Finance without (exotic) risk

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August 12, 2024

Abstract

We address the joint hypothesis problem in cross-sectional asset pricing by using measured analyst expectations of earnings growth. We construct a firm-level measure of Expectations Based Returns (EBRs) that uses analyst forecast errors and revisions and shuts down any cross-sectional differences in required returns. We obtain three results. First, variation in EBRs accounts for a large chunk of cross-sectional spreads in value, investment, size, and momentum factors. Second, time variation in the spreads is predictable, and proxied by predictable time variation in EBRs due to expectations. This result holds even controlling for scaled price variables, which may1 capture discount rate differentials. Third, firm characteristics typically viewed as capturing risk predict disappointment of expectations (and of EBRs). Overall, return spreads typically attributed to exotic risk factors are explained by predictable movements in non-rational expectations about firms' earnings growth.

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1. Introduction.

The capital asset pricing model (CAPM, Sharpe 1964) represents a major contribution to the understanding of financial markets. Starting from mean variance preferences and rational expectations, it offers a theory of returns that became the cornerstone of the efficient markets hypothesis (EMH): average return differences across stocks are determined by their differential exposures to market risk. Subsequent evidence on return differentials not tied to such exposure challenged the CAPM, casting doubt on the EMH (Basu 1977, 1983; Rosenberg et al. 1985; Banz 1981). However, as pointed out by Fama (1970) and Fama and French (1993), this evidence is not necessarily a rejection of the EMH, but possibly of the CAPM model of risk. This came to be known as the joint hypothesis problem: without observing expectations or risk, any test of market efficiency is also a test of a model of risk.

Mainstream finance has dealt with this problem by keeping rational expectations and introducing new risk factors (Fama and French 1993, 2015), an approach that has powered research in cross-sectional asset pricing for the past 30 years. In this approach, documented excess returns relative to the CAPM reflect premia for exposure to additional risk factors. It has however proved challenging to link these risk factors to tangible risks such as bankruptcy and distress (La Porta et al 1997). Behavioral finance has instead relaxed rational expectations, allowing for belief extrapolation, over- and underreaction, or other biases (e.g., Lakonishok et al 1994, Barberis et al. 1998, Hong and Stein 1999, Jegadeesh and Titman 2011, Daniel and Hirshleifer 2015, Barberis et al 2015, Kozak et al. 2018, van Binsbergen et al 2023). Still, returns are matched to a model of expectations, not to measured expectations.

We deal with the joint hypothesis problem by using measured expectations about the future earnings growth of US listed firms, so that the rationality of these expectations and their ability to explain cross sectional patterns in returns can be assessed directly. In recent years, it has become possible to measure such expectations using surveys of market analysts and other

investors, which has proved useful in a variety of domains (e.g., La Porta 1996, Greenwood and Shleifer 2014, Giglio and Kelly 2018, Bordalo, Gennaioli, La Porta, Shleifer BGLS 2019, 2024, de la O and Myers 2021, 2024, Nagel Xu 2022, Jiang et al 2022, Bianchi et al. 2024). We tie cross-sectional returns to measured expectations of firm level fundamentals, which allows us to trace not only changes in market wide optimism as in BGLS (2024), but also co-movement across different portfolios of stocks. We then ask: can leading cross-sectional return spreads typically attributed to risk factors come from expectations? We show that, to a significant extent, the answer is yes.

In Section 2, we use the Campbell-Shiller decomposition and measured expectations to construct firm level *expectations-based returns* (EBRs), which attribute all variation in returns to observed belief errors and revisions, while shutting down any cross sectional and time series variation in required return. In our key test, we show that variation in EBRs quantitatively explains most of the contemporaneous returns of the long-short book-to-market and size portfolios (HML and SMB, Fama and French 1993). That is, the residual spread after accounting for expectations – the new target for risk-based stories – is close to zero and insignificant. HML and SMB are puzzles of expectations, with little room for risk.

We then extend the analysis to the other standard factors in the literature, namely investment and profitability (making up the Fama French 2015 five factor model), as well as momentum (Jegadeesh and Titman 1993). Here as well, after accounting for variation in EBRs there is little left to explain, except for profitability (where we face the challenge of attrition of low profitability firms with negative earnings). These results hold for short horizons typical of cross-sectional analyses (Fama and French 1993, 2015) but also longer horizons common to reversal anomalies (de Bondt and Thaler 1985) and the aggregate stock market. They also hold after accounting for aggregate market optimism, showing that EBRs capture systematic cross-sectional variation that affects cross sectional spreads.

Why do EBRs explain cross sectional spreads? One mechanism is non-rational expectations: average spreads materialize because the realized earnings growth of stocks in the portfolio's short arm systematically disappoints compared to that of stocks in its long arm. This is in line with growing evidence of systematic overreaction of long-term earnings growth forecasts, LTGs (BGLS 2024). Consistent with this mechanism, we show that realized spreads have large and significant loadings on forecast errors, to an extent that leaves little room for risk to explain observed average return differentials.

One challenge to this interpretation is the measurement of expectations: if analysts mechanically extract expectations from prices, potential risk-driven price movements may be erroneously interpreted as informative about future earnings growth. To address this question, we move beyond the average predictability and look at the variation in cross-sectional spreads over time. We first ask whether future cross-sectional spreads and EBRs are predictable using current portfolio-level expectations *and* scaled price variables. Because the latter capture both market expectations and required returns, in an efficient market they should be the only source of predictability even if measured expectations are mechanically inferred from prices and capture shocks to required returns. We find that expectations predict future return spreads to an extent that completely dwarfs price-ratio-based predictability, contrary to the inference from prices hypothesis.[2]

Instead, cross-sectional spreads are driven by predictable changes in earnings growth forecasts, as proxied by predicted EBRs. They are particularly high after periods when analysts are very optimistic about the portfolio's short arm. They are predictably low – and even predictably negative – otherwise. Cross sectional spreads arise due to non-rationality of expectations, and reflect market inefficiency, with little room left for (time varying) risk.

[2] In our data, price ratios have very low predictive power for returns even in univariate regressions. We report a large set of tests on the inference from prices hypothesis in Section 2.5.

In the second test we predict future firm level EBRs using firm characteristics such as book to market, size, investment, etc. These characteristics are typically viewed as risk factors but have not been reliably connected to identifiable risks. We show that, in contrast, the same characteristics are tied to non-rational beliefs: high book to market, high investment, and other characteristics predict future belief disappointment and downward forecast revisions. Market inefficiency links characteristics to predictable returns.

Our results have significant implications for the risk-based analysis of cross-sectional return spreads. They suggest, most importantly, that if documented return patterns reflect expectations and not risk, then the corrections for "risk factors" in the computation of abnormal returns are simply wrong. Many empirical findings in finance might have been incorrectly discarded because they were attributed to compensation for risk and thus deemed unsurprising. They might have instead been driven by expectations or other forces. Other work seeks to more agnostically document patterns of price distortions, or alphas, relative to simple risk models (e.g., van Binsbergen and Opp 2019, van Binsbergen et al 2023). Our results suggest that such findings may reflect systematic expectation errors, and more broadly that linking return patterns to data on measured expectations is a productive way forward.

Our work contributes to fast-growing research showing that measured expectations allow an empirically disciplined and theoretically structured approach to asset prices that helps solve the joint hypothesis problem. Research following La Porta (1996) showed that LTG predicts low returns due to its overreacting to good news and subsequently correcting (BGLS 2019, 2024). Aggregate LTG is also excessively volatile, leading to sufficiently volatile valuations to quantitatively explain Shiller's (1981) excess volatility puzzle (Bordalo et al. 2024). De la O and Myers (2021) show that volatility of valuation ratios reflects short term earnings expectations. BGLS (2024) show that overreaction leads to departures from market efficiency: forecast errors of aggregate LTG are predictable, and these errors and their

correction account for essentially all predictability of market level returns from valuation ratios (see also Nagel and Xu 2022, Adam and Nagel 2023). Frey (2023) finds that many suggested risk factors instead predict convergence of earnings growth forecasts between the long and short arms of the factor. Expectations thus explain return puzzles for the aggregate market without time varying required returns. Here we offer a new method using EBRs to develop a systematic analysis of classical cross-sectional return spreads.

Taken together, these results imply that addressing the joint hypothesis problem using data on expectations should become a standard tool in asset pricing. Our findings connect to recent attempts to introduce new risk factors such as duration (Lettau and Wachter 2007, van Binsbergen and Koijen 2017, Gormsen and Lazarus 2023), or intertemporal versions of CAPM (Campbell and Vuolteenaho 2004, Campbell et al. 2023). These papers do not offer direct measures of risk, nor use data on expectations, and therefore cannot rule that these patterns are generated by incorrect beliefs, which often yield pricing biases that are horizon-dependent and time varying (Giglio and Kelly 2018, BGLS 2019, 2024).

In the next section we describe our conceptual framework and data. Section 3 revisits the Fama French three factor model and shows that both value and size premia can be explained in terms of expectations, with no need for risk premia. Section 4 extends this analysis to additional factors. Section 5 ties the evidence on factor returns directly to predictable corrections of expectations errors and shows that in fact characteristics capture biased expectations. Section 6 concludes.

2. Concepts and Methods

2.1 Risk in Efficient Markets Finance

Following Campbell and Shiller (1987, 1988), the log return $r_{i,t+1}$ obtained from holding the stock of a generic firm i between t and $t+1$ can be approximated as:

$$r_{i,t+1} = \alpha\left(p_{i,t+1} - d_{i,t+1}\right) + g_{i,t+1} - \left(p_{i,t} - d_{i,t}\right) + k, \quad (1)$$

where $p_{i,t}$ is the firm's log price at t, $d_{i,t}$ is its log dividend, $g_{i,t+1} = d_{i,t+1} - d_{i,t}$ is its dividend growth between t and $t+1$, while k and α are constants that depend on the mean log price dividend ratio.[3] By iterating Equation (1) forward and ruling out "bubbles" we obtain the ex-post identity:

$$p_{i,t} - d_{i,t} = \frac{k}{1-\alpha} + \sum_{s\geq 0} \alpha^s g_{i,t+1+s} - \sum_{s\geq 0} \alpha^s r_{i,t+1+s}. \quad (2)$$

Ex-ante, then, the equilibrium price $p_{i,t}^e$ for the stock is obtained by taking the expectation of Equation (2) using market beliefs $\widetilde{\mathbb{E}}_t(.)$. If the market requires a constant compensation r_i for the firm's risk, and thus expects r_i as a future return, we obtain:

$$p_{i,t}^e - d_{i,t} = \frac{k - r_i}{1-\alpha} + \sum_{s\geq 0} \alpha^s \widetilde{\mathbb{E}}_t\left(g_{i,t+1+s}\right). \quad (3)$$

Plugging the equilibrium price into Equation (1), the realized stock return satisfies:

$$r_{i,t+1} = r_i + \left[g_{i,t+1} - \widetilde{\mathbb{E}}_t\left(g_{i,t+1}\right)\right] + \sum_{s\geq 1} \alpha^s \left(\widetilde{\mathbb{E}}_{t+1} - \widetilde{\mathbb{E}}_t\right)\left(g_{i,t+1+s}\right), \quad (4)$$

which is higher if the firm is riskier, the required return r_i is higher, or if good news are received on the firm, either as a positive dividend growth surprise (the term in square brackets), or as an upward revision of expectations of future growth (the sum).

Traditional asset pricing builds on efficient markets, the hypothesis that market expectations are rational. This implies that news in Equation (4) cannot be systematically positive or negative, so that the average one period return $\overline{r}_{i,1}$ is simply the required return:

$$\overline{r}_{i,1} = r_i. \quad (5)$$

With rational expectations, if stock or portfolio i earns a higher average return than j, $\overline{r}_{i,1} > \overline{r}_{j,1}$, then it must have a higher risk exposure and thus a higher required return, $r_i > r_j$.

[3] As in Campbell and Mei (1993), we equalize k and α across firms and set $\alpha = 0.9981$, $k = 0.0138$.

Research maintaining the rational expectations assumption starts from Equation (5), and searches for the model of risk r_i matching the observed average return $\overline{r}_{i,1}$. This has led to the creation of "risk factors" often based on firm-level characteristics such as book to market, size, investment, and profitability (Fama and French 1993, 2015), but also on their recent returns (momentum, Jegadeesh Titman 1993). The interpretation of these factors as capturing genuine sources of investor risk, however, remains problematic.

By using measured expectations of future firm level fundamentals, we work with Equation (4) without having to assume (5). This allows us to assess how much of the average return spreads can be accounted for by measured expectations, and hence what is left for risk to explain. We first lay out our strategy, and then describe how we implement it empirically.

2.2 Expectations Based Returns (EBRs)

The pillar of our approach is the theoretical concept of "Expectations Based Returns" or EBR. We define EBR as the part of a firm's realized stock return that is *exclusively* due to the forecast error and expectation revisions in Equation (4), while deliberately shutting down any cross-firm variation in risk, as captured by r_i. The realized EBR is obtained from Equation (4) by replacing the firm-specific required return r_i by the average market return r:

$$\mathrm{EBR}_{i,t+1} = r + \left[g_{i,t+1} - \widetilde{\mathbb{E}}_t\left(g_{i,t+1}\right)\right] + \sum_{s\geq 1} \alpha^s \left(\widetilde{\mathbb{E}}_{t+1} - \widetilde{\mathbb{E}}_t\right)\left(g_{i,t+1+s}\right), \qquad (6)$$

Substituting (6) into (4) we obtain the key equation that decomposes realized return into the true excess returns $(r_i - r)$ and the expectations-based return:

$$r_{i,t+1} = (r_i - r) + \mathrm{EBR}_{i,t+1}. \qquad (7)$$

Suppose we could perfectly measure $\mathrm{EBR}_{i,t+1}$. A regression of a firm's realized return $r_{i,t+1}$ on its contemporaneous $\mathrm{EBR}_{i,t+1}$ should then give a unit slope and, crucially, a regression

constant that offers an unbiased estimate of $(r_i - r)$. Constructing EBRs for the long (L) and short (S) factor portfolios would then yield:

$$\left(r_{L,t+1} - r_{S,t+1}\right) = (r_L - r_S) + \left(\mathrm{EBR}_{L,t+1} - \mathrm{EBR}_{S,t+1}\right), \quad (8)$$

so the constant term now identifies the pure risk-based return spread. A finding that $r_L - r_S = 0$ says that non-rational expectations are enough to account for observed return differences. If instead $r_L - r_S > 0$, the intercept gives us a magnitude of the "needed" cross sectional risk premium. On the other hand, $r_L - r_S < 0$ means that the standard factor return is entirely due to non-rationality: the long arm is safer than the short arm, a theoretical possibility.

We use measured expectations of future earnings growth to construct a proxy for $\mathrm{EBR}_{i,t+1}$. We next show how such a proxy is constructed. Of course, analyst expectations are likely to imperfectly proxy for market expectations and hence for $\mathrm{EBR}_{i,t+1}$. Our strategy takes this into account, and proposes a way to adjust for specific forms of measurement error.

2.3 Data and Construction of EBRs

Expectations data. We obtain monthly firm level data on analyst forecasts of future earnings growth of listed firms from the IBES Unadjusted US Summary Statistics file. We focus on the median forecasts of a firm's earnings per share (EPS_{it}) and of its long-term earnings growth (LTG_{it}), defined as the "...expected annual increase in operating earnings over the company's next full business cycle. These forecasts refer to a period of between three to five years." This data is available starting on 3/1976 for EPS_{it} and 12/1981 for LTG_{it}. EPS_{it} forecasts are for fixed horizons. To work with monthly data, and to fill in any missing forecasts, we interpolate EPS_{it} at horizons of 1 to 5 years (in one-month increments).

We collect median forecast data on dividends for the upcoming fiscal year from IBES, and use them to compute the stock's expected payout ratio. Although IBES began tracking dividend forecasts in 1994, the data did not become broadly available until 2002. Our dataset

includes expected payout data for approximately 56% of the observations from 2002 to 2023, and for 25% of observations across the entire sample.

Other data. We obtain monthly data on shares outstanding and returns from CRSP, from 1981 to 12/2022. We obtain quarterly and annual accounting data from COMPUSTAT (also through 12/2022) and data on the risk-free rate (the return of the 90-day t-bill) from CRSP. We define book to market (BM) and investment following Fama and French (2015) and use NYSE breakpoints to assign stocks to quintile portfolios of BM and investment.

To match our data to the method used for computing portfolio returns in Ken French's website, we define the raw monthly expectation-based return $\mathrm{EBR}^{\mathrm{r}}_{i,t,t+1}$ of firm i between months t and $t+1$ as:

$$\mathrm{EBR}^{\mathrm{r}}_{i,t,t+1} = \frac{D_{i,t+1} + \tilde{P}^{a}_{i,t+1}}{\tilde{P}^{a}_{i,t}}, \tag{9}$$

where, critically, $\tilde{P}^{a}_{i,t}$ is a price index that depends on analyst earnings growth expectations but shuts down any variation in required returns, across firms and over time. We construct this index, which we dub "analyst' price", based on the Campbell Shiller decomposition and the assumption of constant (across firms and over time) returns in Equation (3).

We set the required return r for all firms at the average in-sample realized annual market return, $r = 10.72\%$. We then write the analyst price $\tilde{P}^{a}_{i,t}$ as the present value of the firm's expected cash flows. Specifically, for each firm i at each time t (in months) we set:

$$\tilde{P}^{a}_{i,t} = \sum_{s=1,\ldots,5} \frac{\widetilde{\mathbb{E}}^{a}_{t} DPS_{i,t+12s}}{(1+r)^{s}} + \frac{1+g}{(1+r)^{5}} \frac{\widetilde{\mathbb{E}}^{a}_{t} DPS_{i,t+60}}{r-g}. \tag{10}$$

We derive expected dividends per share from expected earnings per share, as follows. We proxy expected earnings per share with analyst short term earnings expectations $\widetilde{\mathbb{E}}^{a}_{t} EPS_{i,t+12s}$ up to the second fiscal year; starting with the last non-missing positive EPS forecast and up to five years out, analysts expect EPS_{it} to grow at the rate LTG_{it}. To translate

expected earnings into expected dividends, we use the expected payout ratio implied from analysts' expectations of dividends and earnings. Specifically, we assume a constant ratio equal to the average expected payout ratio $\frac{\widetilde{\mathbb{E}}_t^a DPS_{i,t+12}}{\widetilde{\mathbb{E}}_t^a EPS_{i,t+12}}$ in our sample for those firms which paid dividends that year, $DPS_{i,t+12} > 0$, which equals 0.41.[4]

We do not observe analyst forecasts for very long horizons. For the terminal value which captures cash flows beyond year five, we again assume a terminal payout ratio of 0.41, and we set the continuation value of expected cash flow growth g to match the average stock price across all firms and months in 1981-2022. Since the required return r and growth in the very long term g are constant and common to all firms, differences in the price index $\tilde{P}_{i,t}^a$ across firms arise exclusively from differences in expectations.

The firm level raw EBR is extended to the monthly raw return of a portfolio π using an equal weighted average, $\mathrm{EBR}^{\mathrm{r}}_{\pi,t,t+1} = \frac{1}{|\pi|}\sum_{i\in\pi} \mathrm{EBR}^{\mathrm{r}}_{i,t,t+1}$.[5] Our results also hold when using value weighted portfolios (see Appendix B1). To compute (log) returns over longer horizons t to $t+h$, we compute firm level monthly raw returns $\mathrm{EBR}^{\mathrm{r}}_{i,t+j-1,t+j}$ for each of the next h months and aggregate up to portfolio raw returns. We then rebalance portfolios at the end of each month *j* and compound monthly EBRs to obtain the *log* return (where for simplicity we use the same notation as for EBRs based on market beliefs, Equation 6):

$$\mathrm{EBR}_{\pi,t,t+h} = \sum_{j=1}^{h} \alpha^{j-1} \ln\left(\mathrm{EBR}^{\mathrm{r}}_{\pi,t+j-1,t+j}\right)$$

[4] Our results are robust to different specifications of the payout ratio. An alternative specification sets the expected payout ratio to zero if the firm did not pay a dividend the previous year. This has a correlation with our main specification of over 97%. The Appendix shows our results are unchanged with this measure.

[5] IBES surveys analysts in the middle of each month (i.e. the Thursday before the third Friday of every month, see IBES Unadjusted US Summary Statistics file). We use CRSP daily file to compute actual returns over the same periods as EBRs. Results are similar if we compute actual returns using calendar months, but the correlation between one- and three-months EBRs and returns is slightly stronger when using IBES.

