline in the dispersion of the surprises suggests that the forecasts have become more accurate overall.

7 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 forming biased beliefs in general.

The first issue mirrors the joint hypothesis problem in tests of market efficiency — one must take a stand 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 over our sample period between 1985 and 2019, but this may not be the case in reality. For example, Hou and van Dijk (2019) argue 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 follows: 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 we study many hedged portfolios that are well diversified. It is hard to argue why cash flow shocks are so pervasively 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 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 (e.g., Ke and Yu, 2006). Investors' beliefs, which would be otherwise unbiased, may be distorted by analysts' misleading forecasts.

We do not take a stand on how much of the biased beliefs are from the agency problem and how much of the biases are from nature. However, if we adopt the incentive misalignment interpretation, it is unclear why analysts' incentives appear to differ so significantly by firm characteristics and why their incentives lead them to be biased in the level and/or growth forecasts depending on firm characteristics. We believe this is an important and general question that deserves separate investigation. We also refrain from discussing the potential mechanism that drives the two types of biases. We focus on, and only on, showing the sharp distinction between cash flow level and growth biases, and their implications for asset prices.

8 Conclusion

In this paper, we provide the first study of biased expectations in multiple dimensions. Motivated by Gordon's classic growth model and using analysts' earnings term structure forecasts, we find strong evidence for the separability of the two beliefs on the level and growth of cash flows, respectively. Out of 123 anomalies that are potential violations of market efficiency, we find that biases in the two beliefs can explain about 50% of their variations. Interestingly, the level bias is often associated with large initial alphas of the anomalies, whereas the growth bias is usually responsible for persistent alphas. The changes in biased beliefs also provide an explanation for the recent alpha decay because of the improved forecast accuracy by analysts. Our results suggest that it will be fruitful to model or analyze subjective beliefs in high dimensions. Future research may extend our framework to other stock markets or other asset classes.

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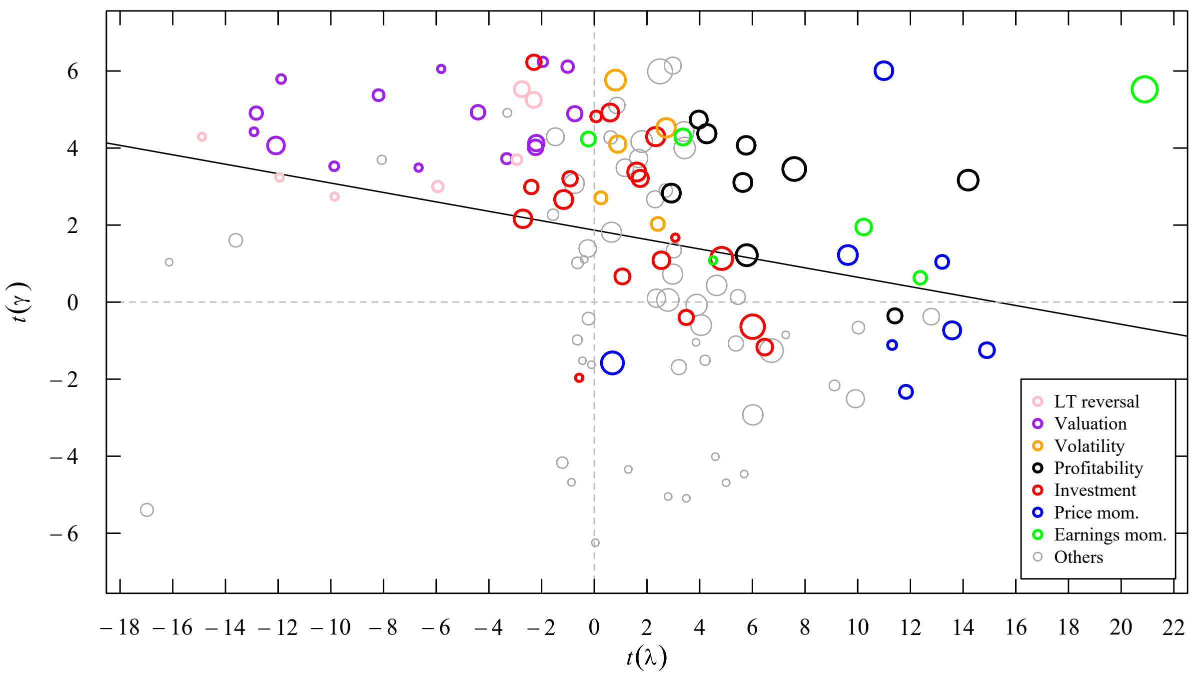

