

Belief Overreaction and Stock Market Puzzles

Pedro Bordalo

Oxford University

Nicola Gennaioli

Bocconi University

Rafael La Porta

Brown University

Andrei Shleifer

Harvard University

We construct an index of long-term expected earnings growth for S&P 500 firms and show that it has remarkable power to jointly predict future errors in expectations and stock returns, in both the aggregate market and the cross section. The evidence supports a mechanism whereby good news causes investors to become too optimistic about long-term earnings growth. This leads to inflated stock prices and, as beliefs are systematically disappointed, subsequent low returns in the aggregate market. Overreaction of long-term expectations helps resolve major asset-pricing puzzles without time-series or cross-sectional variation in required returns.

Gennaioli thanks the Italian Ministry of Education for Financial Support (PRIN [Progetti di Ricerca di Interesse Nazionale] grant). We are grateful to Nick Barberis, Francesca Bastianello, John Campbell, Kent Daniel, Paul Fontanier, Spencer Kwon, Yueran Ma, Peter Maxted, Dev Patel, Jesse Shapiro, Adi Sunderam, and the reviewers and editor of this journal for extremely helpful comments. Julien Manili provided outstanding research assistance. This paper was edited by Harald Uhlig.

Electronically published April 5, 2024

Journal of Political Economy, volume 132, number 5, May 2024.

© 2024 The University of Chicago. All rights reserved. Published by The University of Chicago Press.
<https://doi.org/10.1086/727713>

I. Introduction

In the textbook asset-pricing model, the price of a stock is the rational expectation of future dividends discounted by a time-invariant required return. That required return is higher for stocks that are riskier, in the sense of being more exposed to aggregate market movements. Over the past 4 decades, this approach has been challenged by two key findings. First, the return on the aggregate stock market is predictably low following periods of high valuations, as measured, for instance, by a high aggregate price-to-dividend ratio (Campbell and Shiller 1988). This fact is inconsistent with the assumed time invariance of required returns. Second, large cross-sectional average-return differences are traceable to firm characteristics, not to market exposure. For instance, high-market-to-book stocks have lower average returns than low-market-to-book ones (Fama and French 1993). Ultimately, the key stock market puzzles concern excessive return predictability, in both the time series and the cross section.

The conventional approach to these puzzles enriches the theory of required returns while maintaining rational expectations of future dividends. In the time series, required returns are assumed to vary because of changes in risk preference (e.g., Campbell and Cochrane 1999) or in long-run or disaster risk (Rietz 1988; Bansal and Yaron 2004; Barro 2006). In the cross section, required returns are assumed to vary because of exposure to characteristics-based “risk factors” (Fama and French 1993). A challenge for this approach is that investors should rationally expect low future returns during a stock market boom. In survey expectations of returns, however, the opposite is the case (Greenwood and Shleifer 2014). A deeper problem is that changes in risk preference and risk are hard to measure, and cross-sectional risk factors remain a black box.

In this paper, we try to address these puzzles by pursuing an orthogonal approach: keep required returns constant and relax rational expectations. In this approach, return predictability arises from the eventual correction of systematic pricing errors caused by nonrational beliefs. Using data on analyst expectations of future earnings growth of listed firms, we empirically characterize belief errors and connect them to realized returns. We show that errors in expectations of aggregate long-term earnings growth, LTG, offer a promising source of return predictability in both the time series and the cross section, helping to reconcile key anomalies.

In the first part of the paper, we study survey expectations and return predictability in the time series. Section II shows that high expected aggregate long-term earnings growth predicts sharply lower future aggregate stock returns. The predictive power of LTG is robust to controlling for the current price-dividend ratio and other prominent macroeconomic predictors of returns. Expectations of short-term earnings growth, in contrast, do not predict future returns.

Section III studies the mechanism linking beliefs and return predictability, documenting three facts. First, LTG overreacts: upward LTG revisions predict future disappointment of growth forecasts. Second, such predicted disappointment is associated with low returns. Third, this association accounts for a large share of the link between the price-dividend ratio and future returns. These findings point to a mechanism in which overreaction to good news causes excess optimism and inflated stock prices. Going forward, systematically disappointing aggregate earnings growth causes a price reversal and hence low returns.

In section IV, we consider cross-sectional return differences. We ask whether variation in the aggregate LTG, which captures systematic belief biases, can also produce cross-sectional return comovement and average-return spreads. We first revisit the return spread earned by stocks with low LTG compared to that of stocks with high LTG (La Porta 1996). We find that this spread varies systematically with aggregate LTG: current optimism about aggregate fundamentals is followed by lower returns and more disappointing forecast errors for high-LTG stocks than for low-LTG ones. This evidence is consistent with a mechanism in which high-LTG stocks exhibit stronger overreaction to aggregate good news, perhaps because these firms belong to the “hot” sector of the moment. Remarkably, we find that a similar mechanism also sheds light on the well-known book-to-market, profitability, and investment factors (Fama and French 1993). The short arm in these factors disappoints more sharply, both in returns and in realized earnings growth, after periods of high aggregate optimism, again measured with aggregate LTG.

Our evidence indicates that high aggregate LTG captures overvaluation of the aggregate market and specific stocks, in the sense of having subsequent low returns. In the language of standard finance, these are periods of low risk aversion, when the price of the aggregate market, and particularly that of risky firms, is elevated. One concern is that survey expectations spuriously capture time-varying risk aversion. This could occur if analysts mechanically infer expectations of long-term growth by fitting stock prices. Two findings, however, show that LTG is a genuine proxy for expectations. First, the predictive power of LTG for returns is robust to controlling for price ratios, which suggests that it is unlikely to just be inferred from these ratios. Second, excess optimism in LTG reflects an overreaction to news: both LTG revisions and subsequent errors are predictable from news about fundamentals, even after stock returns are controlled for.

A few recent papers study stock market puzzles using measured expectations.¹ Bordalo et al. (2019) account for the La Porta (1996) LTG spread

¹ De Bondt and Thaler (1985, 1990), Frankel and Lee (1998), Lee, Myers, and Swaminathan (1999), Bacchetta, Mertens, and van Wincoop (2008), Bordalo et al. (2020a), and d'Arienzo (2020) also use beliefs data to study asset prices; see also Barsky and De Long

through belief overreaction, but they do not connect the spread in returns and forecast errors to systematic belief biases. Using analysts' forecasts of short-term earnings growth, De la O and Myers (2021) construct a dividend discount index and show that it strongly correlates with the aggregate price-to-earnings ratio. This exercise showcases the usefulness of expectations data but does not shed light on return predictability: unlike LTG, short-term expectations do not predict stock returns. Nagel and Xu (2022) show that past aggregate dividend growth correlates negatively with future aggregate returns and positively with earnings growth expectations. However, they do not directly connect expectations to forecast errors and returns and therefore do not show that return predictability is driven by belief overreaction. In fact, the growth of past dividends might affect required returns through consumption, as in Campbell and Cochrane (1999). Furthermore, to the extent that past dividend growth correlates with expectations, it does so only partially: beliefs and stock prices may overreact to other news, such as the arrival of new technologies.

More broadly, we are the first to show that a parsimonious mechanism of belief overreaction throws new light on both aggregate return predictability and cross-sectional return differentials by characterizing the joint behavior of returns and forecast errors.

Our work offers a new angle on macro volatility. In macroeconomics, departures from rational expectations typically take the form of rational inattention (Sims 2003; Woodford 2003; Gabaix 2019) or overconfidence (Kohlhas and Walther 2021). These mechanisms generate rigidity in consensus beliefs and prices (Mankiw and Reis 2002). We document the importance of the opposite phenomenon of belief overreaction. Compared to Bordalo et al. (2020c), who find overreaction by individual professional forecasters, we find overreaction in consensus expectations and connect it to excess stock market volatility. Our analysis points to belief volatility as a source of macro-financial volatility, in line with recent work in macroeconomics (Bordalo et al. 2021; L'Huillier, Singh, and Yoo 2023; Bianchi, Ilut, and Saijo 2024).

II. Predictability of Aggregate Stock Returns: Data and Basic Facts

We gather monthly data on analyst forecasts for firms in the S&P 500 index from the IBES (Institutional Brokers' Estimate System) Unadjusted US Summary Statistics file. We focus on median forecasts of a firm's earnings per share ($EPS_{i,t}$) and long-term earnings growth ($LTG_{i,t}$). IBES defines

(1993), Daniel, Hirshleifer, and Subrahmanyam (1998), and Kojien and Van Nieuwerburgh (2011). Cutler, Poterba, and Summers (1990), De Long et al. (1990b), Barberis et al. (2015, 2018), and Adam, Marcet, and Beutel (2017) study price extrapolation, which is also consistent with returns expectations data (Greenwood and Shleifer 2014; Giglio et al. 2021).

LTG 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.”² Data coverage starts in 1976:3 for $EPS_{i,t}$ and in 1981:12 for $LTG_{i,t}$. (Data on dividend forecasts start in 2002 and use shorter horizons.) We fill in missing forecasts by linearly interpolating $EPS_{i,t}$ at horizons ranging from 1 to 5 years (in 1-year increments). Beyond the second fiscal year we assume that analysts expect $EPS_{i,t}$ to grow at the rate $LTG_{i,t}$, starting with the last nonmissing positive EPS forecast.

Analysts may distort their forecasts as a result of agency conflicts. As shown in Bordalo et al. (2019), this is unlikely to affect the time-series variation in forecasts, which is key here. Furthermore, all brokerage houses typically cover S&P 500 firms, so investment-banking relationships and analyst sentiment are unlikely to influence the decision to cover firms in the S&P 500.³ Our focus on median forecasts further alleviates these concerns, reducing the impact of outliers.

We aggregate the earnings forecasts of S&P 500 firms into an index of aggregate beliefs. We multiply each forecast $EPS_{i,t}$ by the number of shares outstanding in month t and sum these forecasts across all S&P 500 firms. We then divide this aggregate earnings forecast by the total number of shares in the S&P 500 index to obtain the expected earning per share EPS_t . (Log) earnings growth 1 or 2 years ahead is computed on the basis of EPS_t .⁴

We aggregate LTG forecasts by value-weighting firm-level forecasts:

$$LTG_t = \sum_{i=1}^S LTG_{i,t} \frac{P_{i,t} \cdot Q_{i,t}}{\sum_{i=1}^S P_{i,t} \cdot Q_{i,t}},$$

where S is the number of firms in the S&P 500 index with IBES data on $LTG_{i,t}$, $P_{i,t}$ is the stock price of firm i at time t , and $Q_{i,t}$ is the number of shares outstanding of firm i at time t .⁵

² It is not obvious whether LTG captures $g = (\tilde{E}[(1 + g_1) \dots (1 + g_T)]^{1/T} - 1$, or the average point estimate $g = (\hat{g}_1 + \dots + \hat{g}_T)/T$. We take the former interpretation, but the distinction is not key for studying return predictability.

³ For example, in December of 2018, 19 analysts followed the median S&P 500 firm, while four analysts followed the median firm not in the S&P 500. Analysts are also less likely to rate as “buy” firms in the S&P 500 index.

⁴ The number of shares in the index (what S&P refers to as the “divisor”) is the ratio of the market capitalization of S&P 500 and that of the S&P 500 index. It is 100 in the base year and is adjusted for shares outstanding, the index composition, and corporate actions. We compute growth forecasts using aggregate earnings because many firm-level observations have zero or very low current earnings. We set an observation in a given month to missing if the market cap of firms for which we have forecasts at a given horizon is less than 90% of the market cap of the index.

⁵ Nagel and Xu (2022) weigh $LTG_{i,t}$ using firm-level earnings forecasts. The correlation between their index and our LTG is 95.44%. Since stocks with high LTG often have negative earnings, our preferred measure is LTG_t .

Figure 1 plots 1-year-ahead and long-term expected earnings growth. The latter (LTG_t) is more persistent than expected short-term growth. In particular, it does not exhibit short-run reversals, such as the expected short-term growth peak in 2009. As we show below, the persistence of LTG_t is crucial, for it allows it to capture the low-frequency predictability of returns.

De la O and Myers (2021, 2022) use measured expectations of 1-year-ahead earnings growth to construct a discounted expected stock market index. They show that this index is highly correlated with the actual price-earnings ratio. One issue is whether the correlation arises because expectations of earnings track current earnings or because they capture stock price anomalies (Adam and Nagel 2022). From the viewpoint of market efficiency, the key question is whether beliefs produce excessive price variation and hence return predictability.