For example, the one-month log EBR equals $\ln(\mathrm{EBR}^{\mathrm{r}}_{\pi,t,t+1})$ which, under the Campbell Shiller approximation of Equation (1), takes the form of Equation (6). Finally, we obtain EBRs for factor portfolios as the difference between the returns of the portfolio's long and short arms. Specifically, we compute EBRs for the following long-short portfolios:

1. High-Minus-Low book-to-market (HML): EBR of a portfolio that is long value stocks ($\pi = V$, top quintile book-to-market firms) and short growth stocks ($\pi = G$, bottom quintile). Thus, $\mathrm{EBR}_{HML,t,t+h} = \mathrm{EBR}_{V,t,t+h} - \mathrm{EBR}_{G,t,t+h}$.
2. Small Minus Big Size (SMB): EBR of a portfolio that is long small stocks ($\pi = S$, bottom quintile market equity) and short big stocks ($\pi = B$, top quintile), *i.e.* $\mathrm{EBR}_{SMB,t,t+h} = \mathrm{EBR}_{S,t,t+h} - \mathrm{EBR}_{B,t,t+h}$.
3. Conservative Minus Aggressive Investment (CMA): EBR of a portfolio that is long conservative stocks ($\pi = C$, bottom quintile investment-to-asset ratio) and short aggressive ones ($\pi = A$, top quintile). $\mathrm{EBR}_{CMA,t,t+h} = \mathrm{EBR}_{C,t,t+h} - \mathrm{EBR}_{A,t,t+h}$.
4. Robust Minus Weak Profitability (RMW): EBR of a portfolio that is long robust profitability ($\pi = R$, top quintile operating profitability) and short weak profitability stocks ($\pi = W$,, bottom quintile). $\mathrm{EBR}_{RMW,t,t+h} = \mathrm{EBR}_{R,t,t+h} - \mathrm{EBR}_{W,t,t+h}$.
5. Winners Minus Losers momentum (WML): EBRs of a portfolio that is long winning stocks ($\pi = W$, top quintile prior returns between periods $t-11$ and $t-1$) and short losing stocks ($\pi = L$, bottom quintile), i.e. $\mathrm{EBR}_{WML,t,t+h} = \mathrm{EBR}_{W,t,t+h} - \mathrm{EBR}_{L,t,t+h}$.

Following the notation above, we refer to the generic long-short portfolio as LMS.

Our sample consists of monthly firm level observations from 1981 to 2023 for which LTG_t and LTG_{t+h} exist.[6] This requirement restricts our sample from the 2 million observations

[6] We also restrict the sample to firms with data on size and positive book-to-market in June of year *t* plus standard CRSP requirements (i.e. common stock listed on a major US exchange).

in the CRSP/Compustat database to about 1.3 million observations for $h = 1$ and 1.1 million for $h = 12$. The sample drops firms that tend to be smaller in market cap, but the samples are comparable in characteristics such as book to market (0.63 in the full sample, 0.61 in our samples), size ($7.2bn vs $7.8bn), investment (0.19 for both), and others, see Appendix B1. As a robustness check, we dropped the requirement that firms have data on LTG_{t+h} and computed actual returns for the sample of firms for which LTG_t exists. This sample is very similar to our sample in all characteristics.

2.4 Raw Portfolio EBRs and Correlations with Actual Returns

Table 1 reports the average return of factor portfolios in our sample, the target of our exercise, and the average EBRs of the same portfolios.

Table 1. Average returns and EBRs of portfolios

Note: Panel A presents sample means of log portfolio returns over holding horizons *h* ranging from one month to five years, following the methodology outlined on the website of Ken French. Portfolios are formed independently based on quintiles. Results are displayed for the following five quintile portfolios: (1) book-to-market, with *Growth* stocks in bottom quintile and *Value* stocks in the top quintile, (2) investment, *Aggressive* stocks in the bottom quintile and *Conservative* ones in the top quintile, (3) size, *Big* stocks in the top quintile and *Small* ones in the bottom quintile, (4) Profitability, *Weak* profitability in the bottom quintile and *Robust* profitability in the top quintile), and (5) Momentum, *Losers* stocks in the bottom quintile and *Winners* stocks in the top quintile. Panel B presents sample means of log expectation-based returns (EBRs) returns computed following Equation 10 in the text for the same groupings of stocks. Portfolio returns and EBRs are equally weighted with monthly rebalancing. The sample period extends from December 1981 to December 2023.

Panel A. Average portfolio returns

Holding Horizon	Growth	Value	Aggr.	Cons.	Big	Small	Weak	Robust	Losers	Winners
1 Month	10.3%	15.7%	9.0%	14.9%	11.8%	14.4%	11.3%	13.5%	9.4%	15.4%
3 Months	10.1%	15.0%	8.7%	14.5%	11.4%	14.3%	11.0%	13.1%	9.2%	14.3%
1 Year	11.2%	15.3%	9.7%	14.9%	11.9%	15.3%	11.7%	13.4%	12.6%	12.9%
3 Years	11.7%	15.0%	10.8%	14.1%	12.1%	14.5%	12.5%	13.1%	13.2%	12.4%
5 Years	11.6%	14.1%	11.0%	13.4%	11.6%	13.8%	12.6%	12.4%	12.8%	12.0%

Panel B. Average portfolio expectation-based returns

Holding Horizon	Growth	Value	Aggr.	Cons.	Big	Small	Weak	Robust	Losers	Winners
1 Month	10.8%	13.7%	7.3%	15.5%	11.4%	10.4%	16.0%	9.4%	-16.0%	33.1%
3 Months	9.9%	13.2%	6.5%	15.0%	11.0%	10.0%	15.0%	9.1%	-13.4%	30.0%
1 Year	9.2%	13.7%	6.7%	14.5%	10.2%	11.6%	14.2%	9.3%	-0.6%	20.0%
3 Years	9.4%	13.0%	8.1%	13.1%	10.2%	11.2%	13.2%	9.8%	8.1%	12.7%

5 Years	9.6%	12.3%	8.8%	12.6%	10.1%	10.8%	13.1%	9.7%	9.2%	11.6%

In line with existing work, Panel A shows that portfolios in the long arm exhibit higher average returns than those in the short arm, at both long and short horizons. An assessment of the statistical significance of the long-short return spreads (Tables 4 and 8 below) reveals that the value and investment spreads are large and significant at all horizons in our sample, with annualized spreads between 3 and 5%. Momentum spreads are large and significant at horizons of under a year, with annualized spreads of around 5%. These are key targets of our analysis. The size spreads are instead not significant in our sample, which is also in line with the literature. Fama and French (2015) and others note that the size anomaly has weakened in recent decades relative to the earlier sample in Fama French (1993). Average profitability spreads are not significant in our sample period.[7]

Panel B shows that EBRs display quantitatively similar patterns for HML, SMB, CMA, and WML. For these portfolios, target and explanatory variables have similar magnitudes and go in the same direction, suggesting that i) expectation errors and revisions captured by in EBRs differ systematically across portfolios, and ii) systematic differences in EBRs align with average return differences. The exception is profitability for which we observe the reverse spread, which may again be driven by attrition of unprofitable firms with negative earnings, whose expectations-based returns are unmeasured but may be low.

While average return spreads have been the focus of the literature, it is only one dimension of comparison between EBRs and true returns. For EBRs to be a good proxy for the true returns, the two must also be positively correlated over time. This is a particularly important dimension given that time variation of realized spreads is very large (as shown in

[7] There is also no systematic profitability spread when forming quintile portfolios on the full CRSP / COMPUSTAT sample in our sample period of 1981 – 2023. Using double sorts on size and profitability (as in Fama French 2015), a profitability spread emerges within big firms.

Figures 1 and 2 below). The "perfect proxy" benchmark of Equation (8) implies that the correlation coefficient should be one, because the variance in realized return is entirely driven by EBRs. We compute the correlation between $EBR_{\pi,t+h}$ and $r_{\pi,t+h}$ for the long and short portfolios of HML, SMB, CMA, RMW and WML. We consider horizons h of $\{1, 3, 12, 36, 60\}$ months, covering the short horizons typical of the cross-sectional analysis (Fama and French 1993, 2015) as well as longer horizons typical of reversal anomalies (de Bondt and Thaler 1985) and aggregate stock market variation. Table 2 reports the results.

Table 2. Portfolio level correlations for actual and expectation based returns.

Note: The table presents pairwise correlations between log returns and expectation-based returns (EBRs) for portfolios of stocks formed on book-to-market, investment, size, profitability, and momentum sorts over holding horizons ranging from one month to five years. The sample period is from December 1981 to December 2023.

Holding Horizon	Growth	Value	Aggr.	Cons.	Big	Small	Weak	Robust	Losers	Winners
1 Month	8%	19%	10%	16%	7%	16%	12%	12%	11%	6%
3 Months	22%	35%	24%	31%	23%	30%	29%	22%	28%	25%
1 Year	36%	52%	41%	37%	35%	46%	43%	34%	48%	42%
3 Years	43%	52%	52%	36%	34%	61%	46%	37%	54%	51%
5 Years	36%	41%	43%	28%	24%	48%	39%	28%	36%	37%

The correlations between contemporaneous returns and EBRs are positive, and large at long horizons, but in all cases the correlation coefficient is less than one, the theoretical "perfect proxy" benchmark. There are three potential reasons for this. First, analyst beliefs may depart from market beliefs due to (unobserved) disagreement between the marginal investor and the analyst consensus. Second, analyst beliefs only cover horizons up to 5 years out, so our proxy for EBRs surely misses longer term variation in market expectations. Third, the required return spread in Equation (8) may be time varying, so it yields a distinct source of return variation not captured by earnings growth expectations. This seems unlikely given that both fundamental risk and investor preferences toward it arguably vary more at lower frequencies, but

correlations between returns and EBRs are uniformly and counterfactually higher at these frequencies.[8]

2.5 Measured Expectations versus Market Expectations

A critique of our analysis concerns the validity of analyst forecasts as a proxy for market expectations of earnings growth. One concern is measurement noise, which however works against our finding a systematic correlation between EBRs and returns. To deal with the noise, we regress returns on contemporaneous EBRs, as in Equation (8). The estimated coefficients then optimally extract the information contained in EBRs. Still, the measurement error contaminates the regression constant in (8), which is our measure of risk-based spread. In the next section we present one method to adjust the estimated constant under specific assumptions about measurement error in EBRs.

Another concern, in the opposite direction, is that analysts might infer earnings growth expectations from market prices under the erroneous assumption of constant, and perhaps CAPM-based, returns. In this case, analysts might erroneously incorporate into cash flow expectations priced information about required returns. Note that if equity analysts infer cash flow expectations from prices while correctly adjusting for the true model of risk, then they would in fact recover market expectations about earnings growth.

We present two types of tests that reject the hypothesis of erroneous inference from prices. The first set of tests shows that changes in measured beliefs respond to realized fundamentals, and do not appear to mechanically respond to prices. BGLS (2004) show that revisions in LTG at both the market and the firm levels are more reliably explained by past earnings growth than by past stock returns. We extend this analysis to the cross-section of

[8] The fact that the correlation is lower than one may also capture other drivers of stock returns such as market liquidity or investor demand, especially at high frequencies.

stocks and show that EBR spreads strongly respond to news. The fact that expectations do not mechanically respond to prices is also already visible in the correlations of less than 1 in Table 2. For brevity, we report this analysis in the Appendix.

The second, and crucial, set of tests concerns the central implication of the erroneous inference hypothesis that expectations predict returns through information on discount rates incorporated in prices. To this end, we perform a range of return predictability exercises, comparing the predictive power of valuation ratios to that of expectations. If expectations surreptitiously capture discount rate variation embedded in market prices, their predictive power in a horse race with price ratios would be absorbed by these ratios. BGLS (2024) show that measured expectations predict *future* returns both in the aggregate and at the firm level even controlling for current scaled price variables such as the (aggregate or firm-level) price dividend ratio. In Section 5, we expand this analysis to EBRs and the cross-sectional portfolios and show that expectation variables dwarf the predictive power of price ratios. This is contrary to the erroneous inference from prices hypothesis, and instead suggests that expectations predict returns because they entail systematic errors and revisions, in line with evidence that anomaly returns are realized during news events (La Porta et al 1997, Engelberg et al 2018).

The return predictability exercises are of independent interest because they allow us to assess whether market inefficiency entails systematic time variation in cross-sectional spreads, just as it produces systematic return variation in the aggregate market as shown in BGLS (2024). We conclude that measured expectations contain genuine information about non-rational market beliefs that affects prices and helps predict future returns.[9]

[9] In line with these findings, a literature in accounting argues that analysts' earnings expectations are informative about expectations of market participants (Decaire Graham 2024). Bradshaw (2004) shows that analysts' expectations of long-term growth have strong explanatory power for their stock recommendations, suggesting that analysts view increases in LTG as a positive shock to cash flows, and potential undervaluation of the firm, not as a drop in required returns. Jung, Shane, and Yang (2012) further show that prices respond more strongly to analyst recommendations when these are accompanied by LTG forecasts, suggesting a similar view by market participants.

3. EBRs and the Value and Size Premia

To study whether EBRs help account for cross sectional spreads, we proceed as follows. In Section 3.1, we assess the roles of expectations versus risk by constructing EBRs for the value minus growth and small minus big long-short portfolios (from Fama and French's three factor model) and using them to estimate Equation (8). We then allow analyst expectations to be an imperfect proxy for market beliefs about earnings growth, and correct the coefficients obtained from estimating Equation (8) for measurement error. Our empirical analysis shows that such discrepancies indeed exist but that accounting for them usually makes little difference for the entailed required return differential $r_L - r_S$.

In Section 3.2 we assess the contribution of different components of EBR by separately introducing into (8) the realized forecast errors and forecast revisions at different horizons, which offers a direct test of Equation (4) without making the parametric restrictions embedded in the construction of the analyst price. After accounting for EBRs, there is little systematic variation in the value and size spreads left for risk to explain. In Section 4, we repeat the analysis for the other long-short portfolios.

3.1 EBRs Explain the Value and Size Premia

Table 3, Panel A reports regressions of the actual value and size long-short portfolio spreads $r_{LMS,t+h}$ on $\text{EBR}_{LMS,t+h}$, as specified in Equation (8), for various horizons h. In this regression, the constant term represents a first estimate of the required return spread, under the assumption that analyst beliefs are a perfect proxy for market beliefs.

Table 3
Expectation based returns and the HML and SMB spreads

Note: Panel A presents univariate regression results of log returns for the portfolio that is long value and short growth (HML) on expectation-based returns (EBRs) for that portfolio (columns 1 to 5) and similarly for the portfolio long small firms and short big firms (columns 6 to 10). Separate regressions are estimated for horizons h of one-month, three-month, one-year, three-year, and five-year horizon. Panel B extends the analysis by adding the expectation-based returns for the market portfolio ($\text{EBR}_{Mkt,t+h}$), which includes all the stocks in the sample.

Standard errors are corrected for overlapping observations using the Newey-West (1987) procedure. The sample period is December 1981 to December 2023. Superscripts: [a] significant at the 1% level, [b] significant at the 5% level, [c] significant at the 10% level.

Panel A

			$r_{HML,t+h}$					$r_{SMB,t+h}$		
	$h=1$	$h=3$	$h=12$	$h=36$	$h=60$	$h=1$	$h=3$	$h=12$	$h=36$	$h=60$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$EBR_{LMS,t,t+h}$	0.5067[a]	0.8313[a]	1.0274[a]	1.1719[a]	1.1723[a]	0.5698[a]	0.7813[a]	1.1470[a]	1.1858[a]	1.0915[a]
	(0.1527)	(0.1638)	(0.1156)	(0.2274)	(0.1842)	(0.1304)	(0.1559)	(0.1779)	(0.1787)	(0.2321)
Constant	0.0032[c]	0.0052	-0.0055	-0.0269	-0.0308	0.0027	0.0092[c]	0.0177	0.0365	0.0698
	(0.0018)	(0.0046)	(0.0140)	(0.0462)	(0.0424)	(0.0017)	(0.0049)	(0.0134)	(0.0291)	(0.0485)
Obs	504	502	493	469	445	504	502	493	469	445
Adj R^2	4%	16%	46%	45%	50%	5%	12%	34%	55%	49%

Panel B

			$r_{HML,t+h}$					$r_{SMB,t+h}$		
	$h=1$	$h=3$	$h=12$	$h=36$	$h=60$	$h=1$	$h=3$	$h=12$	$h=36$	$h=60$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$EBR_{LMS,t+h}$	0.3965[b]	0.7954[a]	1.0884[a]	1.2214[a]	1.1425[a]	0.4514[a]	0.6816[a]	1.1747[a]	1.2365[a]	1.2018[a]
	(0.1561)	(0.1732)	(0.1452)	(0.2369)	(0.2260)	(0.1390)	(0.1640)	(0.1902)	(0.2469)	(0.2735)
$EBR_{Mkt,t+h}$	0.3438[c]	0.0824	-0.1408	-0.2122	-0.3558[b]	0.3564[c]	0.2144	-0.0546	-0.0923	-0.1987
	(0.1813)	(0.1511)	(0.1374)	(0.1629)	(0.1676)	(0.1839)	(0.1532)	(0.1387)	(0.2143)	(0.2551)
Constant	0.0002	0.0032	0.0065	0.0344	0.1591[c]	-0.0005	0.0037	0.0230	0.0644	0.1705
	(0.0026)	(0.0059)	(0.0167)	(0.0661)	(0.0893)	(0.0025)	(0.0066)	(0.0225)	(0.0857)	(0.1586)
Obs	504	502	493	469	445	504	502	493	469	445
Adj R^2	6%	16%	47%	47%	57%	6%	12%	34%	55%	50%

EBRs and actual returns are significantly positively correlated for the HML and SMB portfolios, especially at longer horizons. The R^2 also sharply rises with the horizon: it is 6% at one month, and 40% or more at horizons of one to five years. Expectations thus contain substantial information about the news perceived by the market. Consistent with Equation (8), the estimated coefficient on EBRs is close to one, and is statistically indistinguishable from one, for most horizons. It is smaller than one at the monthly horizon, suggesting that analyst forecasts are a noisier proxy for market beliefs at higher frequencies.

The estimate for the risk premium for HML, the regression constant, is small in magnitude and statistically indistinguishable from zero at all horizons over one month. The

estimate for the risk premium for SMB is also statistically indistinguishable from zero at all horizons, except three months. After accounting for the average difference in "market perceived news" though EBRs, there is no systematic value or size spreads left for risk to explain. This is our first joint hypothesis assessment: after accounting for expectations, no risk premium difference is needed to explain the average HML and SMB return spreads.

BGLS (2024) show that lagged aggregate optimism, as measured by high expectations of long-term aggregate earnings growth, high $\mathrm{LTG_t}$, predicts both aggregate disappointment and a larger subsequent HML spread, suggesting that at least part of the value spread is driven by a predictable, aggregate expectations based 'factor'. Is the explanatory power of portfolio level EBR in Table 3, Panel A due to this aggregate factor, or does it unveil further sources of expectation based cross sectional spreads?

To answer this question, we compute the market-level expectations-based return $\mathrm{EBR}_{Mkt,t,t+h}$,[10] and run a horse race between the aggregate EBR, $\mathrm{EBR}_{Mkt,t,t+h}$, and the portfolio ones $\mathrm{EBR}_{HML,t,t+h}$ and $\mathrm{EBR}_{SMB,t,t+h}$, in accounting for the contemporaneous observed return spread, Table 3 Panel B. The question is not only whether the portfolio EBR survives in the regression, but also how much adding $\mathrm{EBR}_{Mkt,t,t+h}$ affects the regression R^2 and the estimated constant compared to Panel A.

The results of Panel B indicate that the cross-sectional value spread is mostly accounted for by cross sectional movement in expectations. The estimated coefficients on $\mathrm{EBR}_{HML,t+h}$ and $\mathrm{EBR}_{SMB,t+h}$ remain similar to those in Panel A and are always statistically significant. The proxy for market-wide growth in optimism, $\mathrm{EBR}_{Mkt,t+h}$ plays some role at the one month and 5 years horizons: it adds a bit of explanatory power in terms of R^2, and it causes the regression constant to shrink, further reducing the need for required return differentials. Broadly speaking, the

[10] Analogously to portfolio EBRs, the market EBR is $\mathrm{EBR}_{Mkt,t,t+h} = \ln\left(\sum_{j=1}^{h} \alpha^{j-1} \frac{1}{|M|} \sum_{i \in Mkt} \mathrm{EBR}_{i,t+j-1,t+j}\right)$, see Section 2.2.

value and size premia are largely due to cross sectional cycles in expectations, as proxied by $\text{EBR}_{HML,t,t+h}$ and $\text{EBR}_{SMB,t,t+h}$. This finding is consistent with the results in BGLS (2024), who find similar expectational boom and bust patterns in the aggregate stock market.

As seen in Table 3, EBRs are a good proxy for market expectations, consistent with a research showing their explanatory power for prices and returns (BGLS 2019, 2024, De la O and Myers 2021, 2024, Nagel and Xu 2022), but not a perfect measure, especially at short horizons. We next allow analyst expectations to constitute an imperfect proxy of market beliefs and develop a correction for the estimated required return differential that takes measurement error into account. Our correction assumes the following affine stochastic relation between analyst forecasts $\widetilde{\mathbb{E}}_{it}^{a}$ and market forecasts $\widetilde{\mathbb{E}}_{it}$ at time t about stock i:

$$\widetilde{\mathbb{E}}_{it}^{a} = \beta + \tau \cdot \widetilde{\mathbb{E}}_{it} + \sigma \cdot \varepsilon_{it}. \tag{11}$$

where ε_{it} is an iid possibly stock specific white noise shock. This specification allows for three distortions: $\beta > 0$ may capture analysts' systematic over-optimism relative to the market, which may be due to agency problems, τ captures analysts' distorted reaction to news compared to the market, where analyst reaction is excessive relative to the market for $\tau > 1$ and insufficient for $\tau < 1$, while $\sigma > 0$ is the volatility of the iid white noise term.

As we show in Appendix A, given the measurement error structure in (10), we can use the estimated constant κ and slope γ in Table 3 and other moments estimated in the data to recover the distortion parameters and adjust the original estimate of the required return spread κ for measurement error. Out of parameters (β, τ, σ) the analysts' systematic bias β is not relevant for the spread because it cancels out when comparing different portfolios. By contrast, noisier expectations, higher σ, or excess reaction to news by analysis, $\tau > 1$, both dampen the regression slope γ. This, in turn, affects the spread estimate κ.