Figure 1: **Level bias, growth bias, and anomalies.** This figure plots the locations of 123 anomaly portfolios in the level-growth-bias space. The circle size increases with the average alpha of the group. The data behind this figure is in Table 5. The horizontal axis $t(\lambda)$ measures the extent to which the anomaly consistently captures level bias. $t(\lambda)$ measures the extent to which the anomaly consistently captures growth bias. 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%

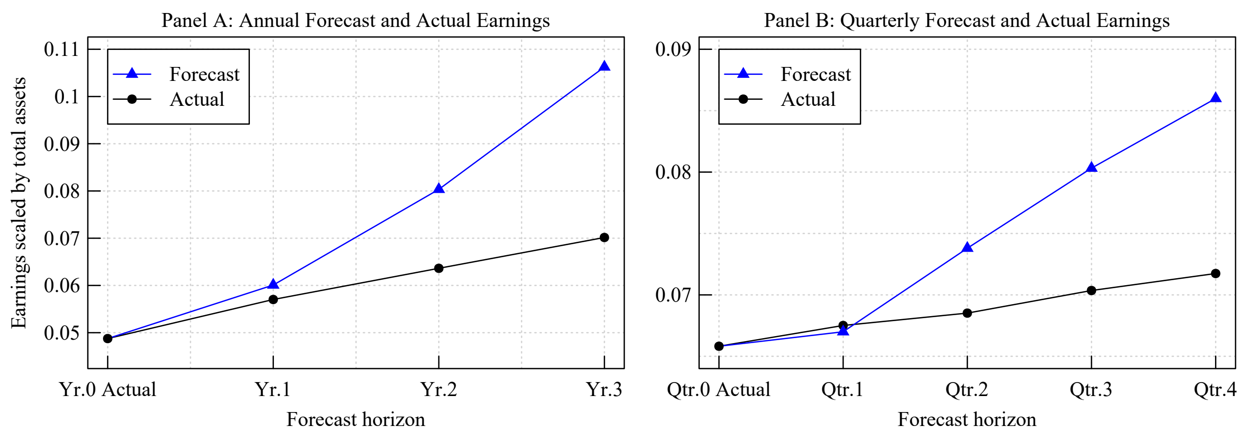

Figure 2: **Unconditional forecast and actual earnings term structure.** This figure plots the unconditional average earnings forecasts over different horizons and the corresponding actual earnings. We scale all earnings by lagged total assets. We annualize the quarterly earnings by multiplying them by four. The sample includes stock-month observations with available forecasts 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.

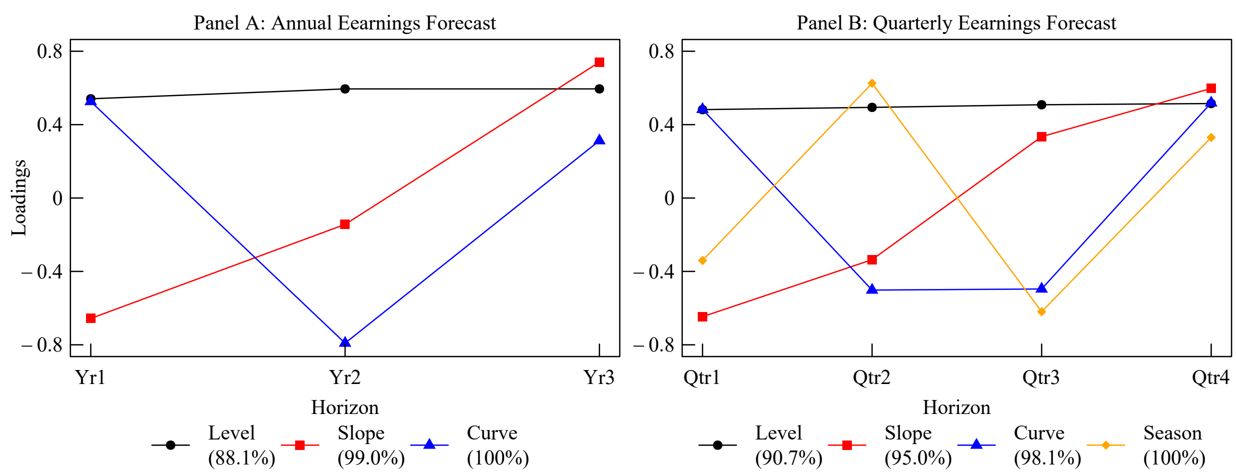

Figure 3: **Principal component analysis on analysts' annual and quarterly earnings forecast term structure.** This figure shows the loadings of the earnings forecast principal components on forecasts at different horizons. These values correspond to those in Panel B of Table 1. The Level, Slope, Curve, and Season are the first, second, third, and fourth PCs. The numbers in parentheses indicate the proportions of the variance cumulatively explained by the PCs. The sample includes stock-month observations that have non-missing data on consensus earnings forecasts and non-missing corresponding actual earnings at the three annual or four quarterly horizons.