To address this issue, we regress future cumulative raw aggregate stock returns over 1, 3, and 5 years on our three measures of expected earnings growth: at 1 and 2 years and long-term. Table 1 reports the results. We also run a horse race between the different expectations measures. In this and other tests, we focus on raw returns, but the results are very similar

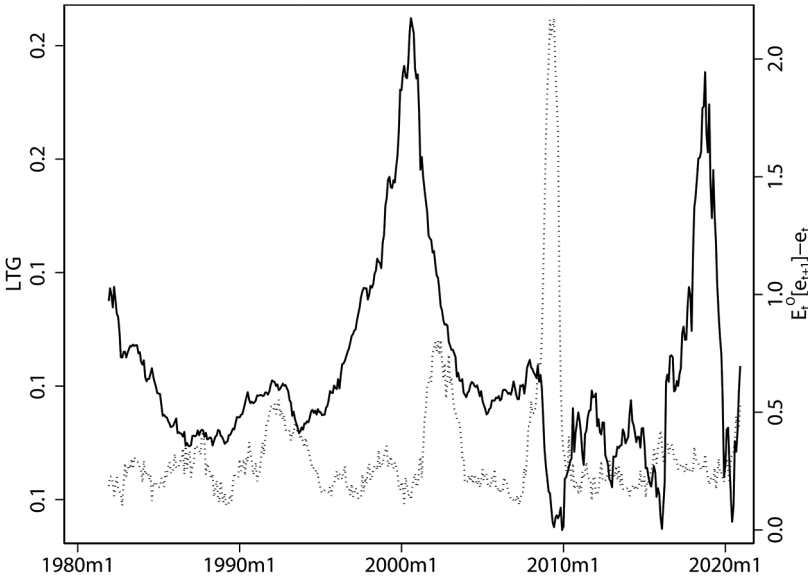


FIG. 1.—Expected short- and long-term growth in earnings (respectively, $E_t^O[e_{t+1}] - e_t$ [dotted line] and LTG_t [solid line], where $e_t = \log \text{EPS}_t$ and E_t^O represents measured expectations). The scale for short-term earnings ($E_t^O[e_{t+1}] - e_t$) is on the right. The sample period is 1981:12–2020:12.

TABLE 1
RETURN PREDICTABILITY AND EXPECTATIONS OF EARNINGS GROWTH

	r_{t+1} (1)	$\sum_{j=1}^3 \alpha^{j-1} r_{t+j}$ (2)	$\sum_{j=1}^5 \alpha^{j-1} r_{t+j}$ (3)
A. Returns and LTG ($N = 409$)			
LTG_t	-.2389** (.0928)	-.4019*** (.0944)	-.4349*** (.0831)
Adjusted R^2 (%)	9	24	25
B. Returns and Growth Forecast for Year 1 ($N = 404$)			
$\mathbb{E}_t^O[e_{t+1}] - e_t$	-.0335 (.1027)	.0467 (.0716)	.1556*** (.0587)
Adjusted R^2 (%)	0	0	3
C. Returns and Growth Forecast for Year 2 ($N = 404$)			
$\mathbb{E}_t^O[e_{t+2}] - e_{t+1}$	-.0527 (.0885)	.0408 (.1556)	.2113 (.1686)
Adjusted R^2 (%)	0	0	6

NOTE.—We examine the association between earnings growth forecasts and returns at different horizons. The dependent variables are the (log) 1-year return in col. 1 and the discounted value of the cumulative 3- and 5-year returns in cols. 2 and 3, respectively. Here, $\alpha = 1/(1 + e^{dp})$, where dp is the average price-dividend ratio in our sample ($\alpha = 0.9779$). The independent variables are the forecast for earnings growth: (a) in the long run, LTG_t ; (b) 1 year ahead, $\mathbb{E}_t^O[e_{t+1} - e_t]$; and (c) between years $t + 1$ and $t + 2$, $\mathbb{E}_t^O[e_{t+2} - e_{t+1}]$. All variables are standardized, and intercepts are not shown. The sample period is 1981:12–2015:12. We adjust standard errors for serial correlation using the Newey-West (1987) correction (number of lags ranges from 12 in the first column to 60 in the last one).

** Significant at the 5% level.
*** Significant at the 1% level.

if we use excess returns; see table B.1, in appendix B (apps. A–E, including tables B.1–E.1, are available online).

High current expectations of long-term earnings growth strongly predict low future returns. The LTG_t accounts for 25% of variation in realized returns over the following 5 years.⁶ Expectations of short-term earnings growth do not instead predict returns or have a very weak explanatory power (1-year-ahead expectations account for only 3% of 5-years-ahead return variation). To our knowledge, this is the first time-series evidence of strong return predictability using measured expectations of fundamentals.

⁶ It is well known that the ordinary least squares (OLS) estimator in predictive regressions using lagged stochastic regressors, such as LTG_t , may be biased (Stambaugh 1999). The bias arises because errors in the regression for returns may be correlated with future values of LTG_t . Following Kothari and Shanken (1997), we use simulations to compute the coefficient that we would estimate under the null of no predictability and bootstrap a p -value for the OLS value in table 1. See app. E for details of the methodology and table E.1 for the results, which confirm those in table 1. Even a priori, the Stambaugh bias is unlikely to be important for LTG (as compared to the usual price-scaled variables). The correlation between the residuals of univariate regressions of annual returns r_{t+1} and LTG_{t+1} on LTG_t is 0.07. Kothari and Shanken report that the correlation between shocks to book-to-market ratio and those to annual returns is -0.80 .

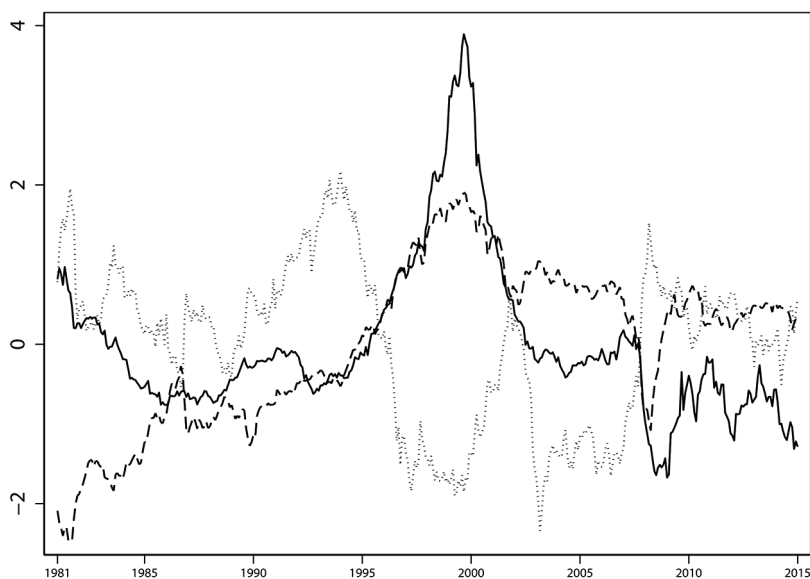


FIG. 2.—Standardized values of expected long-term growth in earnings, 5-year return, and price-dividend ratio (respectively, LTG_t [solid line], $\sum_{j=1}^5 \alpha^{j-1} r_{t+j}$ [dotted line], and $p_t - d_t$ [dashed line]). The sample period is 1981:12–2015:12.

The lack of predictive power of short-term growth expectations suggests that this proxy likely captures earnings variation rather than mispricing.⁷

We next assess two questions. First, does the predictive power of LTG actually reflect nonrational market beliefs? Second, how does it compare to stock return predictors studied in previous work? As a first step, figure 2 graphs LTG and the price-dividend ratio together with realized stock returns in the coming 5 years.

The LTG and the price-dividend ratio are positively correlated, as one would expect if current stock prices, $p_t - d_t$, are determined in part by expectations of long-term earnings growth, LTG_t . In the internet bubble of 1999–2000, both LTG and the price-dividend ratio were very high, compared to historical values, followed by disappointing stock returns, consistent with stock prices reflecting excessively optimistic expectations of long-term earnings growth. In the financial crisis of 2008, both LTG and the price-dividend ratio fell sharply, followed by high stock returns, consistent with stock prices after the crash reflecting excessive pessimism about future economic performance. Movements in LTG orthogonal to movements in the price-dividend ratio allow us to assess whether LTG contains independent

⁷ De la O and Myers (2022) show that short-term earnings expectations predict returns at a very long (10-year) horizon, consistent with table 1, panel B. However, this relationship disappears once we control for LTG (see also table 2).

information useful to predict future returns. This can also help address the concern that LTG_t spuriously reflects time-varying required returns, which could happen if analysts estimate LTG_t by fitting the growth rate that justifies the current stock price while erroneously assuming that required returns are constant.

Table 2, panel A, performs several tests by controlling in the predictive regressions of table 1 for price variables and for proxies of required

TABLE 2
RETURN PREDICTABILITY, EXPECTATIONS, AND MEASURES OF REQUIRED RETURNS

	(1)	(2)	(3)	(4)	(5)	(6)
A. LTG and Proxies for Time-Varying Returns						
LTG_t	-.2350** (.1162)	-.4675*** (.1081)	-.4522*** (.1033)	-.5569*** (.1179)	-.3946*** (.1016)	-.4881*** (.1036)
X_t	-.5826*** (.1397)	-.1803 (.1662)	-.1387 (.1035)	.1894 (.1766)	.3852** (.1782)	.1001 (.0851)
Observations	409	409	409	137	193	404
Adjusted R^2 (%)	52	28	27	28	47	26
Adjusted R^2 X_t (%)	48	7	9	0	19	3
X_t	$p_t - d_t$	$p_t - e_t$	spc_t	cay_t	$SVIX_t^2$	$\mathbb{E}_t^O[e_{t+1}] - e_t$
B. LTG and Other Predictors of Stock Returns						
LTG_t	-.4345*** (.1031)	-.4682*** (.1217)	-.4761*** (.1198)	-.7542*** (.2648)	-.5052*** (.1002)	-.3450*** (.0483)
X_t	.1672 (.1365)	.1945 (.1994)	.2297 (.1875)	-.2800 (.2708)	.3848*** (.1346)	-.6142*** (.1177)
Observations	409	409	372	134	409	137
Adjusted R^2 (%)	27	29	37	27	40	59
Adjusted R^2 X_t (%)	12	8	15	10	15	48
X_t	Term Spread $_t$	Credit Spread $_t$	Uncertainty Index $_t$	Kelly-Pruitt MRP $_t$	$\mathbb{E}_t^O[\pi_{t+1}]$	Δd_t

NOTE.—The dependent variable is the discounted value of the cumulative return between years t and $t + 5$. All regressions include the forecast for earnings growth in the long-run LTG_t . In panel A, the additional independent variables are (a) the price-dividend ratio, $p_t - d_t$, in col. 1, (b) the price-earnings ratio, $p_t - e_t$, in col. 2, (c) the Campbell and Cochrane (1999) surplus-consumption ratio, spc_t , in col. 3, (d) the Lettau and Ludvigson (2001) consumption-wealth ratio, cay_t , in col. 4, (e) the Martin (2017) expected 1-year return on the market, $SVIX_t^2$, in col. 5, and (f) the forecast for 1 year ahead, $\mathbb{E}_t^O[e_{t+1}] - e_t$, in col. 6. In panel B, the additional independent variables are (a) the term spread, defined as the log difference between the gross yield of 10- and 1-year US government bonds from the St. Louis Fed in col. 1, (b) the credit spread, defined as the log difference between the gross yields of BAA and AAA bonds from the St. Louis Fed in col. 2, (c) the Baker, Bloom, and Davis (2016) economic policy uncertainty index in col. 3, (d) the Kelly and Pruitt (2013) optimal forecast of aggregate equity market returns (MRP = main return prediction) in col. 4, (e) the forecast for CPI inflation in year $t + 1$ by the Survey of Professional Forecasters, $\mathbb{E}_t^O[\pi_{t+1}]$, in col. 5, and (f) the Nagel and Xu (2022) experienced dividend growth, Δd_t , in col. 6. The adjusted R^2 X_t is the adjusted R^2 value from a univariate regression of 5-year returns on X_t . The sample period is 1981:12–2015:12. Data are quarterly in col. 4 of panel A and cols. 4 and 6 of panel B and monthly elsewhere. All variables are standardized, and intercepts are not shown. We adjust standard errors for serial correlation using the Newey-West (1987) correction (with 60 lags).

** Significant at the 5% level.
*** Significant at the 1% level.

returns. Columns 1 and 2 assess the predictive power of LTG_t , controlling for the current price-dividend and price-earnings ratios, respectively. If LTG_t is reverse engineered from stock prices, these controls should eliminate its explanatory power. If instead LTG_t retains some explanatory power, it must be because it captures market expectations about long-term fundamentals (with price ratios instead capturing the independent role of expectations at other horizons as well as, perhaps, variation in required returns). Note that these are challenging tests: prices incorporate market expectations, while LTG_t is a noisy proxy for them. This means that even if all price variation was due to expectations, as opposed to required returns, controlling for market prices may overshadow the predictive power of LTG_t .

To further assess the ability of LTG_t to capture beliefs, columns 3–5 control for the three leading proxies of time-varying required returns: surplus consumption (*spc*; Campbell and Cochrane 1999), the consumption-wealth ratio (*cay*; Lettau and Ludvigson 2001), and $SVIX^2$ (Martin 2017). The first proxies for fluctuations of marginal utility in habit formation models, the second for required returns in a large class of rational-expectations models, and the third for the required return of a rational log utility investor fully invested in the market.

