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# Long-Term Expectations and Aggregate Fluctuations

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## I. Introduction

The stock market is volatile, as is aggregate economic activity, and the two are connected. At least since Burns and Mitchell (1938), we know that measures of investment and production rise and then fall together across sectors, a phenomenon called the "business cycle." We also know that the aggregate stock market is extremely volatile (LeRoy and Porter 1981; Shiller 1981). Importantly, financial and real volatility are connected: Burns and Mitchell (1938) included the S&P 500 as a leading indicator of gross domestic product (GDP) growth, and subsequent work confirmed that higher stock returns today predict higher future aggregate activity (Merton 1980; Stock and Watson 2003; Backus, Routledge, and Zin 2009).

What drives these patterns? Business cycles are typically traced to the rational response of firms and households to persistent "fundamental" shocks to technology, demand, taxes, and so forth (Ramey 2016). For instance, a positive productivity shock increases current output and rational expectations about future productivity. Households then consume more, and firms hire more labor and invest. An aggregate expansion follows, which gradually reverts as the productivity shock dies out. In principle, such shocks could explain stock market volatility, because stocks are just claims on firms' fluctuating profits. In practice, they do not. Shiller (1981) famously documented an "excess volatility" puzzle: measures of current and rationally expected corporate dividends or earnings are too

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stable to account for stock price movements. What drives excess stock price volatility, then? And, going back to the business cycle, does the driver of stock market volatility also affect real activity?

Conventional macro-finance theory addresses these questions by maintaining rational expectations while allowing for variation in investors' required returns, due to changing price or quantity of risk (e.g., Campbell and Cochrane 1999; Barro 2009; Bansal, Kiku, and Yaron 2010). This approach delivers financial and real volatility but is hard to test directly because time-varying risk preferences are difficult to measure. Also, these theories rely on a variation in expected returns that is counterfactual compared with survey measures. In this paper, we follow a different route: we keep required returns constant but allow expectations to be nonrational. Key to our strategy is the use of data on stock analysts' consensus expectations of the earnings growth of S&P 500 firms. One measure turns out to be critical: the analysts' forecast of a firm's long-term earnings growth (LTG), which captures expectations of fundamentals over a 3-to-5-year horizon. Our main variable is the consensus LTG forecast, aggregated across firms in the S&P 500 index.

In the *General Theory* (1936), Keynes stressed the centrality of expectations of long-term profits, also referred to as "animal spirits." Changing business conditions, he argued, could cause excessive changes in these expectations. In good times, the long-term beliefs can be too optimistic, causing a boom in asset prices and real investment, and conversely in bad times. This mechanism can help reconcile excess financial and real volatility, because beliefs about the long term amplify shocks. We use the data on LTG to ask three questions. First, can expectations of earnings growth account for Shiller's excess volatility puzzle and for variation in other business cycle predictors such as interest rates and credit spreads? Second, can such expectations also shed light on the dynamics of real investment, and of other business cycle indicators, including investment shocks? Third, and crucially, what is the role of the nonrationality, measured by analysts' predictable forecast errors?

Starting with Shiller's excess volatility puzzle, in Section II we show that the present value of short- and long-term expected earnings for S&P 500 firms, computed using a constant required return, fully explains observed stock market fluctuations in our sample, 1980–2022. LTG "does the job" because it departs from rationality in a precise way: it is excessively volatile relative to the realized subsequent earnings growth. When LTG is high relative to historical standards, analyst forecasts of short- and long-term profits are systematically disappointed in the future, inconsistent with rationality. High LTG also correlates with higher survey expectations of stock returns, in contrast with standard theories, in which investors expect low returns in good times. High LTG thus proxies for excess optimism: it points to investors being too bullish about future profits and stock returns.

In Section III, we show that the explanatory power of LTG reaches beyond the stock market: higher LTG predicts near-term increases and long-term declines in short- and long-term interest rates, and the reverse pattern for credit spreads. The connection between LTG and the financial cycle is strong: in our local projections (Jorda 2005) we control for, among other things, 12 quarterly lags of the dependent variable, allowing for a very rich pattern of "fundamental" mean reversion. This evidence offers additional support to the hypothesis that boom-bust dynamics in nonrational expectations about the long term act as an important driver of the volatility of key asset prices.

In Section IV, we connect LTG to real activity. Using local projections again, we show that—consistent with Keynes's view—a 1-standard-deviation increase in LTG fuels an investment boom: growth in the investment-to-capital ratio is 3% higher than conventional levels in the following year, corresponding to a 0.4-standard-deviations increase. Crucially, the investment boom sharply reverts 2 years later, and that reversal is fully explained by the predictable disappointment of the initially high LTG. Excess volatility in expectations may thus drive significant investment fluctuations, with overoptimism breeding excessive investment in the short-run and a long-run correction. We confirm this link at the firm level, controlling for any aggregate shocks, including to required returns.

Finally, we connect LTG to conventional business cycle analysis (Sec. V). We show that, in the short term, higher LTG acts like a positive shock: it predicts growth in consumption, employment, and wages. Importantly, though, LTG also predicts a longer-term reversal in these variables. Granger causality tests support the hypothesis that the link goes from LTG to the macroeconomy rather than the other way around. In sum, a directly measured and clearly interpretable variable—changes in the long-term profit expectations of individual firms—predicts aggregate boom-bust comovement among macro variables as well as with financial variables.

As a final exercise, we link LTG to a shock that directly maps to investment volatility, capturing Keynes's notion of the "marginal efficiency of investment" (MEI), the ease with which investment is transformed into capital. Building on Greenwood, Hercowitz, and Huffman (1988), Justiniano, Primiceri, and Tambalotti (2011) estimate shocks to MEI in a dynamic stochastic general equilibrium (DSGE) model and show that they account for 60%–85% of US business cycle fluctuations. We find that higher LTG is positively correlated with contemporaneous MEI shocks, but it predicts negative MEI shocks in the future. This suggests that estimated shocks may partly capture predictable disappointment of excess optimism.

In sum, LTG emerges as a "miracle" variable that, based on a clear theoretical foundation: (i) helps account for the volatility of equities and of safe and risky bonds, (ii) helps explain boom-bust cycles in economic activity, and (iii) does so through predictable disappointment of optimism (as in Minsky 1977). It is challenging to produce business cycle comovement in rational expectations models (Jaimovich and Rebelo 2009). Recent work remedies this problem using shocks that comove with credit spreads or the stock market, such as MEI itself or "risk shocks" (Christiano, Motto, and Rostagno 2014). These shocks, estimated in DSGE models, are engineered to account for large business cycle variation, but they often do not admit a clear economic interpretation. Overreaction in expectations of long-term profits is an intuitive and interpretable source of comovement, and it jointly accounts for changes in the desire to invest and in financial markets' desire to lend. Although we cannot prove that excess volatility in beliefs is the cause of investment cycles, the data indicate that this possibility must be seriously considered, if not adopted as a working hypothesis.

We contribute to two large literatures. The first is recent behavioral work combining expectations and asset price data. Earlier work studied expectations of stock returns and found that they are extrapolative, rather than rational (Bacchetta, Mertens, and Wincoop 2009; Amromin and Sharpe 2014; Greenwood and Shleifer 2014; Barberis et al. 2015, 2018; Giglio et al. 2021). Expectations of bond risk premia also depart from rationality (Greenwood and Hanson 2013; Piazzesi, Salomao, and Schneider 2015; d'Arienzo 2020). Closer to our paper, a line of research studies expectations of future fundamentals, and in particular LTG. La Porta (1996) introduces LTG into finance, showing that its variation across stocks predicts stock returns. Bordalo et al. (2019) account for this fact using a model of diagnostic expectations. The same authors (Bordalo et al. 2024) show, in the aggregate stock market, that LTG jointly predicts forecast errors and returns, and that systematic changes in LTG account for the predictive power of the price-dividend ratio for returns. Here we show that expectations data also resolve Shiller's excess volatility puzzle and link LTG to fluctuations in interest rates, credit spreads, and the business cycle more broadly.

The second body of work studies fluctuations in investment and economic activity. Several papers link the stock market to investment based on Tobin's Q (Fazzari, Hubbard, and Petersen 1988; Barro 1990; Lamont 2000; Morck, Shleifer, and Vishny 1990). They find that stock returns predict firm-level investment better than estimates of Q itself. Gennaioli, Ma, and Shleifer (2016) show that chief financial officer (CFO) optimism about 12-months-ahead profits spurs firm-level investment, dwarfing the role of stock returns. Here we focus on long-term expectations and connect investment to excess stock market volatility. Other papers study the role of expectations and news in the business cycle (e.g., Beaudry and Portier 2006; Lorenzoni 2009). Angeletos, Collard, and Dellas (2018, 2020) argue that the cycle reflects demand shocks unrelated to long-run total factor productivity (TFP), and they conjecture that these are due to expectations of short-run output. Their shock is estimated from a vector autoregression (VAR) and built to maximize explanatory power, but it is not easily interpretable. Our approach is conceptually related to theirs, because departures from rationality also disconnect beliefs from future TFP, but it underscores the importance and promise of using a transparent measure of expectations, LTG, which unveils a new link between nonrational overreacting beliefs and aggregate volatility.

Finally, a growing literature in macro relaxes rationality by assuming either rational inattention/frictions (Angeletos and Lian 2016, 2022, 2023; Gabaix 2019; Angeletos, Huo, and Sastry 2020), overreaction (Bianchi, Ilut, and Saijo 2023; Bordalo et al. 2023; L'Huillier, Singh, and Yoo 2023; Maxted 2023), or learning from extreme events (Kozlowski, Veldkamp, and Venkateswaran 2019, 2020). Bordalo et al. (2023) structurally estimate a real business cycle (RBC) model with diagnostic expectations using data on CFO earnings forecasts. They show that the overreaction of CFO expectations plays a quantitatively important role in driving investment at the firm level by shaping both the demand and the supply of funds. Our innovation here is to explicitly connect financial markets, which are excessively volatile relative to a clear benchmark, to recurrent economic fluctuations.