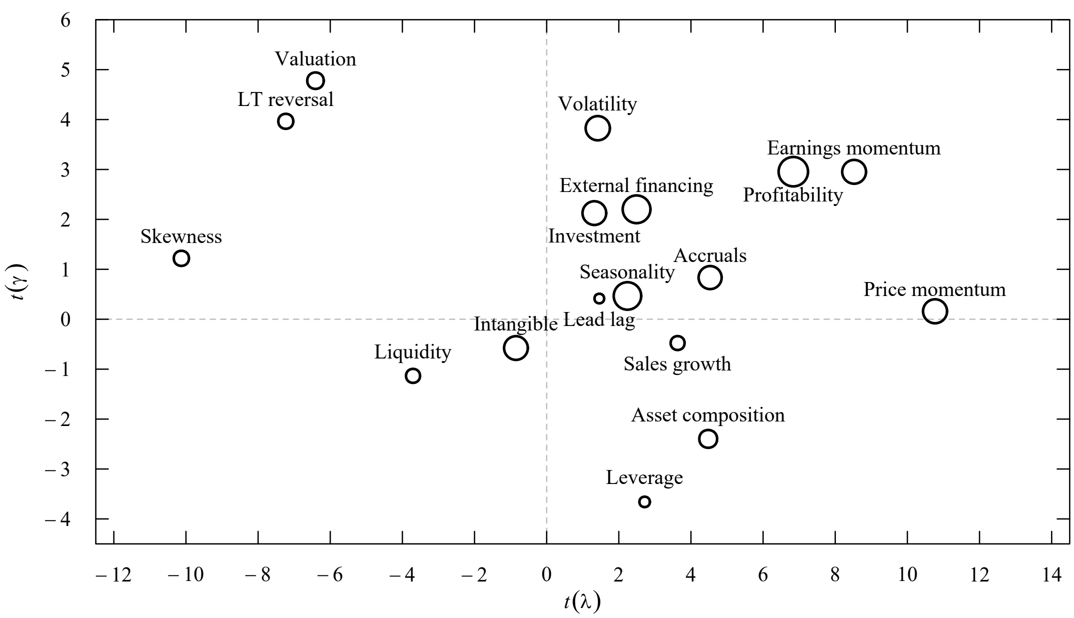

Figure 4: **Level bias, growth bias, and anomalies.** This figure plots the locations of 17 anomaly groups in the level-growth-bias space. We average the t-values of λ and γ within each category. The circle size increases with the average alpha of the group. The data behind this figure is in Table 5.

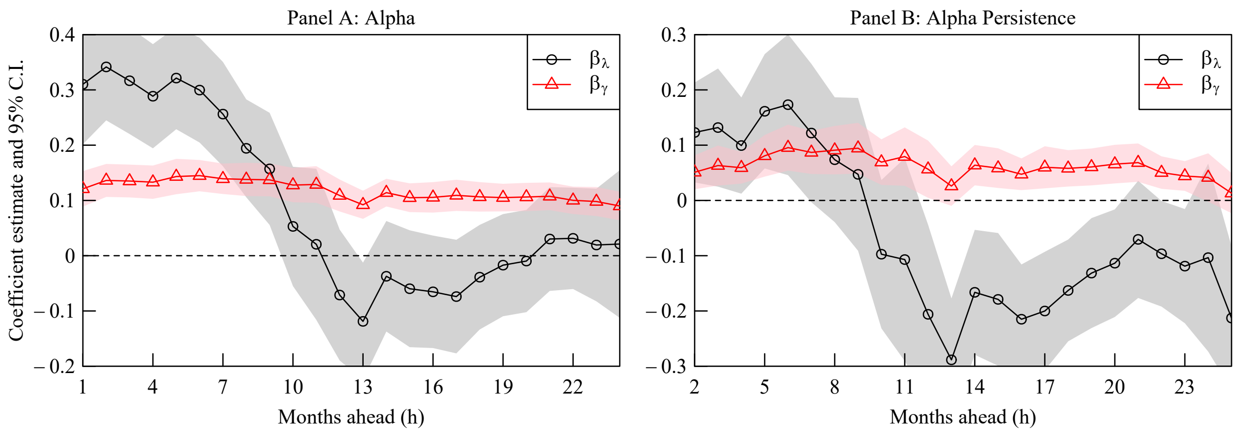

Figure 5: **Level, growth, and the magnitude and persistence of alphas.** This figure shows the bootstrapped average OLS regression coefficients (β_λ and β_γ) from: $\alpha_{h,i} = \beta_0 + \beta_\lambda \lambda_i + \beta_\gamma \gamma_i + \beta_{\alpha_1} \alpha_{1,i} + \epsilon_i$. h indexes for the number of months since the formation of the factor portfolio. i indexes for factor. 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 the factors with replacement.