Columns 1–5 in panel A show that LTG_t is unlikely to proxy for required returns. Its explanatory power is robust to controlling for prices (cols. 1 and 2). This finding rules out the possibility that LTG is inferred from prices themselves and indicates that the price-dividend ratio predicts returns at least in part because it captures market expectations. Compared to predicting returns using only the price-dividend ratio, LTG adds modest explanatory power in terms of adjusted R^2 , but this is expected: the two variables are conceptually highly correlated under the interpretation that beliefs about long-term earnings determine market prices (together with beliefs at different horizons). One question is whether one can assess the extent to which nonrational beliefs account for the price-dividend ratio's predictive power. In section III, we offer a test of this hypothesis based on our theory.

The explanatory power of LTG_t is also robust to controlling for proxies of time-varying required returns (cols. 3–5). The coefficient on LTG_t is fairly stable between -0.4 and -0.5 and highly statistically significant. The *spc* and *cay* proxies are themselves insignificant and do not add explanatory power. The index $SVIX^2$ adds explanatory power, but in a way orthogonal to LTG_t ; the R^2 of $SVIX^2$ alone is 19%. Overall, then, columns 1–5 in panel A validate LTG_t as a measure of beliefs and confirm its high predictive power for returns. In the case of these model-based proxies for risk, LTG adds substantial explanatory power. These model-based proxies are themselves dependent on stock prices, but their limited predictive role compared to that of LTG suggests that beliefs play a significant role.

In panel B of table 2, we compare the explanatory power of LTG_t to that of determinants or predictors of stock prices/returns from previous work. In panel A, column 6, we control for short-term earnings growth expectations. The predictive power of LTG_t is robust to introducing this control, which is itself insignificant, consistent with table 1. In panel B, columns 1–4, we control for well-established macroeconomic predictors of stock returns: the term spread, the credit spread, Bloom's uncertainty index, and the Kelly-Pruitt factor (Kelly and Pruitt 2013). None of these predictors is statistically significant once we control for LTG_t , and the gain in R^2 compared to table 1 is modest. Adding LTG_t as a predictor significantly increases explanatory power for future returns, compared to using these variables alone.

Finally, we consider the role of expected long-term inflation and past dividend growth. De la O and Myers (2022) view expected long-term inflation as a determinant of beliefs about real fundamentals: excessively high (low) expected inflation should be associated with excess pessimism (optimism) about future earnings, predicting high (low) future returns. In column 5 of panel B, the predictive power of LTG_t is shown to be robust to controlling for expected long-term inflation, confirming that it captures significant variation in real expected fundamentals.⁸

We control for past dividend growth on the basis of Nagel and Xu (2022), who see it as causing excess optimism about future dividend growth, in turn leading to low future returns. Column 6 of panel B shows that LTG_t is robust to this control as well. This evidence strengthens the link between beliefs and return predictability: past dividend growth may affect returns by also changing preferences and hence discount rates. In addition, even if past dividends affect only expectations, the predictive power of LTG_t shows that beliefs do not reflect just past performance but also news about the future (Daniel and Titman 2006). This resonates

⁸ On the basis of the predictive role of long-term inflation expectations, De La O and Myers (2022) argue that expectations about real short-term earnings growth is what predicts returns, not LTG . This conclusion is flawed for three reasons. First, the predictive role of long-term inflation expectations may be spurious, for it reflects the high inflation of the 1970s, which was followed by low inflation and high stock returns in the 1980s. Second, their analysis does not address the basic fact that the predictive power of short-term earnings growth expectations for returns is weak (table 1, panel B) and disappears when one controls for LTG_t (table 2, panel A, col. 6). On a related note, short-term inflation expectations would seem to be more relevant than long-term ones for their emphasis on short-term real earnings growth. Third, they propose a test that is sufficient but not necessary for return predictability and use the wrong definition of LTG_t as growth between years 3 and 5. When the correct definition of cumulative growth over the next 3–5 years is used, LTG_t passes the test. Specifically, future LTG_t errors, both actual and predicted using the model in table 4, are negatively correlated with the current price-dividend ratio, $\text{Cov}(p_t - d_t, \Delta e_{t,t+5}/5 - LTG_t) = -0.2681$ ($p = .077$) and $\text{Cov}(p_t - d_t, \Delta \hat{e}_{t,t+5}/5 - LTG_t) = -0.3915$ ($p = .055$). Section III performs a more systematic “horse race” to assess the extent to which the predictive power of $p_t - d_t$ for returns is due to predictable LTG_t reversals.

TABLE 3
DETERMINANTS OF LTG REVISIONS

	Dependent Variable: ΔLTG_t					
	(1)	(2)	(3)	(4)	(5)	(6)
LTG_{t-1}	-.4349*** (.1616)	-.4624*** (.1090)	-.5451*** (.1489)	-.4393*** (.1429)	-.3232*** (.1187)	-.3338*** (.1510)
$e_t - \text{cae}_{t-5}$.3938*** (.0827)	.3006*** (.0561)	.3409*** (.0570)	.3274*** (.0770)	.3883*** (.0889)	.4663*** (.1173)
r_{t-1}		.0572 (.1023)				
$E_t^o[r_{t+1}]$.0858 (.0959)				
X_t			.2828*** (.0945)	.2291*** (.0655)	-.0928 (.1214)	.1459 (.1754)
Observations	457	76	457	457	148	193
Adjusted R^2 (%)	31	38	37	36	31	52
X_t			$p_t - d_t$	spc_t	cay_t	SVIX_t^2

NOTE.—We study the association between 1-year changes in the forecast for growth in earnings in the long run and predictors of returns (empirical and theoretical). The dependent variable is the change in the forecast for growth in earnings in the long-run LTG_t between years t and $t - 1$, ΔLTG_t . The independent variables are (a) the 1-year lagged value of LTG_t , (b) the log of earnings for the S&P 500 in year t relative to cyclically adjusted earnings in year $t - 5$, $e_t - \text{cae}_{t-5}$, (c) the (log) return on the S&P 500 between years $t - 1$ and t , r_{t-1} , (d) the forecast for the S&P 500's 1-year return from the Graham and Harvey survey, $E_t^o[r_{t+1}]$, (e) the price-dividend ratio, $p_t - d_t$, in col. 3, (f) the Campbell and Cochrane (1999) surplus-consumption ratio, spc_t , in col. 4, (g) the Lettau and Ludvigson (2001) consumption-wealth ratio, cay_t , in col. 5, and (h) the Martin (2017) expected return on the market, SVIX^2 , in col. 6. Data are monthly (quarterly) in cols. 1, 3, 4, and 6 (2 and 5). All variables are standardized, and intercepts are not shown. The sample period is 1981:12–2020:12. Newey-West (1987) standard errors are shown in parentheses (with 12 lags).

** Significant at the 5% level.
*** Significant at the 1% level.

with Kindleberger’s (1978) idea that new technologies help inflate asset bubbles.⁹

If LTG_t predicts returns, what determines its evolution? An analysis of this issue also provides useful input into the rest of our study. Table 3 reports, in column 1, the regression of the 1-year revision ΔLTG_t on lagged beliefs, LTG_{t-1} , and on earnings surprises relative to cyclically adjusted earnings, $e_t - \text{cae}_{t-5}$. The coefficient on LTG_{t-1} provides information on the persistence of beliefs and that on $e_t - \text{cae}_{t-5}$ information on whether beliefs respond to sustained earnings growth (which is more relevant to assessing long-term fundamentals than temporary growth episodes). Of course, because LTG_t may also be updated on the basis of news about the

⁹ The results of table 2 hold at a 3-year horizon and when including other predictors (table B.2, in app. B).

Hillenbrand and McCarthy (2022) regress the price-earnings ratio on measured beliefs and on required return proxies. The R^2 of the regression using measured beliefs is 77%, which increases to 84% when proxies for required returns are added. In this analysis, consistent with our results, LTG_t is the variable with largest explanatory power.

future, we should not expect past fundamentals to account for 100% of its revisions.

Column 2 presents an additional test that LTG_t is not mechanically set to fit market prices or required returns by controlling for stock returns in the past year and for 1-year-ahead expected return from the CFO Survey (chief financial officers; <https://www.richmondfed.org/cfosurvey>). In columns 3–6, we control for the price-dividend ratio and the proxies for discount rates we used in table 2. If market prices move with news about future fundamentals, LTG_t revisions will correlate with contemporaneous returns as well as with price ratios. A key aspect of this exercise is to check whether theory-based drivers of expectations, such as recent growth in fundamentals, predict revisions even after prices are controlled for.

In column 1, the coefficient on LTG_{t-1} is negative and less than 1 in magnitude, showing that LTG_t is quite persistent but tends to mean-revert. The positive coefficient on $e_t - cae_{t-5}$ further suggests that LTG_t is revised upward after periods of sustained earnings growth. These two forces alone account for roughly one-third of the variation in LTG revisions.

None of these conclusions change materially when we control for past and expected returns, the price-dividend ratio, and the required return proxies. The evidence confirms that the change in LTG_t reflects genuine belief revisions about future fundamentals. Two out of four controls are insignificant, and they mostly only marginally improve explanatory power.¹⁰

Overall, we have shown that LTG_t strongly predicts future aggregate stock returns and that it offers a good proxy for market expectations of long-term fundamentals. How are beliefs, as measured by LTG_b and returns connected? We study this question next.

III. Expectations and Stock Returns

Following Campbell and Shiller (1987, 1988), the log return r_{t+1} obtained by holding the stock market between t and $t + 1$ can be approximated as

$$r_{t+1} = \alpha p_{t+1} + (1 - \alpha)d_{t+1} - p_t + k, \quad (1)$$

where p_t is log stock price at t and d_{t+1} is the log dividend at $t + 1$, while $k > 0$ and $\alpha \in (0, 1)$ are constants. Iterating equation (1) forward and imposing the transversality condition, we obtain

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

where $g_{t+s+1} \equiv d_{t+s+1} - d_{t+s}$ is dividend growth between $t + s$ and $t + s + 1$.

¹⁰ Table B.4, in app. B, shows that the results are robust to controlling for further measures of required returns, as well as for lagged 5-year returns (as a proxy for expectations of returns; Greenwood and Shleifer 2014).

The average firm in the economy, which we call “the market,” has dividend growth

$$g_{t+1} = \mu g_t + v_{t+1}, \quad (3)$$

where v_{t+1} is an independently and identically distributed Gaussian shock with mean zero and variance σ_v^2 and $\mu \in [0, 1]$. In Bordalo et al. (2020b), we showed that our key results hold under a general covariance stationary process. The shock v_{t+1} captures tangible news arriving at $t + 1$, such as earnings news, proxied, for instance, by the measure $e_t - cae_{t-5}$, but it can also capture intangible news learned at t but affecting future earnings, such as the introduction of a new technology. We write $v_{t+1} = \tau_{t+1} + \eta_t$, where τ_{t+1} is tangible news, η_t is intangible news, and the variance of v_{t+1} reflects the two components, $\sigma_v^2 = \sigma_\tau^2 + \sigma_\eta^2$. By using expectations data, we can capture both tangible and intangible news. Table 2 shows that intangible news is important: expectations data have considerable explanatory power, even when past fundamentals are controlled for.¹¹

In equation (2), the variation in the current price-dividend ratio is due to expected variation in future dividend growth (captured by the g_{t+1+s} terms), required returns (captured by the r_{t+1+s} terms), or both. Rational-expectations theories of return predictability rely only on the second source of variation. In these theories, expectations of fundamentals $\mathbb{E}_t(g_{t+s+1})$ are formed by optimally using equation (3), while rational expectations of future returns $\mathbb{E}_t(r_{t+s+1})$ are also formed using the true model of required returns (which we do not need to specify). Under rational expectations, the realized stock return between t and $t + 1$ is then given by

$$r_{t+1} = \mathbb{E}_t(r_{t+1}) + \sum_{s \geq 0} \alpha^s (\mathbb{E}_{t+1} - \mathbb{E}_t)(g_{t+1+s}) - \sum_{s \geq 1} \alpha^s (\mathbb{E}_{t+1} - \mathbb{E}_t)(r_{t+1+s}), \quad (4)$$

so that realized returns are driven by three components: the required return between t and $t + 1$, $\mathbb{E}_t(r_{t+1})$; rational belief revisions about future dividends, $(\mathbb{E}_{t+1} - \mathbb{E}_t)(g_{t+1+s})$; and rational belief revisions about future returns, $(\mathbb{E}_{t+1} - \mathbb{E}_t)(r_{t+1+s})$. Because rational belief revisions reflect news arriving at $t + 1$, they are unpredictable at time t . As a result, under rational expectations return predictability is due only to variation in $\mathbb{E}_t(r_{t+1})$.