## II. Shiller's Excess Volatility Puzzle

Campbell and Shiller (1987, 1988) express the price-dividend ratio of a stock with the identity:

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

where $p_t$ is the log price at $t$, $d_t$ is its log dividend, $g_{t+1+s} = d_{t+1+s} - d_{t+s}$ is dividend growth between $t + s$ and $t + s + 1$ and $r_{t+1+s}$ is the realized stock return over the same horizon. Here, $k$ is a constant, and $\alpha = e^{pd}/(1 + e^{pd}) < 1$ depends on the average log price-dividend ratio $pd$.

In equation (1), variation in the price-dividend ratio is due to variation either in expected future dividend growth, captured by the $g_{t+1+s}$ terms, or in required returns, captured by the $r_{t+1+s}$ terms. Under rationality and a constant required return $r$, the stock price is given by:

$$p_t^R = d_t + \frac{k - r}{1 - \alpha} + \sum_{s\geq 0} \alpha^s \mathbb{E}_t(g_{t+1+s}). \tag{2}$$

Price variation comes from changes in the dividend $d_t$ and in expectations of future dividend growth. The intuition for Shiller's puzzle is that the weighted average of dividend growth on the right-hand side of equation (2) should be less volatile than realized dividend growth. But the latter has low volatility itself, so equation (2) cannot account for the large observed volatility of the observed stock price $p_t$.

To quantify this idea, Shiller constructed a proxy $p_t^*$ for the rational price in equation (2) assuming, at each $t$, perfect foresight of future dividends and a value for the rational stock price in the last sample period. We replicate the exercise over 1981–2022 using earnings, which matches our expectations data (little changes if we use dividends instead; see app. A, http://www.nber.org/data-appendix/c14860/appendix.pdf). Given the terminal realized earnings per share $D_{2022} = 66.92$, we set the terminal log stock price to $p_{2022}^* = \ln(D_{2022}/(r - g))$. This is the present discounted value of expected earnings at that time, under the assumption of constant average earnings growth $g$. We set $r = 8.75\%$, which is the average realized return over the sample period, and $g = 5.79\%$, which is also the sample average.

Given the terminal price-dividend ratio $p_{2022}^{\mathrm{RE}} - d_{2022}$, the rational proxy $p_t^*$ at earlier dates is computed backward, using at each $t < 2022$ the future realized dividend growth rates:

$$p_t^* = d_t + \frac{1 - \alpha^{T-t}}{1 - \alpha}(k - r) + \sum_{s=t}^{T} a^{s-t}(d_{s+1} - d_s) + \alpha^{T-t}(p_{2022}^* - d_{2022}), \tag{3}$$

where $\alpha = 0.9981$ (at a monthly frequency) and $k = -\log(\alpha) - (1 - \alpha)\log(1/(\alpha - 1)) = 0.0138$. Figure 1 plots the rational proxy $p_t^*$ (dotted line) against the actual stock price $p_t$ (solid line). Shiller's puzzle is the fact

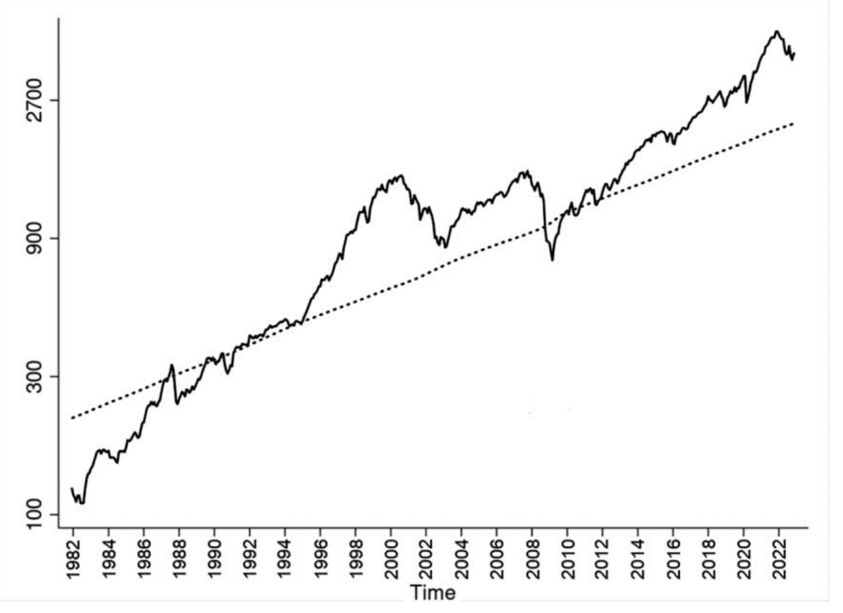


**Fig. 1.** S&P 500 versus Shiller Index $p^*$. The figure shows the log scale level of the S&P 500 index (solid line) against the log scale rational benchmark (dotted line) computed according to equation (3). A color version of this figure is available online.

that $p_t^*$ is virtually a straight line, whereas the actual stock price $p_t$ displays large boom-bust patterns, with periods of sustained over-/undervaluation compared with $p_t^*$.

Most asset pricing research since Shiller (1981) has sought to account for stock price volatility by constructing theories of investor preferences that admit variation in the price and quantity of risk. Behavioral finance has instead mostly focused on extrapolative expected returns (e.g., Barberis et al. 2015, 2018; Hirshleifer, Li, and Yu 2015, building on evidence in Bacchetta et al. 2009 and Greenwood and Shleifer 2014, among others). A smaller body of work has relaxed the assumption of rational expectations of dividends (see, e.g., De Long et al. 1990; Barsky and De Long 1993; Barberis, Shleifer, and Vishny 1998; and more recently Bordalo et al. 2019, 2024). In this approach, which we adopt here, the terms $\mathbb{E}_t(g_{t+1+s})$ in equation (2) are replaced by nonrational expectations $\tilde{\mathbb{E}}_t(g_{t+1+s})$. As long as these expectations display high volatility, stock prices will as well. We next assess this hypothesis using expectations data.

*A. Measured Expectations of Future Fundamentals*

We gather monthly data on analyst forecasts for firms in the S&P 500 index from the Institutional Brokers' Estimate System (IBES) Unadjusted US Summary Statistics file. Forecasts of dividends per share are only available starting from 2002 and for short horizons. To expand temporal coverage and to have longer-run forecasts, we construct an earnings-based price proxy that uses analyst forecasts of earnings per share. We perform a robustness exercise using forecasted dividends; see appendix A, http://www.nber.org/data-appendix/c14860/appendix.pdf.

We focus on median forecasts of a firm's earnings per share ($\mathrm{EPS}_{it}$) and of its long-term earnings growth ($\mathrm{LTG}_{it}$). IBES defines 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." $\mathrm{LTG}_t$ captures expectations of earnings growth over the business cycle, the other phenomenon of interest here. Data coverage starts in March 1976 for $\mathrm{EPS}_{it}$ and December 1981 for $\mathrm{LTG}_{it}$. We fill in missing forecasts by linearly interpolating $\mathrm{EPS}_{it}$ at horizons ranging from 1 to 5 years (in 1-year increments). Beyond the second fiscal year, we assume that analysts expect $\mathrm{EPS}_{it}$ to grow at the rate $\mathrm{LTG}_{it}$ starting with the last nonmissing positive EPS forecast.

Survey expectations refer to the individual firms that analysts follow. Following Bordalo et al. (2024), at each $t$ we aggregate the expected earnings per share of S&P 500 firms into indices of 1- and 2-years-ahead expected earnings, $\mathrm{EPS}_{t,t+1}$ and $\mathrm{EPS}_{t,t+2}$, respectively. We then aggregate the LTG expectations into an aggregate index $\mathrm{LTG}_t$. Log earnings growth 1 or 2 years ahead are computed based on $\mathrm{EPS}_{t,t+s}$. Short- and long-term expectations are volatile, as shown in figure 2. But they capture different kinds of fluctuations. Short-term expectations move mainly due to short-term mean reversion of earnings growth (e.g., these expectations are highest during the crash of 2008). LTG instead captures persistent fluctuations in the estimated growth potential. This will be important for connecting stock market and business fluctuations.

One concern is that analysts may distort their forecasts due to agency. For instance, sell-side analysts may choose to be more optimistic than buy-side ones. Such distortions are arguably stable and hence unlikely to materially affect the time-series variation in forecasts. This is especially true for S&P 500 firms, which are followed by virtually all brokerage houses, so investment banking relationships or analyst sentiment is unlikely to influence the decision to cover firms in the index.[1] Our use of