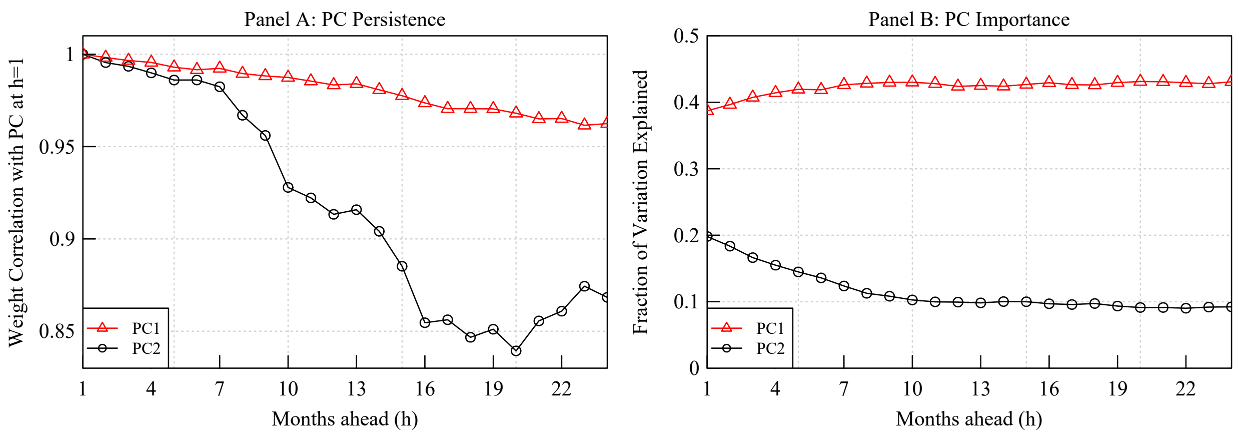

Figure 6: **Principal component portfolios persistence and importance.** Panel A plots the correlations between the weights of the PCs extracted from anomaly portfolio returns in month one and month h since portfolio formation. A high value means the PC for the month-h returns is similar to the PC for 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.

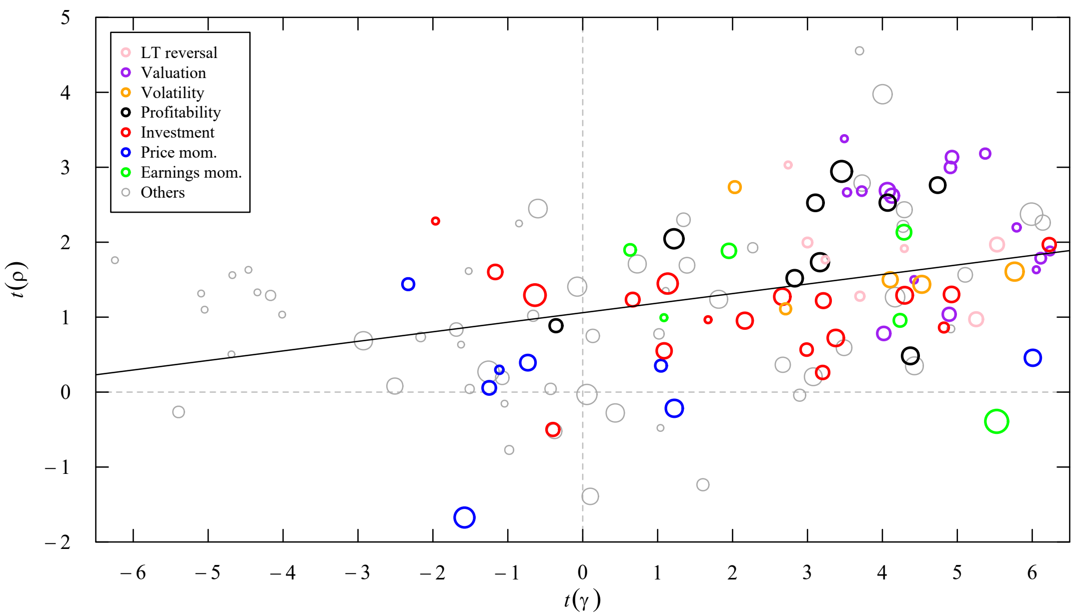

Figure 7: **Factor momentum and growth bias.** This figure plots the locations of 123 anomalies in the $t(\rho)$-$t(\gamma)$ space. ρ is estimated for each anomaly with the regressions $R_{i,t} = a_i + \rho_i R_{i,t-1} + \eta_{i,t}$, where $R_{i,t}$ is the return of factor i in month t. The slopped solid 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%.