In our approach to predictability, in contrast, required and hence expected returns are constant at r , but beliefs about future fundamentals are formed using a distorted operator $\tilde{\mathbb{E}}_t(g_{t+1+s})$, not by optimal forecasts using equation (3). Here, realized returns are given by

¹¹ We perform a systematic analysis of tangible (i.e., measured in terms of fundamentals) vs. intangible news in app. D. We find that the predictive power of past fundamentals is typically economically smaller and statistically less significant than that of measured beliefs, suggesting an important role for intangible news.

$$r_{t+1} = r + \sum_{s \geq 0} \alpha^s (\tilde{\mathbb{E}}_{t+1} - \tilde{\mathbb{E}}_t)(g_{t+1+s}). \quad (5)$$

Critically, the belief revision $(\tilde{\mathbb{E}}_{t+1} - \tilde{\mathbb{E}}_t)(g_{t+1+s})$ occurring at $t + 1$ is no longer pure “news.” It is also shaped by systematic belief distortions prevailing at t . These distortions, embedded in the time- t forecast $\tilde{\mathbb{E}}_t(g_{t+1+s})$, are the source of return predictability in our approach.¹²

To characterize the predictions from equation (5), we lay out a reduced-form model of beliefs that nests the leading departures from rationality studied in macroeconomics and finance: overreaction to news, as in models of diagnostic expectations (Bordalo, Gennaioli, and Shleifer 2018; Bordalo et al. 2019) but also as in earlier models (e.g., Barberis, Shleifer, and Vishny 1998), and underreaction to news, as in models of rational or non-rational inattention (Sims 2003; Huang and Liu 2007; Gabaix 2012; Bouchaud et al. 2019). The model highlights the distinctive predictions of these theories with respect to the forecast errors and their link to return predictability.

A. Nonrational Beliefs and Their Empirical Predictions

We model departures from rationality as a time-varying distortion ϵ_t whose impact on beliefs decays with the forecast horizon according to the true persistence μ of fundamentals:

$$\tilde{\mathbb{E}}_t(g_{t+s}) = \mathbb{E}_t(g_{t+s}) + \mu^{s-1} \epsilon_t, \quad (6)$$

where $s \geq 1$ and $\mathbb{E}_t(g_{t+s}) = \mu^{s-1}(\mu g_t + \eta_t)$ is the rational forecast based on equation (3).

The distortion ϵ_t follows an AR(1) process, $\epsilon_t = \rho \epsilon_{t-1} + u_t$, where $\rho \in [0, 1]$ and u_t is an expectations shock. Parameter ρ captures the observed persistence in LTG _{t} . We impose $\rho < \mu$ to reproduce one key fact in table 3: the negative correlation between LTG _{t} revisions and lagged forecast LTG _{$t-1$} ; that is, $\text{Cov}(\tilde{\mathbb{E}}_{t+1}(g_{t+s}) - \tilde{\mathbb{E}}_t(g_{t+s}), \tilde{\mathbb{E}}_t(g_{t+s})) < 0$. This implies that excess optimism or pessimism gradually yet systematically revert over time.

The over- versus underreaction in beliefs is incorporated into the expectations shock u_t . We assume that u_t is proportional to news, captured by the rational belief revision at t . Formally, $u_t = \theta(\mu \tau_t + \eta_t)$. If $\theta = 0$, expectations are rational. If $\theta > 0$, investors overreact, exaggerating the impact of news on expectations. If $\theta < 0$, investors underreact, dampening the effect of news on expectations. We assume that $\theta > -1$, which ensures that good news is not viewed as bad and vice versa. Appendix A shows that,

¹² For simplicity, we abstract from the theoretical possibility that expectations of returns exhibit predictable revisions. While this assumption allows us to focus on the role of measured expectations of fundamentals, future work may enrich eq. (5) by adding predictable return variation (e.g., via price extrapolation).

for $\theta > 0$, equation (6) is a special case of the diagnostic-expectations model (Bordalo, Gennaioli, and Shleifer 2018).¹³

Equations (5) and (6) yield our two empirical tests, one on the predictability of forecast errors and the other on predictability of returns from predictable forecast errors. The first test detects whether beliefs over- or underreact ($\theta \leq 0$) by using the predictability of future forecast errors based on current expectations revisions.

PROPOSITION 1. Under equation (6), the forecast error predictability regression,

$$g_{t+s} - \tilde{\mathbb{E}}_t(g_{t+s}) = \beta_0 + \beta_1(\tilde{\mathbb{E}}_t(g_{t+s}) - \tilde{\mathbb{E}}_{t-1}(g_{t+s})) + \beta_2\tilde{\mathbb{E}}_{t-1}(g_{t+s}) + z_{t+s}, \quad (7)$$

has $\beta_1 < 0$ if and only if beliefs overreact to news, $\theta > 0$. In addition, $\theta > 0$ implies that $\beta_2 < 0$.

Consistent with Bordalo et al. (2020c), who build on Coibion and Gorodnichenko (2015), a negative association $\beta_1 < 0$ between the current forecast revision $\tilde{\mathbb{E}}_t(g_{t+s}) - \tilde{\mathbb{E}}_{t-1}(g_{t+s})$ and the future forecast error $g_{t+s} - \tilde{\mathbb{E}}_t(g_{t+s})$ is indicative of overreaction to current news. After good news (i.e., a positive revision), beliefs become too optimistic, predicting future disappointment (i.e., a negative error). Underreaction entails the opposite association. Proposition 1 also says that if beliefs overreact, then the lagged forecast $\tilde{\mathbb{E}}_{t-1}(g_{t+s})$ also negatively predicts forecast errors. Indeed, the belief distortion ϵ_t is persistent, so high lagged forecasts incorporate overreaction to past news, which also predicts future disappointment.

Our second, and key, test links systematic forecast errors in earnings growth to return predictability. It is obtained from equations (3), (5), and (6).

PROPOSITION 2. The realized return at $t + 1$ is given by

$$r_{t+1} = r + \left(\frac{1 - \alpha\rho}{1 - \alpha\mu} \right) \mathbb{E}_t[g_{t+1} - \tilde{\mathbb{E}}_t(g_{t+1})] + \omega_{t+1}, \quad (8)$$

where $\omega_{t+1} = [(1 + \alpha\theta)/(1 - \alpha\mu)]\tau_{t+1} + \alpha[(1 + \theta)/(1 - \alpha\mu)]\eta_{t+1}$ is a combination of tangible and intangible news.

The realized return depends on news arriving at $t + 1$, captured by ω_{t+1} , but also on the $t + 1$ forecast error predictable using information available at t . This positive association between future returns and predictable forecast errors connects our two tests.

PREDICTION 1. The LTG_{*t*} overreacts, $\theta > 0$, if and only if forecast errors in earnings growth and future stock returns are both negatively predicted by the current LTG_{*t*} revision. If $\theta > 0$, then lagged LTG_{*t*} also negatively predicts both forecast errors and returns.

¹³ Our model rules out nonfundamental noise (Black 1986; De Long et al. 1990a). It can be easily introduced in the analysis to capture an extreme form of overreaction, in which beliefs react to wholly irrelevant factors.

If upward LTG revisions and high lagged LTG predict stronger disappointment of earnings growth expectations (i.e., more negative forecast errors), then beliefs overreact. In our theory, then, upward LTG revisions and high lagged LTG additionally imply a currently inflated stock market, in turn predicting lower future stock returns. Using expectations data, we can now test for this joint predictability of forecast errors and returns.

B. Predictability of Aggregate Stock Returns

Table 4 tests prediction 1, combining propositions 1 and 2. Column 1 tests equation (7) from proposition 1: it predicts the forecast error in the 5-years-ahead earnings growth using the 1-year LTG_{*t*} revision and the lagged forecast, LTG_{*t*-1}. Column 2 uses the same explanatory variables to predict 5-years-ahead returns. Column 3 performs an instrumental variable strategy testing equation (8) from proposition 2: in the first stage, we predict forecast errors using the model in column 1; in the second stage, we use

TABLE 4
PREDICTABILITY OF FORECAST ERRORS AND RETURNS (*N* = 397)

	$\Delta_5 e_{t+5}/5 - \text{LTG}_{it}$ (1)	$\sum_{j=1}^5 \alpha^{j-1} r_{it+j}$ (2)	$\sum_{j=1}^5 \alpha^{j-1} r_{it+j}$ (3)	$\sum_{j=1}^5 \alpha^{j-1} r_{it+j}$ (4)
ΔLTG_t	-.8407*** (.1528)	-.6403*** (.0766)		
LTG_{t-1}	-.2157 (.1374)	-.5252*** (.0870)		
$\Delta_5 e_{t+5}/5 - \text{LTG}_t$.8460*** (.2474)	.3853*** (.1200)
$p_t - d_t$				-.6377*** (.1786)
Adjusted <i>R</i> ² (%)	25	31		48
Montiel-Pflueger <i>F</i> -statistic			10.97	
Instrument			$\text{LTG}_{t-1}, \Delta \text{LTG}_t$	

NOTE.—This table links aggregate forecast errors and market returns. We report regressions using as dependent variable the error in forecasting 5-year growth in aggregate earnings in col. 1 and the discounted value of the cumulative market return between years *t* and *t* + 5 in cols. 2–4. Five-year cumulative market returns ($\sum_{j=1}^5 \alpha^{j-1} r_{it+j}$) are computed with monthly data and run from *t* + 1/12 through *t* + 60/12. We define the forecast error as the difference between (a) the annual growth in earnings per share between years *t* and *t* + 5, $\Delta_5 e_{t+5}/5$, and (b) the expected long-term growth in earnings, LTG_{*t*}. The independent variables are the 1-year change in LTG_{*t*}, ΔLTG_t ; the lagged expected long-term growth in earnings, LTG_{*t*-1}; and the predicted forecast error, $\Delta_5 e_{t+5}/5 - \text{LTG}_t$. We assume that earnings are reported with a 3-month lag (i.e., we define *e_t* as earnings for the calendar period *t* – 1/4). We report OLS estimates in cols. 1 and 2 and second-stage instrumental variable (IV) results in col. 3. The IVs are ΔLTG_t and LTG_{*t*-1}. In col. 4, we combine the predicted forecast error from col. 1 with the price-dividend ratio, *p_t* – *d_t*. Except for ΔLTG_t , all variables are standardized. Intercepts are not shown. The sample period is 1982:12–2015:12. Newey-West (1987) standard errors are in parentheses (with 60 lags).

*** Significant at the 1% level.

the fitted forecast errors to predict returns. In column 4, we perform a robustness test: we add the current price-dividend ratio as a regressor.

Column 1 shows that beliefs overreact, $\theta > 0$. Upward LTG_t revisions predict future disappointment, suggesting that beliefs become too optimistic when good news arrives. This confirms, at the level of the S&P 500 index, the results of Bordalo et al. (2019) at the level of stock portfolios. Here we find overreaction at the consensus level (remember that we are using the median LTG forecast). This is a strong result: information frictions can bias consensus error predictability tests in favor of underreaction even if individual forecasters overreact (Woodford 2003; Bordalo et al. 2020c). A higher lagged forecast LTG_{t-1} also predicts lower forecast error. This association is not significant at conventional levels, but our other results show statistical significance for LTG_{t-1} .¹⁴

Column 2 connects belief overreaction to return predictability. Upward LTG_t revisions and higher lagged forecast LTG_{t-1} predict sharply lower future stock returns, consistent with our mechanism. Overreaction to current news causes excessive upward LTG_t revisions, high ϵ_t , and hence an excessive stock market boom at t . This is followed by belief disappointment, a downward price correction, and hence low returns r_{t+1} . Higher lagged forecast LTG_{t-1} also predicts low future returns for the same reason.

Column 3 links predictable forecast errors to future returns. Consistent with equation (8), periods of excess pessimism in which future forecast errors are systematically high (growth is above expectations) are, on average, followed by high stock returns. Conversely, periods of excess optimism in which future forecast errors are systematically low (growth is below expectations) are, on average, followed by low returns. Column 4 shows that, as in table 2, this holds even after the price-dividend ratio is controlled for, confirming that the link between forecast errors and returns is unlikely to be due to reverse-engineering LTG from stock prices. In this exercise, LTG_t proxies for beliefs at a specific horizon, while $p_t - d_t$ captures beliefs at other horizons (which may be affected by independent factors) and required return variation.

Quantitatively, the effects are sizable. In column 2, a 1-standard deviation-higher revision ΔLTG_t (equal to 0.62) is associated with a roughly 0.4-standard deviations-lower future return, and a 1-standard deviation-higher lagged forecast LTG_{t-1} (equal to 1) is associated with a roughly 0.5-standard deviations-lower future return. These effects imply reductions in 5-year log returns of 0.13 and 0.17, respectively. Since the average monthly log

¹⁴ One may worry that measurement error in LTG , may create a spurious negative correlation between forecast errors and ΔLTG_t . However, (i) forecast errors are predictable from LTG revisions instrumented by past growth in fundamentals (table B.6, in app. B), and (ii) revisions of LTG , negatively predict returns, consistent with overreaction (table 4, col. 2). Table B.5 shows that the results in table 4 follow through at the 3-year horizon.

return is 0.007, this corresponds to losing 19–25 months' worth of returns over 5 years.

The explanatory power of expectations is also high in terms of R^2 : the model in column 2 accounts for 31% of return variation at a 5-year horizon. The explanatory power of expectations is much higher than that of past fundamentals. Our measure of earnings growth in the past 5 years, $e_t - cae_{t-5}$, negatively predicts returns, but with an R^2 of only 13%.