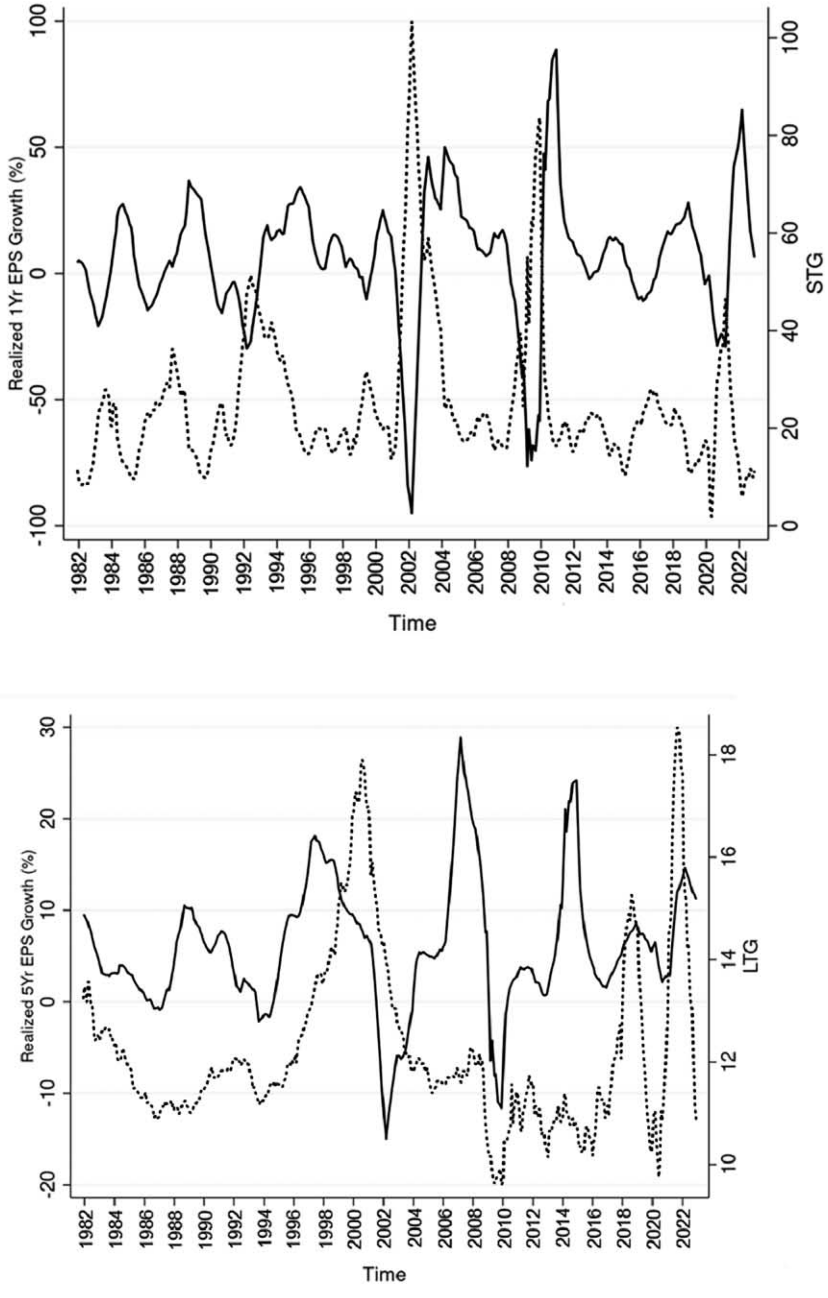


**Fig. 2.** Volatility of earnings growth and expectations. The figure plots 1-year earnings per share (EPS) growth between $t-4$ and $t$ against expectations for four-quarter earnings growth between $t$ and $t+4$ (STG, top panel) and 5-year EPS growth between $t-20$ and $t$ against expectations for 5-year earnings growth between $t$ and $t+20$ (LTG, bottom panel). Here, LTG (STG) is calculated by value weighting firm-level forecasts for expected 1-year (5-year) growth in EPS. A color version of this figure is available online.

median forecasts further reduces the impact of outliers. More broadly, strategic analyst distortions should if anything reduce the ability of LTG to capture updating of market beliefs, introducing noise. Contrary to this notion, Bordalo et al. (2019) show that LTG responds to news: firms that obtain a high LTG forecast do so after a sequence of positive surprises over 2–3 years.

Another concern is that analysts estimate expected earnings growth using stock prices themselves, while assuming constant required returns. Bordalo et al. (2024) examine this possibility extensively for their main measure of expectations, LTG, and find strong evidence against it. First, revisions in LTG are more reliably explained by past earnings growth than by past stock returns, at both aggregate and firm levels. Thus, stock price changes are not mechanically incorporated into LTG. Second, LTG predicts future stock returns at both aggregate and firm levels even after controlling for the aggregate- and the firm-level price/earnings ratio, respectively, and in fact reduces the latter's predictive power. Thus, not only is LTG not mechanically related to stock prices, but it contains genuine variation in beliefs that in turn affects prices themselves. In sum, LTG offers a valuable proxy for market beliefs about future fundamentals.

## *B. The Expectations-Based Stock Price Index*

We build an expectations-based price index $\tilde{p}_t$ by computing the earnings-based ratio:

$$\tilde{p}_t = e_t + \frac{\tilde{k} - r}{1 - \alpha} + \ln\left(\frac{\mathrm{EPS}_{t,t+1}}{\mathrm{EPS}_t}\right) + \alpha \ln\left(\frac{\mathrm{EPS}_{t,t+2}}{\mathrm{EPS}_{t,t+1}}\right) + \sum_{s=2}^{10} \alpha^s \mathrm{LTG}_t + \frac{\alpha^{10}}{1 - \alpha} g. \quad (4)$$

Here, $\alpha$ and $r$ are as before, and $\tilde{k} = k + (1 - \alpha)\mathrm{de} = 0.0123$, where de is the average log payout ratio.

The key difference with Shiller's computation is the use of expectations data. We measure expected growth between $t$ and $t + 2$ using forecasted earnings. We use $\mathrm{LTG}_t$ to capture expected earnings growth at business cycle frequencies, specifically between $t + 3$ and $t + 10$. We employ $\mathrm{LTG}_t$ up to 10 years ahead because this is the average duration of a business cycle in our data. To compute the price index, we agnostically set the expected growth rate beyond $t + 11$ to be $g = 3.73\%$. This is the value at which the average value of index $\tilde{p}_t$ matches the average stock price $p_t$ in the sample.[2] Obviously, then, success in our exercise is not judged by the extent to which average price levels match but by the extent to which time variation in our index $\widetilde{p}_t$ tracks time variation in $p_t$. We use nominal earnings, but results are robust when accounting for inflation (app. A, http://www.nber.org/data-appendix/c14860/appendix.pdf). Expectations for the very long term may also play a significant role in shaping stock prices, but, unfortunately, we do not have data about them. Imposing constant expected growth after $t + 10$ reduces our ability to account for prices, because arguably expectations of the far future also move.

Figure 3 adds our price index $\widetilde{p}_t$ to figure 1 (dashed line). The match is not perfect, but $\widetilde{p}_t$ captures low-frequency price movements remarkably well. When the actual price $p_t$ is above the rational benchmark, $p_t^*$, so is $\widetilde{p}_t$; and conversely when $p_t$ is below the benchmark. The index fails to capture the depressed market in the 1980s but does a very good job at capturing the internet bubble of the late 1990s, and the 2008 crisis. Earnings expectations suffer an excessive price drop during COVID-19, when actual earnings tanked, confirming that these beliefs are not mechanically inferred from prices.

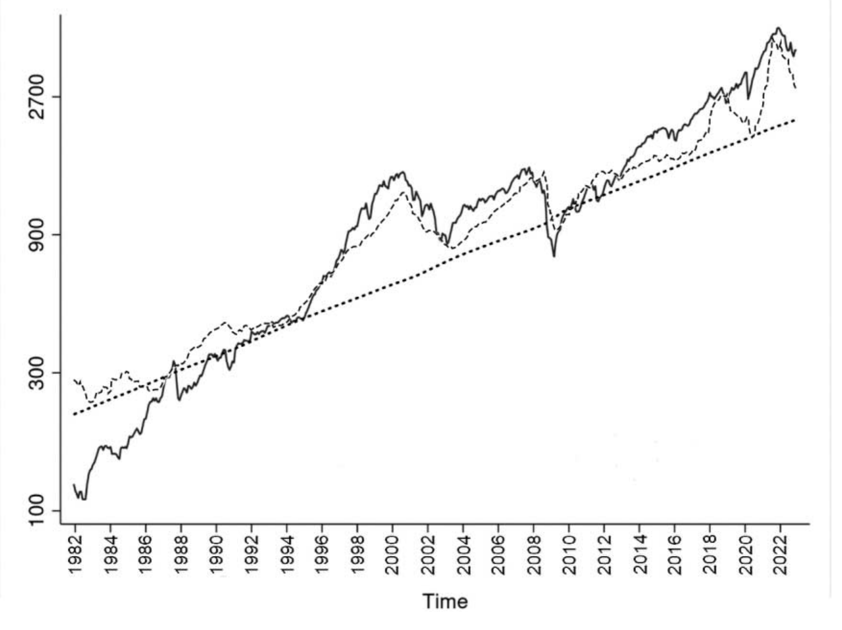


**Fig. 3.** S&P 500 versus Shiller Index $p^*$ and Expectations-Based Index $\widetilde{p}_t$. We plot in log scale the levels of the S&P 500 index (solid line), the rational benchmark index ($p_t^*$, dotted line, eq. [3]), and the price index based on earnings forecasts ($\tilde{p}_t$, dashed line, eq. [4]). A color version of this figure is available online.

To assess the quantitative ability of beliefs to deliver realistic price volatility, table 1 reports the standard deviations of 1-year changes in our index $\widetilde{p}_t$ and in the actual stock price $p_{t.}$ We also report the standard deviation of the rational price $p_t^*$. Our index delivers a realistic amount of price volatility, much higher than that obtained using the rational benchmark.

Overall, measured earnings expectations go a long way toward solving Shiller's excess volatility puzzle. Excess volatility of measured beliefs parsimoniously accounts for excess volatility in the stock market. This finding lines up with recent evidence that short-term earnings growth expectations help account for variation in the price-dividend ratio (De La O and Myers 2021).

Compared with De La O and Myers (2021), our use of LTG proves critical for explaining a large range of anomalies. Although much variation in short-term earnings expectations reflects mechanical mean reversion, LTG captures slow-moving forecasts of long-term growth opportunities. Forming beliefs about the long term is inherently more difficult and, in line with Keynes's argument, may exhibit significant departures from rationality. Because beliefs about the long term are central for investment decisions, this mechanism may help explain market movements.

Consistent with this hypothesis, Bordalo et al. (2024) show that, although short-term expectations are fairly accurate, LTG exhibits a marked departure from rationality that takes the form of overreaction, or excess volatility. That is, high LTG, as well as increases in LTG, predicts disappointment of earnings growth expectations at a 3-to-5-year horizon. This finding contradicts rationality because statistically optimal

**Table 1**
Volatility of Log Price Changes

| | Earnings Index | | |
|---|---|---|---|
| | $\Delta p$ | $\Delta p^*$ | $\Delta \tilde{p}$ |
| Variance (%) | 15.7 | .7 | 15.3 |
| Conf. interval (%) | 14.7–16.7 | .6–.7 | 14.4–16.3 |

Note: The table reports the standard deviation and 95th confidence interval of a 1-year change in (*a*) the log of the price of the S&P 500 index, $\Delta p$, (*b*) the rational benchmark index, $\Delta p^*$ (eq. [3]), and (*c*) the price index based on earnings forecasts (eq. [4]), $\Delta \tilde{p}$. The sample period is December 1982 to December 2022.

forecasts should not exhibit predictable errors using a variable, current LTG, which is in the analyst's information set. Bordalo et al. (2024) also find that high current LTG predicts future low stock returns whereas short-term earnings expectations do not, stressing the key role of long-term expectations in explaining market inefficiency.