Table 1: Principal Component Analysis and Correlations

Panel A (Panel B) shows the eigenvectors from a principal components analysis on analysts' consensus earnings forecasts (corresponding actual earnings) at different annual and quarterly horizons. The last rows in Panels A and B indicate the cumulative proportion of variance accounted for by the PCs. 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. Forecasts are scaled by the firm's total assets. We cross-sectionally winsorize the variables each month at the second and ninety-eighth percentiles. The unit of observation is firm-month. The sample period is from July 1985 to June 2019.

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	0.54	−0.66	0.53	Qtr1	0.48	−0.65	0.48	−0.34
Yr.2	0.59	−0.14	−0.79	Qtr2	0.49	−0.34	−0.50	0.63
Yr.3	0.59	0.74	0.31	Qtr3	0.51	0.33	−0.50	−0.62
				Qtr4	0.52	0.60	0.52	0.33
Cum. Prop	88.1%	99.0%	100.0%		90.7%	95.0%	98.1%	100.0%

Panel B: Principal component analysis on the actual earnings term structure

Annual Earnings				Quarterly Earnings				
Horizon	PC1	PC2	PC3	Horizon	PC1	PC2	PC3	PC4
Yr.1	0.45	−0.65	0.62	Qtr1	0.45	−0.58	0.54	−0.42
Yr.2	0.58	−0.32	−0.75	Qtr2	0.49	−0.42	−0.32	0.69
Yr.3	0.68	0.69	0.23	Qtr3	0.52	0.21	−0.63	−0.54
				Qtr4	0.54	0.66	0.46	0.24
Cum. Prop	89.1%	96.9%	100.0%		85.7%	92.6%	97.0%	100.0%

Panel B: Correlation between growth forecasts and forward growth forecasts

	$F[\pi_1]-\pi_0$	$F[\pi_2]-F[\pi_1]$	$F[\pi_3]-F[\pi_2]$
$F[\pi_1]-\pi_0$	1	0.23	0.09
$F[\pi_2]-F[\pi_1]$	0.23	1	0.66
$F[\pi_3]-F[\pi_2]$	0.09	0.66	1

Table 2: The Correlation Structure of Growth Forecasts

This table presents the results from regressions in which the dependent variables are the forward earnings growth forecasts from year 1 to year 2 ($F[\pi_2] - F[\pi_1]$) and the forward earnings growth forecasts from year 2 to year 3 ($F[\pi_3] - F[\pi_2]$). The independent variables are growth forecasts and forward growth forecasts from year 0 to year 1 ($F[\pi_1] - \pi_0$), and from year 1 to year 2 ($F[\pi_2] - F[\pi_1]$). All variables are scaled by lagged total assets. t-values are reported in the parentheses. Standard errors are two-way clustered by firm and month.

	$F[\pi_2] - F[\pi_1]$	$F[\pi_3] - F[\pi_2]$	
$F[\pi_1] - \pi_0$	0.06	0.09	
	(1.86)	(1.49)	
$F[\pi_2] - F[\pi_1]$			0.70
			(10.79)
Constant	0.02	0.03	0.01
	(30.22)	(21.31)	(8.84)
N	383,115	383,115	383,115
Adj.R^2	1.2%	1.2%	25.2%

Table 3: Growth Forecasts at Different Horizons and Stock Return

This table reports the monthly value-weighted CAPM (Fama-French-Carhart six-factor model) alphas in Panel A (Panel B) and t-values in parentheses. We sort portfolios by analysts' growth forecasts over the first year, the second year, and the third year into quintiles. Growth forecasts are scaled by the firms' market value of equity. Forecasts increase from Q1 to Q5. The H−L column reports the alphas on the long-short portfolios that buy stocks in the top forecast quintile and sell those in the bottom quintile. The sample period starts in July 1985 and ends in June 2019. Standard errors are Newey-West adjusted with 12 lags.

Panel A: CAPM Alpha

	Growth and Forward Growth Forecast Quintiles					
Sort by	Q1 (Low)	Q2	Q3	Q4	Q5 (High)	H−L
$F[\pi_1] - \pi_0$	−0.23	0.04	0.13	0.08	−0.02	0.21
	(−2.28)	(0.72)	(1.91)	(1.12)	(−0.21)	(1.45)
$F[\pi_2] - F[\pi_1]$	0.08	0.16	0.07	−0.08	−0.38	−0.46
	(0.94)	(2.06)	(0.94)	(−0.85)	(−2.43)	(−2.18)
$F[\pi_3] - F[\pi_2]$	0.00	0.16	0.06	0.04	−0.26	−0.26
	(0.00)	(2.37)	(0.71)	(0.36)	(−1.58)	(−1.39)