Do beliefs about long-term growth help account for the predictive power of the price-dividend ratio? We address this question using the exact relationship between returns and news in equations (4) and (5). Under rational expectations (eq. [4]), $p_t - d_t$ predicts future returns by acting as an inverse measure of the required return $\mathbb{E}_t(r_{t+1})$. In this case, $p_t - d_t$ is orthogonal to proxies for the news affecting r_{t+1} . Under belief overreaction and constant required returns (eq. [5]), in contrast, high $p_t - d_t$ signals excess optimism. Thus, it predicts low returns by predicting negative future “news,” as measured by systematic negative expectations revisions, $(\tilde{\mathbb{E}}_{t+k} - \tilde{\mathbb{E}}_t)(g_{t+1+s}) < 0$. A key implication follows: under rational expectations, the explanatory power of $p_t - d_t$ is unaffected if future returns r_{t+1} are purified from expectation revisions at $t + 1$. Under belief overreaction, in contrast, the explanatory power of $p_t - d_t$ is reduced, because part of the expectation revisions in $t + 1$ captures systematic reversal of overreaction at t .

We test this implication using a two-stage test. In the first stage, we regress realized returns r_{t+k} at the 1-, 3-, and 5-year horizons, $k = 1, 3, 5$, on the LTG_{*t*} news occurring at the same horizon. We proxy news by the 1-year LTG revisions and by the LTG forecast errors occurring between $t + 1$ and $t + k$. The return residuals \tilde{r}_{t+k} from this regression purify the return r_{t+k} from variation due to future LTG news. In the second stage, we use $p_t - d_t$ to predict residuals \tilde{r}_{t+k} . Under rationality, the coefficient on $p_t - d_t$ should not change when predicting raw returns or residuals. Under overreaction, the coefficient's magnitude should be smaller in the latter case.

Table 5 reports the results of this exercise. For brevity, we report only the second-stage result (the first stage is in table B.7, in app. B, and shows, intuitively, that better news entail higher returns). Columns 1, 3, and 5 report the coefficients from regressing raw returns r_{t+k} on $p_t - d_t$. Columns 2, 4, and 6 report the coefficients for residualized returns \tilde{r}_{t+k} .

Overreaction in the expectations of long-term growth, reflected in systematic LTG revisions and forecast errors, accounts for a large chunk of the price-dividend ratio's predictive power at medium- to long-term horizons. At the 1-year horizon, LTG matters little, in the sense that the estimated coefficient in column 1 is indistinguishable from that in column 2. At the 3- and 5-year horizons, in contrast, the effect is dramatic: after returns that are due to LTG news are removed, the magnitude of the estimated

TABLE 5
PREDICTABILITY FROM THE PRICE-DIVIDEND RATIO ($N = 361$)

	r_{t+1}		$\sum_{j=1}^3 \alpha^{j-1} r_{t+j}$		$\sum_{j=1}^5 \alpha^{j-1} r_{t+j}$	
	Raw (1)	Residual (2)	Raw (3)	Residual (4)	Raw (5)	Residual (6)
$p_t - d_t$	-.3742** (.1481)	-.3017*** (.0959)	-.6219*** (.2018)	-.2537*** (.0903)	-.8204*** (.2125)	-.1670* (.0982)
R^2 (%)	10	10	28	13	48	10
Adjusted R^2 (%)	10	9	27	13	48	10

NOTE.—This table examines why the price-dividend ratio ($p_t - d_t$) predicts stock market returns. We proceed in two steps. In the first step, we regress realized returns r_{t+k} at the 1-, 3-, and 5-year horizons ($k = 1, 3, 5$) on 1-year revisions in long-term growth in earnings occurring between $t + 1$ and $t + k$ (i.e., ΔLTG_{t+1} through ΔLTG_{t+k}) and long-term forecast errors occurring between $t + 1$ and $t + k$ (i.e., $\Delta_5 e_{t+1} - \text{LTG}_{t-4}$ through $\Delta_5 e_{t+k} - \text{LTG}_{t+k-5}$), presented in table B.7. We generate return residuals \tilde{r}_{t+k} from these first-stage regressions. In the second step, we use $p_t - d_t$ to predict r_{t+k} in cols. 1, 3, and 5 and \tilde{r}_{t+k} in cols. 2, 4, and 6. Except for ΔLTG_t , all variables are standardized. Intercepts are not shown. The sample period is 1985:12–2015:12. Newey-West (1987) standard errors are in parentheses (with 12 lags in cols. 1–2, 36 lags in cols. 3–4, and 60 lags in cols. 5–6).

- * Significant at the 10% level.
- ** Significant at the 5% level.
- *** Significant at the 1% level.

coefficient for $p_t - d_t$ drops by factors of 2.5 at the 3-year horizon and more than 5 at the 5-year horizon.¹⁵ This evidence suggests that the bulk of the price-dividend ratio’s predictive power is due to its ability to capture nonrational beliefs, in particular systematic reversals of overreaction, as proxied by LTG news.

C. Predictability of Firm-Level Stock Returns

The results in table 4 might be influenced by a few outlier episodes, such as the internet bubble. To address this concern we test prediction 1 at the firm level, controlling for all common shocks (including shocks to required returns) by using time dummies. We can also include firm fixed effects, which control for constant differences in average returns across firms.

Table 6 shows the results. Column 1 predicts forecast errors for a firm’s 5-years-ahead earnings growth, using the 1-year changes in a firm’s forecast $\Delta \text{LTG}_{i,t}$ and the lagged forecast $\text{LTG}_{i,t-1}$. Column 2 uses the same

¹⁵ Results are similar if we proxy for LTG news using only revisions, not errors (table B.8, in app. B). The R^2 of 48% in col. 5 is equal to that of col. 4 in table 4, which also uses a forecast error predictor. This is a coincidence, because the two regressions are estimated in different samples (i.e., the sample period for table 5 starts in December of 1985, rather than December of 1982 for table 4, because that is when we can first compute $e_{t+1} - \text{LTG}_{t-4}$). Using the same sample as in table 4 reduces the R^2 in col. 5 to 44.9%.

TABLE 6
FIRM-LEVEL RESULTS

	$\Delta_5 e_{i,t+5}/$ 5 - LTG _{<i>i,t</i>}	$\sum_{j=1}^5 \alpha^{j-1} r_{i,t+j}$	$\sum_{j=1}^5 \alpha^{j-1} r_{i,t+j}$	$\sum_{j=1}^5 \alpha^{j-1} r_{i,t+j}$	$\sum_{j=1}^5 \alpha^{j-1} r_{i,t+j}$	$\sum_{j=1}^5 \alpha^{j-1} r_{i,t+j}$
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta \text{LTG}_{i,t}$	-.3286*** (.0246)	-.1774*** (.0409)				
$\Delta \text{LTG}_{i,t-1}$	-.3638*** (.0252)	-.2162*** (.0446)				
$\Delta_5 e_{i,t+5}/5 - \text{LTG}_{i,t}$.5757*** (.0923)	.3688*** (.0581)	.4869*** (.1057)	.4702*** (.0922)
$p_{i,t} - d_{i,t}$				-.4498*** (.1113)		
$p_{i,t} - e_{i,t}$					-.2962*** (.0676)	
Observations	371,525	371,525	371,525	259,727	371,525	268,156
Adjusted <i>R</i> ² (%)	4	1		3	3	
Kleibergen-Paap <i>F</i> -statistic	107.3	182.6
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Instrument	LTG _{<i>i,t-1</i>} , ΔLTG _{<i>i,t</i>}	LTG _{<i>i,t-1</i>} , ΔLTG _{<i>i,t</i>}

NOTE.—We present firm-level regressions for all US firms in the IBES sample. We define firm-level forecast errors as the difference between (a) the growth in firm *i*'s earnings per share between year *t* and *t* + 5, $\Delta_5 e_{i,t+5}/5$, and (b) the expected long-term growth in firm *i*'s earnings, LTG_{*i,t*}. In col. 1, we perform an OLS regression of the error in forecasting the 5-year earnings growth on (a) the 1-year revision of the forecast for a firm's long-term earnings growth, $\Delta \text{LTG}_{i,t}$ and (b) the lagged forecast LTG_{*i,t-1*}. In col. 2, we perform an OLS regression of the discounted cumulative (log) return for firm *i* between years *t* and *t* + 5, $\sum_{j=1}^5 \alpha^{j-1} r_{i,t+j}$, on the same two independent variables. In col. 3, we perform an IV regression of stock returns, $\sum_{j=1}^5 \alpha^{j-1} r_{i,t+j}$, on the forecast errors fitted in col. 1. In cols. 4 and 5, we perform an OLS regression of 5-year returns, $\sum_{j=1}^5 \alpha^{j-1} r_{i,t+j}$, on the forecast errors fitted in col. 1 and controlling for the price-dividend ratio in col. 4 (for observations with positive dividends) and the price-earnings ratio in col. 5 (for observations with positive earnings). In col. 6, we return to the benchmark specification in col. 3 but exclude from the sample the years 1998–2002 and 2007–9. Except for $\Delta \text{LTG}_{i,t}$, all variables are standardized. Regressions include time and firm fixed effects, which we do not report. Except in col. 6, the sample period is 1982:12–2015:12. We report Driscoll-Kraay standard errors with autocorrelation of up to 60 lags.

*** Significant at the 1% level.

regressors to predict the firm's stock returns over the next 5 years. Column 3 uses the errors fitted in column 1 as instruments to predict returns.¹⁶ In line with table 4, in column 4 we control for the firm's price-dividend ratio (restricting to the observations where dividends are paid), and in column 5 we control for the price-earnings ratio (using observations

¹⁶ Following Bordalo et al. (2019), here we consider all domestic common stocks in the IBES Unadjusted US Summary Statistics file, which includes stocks listed on major US stock exchanges (i.e., the New York Stock Exchange [NYSE], the American Stock Exchange [AMEX], and NASDAQ) except for closed-end funds and real estate investment trusts. From the IBES Detail History Tape file we obtain analyst earnings forecasts.

with positive earnings). To assess the role of the episodes in our data with the greatest returns, in column 6 we exclude the years 1998–2002 and 2007–9.

Column 1 again shows strong evidence of overreaction. Upward firm-level $LTG_{i,t}$ revisions predict future disappointment (negative forecast errors), and the same does a high lagged forecast $LTG_{i,t-1}$, in line with the aggregate results. Column 2 confirms, at the firm level, the result on return predictability: higher firm-level forecast revisions $\Delta LTG_{i,t}$ and lagged forecast $LTG_{i,t-1}$ are associated with sharply lower returns. The R^2 in column 2 is lower than that for the aggregate market, perhaps because there are many sources of idiosyncratic and unpredictable variation in firm-level returns. Still, coefficient magnitudes are sizable: a 1–standard deviation–higher forecast revision (equal to 0.53) or lagged forecast (equal to 1) is followed by a 0.09 (0.22)–standard deviation–lower return at the firm level.

Column 3 confirms the direct link between predictable disappointment and predictable returns: periods in which beliefs about a firm are overpessimistic (overoptimistic), in the sense that they are systematically followed by earnings growth predictably above (below) expectations, are also periods in which the firm's stock return is higher (lower). Columns 4 and 5 show that the results are robust to controlling for the price-dividend ratio (for the observations that pay dividends) and the price-earnings ratio, providing further evidence that LTG is not inferred from prices. In column 6, we exclude the years of the internet bubble and the financial crisis: our results are not driven by the episodes with largest returns in the data.¹⁷

In sum, measured expectations display strong overreaction to news and boom-bust stock price dynamics: good news leads to excessive optimism, which is associated with an inflated stock price and a future price reversal when overoptimism is disappointed. The same mechanism operates for both the aggregate market and individual firms, indicating its generality.

IV. Return Predictability in the Cross Section

Decades of asset-pricing research have unveiled puzzling differences in average returns across stocks grouped on the basis of observed characteristics such as the book-to-market ratio, profitability, and so on. Such predictability is systematic. For instance, high-book-to-market stocks tend to do poorly together, compared to low-book-to-market stocks, and likewise for other characteristics (Fama and French 1993). Some scholars view such cross-sectional return predictability as reflecting differential exposure to systematic risk factors (Fama and French 1993; Cochrane 2011). Other

¹⁷ In app. B, we extend the results of table 6 by predicting returns at a 3-year horizon (table B.9) as well as by instrumenting revisions by using fundamental growth (table B.10).

scholars argue instead that it reflects systematic psychological factors (De Long et al. 1990a, 1990b; Lakonishok, Shleifer, and Vishny 1994; Kozak, Nagel, and Santosh 2018).

Expectations data allow us to empirically assess this debate. We just showed that expectations about aggregate long-term earnings growth, LTG_t , capture systematic overreaction in market beliefs. Can such systematic overreaction also shed light on the comovement of returns in the cross section? In section IV.A, we address this question by focusing on the cross-sectional return spread between high- and low- LTG firms (La Porta 1996). Section IV.B broadens the analysis to consider the returns of Fama-French (1993) factors.

A. *LTG and Time Variation in the LTG Spread*

La Porta (1996) showed that firms in the top LTG decile have predictably lower stock returns than firms in the bottom LTG decile. Bordalo et al. (2019) show that a model in which beliefs about a firm's long-term earnings growth overreact can account for this finding. Here we ask a new question: Do the returns of stocks in the top or bottom LTG decile comove with aggregate LTG_t , causing systematic variation in the LTG cross-sectional spread? Addressing this question is a key first step to understanding whether systematic belief biases shape cross-sectional mispricing.