Parameters σ and τ can be recovered using two moments of the data. The first is the regression slope γ, and its deviation from one. The second is the gap between the covariance

of observed earnings growth g_{it} with $EBR_{i,t}$ and its covariance with actual returns $r_{i,t}$.[11] Under the maintained assumption that the required return is constant, the two covariances should be equal. This yields a data moment to back out an additional parameter distorting analyst expectations compared to market ones. This estimation only uses the restriction that the required return is constant but allows for any possible risk model satisfying that restriction, including conventional unconditional factor models of risk premia.[12]

Applying this method, we find that the average τ is 1.26 so that analysts tend to respond to news more strongly than the market. We can use these estimated parameters to adjust the estimated constant κ of the required return premium of the HML and SMB portfolios that account for measurement error in analyst expectations. Table 4 compares the actual return spread between the value and growth portfolios, and the small and big firm portfolios, to the adjusted required return measure (both measures are annualized).[13]

Table 4
Expectation based estimates of the HML and SMB required return spreads

Note: the table presents estimates of the required return premia for the portfolio that is long value and short growth (HML, Columns 1 to 5) and for the portfolio that is long small firms and short big firms (SMB, Columns 6 to 10). The adjustment allows for three distortions in expectation-based returns (EBRs) as described in Equation (11). As benchmarks, we report (in the first row) the sample long-short spreads for the relevant portfolios for horizons of one-month, three-month, one-year, three-year, and five-year horizons. The second row reports the intercept from a univariate regression of annualized log returns of relevant long-short portfolio and horizon *h* on their EBRs. The last row reports annualized estimates of the required risk premia. Standard errors are corrected for overlapping observations using the Newey-West (1987) procedure. The sample period extends from December 1981 to December 2018. Superscripts: [a] significant at the 1% level, [b] significant at the 5% level, [c] significant at the 10% level.

	$r_{HML,t+h}$					$r_{SMB,t+h}$				
	$h=1$	$h=3$	$h=12$	$h=36$	$h=60$	$h=1$	$h=3$	$h=12$	$h=36$	$h=60$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Average	0.0535[a]	0.0484[b]	0.0411[b]	0.0338[b]	0.0259[b]	0.0263	0.0290	0.0340	0.0241	0.0216

[11] The adjusted estimate is equal to (where variables capture differences between long and short portfolios):

$$r = \kappa + \left[\gamma - \frac{cov(r_t, g_t) - var(g_t)}{cov(\mathrm{EBR}_t, g_t) - var(g_t)}\right]\overline{\mathrm{EBR}_t} + \frac{cov(r_t, g_t) - cov(\mathrm{EBR}_t, g_t)}{cov(\mathrm{EBR}_t, g_t) - var(g_t)}\overline{g}_t$$

If there is no measurement error, not only $\gamma = 1$, but the covariance of actual return and cash flow growth is identical to the covariance of EBRs and cash flow growth, $cov(r_t, g_t) = cov(\mathrm{EBR}_t, g_t)$, so the estimate for the required risk premium is equal to the estimated regression constant, $r = \kappa$, as in Equation (7).

[12] This exercise also allows to estimate the extent to which time variation in required returns unrelated to time variation in non-rational analyst expectations may be needed to account for the return spread observed on average. A direct horse race between possibly time varying required returns and time varying expectations is performed in our return-spread predictability tests in Section 5.

[13] In Appendix A we extend this method by allowing distortion coefficients β, τ, σ to differ across portfolios.

spread	(0.0206)	(0.0196)	(0.0200)	(0.0153)	(0.0127)	(0.0213)	(0.0202)	(0.0210)	(0.0182)	(0.0154)
Constant κ	0.0387[c]	0.0207	-0.0055	-0.0090	-0.0062	0.0319	0.0368[c]	0.0177	0.0122	0.0140
	(0.0213)	(0.0183)	(0.0140)	(0.0154)	(0.0085)	(0.0209)	(0.0188)	(0.0134)	(0.0097)	(0.0097)
Adjusted κ	0.0257	0.0150	-0.0091	-0.0029	-0.0007	0.0362	0.0379	0.0130	0.0207	0.0298

Correcting for measurement error confirms our previous results, and yields estimated true spreads for HML that are even closer to zero than those in Table 3. The value-growth puzzle appears to be entirely about expectations of future earnings growth being bullish for growth stocks and bearish for value stocks, compared to reality. In our sample, the average SMB spread is not significant, yet expectations play an important role in explaining its variation over time, as shown in Table 3.

In sum, the evidence shows that the observed cross-sectional differences in expectations fully account for HML and SMB spreads. Growth stocks do worse when optimism for them drops relative to that for value stocks, and similarly for big stocks relative to small ones. Growth stocks do worse on average because such optimism happens more than its reverse, rather than because growth stocks are less risky. But in principle, it is entirely possible that the value and size spreads are negative when the prospects of high growth (resp. big) firms are underestimated relative to those of value (resp. small) firms. This in fact occasionally happens, as shown in Figure 1 which plots the time series of the HML and SMB spreads, and the corresponding EBR spreads. Understanding the predictable time variation in analyst expectations and its connection to the realized return spreads is thus key to explaining cross sectional spreads, which we tackle in Section 5.

Panel A: value

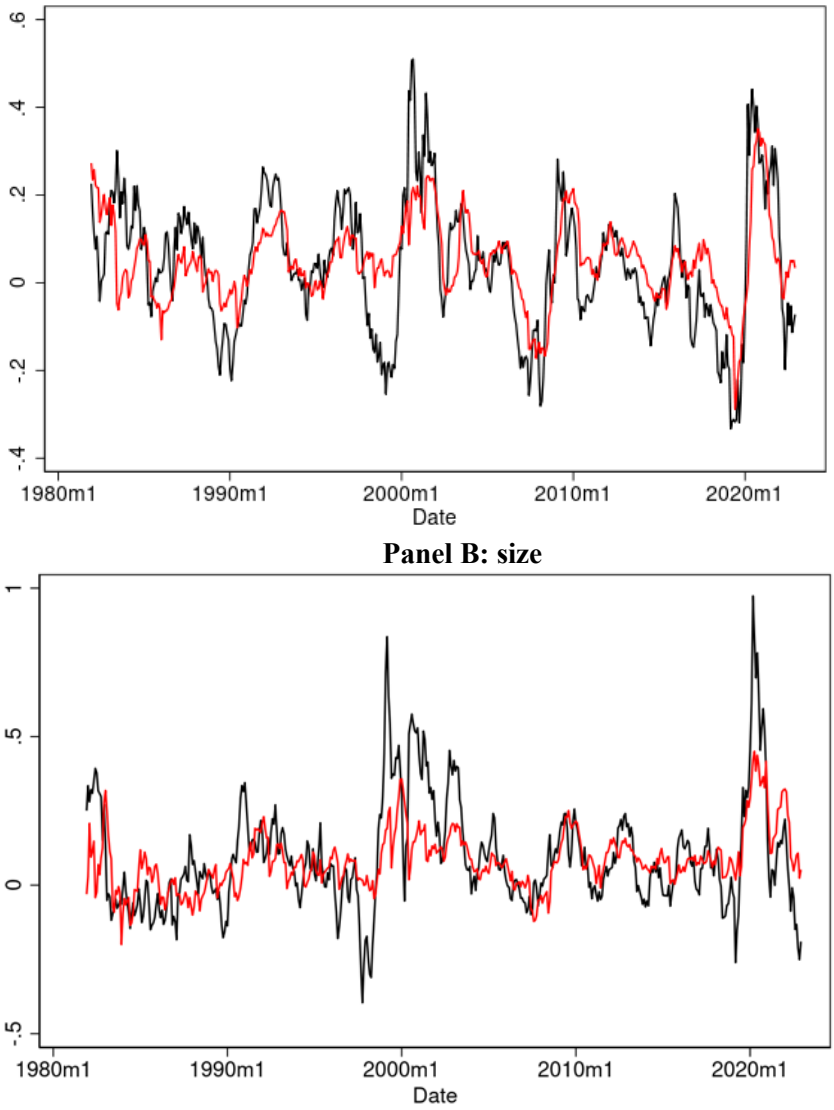


Figure 1. Actual and expectation-based return spreads, HML and SMB.

Note: Panel A plots one-year log returns (black line) and expectations-based returns (EBRs) following Equation (10) in the text EBRs (red line) for the portfolio that is long value stocks and short growth stocks (HML). Panel B plots one-year log returns (black line) and EBRs (red line) for the portfolio that is long small stocks and short big stocks (SMB). The sample period 1981:12–2020:12.

3.3 An Alternative Joint-Hypothesis Strategy: Decomposing EBRs

Instead of computing EBRs, we can assess the role of growth expectations in driving returns, Equation (4), by directly regressing realized returns on contemporaneous forecast errors and revisions at different horizons. This strategy is informative for two reasons. First, it relaxes the parametric restrictions embedded in our computation of EBRs, allowing measured expectations to also capture correlated unmeasured variation in beliefs at longer horizons.

Second, it allows to separately assess the explanatory of different components of EBRs: the forecast error and forecast revisions at different horizons.

We perform the decomposition at the yearly horizon or above (earnings are published quarterly so we refrain from computing forecast errors at a 1- or 3-month frequency). For one and three years horizons, $h = 12, 36$, we compute the firm level forecast error as the difference between realized one or three year earnings growth and the growth expected one or three years prior $FE_{i,t+h} = \ln\left(\frac{EPS_{i,t+h}}{EPS_{i,t}}\right) - \ln\left(\mathbb{E}_t\left(\frac{EPS_{i,t+h}}{EPS_{i,t}}\right)\right)$. At five year horizons, we compute the forecast error using LTG as $FE_{i,5} = \ln\left(\frac{EPS_{i,t+h}}{EPS_{i,t}}\right)/5 - LTG_{i,t}$. We then compute forecast revisions as follows. Revisions of short term growth forecasts, at horizons $h = 12{,}24$ are computed as $\Delta_h STG_{i,t+h} = (\mathbb{E}_{t+h} - \mathbb{E}_t) ln\left(\frac{EPS_{i,t+h+1}}{EPS_{i,t+h}}\right)$ and those of long term forecasts by $\Delta_h LTR_{i,t+h} = LTG_{i,t+h} - LTG_{i,t}$.

We aggregate each measure of forecast error and revision at the portfolio level, e.g. for forecast error we compute $FE_{\pi,t+h} = \frac{1}{|\pi|}\sum_{i\in\pi} FE_{i,t+h}$ and we analogously aggregate forecast revisions. We use the differences in these aggregated forecast errors and revisions between the long and short portfolios as explanatory variables for contemporaneous long minus short return spreads.[14] Table 5 shows the results.

Table 5
Portfolio level forecast errors and revisions predict spreads

Note: This table presents multivariate regressions of log returns for the long-short value minus growth (HML) and small minus big (SMB) portfolios for horizons (h) of one-year, three-years, and five-years. The independent variables include: (a) spreads in forecast errors between t and $t+h$, (b) spreads in forecast revisions between t and $t+h$ of one-year earnings growth in year $t+h+1$, and (c) spreads in changes in long-term growth forecasts between t and $t+h$. Panel B presents analogous results for the portfolio that small stocks and short big stocks (SMB). Standard errors are corrected for overlapping observations using the Newey-West (1987) procedure. The sample period spans from December 1981 to December 2023. Superscripts: [a] significant at the 1% level, [b] significant at the 5% level, [c] significant at the 10% level.

	$r_{HML,t,t+12}$	$r_{HML,t,t+36}$	$r_{HML,t,t+60}$	$r_{SMB,t,t+12}$	$r_{SMB,t,t+36}$	$r_{SMB,t,t+60}$
$(1-E_t)\,\Delta_h e_{LMS,t+h}$	0.1318[a]	0.1743[a]	0.1413[a]	0.1108[a]	0.1386[a]	0.0616
	(0.0134)	(0.0261)	(0.0376)	(0.0202)	(0.0347)	(0.0475)

[14] Following the logic of the Campbell-Shiller firm-level decomposition, we are averaging logs, which implicitly drops firms with negative $EPS_{i,t}$ and/or $EPS_{i,t+h}$.

$(E_{t+h} - E_t)\Delta_h e_{LMS,t+h+12}$	0.0808[a]	0.0575[b]	-0.0240	0.0313[c]	0.0144	-0.0255
	(0.0127)	(0.0248)	(0.0289)	(0.0188)	(0.0261)	(0.0365)
$\Delta_h LTG_{LMS,t+h}$	0.0276[a]	0.0182	0.0665[c]	-0.0217	0.0213	0.0783[b]
	(0.0094)	(0.0207)	(0.0346)	(0.0137)	(0.0288)	(0.0364)
Constant	-0.1111[a]	-0.2847[a]	-0.3308[a]	-0.0728[a]	-0.1219[b]	-0.1031
	(0.0213)	(0.0634)	(0.0872)	(0.0179)	(0.0473)	(0.0749)
Obs	493	469	445	493	469	445
Adj R^2	53%	48%	45%	32%	40%	21%

Two results stand out. First, the expectation components are strongly predictive of HML and SMB spreads, with forecast errors playing a dominant role in the multivariate regression (note that the regressors are standardized). The pre-eminence of forecast errors for explaining both HML and SMB suggests that returns reflect a disappointment in the short arm compared to the long arm, e.g. of growth stocks compared to value stocks for HML. Portfolio expectations revisions also play a role, so part of the HML spread is accounted for by systematically lower upward revisions or larger downward revisions of future prospects for growth firms relative to value firms, particularly over the first two years.

Consistent with our previous findings, the constant terms in Table 5 suggest that the average returns spreads are entirely explained by expectations. The regression constants in Table 5 are all negative, and often statistically significant, but we cannot interpret this finding as cleanly as in Table 3 given that this test is less theoretically disciplined.[15]

In sum, estimating Equation (7) shows that the systematic return spreads on the Fama French HML and SMB factors are explained by EBRs, and in particular by systematic differences in forecast errors and revisions (Tables 3 and 5). Taking these into account, there is little evidence of systematic differences in required returns (Table 4).

[15] We consider the robustness of these results when controlling for the price dividend ratio $pd_{LMS,t} = pd_{L,t} - pd_{S,t}$, as a proxy for the difference in required returns across portfolios. Appendix D shows that the expectation components continue to predict returns, while $pd_{LMS,t}$ are weak, negative predictors of returns (and statistically insignificant at 1 year horizon). Interestingly, the coefficient on forecast errors drops dramatically, consistent with the view that prices are capturing expectations as well.

4. Other FF factors

We repeat the analysis of Section 3 for the investment, profitability and momentum factors. Table 6 presents our baseline estimates of equation (8) for these factors.

Table 6
Actual and expectations based long short portfolio return spreads

Note: This table presents univariate regression results for log returns against expectation-based returns (EBRs) for three distinct long-short (LMS) portfolios. The portfolios examined are: (1) CMA, which is long stocks in lowest quintile of one-year asset growth and short stocks in highest quintile, (2) RMW, which is long stocks in the highest quintile of operating profitability and short stocks in the lowest quintile, and (3) WML, which is long stocks in the top quintile of returns during period $t-11$ through $t-1$ and short stocks in the bottom quintile of returns during the same period. We estimate separate regressions for one-month, three-months, one-year, three-years, and five-years horizons. Standard errors are corrected for overlapping observations using the Newey-West (1987) procedure. The sample period extends from December 1981 to December 2023. Superscripts: [a] significant at the 1% level, [b] significant at the 5% level, [c] significant at the 10% level.

	$r_{LMS,t+1}$	$r_{LMS,t+3}$	$r_{LMS,t+12}$	$r_{LMS,t+36}$	$r_{LMS,t+60}$
Investment (CMA)	(1)	(2)	(3)	(4)	(5)
$EBR_{LMS,t,t+h}$	0.2743[a]	0.4859[a]	0.8019[a]	0.7562[a]	0.8602[a]
	(0.0945)	(0.0931)	(0.1291)	(0.1857)	(0.1404)
Constant	0.0030[b]	0.0041	-0.0116	-0.0142	-0.0424
	(0.0012)	(0.0032)	(0.0130)	(0.0411)	(0.0282)
Adj R^2	3%	10%	36%	27%	42%
Profitability (RMW)					
$EBR_{LMS,t,t+h}$	0.2975[a]	0.4276[a]	0.4877[a]	0.5502[a]	0.6400[a]
	(0.1087)	(0.1101)	(0.1464)	(0.0756)	(0.0830)
Constant	0.0035[b]	0.0118[a]	0.0406[a]	0.0755[a]	0.0965[a]
	(0.0014)	(0.0035)	(0.0107)	(0.0161)	(0.0202)
Adj R^2	2%	7%	16%	33%	42%
Momentum (WML)					
$EBR_{LMS,t,t+h}$	0.1214	0.5786[a]	0.7418[a]	0.7299[a]	0.5738[a]
	(0.0991)	(0.1268)	(0.1692)	(0.1427)	(0.1343)
Constant	0.0000	-0.0499[a]	-0.1499[a]	-0.1251[a]	-0.1055[a]
	(0.0044)	(0.0166)	(0.0412)	(0.0313)	(0.0323)
Adj R^2	0%	10%	29%	50%	33%
Obs	504	502	493	469	445

As with HML and SMB, expectation-based returns have strong explanatory power for actual returns. The slope coefficients are large, statistically significant, and increase with the holding horizon. For CMA and RMW, their magnitudes are comparable to those obtained for

HML and SMB returns: for investment the coefficients are close to, or statistically indistinguishable from, the benchmark value of 1 for longer horizons. For momentum, and especially for profitability, they are lower than 1 although still substantial throughout.

Turning to our main test, the intercepts are either small and statistically indistinguishable from zero, or negative, except for one month horizon for investment and profitability. EBRs thus account for the average return spread for all factors except profitability. The negative coefficients for momentum may be consistent with a negative spread in required returns whereby winners are deemed safer than losers.

For profitability, intercepts are positive and significant. This is in line with the finding in Table 1 that the average EBR is higher for low profitability firms, while actual returns are directionally higher for high profitability firms. Recall, however, that comparing average EBR spreads to average return spreads, as in Equation (8), yields an upward-biased measure of required returns when the estimated slope γ is smaller than 1 (see footnote 6), which is particularly pronounced for profitability. We therefore adjust the estimated required return for measurement error across portfolios and present the results in Table 7.

Table 7
Expectation based estimates of long-short portfolios required return spread

Note: the table estimates of the required return premia (adjusted κ) for the portfolio that is long conservative and short aggressive investment stocks (CMA), long robust and short weak profitability stocks (RMW), and long winners and short momentum stocks (RMW). The adjustment allows for three distortions in expectation-based returns (EBRs) as described in Equation (11). As benchmarks, we report (in the first row) the sample long-short spreads for the relevant portfolios for horizons of one-month, three-month, one-year, three-year, and five-year horizons. The second row reports the intercept from a univariate regression of annualized log returns of relevant long-short portfolio and horizon *h* on their EBRs. The last row reports annualized estimates of the required risk premia. Standard errors are corrected for overlapping observations using the Newey-West (1987) procedure. The sample period extends from December 1981 to December 2023. Superscripts: [a] significant at the 1% level, [b] significant at the 5% level, [c] significant at the 10% level.

	$r_{LMS,t+1}$	$r_{LMS,t+3}$	$r_{LMS,t+12}$	$r_{LMS,t+36}$	$r_{LMS,t+60}$
Investment (CMA)	(1)	(2)	(3)	(4)	(5)
Average	0.0588[a]	0.0571[a]	0.0515[a]	0.0329[a]	0.0249[a]
spread	(0.0124)	(0.0113)	(0.0106)	(0.0081)	(0.0068)
Constant κ	0.0361[b]	0.0162	-0.0116	-0.0047	-0.0085
	(0.0140)	(0.0123)	(0.0130)	(0.0137)	(0.0056)
Adjusted κ	-0.0212	-0.0240	-0.0264	-0.0076	-0.0068

Profitability (RMW)					
Average	0.0221	0.0219	0.0168	0.0061	-0.0029
spread	(0.0169)	(0.0143)	(0.0140)	(0.0063)	(0.0063)
Constant κ	0.0419[b]	0.0474[a]	0.0406[a]	0.0252[a]	0.0193[a]
	(0.0167)	(0.0135)	(0.0107)	(0.0054)	(0.0040)
Adjusted κ	0.0510	0.0289	-0.0127	0.0237	0.0075
Momentum					
Average	0.0601[b]	0.0512[b]	0.0025	-0.0082	-0.0077
spread	(0.0271)	(0.0232)	(0.0216)	(0.0119)	(0.0084)
Constant κ	0.0006	-0.1996[a]	-0.1499[a]	-0.0417[a]	-0.0211[a]
	(0.0532)	(0.0618)	(0.0412)	(0.0104)	(0.0065)
Adjusted κ	-0.2795	-0.2904	-0.1709	-0.0541	-0.0316

The adjustment broadly confirms the earlier findings. For investment the correction proves important for spreads at short rather than long horizons. For profitability and momentum, EBRs may have more noise and the corrections are accordingly larger. For profitability the estimated required return spreads decline, especially at longer horizons. The corrections for momentum are in line with the earlier interpretation that firms in the long portfolio (winners) are if anything viewed as safer than those in the short portfolio.

These patterns are confirmed in the EBR decomposition exercise, which is reported in the Appendix B2: spreads in forecast errors and revisions positively and significantly predict return spreads and the intercepts are either small and insignificant -- for investment and profitability -- or negative for size, momentum, as well as for HML (Table 4).