Panel B: Fama-French-Carhart Six Factor Alpha

Sort by	Q1 (Low)	Q2	Q3	Q4	Q5 (High)	H−L
$F[\pi_1] - \pi_0$	0.03	0.06	0.03	−0.03	−0.10	−0.13
	(0.25)	(0.92)	(0.40)	(−0.41)	(−1.03)	(−0.82)
$F[\pi_2] - F[\pi_1]$	0.11	0.02	−0.05	−0.03	−0.16	−0.27
	(1.56)	(0.32)	(−0.80)	(−0.34)	(−1.25)	(−1.69)
$F[\pi_3] - F[\pi_2]$	−0.11	0.02	−0.03	0.11	0.08	0.19
	(−1.63)	(0.36)	(−0.43)	(1.40)	(0.55)	(1.17)

Table 4: Descriptive Statistics: Level Surprise, Growth Surprise, and Anomalies

Panel A reports the stock- and factor-level summary statistics for the surprises. $LSurp$ and $GSurp$ are the ex post level surprise and growth surprise defined in Equation (2). λ and γ are the average level and growth surprise spread of the anomaly portfolios. $t(.)$ are the t-values associated with the estimates. α is the value-weighted monthly CAPM alpha of the anomaly long-short portfolio. The last row displays the correlation coefficients between the estimates. Panel B reports the number of factors that are statistically significantly associated with level and/or growth biases, defined by $t(\lambda)$ and $t(\gamma)$ being greater than 1.96 or 3, and their average CAPM alphas and average t-values of the alphas.

Panel A: Summary statistics

	N	Mean	SD	Min	p25	p50	p75	Max
Stock-month-level sample:								
$LSurp(\%)$	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
Factor-level sample:								
$LSurp$ 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
$GSurp$ 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

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

Panel B: Level and growth anomalies

	Level	Level only	Growth	Growth only	Either	Both	Neither	All
***t*-value > 1.96 cutoff**								
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
***t*-value > 3 cutoff**								
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 5: Level Bias, Growth Bias and Anomalies

This table shows the average λ, γ, α and the corresponding average t-values by anomaly category. The detailed list of the anomalies, their categorization, and the individual estimates are in Table B.3 in the Appendix.

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
Long-term 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	

Table 6: Expectation Biases in Principal Component Anomaly Portfolios

This table reports the first ten principal component anomalies of 123 HML-style long-short anomaly portfolios. λ and γ are the average level and growth bias spreads for the principal components. $t(\alpha)$ and $t(\beta)$ are the t-values of the CAPM alpha and market 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 7: Level, Growth and the Magnitude and Persistence of Alphas

This table reports the results from OLS estimates from regressing the 123 anomaly portfolios' CAPM 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 horizon h. i indexes for anomaly portfolios. The first panel excludes the regressor $\alpha_{1,i}$. 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 8: Conditional Bias Estimates and Stock Return

Panel A reports the monthly value-weighted Fama-French-Carhart six-factor model alphas on portfolios formed on conditional bias estimates by van Binsbergen et al. (2022). Portfolios are formed by quintiles of the average bias estimates (Average BE) and the growth bias estimates (ΔBE) for the two-quarter, three-quarter, and two-year horizons. Panel B reports the results from factor spanning tests in which the factors are the market factor and the long-short portfolio returns associated with average BE, ΔBE_{2Q}, ΔBE_{3Q} and ΔBE_{2Y}. The sample period starts in February 1986 and ends in June 2019. Standard errors are Newey-West adjusted with 12 lags.

Panel A: Fama-French-Carhart six-factor alpha

	Conditional Bias Estimate Quintile					
Sort by	Q1 (Low)	Q2	Q3	Q4	Q5 (High)	H−L
Average BE	0.41	0.02	0.00	−0.25	−0.72	−1.13
	(5.39)	(0.48)	(−0.05)	(−3.11)	(−7.62)	(−8.23)
ΔBE_{2Q}	0.35	0.14	−0.11	−0.23	−0.51	−0.86
	(5.39)	(1.99)	(−2.06)	(−2.93)	(−6.92)	(−9.11)
ΔBE_{3Q}	0.19	0.13	0.03	−0.09	−0.54	−0.74
	(2.03)	(2.12)	(0.77)	(−1.24)	(−4.63)	(−4.00)
ΔBE_{2Y}	0.65	0.10	−0.04	−0.20	−0.86	−1.51
	(8.73)	(1.86)	(−0.82)	(−3.03)	(−8.82)	(−10.24)