We next further characterize LTG's nonrationality and its ability to predict financial markets. Starting with nonrationality, we first assess whether high current LTG predicts disappointment at both long and short horizons, controlling also for expectations about the short term. We also assess whether current LTG predicts current and future expectations of 12-months-ahead stock returns. These new rationality tests shed light on the link between excess financial volatility and real activity.

We use the current level of LTG to predict future errors in expectations of earnings growth, where the latter are defined as current forecast minus future realization (so high values indicate excess optimism). We consider errors over several horizons and at several points in time: rows 1–3 of table 2 concern short-term forecasts, that is, about 1-year and 2-year earnings growth, and forecasts about 5-year growth (LTG), respectively. These dependent variables are then measured both contemporaneously with $LTG_t$ and into the future at horizons $t + h$, where $h = 0, \ldots, 10$.

The results support the view that high LTG captures periods of excess aggregate optimism: it systematically predicts positive forecast errors and thus future disappointment of earnings growth expectations. Disappointment persists at least four quarters out, suggesting that LTG is a source of persistent excessive optimism, which eventually reverts. In contrast, expectations about short-term growth do not predict forecast errors (see app. A, http://www.nber.org/data-appendix/c14860/appendix.pdf). This finding strengthens the interpretation of excess stock price volatility as being due to the excess volatility of long-term beliefs. It also suggests that excess volatility of beliefs may drive volatility in real investment, because high LTG captures persistent optimism about the full-term structure of expectations, proxying for times in which the perceived returns to investment are high.

In the fourth row of table 2, we use LTG to predict current and future CFO expectations about 12-months-ahead stock returns. Higher current LTG predicts higher return expectations in the near term.[3] This evidence is also inconsistent with rational models, which predict that in good times rational investors require, and expect, lower returns. It confirms that periods of high LTG exhibit high optimism across the board, and not low required returns as the rational approach postulates.

**Table 2**
Long-Term Earnings Growth, Forecast Errors, and Expectations of Stock Returns

| | Time Horizon ($h$) of Dependent Variable (Quarters) | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
| | A. Estimates from $y_{t+h} = B_h \mathrm{LTG}_t + \varepsilon_{t+h}$ | | | | | | | | | | |
| Dependent Variable | Independent Variable: $\mathrm{LTG}_t$ | | | | | | | | | | |
| $y_{t+h} = \mathrm{STG1}_{t+h} - \Delta_4 e_{t+h+4}$ | 9.99** | 12.58** | 13.82** | 13.80** | 13.21** | 12.25** | 11.15** | 9.67** | 7.47** | 5.26* | 3.35 |
| | [2.88] | [2.53] | [2.14] | [2.09] | [2.06] | [2.03] | [2.01] | [2.11] | [2.23] | [2.36] | [2.39] |
| $y_{t+h} = \mathrm{STG2}_{t+h} - (\Delta_8 e_{t+h+8}/2)$ | 5.36** | 5.58** | 5.53** | 5.23** | 4.18* | 3.42 | 1.96 | .66 | −.36 | −1.18 | −2.12 |
| | [1.40] | [1.50] | [1.71] | [1.95] | [1.97] | [2.15] | [1.93] | [1.67] | [1.68] | [1.69] | [1.46] |
| $y_{t+h} = \mathrm{LTG}_{t+h} - (\Delta_{20} e_{t+h+20}/5)$ | 3.69** | 3.49** | 3.04** | 2.38** | 1.53+ | .58 | −.33 | −1.14 | −1.63+ | −1.81* | −1.69+ |
| | [.74] | [.74] | [.75] | [.78] | [.82] | [.86] | [.90] | [.90] | [.87] | [.85] | [.87] |
| | B. Estimates from $y_{t+h} = B_h \mathrm{LTG}_t + \boldsymbol{X}_t + \varepsilon_{t+h}$ | | | | | | | | | | |
| Dependent Variable | Independent Variable: $\mathrm{LTG}_t$ | | | | | | | | | | |
| $y_{t+h}$ = Expected 1Y S&P 500 | .36 | .61* | .45 | .43 | .34 | .25 | −.38 | −.75* | −.61* | −.19 | .09 |
| return $(\mathrm{cfo})_{t+h}$ | [.25] | [.25] | [.31] | [.34] | [.37] | [.43] | [.25] | [.28] | [.27] | [.30] | [.27] |

Note: The estimates measure the impact of a one-standard-deviation change in $\mathrm{LTG}_t$ on the dependent variable. In panel A, forecast errors $\mathrm{STG1}_{t+h} - \Delta_4 e_{t+h+4}$ are the percentage point difference in 1-year forecast growth in earnings at time $t + h$ and realized 1-year growth at $t + h + 4$. Forecast errors $\mathrm{STG2}_{t+h} - \Delta_8 e_{t+h+8}$ are the percentage point difference in 2-year forecast growth in earnings and realized 2-year growth at $t + h + 8$. Forecast errors $\mathrm{LTG}_{t+h} - \Delta_{20} e_{t+h+20}/5$ are the percentage point difference in 5-year forecast growth in earnings at $t$ and realized 5-year earnings growth at $t + h + 20$. Here, $\mathrm{LTG}_t$ is aggregate market expectation for 5-year earnings per share growth, calculated by value weighting firm-level forecasts. All regressions in panel A are unconditional. In panel B, Expected 1Y S&P 500 $(\mathrm{cfo})_{t+h}$ is the average expectation of 1-year returns on the S&P 500 of major US chief financial officers (CFOs) from the Richmond Fed's CFO survey. Controls $\boldsymbol{X}_t$ are 12 lags of the dependent variable. Heteroskedasticity-consistent standard errors reported in parentheses are computed according to Huber-White.

$^{+}p < .10$.

$^{*}p < .05$.

$^{**}p < .01$.

The finding that LTG captures waves of excess optimism and can account for stock price volatility suggests that excess volatility may be caused by nonrational fluctuations in beliefs. The predictable LTG errors in table 2 are in line with overreaction and constitute deeper departures from rationality than rational inattention, noise, or overconfidence (Bordalo et al. 2020, 2024; Bordalo, Gennaioli, and Shleifer 2022). Because belief “frictions” cause sluggish incorporation of public signals into the consensus belief and hence the macroeconomy, they cannot account for excess volatility of prices and beliefs.[4]

The key question is therefore whether the overreaction of LTG can account for macro-financial cycles. Supporting evidence comes from Bordalo et al. (2024). They show that higher LTG optimism, which is associated with high stock prices, predicts lower returns at a horizon of 3–5 years. Expectations of short-term earnings growth instead do not predict returns. In fact, Bordalo et al. (2024) show that the systematic disappointment of LTG accounts for most of the predictability of returns from the aggregate price-dividend ratio. Overreacting long-term beliefs have a strong explanatory power, so that variation in required returns may be less necessary than is commonly assumed, if at all.

We next move beyond stock market efficiency and study whether LTG helps predict movement in other financial markets and in the real economy. The next section studies how changes in LTG affect changes in interest rates and credit spreads, which have also been used to predict economic activity. We then study the role of changes in LTG on fluctuations in real investment (Sec. IV) and other business cycle indicators (Sec. V).

## III. LTG and the Financial Cycle

To link LTG to interest rates and spreads, we minimally modify a standard asset pricing model allowing for nonrational, overreacting beliefs about fundamentals. The model is standard in all other respects. This implies that it does not match unconditional phenomena such as the equity premium or the risk-free-rate puzzles. An endowment economy follows an AR(1) autoregressive process for output growth:

$$g_{t+1} = \mu g_t + v_{t+1}. \tag{5}$$

Instead, investors use an incorrect model, in which output growth follows:

$$\tilde{g}_{t+1} = \mu g_t + \omega_t + v_{t+1}, \tag{6}$$

where $\omega_t$ summarizes the time-varying belief distortions. When $\omega_t > 0$, beliefs are excessively optimistic about future growth. The belief distortion $\omega_t$—which we refer to as optimism at $t$—is persistent, and it compounds reactions to present and past news $v_{t-s}$:

$$\omega_t = \rho\omega_{t-1} + \theta v_t. \tag{7}$$

When $\theta > 0$, beliefs overreact: in equation (6), the current news $v_t$ causes beliefs about growth to shift by $(\mu + \theta)v_t$, which is larger in magnitude than the rational $\mu v_t$. If $\theta < 0$, beliefs underreact. If $\theta = 0$, expectations are rational. Equation (7) captures the two key features of LTG$_t$: its persistence and boom-bust dynamics, with periods of sustained overoptimism followed by disappointment. Bordalo et al. (2024) show that when $\theta > 0$, equations (6) and (7) are a special case of the diagnostic expectations model, in which overreaction to past shocks exhibits a geometric decay, the "distant memory" specification studied in Bianchi et al. (2023).

This formalization captures the minimal features of belief overreaction, so it misses realistic ingredients that are important to quantitatively match overreaction in the data. First, investors overreact only to tangible cash flow news $v_t$. In reality, investors may also overreact to intangible news about future prospects, such as new technologies. We provide evidence for the latter channel in Bordalo et al. (2024). Second, the model does not feature a production side, which is key for understanding and quantitatively assessing the nexus between belief overreaction and aggregate investment. This aspect is studied in Bordalo, Gennaioli, Shleifer, and Terry (2021), who build and structurally estimate an RBC model using measured CFO forecasts and show the importance of belief overreaction for credit and investment cycles.

The representative consumer has constant absolute risk aversion utility with risk aversion parameter $\gamma$. Asset prices are set according to the first-order condition:

$$\tilde{\mathbb{E}}_t[R_{t+1}B(1 + g_{t+1})^{-\gamma}] = 1, \tag{8}$$

where $B < 1$ is the rate of time preference, $g_{t+1}$ is real consumption growth (equal to the exogenous output growth in this endowment economy), and $R_{t+1}$ is the realized asset return. The equilibrium return equalizes the consumer's current and future expected marginal utility of consumption. The key difference with a standard model is that in equation (8) the expectation is taken with respect to the possibly nonrational beliefs in equation (6).