In sum, the investment, size and momentum puzzles are solved with expectations. As with HML, the market does not see conservative firms as riskier than aggressive ones, nor winners as riskier than losers. Instead, analysts and the market appear to hold systematically bullish expectations about firms in the short portfolios, compared to firms in the long portfolio, and the former do worse on average because that relative optimism systematically decreases.

Our evidence suggests the same may be true for profitability. Figure 2 plots the time series of actual and expectation-based spreads of these long-short portfolios.

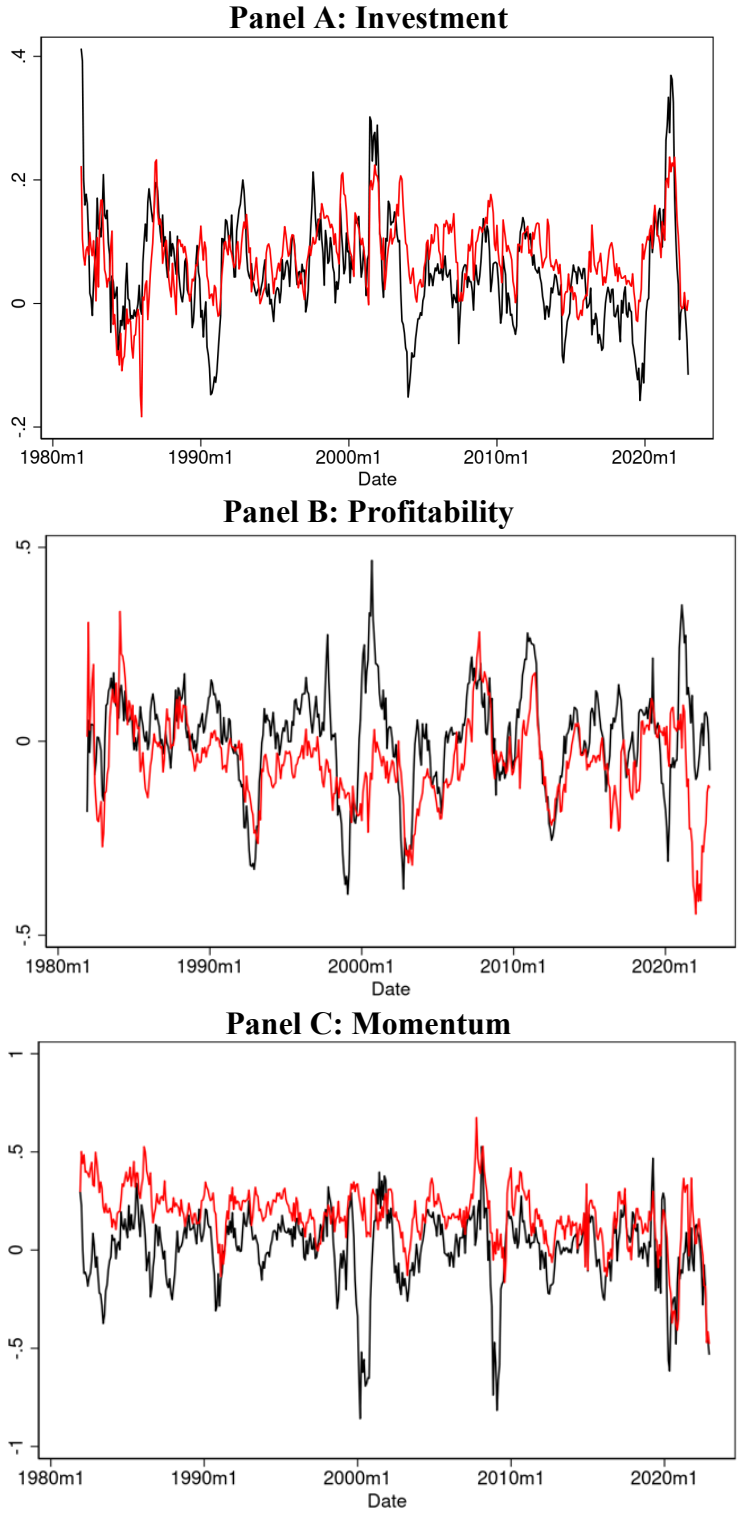


Figure 2. Actual and expectation-based return spreads, CMA, RMW and WML.
Note: Panel A plots one-year log returns (black line) and expectations-based returns (EBRs) following Equation (10) in the text EBRs (red line) for the portfolio that is long conservative stocks and short aggressive stocks (CMA). Panel B plots one-year log returns (black line) and EBRs (red line) for the

portfolio that is long robust stocks and short weak stocks (RMW). Panel C plots one-year log returns (black line) and EBRs (red line) for the portfolio that is long winners and short losers (WML). The sample period 1981:12–2020:12.

Relative to Table 6, Figure 2 further shows that EBR spreads track actual spreads well across time. As for book to market and size (Figure 1), EBRs systematically capture periods of high spreads but also correctly account for periods of negative spreads. The ability to account for the time variation in spreads, and in particular negative spreads, is a key implication of the expectations mechanism. EBRs exhibit less extreme fluctuations than actual returns despite the fact that the slope coefficients are often in the neighbourhood of 1. This may correspond to periods where expectations for growth beyond 5 years matter and correlate with LTG (variation in such expectations is currently shut down in EBRs), or where the distribution of expectations beyond that of the median analyst plays a role.

5. Predictable returns and market efficiency.

The central puzzle that motivates our paper is the predictability of cross-sectional return spreads from firm characteristics, which are sometimes interpreted are proxies for risk. While the literature has focused on the average predictability, cross sectional spreads have dramatic variation over time. As shown in Figures 1 and 2, both the average and the time variation of spreads are explained by *contemporaneous* EBRs, which capture errors and revisions in expectations of earnings growth.

Informed by these findings, we now ask two questions that circle back to return predictability. First, given extensive evidence on the predictability of forecast errors and revisions (BGLS 2019, 2024, de la O and Myers 2021, Nagel Xu 2022), can *future* cross-sectional returns be predicted using current measured expectations? And, if so, do current expectations contain genuine information about market expectations, as opposed to reflecting risk premia inferred from scaled price ratios? Second, what is the relationship between

expectations and firm characteristics that have been shown to predict returns? Do standard firm characteristics predict future EBRs (and hence future forecast errors and revisions) and not just returns, in which case they are unlikely to be stand-ins for risk?

An affirmative answer to the first question offers evidence for market inefficiency: non-rational expectations – not required returns embedded in prices – are the source of return predictability. An affirmative answer to the second question ties market inefficiency to firms' characteristics, as these characteristics predict the forecast errors that produce return spreads. Given the notorious difficulty of showing that characteristics are connected to tangible risks, this evidence would offer a direct mechanism for how characteristics matter.

5.1 Predicting Portfolio Return Spreads from Expectations

We examine return predictability by first assessing whether *current* measured expectations predict *future* return spreads. In setting up the analysis, it is important to bear in mind two competing mechanisms. If measured expectations capture true market expectations, then such predictability reflects market inefficiency, and suggests market expectations are not rational. On the other hand, analyst forecasts might not be a valid a proxy for market expectations in a way that produces this predictability if analysts infer earnings growth from market prices under the erroneous assumption of constant, and perhaps CAPM-based, returns. Analysts then wrongly incorporate in cash flow expectations priced information about required returns.[16] This mechanism might explain not only predictability of returns from expectations but also our earlier finding that EBRs explain contemporaneous returns.

We directly test both mechanisms, starting with erroneous inference from prices. BGLS (2024) regress future returns, at both aggregate and firm levels, on current expectations, controlling for current valuation ratios such as the price dividend ratio. If measured

[16] In particular, if equity analysts infer cash flow expectations from prices while correctly adjusting for the true model of risk, then they would in fact recover market expectations about earnings growth.

expectations are extracted from prices, then: i) prices should have strong predictive power on their own, and ii) controlling for prices would remove most or all predictive power from expectations. BGLS (2024) instead find high return predictability from expectations conditional on price ratios. This test is very demanding because current prices also contain information about longer term unmeasured expectations and because analyst expectations are only a proxy for market expectations embedded in prices.

Here we expand this analysis to the cross-sectional portfolios. We regress the future return spread $r_{LMS,t,t+h}$ of the long short portfolio LMS on the difference in dividend to price ratio between the long and short portfolios, $dp_{LMS,t} = \ln DP_{L,t} - \ln DP_{S,t}$, and on current and lagged expectations proxies including: the current LTG revision $\Delta_{12} LTG_{LMS,t}$, the lagged LTG portfolio level $LTG_{LMS,t-12}$, the current portfolio short term growth forecast $\mathbb{E}_t\left[\ln EPS_{LMS,t+24} - \ln EPS_{LMS,t+12}\right]$, lagged ranked forecast errors, $FE_{LMS,t-l,t}$ for $l = 12, 36,$ and 60 months (to account for potential persistence in errors), as well as the current revision $\Delta_{12} LTG_{M,t}$ and lagged value $LTG_{M,t}$ of the aggregate market portfolio. All variables are standardized to allow for a quantitative comparison of explanatory power.

Table 9 presents the results for the 1-month and 1-year horizon for each factor, with other horizons reported in the Appendix C1. The last row of Table 9 presents the R^2 of a univariate regression of $r_{LMS,t,t+h}$ on $dp_{LMS,t}$.

Table 9
Predicting future return spreads from expectations data

Note: the table presents regressions of log returns for portfolios that are long value and short growth stocks (HML), long small and short big stocks (SMB), long conservative and short aggressive investment stocks (CMA), long robust and short weak profitability stocks (RMW), and long winner and short momentum stocks (WML). Separate regressions are estimated for horizons (h) one-month and one year. The set of independent variables includes: (a) the lagged portfolio forecast for long-term growth in earnings at $t - 12$, (b) the change in the portfolio forecast for long-term growth in earnings between $t - 12$ and t, (c) the portfolio forecast for one-year growth in earnings at t, (d) the ranked forecast error in portfolio earnings between $t - 12$ and t, (e) the ranked forecast error in portfolio earnings between $t - 36$ and t, (f) the ranked forecast error in portfolio earnings between $t - 60$ and t, (g) the forecast for long-term growth in aggregate earnings at $t - 12$, (h) the change in the aggregate forecast for long-term growth in earnings between $t - 12$ and t, (i) the lagged aggregate forecast for long-term growth in earnings at $t - 12$, and (j) the portfolio log dividend-to-price ratio ($dp_{LMS,t}$) at time t. Portfolio forecast errors are ranked from 0 (lowest percentile) to 1 (top percentile). All independent variables are standardized. The last row reports the R^2 from a univariate regression of $ret_{LMS,t+h}$

on $dp_{LMS,t}$. Standard errors are corrected for overlapping observations using the Newey-West (1987) procedure. The sample period spans from December 1981 to December 2023. Superscripts: [a] significant at the 1% level, [b] significant at the 5% level, [c] 0% level.

	$r_{HML,t+h}$		$r_{SMB,t+h}$		$r_{CMA,t+h}$		r_{RMWt+h}		$r_{WML,t+h}$	
	$h=1$	$h=12$	$h=1$	$h=12$	$h=1$	$h=12$	$h=1$	$h=12$	$h=1$	$h=12$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$LTG_{LMS,t-12}$	-0.0642[b]	-0.4231[b]	0.0084	0.0631	-0.0199[b]	-0.0980	0.0104	0.1252	-0.0424[b]	-0.2346[a]
	(0.0253)	(0.2080)	(0.0101)	(0.0925)	(0.0092)	(0.0741)	(0.0141)	(0.0901)	(0.0171)	(0.0899)
$\Delta_{12}LTG_{LMS,t}$	-0.0001	-0.0836[b]	-0.0010	-0.0009	0.0011	-0.0005	0.0004	0.0083	-0.0038	-0.0431[c]
	(0.0043)	(0.0327)	(0.0047)	(0.0283)	(0.0026)	(0.0151)	(0.0023)	(0.0138)	(0.0060)	(0.0220)
$E_t[\ln EPS_{LMS,t+24} - \ln EPS_{LMS,t+12}]$	0.0408[a]	0.2715[a]	0.0226[c]	0.1089	0.0152	0.0264	0.0159	-0.0486	0.0761[a]	0.4058[a]
	(0.0126)	(0.0790)	(0.0127)	(0.0910)	(0.0108)	(0.0721)	(0.0133)	(0.0778)	(0.0234)	(0.1285)
$(1-E_t)$ $\Delta_{12}e_{LMS,t}$ $rank$	-0.0032	0.0492	0.0284[b]	-0.0708	0.0093	0.0353	-0.0042	-0.0656[c]	0.0055	-0.0221
	(0.0102)	(0.0596)	(0.0139)	(0.0907)	(0.0059)	(0.0376)	(0.0056)	(0.0381)	(0.0074)	(0.0446)
$(1-E_t)$ $\Delta_{36}e_{LMS,t}$ $rank$	-0.0043	0.0421	0.0121	0.1344[c]	-0.0275[b]	-0.2666[a]	0.0092[c]	0.0694[c]	0.0180[b]	0.0250
	(0.0126)	(0.1424)	(0.0157)	(0.0702)	(0.0136)	(0.0847)	(0.0052)	(0.0391)	(0.0091)	(0.0607)
$(1-E_t)$ $\Delta_{60}e_{LMS,t}rank$	0.0255[b]	0.0480	-0.0249[c]	-0.0617	0.0383[a]	0.2341[a]	-0.0069	-0.0788[b]	-0.0068	0.0101
	(0.0114)	(0.1257)	(0.0138)	(0.0959)	(0.0141)	(0.0745)	(0.0049)	(0.0354)	(0.0087)	(0.0393)
$\Delta_{12}LTG_{Mkt,t}$	0.0010	0.0180	-0.0005	-0.0225	0.0003	0.0143	0.0011	0.0386[c]	0.0018	0.0063
	(0.0026)	(0.0276)	(0.0051)	(0.0249)	(0.0017)	(0.0107)	(0.0031)	(0.0204)	(0.0031)	(0.0180)
$LTG_{Mkt,t-12}$	0.0047[c]	0.0339	0.0036	0.0424[b]	0.0033[b]	0.0165[b]	0.0041	0.0396	0.0047	-0.0171
	(0.0026)	(0.0277)	(0.0035)	(0.0210)	(0.0013)	(0.0082)	(0.0034)	(0.0247)	(0.0037)	(0.0290)
$dp_{LMS,t}$	-0.0286	-0.0252	0.0084	0.1819	-0.0139	0.0898	0.0183	0.0955	-0.0148	0.0841
	(0.0252)	(0.2014)	(0.0101)	(0.1291)	(0.0156)	(0.0945)	(0.0230)	(0.1715)	(0.0182)	(0.0866)
Constant	-0.0490[a]	-0.3886[b]	-0.0329	-0.1890	-0.0184[c]	-0.1353[c]	-0.0203	-0.1889	-0.0384	0.2017
	(0.0181)	(0.1802)	(0.0292)	(0.1537)	(0.0110)	(0.0811)	(0.0212)	(0.1346)	(0.0239)	(0.2085)
Obs	444	433	444	433	444	433	444	433	444	433
Adjusted R^2	5%	16%	3%	19%	7%	31%	0%	14%	9%	26%
Univariate R^2	0%	3%	0%	7%	0%	8%	0%	0%	0%	4%

Lagged expectations have strong predictive power for the future HML return spread, even at the short 1-month horizon, a challenging test, and increasing at the 1-year horizon. This is driven in particular by the role of lagged optimism about both short- and long-term earnings growth. Contrary to the inference from prices hypothesis, the predictive power of expectations dwarfs that of prices. In the horse race of Table 9, the dividend price ratio is never significant and often has the wrong sign, whereas where one standard deviation of the expectations

variables can explain up to 0.13 or 0.42 standard deviations of spreads, depending on the factor (as before, predictive power is lower for profitability). In fact, the dividend price ratio's predictive power in univariate regressions is negligible, as seen by the univariate R^2 shown in the last row. Adding lagged expectations leads to a dramatically higher adjusted R^2 in all specifications. At longer horizons, expectations account for up to 60% of variation in return spreads across factors, and these results are robust to using other valuation ratios, such as price earnings or book to market (Appendix C1).[17]

Taken together, our results show that returns are predictable by measured expectations of earnings growth at the portfolio level (as well as at the aggregate and firm level, BGLS 2024). There is no evidence that these expectations erroneously capture discount rates inferred from prices. The Appendix offers further evidence against this hypothesis.[18]

How then do expectations predict future returns? Linking to our earlier evidence that EBRs explain contemporaneous spreads, future return spreads may be explained, at least in

[17] Price earnings ratio spreads are not significant in the horse race with expectations, while book to market is significant at longer horizons for some factors (size and momentum). The predictive power of expectations is very similar to that in Table 9. As noted above, this is consistent with market growth expectations driving cross sectional spreads, because prices incorporate those expectations. Note that for aggregate returns, which are strongly predicted by aggregate pd, yet also in that case current measured expectations explain future aggregate returns controlling for prices (BGLS 2024).

[18] Appendix B shows that changes in measured beliefs respond to realized fundamentals and do not appear to mechanically respond to prices. Controlling for actual return spreads $r_{LMS,t+h}$, EBRs strongly responds to news, in terms of both contemporaneous realized growth $\Delta_h e_{LMS,t+h}$ and realized forecast errors, which are a broader proxy for news including forward looking news. This holds at both at the portfolio (Appendix B2) and the firm level (Appendix B3). Accounting for forecast errors leads to a substantial increase in the adjusted R^2, as well as a drop in the correlation of EBR and actual returns in most cases. The lack of a mechanical correlation between beliefs and prices is also evident from the fact that realized returns and EBRs are imperfectly correlated (R^2s are below one in Tables 3 and 7, see also Figures 1 and 2). BGLS (2024) show that changes in LTG at both the market and the firm level are more reliably explained by past earnings growth than by past stock returns.

Chaudhry (2024) shows that price shocks from indexation (Pavlova and Sikorskaya 2023) and mutual fund flows (Lou 2012) impact analysts' cash flow expectations, and argues for a mechanical impact of prices on expectations. However, this argument relies on the rational expectations assumption that forecast revisions should not be predictable on the basis of past information (including that leading to indexation). However, with non-rational expectations, revisions are predictable even if analysts do not learn from prices, which renders this test not valid.

Appendix C extends the predictability analysis in Tables 9 and 10 to the firm level. Specifically, we predict firm level EBRs using the expectation variables in Table 9, and then run a horse race between predicted future firm level EBRs and current firm level valuation ratios to explain future firm level returns. Predicted EBRs again explain future returns at all horizons and firm valuation ratios have little predictive power except at long horizons, confirming that expectations are not spuriously capturing information about required returns.

part, by the unfolding of predictable market expectations errors as proxied by predictable EBRs. To assess this mechanism linking expectation non-rationality to market inefficiency, we perform two exercises. First, we use the expectation variables in Table 9 to predict future EBR spreads of long-short portfolios at time $t+1$. This assesses the non-rationality of expectations, because EBRs, as a combination of forecast errors and revisions, should not be predictable if expectations are rational. We also control for the price dividend ratio, which would absorb predictability of future EBRs under the erroneous inference from prices hypothesis. The results are reported in Table 10 Panel A for 1-month and 1-year horizons as in Table 9, with other horizons reported in Appendix C.

In the second exercise, we show that EBRs predicted from expectations explain returns. Specifically, we use the same expectation variables (but not the valuation ratio) as the first stage to construct at each t a predicted EBR spread of long short portfolios at time $t+1$, which we denote by $\widehat{\mathrm{EBR}}_{LMS,t\to t+1}$. In the second stage, we test the ability of the predicted EBR differential to predict portfolio returns:

$$r_{L,t+1} - r_{S,t+1} = \beta_0 + \beta_1 \cdot \widehat{\mathrm{EBR}}_{LMS,t\to t+1} + v_{t+1} \tag{9}$$

Compared to Equation (8), this test ties return differentials to error predictability, the hallmark of non-rationality, and allows for a quantitative assessment of the role of predictable EBRs in explaining actual spreads. The results are reported in Table 10 Panel B.

Table 10
Non-rational expectations and predictable returns

Note: Panel A presents OLS regressions of log expectations-based returns (EBRs) for portfolios that are long value and short growth stocks (HML), long small and short big stocks (SMB), long conservative and short aggressive investment stocks (CMA), long robust and short weak profitability stocks (RMW), and long winner and short momentum stocks (WML). The set of independent variables includes: (a) the lagged portfolio forecast for long-term growth in earnings at $t-12$, (b) the change in the portfolio forecast for long-term growth in earnings between $t-12$ and t, (c) the portfolio forecast for one-year growth in earnings at t, (d) the ranked forecast error in portfolio earnings between $t-12$ and t, (e) the ranked forecast error in portfolio earnings between $t-36$ and t, (f) the ranked forecast error in portfolio earnings between $t-60$ and t, (g) the forecast for long-term growth in aggregate earnings at $t-12$, (h) the change in the aggregate forecast for long-term growth in earnings between $t-12$ and t, (i) the lagged aggregate forecast for long-term growth in earnings at $t-12$, and (j) the portfolio log dividend-to-price ratio ($dp_{LMS,t}$) at time t. Portfolio forecast errors are ranked from 0 (lowest percentile) to 1 (top percentile). All independent variables are standardized. Panel B presents instrumental variable regressions of log returns for the HML, SMB, CMA, RMW, and WML portfolio on expectations-based returns (EBRs) for the relevant portfolio. The set of instrumental variables includes all

independent variables in Panel A with the exception of $dp_{LMS,t}$. In both panels, separate regressions are estimated for one- month and one-year horizons. We present Kleinbergen Paap (KP) and Montiel Pflueger (MP) F-statistics. The sample period spans from December 1981 to December 2023. Superscripts: [a] significant at the 1% level, [b] significant at the 5% level, [c] 0% level.