To make progress, in table 7 we regress the 5-year log return of portfolios of stocks sorted by LTG on our proxies for aggregate overoptimism, namely, the forecast revision ΔLTG_t and the lagged forecast LTG_{t-1} . We also add the contemporaneous market return, which captures the capital asset-pricing model (CAPM) comovement on the basis of fundamental risk exposure. Column 1 reports the regression results for the low- LTG (LLTG) portfolio, defined as the bottom decile of stocks on the basis of their median LTG . Column 2 presents the same regression for the high- LTG (HLTG) portfolio, defined as the top decile of stocks on the basis of their median LTG . Column 3 estimates the same model for the return on the low-minus-high- LTG portfolio. We call this portfolio "pessimism minus optimism" LTG , or PMO, adopting the Fama-French convention of forming a portfolio whose long arm is the group of firms earning a higher average return, LLTG in our case. Columns 4–7 add to column 3 regressions the three conventional proxies for discount rates.

There is a strong systematic variation in the LTG spread. HLTG stocks appear to do worse in bad times than LLTG stocks (the PMO return loads negatively on the market).¹⁸ Thus, the LTG spread cannot be explained by

¹⁸ The market loading of the PMO portfolio is not the difference between the LLTG loading in col. 1 and the HLTG loading in col. 2, because the variables are standardized and LLTG has lower variance than HLTG.

TABLE 7
MARKET RETURN AND LTG PORTFOLIO RETURNS

	DEPENDENT VARIABLE: (Log) 5-YEAR RETURN						
	LLTG	HLTG	PMO				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ΔLTG_t	.2200* (.1128)	-.7177*** (.1545)	.6550*** (.1340)	.5952*** (.1301)	.5844*** (.1337)	.7051*** (.2046)	.6963*** (.1417)
LTG_{t-1}	.2428* (.1356)	-.4452*** (.0774)	.4355*** (.0963)	.3968*** (.0877)	.3816*** (.0893)	.3508*** (.0668)	.5079*** (.0661)
$\ln(\text{Mkt}_{t,t+5})$.9399*** (.0995)	.5406*** (.0793)	-.1900*** (.0713)	-.1808*** (.0677)	-.2542*** (.0954)	-.1769 (.1576)	-.3464*** (.0642)
X_t				.1149 (.0705)	.1274* (.0759)	.0086 (.1154)	-.2800*** (.0808)
Observations	397	397	397	397	133	193	397
Adjusted R^2 (%)	78	84	69	71	71	73	75
X_t				spc_t	cay_t	SVIX_t^2	$p_t - d_t$

NOTE.—We predict the return for portfolios formed by the forecast for long-term growth in earnings for firm i , $LTG_{i,t}$, using expectations about earnings growth for the market. On each month between December 1982 and December 2015, we form decile portfolios based on $LTG_{i,t}$, and report regression results for the 5-year cumulative (log) returns on (a) the lowest decile (LLTG) in col. 1, (b) the highest decile (HLTG) in col. 2, and (c) the difference between the two (PMO = LLTG – HLTG) in cols. 3–7. The independent variables are (a) the 1-year forecast revision for long-term growth in aggregate earnings, ΔLTG_t , (b) the 1-year lagged forecast, LTG_{t-1} , (c) the (log) 5-year return of the CRSP (Center for Research in Security Prices) value-weighted index between t and $t + 5$, $\ln(\text{Mkt}_{t,t+5})$, (d) the Campbell and Cochrane (1999) surplus-consumption ratio, spc_t , in col. 4, (e) the Lettau and Ludvigson (2001) consumption-wealth ratio, cay_t , in col. 5, (f) the Martin (2017) expected return on the market SVIX_t^2 in col. 6, and (g) the price-dividend ratio, $p_t - d_t$, in col. 7. Except for ΔLTG_t , variables are standardized. Intercepts are not shown. The sample period is 1982:12–2015:12. Newey-West (1987) standard errors are in parentheses (with 60 lags).

* Significant at the 10% level.

*** Significant at the 1% level.

the fact that LLTG stocks are riskier in the standard CAPM sense. A more promising avenue is to look at the LTG_t proxies: HLTG stocks are more exposed to waves of aggregate optimism, compared to LLTG stocks. In columns 1 and 2, good news about long-term earnings growth, reflected in high LTG_t revisions, is followed by higher returns for LLTG stocks and lower returns for HLTG stocks. The same holds when the lagged forecast LTG_{t-1} is high. Thus, in column 3, the PMO spread is higher after periods of aggregate optimism, as a result of the good performance of LLTG stocks, the long arm of the portfolio, and the poor performance of HLTG stocks, the short arm of the portfolio.

The specification in column 3 accounts for 69% of the time variation in the LTG spread, compared to only 38% of the market return alone. Measures of discount rates play no role in explaining the data (see cols. 4–6). Furthermore, the magnitude of the PMO spread explained by aggregate expectations is very significant: relative to a long-term average of 5.5% per year, the spread increases to 23.5% per year as LTG_{t-1} goes from

its average of 12.2% to 15.5% (a 2-standard deviations increase). This suggests that the average aggregate LTG captures some level of overoptimism, corresponding to the overvaluation of the HLTG firms.¹⁹

To study how aggregate optimism can create cross-sectional comovement, we introduce firm heterogeneity into our model. For simplicity, we abstract from intangible news by setting $\eta_t = 0$, but this is not critical (see n. 21). Each firm i exhibits AR(1) dividend growth:

$$g_{i,t+1} = \mu g_{i,t} + v_{i,t}. \quad (9)$$

As in equation (6), expected growth at horizon $s \geq 1$ for firm i is believed to be

$$\tilde{\mathbb{E}}_t(g_{i,t+s}) = \mathbb{E}_t(g_{i,t+s}) + \mu^{s-1} \epsilon_{i,t}. \quad (10)$$

The firm-specific belief distortion continues to follow an AR(1) process, $\epsilon_{i,t} = \rho \epsilon_{i,t-1} + u_{i,t}$, with persistence $\rho \in [0, 1]$, where $u_{i,t}$ is a firm-level expectations shock.

As in standard cross-sectional asset pricing, firm-level and aggregate shocks are connected. The firm-level fundamental shock is the product $v_{i,t} = v_i \times v_t$ of the aggregate fundamental shock v_t and a parameter $v_i > 0$ capturing the firm's exposure to it. This is the standard CAPM exposure to fundamental risk, which varies across firms. Similarly, the firm-level expectations shock $u_{i,t}$ can be written as the aggregate expectation shock u_t times a firm-specific exposure to it. Think of it as a firm-specific degree of belief overreaction θ_i , so that $u_{i,t} = \theta_i \times v_t$. This key new aspect creates differential exposure of firms to aggregate optimism and pessimism.²⁰ The firm-level belief distortion is then proportional to the aggregate one, $\epsilon_{i,t} = (\theta_i/\theta) \epsilon_t$.

A firm may be more exposed to aggregate optimism because it belongs to the "hot" sector of the moment or because it is similar enough to firms in such sectors (as in Bordalo et al. 2021). For instance, optimism about the aggregate market may be due to the rapid growth of some high-tech firms. Such optimism may contaminate other high-tech firms because of higher fundamentals (high v_i) but also because of mere similarity, which increases θ_i for given v_i . The distinction between these two effects is key for understanding returns. To see why, note that using equations (1), (9),

¹⁹ The results of table 7 hold when the contemporaneous price-dividend ratio is controlled for (table C.1, in app. C) and at a 3-year horizon (table C.2, panel A). Bordalo et al. (2019) show that the average (value-weighted) PMO at a 1-year horizon is 6.4%, similar to 5.5% in table 7. We use value-weighted portfolios because of our focus on the S&P 500 index.

²⁰ The assumption that firms' fundamentals and beliefs perfectly comove with the market makes the model tractable. Appendix A shows that this assumption is not necessary. Enriching the model with idiosyncratic fundamental shocks would yield the additional implication that the LTG spread reflects also the overreaction of HLTG firms to good firm-level fundamental news, as in Bordalo et al. (2019), not only the average degree of market overoptimism ϵ_t .

and (10) we can show (see app. A) that the realized return for firm i is given by

$$r_{i,t+1} - r_i = \left(\frac{v_i + \alpha\theta_i}{1 + \alpha\theta} \right) (r_{t+1} - r) - \left(\frac{1 - \alpha\rho}{1 - \alpha} \right) \left(\frac{\theta_i - \theta v_i}{\theta + \alpha\theta^2} \right) \epsilon_t, \quad (11)$$

where θ is market overreaction and r_i is the firm-specific required return, while $r_{t+1} - r$ is the realized market return in excess of the required one.²¹ The firm's realized return depends on the excess market return $r_{t+1} - r$ and on past excess optimism ϵ_t , according to firm-specific coefficients. If a firm's exposure to aggregate optimism is shaped only by its exposure to market fundamentals, $\theta_i = \theta v_i$, the model boils down to the CAPM. The return of firm i loads with coefficient v_i on the market return, which is the only source of comovement. Even though the aggregate market displays excess volatility and return predictability, the cross section is correctly priced in terms of market exposure. Thus, the case $\theta_i = \theta v_i$ cannot explain table 7.

If instead firms overreact more or less than warranted by their exposure to fundamentals, $\theta_i \neq \theta v_i$, the CAPM breaks down. Now the realized market return captures the firm's reaction to current aggregate shocks, while aggregate excess optimism ϵ_t captures the firm's relative overreaction to past shocks. Firms that overreact more than the average, $\theta_i - \theta v_i > 0$, exhibit a stronger comovement with the market, because of stronger overreaction to current news v_{t+1} . Critically, they are also more inflated during periods of high aggregate optimism ϵ_t . Thus, they exhibit stronger reversals in the future, in beliefs and in returns. The reverse holds for firms that overreact less than the average firm, $\theta_i - \theta v_i < 0$.²²

We can examine whether this mechanism is at play by considering forecast errors. In our model, the belief distortion for firm i (which is inversely related to the forecast error) is given by

$$\epsilon_{i,t} = \frac{\theta_i}{\theta} \epsilon_t. \quad (12)$$

Excess optimism $\epsilon_{i,t}$ about firm i at time t is proportional to aggregate excess optimism ϵ_t , with a proportionality coefficient that increases in the extent θ_i to which beliefs about firm i overreact compared to beliefs about the market θ .

Denote by (v_H, θ_H) the exposure to fundamental risk and to belief overreaction of high-LTG firms and by (v_L, θ_L) the exposures of low-LTG ones. We obtain the following result.

²¹ Appendix A shows that under our assumptions, if investors have mean variance preferences and are naïve about ϵ_t , the required return r_i can be endogenized and is determined as in the CAPM: $r_i = r_f + v_i(r - r_f)$.

²² Intangible news simply adds to eq. (11) a third factor capturing news η_{t+1} . For simplicity, we omit this factor.

PREDICTION 2. The beliefs about LLTG firms overreact to aggregate news less than those about HLTG firms, $\theta_L < \theta_H$, if and only if forecast errors in earnings growth for the PMO portfolio are positively predicted by the current revision ΔLTG_t and the lagged forecast LTG_{t-1} . If $\theta_L < \theta_H$ and in addition the two portfolios are similarly exposed to fundamental risk, $v_L \approx v_H$, the same LTG proxies predict a higher PMO spread.

We can thus assess whether high-LTG firms overreact more than low-LTG ones, $\theta_L < \theta_H$, by testing whether high-LTG firms disappoint more than low-LTG ones after periods of aggregate optimism. If so, the PMO spread should widen after periods of high aggregate optimism, as in table 7. Aggregate overreaction appears to drive the behavior of cross-sectional returns and errors.

Table 8 studies forecast errors. Column 1 regresses the forecast errors for 5-years-ahead earnings growth for the LLTG portfolio on the current forecast revision ΔLTG_t and lagged forecast LTG_{t-1} . Column 2 does the same for the HLTG portfolio and column 3 for the PMO portfolio.

The results point to stronger overreaction to aggregate news for HLTG than for LLTG firms, $\theta_H > \theta_L$. Higher aggregate forecast revisions ΔLTG_t

TABLE 8
FORECAST ERRORS OF LTG PORTFOLIOS ($N = 397$)

	DEPENDENT VARIABLE: 5-YEAR FORECAST ERROR		
	LLTG (1)	HLTG (2)	PMO (3)
ΔLTG_t	-.1997 (.1608)	-.7937*** (.1791)	.7367*** (.1451)
LTG_{t-1}	-.0302 (.1894)	-.7374*** (.0691)	.7549*** (.1145)
Adjusted R^2 (%)	1	56	57

NOTE.—This table predicts forecast errors for portfolios formed on the basis of expected long-term growth in earnings for firm i , $\text{LTG}_{i,t}$, using beliefs about aggregate earnings growth. On each month between December 1982 and December 2015, we form decile portfolios based on $\text{LTG}_{i,t}$ and report regressions for the forecast errors in predicting earnings growth between t and $t + 5$ of the following three portfolios: (a) the lowest decile (LLTG) in col. 1, (b) the highest decile (HLTG) in col. 2, and (c) the difference between the two (PMO = LLTG – HLTG) in col. 3. We define portfolio errors as the mean forecast error of the firms in the relevant LTG portfolio, i.e., the time- t average difference between (1) the annual growth in firm i 's earnings per share between years t and $t + 5$, $\Delta_5 \ell_{i,t+5}/5$, and (2) the expected long-term growth in firm i 's earnings, $\text{LTG}_{i,t}$. The independent variables are (a) the 1-year forecast revision for aggregate earnings, ΔLTG_t , and (b) the lagged 1-year forecast, LTG_{t-1} . Except for ΔLTG_t , variables are standardized. Intercepts are not shown. The sample period is 1982:12–2015:12. We adjust standard errors for serial correlation using the Newey-West (1987) correction (with 60 lags).