Under rational expectations, time variation in returns is entirely shaped by the intertemporal rate of substitution, $g_{t+1}^{-\gamma}$, also called the stochastic discount factor. When consumption growth $g_{t+1}$ is expected to be higher, the consumer is more affluent in the future compared with the present. Thus, they desire to consume more today, which pushes required returns up, and vice versa when consumption growth is low. Because actual consumption is fairly stable, this theory is a poor description of time variation in asset returns, which goes back to Shiller's excess volatility puzzle for stocks. The conventional fix has been to modify consumer preferences in ways that enhance the volatility in the marginal rate of substitution. Consider instead what happens when, consistent with survey expectations, we relax belief rationality. By exploiting equation (7), we can rewrite equation (8) as

$$\mathbb{E}_t[R_{t+1}B(1 + g_{t+1})^{-\gamma}M(g_{t+1}, g_t, \omega_t)] = 1. \tag{9}$$

The pricing equation under nonrational beliefs can be written as the rational pricing equation in which the new term $M(g_{t+1}, g_t, \omega_t)$ captures the investor's belief distortions. This term replaces nonstandard preferences, but crucially it is not observationally equivalent to them: shifts in beliefs can be disciplined using the expectations data.

Assuming, as is commonly done, joint lognormality of returns and fundamentals, equation (9) pins down the equilibrium risk-free rate and risk premium. These are respectively given by

$$r_{t+1}^{f} = -\log B - \frac{1}{2}\gamma^2\sigma_g^2 + \gamma(\mu g_t + \omega_t), \tag{10}$$

$$\mathbb{E}_t(r_{t+1}) - r_{t+1}^{f} = \left(\gamma - \frac{\omega_t}{\sigma_g^2}\right)\sigma_{rg}, \tag{11}$$

where $\sigma_g^2$ is the unconditional variance of consumption growth and $\sigma_{rg}$ is the covariance between the asset return and consumption.

Consider the risk-free rate in equation (10). Here the new term is $\omega_t$: during times of excessive optimism about future growth, the consumer is reluctant to save (they may actually want to borrow against future income). The risk-free rate is then higher. This yields two new predictions. Higher optimism $\omega_t$, proxied by upward revisions of $\text{LTG}_t$, should be associated with: (i) a higher current interest rate $r^f_{t+1}$ and (ii) reversal of interest rates $r^f_{t+s}$ in the future. Interest rate reversals are in part due to fundamental mean reversion in output growth (due to $\mu < 1$), but they can also be due to the disappointment of excess optimism $\omega_t$ in the future, because $\rho < 1$. The latter term is responsible for the excess volatility that a rational fundamentals-based approach cannot account for.

Consider next the risk premium in equation (11). Again, the new term here is $\omega_t$: when the consumer becomes more optimistic about future growth, the risk premium is persistently low. This yields two predictions about the time variation in returns, which mirror those for interest rates. Higher current optimism about future fundamentals, captured by upward revisions of LTG, should: (i) be associated with higher contemporaneous realized excess returns on risky assets (because upward belief revisions come with good news) and (ii) predict low average realized excess return $\mathbb{E}_t(r_{t+s}) - r^f_{t+s}$ on the same assets in the future. In Bordalo et al. (2024), we studied these predictions for stock returns, and here we test them for credit spreads: upward LTG revisions should come with low credit spreads in the near term and a predictable increase in future spreads, due to systematic future disappointment in risky bond returns (due, e.g., to higher-than-expected defaults).

We test these predictions by studying the association between the quarterly change in $\text{LTG}_t$ and three contemporaneous and future outcomes: the 1- and 10-year interest rates and the Baa credit spread. We perform quarterly local projections (Jorda 2005) using as an independent "shock" the yearly $\text{LTG}_t$ change and using as outcomes the year-on-year changes in the variables above. We start from the contemporaneous correlation between the shock and each outcome, $h = 0$, and then predict the outcome variable for future quarters $h = 1, \ldots, 10$.

Following standard practice, we control for 12 lags of the dependent variable. Among other things, this allows us to account for a rich pattern of fundamental mean reversion. We also control for 12 lags in yearly changes in the policy rate, 12 lags of yearly consumer price index (CPI) inflation, and 12 lags of the yearly log change in the S&P 500 index. These controls assuage concerns that our LTG shock may capture fundamental mean reversion, the monetary policy response, and the potentially time-varying required return embodied in stock valuations, resulting in a demanding exercise.

Table 3 reports the estimated coefficients. Consistent with equation (10), an increase in optimism is associated with contemporaneously higher short- and long-term interest rates (panels A and B). This is followed by positive predictability at short horizons $h = 1, 2, 3$ (which is at least in part mechanical due to overlapping quarters). After a period of stability, six-quarters-ahead interest rates revert and decline. This may be due to reversal of optimism about future earnings, which, again consistent with equation (10), reduces demand for funds by consumers and firms, reducing real interest rates.

The evolution of risk premia helps detect the role of systematic forecast errors. Consider panel C, which reports results for the Baa spread. Growing optimism about future earnings growth, due, for instance, to high recent growth, is associated with lower contemporaneous spreads, as captured by the negative coefficient at $h = 0$. Between three and six quarters ahead, the credit spread stabilizes. Consistent with belief overreaction, though, the credit spread eventually reverts: starting from quarter 5, the coefficient turns positive, indicating a predictable tightening of credit markets. In the model, this tightening reflects systematically disappointing future "news."

Since the 2008 financial crisis, a large body of work has used the credit spread as a barometer for financial and real activity. A lower spread is associated with an expansion of output and investment, whereas its widening is predictable and associated with economic and financial reversals (Krishnamurthy and Muir 2017; Lopez-Salido, Stein, and Zakrajsek 2017). Greenwood and Hanson (2013) show that low credit spreads predict negative excess returns on risky bonds, consistent with excess optimism at these times. Our findings offer direct evidence of this channel and underscore the importance of beliefs about LTG.

## IV. LTG and Boom-Bust Investment Cycles

The explanatory power of LTG for boom-bust financial dynamics is consistent with Keynes's view that expectations of long-term profits are an important source of volatility in financial markets. Keynes connected the same expectations, which he called animal spirits, to real activity, and in particular to firms' desire to invest. Following this insight, we next assess whether financial and business cycle volatility can be reconciled by studying the connection between LTG and real investment, both in the aggregate and at the firm levels. Relative to Gennaioli et al. (2016), who document the link between CFOs' short-term expectations of earnings growth and investment, we focus on long-term expectations, connecting investment cycles to excess financial volatility.

**Table 3**
Estimate of $\Delta_4 \text{LTG}_t$ on Asset Prices

| | $B_h$ Estimates from: $\Delta_4 y_{t+h} = B_h \Delta_4 \text{LTG}_t + \boldsymbol{X}_t + \varphi_{t+h}$ Time Horizon ($h$) of Dependent Variable | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
| | A. Dependent Variable $\Delta_4$ tbill $1\text{y}_{t+h}$ | | | | | | | | | | |
| $\Delta_4 \text{LTG}_t$ | .21** | .40** | .44** | .39** | .12 | −.19 | −.37** | −.49** | −.62** | −.74** | −.82** |
| | [.07] | [.07] | [.09] | [.12] | [.13] | [.13] | [.13] | [.12] | [.13] | [.15] | [.17] |
| $N$ | 151 | 151 | 151 | 151 | 151 | 151 | 151 | 151 | 151 | 151 | 151 |
| $\text{AR}^2$ | .85 | .66 | .48 | .25 | .17 | .24 | .33 | .38 | .35 | .30 | .24 |
| | B. Dependent Variable $\Delta_4$ tbill $10\text{y}_{t+h}$ | | | | | | | | | | |
| $\Delta_4 \text{LTG}_t$ | .18* | .35** | .41** | .40** | .16 | −.09 | −.24* | −.32** | −.32** | −.40** | −.48** |
| | [.07] | [.08] | [.08] | [.09] | [.12] | [.12] | [.10] | [.11] | [.12] | [.12] | [.13] |
| $N$ | 151 | 151 | 151 | 151 | 151 | 151 | 151 | 151 | 151 | 151 | 151 |
| $\text{AR}^2$ | .77 | .60 | .49 | .37 | .25 | .27 | .30 | .29 | .24 | .20 | .16 |

| | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | C. Dependent Variable $\Delta_4$ Baa Credit Spread $10y_{t+h}$ | | | | | | | | | | |
| $\Delta_4 LTG_t$ | $-.10$ | $-.13^{*}$ | $-.12^{+}$ | $-.08$ | .08 | $.19^{+}$ | $.23^{*}$ | $.22^{*}$ | $.19^{*}$ | $.16^{+}$ | .12 |
| | [.07] | [.06] | [.06] | [.07] | [.09] | [.11] | [.10] | [.09] | [.09] | [.09] | [.10] |
| $N$ | 151 | 151 | 151 | 151 | 151 | 151 | 151 | 151 | 151 | 151 | 151 |
| $AR^2$ | .74 | .55 | .42 | .28 | .19 | .22 | .23 | .18 | .07 | $-.03$ | $-.06$ |

Note: The estimates measure the impact of a one-standard-deviation change in $\Delta_4 LTG_t$ on the dependent variables. The set of controls $\boldsymbol{X}_t$ include 12 lags of changes in the dependent variable, 12 lags of changes in the policy interest rate, 12 lags of yearly CPI inflation, and 12 lags of the yearly S&P 500 return. Here, $\Delta_4$ tbill $1y_{t+h}$ is the four-quarter percentage point change in the Federal Reserve's 1-year Treasury bond (DGS1). Here, $\Delta_4$ tbill $10y_{t+h}$ is the four-quarter percentage point change in the Federal Reserve's 10-year Treasury bond (DGS10). Here, $\Delta_4$ Baa credit spread $10y_{t+h}$ is the four-quarter percentage point change in the yield spread between Moody's 10-year Baa bond (Baa) and the US 10-year Treasury bond (DGS10). Here, $\Delta_4 LTG_t$ is the four-quarter percentage point change in aggregate market expectation for 5-year earnings per share growth, calculated by value weighting firm-level forecasts. Heteroskedasticity-consistent standard errors reported in parentheses are computed according to Huber-White.

$^{+}p < .10$.

$^{*}p < .05$.

$^{**}p < .01$.