Panel A: Predicting future expectation-based spreads from expectations data

	$EBR_{HML,t+h}$		$EBR_{SMB,t+h}$		$EBR_{CMA,t+h}$		$EBR_{RMW,t+h}$		$EBR_{WML,t+h}$	
	$h=1$	$h=12$	$h=1$	$h=12$	$h=1$	$h=12$	$h=1$	$h=12$	$h=1$	$h=12$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$LTG_{LMS,t-12}$	-0.0224[a]	-0.2863[a]	-0.0037	-0.0521[a]	-0.0069	-0.0411	-0.0048	-0.0527	-0.0078	-0.1049[a]
	(0.0066)	(0.1017)	(0.0028)	(0.0201)	(0.0043)	(0.0367)	(0.0046)	(0.0457)	(0.0051)	(0.0335)
$\Delta_{12}LTG_{LMS,t}$	-0.0023	-0.0638[a]	-0.0011	-0.0011	-0.0013	0.0086	0.0023[a]	0.0275[a]	-0.0065[a]	-0.0749[a]
	(0.0016)	(0.0188)	(0.0012)	(0.0104)	(0.0013)	(0.0083)	(0.0008)	(0.0083)	(0.0022)	(0.0143)
$E_t[\ln EPS_{LMS,t+24} - \ln EPS_{LMS,t+12}]$	0.0170[a]	0.1727[a]	0.0137[a]	0.0964[a]	0.0060	0.0870[b]	0.0106[a]	0.1073[a]	0.0082[b]	0.1838[a]
	(0.0034)	(0.0409)	(0.0031)	(0.0339)	(0.0042)	(0.0387)	(0.0039)	(0.0361)	(0.0042)	(0.0387)
$(1-E_t)$ $\Delta_{12}e_{LMS,t}$ $rank$	0.0124[a]	0.0549[b]	0.0174[a]	0.0502[c]	0.0033	0.0059	0.0001	-0.0439[b]	0.0055[c]	0.0156
	(0.0028)	(0.0236)	(0.0042)	(0.0284)	(0.0028)	(0.0202)	(0.0020)	(0.0170)	(0.0029)	(0.0220)
$(1-E_t)$ $\Delta_{36}e_{LMS,t}$ $rank$	-0.0046	0.0086	-0.0002	0.0920[a]	-0.0054	-0.1296[a]	0.0023	0.0434[b]	-0.0013	0.0014
	(0.0046)	(0.0709)	(0.0054)	(0.0322)	(0.0051)	(0.0441)	(0.0022)	(0.0211)	(0.0033)	(0.0323)
$(1-E_t)$ $\Delta_{36}e_{LMS,t}rank$	0.0037	0.0184	0.0006	-0.0791[a]	0.0112[c]	0.1606[a]	-0.0013	-0.0435[b]	0.0068[b]	0.0166
	(0.0035)	(0.0459)	(0.0046)	(0.0246)	(0.0058)	(0.0415)	(0.0018)	(0.0205)	(0.0031)	(0.0262)
$\Delta_{12}LTG_{Mkt,t}$	0.0028[a]	0.0238[b]	-0.0007	0.0092	0.0017[c]	0.0045	-0.0003	-0.0158	0.0038[b]	0.0371[a]
	(0.0009)	(0.0100)	(0.0011)	(0.0076)	(0.0009)	(0.0078)	(0.0010)	(0.0108)	(0.0016)	(0.0115)
$LTG_{Mkt,t-12}$	0.0037[a]	0.0298[b]	-0.0002	0.0190[a]	0.0020[a]	0.0084	-0.0015	-0.0165	0.0062[a]	0.0355[a]
	(0.0009)	(0.0126)	(0.0009)	(0.0064)	(0.0007)	(0.0057)	(0.0013)	(0.0163)	(0.0014)	(0.0114)
$dp_{LMS,t}$	-0.0245[a]	-0.0909[a]	-0.0095	-0.0220	-0.0230[a]	0.0616	-0.0132	-0.0408	-0.0123	0.0014
	(0.0093)	(0.0269)	(0.0060)	(0.0525)	(0.0084)	(0.0616)	(0.0105)	(0.0956)	(0.0083)	(0.0540)
Constant	-0.0356[a]	-0.3164[a]	-0.0018	-0.0911[c]	0.0003	0.0000	0.0091	0.1169	-0.0103	0.0267
	(0.0062)	(0.0938)	(0.0070)	(0.0492)	(0.0065)	(0.0525)	(0.0087)	(0.0881)	(0.0104)	(0.0848)
Obs	442	433	442	433	442	433	442	433	442	433
Adjusted R^2	20%	29%	15%	45%	6%	26%	7%	28%	11%	49%
Univariate R^2	1%	0%	1%	16%	2%	1%	3%	1%	0%	1%

Panel B: Instrumented expectation-based returns explain actual spreads

	$r_{HML,t+h}$		$r_{SMB,t+h}$		$r_{CMA,t+h}$		$r_{RMW,t+h}$		$r_{WML,t+h}$	
	$h=1$	$h=12$	$h=1$	$h=12$	$h=1$	$h=12$	$h=1$	$h=12$	$h=1$	$h=12$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\widehat{EBR}_{LMS,t,t+h}$	1.1261[a]	1.1423[a]	1.2027[a]	0.8840[a]	1.4193[a]	1.3163[a]	0.1028	-0.0538	1.2837[a]	0.9145[a]
	(0.3466)	(0.2160)	(0.3327)	(0.2494)	(0.4412)	(0.2421)	(0.4756)	(0.2537)	(0.4667)	(0.2791)
Constant	0.0008	-0.0168	0.0032	0.0265[c]	-0.0064[c]	-0.0655[a]	0.0017	0.0064	-0.0464[b]	-0.1730[a]
	(0.0020)	(0.0134)	(0.0019)	(0.0142)	(0.0034)	(0.0205)	(0.0030)	(0.0185)	(0.0191)	(0.0546)
Obs	444	433	444	433	444	433	444	433	444	433
KP F-stat	10.4	6.3	8.5	13.2	4.2	4.6	4.8	7.3	7.9	8.9

MP F-stat	10.5	3.8	7.6	9.2	3.5	4.0	3.7	3.7	6.1	10.3

Panel A shows that, on average, analyst differential optimism about long term growth of the short arm – as measured by low $LTG_{LMS,t-12}$ and $\Delta_{12}LTG_{LMS,t}$ – negatively predicts subsequent forecast errors and revisions, and hence high EBRs, in line with previously documented analyst overreaction to news (BGLS 2019, 2024). Analyst differential optimism about short term growth instead positively predicts future spreads. Controlling for these measures, aggregate long-term optimism tends to predict higher EBR spreads, as in BGLS (2024), but not uniformly so. As for actual spreads (Table 9), the dividend price ratio has negligeable predictive power for EBRs: univariate R^2 are generally tiny,[19] and in the horse race the coefficient is generally insignificant, and if anything has the wrong sign. These results confirm that expectations systematically depart from rationality and in particular predict future EBRs with a pattern very similar to how they predict actual future spreads (Table 9, panel A).

Panel B shows that actual spreads load strongly on predicted EBRs, with all coefficients strongly significant and indistinguishable from 1, except for profitability where we knew from Table 7 that EBRs do not predict returns. Intercepts for actual return spreads are mostly small and insignificant, and in some cases negative, confirming that EBRs, and in particular their predictable component, can account for the totality of the observed spreads in actual returns. Overall, these results show that predictable expectational errors and revisions explain not only average spreads, but also their time variation. This is consistent with the fact that future return spreads capture, at least in part, unfolding of predictable market expectations errors, where the latter are proxied by predictable EBRs.[20]

[19] The price dividend ratio predicts EBR spreads for the SMB long short portfolio in a univariate regression but this predictive power is absorbed by the expectations variables in the horse race.

[20] Table 10 is a predictive exercise, which highlights the correlation between predicted EBRs and actual returns. While our interpretation does not strictly require an IV interpretation, we assess the strength of our expectation-based instruments using Kleinbergen Paap (2006) and Montiel Pflueger (2013) F-statistics. In line with previous results, the predictability from lagged expectations is stronger for HML, SMB and WML, with instruments in about half the specifications exceeding the heuristic of an F-stat of 10. For CMA and RMW, instruments are

To visualize this point, Figure 3 plots the predicted 1-year return spreads from Table 10 Panel B (first stage) against the realized spreads.

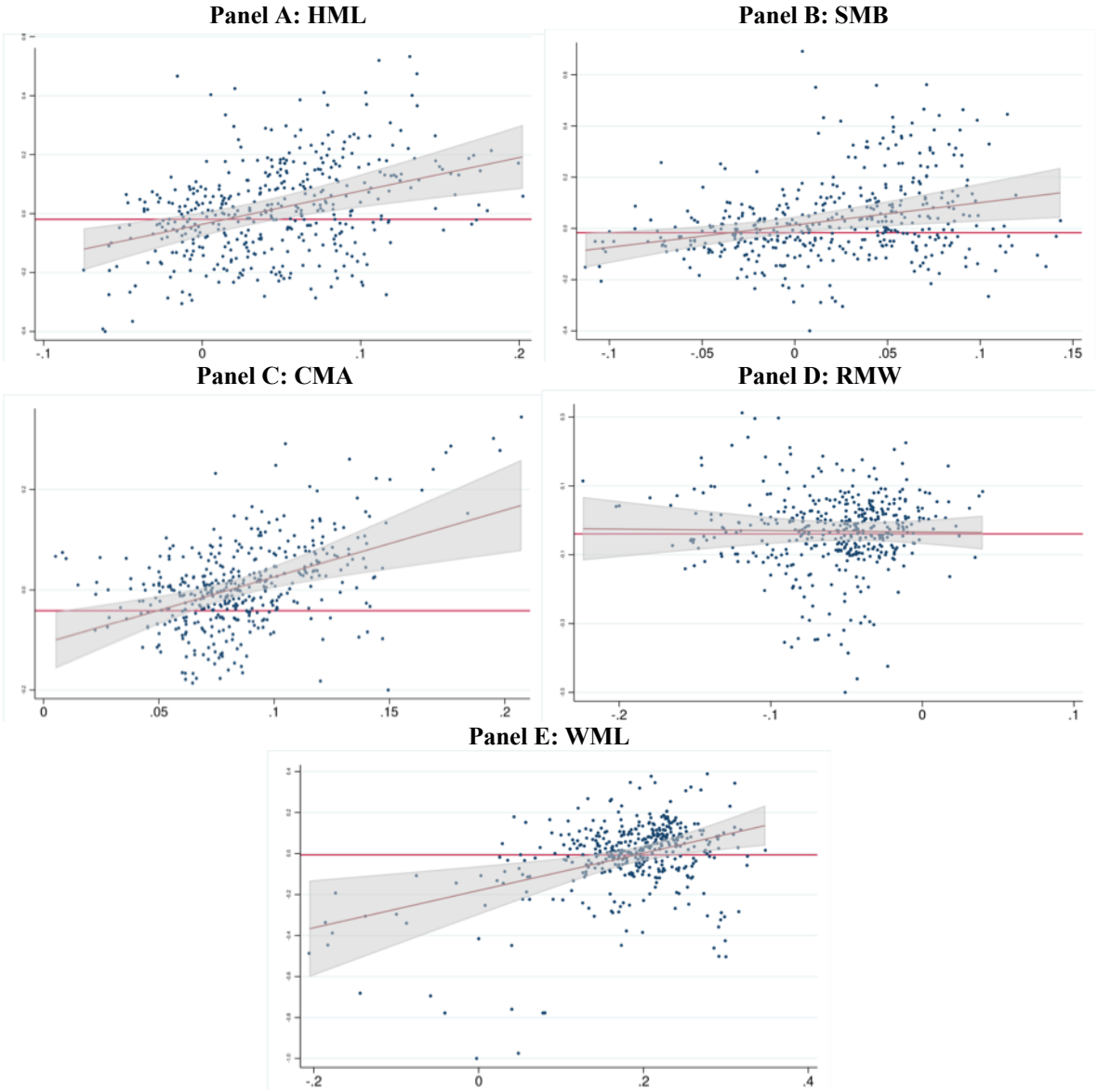


Figure 3. Predicted and realized return spreads

Note. The Figure plots one-year returns for portfolios that are long value and short growth stocks (HML), long small and short big stocks (SMB), long conservative and short aggressive investment stocks (CMA), long robust and short wea profitability stocks (RMW), and long winner and short momentum stocks (WML) against the predicted expectation-based return (EBR) for the relevant portfolio. See Panel B in Table 10 for the list of variables used to generate predicted EBRs. We show 95% confidence bands around predicted EBRs. Standard errors are based on Newey-West (1987) standard errors.

Figure 3 shows that the predicted long minus short return spread covers a large range, and helps account not only for substantial variation among positive spreads but also for

weak. These instruments are stronger for horizons above one year, with 8 (5) out of 10 KP (MP) F-statistics exceeding 10.

negative spreads. Predictably large spreads tend to arise following periods when beliefs about firms in the short arm are particularly bullish, in line with a correction to overly optimistic beliefs about the short arm, as in the overreaction mechanism documented by BGLS (2024) for the aggregate market. Conversely, negative spreads tend to be associated with optimistic beliefs about aggregate growth but not disproportionately so for firms in the short arm. These periods may be subject to increases in optimism about the short arm, as illustrated by the underperformance of value portfolios during the late 1990s and mid 2010s stock market boom.

Predictable time variation in return spreads is a challenge to the view that characteristics predict returns by capturing discount rates (Fama French 1995). A large literature has sought to explain such time variation under a decomposition of returns into shocks to discount rates or shocks to cash flow expectations, similar to Equation (4). This approach typically assumes that changes in prices or characteristics such as book to market capture shocks to discount rates, and to assign residual movement in returns to shocks to earnings forecasts (Vuolteenaho 2002, Campbell and Vuolteenaho 2004). This work has found a small role for discount rate shocks in accounting for time variation in cross-sectional spreads (Lochstoer and Tetlock 2020, Campbell et al. 2023), consistent with our finding that valuation ratios fail to predict return spreads.

Our approach shows instead that non-rational expectations give rise to predictable shocks to expectations of earnings. In a return decomposition, the action does come from shocks to cash flow expectations, but these expectations are not rational and – crucially – the shocks to the cash flow term are predictable from lagged expectations. Instead of driving discount rates (as in duration models), such expectation shocks capture market inefficiency. Predictability of negative spreads among characteristics sorted portfolios is not consistent with the notion that characteristics (or prices) encode differences in required returns. We next examine whether characteristics may instead be linked to predictable EBRs.

5.2 Characteristics and EBRs.

We next assess the predictability of EBRs, and hence of expectations errors, from characteristics. This test closes the circle in our investigation of the extent to which standard characteristics proxy for market inefficiency as opposed to risk.

Table 11 regresses, at the firm level, future EBRs on current characteristics. In Columns 1 through 5 we examine how firm level book to market, size, investment, profitability and momentum predict future EBRs. Columns 6 to 10 control for the expectation variables used in Table 9 to predict portfolio level returns, which allows us to assess whether characteristics hold predictive power over and above measured expectations, and vice versa. We do not include firm fixed effects here, because they would potentially absorb the role of the measured characteristics themselves.

Table 11
Characteristics predict firm level expectation based returns

Note: This table presents regressions of firm level log expectations-based returns (EBRs) at horizons (h) of one-month, three-months, one-year, three-years, and five-years. The independent variables include: (a) log book-to-market ($\ln bm_{i,t}$) at time t, (b) one-year growth in assets between $t-1$ and t ($Inv_{i,t}$), (c) log market value of equity at time t, (d) operating profitability at time t ($op_{i,t}$), and (e) returns between periods $t-11$ and $t-1$ ($r_{i,t-11\to t-1}$). Standard errors are corrected for overlapping observations and cross-correlations using the Driscoll and Kraay (1998) procedure. The sample period spans from December 1981 to December 2023. Superscripts: [a] significant at the 1% level, [b] significant at the 5% level, [c] significant at the 10% level.

	$EBR_{i,t,t+1}$	$EBR_{i,t,t+3}$	$EBR_{i,t,t+12}$	$EBR_{i,t,t+36}$	$EBR_{i,t,t+60}$
	(1)	(2)	(3)	(4)	(5)
$bm_{i,t}$	0.0056[a]	0.0160[a]	0.0573[a]	0.1113[a]	0.1434[a]
	(0.0003)	(0.0019)	(0.0081)	(0.0138)	(0.0202)
$size_{i,t}$	0.0082[a]	0.0115[a]	-0.0717[a]	-0.2916[a]	-0.3975[a]
	(0.0002)	(0.0017)	(0.0055)	(0.0207)	(0.0306)
$Inv_{i,t}$	-0.0067[a]	-0.0215[a]	-0.0705[a]	-0.0854[a]	-0.0869[a]
	(0.0004)	(0.0022)	(0.0056)	(0.0095)	(0.0107)
$op_{i,t}$	-0.0014[b]	-0.0048[c]	-0.0050	0.0034	-0.0098
	(0.0006)	(0.0025)	(0.0110)	(0.0213)	(0.0313)
$r_{i,t-12\to t-1}$	0.0176[a]	0.0502[a]	0.0806[a]	0.0357[b]	0.0305[b]
	(0.0002)	(0.0046)	(0.0150)	(0.0155)	(0.0143)
Obs	878,185	818,858	775,234	596,792	475,520

Adj R^2	0%	1%	2%	10%	17%

On their own, characteristics have strong and highly significant predictive power for forecast errors and revisions (columns 1 to 5). Low book to market, high investment and low past returns predict subsequent disappointment and low EBRs at all horizons, consistent with the average spread of the corresponding factors.[21] Interestingly, large firms have higher short term EBRs but lower EBRs at horizons of one year and longer. Of all characteristics, only profitability does not reliably predict EBRs once other characteristics are controlled for.

The final step of our analysis is a mediation exercise (MacKinnon 2012). To obtain an estimate of the share of return predictability from characteristics that works through their ability to predict analyst expectations (versus the share that works through their direct predictive ability after controlling for EBRs), we regress firm level realized returns on contemporaneous EBRs and lagged firm characteristics. The exercise shows that to a large extent characteristics predict returns precisely because they capture distorted expectations. These tests quantify the extent to which characteristic-based predictability reflects the expectations channel, and thus market inefficiency, as in Equation (8), and shed new light on time variation in average return spreads.

Specifically, we run the regression:

$$r_{i,t+h} = a_r + b \cdot \mathrm{EBR}_{i,t,t+h} + c_{bm} \cdot bm_{i,t} + c_{inv} \cdot inv_{i,t} + c_{size} \cdot size_{i,t} + c_{prof} \cdot op_{i,t} + c_{mom} \cdot r_{i,t-12\to t-1} + \epsilon_{t+h}, \qquad (12)$$

where coefficients c_χ capture the predictive power of characteristic χ for returns that is independent of the firm level EBR. The predictive power of a characteristic such as book to

[21] These results are consistent with recent work linking characteristics and expectations data. Frey (2023) examines a large number of factors and finds that short term growth expectations between the long and short arm to converge. Gormsen and Lazarus (2023) find that characteristics associated with the short arm of factors, such as low book to market, high investment, low profitability, high beta and low payout, predict high LTG. In Gormsen and Lazarus' interpretation, LTG captures the duration risk of different stocks.

market working through EBRs can then be quantified as $b \cdot d_{bm}$, where d_{bm} is the coefficient on the regression that predicts EBRs from characteristics (Table 12, columns 1 to 5):

$$\mathrm{EBR}_{i,t,t+h} = a_{ebr} + d_{bm} \cdot bm_{i,t} + d_{inv} \cdot inv_{i,t} + d_{size} \cdot size_{i,t} + d_{prof} \cdot op_{i,t} + d_{mom} \cdot r_{i,t-12\to t-1} + \varepsilon_{t+h}. \qquad (13)$$

Finally, the predictive power of book to market working through EBRs, $b \cdot d_{bm}$, can be compared to the independent predictive power c_{bm} of book to market alone. This exercise offers a lower bound on the role of expectations: our measured analyst beliefs in fact contain only partial information about market beliefs, not only due to measurement noise, but also because we observe expectations only for specific forecast horizons.

Table 12 shows the empirical results, reporting Equation (13) in Panel A.

Table 12
Return predictability from characteristics is mediated by expectations

Note: Panel A presents regressions of log firm-level returns at horizons (h) of one month, three months, one year, three years, and five years. The independent firm-level variables include: (a) log book-to-market ($\ln bm_{i,t}$) at time t, (b) log market value of equity at time t, (c) one-year growth in assets between $t-1$ and t ($Inv_{i,t}$), (d) operating profitability at time t ($op_{i,t}$), and (e) returns between periods $t-11$ and $t-1$ ($r_{i,t-11\to t-1}$). Standard errors are corrected for overlapping observations and cross-correlations using the Driscoll and Kraay (1998) procedure. The sample period spans from December 1981 to December 2023. Panel B shows the share of predictability of log firm-level returns at each horizon h accounted for by $Inv_{i,t}$ and $\ln bm_{i,t}$ as detailed in Equations (12,13) and in the text. Superscripts: [a] significant at the 1% level, [b] significant at the 5% level, [c] significant at the 10% level.