Panel B: Spanning test

	Average BE	ΔBE_{2Q}	ΔBE_{3Q}	ΔBE_{2Y}
Intercept	0.24	−0.33	−0.55	−0.58
	(2.29)	(−2.37)	(−3.05)	(−6.75)
Mkt−rf	0.08	0.03	0.06	0.02
	(3.16)	(0.63)	(1.60)	(0.66)
Average BE		0.41	0.11	0.67
		(4.34)	(0.80)	(11.12)
ΔBE_{2Q}	0.26		−0.11	0.07
	(3.65)		(−1.27)	(1.06)
ΔBE_{3Q}	0.06	−0.10		0.10
	(0.89)	(−1.28)		(1.43)
ΔBE_{2Y}	0.78	0.14	0.21	
	(12.09)	(1.09)	(1.66)	
Adj.R^2	0.77	0.41	0.14	0.73
N	401	401	401	401

Table 9: 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 10: Level and Growth Biases before and after 2003

This table reports the average level and growth bias spreads 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 July 1985 to December 2002. The post-2003 sample is from January 2003 to June 2019.

			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 11: 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 July 1985 to December 2002 minus the average spread from January 2003 to June 2019. Alpha decay and Sharpe Ratio decay are computed analogously. Alpha is the CAPM alpha of the HML-style factor portfolio. The Sharpe Ratio is the average divided by the standard deviation of monthly portfolio return (multiplied by 100 for exposition purposes). The t-values of H−L are from 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 (×100)	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 (×100)	0.74	3.24	3.94	5.64	6.74	6.00	2.74

Table 12: 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 averages, 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 samples (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

Appendix

A.1 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:

$$ME_0 = \delta_1 \mathbb{E}[\pi_1] + \delta_2 \mathbb{E}[\pi_2] + \delta_3 \mathbb{E}[\pi_3], \tag{A.1}$$

where π_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 $\mathbb{F}[.]$, which take the general forms below:

$$\begin{aligned} \mathbb{F}[\pi_1] &= \mathbb{E}[\pi_1] + \eta, \\ \mathbb{F}[g] &= \mathbb{E}[g] + \xi. \end{aligned} \tag{A.2}$$

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:

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

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

$$ME_0 \approx \delta_1(\bar{\pi}_1 + \eta) + \delta_2(\bar{\pi}_1 + \eta)(1 + \bar{g} + \xi) + \delta_3(\bar{\pi}_1 + \eta)(1 + 2\bar{g} + 2\xi). \tag{A.4}$$

The term structure of forecast error—the case of market-to-book: Let K be the total assets of the firm. If the firm is fully 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:

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

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

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

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 market-to-book equity (MB) are likely to be 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 small $\bar{g} \approx 0$ 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 cross-sectional regression coefficient of forecast errors at horizons 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 that correlate with η or ξ.

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 slopes. If x primarily captures biased beliefs about the cash flow growth, it should predict forecast errors at further horizons with larger slopes.*

We empirically implement this procedure and present the results in the left panels of Table B.1 in the Online Appendix. In particular, we regress firms' forecast error at different horizons on log(BM) and past twelve-month return. We find that log(BM) indeed predicts longer-horizon forecast errors with larger slopes (see the left panel of Panels A and B). In contrast, log(BM) predicts a negative quarterly earnings surprise. These results suggest that log(BM) captures the growth bias but does not capture level bias. The bottom panels of Panels A and B show that the past 12-month return primarily captures the level bias but not the growth bias, as indicated by the slopes of similar magnitudes across horizons. We also implement this test using a portfolio approach and find consistent results (see Table B.2).

Online Appendix

B.1 Slow correction of growth forecast error

We show that abnormal returns earned by anomalies related to growth bias are persistent. This implies that investors correct growth forecast errors only slowly. This result is consistent with De La O et al. (2023), who estimate a constant gain learning model using analysts' long-term growth forecast revisions. For the level forecast errors, the correction is faster. In this subsection, we confirm this slow correction in the belief space. For brevity, we focus on just two prominent anomalies — value and momentum — to make our point in this subsection, but the patterns they exhibit are representative of the whole sample of anomalies.

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.[14]

Table B.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

[14] Please see Appendix A.1 for an illustrative model that details the intuition of this test.

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' fourth-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 coefficient 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, consistent with Doukas et al. (2002). However, the second and third columns show that log(BM) is significantly associated with higher year two and year three forecast surprises (relative to the current forecasts), with coefficients of 0.58 and 1.82. Thus, analysts, despite being overly optimistic about value firms for year one, are overly pessimistic about these firms for year two and year three. The coefficient estimates increase from year two to year three, 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 predicts analysts' forecast revisions. A one-standard-deviation increase in log(BM) is associated with 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$\to$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 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 nearly equal to 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 highlights 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 one and year two, but is uncorrelated with forecast errors in year 3. The results in the "Revision" panel show that analysts shift the forecast term structure in parallel with some rotation that reflects an upward revision in the 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 suggests that belief correction and distortion can happen at the same time because they take effect at different horizons. 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 predicts 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.