We estimate local projections for aggregate year-on-year change in investment, controlling for 12 lags of the dependent variable, of yearly changes in the policy interest rate, of CPI inflation, and of the yearly S&P 500 return. Our main shock is again the yearly change in $\text{LTG}_t$. The results are reported in table 4, panel A, first row. A 1-standard-deviation increase in $\text{LTG}_t$ is associated with an increase in investment that persists until four quarters later, peaking at a 3% increase in the investment-to-capital ratio in the year after the forecast, which corresponds to roughly 0.4 standard deviations of year-on-year investment growth (7.4%). Investment stabilizes for two quarters and then declines by a similar amount.

This behavior is consistent with a mechanism in which excess optimism about LTG fuels a short-run investment boom, which reverts into a bust when beliefs are disappointed and adjust downward. The boom may result from growing demand for capital by firms as well as from an outward shift in the supply of funds. The supply channel is consistent with the reduction in the credit spread documented in table 3, and also with the analysis in Bordalo, Gennaioli, Shleifer, and Terry (2021), who show in an estimated RBC model that shifts in the supply of funds play a quantitatively important role in transmitting changes in expectations to the real economy. In fact, the short-run increase in investment may be predominantly due to a relaxation of capital market "frictions" rather than to new investment plans.[5] The ability of changes in LTG to jointly shift the demand and supply of capital can help account for aggregate comovement, which is otherwise hard to explain based solely on investment shocks or news (Jaimovich and Rebelo 2009; Christiano et al. 2014).

One important question is whether the long-run investment decline estimated in table 4 is connected to the disappointment of optimistic expectations (again, this decline is unlikely to be due to fundamental mean reversion given the 12 investment lags in table 4). We add to the specification of panel A the predictable component of LTG forecast errors estimated in table 2, row 3. The idea here is to check whether times of high excess optimism, in the sense that current LTG is so high that it predictably leads to large future disappointment, predict future investment busts. The estimation results in panel B support this mechanism. Excess LTG optimism, captured by predictable disappointment, accounts for the entire future reversal in aggregate investment growth, which begins to materialize around five quarters ahead. As before, the effects are large in magnitude, with 1-standard-deviation increase in $\widehat{\text{FE}}_t$ leading to a

0.27-standard-deviation drop in investment growth 2 years later. Controlling for predictable disappointment, the current LTG shock exerts a much more benign effect: it stimulates investment in the near term, just like a good fundamental shock.

In figure 4, we take this analysis one step further to show that overoptimism at time *t*, measured by predictable forecast errors, is associated with investment that is cumulatively lower than its initial level. That is, reversals go beyond correcting for initially high investment in a mean reverting way. Instead, they predictably lead to investment 3–5 years ahead that is lower than if no shock to optimism had occurred at time *t*. This is consistent with excessive optimism at *t* causing excessive investment in the first year, leading to (i) disappointment in expectations going forward, as well as (ii) a cutback of "inefficient" investment in the subsequent years (assessing the inefficiency of this contraction is, however, beyond the scope of this paper).

One concern in the analysis is that the connection between LTG and investment dynamics may be contaminated by a few large aggregate fundamental shocks such as the collapse of the dotcom bubble or the Great Recession. To assess robustness, we estimate in table 5 the specifications of table 4 at the firm level. In this specification, the shock is the change in firm-level LTG and the proxy for overoptimism is the future forecast error of the firm's earnings growth predicted from the current firm-level LTG. Crucially, in this regression we can introduce time dummies, which control for any aggregate shock, including those potentially affecting required returns. We also add firm fixed effects, which additionally control for firm-level differences in average profitability and risk.

Column 1 shows that, just like at the aggregate level, high firm-level LTG predicts future disappointment in earnings growth. High LTG is thus a proxy for firm-level excess optimism about the long term. Columns 2–6 show that, as in the aggregate investment regressions, an upward LTG revision at the firm level is associated with high year-on-year investment in the near term, but going forward there is also a large and predictable investment decline.[6]

This section delivers a simple yet important message. Expectations of long-term growth can reconcile excess financial volatility with volatility in real investment. This is possible because long-term expectations are excessively volatile and display optimism and predictable disappointment that can jointly account for boom-bust patterns in financial markets and real investment.

**Table 4**
Estimate of $\Delta_4$LTG and Forecast Errors on Investment-to-Capital

| | Time Horizon of Dependent Variable (Quarters) | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
| | A. Estimates from $\Delta_4\text{investment-to-capital}_{t+h} = B_h \Delta_4 \text{LTG}_t + \boldsymbol{X}_t + \varepsilon_t$ | | | | | | | | | | |
| $\Delta_4\text{LTG}_t$ | .70** | 1.83** | 2.65** | 3.21** | 2.45** | .57 | −1.27 | −2.58** | −2.63** | −1.83** | −.68 |
| | [.20] | [.42] | [.50] | [.53] | [.60] | [.79] | [.81] | [.74] | [.64] | [.63] | [.60] |
| $AR^2$ | .94 | .85 | .75 | .59 | .36 | .13 | .11 | .17 | .22 | .19 | .15 |
| $N$ | 150 | 150 | 150 | 150 | 150 | 150 | 150 | 150 | 150 | 150 | 150 |
| | B. Estimates from $\Delta_4\text{investment-to-capital}_{t+h} = B_h \Delta_4 \text{LTG}_t + \delta_h \widehat{FE}_t + \boldsymbol{X}_t + \varepsilon_t$ First stage: $\text{LTG}_t - \Delta_{20} e_{t+20}/5 = \Phi \text{LTG}_t + \varepsilon_t \rightarrow \widehat{\text{FE}}_t$ | | | | | | | | | | |
| $\Delta_4\text{LTG}_t$ | .85** | 1.67** | 2.20** | 2.80** | 2.47** | $1.47^{+}$ | .55 | −.24 | −.84 | −.75 | −.24 |
| | [.31] | [.49] | [.64] | [.86] | [.89] | [.88] | [.84] | [.76] | [.69] | [.73] | [.82] |

| | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| $\widehat{\mathrm{FE}}_t$ | .13 | .30 | .29 | .07 | −.44 | −1.15* | −1.70** | −2.02** | −1.98** | −1.80** | −1.61** |
| | [.14] | [.24] | [.33] | [.43] | [.46] | [.47] | [.44] | [.39] | [.36] | [.37] | [.42] |
| $AR^2$ | .95 | .87 | .75 | .57 | .37 | .17 | .15 | .20 | .25 | .25 | .20 |
| $N$ | 138 | 138 | 138 | 138 | 138 | 138 | 138 | 138 | 138 | 138 | 138 |

Note: The estimates measure the impact of a one-standard-deviation change in $\Delta_4\mathrm{LTG}_t$ and $\widehat{\mathrm{FE}}_t$ on the four-quarter log growth in investment-to-capital, $\Delta_4$ investment-to-capital. The set of controls include 12 lags of dependent variable, 12 lags of four-quarter percentage point changes in the policy interest rate, 12 lags of yearly CPI inflation, and 12 lags of the log four-quarter S&P 500 return. Here, $\Delta_4$ investment-to-capital is the four-quarter log change in the ratio of nonresidential investment (PNFI) to the previous year's cost of capital (K1NTOTL1ES000). Here, $\Delta_4\mathrm{LTG}_t$ is the four-quarter percentage point change in aggregate market expectation for 5-year earnings per share growth, calculated by value weighting firm-level forecasts. Here, $\mathrm{FE}_t$ is defined as the difference between (*a*) aggregate market expectation for 5-year earnings per share growth, $\mathrm{LTG}_t$, and (*b*) the average annual growth in aggregate earnings per share between quarter $t$ and $t + 20$, $\Delta_{20}e_{t+20}/5$. Here, $\widehat{\mathrm{FE}}_t$ are fitted values from the regression of $\mathrm{FE}_t$ on $\mathrm{LTG}_t$. Heteroskedasticity-consistent asymptotic standard errors reported in parentheses are computed according to Huber-White.

$^{+}p < .10$.
$^{*}p < .05$.
$^{**}p < .01$.

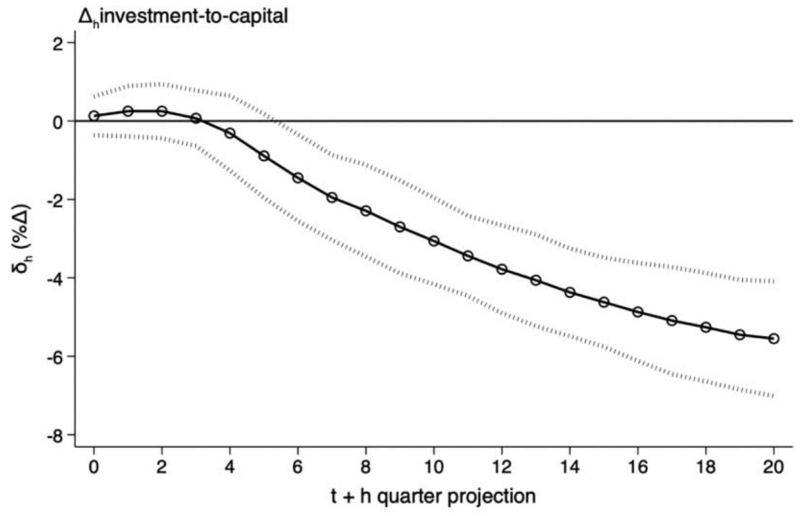


**Fig. 4.** Impulse response of cumulative investment growth to predictable forecast errors. The figure shows the cumulative impact of a one-standard-deviation change in $\widehat{\mathrm{FE}}_t$ on $\Delta_h$ investment-to-capital$_{t+h}$. The regression specification is: $\Delta_h$ investment-to-capital$_{t+h}$ = $B_h\Delta_4\mathrm{LTG}_t + \boldsymbol{\delta}_h\widehat{\mathrm{FE}}_t + \boldsymbol{X}_t + \varepsilon_{t+h}$. The set of controls include 12 lags of yearly growth in investment-to-capital$_t$, 12 lags of changes in the policy interest rate, 12 lags of yearly CPI inflation, and 12 lags of the yearly S&P 500 return. $\Delta_h$ investment-to-capital is the $h$-quarter log change in the ratio of nonresidential investment (PNFI) to the previous year's cost of capital (K1NTOTL1ES000). Here, $\mathrm{LTG}_t$ is the aggregate market expectation for 5-year earnings per share growth, calculated by value weighting firm-level forecasts. Here, $\mathrm{FE}_t$ is defined as the difference between (*a*) aggregate market expectation for 5-year earnings per share growth, $\mathrm{LTG}_t$, and (*b*) the average annual growth in earnings per share between quarter $t$ and $t + 20$, $\Delta_{20}e_{t+20}/5$. Here, $\widehat{\mathrm{FE}}_t$ are fitted values from the regression of $\mathrm{FE}_t$ on $\mathrm{LTG}_t$. Heteroskedasticity-consistent asymptotic standard errors reported in parentheses are computed according to Huber-White.