*** Significant at the 1% level.

directionally predict belief disappointment in the LLTG portfolio (col. 1) but even stronger disappointment in the HLTG portfolio (col. 2). Likewise, a higher lagged forecast LTG_{t-1} predicts disappointment for the HLTG portfolio but not for the LLTG one. As a result of these patterns, the PMO LTG portfolio exhibits systematically positive earnings growth surprises after periods of aggregate optimism, captured by the positive coefficients in column 3. These positive surprises reflect lower disappointment in the long arm of the portfolio, LLTG, compared to the short arm, HLTG.²³

We can connect tables 7 and 8 using our model. The positive predictability of PMO forecast errors in table 7 points to excess pessimism about LLTG firms, compared to HLTG ones, in good times, $\theta_H - \theta_L > 0$. The positive predictability of PMO returns in table 7 suggests that in the same good times LLTG firms are undervalued compared to HLTG ones, $\theta_H - \theta_L > \theta(v_H - v_L)$. The two conditions are met if the fundamental exposure of HLTG firms is not much larger than that of LLTG firms. In fact, the two conditions are identical if these firms are similarly exposed, $v_H - v_L \approx 0$. In this case, tables 7 and 8 are two sides of the same coin.²⁴ Here we do not try to measure the exposures of HLTG and of LLTG firms to fundamental risk, but the message is clear. Differential overreaction of firms to aggregate news offers a parsimonious account of comovement of forecast errors and returns in the cross section, even absent any differential exposure to aggregate risk. This approach is able to account for the PMO spread and once again underscores the importance of using beliefs as predictors of returns.

B. LTG and the Fama-French Risk Factors

In a series of influential papers, Fama and French (1993, 2015) show that, over and beyond the standard market factor, cross-sectional spreads and return comovement are to a large extent explained by other return factors constructed using firm characteristics, such as book-to-market ratio, size, profitability, and investment. The efficient-markets explanation for these

²³ In table 8, we focus on predictability at the 5-year horizon to match table 7. The results are robust to shorter horizons (table C.2, panel B, in app. C). Bordalo et al. (2019) document that average forecast errors of portfolios with high vs. low LTG at the 1-year horizon are positive. The results are also robust to the prediction of value-weighted, as opposed to equal-weighted, forecast errors (table C.3).

²⁴ Note also that, in table 7, the return of the PMO portfolio loads negatively on the market factor. Equation (11) accounts for this fact, provided that $\alpha(\theta_H - \theta_L) > v_L - v_H$. Similar fundamental exposure by high- and low-LTG firms, $v_H - v_L \approx 0$, guarantees this result as well. When $v_H - v_L \approx 0$, our model reconciles tables 7 and 8, and furthermore the PMO spread is entirely due to overreaction. In this case, the contemporaneous market return in table 6 captures the excess overreaction of HLTG stocks to contemporaneous news, whereas the beginning-of-period LTG proxies capture the excess overreaction of the same firms to past news. Compared to LLTG firms, contemporaneous overreaction drives up the return of HLTG firms, while disappointment of past overreaction drives it down.

findings is that these factors reflect sources of risk to which firms are differentially exposed. Attempts to directly measure these risks have, however, proved elusive, leading some researchers to argue that these factors can at least in part capture relative undervaluation of stocks in the long arm of the factor-return portfolio due to systematic belief biases (Lakonishok, Shleifer, and Vishny 1994). Our previous analysis of the LTG spread suggests that aggregate expectations LTG_t can be regarded as a proxy for such systematic biases. This raises the question of whether this proxy, in line with the logic of equation (11), can shed light on the Fama-French factors.

We conclude by showing that this connection may be promising. Table 9 regresses the 5-year returns (panel A) and forecast errors (panel B) of the Fama-French (2015) factor portfolios—book-to-market ratio (high minus low [HML BM]), profitability (robust minus weak [RMW]), investment (conservative minus aggressive [CMA]), and size (small minus big [SMB])—on our measures of aggregate excess optimism: the aggregate LTG_t revision and lagged forecast LTG_{t-1} . For returns, we also use the contemporaneous market return as a control.

The coefficients on the LTG proxies in the return regression are all positive, suggesting that part of the cross-sectional return differentials indeed reflects undervaluation of the long arm of the portfolio during times of aggregate optimism (compared to the short arm). The explanatory power of LTG is high: using the market factor alone accounts for only 0.35% of the HML BM return, 25% of the RMW return, 13% of the CMA return, and 40% of the SMB return (see table C.6, in app. C). Aggregate optimism helps explain cross-sectional comovement.²⁵

In line with the analysis of the PMO spread, we next ask whether comovement is due to belief overreaction that is weaker for stocks in the long arm of the portfolio than for those in the short arm. To address this question, in panel B we study forecast error predictability. Consider the HML BM portfolio in column 1. Higher aggregate optimism predicts positive surprises (less belief disappointment) in long-term earnings growth for high-BM stocks, compared to low-BM ones. This points to weaker overreaction for high-BM stocks compared to low-BM ones, $\theta_{HBM} < \theta_{LBM}$. The undervaluation of high-BM stocks during periods of aggregate optimism in panel A can thus reflect their weaker overreaction. The mechanisms for the PMO LTG and HML BM return spreads are similar.

²⁵ The predictive power of LTG_t in panel A is robust to a shorter, 3-year horizon (table C.4, in app. C) as well as to including proxies for required returns. In particular, in the spirit of Lettau and Ludvigson (2001), we can include in the regression cay alone and cay interacted with the contemporaneous market return (table C.5). This causes the LTG revision to be insignificant in the RMW regression but modestly improves the regression R^2 , which becomes 70% for HML, 35% for RMW (for which cay is itself insignificant), 66% for CMA, and 66% for SMB.

TABLE 9
PREDICTABILITY OF FACTOR RETURNS AND FORECAST ERRORS (N = 397)

	HML (1)	RMW (2)	CMA (3)	SMB (4)
A. Returns and Forecasts about Growth (Dependent Variable: 5-Year (log) Return)				
ΔLG_t	.9650*** (.1410)	.3642** (.1819)	.9260*** (.2579)	.3074 (.1914)
LTG_{t-1}	.9025*** (.1197)	.2115 (.1892)	.6732*** (.1377)	.5340*** (.0962)
$\ln(\text{Mkt}_{t,t+5})$.4189*** (.1462)	-.3736** (.1745)	.0344 (.1681)	-.4179*** (.1037)
Adjusted R^2 (%)	62	30	52	59
B. Forecast Errors and Forecasts about Growth (Dependent Variable: 5-Year Forecast Error)				
ΔLG_t	.2283** (.1144)	.5046** (.2049)	.4345** (.1948)	-.4695*** (.1663)
LTG_{t-1}	.3320*** (.0926)	.3279*** (.0992)	.2985** (.1494)	-.2408* (.1289)
Adjusted R^2 (%)	16	6	14	10

NOTE.—This table links beliefs about growth in earnings to Fama-French factor returns (panel A) and forecast errors (panel B). The dependent variables in panel A are the compounded (log) return between years t and $t + 5$ of the following four factors: (a) high minus low book-to market ratio (HML) in col. 1, (b) robust minus weak profitability (RMW) in col. 2, (c) conservative minus aggressive investment (CMA) in col. 3, and (d) small minus big size (SMB) in col. 4. The dependent variables in panel B are the forecast errors in predicting the growth in earnings between t and $t + 5$ for the HML, RMW, CMA, and SMB portfolios. We define portfolio errors as the mean forecast error of the firms in the relevant LTG portfolio, i.e., the time- t average difference between (1) the annual growth in firm i 's earnings per share between years t and $t + 5$, $\Delta_5 e_{i,t+5}/5$, and (2) the expected long-term growth in firm i 's earnings, $\Delta LG_{i,t}$. In panel A, the independent variables are (a) the 1-year revision in aggregate earnings growth forecast, ΔLG_t , (b) the 1-year lagged forecast, LTG_{t-1} , (c) the (log) 5-year return of the CRSP value-weighted index between t and $t + 5$, $\ln(\text{Mkt}_{t,t+5})$. In panel B, the independent variables are ΔLG_t and LTG_{t-1} . Except for ΔLG_t , variables are standardized. Intercepts are not shown. The sample period is 1982:12–2015:12. We adjust standard errors for serial correlation using the Newey-West (1987) correction (with 60 lags).

* Significant at the 10% level.

** Significant at the 5% level.

*** Significant at the 1% level.

The same message holds for the RMW and CMA factors: columns 2 and 3 in panel B show that, after times of aggregate optimism, firms that are highly profitable and invest conservatively exhibit less belief disappointment than firms that are less profitable and invest aggressively, respectively. This is also consistent with the fact that, during the same times, profitable or conservative firms are relatively undervalued, as captured by columns 2 and 3 in panel A. In terms of proposition 2 and equation (11), the weaker overreaction of the portfolios' long arms (panel B) and their relative undervaluation (panel A) can be jointly explained if the short arm

of the portfolio is not much more exposed to fundamental risk than the long arm, as in the case of the PMO LTG spread.²⁶

The findings for the SMB factor are not as clear. In panel B, small firms experience sharper belief disappointment than big firms, suggesting that $\theta_s > \theta_b$, and yet they appear to be undervalued, compared to big firms during times of excess optimism (col. 4, panel A). There is no direct connection between return and forecast error predictability for the size factor. Equation (11) is consistent with the results in table 9 if small firms are sufficiently more exposed to fundamental risk than large firms $v_s > v_b$. Small firms may then be undervalued in good times because they display small overreaction compared to their market exposure, $\theta_s - \theta v_s < \theta_b - \theta v_b$, and yet disappoint after good times because they display larger absolute overreaction, $\theta_s > \theta_b$.²⁷ The SMB factor is not easily accommodated by our model.

Overall, our results bring together return predictability for the aggregate stock market and for the cross section in terms of a common mechanism of overreacting expectations. High aggregate LTG captures overvaluation of stocks in the aggregate but particularly stocks with low book-to-market ratio, low profitability, and aggressive investing, which overreact more to aggregate conditions. Such overvaluation leads to lower subsequent returns, both for the market and for firms with those characteristics. Overoptimism acts similarly to lower risk aversion, if the short arms of the factors were indeed riskier along the lines of Fama and French (1993).²⁸ But the expectations approach goes farther: it explains that overoptimism arises in response to news, that forecast errors about factors are systematically predictable from aggregate optimism, and that those predictable errors, in turn, help explain factor returns.

²⁶ According to eq. (11), the nonnegative loadings on the market factor for HML BM and CMA in panel A additionally require a sufficiently stronger exposure to fundamentals of the long arm of the portfolio, compared to the short arm.

²⁷ Specifically, one needs that $0 < \theta_s - \theta_b < \max[\theta(v_s - v_b), (v_b - v_s)/\alpha]$.

²⁸ There is little evidence that this is the case in terms of market beta and volatility, either for HML (La Porta et al. 1997) or for PMO (Bordalo et al. 2019). In app. C, we show that high-beta stocks are also more exposed to aggregate overreaction, which helps explain their underperformance (table C.7). However, recent work has shown that the standard risk factors load on stocks whose cash flows are relatively more concentrated in the short term and for which long-term growth expectations are also lower (Weber 2018; Gormsen and Lazarus 2023). Gormsen and Lazarus (2023) propose aversion to short-term cash flow variation as a risk-based explanation for these factors' average returns. The fact that returns on the factors are (partially) linked to errors in long-term growth forecasts, which are in turn predictable from fundamental aggregate shocks, helps explain the negative correlation between market returns and factor returns documented in Gormsen (2021), under the unifying mechanism of overreacting expectations. We leave it to future work to evaluate in a systematic way the ability of overreacting beliefs to account for conventional cross-sectional return anomalies.

V. Conclusion

Measured overreaction in expectations of long-term fundamentals emerges as a credible mechanism behind leading aggregate and cross-sectional stock market puzzles, even assuming that required returns are constant in the time series and in the cross section and assuming no price extrapolation. Good news causes investors to become too optimistic about long-term fundamentals of the average firm or of particular firms. This inflates both the market and individual firm valuations, leading to predictably low future returns, in absolute terms or compared to other firms, as earnings expectations are disappointed. The mechanism is empirically confirmed by the joint predictability of returns and forecast errors, in both the aggregate market and the cross section.