Panel A: Explaining Returns

	$r_{i,t+1}$	$r_{i,t+3}$	$r_{i,t+12}$	$r_{i,t+36}$	$r_{i,t+60}$
	(1)	(2)	(3)	(4)	(5)
$\mathrm{EBR}_{i,t,t+h}$	0.1579[a]	0.2168[a]	0.4077[a]	0.5222[a]	0.5589[a]
	(0.0010)	(0.0065)	(0.0164)	(0.0227)	(0.0267)
$\ln bm_{i,t}$	-0.0080[a]	-0.0135[a]	-0.0195[b]	-0.0043	0.0064
	(0.0004)	(0.0032)	(0.0086)	(0.0109)	(0.0134)
$\ln size_{i,t}$	0.0040[a]	-0.0295[a]	-0.1296[a]	-0.2229[a]	-0.2831[a]
	(0.0002)	(0.0026)	(0.0103)	(0.0255)	(0.0418)
$Inv_{i,t}$	0.0115[a]	0.0135[a]	0.0199[a]	0.0470[a]	0.0764[a]
	(0.0003)	(0.0028)	(0.0074)	(0.0149)	(0.0179)
$op_{i,t}$	0.0093[a]	0.0175[a]	0.0457[a]	0.0720[a]	0.0856[a]
	(0.0006)	(0.0035)	(0.0103)	(0.0213)	(0.0272)
$r_{i,t-12\to t-1}$	-0.0058[a]	-0.0124[a]	-0.0596[a]	-0.0774[a]	-0.0824[a]
	(0.0002)	(0.0030)	(0.0109)	(0.0184)	(0.0194)
Obs	878,185	818,858	775,211	596,734	475,452
Adj R^2	2%	7%	31%	52%	59%

Panel B: Share of predictability from characteristics via expectations

bm	7%	20%	54%	55%	51%
$size$	24%	-9%	18%	41%	44%
inv	11%	26%	60%	92%	115%
op	-2%	-5%	-5%	2%	-6%
$r_{i,t-12\to t-1}$	-125%	-975%	-126%	-32%	-26%

Panel A shows that EBR has substantial explanatory power: conditioning on characteristics, b is large and significant, consistent with Table 9. The converse is also true (c_χ are large and significant) which, on its own, is consistent both with a characteristic based required return and with the earlier remark that our measures of market beliefs are partial. Momentum has the wrong sign in Table 12 but the correct sign in Table 11, suggesting all of the predictability is captured by EBR.

We next compute a lower bound for the expectation-channel share of the predictability of characteristic $\chi = bm, size, inv, prof, mom$ as $\frac{b \cdot c_\chi}{b \cdot c_\chi + d_\chi}$, which are reported in Table 12 panel B. At horizons of 1 year or longer, most predictability from bm and inv, and a substantial share of predictability from $size$, works through the expectations channel.[22] There is no explanatory power for profitability, in line with the result from Table 9 that, controlling for other characteristics, dp does not predict EBRs. These results offer direct evidence that analyst expectations help explain the documented predictive power of firm characteristics for future returns.

6.Taking stock

[22] As a further test, we offer another lower bound on the role of expectations by following the residualization strategy in BGLS (2024). Specifically, we first regress returns $r_{i,t+h}$ at the firm level using a saturated specification of *contemporaneous* expectations measures. These regressions achieve R^2s ranging from 27% to 48%. We next regress the residuals of this regression on firm level book to market $bm_{i,t}$. Appendix C2 shows that the predictive power of characteristics drops dramatically in magnitude and significance and ceases to be significant for horizons of 1 year or above, once expectations are controlled for in this way. Under efficient markets, the predictive power of characteristics for returns should be unaffected.

We started the paper with a simple question: does understanding the cross-section of stock returns need exotic risk factors, first introduced by Fama and French (1993)? The evidence we presented says no. Rather, the risk premia identified by Fama and French appear to reflect corrections of measurable expectations errors about earnings growth. Relaxing the assumption of rational expectations allows us to use the classical dividend discount model and observed expectations of future cash flows to account for the cross-sectional evidence on stock returns. We view this result as a victory for financial economics, because it shows that we do not need exotic risk factors, to explain the data.

Our evidence shows that spreads are generated because expectations about future growth of firms in the short arm of the portfolios are systematically too optimistic, and those about firms in the long arm too pessimistic, so that the long portfolio outperforms the short one as expectation errors are corrected in the future. Characteristics such as book to market or investment predict returns at least in part because they predict differential optimism and forecast errors. Notably, the same mechanism helps account for momentum. Predictability from other characteristics may also work through expectations. This, of course, has significant implications not just for cross sectional (and time series) asset pricing, but also for firm investment policies, financial policies, and other decisions. We conclude by highlighting two follow-up questions.

The first question concerns the structure of expectations. Analyst beliefs can reproduce return co-movements across firms sharing similar characteristics because expectations themselves comove within groups of characteristics. Where does such co-movement come from, and why does it lead firms with certain characteristics to be over-priced? One possibility is that co-movement reflects the non-rational reaction of beliefs to common shocks hitting groups of firms or sectors, but co-movement in beliefs may also reflect spurious similarity of firms to their peers (Sarkar 2024). Understanding the structure of expectations may also shed

light on the evidence that idiosyncratic risk is priced (Campbell et al 2001), because such firm-specific return differentials may also reflect time varying optimism about firm growth rather than compensation for firm specific risk.

The second question concerns the required rate of return that the dividend discount model relies on. What are its properties and determinants? In standard theory one component is the risk premium, which depends on the curvature of the utility of wealth and the quantity of risk, another component is interest rates, which are determined by time preference and technology. Yet, a large body of work using experimental and field data, including applications to the stock market (Benartzi and Thaler 1995, Barberis 2018), shows that risk attitudes depend on factors other than the marginal utility of wealth. It is also well known that interest rates themselves are highly volatile (Shiller 1980, Singleton 1980, Giglio and Kelly 2018). Psychology may also help understand where the required return comes from.

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Appendix

Appendix B: Expectation Based Returns (EBRs), assumptions and robustness

B.1 Samples and robustness.

In this Section, we assess the robustness of our construction of EBRs to alternative choices regarding sample selection, assumptions about payout ratios, and value weighting portfolio EBRs. Table B.1 compares our main sample, defined in Section 2.2, to the full CRSP / COMPUSTAT sample.

Table B1.
Sample descriptive statistics

Note: The table presents descriptive statistics for the sample of firms that meet the CRSP/COMPUSTAT data requirements of Fama and French (1992) and the subsample with an expectation-based return (EBR) for July of year t (*our sample*). We report sample means for: (1) the book-to-market ratio, (2) the one-year change in total assets in fiscal year *t-1* divided by t-2 total assets (*investment*), (3) annual revenues minus cost of goods sold, interest expense, and selling, general, and administrative expenses divided by book equity (*operating profitability*), (4) the return between *t-11* and *t*, (5) the ratio of the 3-year moving average of earnings per share to price, (6) , (7) the dividend to price ratio, and (8) the average number of observations. For each variable we report sample mans for the two samples, their difference, the standard error for the difference, the z-stat, and the significance of the difference of the two means.

	Sample mean		gap	Standard error	Z-stat	p
	All CRSP/ COMPUTAT	Our Sample				
book-to-market	0.6365	0.6109	0.0256	0.0038	6.72	0.0%
investment	0.1905	0.1918	-0.0013	0.0020	-0.67	50.3%
operating profitability	0.3320	0.3256	0.0064	0.0378	0.17	86.6%
market capitalization (mill)	7,256	7,842	-586	65	-8.99	0.0%
Lagged one-year return	0.1527	0.1687	-0.0160	0.0020	-8.12	0.0%
earnings-to-price ratio	0.0202	0.0452	-0.0250	0.0035	-7.06	0.0%
cape ratio	0.0300	0.0461	-0.0161	0.0024	-6.63	0.0%
dividend-to-price ratio	0.0159	0.0165	-0.0006	0.0001	-6.87	0.0%
observations	2,162	1,786	375.8	34.8	10.80	0.0%

Next, we show that the results of Tables 1 and 2 on how portfolio level EBRs compare to actual returns are unchanged under an alternative payout definition. We use the expected payout ratio implied from analysts' expectations of dividends and earnings, namely $\widetilde{\mathbb{E}}_t DPS_{i,t+12} / \widetilde{\mathbb{E}}_t EPS_{i,t+12}$ for observations with available expectations of dividends. When this data is not available, we set the expected payout ratio to zero if the firm did not pay a dividend the previous

year. If the firm did pay a dividend the previous year, we set the payout ratio to the average expected payout ratio $\frac{\widetilde{\mathbb{E}}_t DPS_{i,t+12}}{\widetilde{\mathbb{E}}_t EPS_{i,t+12}}$ in our sample for those firms which paid dividends that year, $DPS_{i,t+12} > 0$, which equals 0.41. In the text we assumed a constant payout ratio, equal to 0.41, which has a correlation with the above specification of over 97%.

Table B2.
Expectation Based Returns with Alternative Measures of Payout Ratio

Note: Panel A presents sample means of log expectation-based returns (EBR) returns for portfolios of stocks formed on book-to-market, investment, size, profitability and momentum over holding horizons ranging from one month to five years. EBRs are computed following Equation (10) in the text with the payout ratio set to: (1) the ratio of expected dividends-to-earnings in period *t+12* (i.e. $\widetilde{\mathbb{E}}_t DPS_{i,t+12}/\widetilde{\mathbb{E}}_t EPS_{i,t+12}$) for those observations where expectations of dividends are available, or (2) zero if the firm did not pay a dividend the previous year and $\widetilde{\mathbb{E}}_t DPS_{i,t+12}$ is unavailable, or (3) the average expected payout ratio $\frac{\widetilde{\mathbb{E}}_t DPS_{i,t+12}}{\widetilde{\mathbb{E}}_t EPS_{i,t+12}}$ in our sample for those firms which paid dividends in the previous year but do not have $\widetilde{\mathbb{E}}_t DPS_{i,t+12}$. Portfolio EBRs are equally weighted with monthly rebalancing. Panel B shows pairwise correlations between log returns and EBR for portfolios of stocks formed on book-to-market, investment, size, profitability and momentum sorts over holding horizons ranging from one month to five years. The sample period extends from December 1981 to December 2023.

Panel A: EBRs

Holding Horizon	Growth	Value	Aggressive	Conservative	Small	Big	Weak	Robust	Losers	Winners
1 Month	10.7%	13.5%	15.0%	7.4%	10.2%	11.5%	15.2%	9.7%	-16.0%	33.0%
3 Months	9.9%	13.0%	14.6%	6.7%	9.9%	11.1%	14.4%	9.4%	-13.4%	30.0%
1 Year	9.2%	13.7%	14.4%	6.9%	11.6%	10.3%	13.9%	9.6%	-0.8%	20.2%
3 Years	9.4%	13.1%	13.0%	8.2%	11.3%	10.3%	13.1%	10.0%	7.9%	12.9%
5 Years	9.6%	12.5%	12.6%	8.9%	10.9%	10.2%	13.0%	9.9%	9.2%	11.8%

Panel B: Correlation between returns and EBRs

Holding Horizon	Growth	Value	Aggressive	Conservative	Small	Big	Weak	Robust	Losers	Winners
1 Month	7%	18%	14%	9%	14%	9%	11%	12%	11%	5%
3 Months	22%	34%	30%	24%	29%	23%	28%	21%	27%	25%
1 Year	35%	50%	36%	40%	45%	33%	43%	32%	46%	42%
3 Years	43%	49%	35%	51%	60%	30%	46%	33%	52%	49%
5 Years	34%	37%	25%	40%	47%	16%	38%	23%	35%	32%

Next, we show our baseline analysis in Tables 3 and 6 is robust to value weighting portfolio EBRs.

Table B3.
Value weighted EBRs and Returns

Note: This table presents univariate regression results of log value-weighted returns for portfolios of stocks formed on book-to-market and size (Panel A), investment and profitability (Panel B), and momentum (Panel C) over holding horizons ranging from one month to five years. The independent variable is the value-weighted expectation-based returns (EBR) for the relevant portfolio. Standard errors are corrected for overlapping

observations using the Newey-West (1987) procedure. The sample period is December 1981 to December 2023. Superscripts: [a] significant at the 1% level, [b] significant at the 5% level, [c] significant at the 10% level.

Panel A: book to market and size

	Book-to-market (HML)					Size (Small minus Big)				
	1 Mo	3 Mo	1 Yr	3 Yr	5 Yr	1 Mo	3 Mo	1 Yr	3 Yr	5 Yr
	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
EBR_{LMS}	0.2398[b]	0.5377[a]	0.8245[a]	1.0648[a]	1.0778[a]	0.6007[a]	0.9965[a]	1.1643[a]	1.2857[a]	1.1787[a]
	(0.0991)	(0.1401)	(0.1314)	(0.1598)	(0.1757)	(0.1438)	(0.1868)	(0.1879)	(0.2032)	(0.2162)
Constant	0.0012	0.0028	0.0025	-0.0131	-0.0106	0.0049[b]	0.0098[c]	-0.0020	-0.0615	-0.0677
	(0.0020)	(0.0051)	(0.0157)	(0.0368)	(0.0469)	(0.0019)	(0.0051)	(0.0193)	(0.0423)	(0.0516)
Obs	504	502	493	469	445	504	502	493	469	445
Adj R^2	2%	11%	37%	56%	59%	6%	19%	38%	54%	49%

Panel B: profitability and investment

	Profitability (Robust minus Weak)					Investment (CMA)				
	1 Mo	3 Mo	1 Yr	3 Yr	5 Yr	1 Mo	3 Mo	1 Yr	3 Yr	5 Yr
	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
EBR_{LMS}	0.0645	0.3204[a]	0.5553[a]	0.5242[a]	0.5076[a]	0.3024[a]	0.4724[a]	0.8755[a]	0.9631[a]	0.9690[a]
	(0.0806)	(0.0898)	(0.1197)	(0.1159)	(0.0944)	(0.0711)	(0.0852)	(0.1293)	(0.1317)	(0.0974)
Constant	0.0016	0.0080[b]	0.0417[a]	0.0654[a]	0.0603	0.0018	0.0049	0.0071	-0.0022	-0.0061
	(0.0016)	(0.0038)	(0.0120)	(0.0235)	(0.0367)	(0.0014)	(0.0038)	(0.0126)	(0.0269)	(0.0336)
Obs	504	502	493	469	445	504	502	493	469	445
Adj R^2	0%	6%	23%	33%	40%	4%	11%	33%	52%	56%

Panel C: momentum

	1 Mo	3 Mo	1 Yr	3 Yr	5 Yr
	(1)	(2)	(3)	(4)	(5)
EBR_{LMS}	0.1561	0.5484[a]	0.5909[a]	0.7103[a]	0.5882[a]
	(0.1035)	(0.0979)	(0.0914)	(0.1351)	(0.1518)
Constant	-0.0034	-0.0440[a]	-0.1040[a]	-0.1347[a]	-0.1151[b]
	(0.0043)	(0.0111)	(0.0230)	(0.0446)	(0.0535)
Obs	504	502	493	469	445
Adj R^2	1%	11%	21%	37%	25%

B2. EBR spreads and realized return spreads

We reproduce the EBR decomposition analysis of Table 5 for all factors. We further control for the spread in portfolios' price dividend ratios as a means to control for spreads in discount rates incorporated in lagged valuation ratios.

Table B4.
Portfolio level forecast errors and revisions predict spreads

Note: This table presents univariate regression results of log value-weighted returns for portfolios of stocks formed on book-to-market and size (Panel A), investment, profitability and momentum (Panel B) over holding horizons ranging from one year to five years. The independent variables include the long-short: (a) forecast error between t and $t+h$, (b) forecast revisions between t and $t+h$ of one-year earnings growth in year $t+h+1$, and (c) changes in long-term growth forecasts between t and $t+h$, and (d) log dividend-to-price ratio. Standard errors are corrected for overlapping observations using the Newey-West (1987) procedure. The sample period spans from December 1981 to December 2023. Superscripts: [a] significant at the 1% level, [b] significant at the 5% level, [c] significant at the 10% level.

Panel A: Book to market and Size

	Book-to-Market (HML)			Size (SMB)		
	$r_{HML,t+12}$	$r_{HML,t+36}$	$r_{HML,t+60}$	$r_{HML,t+12}$	$r_{HML,t+36}$	$r_{HML,t+60}$
$(1\text{-}E_t)\ \Delta e_{LMS,t+h}$	0.1302[a]	0.1745[a]	0.1351[a]	0.1035[a]	0.1295[a]	0.0381
	(0.0136)	(0.0267)	(0.0376)	(0.0204)	(0.0367)	(0.0486)
$(E_{t+h}\text{-}E_t)\ \Delta e_{LMS,t+h+1}$	0.0800[a]	0.0572[b]	-0.0249	0.0334[c]	0.0109	-0.0340
	(0.0128)	(0.0247)	(0.0284)	(0.0185)	(0.0262)	(0.0351)
$\Delta_h LTG_{LMS,t+h}$	0.0278[a]	0.0197	0.0486	-0.0280[b]	0.0175	0.0799[b]
	(0.0094)	(0.0212)	(0.0345)	(0.0139)	(0.0291)	(0.0351)
$\ln(dp_{LMS,t})$	0.0030	-0.0040	0.0500	0.0252[c]	0.0239	0.0662
	(0.0106)	(0.0263)	(0.0351)	(0.0148)	(0.0342)	(0.0485)
Constant	-0.1149[a]	-0.2827[a]	-0.3671[a]	-0.1410[a]	-0.1896[c]	-0.2954[c]
	(0.0259)	(0.0661)	(0.0916)	(0.0442)	(0.1069)	(0.1545)
Obs	493	469	445	493	469	445
Adj R^2	53%	48%	48%	34%	40%	26%

Panel B: Investment, Profitability, Momentum

	Investment (CMA)			Profitability (RMW)			Momentum (WML)		
	$r_{HML,t+12}$	$r_{HML,t+36}$	$r_{HML,t+60}$	$r_{HML,t+12}$	$r_{HML,t+36}$	$r_{HML,t+60}$	$r_{HML,t+12}$	$r_{HML,t+36}$	$r_{HML,t+60}$
$(1\text{-}E_t)\ \Delta e_{HML,t+h}$	0.0649[a]	0.0737[a]	0.1023[a]	0.0489[a]	0.0652[a]	0.0143	0.1325[a]	0.1796[a]	0.0706[b]
	(0.0089)	(0.0126)	(0.0199)	(0.0155)	(0.0173)	(0.0167)	(0.0269)	(0.0292)	(0.0342)
$(E_{t+h}\text{-}E_t)\ \Delta e_{HML,t+h+1}$	0.0497[a]	0.0400[a]	0.0333[b]	0.0225	0.0075	0.0215	0.0833[a]	0.0668[a]	0.0239
	(0.0081)	(0.0123)	(0.0134)	(0.0159)	(0.0173)	(0.0164)	(0.0228)	(0.0236)	(0.0257)
$\Delta_h LTG_{HML,t+h}$	0.0149[b]	0.0428[a]	-0.0207	-0.0201	-0.0135	-0.0095	0.0187	0.0428[c]	0.0012
	(0.0065)	(0.0137)	(0.0201)	(0.0127)	(0.0147)	(0.0217)	(0.0176)	(0.0249)	(0.0393)
$\ln(dp_{HML,t})$	0.0128[c]	-0.0131	0.0198	-0.0127	-0.0344[b]	-0.0099	0.0150	-0.0325	0.0602
	(0.0067)	(0.0135)	(0.0185)	(0.0132)	(0.0164)	(0.0255)	(0.0164)	(0.0237)	(0.0371)
Constant	0.0225	0.0451	0.0524	0.0326	0.0439	0.0594	-0.1582[a]	-0.0900[b]	0.0145
	(0.0157)	(0.0319)	(0.0515)	(0.0245)	(0.0274)	(0.0460)	(0.0377)	(0.0352)	(0.0478)
Obs	493	469	445	493	469	445	493	469	445
Adj R^2	46%	47%	39%	11%	20%	4%	30%	46%	16%

Section 2.5 discusses the hypothesis that analyst expectations may surreptitiously capture discount rates that may be incorporated in prices. Here we show, following BGLS (2024), that changes in measured beliefs respond to realized fundamentals, and do not appear to mechanically respond to prices. Table B5 regresses portfolio level EBRs on *contemporaneous* portfolio level returns (which would drive the results if analysts mechanically infer forecasts from prices), as well as on contemporaneous cash flow news.

Table B5.
Expectation based portfolio returns and contemporaneous news

Note: The table presents portfolio-level regressions of expectation-based returns (EBR) at horizons (h) of one- and 3-months, and one-, three- and five-years. In each panel, the independent variables in the first regression are: (a) log returns between t and $t + h$. (b) earnings growth between t and $t + h$, and (c) the forecast error for earnings growth between t and $t + h$. The independent variable in the second regression is (a) log returns between t and $t + h$. Panel A presents results for book to market and size, Panel B for investment and profitability, and Panel C for momentum. Standard errors are corrected for overlapping observations using the Newey-West (1987) procedure. The sample period spans from December 1981 to December 2023. Superscripts: [a] significant at the 1% level, [b] significant at the 5% level, [c] significant at the 10% level.

