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ABSTRACT

In line with Keynes' intuition, volatility in the stock market and in real economic activity are linked by expectations of long term profits. We show that analysts' optimism about the long term earnings growth of S&P 500 firms is associated with a near term boom in major US financial markets, real investment, and other business cycle indicators. The same optimism however predicts disappointing earnings growth and a contraction in financial markets and real activity one to two years later. Overreaction of measured long term profit expectations emerges as a promising mechanism for reconciling Shiller's excess volatility puzzle with the business cycle.

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1 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 (e.g., 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 GDP growth, and subsequent work confirmed that higher stock returns today predict higher future aggregate activity (Merton 1980; Stock and Watson 2003; Backus et al. 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, etc. (Ramey 2016). For instance, a positive productivity shock increases current output and rational expectations about future productivity. Households then consume more, firms hire more labour 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 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 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 to survey measures. In this paper we follow a different route: we keep required returns constant but allow expectations to be non-rational. 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 three to five years horizon. Our main variable is the consensus LTG forecast, aggregated across firms in the S&P500 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 non-rationality, 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 non-rational 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' view – a one 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 over-optimism 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 (Section 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 co-movement 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' notion of the "Marginal Efficiency of Investment" (MEI), the ease which is investment is transformed into capital. Building on Greenwood et al. (1998), Justiniano et al. (2011) estimate shocks to MEI in a DSGE model and show that they account for 60 to 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 co-movement in rational expectations models (Jaimovich and Rebelo 2009). Recent work remedies this problem using shocks that co-move 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 co-movement, and it jointly accounts for changes in the desire to invest and in financial markets' desire to lend. While 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 behavioural 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, Greenwood and Shleifer 2014, Amromin and Sharpe 2014, Barberis et al 2015, 2018, Giglio et al 2021). Expectations of bond risk premia also depart from rationality (Greenwood and Hansen 2013, Piazzesi, Salomao and Schneider 2015, D'Arienzo 2021). Closer to our paper, a line of research studies expectations of future fundamentals, and in particular LTG. LaPorta (1996) introduces LTG into finance, showing that its variation across stocks predicts stock returns. Bordalo, Gennaioli, LaPorta, and Shleifer (BGLS 2019) account for this fact using a model of diagnostic expectations. The same authors (BGLS 2022) 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 (Barro 1990, Fazzari, Hubbard, and Petersen 1988, Morck et al 1990, Lamont 1990). They find that stock returns predict firm level investment better than estimates of Q itself. Gennaioli, Ma, and Shleifer (2016) show that 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 TFP, and conjecture that these are due to expectations of short run output. Their shock is estimated from a VAR and built to maximize explanatory power, but is not easily interpretable. Our approach is conceptually related to theirs, because departures from rationality also disconnect beliefs from future TFP, but underscores the importance and promise of using a transparent measure of expectations, LTG, which unveils a new link between non rational overreacting beliefs and aggregate volatility.

Finally, a growing literature in macro relaxes rationality by assuming either rational inattention/frictions (Gabaix 2019, Angeletos, Huo, and Sastry 2020, Angeletos and Lian 2016, 2022, 2023), overreaction (Bordalo, Gennaioli, Shleifer, and Terry, BGST 2023, Bianchi et al 2023, L'Huillier et al 2023, Maxted 2023), or learning from extreme events (Kozlowski, Veldkamp, Venkatesvaran 2019, 2020). BGST (2023) structurally estimate an 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.

I. 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 $t+1+1$ and r_{t+1+s} is the realized stock return over the same horizon. 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 either to variation 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 (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.