A skeptic may argue that measured long-term expectations surreptitiously incorporate variation in discount rates. We consider this possibility but do not find support for it. In particular, beliefs about long-term growth have remarkable predictive power for aggregate returns even when we control for leading proxies for required returns and for the price-dividend ratio. At the firm level, these beliefs predict a firm's future return even after introduction of time fixed effects, which controls for common shocks to required returns. Finally, revisions in measured beliefs are in good part driven by earnings news and not by past stock returns or expected stock returns. These results further strengthen our overreacting-expectations interpretation of the evidence.

Cochrane (2001) writes about the possibility that price movements may reflect irrational exuberance (Shiller 2000), "Perhaps, but is it just a coincidence that this exuberance comes at the top of an unprecedented economic expansion, a time when the average investor is surely feeling less risk averse than ever, and willing to hold stocks despite historically low risk premia?" Our analysis shows that this fact is not a coincidence but obtains for a different reason: at the top of an unprecedented expansion, the average investor is more optimistic, rather than less risk averse. This possibility is also confirmed by growing evidence from survey expectations of managers, professional forecasters, and individual investors (Bordalo, Gennaioli, and Shleifer 2022). The data suggest that belief overreaction holds significant promise for explaining many macrofinancial puzzles.

Data Availability

Code, publicly available data, and information about obtaining the proprietary data required for replicating the tables and figures in this article can be found in Bordalo et al. (2023), in the Harvard Dataverse, <https://doi.org/10.7910/DVN/WN1FE1>.

References

- Adam, Klaus, Albert Marcet, and Johannes Beutel. 2017. "Stock Price Booms and Expected Capital Gains." *A.E.R.* 107 (8): 2352–408.
- Adam, Klaus, and Stefan Nagel. 2022. "Expectations Data in Asset Pricing." Working Paper no. 29977 (May), NBER, Cambridge, MA.
- Bacchetta, Philippe, Elmar Mertens, and Eric van Wincoop. 2008. "Predictability in Financial Markets: What Do Survey Expectations Tell Us?" *J. Internat. Money and Finance* 28 (3): 406–26.
- Baker, Scott, Nicholas Bloom, and Steven Davis. 2016. "Measuring Economic Policy Uncertainty." *Q.J.E.* 131 (4): 1593–636.
- Bansal, Ravi, and Amir Yaron. 2004. "Risks for the Long Run: A Potential Resolution of Asset Pricing Puzzles." *J. Finance* 59 (4): 1481–509.
- Barberis, Nicholas, Robin Greenwood, Lawrence Jin, and Andrei Shleifer. 2015. "X-CAPM: An Extrapolative Capital Asset Pricing Model." *J. Financial Econ.* 115 (1): 1–24.
- . 2018. "Extrapolation and Bubbles." *J. Financial Econ.* 129 (2): 203–27.
- Barberis, Nicholas, Andrei Shleifer, and Robert Vishny. 1998. "A Model of Investor Sentiment." *J. Financial Econ.* 49 (3): 307–43.
- Barro, Robert. 2006. "Rare Disasters and Asset Markets in the Twentieth Century." *Q.J.E.* 121 (3): 823–66.
- Barsky, Robert, and J. Bradford De Long. 1993. "Why Does the Stock Market Fluctuate?" *Q.J.E.* 108 (2): 291–312.
- Bianchi, Francesco, Cosmin Ilut, and Hikaru Saijo. 2024. "Diagnostic Business Cycles." *Rev. Econ. Studies* 91 (1): 129–62.
- Black, Fischer. 1986. "Noise." *J. Finance* 41 (3): 528–43.
- Bordalo, Pedro, Nicola Gennaioli, Spencer Y. Kwon, and Andrei Shleifer. 2020a. "Diagnostic Bubbles." *J. Financial Econ.* 141 (3): 1060–77.
- Bordalo, Pedro, Nicola Gennaioli, Rafael La Porta, and Andrei Shleifer. 2019. "Diagnostic Expectations and Stock Returns." *J. Finance* 74 (6): 2839–74.
- . 2020b. "Expectations of Fundamentals and Stock Market Puzzles." Working Paper no. 27283 (June), NBER, Cambridge, MA.
- . 2023. "Replication Data for: 'Belief Overreaction and Stock Market Puzzles.'" Harvard Dataverse, <https://doi.org/10.7910/DVN/WN1FE1>.
- Bordalo, Pedro, Nicola Gennaioli, Yueran Ma, and Andrei Shleifer. 2020c. "Overreaction in Macroeconomic Expectations." *A.E.R.* 110 (9): 2748–82.
- Bordalo, Pedro, Nicola Gennaioli, and Andrei Shleifer. 2018. "Diagnostic Expectations and Credit Cycles." *J. Finance* 73 (1): 199–227.
- . 2022. "Overreaction and Diagnostic Expectations in Macroeconomics." *J. Econ. Perspectives* 36 (3): 223–44.
- Bordalo, Pedro, Nicola Gennaioli, Andrei Shleifer, and Stephen J. Terry. 2021. "Real Credit Cycles." Working Paper no. 28416 (February), NBER, Cambridge, MA.
- Bouchaud, Jean-Philippe, Philipp Krüger, Augustin Landier, and David Thesmar. 2019. "Sticky Expectations and the Profitability Anomaly." *J. Finance* 74 (2): 639–74.
- Campbell, John, and John Cochrane. 1999. "By Force of Habit: A Consumption-Based Explanation of Aggregate Stock Market Behavior." *J.P.E.* 107 (2): 205–51.
- Campbell, John, and Robert Shiller. 1987. "Cointegration and Tests of Present Value Models." *J.P.E.* 95 (5): 1062–88.
- . 1988. "The Dividend-Price Ratio and Expectations of Future Dividends and Discount Factors." *Rev. Financial Studies* 1 (3): 195–228.
- Cochrane, John. 2001. *Asset Pricing*. Princeton, NJ: Princeton Univ. Press.
- . 2011. "Presidential Address: Discount Rates." *J. Finance* 66 (4): 1047–108.

- Coibion, Olivier, and Yuriy Gorodnichenko. 2015. "Information Rigidity and the Expectations Formation Process: A Simple Framework and New Facts." *A.E.R.* 105 (8): 2644–78.
- Cutler, David, James Poterba, and Lawrence Summers. 1990. "Speculative Dynamics and the Role of Feedback Traders." *A.E.R.* 80 (2): 63–68.
- Daniel, Kent, David Hirshleifer, and Avanidhar Subrahmanyam. 1998. "Investor Psychology and Security Market Under- and Overreactions." *J. Finance* 53 (6): 1839–85.
- Daniel, Kent, and Sheridan Titman. 2006. "Market Reactions to Tangible and Intangible Information." *J. Finance* 61 (4): 1605–43.
- D'Arienzo, Daniele. 2020. "Excess Volatility from Increasing Overreaction." Working paper.
- De Bondt, Werner, and Richard Thaler. 1985. "Does the Stock Market Overreact?" *J. Finance* 40 (3): 793–805.
- . 1990. "Do Security Analysts Overreact?" *A.E.R.* 80 (2): 52–57.
- De la O, Ricardo, and Sean Myers. 2021. "Subjective Cash Flow and Discount Rate Expectations." *J. Finance* 76 (3): 1339–87.
- . 2022. "When Do Subjective Expectations Explain Asset Prices?" Working paper.
- De Long, J. Bradford, Andrei Shleifer, Lawrence Summers, and Robert Waldmann. 1990a. "Noise Trader Risk in Financial Markets." *J.P.E.* 98 (4): 703–38.
- . 1990b. "Positive Feedback Investment Strategies and Destabilizing Rational Speculation." *J. Finance* 45 (2): 379–95.
- Fama, Eugene F., and Kenneth R. French. 1993. "Common Risk Factors in the Returns on Stocks and Bonds." *J. Financial Econ.* 33 (1): 3–56.
- . 2015. "A Five-Factor Asset Pricing Model." *J. Financial Econ.* 116 (1): 1–22.
- Frankel, Richard, and Charles Lee. 1998. "Accounting Valuation, Market Expectation, and Cross-Sectional Stock Returns." *J. Accounting and Econ.* 25 (3): 283–319.
- Gabaix, Xavier. 2012. "Variable Rare Disasters: An Exactly Solved Framework for Ten Puzzles in Macro-Finance." *Q.J.E.* 127 (2): 645–700.
- . 2019. "Behavioral Inattention." In *Handbook of Behavioral Economics: Applications and Foundations*, vol. 2, edited by B. Douglas Bernheim, Stefano Della-Vigna, and David Laibson, 261–343. Amsterdam: North-Holland.
- Giglio, Stefano, Matteo Maggiori, Johannes Stroebel, and Stephen Utkus. 2021. "Five Facts about Beliefs and Portfolios." *A.E.R.* 111 (5): 1481–522.
- Gormsen, Niels. 2021. "Time Variation of the Equity Term Structure." *J. Finance* 76 (4): 1959–99.
- Gormsen, Niels, and Eben Lazarus. 2023. "Duration-Driven Returns." *J. Finance* 78 (3): 1393–447.
- Greenwood, Robin, and Andrei Shleifer. 2014. "Expectations of Returns and Expected Returns." *Rev. Financial Studies* 27 (3): 714–46.
- Hillenbrand, Sebastian, and Odhrain McCarthy. 2022. "Heterogeneous Investors and Stock Market Fluctuations." Manuscript, New York Univ.
- Huang, Lixin, and Hong Liu. 2007. "Rational Inattention and Portfolio Selection." *J. Finance* 62 (4): 1999–2040.
- Kelly, Bryan, and Seth Pruitt. 2013. "Market Expectations in the Cross-Section of Present Values." *J. Finance* 68 (5): 1721–56.
- Kindleberger, Charles. 1978. *Manias, Panics, and Crashes*. New York: Basic Books.
- Kohlhas, Alexandre, and Ansgar Walther. 2021. "Asymmetric Attention." *A.E.R.* 111 (9): 2879–925.
- Koijen, Ralph, and Stijn Van Nieuwerburgh. 2011. "Predictability of Returns and Cash Flows." *Ann. Rev. Financial Econ.* 3:467–91.

- Kothari, S. P., and Jay Shanken. 1997. "Book-to-Market, Dividend Yield, and Expected Market Returns: A Time-Series Analysis." *J. Financial Econ.* 44 (2): 169–203.
- Kozak, Serhiy, Stefan Nagel, and Shrihari Santosh. 2018. "Interpreting Factor Models." *J. Finance* 73 (3): 1183–223.
- Lakonishok, Josef, Andrei Shleifer, and Robert Vishny. 1994. "Contrarian Investment, Extrapolation, and Risk." *J. Finance* 49 (5): 1541–78.
- La Porta, Rafael. 1996. "Expectations and the Cross-Section of Stock Returns." *J. Finance* 51 (5): 1715–42.
- La Porta, Rafael, Josef Lakonishok, Andrei Shleifer, and Robert Vishny. 1997. "Good News for Value Stocks: Further Evidence on Market Efficiency." *J. Finance* 52 (2): 859–74.
- Lee, Charles, James Myers, and Bhaskaran Swaminathan. 1999. "What Is the Intrinsic Value of the Dow?" *J. Finance* 54 (5): 1693–741.
- Lettau, Martin, and Sydney Ludvigson. 2001. "Consumption, Aggregate Wealth, and Expected Stock Returns." *J. Finance* 56 (3): 815–49.
- L'Huillier, Jean-Paul, Sanjay Singh, and Donghoon Yoo. 2023. "Incorporating Diagnostic Expectations into the New Keynesian Framework." *Rev. Econ. Studies*, forthcoming.
- Mankiw, N. Gregory, and Ricardo Reis. 2002. "Sticky Information versus Sticky Prices: A Proposal to Replace the New Keynesian Phillips Curve." *Q.J.E.* 117 (4): 1295–328.
- Martin, Ian. 2017. "What Is the Expected Return on the Market?" *Q.J.E.* 132 (1): 367–433.
- Nagel, Stefan, and Zhengyang Xu. 2022. "Asset Pricing with Fading Memory." *Rev. Financial Studies* 35 (5): 2190–245.
- Newey, Whitney, and Kenneth West. 1987. "A Simple, Positive Semi-definite Heteroscedasticity and Autocorrelation Consistent Covariance Matrix." *Econometrica* 55 (3): 703–8.
- Rietz, Thomas. 1988. "The Equity Risk Premium: A Solution." *J. Monetary Econ.* 22 (1): 117–31.
- Shiller, Robert. 2000. *Irrational Exuberance*. Princeton, NJ: Princeton Univ. Press.
- Sims, Christopher. 2003. "Implications of Rational Inattention." *J. Monetary Econ.* 50 (3): 665–90.
- Stambaugh, Robert F. 1999. "Predictive Regressions." *J. Financial Econ.* 54 (3): 375–421.
- Weber, Michael. 2018. "Cash Flow Duration and the Term Structure of Equity Returns." *J. Financial Econ.* 128 (3): 486–503.
- Woodford, Michael. 2003. "Imperfect Common Knowledge and the Effects of Monetary Policy." In *Knowledge, Information, and Expectations in Modern Macroeconomics: In Honor of Edmund S. Phelps*, edited by Philippe Aghion, Roman Frydman, Joseph Stiglitz, and Michael Woodford, 25–58. Princeton, NJ: Princeton Univ. Press.