Panel A: book to market and size

	$EBR_{HML,t+h}$					$EBR_{SMB,t+h}$				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	1 Mo	3 Mo	1 yr	3 yrs	5 yrs	1 Mo	3 Mo	1 yr	3 yrs	5 yrs
$r_{LMS,t+h}$	0.6313[a]	0.4407[a]	0.2819[a]	0.2631[a]	0.2765[a]	0.6313[a]	0.4407[a]	0.2819[a]	0.2631[a]	0.2765[a]
	(0.1111)	(0.0753)	(0.0492)	(0.0577)	(0.0637)	(0.1111)	(0.0753)	(0.0492)	(0.0577)	(0.0637)
$\Delta e_{HML,t+h}$	1.7713[a]	0.8254[a]	0.2801[a]	0.2021[a]	0.2096[b]	1.7713[a]	0.8254[a]	0.2801[a]	0.2021[a]	0.2096[b]
	(0.3345)	(0.1355)	(0.0686)	(0.0767)	(0.0912)	(0.3345)	(0.1355)	(0.0686)	(0.0767)	(0.0912)
$(1 - E_t)$ $\Delta_h e_{LMS,t+h}$			0.1342[b]	0.5288[c]	0.8856[c]			0.1342[b]	0.5288[c]	0.8856[c]
			(0.0639)	(0.2761)	(0.5174)			(0.0639)	(0.2761)	(0.5174)
Constant	0.0338[a]	0.0266[a]	-0.0097	0.0085	0.0126	0.0338[a]	0.0266[a]	-0.0097	0.0085	0.0126
	(0.0106)	(0.0094)	(0.0131)	(0.0250)	(0.0326)	(0.0106)	(0.0094)	(0.0131)	(0.0250)	(0.0326)
Obs	493	493	493	469	445	493	493	493	469	445
Adj R^2	24%	36%	57%	56%	63%	24%	36%	57%	56%	63%

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	1 Mo	3 Mo	1 yr	3 yrs	5 yrs	1 Mo	3 Mo	1 yr	3 yrs	5 yrs
$r_{LMS,t+h}$	0.7452[a]	0.5792[a]	0.4476[a]	0.1523[a]	0.4260[a]	0.6280[a]	0.4788[a]	0.2982[a]	0.1954[a]	0.4516[a]
	(0.1312)	(0.0905)	(0.0498)	(0.0530)	(0.0665)	(0.0982)	(0.0694)	(0.0426)	(0.0354)	(0.1002)
Constant	0.0418[a]	0.0379[a]	0.0270[a]	0.0279[b]	0.0817[a]	0.0127	0.0103	0.0041	-0.0036	-0.0138
	(0.0121)	(0.0108)	(0.0086)	(0.0120)	(0.0195)	(0.0104)	(0.0093)	(0.0080)	(0.0097)	(0.0377)
Obs	493	493	493	469	445	493	493	493	469	445

Adj R^2	8%	18%	46%	12%	50%	9%	20%	34%	34%	49%

Panel B: investment and profitability

	$EBR_{CMA,t+h}$					$EBR_{RMW,t+h}$				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	1 Mo	3 Mo	1 yr	3 yrs	5 yrs	1 Mo	3 Mo	1 yr	3 yrs	5 yrs
$r_{LMS,t+h}$	0.6677[a]	0.5822[a]	0.3262[a]	0.1717[b]	0.3588[a]	0.5551[a]	0.4168[a]	0.1457[a]	0.2315[a]	0.3035[a]
	(0.1323)	(0.0955)	(0.0528)	(0.0707)	(0.0763)	(0.0901)	(0.0646)	(0.0349)	(0.0534)	(0.0690)
$\Delta e_{HML,t+h}$	0.4480	0.2204[c]	0.0280	0.2330[a]	0.1873[c]	1.2244[a]	0.5266[a]	0.0126	-0.0411	-0.2125
	(0.2841)	(0.1154)	(0.0521)	(0.0777)	(0.1088)	(0.3545)	(0.1452)	(0.0685)	(0.1020)	(0.1933)
$(1-E_t)$ $\Delta_h e_{LMS,t+h}$			0.2402[a]	0.5612[b]	0.2571			0.3297[a]	1.6494[a]	3.4592[a]
			(0.0470)	(0.2245)	(0.4179)			(0.0535)	(0.2744)	(0.8469)
Constant	0.0675[a]	0.0612[a]	0.0318[a]	0.0951[a]	0.1250[a]	0.0135	0.0083	0.0355[a]	0.0914[a]	0.1208[b]
	(0.0087)	(0.0080)	(0.0069)	(0.0140)	(0.0269)	(0.0098)	(0.0087)	(0.0098)	(0.0296)	(0.0613)
Obs	493	493	493	469	445	493	493	493	469	445
Adj R^2	8%	19%	51%	42%	48%	17%	27%	58%	76%	70%
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	1 Mo	3 Mo	1 yr	3 yrs	5 yrs	1 Mo	3 Mo	1 yr	3 yrs	5 yrs
$r_{LMS,t+h}$	0.7165[a]	0.6256[a]	0.4534[a]	0.1313[b]	0.4898[a]	0.6498[a]	0.5682[a]	0.3335[a]	0.2644[a]	0.6561[a]
	(0.1372)	(0.0978)	(0.0581)	(0.0582)	(0.0699)	(0.1430)	(0.1173)	(0.0821)	(0.0820)	(0.1186)
Constant	0.0750[a]	0.0694[a]	0.0553[a]	0.0626[a]	0.1330[a]	-0.0500[a]	-0.0517[a]	-0.0545[a]	-0.0481[a]	-0.1639[a]
	(0.0074)	(0.0068)	(0.0068)	(0.0111)	(0.0127)	(0.0116)	(0.0110)	(0.0108)	(0.0107)	(0.0228)
Obs	493	493	493	469	445	493	493	493	469	445
Adj R^2	6%	17%	36%	8%	42%	5%	11%	16%	14%	42%

Panel C: momentum (WML)

	$EBR_{WML,t+h}$				
	(1)	(2)	(3)	(4)	(5)
	1 Mo	3 Mo	1 yr	3 yrs	5 yrs
$r_{LMS,t+h}$	0.7864[a]	0.7271[a]	0.2403[a]	0.4357[a]	0.5007[a]
	(0.1248)	(0.0931)	(0.0456)	(0.0851)	(0.1161)
$\Delta e_{HML,t+h}$	0.9235[b]	0.4931[a]	0.1464[c]	-0.0318	0.1481
	(0.4523)	(0.1677)	(0.0749)	(0.1073)	(0.2198)
$(1-E_t)$ $\Delta_h e_{LMS,t+h}$			0.4035[a]	1.3463[a]	0.9940
			(0.0553)	(0.2896)	(0.8039)
Constant	0.1360[a]	0.1146[a]	0.0634[a]	0.0818[a]	0.1166[b]
	(0.0357)	(0.0309)	(0.0190)	(0.0258)	(0.0513)
Obs	493	493	493	469	445

Adj R^2	12%	29%	62%	63%	40%
	(1)	(2)	(3)	(4)	(5)
	1 Mo	3 Mo	1 yr	3 yrs	5 yrs
$r_{LMS,t+h}$	0.7611[a]	0.7223[a]	0.3904[a]	0.2582[a]	0.5731[a]
	(0.1269)	(0.0974)	(0.0627)	(0.0679)	(0.1135)
Constant	0.2016[a]	0.1964[a]	0.2045[a]	0.2151[a]	0.1389[a]
	(0.0161)	(0.0141)	(0.0142)	(0.0219)	(0.0442)
Obs	493	493	493	469	445
Adj R^2	8%	24%	29%	20%	33%

Consistent with our portfolio level results (Tables 3 and 7), portfolio level EBRs have significant loadings on contemporaneous portfolio level returns (Panel A). In turn, Panel B shows that, controlling for actual return spreads $r_{LMS,t+h}$, EBRs strongly responds to news, in terms of both contemporaneous realized growth $\Delta_h e_{LMS,t+h}$ and realized forecast errors, which are a broader proxy for news including forward looking news. In particular, accounting for forecast errors leads to a substantial increase in the adjusted R^2, as well as a drop in the correlation of EBR and actual returns in most cases. Thus, stock returns are not mechanically incorporated into expectations. In the next section we present an analogous firm level result.

B3. Firm level results

In this section we complement our portfolio level analysis with three sets of exercises at the firm level. We first repeat the baseline analysis of Table 3 regressing returns on EBRs, because Equations (8) and (4) for realized returns hold at that level, too. This exercise confirms our findings that EBRs explain contemporaneous returns, and addresses a possible critique of our approach, namely that there it relies on a relatively small number of observations. Next, we show (following Table 5) that the components into of EBRs – forecast errors and revisions – explain returns.

Finally, we repeat the analysis in Table B5, assessing the extent to which firm level EBRs respond to firm level news, controlling for firm level returns, which confirms that expectations respond strongly to news controlling for prices and is evidence for the validity of analyst expectations as proxies for market expectations.

Starting with the baseline analysis, there is substantial firm level variation in beliefs that can be exploited to detect the link between expectations and returns. In BGLS (2024) we already showed robust predictability of returns from lagged expectations at the firm level. Here, in line with Equations (4) and (8), we similarly report the explanatory power of contemporaneous firm level EBR for actual firm level returns.

Table B6.
Expectation based returns and actual returns

Note: This table presents firm level univariate regression results for log returns against expectation-based returns (EBRs) We estimate separate regressions for one-month, three-months, one-year, three-years, and five-years horizons. Each regression is run with (odd columns) and without (even columns) time and firm fixed effects. Standard errors are corrected for overlapping observations using the Newey-West (1987) procedure. The sample period extends from December 1981 to December 2023. Superscripts: [a] significant at the 1% level, [b] significant at the 5% level, [c] significant at the 10% level.

	1 Mo		3 Mo		1 Yr		3 Yrs		5 Yrs	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$EBR_{i,t+h}$	0.1552[a]	0.1734[a]	0.2064[a]	0.2438[a]	0.4141[a]	0.4715[a]	0.5951[a]	0.6612[a]	0.6752[a]	0.7486[a]
	(0.0045)	(0.0099)	(0.0069)	(0.0148)	(0.0152)	(0.0220)	(0.0222)	(0.0238)	(0.0225)	(0.0203)
Constant		0.0027		0.0088		0.0455[b]		0.1207[a]		0.1691[a]
		(0.0028)		(0.0074)		(0.0206)		(0.0380)		(0.0493)
Obs	899,458	899,977	837,316	837,792	790,868	791,014	604738	604,871	479,198	479,282
Adj R^2	3%	3%	7%	7%	25%	26%	45%	47%	51%	54%
F-stat	0.0	0.0	0.1	0.1	0.2	0.3	0.4	0.5	0.5	0.5
Time FE	Y	N	Y	N	Y	N	Y	N	Y	N
Firm FE	Y	N	Y	N	Y	N	Y	N	Y	N

To focus on firm level variation in beliefs, in some specifications we include time and firm fixed effects in firm level regressions. In those specifications, R^2s capture explanatory power relative to the demeaned variables. Firm level EBRs have strong explanatory power for realized returns, and more so at longer horizons. The explanatory power is similar with and without fixed effects. This is an important finding: first, it suggests that firm level differences

in required returns are negligeable (since firm fixed effects do not matter). Second, and related, it suggests that aggregate changes in required returns are also negligeable (since time fixed effects do not matter).

Next we present a firm-level counterpart to Table 5, which decomposes the link between EBRs and returns into EBR's forecast error and forecast revision components.

Table B7.
Forecast errors and revisions predict returns at the firm level

	1 Yr			3 Yrs			5 Yrs		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$(1-E_t)\,\Delta e_{i,t+h}$	0.2946[a]	0.2989[a]	0.3070[a]	0.4556[a]	0.4643[a]	0.4725[a]	0.3996[a]	0.4269[a]	0.4445[a]
	(0.0103)	(0.0107)	(0.0134)	(0.0122)	(0.0138)	(0.0121)	(0.0113)	(0.0132)	(0.0160)
$(E_{t+h}-E_t)\,\Delta e_{i,t+h+1}$	0.2073[a]	0.2158[a]	0.2262[a]	0.2378[a]	0.2552[a]	0.2636[a]	0.1713[a]	0.1553[a]	0.1691[a]
	(0.0076)	(0.0082)	(0.0114)	(0.0074)	(0.0081)	(0.0092)	(0.0058)	(0.0086)	(0.0127)
$\Delta_h LTG_{i,t+h}$	0.0340[a]	0.0351[a]	0.0394[a]	0.0532[a]	0.0490[a]	0.0498[a]	0.0291	0.0196	0.0234
	(0.0044)	(0.0044)	(0.0043)	(0.0122)	(0.0101)	(0.0105)	(0.0250)	(0.0181)	(0.0181)
Constant			0.1432[a]			0.4276[a]			0.6330[a]
			(0.0171)			(0.0325)			(0.0451)
Obs	695,893	696,107	696,107	570,256	570,431	570,431	447,310	447,421	447,421
Adj R^2	28%	30%	28%	44%	46%	43%	35%	37%	36%
Time FE	Y	Y	N	Y	Y	N	Y	Y	N
Firm FE	Y	N	N	Y	N	N	Y	N	N

Note:

Consistent with Equation (4), all three expectations measures have strong explanatory power for the variation of firm level returns over time, with a large aggregate adjusted R^2. Each specification is run with and without time and fixed effects; remarkably, and similar to Table B6, the explanatory power of expectations – both the coefficients and R2 – remains unchanged. In sum, Tables B6 and B8 place sharp limits on the role of required returns in the Campbell Shiller decomposition. In fact, the results are thus consistent with the decomposition

(4) with r_{ih} being a constant that scales with horizon h, as captured by the constant term in columns 3, 6, and 9.[23]

Finally, we replicate Table B5 above at the firm level. Specifically, we examine whether firm level EBRs are explained entirely by *contemporaneous* firm level returns (which would hold if analysts mechanically infer forecasts from prices), or whether they reflect contemporaneous cash flow growth.

Table B7
Expectation based returns and contemporaneous news

Note: Panel A presents firm-level univariate regressions of expectation-based returns (EBR) at horizons (h) of one-month, three-months, one-year, three-years, and five-years. The independent variable is: (a) log returns between t and $t+h$. Panel B presents firm-level multivariate regressions of expectation-based returns (EBR) at horizons (h) of one-month, three-months, one-year, three-years, and five-years. The independent variables include: (a) log returns between t and $t+h$, (b) earnings growth between t and $t+h$, and (c) the forecast error for earnings growth between t and $t+h$. Standard errors are corrected for overlapping observations and cross-correlations using the Driscoll and Kraay (1998) procedure. The sample period spans from December 1981 to December 2023. Superscripts: [a] significant at the 1% level, [b] significant at the 5% level, [c] significant at the 10% level.

Panel A

	$EBR_{i,t+1}$	$EBR_{i,t+3}$	$EBR_{i,t+12}$	$EBR_{i,t+36}$	$EBR_{i,t+60}$
	(1)	(2)	(3)	(4)	(5)
$r_{i,t+h}$	0.1258[a]	0.2355[a]	0.4934[a]	0.6620[a]	0.6843[a]
	(0.0015)	(0.0094)	(0.0156)	(0.0195)	(0.0136)
constant	0.0067[a]	0.0183[a]	0.0296[a]	0.0436[c]	0.0662[b]
	(0.0001)	(0.0023)	(0.0104)	(0.0238)	(0.0319)
Obs	721,554	683,366	731,977	540,744	406,309
Adj R^2	2%	7%	26%	47%	55%

Panel B

	$EBR_{i,t+1}$	$EBR_{i,t+3}$	$EBR_{i,t+12}$	$EBR_{i,t+36}$	$EBR_{i,t+60}$
	(1)	(2)	(3)	(4)	(5)
$r_{i,t+h}$	0.1218[a]	0.2189[a]	0.3700[a]	0.4320[a]	0.4866[a]
	(0.0014)	(0.0091)	(0.0144)	(0.0162)	(0.0154)
$\Delta e_{i,t+h}$	0.0101[a]	0.0326[a]	0.0483[a]	0.0379[a]	0.0430[a]
	(0.0002)	(0.0014)	(0.0031)	(0.0062)	(0.0132)
$(1-E_t)\Delta_h e_{i,t+h}$			0.1037[a]	0.2314[a]	0.2096[a]
			(0.0055)	(0.0112)	(0.0129)
constant	0.0054[a]	0.0135[a]	0.0508[a]	0.1666[a]	0.2204[a]
	(0.0001)	(0.0022)	(0.0080)	(0.0150)	(0.0276)
Obs	721,554	683,366	731,977	540,744	406,309
Adj R^2	3%	9%	38%	61%	65%

[23] In line with the prediction, the coefficients for 1 year horizon are larger for forecast errors and smaller for long term forecasts (note that for long horizons, information about long term forecasts is already included in the other two regressors).

Consistent with our portfolio level results (Tables 3 and 7 in the text, and Table B7 above), firm level EBRs have significant loading on firm level contemporaneous returns, which increase at longer horizons (Panel A). In turn, Panel B shows that, controlling for actual returns $r_{i,t+h}$, EBRs strongly responds to news, in terms of both contemporaneous realized growth $\Delta_h e_{t+h}$ and realized forecast errors, which are a broader proxy for news including forward looking news. In fact, accounting for news leads to a significant drop in the correlation of EBR and actual returns, as well as a substantial increase in the adjusted R^2. Table B8 shows that stock returns are not mechanically incorporated into expectations.

Appendix C: Return predictability

C1. Portfolio level results.

- Table 10 EBRs
    - panel A missing cols (1 table)
    - Table 10 panel B (IV)
        - first stage missing cols
        - full 2nd stage

Table C1
Predicting future return spreads from expectations data and the price dividend ratio spreads

Note: The table presents portfolio-level regressions of log returns ($r_{LMS,t+h}$) at horizons (h) of one-and 3-months, and one-, three- and five-years. In each panel, the independent variables in the first regression are: (a) log dividend-to-price ratio at time *t* ($dp_{LMS,t}$), (b) the lagged portfolio forecast for long-term growth in earnings at $t-12$, (c) the change in the portfolio forecast for long-term growth in earnings between $t-12$ and t, (d) the portfolio forecast for one-year growth in earnings at t, (e) the ranked forecast error in portfolio earnings between $t-12$ and t, (f) the ranked forecast error in portfolio earnings between $t-36$ and t, (g) the ranked forecast error in portfolio earnings between $t-60$ and t, (h) the aggregate forecast for long-term growth in earnings at *t*, (h) the change in the aggregate forecast for long-term growth in earnings between $t-12$ and t, and (i) the lagged aggregate forecast for long-term growth in earnings at $t-12$. Portfolio forecast errors are ranked from 0 (lowest percentile) to 1 (top percentile). In the second regression, the independent variable is (a) log dividend-to-price ratio at time *t* ($dp_{LMS,t}$). Panel A presents results for portfolios that are long value and short growth stocks (HML) and long small and short big stocks (SMB), Panel B for portfolios that are long conservative and short aggressive investment stocks (CMA) and long robust and short weak profitability stocks (RMW), and Panel C for portfolios that are long winner and short momentum stocks (WML). All independent variables are standardized. The last row reports the R^2 from an univariate regression of $ret_{LMS,t+h}$ on $dp_{LMS,t}$. Standard errors are corrected for overlapping observations using the Newey-West (1987) procedure. The sample period spans from December 1981 to December 2023. Superscripts: [a] significant at the 1% level, [b] significant at the 5% level, [c] 0% level.