Book-to-market equity, momentum, and the term structure of forecast error. In Table B.2, we more explicitly show the associations between firm characteristics and the forecast error term structure. We choose book-to-market equity and past stock return as examples. We sort stocks into quintiles by book-to-market equity or past returns. Then we compute the average ex post forecast errors at each horizon, from one quarter ahead to three years ahead (using a consistent sample with all nonmissing forecast errors across horizons). The H − L rows show that firms with high book-to-market equity are associated with a negative surprise at the one-quarter horizon but are associated with increasingly positive forecast errors at longer horizons. Stocks with high past returns, on the other hand, are associated with similar forecast errors across different horizons. These results suggest that book-to-market equity is associated with growth expectation bias, while momentum is associated with level expectation bias.

B.2 The scaling variable: A note

Prior research alternatively uses total assets and market value of equity as the scaling variable for earnings, earnings forecast, and earnings forecast error in different contexts. This choice may seem arbitrary, but many papers show results with different scaling variables to show "robustness" without explaining why one choice may be better than the other in different situations. We briefly clarify the distinction between the two ways of scaling in this subsection. The basic rule we propose is: when studying forecast error as the outcome variable, total assets is a more suitable scaler; when studying abnormal stock return as the outcome and forecast error as the endogenous variable, market value of equity is more appropriate.

When expectation error is the outcome, the economic quantity we care about is the firms' productivity or productivity growth. As in Equation A.6, if a firm characteristic x, such as market-to-book, proxies for the expectation errors, total assets is the correct scaler (ignoring capital structure issues). Using market value of equity to replace K to scale forecast error would mechanically and unduly weaken, or even completely eliminate, the association between x and forecast error because firms with large positive errors, by construction, have high market value of equity. Therefore, dividing the forecast error by market value (dividing the right-hand-side of Equation A.6) by market-to-book, would undo the explanatory power of x.

In contrast, when we aim at predicting stock return using some proxies for the biases η or ξ, such as the (forward) growth forecasts in Table 3, using market value of equity as the scaler is more appropriate. The intuition is that it is not enough to predict expectation errors when predicting return. It also matters how important this error is for the firm's current market valuation. That is, the same dollar amount of earnings forecast error should predict a larger abnormal return for a small firm than for a big firm. To see this more clearly, let us go back to the simple model outlined above. After all forecast errors are corrected, the abnormal return for the previously mispriced firm can be written as:

$$r = \frac{R(.)}{R(.) + B(.)}, \tag{B.1}$$

where $R(.) = R(\frac{ME_0}{K})$ and $B(.) = B(\frac{ME_0}{K})$. Let x be some ex ante noisy proxy for forecast error such that $B(.) = \frac{1}{K}(\beta x + \epsilon)$, where ϵ is the zero-mean noise term and β some constant. Then the expected abnormal return is

$$E[r] = \frac{R(.) + B(.) - B(.)}{R(.) + B(.)} = 1 - \frac{\frac{1}{K}\beta x}{R(.) + B(.)} = 1 - \frac{\beta x}{ME_0}, \tag{B.2}$$

where ME_0 is the market value of equity. This is the reason why, when we form portfolios in Table 3, we use market value of equity as the scaling variable for our x's, growth forecasts at different horizons, but use total assets as the scaling variable when we study the relation between characteristics portfolios and the two expectation errors.

B.3 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 some important reasons why we focus on the forecast term structure in our study.

First, we need precise measures of ex post growth forecast errors. LTG is 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 our desired level of accuracy.

Second, about 8.8% of our sample firms have negative earnings in their previous fiscal year. Among firms with nonmissing 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 in 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 tests in Table B.1, we need to measure the change in growth forecast over earnings announcements. The revision in LTG is driven by two effects: (1) the forecast revision due to new information and (2) the change in the forecasting period. For our purpose, therefore, it would be unclear whether a revision in LTG is caused by an actual correction in belief or the new forecast horizon included is expected to have a different growth rate.

We are perhaps among the first to propose using the earnings forecast term structure to measure growth expectations. We believe this is an important contribution, for it adds a new empirical device for future research.

Table B.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 12-month stock return (skipping the most recent month), 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 Error" 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 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. The growth forecast is the difference between the three-year ahead forecast and the two-year ahead forecast, scaled by lagged total assets. Growth forecast revision 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

Table B.2: The Term Structure of Forecast Errors and Firm Characteristics

At the end of each month, we sort stocks into quintiles by book-to-market or past return from 12 to 2 months ago. 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.

	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

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

This table presents the λ, γ, the CAPM α and their t-values for the 123 characteristics by categories.

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 B.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)

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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)