## V. LTG and the Business Cycle

We now extend our previous results to other measures of economic fluctuations. We show that LTG predicts booms and busts in other major business cycle variables, as well as in estimated shocks that are conventionally considered drivers of investment and the business cycle. Figure 5 presents the first exercise: using local projections, it compares the impulse response of investment to a one-standard-deviation upward LTG revision (as given in table 4, panel A) with the predicted responses of year-on-year growth in GDP, aggregate consumption, employment, wages, and inflation (see app. B, http://www.nber.org/data-appendix/c14860/appendix.pdf

**Table 5**
LTG and Investment at the Firm Level

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | | Estimates from: $\Delta_4 i_{i,t+h} = B_h \Delta_4 \text{LTG}_{i,t} + \delta_h \widehat{\text{FE}}_{i,t} + \varepsilon_{t+h}$ | | | | |
| | $\text{FE}_{i,t}$ | $h = 0$ | $h = 6$ | $h = 12$ | $h = 18$ | $h = 24$ |
| $\text{LTG}_{i,t}$ | .7770** | | | | | |
| | (.0477) | | | | | |
| $\Delta_4\text{LTG}_{i,t}$ | | .3134** | .2066** | .0775+ | .0544** | .0038 |
| | | (.0582) | (.0625) | (.0432) | (.0183) | (.0251) |
| $\widehat{\text{FE}}_{i,t}$ | | −.1021** | −.1218** | −.1963** | −.2081** | −.1514** |
| | | (.0195) | (.0323) | (.0384) | (.0395) | (.0375) |
| $\text{AR}^2$ | .02 | −.03 | −.03 | −.03 | −.03 | −.03 |
| $N$ | 146,151 | 133,545 | 132,166 | 131,122 | 130,213 | 129,461 |
| Firm FE | Y | Y | Y | Y | Y | Y |
| Time FE | Y | Y | Y | Y | Y | Y |

Note: We present firm-level regressions for all US firms in the Institutional Brokers' Estimate System sample. We define firm-level forecast errors as the difference between (*a*) the expected long-term growth in firm *i*'s earnings, $\text{LTG}_{i,t}$, and (*b*) the average annual growth in firm *i*'s earnings per share between quarters $t$ and $t + 20$, $\Delta_{20}e_{i,t+20}/5$. Here, $\Delta_4 i_{i,t+h}$ is the growth rate in firm *i*'s investment between quarters $t + h - 4$ and $t + h$. We define firm *i*'s investment $i_{i,t}$ as the log of $\Delta_4 K_{i,t+h}/K_{i,t+h-4}$, where firm *i*'s capital stock $K_{i,t}$ includes physical, intangible, and knowledge capital following the methodology of Peters and Taylor (2017). In column 1, we perform an ordinary least squares (OLS) regression of the error in forecasting the firm's 5-year earnings growth on $\text{LTG}_{i,t}$. In columns 2–6, we perform an OLS regression of $\Delta_4 i_{i,t+h}$ on (*a*) the forecast errors fitted in column 1 and (*b*) the 1-year revision of the forecast of firm *i*'s long-term earnings growth, $\Delta_4\text{LTG}_{i,t}$. Regressions include time and firm fixed effects (FE), which we do not report. The sample period is 1982:4–2018:1. We report Driscoll-Kraay standard errors with autocorrelation of up to 60 lags.
$^+p < .10$.
$^{**}p < .01$.

#page=10 for the corresponding table). The pattern is clear. In the short run, an upward LTG revision acts as a "good shock": it boosts all these variables. A 1-standard-deviation increase in LTG is associated with a 0.31 standard increase for GDP growth, a 0.47 standard increase for consumption, a 0.67 standard increase for employment growth, and a 0.30 standard increase for wages, as well as a 0.43 pp increase for inflation, over the course of the first year. These magnitudes are remarkable given that the impulse response already controls for many current and lagged variables.

The figure also shows that, in the long run, a current increase in LTG is associated with reversals whose magnitude is comparable with that of the initial boom. These dynamics mimic those of real investment and financial

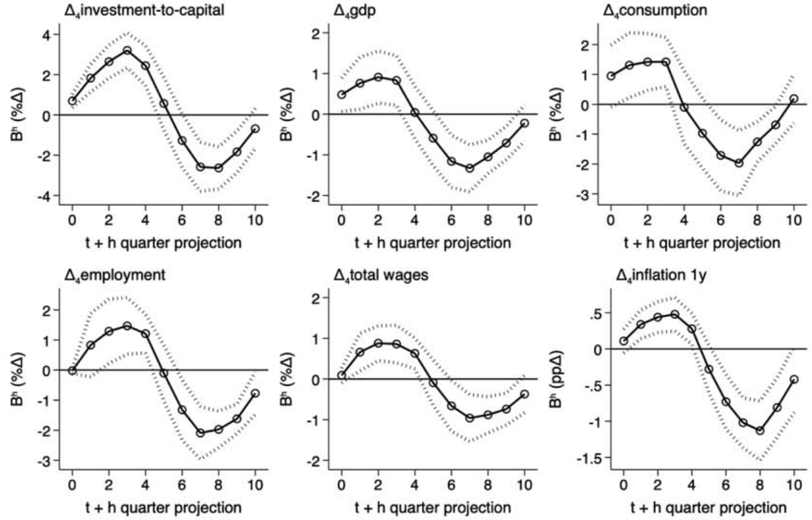


**Fig. 5.** Impulse projections of business cycle variables. The figure shows the impulse response of business cycle variables to the four-quarter percentage point change in aggregate market expectation for 5-year earnings per share growth, $\Delta_4 LTG_t$, using the local projections (Jorda 2005) method. Here, $\Delta_4$ investment-to-capital is the four-quarter log change in the ratio of nonresidential investment (PNFI) to the previous year's cost of capital (K1NTOTL1ES000). Here, $\Delta_4$ gdp is the four-quarter log change in gdp (GDP). Here, $\Delta_4$ consumption is the four-quarter log change in consumption (PCE). Here, $\Delta_4$ employment is the four-quarter log change in total employment (CE16OV). Here, $\Delta_4$ total wages is the four-quarter log change in total wage and salary disbursements (A576RC1). Here, $\Delta_4$ inflation is the four-quarter percentage point change in yearly CPI inflation (CPIAUCSL). The set of controls include 12 lags of dependent variable, 12 lags of four-quarter percentage point changes in the policy interest rate, 12 lags of yearly CPI inflation, and 12 lags of the log four-quarter S&P 500 return. A 95% confidence interval is shown, computed with Huber-White standard errors.

markets, confirming that expectations of long-term growth can reconcile financial and real volatility. To support this interpretation, and to assess endogeneity concerns, we perform a Granger causality test for each variable and LTG. The results are reported in appendix B, http://www.nber.org/data-appendix/c14860/appendix.pdf#page=10. We find that, in a Granger sense, LTG causes investment growth, GDP growth, consumption growth, employment growth, wage growth, and inflation, whereas the reverse is almost never the case, especially at four and eight quarter lags. Although this evidence is not conclusive, it indicates that LTG does not mechanically adjust to the past. It instead reflects beliefs about the future that are not yet incorporated into economic variables.

A large body of work in macroeconomics traces aggregate comovement to the transmission of shocks. These shocks are typically estimated using DSGE models or VARs with identifying restrictions (Ramey 2016). One shortcoming of this approach is that business cycle variation is often attributed to "black box" drivers, which contain statistical information but are not clearly interpretable. Being directly estimated using business cycle variables, these shocks may statistically outperform LTG. However, LTG has the important advantage of offering a source of comovement that is directly measured at the micro-level of individual firms and is clearly interpretable in terms of economic fundamentals as overreacting expectations of long-term profits. In this sense, LTG offers a useful tool to evaluate the nature of estimated shocks.

To illustrate this idea, we conclude by connecting LTG to estimated shocks to the MEI, which are also viewed as key drivers of investment and business cycle volatility. Justiniano et al. (2011) estimate this shock using a canonical DSGE model and find that it accounts for 60%–85% of US postwar fluctuations in GDP growth, hours, and investment. Keynes coined the term "marginal efficiency of investment" to describe firms' propensity to invest and saw it as driven by two factors: the ease of credit and "the state of long-term expectations" or "animal spirits." In Keynes's view, fluctuations in MEI played a key role in the finance and investment-business cycle nexus. Justiniano et al. (2011) formalize MEI as the productivity with which investment goods are transformed into capital. Remarkably, they show that MEI is high during times in which ease of financing is high, as measured by low credit spreads.

What is the correlation between LTG and contemporaneous macroeconomic shocks typically associated with investment? And can LTG help predict future realizations of these shocks? If beliefs amplify macroeconomic volatility, we would expect that current optimism is associated with good recent shocks. At the same time, because the volatility of expectations is excessive and current optimism predicts future disappointment, optimism may help predict bad shocks in the future. This logic connects shocks to MEI to its long-term expectations component, LTG. Keynes also stressed financial factors, but, due to its explanatory power for financial markets, LTG may also subsume part of that channel. That is, changes in LTG can affect MEI by not only directly increasing entrepreneurs' desire to invest (the demand for credit) but also indirectly, by increasing lenders' optimism (the supply of credit). To assess whether this is the case, we predict current and future MEI shocks using (i) the current LTG revision (a "good news" effect), (ii) current LTG overoptimism (i.e., predictable future disappointment), and (iii) credit spreads, to account for an impact of financial markets on MEI that is independent of LTG.