Panel A: value and size

	$r_{HML,t+h}$					$r_{SMB,t+h}$				
	(1)	(2)	(3)	(4)	(5)	(11)	(12)	(13)	(14)	(15)
	$h=1$	$h=3$	$h=12$	$h=36$	$h=60$	$h=1$	$h=3$	$h=12$	$h=36$	$h=60$
$\ln(dp_{p,t})$	-0.0286	-0.0449	-0.0252	0.0849	0.3891[b]	0.0069	0.0473	0.1819	-0.0100	0.4844[b]
	(0.0252)	(0.0636)	(0.2014)	(0.2286)	(0.1726)	(0.0182)	(0.0518)	(0.1291)	(0.1101)	(0.1981)
$LTG_{p,t-1}$	-0.0642[b]	-0.1680[a]	-0.4231[b]	-0.3723[c]	-0.0750	0.0084	0.0247	0.0631	-0.2396[a]	-0.0054
	(0.0253)	(0.0615)	(0.2080)	(0.1982)	(0.2132)	(0.0101)	(0.0299)	(0.0925)	(0.0902)	(0.1455)
$\Delta LTG_{p,t}$	-0.0001	-0.0048	-0.0836[b]	-0.1500[a]	-0.0268	-0.0010	-0.0047	-0.0009	-0.0239	-0.0004
	(0.0043)	(0.0101)	(0.0327)	(0.0373)	(0.0358)	(0.0047)	(0.0121)	(0.0283)	(0.0228)	(0.0353)
$STG_{p,t}$	0.0408[a]	0.1135[a]	0.2715[a]	0.4319[a]	0.4064[a]	0.0226[c]	0.0479	0.1089	0.1546[c]	0.0436
	(0.0126)	(0.0336)	(0.0790)	(0.1314)	(0.1547)	(0.0127)	(0.0329)	(0.0910)	(0.0928)	(0.1207)
$FE_{p,t-1}$ rank	-0.0032	0.0003	0.0492	0.0656	0.0204	0.0284[b]	0.0426	-0.0708	-0.0593	0.2118
	(0.0102)	(0.0259)	(0.0596)	(0.1022)	(0.0869)	(0.0139)	(0.0338)	(0.0907)	(0.1354)	(0.1745)
$FE_{p,t-3}$ rank	-0.0043	-0.0110	0.0421	0.6197[a]	0.2188[c]	0.0121	0.0567	0.1344[c]	0.3293[b]	-0.0071
	(0.0126)	(0.0402)	(0.1424)	(0.2075)	(0.1193)	(0.0157)	(0.0392)	(0.0702)	(0.1366)	(0.1262)
$FE_{p,t-5}$ rank	0.0255[b]	0.0584[c]	0.0480	-0.4667[a]	-0.3948[b]	-0.0249[c]	-0.0683[c]	-0.0617	-0.3859[a]	-0.3280[b]
	(0.0114)	(0.0336)	(0.1257)	(0.1145)	(0.1596)	(0.0138)	(0.0381)	(0.0959)	(0.1293)	(0.1491)
$\Delta LTG_{agg,t}$	0.0010	0.0076	0.0180	-0.0122	0.0729[b]	-0.0005	-0.0040	-0.0225	-0.0026	0.0800[a]
	(0.0026)	(0.0070)	(0.0276)	(0.0335)	(0.0330)	(0.0051)	(0.0111)	(0.0249)	(0.0282)	(0.0295)
$LTG_{agg,t-1}$	0.0047[c]	0.0131[c]	0.0339	0.1253[a]	0.1831[a]	0.0036	0.0090	0.0424[b]	0.1361[a]	0.1615[a]
	(0.0026)	(0.0070)	(0.0277)	(0.0303)	(0.0321)	(0.0035)	(0.0075)	(0.0210)	(0.0196)	(0.0253)
Constant	-0.0490[a]	-0.1450[a]	-0.3886[b]	-0.9186[a]	-1.3266[a]	-0.0329	-0.0598	-0.1890	-0.6645[a]	-0.6692[a]
	(0.0181)	(0.0488)	(0.1802)	(0.1908)	(0.1924)	(0.0292)	(0.0570)	(0.1537)	(0.1598)	(0.2482)
Obs	444	442	433	409	385	444	442	433	409	385
Adjusted R^2	5%	12%	16%	46%	64%	3%	6%	19%	57%	58%
$\ln(dp_{p,t})$	0.0034	0.0341	0.1672	0.1355	0.3480	0.0122	0.0523[c]	0.2055[b]	0.4917[a]	0.6290[a]
	(0.0117)	(0.0366)	(0.1137)	(0.2429)	(0.2984)	(0.0103)	(0.0294)	(0.0919)	(0.1892)	(0.1883)
Constant	0.0025	0.0008	-0.0081	0.0374	-0.0056	0.0103	0.0415[b]	0.1720[a]	0.4232[a]	0.5701[a]
	(0.0033)	(0.0105)	(0.0293)	(0.0638)	(0.0717)	(0.0064)	(0.0187)	(0.0637)	(0.1424)	(0.1527)
Obs	444	442	433	409	385	444	442	433	409	385
Adjusted R^2	0%	0%	3%	1%	5%	0%	2%	7%	19%	26%

Panel B: investment and profitability

	$r_{CMA,t+h}$					$r_{RMW,t+h}$				
	(1)	(2)	(3)	(4)	(5)	(11)	(12)	(13)	(14)	(15)
	$h=1$	$h=3$	$h=12$	$h=36$	$h=60$	$h=1$	$h=3$	$h=12$	$h=36$	$h=60$
$\ln(dp_{p,t})$	-0.0139	-0.0112	0.0898	-0.2042	0.0306	0.0183	0.0486	0.0955	-0.1985	-0.2728
	(0.0156)	(0.0391)	(0.0945)	(0.1959)	(0.1997)	(0.0230)	(0.0539)	(0.1715)	(0.2379)	(0.2799)
$LTG_{p,t-1}$	-0.0199[b]	-0.0472[c]	-0.0980	-0.2228[c]	-0.0126	0.0104	0.0209	0.1252	-0.0862	0.1249
	(0.0092)	(0.0244)	(0.0741)	(0.1299)	(0.1110)	(0.0141)	(0.0289)	(0.0901)	(0.1556)	(0.1280)

$\Delta LTG_{p,t}$	0.0011	0.0003	-0.0005	-0.0852[c]	-0.0301	0.0004	0.0002	0.0083	-0.0122	0.0331[c]
	(0.0026)	(0.0063)	(0.0151)	(0.0449)	(0.0289)	(0.0023)	(0.0042)	(0.0138)	(0.0205)	(0.0186)
$STG_{p,t}$	0.0152	0.0323	0.0264	-0.0040	0.0289	0.0159	0.0289	-0.0486	0.1164	-0.1126
	(0.0108)	(0.0282)	(0.0721)	(0.0964)	(0.1107)	(0.0133)	(0.0256)	(0.0778)	(0.1340)	(0.1035)
$FE_{p,t-1}$ rank	0.0093	0.0176	0.0353	0.0476	-0.0006	-0.0042	-0.0240[c]	-0.0656[c]	-0.0787	-0.1505[b]
	(0.0059)	(0.0155)	(0.0376)	(0.0646)	(0.0893)	(0.0056)	(0.0137)	(0.0381)	(0.0492)	(0.0597)
$FE_{p,t-3}$ rank	-0.0275[b]	-0.0856[a]	-0.2666[a]	-0.1735	-0.0461	0.0092[c]	0.0323[b]	0.0694[c]	0.0903[c]	0.2069[a]
	(0.0136)	(0.0328)	(0.0847)	(0.1122)	(0.1225)	(0.0052)	(0.0130)	(0.0391)	(0.0491)	(0.0689)
$FE_{p,t-5}$ rank	0.0383[a]	0.1032[a]	0.2341[a]	0.2094[b]	0.1351[c]	-0.0069	-0.0216[c]	-0.0788[b]	-0.0267	-0.0711
	(0.0141)	(0.0356)	(0.0745)	(0.0936)	(0.0719)	(0.0049)	(0.0122)	(0.0354)	(0.0402)	(0.0517)
$\Delta LTG_{agg,t}$	0.0003	0.0045	0.0143	-0.0210	-0.0290[b]	0.0011	0.0057	0.0386[c]	0.0201	0.0410[c]
	(0.0017)	(0.0039)	(0.0107)	(0.0137)	(0.0143)	(0.0031)	(0.0070)	(0.0204)	(0.0273)	(0.0211)
$LTG_{agg,t-1}$	0.0033[b]	0.0076[b]	0.0165[b]	0.0213	0.0568[a]	0.0041	0.0109	0.0396	-0.0005	0.0115
	(0.0013)	(0.0030)	(0.0082)	(0.0177)	(0.0125)	(0.0034)	(0.0073)	(0.0247)	(0.0345)	(0.0290)
Constant	-0.0184[c]	-0.0455[c]	-0.1353[c]	-0.0379	-0.1992	-0.0203	-0.0648	-0.1889	0.0068	-0.1750
	(0.0110)	(0.0268)	(0.0811)	(0.1758)	(0.1636)	(0.0212)	(0.0425)	(0.1346)	(0.2071)	(0.1821)
Obs	444	442	433	409	385	444	442	433	409	385
Adjusted R^2	7%	15%	31%	23%	32%	0%	4%	14%	10%	33%

$\ln(dp_{p,t})$	-0.0015	0.0234	0.1899[a]	0.0810	0.1169	0.0005	0.0167	-0.0034	-0.1533	-0.4313[b]
	(0.0095)	(0.0272)	(0.0581)	(0.1023)	(0.0767)	(0.0107)	(0.0262)	(0.0806)	(0.1058)	(0.1676)
Constant	0.0053[b]	0.0090	0.0055	0.0603[c]	0.0610[b]	0.0009	-0.0021	0.0092	0.0515	0.0949[b]
	(0.0024)	(0.0071)	(0.0163)	(0.0336)	(0.0277)	(0.0033)	(0.0087)	(0.0255)	(0.0319)	(0.0426)
Obs	444	442	433	409	385	444	442	433	409	385
Adjusted R^2	0%	0%	8%	1%	1%	0%	0%	0%	3%	13%

Panel C: momentum

	$r_{WML,t+h}$				
	(1)	(2)	(3)	(4)	(5)
	$h = 1$	$h = 3$	$h = 12$	$h = 36$	$h = 60$
$\ln(dp_{p,t})$	-0.0148	-0.0206	0.0841	0.0015	0.0559
	(0.0182)	(0.0353)	(0.0866)	(0.0791)	(0.0874)
$LTG_{p,t-1}$	-0.0424[b]	-0.0918[a]	-0.2346[a]	-0.3881[a]	-0.2687[c]
	(0.0171)	(0.0351)	(0.0899)	(0.0819)	(0.1387)
$\Delta LTG_{p,t}$	-0.0038	-0.0163[c]	-0.0431[c]	-0.0733[c]	0.1043[b]
	(0.0060)	(0.0095)	(0.0220)	(0.0434)	(0.0516)
$STG_{p,t}$	0.0761[a]	0.1762[a]	0.4058[a]	0.3899[a]	0.6095[a]
	(0.0234)	(0.0492)	(0.1285)	(0.1151)	(0.1504)
$FE_{p,t-1}$ rank	0.0055	0.0106	-0.0221	-0.0162	-0.0102
	(0.0074)	(0.0162)	(0.0446)	(0.0690)	(0.0661)
$FE_{p,t-3}$ rank	0.0180[b]	0.0294	0.0250	0.0561	0.1525[c]
	(0.0091)	(0.0220)	(0.0607)	(0.0669)	(0.0857)

$FE_{p,t-5}$ rank	-0.0068	0.0019	0.0101	-0.0628	-0.1330[c]
	(0.0087)	(0.0160)	(0.0393)	(0.0415)	(0.0804)
$\Delta LTG_{agg,t}$	0.0018	0.0068	0.0063	-0.0192	-0.1535[a]
	(0.0031)	(0.0054)	(0.0180)	(0.0504)	(0.0509)
$LTG_{agg,t-1}$	0.0047	0.0118[c]	-0.0171	-0.0964[a]	-0.0723[a]
	(0.0037)	(0.0071)	(0.0290)	(0.0265)	(0.0255)
Constant	-0.0384	-0.0824	0.2017	0.6578[a]	0.3217
	(0.0239)	(0.0551)	(0.2085)	(0.2020)	(0.2253)
Obs	444	442	433	409	385
Adjusted R^2	9%	18%	26%	36%	27%

$\ln(dp_{p,t})$	0.0076	0.0224	0.1328[c]	0.1816	0.1806[c]
	(0.0104)	(0.0220)	(0.0711)	(0.1112)	(0.0924)
Constant	0.0040	0.0093	-0.0068	-0.0487	-0.0726[b]
	(0.0025)	(0.0067)	(0.0217)	(0.0336)	(0.0363)
Obs	444	442	433	409	385
Adjusted R^2	0%	0%	4%	4%	3%

C2. Firm level results

Here we perform, at the firm level, the analysis of Table 10: we first show that firm level future EBRs are predictable from current expectations (Panel A), and then run a horse race between predicted EBRs and current dividend price ratios (Panels B and C), the latter being proxies for required returns. Panels B and C differ in how we handle observations where no dividend was paid.

Table C3.

Note: Panel A presents firm-level regressions of log expectations-based returns (EBRs) over holding horizons (h) of one-month, three-months, one-year, three-years, and five-years. The set of independent variables includes: (a) the lagged portfolio forecast for long-term growth in earnings at $t-12$, (b) the change in the portfolio forecast for long-term growth in earnings between $t-12$ and t, (c) the portfolio forecast for one-year growth in earnings at t, (d) the ranked forecast error in portfolio earnings between $t-12$ and t, (e) the ranked forecast error in portfolio earnings between $t-36$ and t, (f) the ranked forecast error in portfolio earnings between $t-60$ and t, (g) the aggregate forecast for long-term growth in earnings at t, (h) the change in the aggregate forecast for long-term growth in earnings between $t-12$ and t, and (h) the lagged aggregate forecast for long-term growth in earnings at $t-12$. Portfolio forecast errors are ranked from 0 (lowest percentile) to 1 (top percentile). All independent variables are standardized. Panels B and C present firm-level univariate regressions of log returns on the log dividend price ratio (columns 1 to 5). Columns 6 to 10 presend instrumental variable regressions on the log dividend price ratio and the intstrumented log expectations-based return from Panel A, over holding horizons (h) of one-month, three-months, one-year, three-years, and five-years. The last row reports the R^2 from an univariate

regression of $ret_{LMS,t+h}$ on $dp_{LMS,t}$. Standard errors are corrected for overlapping observations and cross-correlations using the Driscoll and Kraay (1998) procedure. The sample period spans from December 1981 to December 2023. Superscripts: [a] significant at the 1% level, [b] significant at the 5% level, [c] 0% level.

Panel A: Predicting firm level expectation based returns

	(1) 1 Mo	(2) 3 Mo	(3) 1 Yr	(4) 3 Yrs	(5) 5 Yrs
$LTG_{i,t-1}$	-0.0018[a]	-0.0083[a]	-0.0463[a]	-0.0733[a]	-0.0750[a]
	(0.0004)	(0.0015)	(0.0062)	(0.0113)	(0.0113)
$\Delta LTG_{i,t-1}$	-0.0003	-0.0037[b]	-0.0307[a]	-0.0721[a]	-0.0730[a]
	(0.0004)	(0.0016)	(0.0054)	(0.0064)	(0.0126)
$STG_{i,t}$	-0.0051[a]	-0.0133[a]	0.0020	0.0159[a]	0.0101
	(0.0005)	(0.0023)	(0.0064)	(0.0057)	(0.0130)
FE_{t-1} rank	0.0099[a]	0.0271[a]	0.0533[a]	0.0574[a]	0.0581[a]
	(0.0004)	(0.0012)	(0.0041)	(0.0084)	(0.0063)
FE_{t-3} rank	-0.0019[a]	-0.0063[a]	-0.0144[b]	-0.0201[b]	-0.0093
	(0.0004)	(0.0015)	(0.0062)	(0.0098)	(0.0091)
FE_{t-5} rank	-0.0010[a]	-0.0034[b]	-0.0102[c]	-0.0297[a]	-0.0584[a]
	(0.0003)	(0.0013)	(0.0056)	(0.0075)	(0.0083)
$\Delta LTG_{A,t-1}$	0.0039[a]	0.0097[a]	-0.0031	-0.0690[a]	-0.0511[b]
	(0.0008)	(0.0037)	(0.0107)	(0.0191)	(0.0257)
$LTG_{A,t-1}$	-0.0023[a]	-0.0082[a]	-0.0311[a]	-0.0407[b]	-0.0319[b]
	(0.0006)	(0.0028)	(0.0107)	(0.0191)	(0.0157)
Constant	0.0264[a]	0.0912[a]	0.2710[a]	0.5164[a]	0.6713[a]
	(0.0041)	(0.0180)	(0.0786)	(0.1494)	(0.1114)
Obs	508,761	489,295	471,414	381,121	310,194
Adj R^2	1%	3%	3%	3%	2%
F-stat	108.6	87	52	61	92

Panel B: Predicted expectation based returns and actual returns

Dependent Variable: $r_{i,t+h}$

	(1) 1 Mo	(2) 3 Mo	(3) 1 Yr	(4) 3 Yr	(5) 5 Yr	(6) 1 Mo	(7) 3 Mo	(8) 1 Yr	(9) 3 Yr	(10) 5 Yr
$\ln(dp_{i,t})$	0.0010	0.0041[b]	0.0180[a]	0.0372[a]	0.0599[a]	0.0008	0.0032	0.0112[c]	0.0259[c]	0.0478[a]
	(0.0007)	(0.0020)	(0.0054)	(0.0137)	(0.0157)	(0.0007)	(0.0020)	(0.0058)	(0.0147)	(0.0178)
Hat $EBR_{i,t}$						0.3616[b]	0.3319[b]	0.4391[a]	0.4115[a]	0.3996[c]
						(0.1512)	(0.1322)	(0.1173)	(0.1314)	(0.2174)
Constant	0.0102[a]	0.0362[a]	0.1620[a]	0.4248[a]	0.7016[a]	0.0072[c]	0.0261[b]	0.0994[a]	0.2817[a]	0.4976[a]
	(0.0038)	(0.0101)	(0.0277)	(0.0515)	(0.0662)	(0.0043)	(0.0119)	(0.0318)	(0.0756)	(0.1228)
Obs	332,582	321,245	312,260	260,142	216,568	332,582	321,245	312,260	260,142	216,568
Adj R^2	0%	0%	0%	1%	1%	0%	0%	1%	1%	1%
F-stat	1.9	4.3	11.1	7.4	14.5	3.8	5.2	13.4	10.7	9.3

Panel C: Predicted expectation based returns and actual returns, alternative payout specification

	Dependent Variable: $r_{i,t+h}$									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	1 Mo	3 Mo	1 Yr	3 Yr	5 Yr	1 Mo	3 Mo	1 Yr	3 Yr	5 Yr
$D_{d_{it}=0}$?	-0.0016	-0.0023	0.0060	0.0320[c]	0.0657[a]	0.0000	0.0015	0.0137	0.0338[c]	0.0648[a]
	(0.0016)	(0.0047)	(0.0130)	(0.0190)	(0.0136)	(0.0014)	(0.0043)	(0.0126)	(0.0180)	(0.0127)
ln(dp$_{i,t}$)?	0.0009	0.0040[c]	0.0184[a]	0.0350[b]	0.0563[a]	0.0007	0.0031	0.0109[c]	0.0215	0.0388[b]
	(0.0008)	(0.0021)	(0.0058)	(0.0144)	(0.0163)	(0.0008)	(0.0021)	(0.0060)	(0.0150)	(0.0181)
Hat EBR$_{i,t}$						0.3749[a]	0.3290[a]	0.4517[a]	0.4656[a]	0.5458[a]
						(0.1396)	(0.1274)	(0.1195)	(0.1589)	(0.1787)
Constant	0.0041	0.0113	0.0515[c]	0.2006[a]	0.3406[a]	0.0022	0.0070	0.0307	0.1175[c]	0.1641[b]
	(0.0030)	(0.0076)	(0.0264)	(0.0631)	(0.0788)	(0.0033)	(0.0083)	(0.0256)	(0.0667)	(0.0810)
Obs	510,440	490,917	472,835	382,088	310,877	510,440	490,917	472,835	382,088	310,877
Adj R^2	0%	0%	0%	0%	0%	0%	0%	1%	1%	1%
F-stat	1.3	2.0	5.2	3.4	12.1	2.8	3.5	8.0	5.2	10.4

We next complement the analysis in Table 12 concerning the link between characteristics and expectations. We first predict returns $r_{i,t+h}$ at the firm level using a saturated specification of *contemporaneous* expectations measures: forecast errors $FE_{i,t+j}$, revisions of long term forecasts $\Delta_j LTG_{i,t+j}$ and of short term forecasts $\Delta_j E_{t+j}\Delta e_{i,t+j+1}$ for $j = 1, \ldots, h$. We also include measures of *lagged* aggregate optimism LTG_t, ΔLTG_{t-1} which BGLS (2024) show predict the future value premium. These regressions achieve R^2s ranging from 27% to 48%. We next regress the residual firm level returns on firm level book to market $bm_{i,t}$. Since $bm_{i,t}$ is scaled by market price, and thus includes a measure of market expectations, this sequential procedure helps better identify the component of returns that is orthogonal to the (noisier) measured expectations component. The regressions do not include time or firm fixed effects, since they seek to capture cross-sectional variation in returns arising from firm level characteristics.

Table C4.
Residualization exercise

Panel A. Book to market and firm level returns

	Dep. Variable: $r_{i,t+h}$				
	(1)	(2)	(3)	(4)	(5)
	h =1 Mo	h = 3 Mo	h = 1 Yr	h = 3 Yrs	h = 5 Yrs

ln($bm_{i,t}$)	0.0049[a]	0.0118[a]	0.0402[a]	0.0746[a]	0.1006[a]
	(0.0012)	(0.0029)	(0.0084)	(0.0183)	(0.0235)
Constant	0.6959[a]	2.0899[a]	8.3633[a]	24.5599[a]	40.0203[a]
	(0.0015)	(0.0037)	(0.0124)	(0.0244)	(0.0302)
Obs	477,256	445,657	506,844	478,353	416,251
Adj R^2	0%	0%	1%	1%	1%
F-stat	18.1	16.8	22.9	16.6	18.3

Panel B. Book to market and firm level residual returns

Dep. Variable: residual $r_{i,t+h}$

	(1)	(2)	(3)	(4)	(5)
	h =1 Mo	h = 3 Mo	h = 1 Yr	h = 3 Yrs	h = 5 Yrs
ln($bm_{i,t}$)	0.0036[a]	0.0058[b]	0.0120[c]	0.0049	0.0024
	(0.0012)	(0.0028)	(0.0064)	(0.0133)	(0.0192)
Constant	-0.0020	-0.0031	-0.0063	-0.0025	-0.0012
	(0.0015)	(0.0032)	(0.0083)	(0.0178)	(0.0231)
Obs	477,256	445,657	401,537	352,841	302,816
Adj R^2	0%	0%	0%	0%	0%
F-stat	9.8	4.3	3.5	0.1	0.0

The Table shows $bm_{i,t}$ has strong predictive power for firm level returns in our sample (columns 1 to 3). The predictive power of $bm_{i,t}$ drops substantially, both in magnitude and in significance, when contemporaneous measured expectations are controlled for. At the 1 year horizon, the slope coefficient drops by more than 40% which, given the limits in the measures of expectations, this is a lower bound for the role of expectations. For longer horizons, the strong predictability of $bm_{i,t}$ is entirely captured by expectations.

These results also complement the finding in BGLS (2024) that the return predictability of the aggregate price dividend ratio for returns on the aggregate market disappears once contemporaneous expectations are taken into account. These two conceptually similar exercises show that return predictability from valuation ratios is to a large extent a predictability of (differential) expectation revisions. This fact implies that characteristics encode information about beliefs, and specifically about departures from rationality.