Table 6 reports the results. As in our previous analysis, upward LTG revisions appear as good shocks: they positively correlate with MEI in the short term. However, high LTG optimism is associated with bad MEI shocks in the future. This is an intriguing finding: it suggests that the estimated MEI shocks do not reflect genuine bad news but rather capture systematic disappointment of excess optimism. Conditional on long-term expectations, the credit spread loses its contemporaneous explanatory power for MEI. This evidence further bolsters the possibility that long-term expectations lie at the core of the nexus between financial and real activity, acting as a driver of excess volatility in both domains, and hence as a source of aggregate comovement.

Christiano et al. (2014) use a DSGE model to estimate "risk shocks," which are shocks increasing the default probability of risky firms in a model with frictional financial markets. The authors show that these shocks, which are estimated to match real and financial volatility (in the credit spread and the stock market), outperform MEI in accounting for business cycle variation. In line with our approach, jointly accounting for real and financial volatility seems to be a key step in accounting for business cycle comovement. Like many estimated shocks, "risk shocks" are hard to directly interpret economically. Perhaps such shocks also capture changes in expectations of future profits, which can drive default risk as perceived by lenders, stock prices, and firms' investment policies, as our empirical analysis shows. In line with this possibility, in appendix B (http://www.nber.org/data-appendix/c14860/appendix.pdf#page=10), we show that a current increase in LTG optimism predicts good news shock informing markets about low risk in the near term (up to eight quarters out), but it also predicts a surprise increase in risk in the future, consistent with the possibility that the combination of anticipated and unanticipated changes in risk may capture overreaction and predictable disappointment of long-term expectations.

In sum, measured expectations of long-term profits can reconcile excess volatility in financial markets and predictable returns with the volatility of investment and the business cycle. This reconciliation is parsimonious and consistent with standard macroeconomic shocks. The key new aspect is the role of overreacting long-term expectations, which are clearly interpretable and have a strong explanatory power. Because expectations move, endogenously, with fundamentals, they act as shock

**Table 6**
Predicting MEI shocks with LTG and Credit Spreads

| | Time Horizon of Dependent Variable (Quarters) | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
| | Estimates from: $\text{mei}_{t+h} = B_h \Delta_4 \text{LTG}_t + \phi_h \text{BaaSpread}_{t+h} + \delta_h \widehat{\text{FE}}_t + \varepsilon_{t+h}$ No Controls | | | | | | | | | | |
| $\Delta_4\text{LTG}_t$ | .19** | .22** | .13 | .07 | .06 | .02 | .06 | −.01 | −.03 | −.05 | −.08 |
| | [.07] | [.07] | [.08] | [.07] | [.06] | [.07] | [.06] | [.07] | [.07] | [.07] | [.09] |
| $\text{BaaSpread}_{t+h}$ | .03 | .19$^+$ | .14 | .06 | .10 | −.01 | .08 | .00 | −.00 | .01 | −.03 |
| | [.11] | [.11] | [.09] | [.08] | [.09] | [.09] | [.08] | [.08] | [.07] | [.07] | [.07] |
| $\widehat{\text{FE}}_t$ | −.11* | −.15** | −.15** | −.13** | −.14** | −.11* | −.12** | −.10* | −.08$^+$ | −.08$^+$ | −.05 |
| | [.05] | [.05] | [.05] | [.05] | [.05] | [.05] | [.05] | [.05] | [.05] | [.04] | [.05] |
| $\text{AR}^2$ | .02 | .06 | .04 | .03 | .04 | .02 | .03 | .01 | .01 | .01 | .00 |
| $N$ | 95 | 95 | 95 | 95 | 95 | 95 | 95 | 95 | 95 | 95 | 95 |

Note: MEI = marginal efficiency of investment; LTG = long-term earnings growth. The estimates measure the impact of a one-standard-deviation change in $\Delta_4\text{LTG}_t$ and $\widehat{\text{FE}}_t$ on $\text{mei}_{t+h}$. The regressions are unconditional (no controls). Here, $\Delta_4\text{LTG}_t$ is the four-quarter percentage point change in aggregate market expectation for 5-year earnings per share growth, calculated by value weighting firm-level forecasts. Here, $\text{FE}_t$ is defined as the difference between (*a*) aggregate market expectation for 5-year earnings per share growth, $\text{LTG}_t$, and (*b*) the average annual growth in earnings per share between quarter $t$ and $t + 20$, $\Delta_{20}e_t - e_{t+20}/5$. Here, $\widehat{\text{FE}}_t$ are fitted values from the regression of $\text{FE}_t$ on $\text{LTG}_t$ (table 5, col. 1). Here, $\text{BaaSpread}_{t+h}$ is the yield spread between Moody's 10-year Baa bond (Baa) and the US 10-year Treasury bond (DGS10). Heteroskedasticity-consistent asymptotic standard errors reported in parentheses are computed according to Huber-White.
$^+p < .10$.
$^*p < .05$.
$^{**}p < .01$.

amplifiers. But this also implies that expectations cannot be treated as shocks: seeking innovations orthogonal to available information may capture the rational component of beliefs but risks precluding predictable expectation reversals, the central feature of overreaction. Overreacting long-term expectations, which are clearly interpretable, have a strong explanatory power, and act as shock amplifiers.

## VI. Conclusion

Using analyst expectations of LTG for individual US listed firms, we provide some evidence that the well-known connection between financial markets and the macroeconomy is due to the influence of nonrational expectations on both. In line with Keynes's intuition, long-term expectations exhibit excess volatility, which in turn correlates with movements of stock prices and returns, interest rates, and credit spreads, as well as with the cyclical behavior of investment and other real quantities. Belief overreaction arises as an important ingredient that appears both qualitatively and quantitatively important to understand volatility, particularly predictable long-term reversals. Several approaches have tried to account for these facts by changing investor preferences in ways that are hard to measure or test. We highlight the promise of a simple, measurable, and realistic ingredient: overreacting expectations as shock amplifiers.

The analysis presented here only scratches the surface of a daunting task: integrating survey data and realistic models of expectation formation into macroeconomic analysis. One challenge is to explore how, through choices of different agents, nonrational expectations affect the propagation mechanism. Doing so calls for developing theoretical macroeconomic models with overreacting beliefs in which the precise consequences of these links can be assessed. There are several recent attempts in this direction (Ilut and Schneider 2014; Angeletos, Huo, and Sastry 2020; Bordalo, Gennaioli, Shleifer, and Terry 2021; Bianchi et al. 2023; L'Huillier et al. 2023, Maxted 2023) but much remains to be done, for instance in understanding the role of beliefs for consumer demand, labor markets, or price setting.

The second open issue is to measure and study the formation of expectations about the long term. The accumulated evidence shows that expectations about fundamentals are important. But expectations about many other outcomes may play important roles. Examples include perceptions of risks (including financial, political, or climate risks), beliefs about returns to investment (including on savings and on human capital), and also second-order expectations about other investors, which were also discussed by Keynes in the *General Theory*. They have been studied under rationality, but new models of expectations open new avenues. Bordalo, Gennaioli, Kwon, and Shleifer (2021) show how diagnostic expectations about others may help account for asset price bubbles, whereas Bastianello and Fontanier (2023) consider wrong beliefs about the information used by others. Systematically measuring a rich set of expectations (and testing for their departures from rationality) will help to understand the propagation of shocks through the economy.

Finally, there is still much to learn about the formation of expectations. The overreaction in LTG appears delayed and persistent. The sluggish adjustment may come from information frictions, as discussed in Bordalo et al. (2020) and Bordalo, Gennaioli, Kwon, and Shleifer (2021). But what drives overreaction, and why is it more prevalent in expectations about the long term? Keynes (1936) argued that because the long term is so uncertain and hard to imagine, these expectations are likely to be shaped by current events, which are easily accessible. This view is consistent with research in psychology that shows more broadly that beliefs about the future are largely formed from experiences retrieved from memory on the basis of prominent cues (Bordalo, Gennaioli, Shleifer, and Terry 2021). Good times bring strong growth to mind and keep risks out of mind. This effect is stronger for longer-term expectations, where most anything can happen or be believed, whereas imagining the near term is naturally strongly anchored to the present.

The psychology of memory and attention can offer important insights in this enterprise. For instance, even irrelevant personal experiences may matter when forming beliefs about aggregate conditions, because these experiences are salient in a person's mind and can help them imagine an uncertain future. In this respect, memory-based theories of beliefs can jointly shed light on the large observed belief heterogeneity and connect it to systematic biases such as under- or overreaction of consensus expectations to specific shocks. The introduction of realistic departures from rationality in macroeconomics is not like opening Pandora's box where "anything can happen." It is part of a long quest for better microfoundations, deeper "parameters," and the ability to incorporate as well as explain a larger body of data.

## Endnotes

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1. For example, in December of 2018, 19 analysts followed the median S&P 500 firm, and 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.

2. That is, $g$ is the average of $g_t$, where the latter solves, at each $t$, the equation $p_t = e_t + (\tilde{k} - r)/(1 - \alpha) + \alpha \ln(\mathbb{E}_t^0 \mathrm{EPS}_{t,t+2}/\mathrm{EPS}_{t,t+1}) + \Sigma_{s=2}^{10} \alpha^s \, \mathrm{LTG}_t + (\alpha^{10}/(1 - \alpha) g_t$. Results are virtually identical if we let LTG decay as observed cyclically adjusted earnings.

3. Here we focus on expectations of CFOs, which are plausibly more sophisticated than the generic market participant. In the appendix, we show that LTG has a similar impact on other measures of expected returns. Moreover, a Granger causality test supports the view that LTG drives expectations of returns, not the reverse.

4. Bordalo et al. (2020) show, for a broad range of macroeconomic outcomes, that although individual forecasters often overreact, contemporaneous information frictions produce rigidity in consensus forecasts, especially at short-term horizons. Table 2 shows that periods of upward LTG revisions capture times in which overreaction occurs even at the aggregate level, leading to excess volatility in aggregate beliefs and predictable boom-bust patterns in expectations and prices (Bordalo et al. 2024).

5. It may also be the case that firm managers update expectations earlier than analysts.

6. The investment reversal in table 5 is consistent with Bordalo, Gennaioli, Shleifer, and Terry (2021), who show, at the firm level, that excess optimism about short-term growth is associated with predictably higher firm-level credit spreads and lower investment. They stress shifts in credit supply. Here we focus on long-term expectations, not on credit, which may play a role in the effects we document.

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