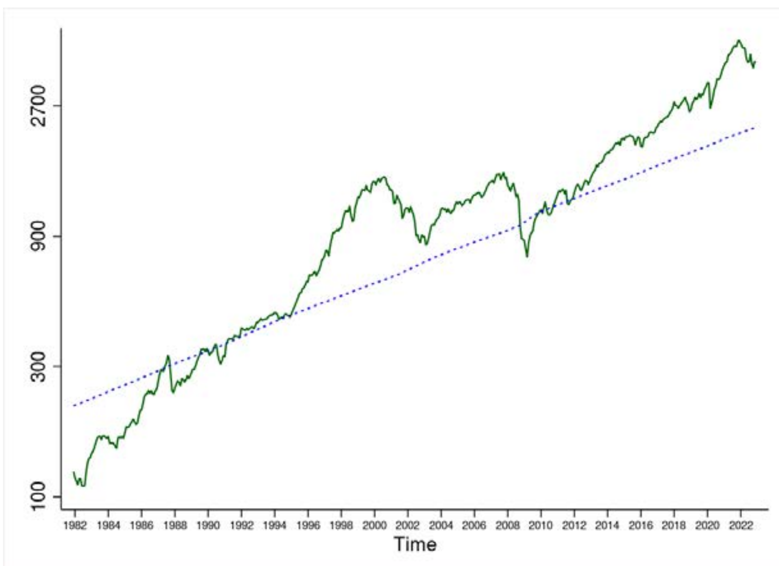
To quantify this idea, Shiller constructed a proxy p_t^* for the rational price in Equation (2) assuming, at each t, perfect foresight of future dividends and a value for the rational stock price in the last sample period. We replicate the exercise over 1981-2022 using earnings, which matches our expectations data (little changes if we use dividends instead, see Appendix A). Given the terminal realized earnings per share D_{2022}= 66.92, we set the terminal log stock price to $p_{2022}^* = \ln\left(\frac{D_{2022}}{r-g}\right)$. 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 $p_{2022}^{RE} - d_{2022}$, the rational proxy p_t^* at earlier dates is computed backwards, using at each t < 2022 the future realized dividend growth rates:

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

where α =0.9981 (at a monthly frequency) and $k = -\log(\alpha) - (1-\alpha)\log\left(\frac{1}{\alpha - 1}\right) = 0.0138$. Figure 1 plots the rational proxy p_t^* (blue) against the actual stock price p_t (green). Shiller's puzzle is the fact that p_t^* is virtually a straight line, while the actual stock price p_t displays large boom-bust patterns around it, with periods of sustained over/undervaluation compared to p_t^*.

Figure 1: SP500 vs Shiller Index p^*



Note: The figure shows the log scale level of the SP500 index (green line) against the log scale rational benchmark (blue line) computed according to equation (3).

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, Mertens, and Wincoop 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., DeLong et al 1990, Barsky and DeLong 1993, and Barberis et al. 1998), and more recently BGLS (2019, 2022). In this approach, which we adopt here, the terms $\mathbb{E}_t(g_{t+1+s})$ in Equation (2) are replaced by non-rational expectations $\widetilde{\mathbb{E}}_t(g_{t+1+s})$. As long as these expectations display high volatility, stock prices will as well. We next assess this hypothesis using expectations data.

II.1 Measured Expectations of Future Fundamentals

We gather monthly data on analyst forecasts for firms in the S&P500 index from the 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.

We focus on median forecasts of a firm's earnings per share (EPS_{it}) and of its long-term earnings growth (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." LTG_t captures expectations of earnings growth over the business cycle, the other phenomenon of interest here. Data coverage starts on 3/1976 for EPS_{it} and 12/1981 for LTG_{it}. We fill in missing forecasts by linearly interpolating EPS_{it} at horizons ranging from 1 to 5 years (in one-year increments). Beyond the second fiscal year we assume that analysts expect EPS_{it} to grow at the rate LTG_{it} starting with the last non-missing positive EPS forecast.

Survey expectations refer to the individual firms that analysts follow. Following BGLS (2022), at each t we aggregate the expected earnings per share of S&P 500 firms into indices of one- and two-year ahead expected earnings, $EPS_{t,t+1}$ and $EPS_{t,t+2}$, respectively. We then aggregate the long-term earnings growth expectations into an aggregate index LTG_t. Log earnings growth one or two years ahead are computed based on $EPS_{t,t+s}$. 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.

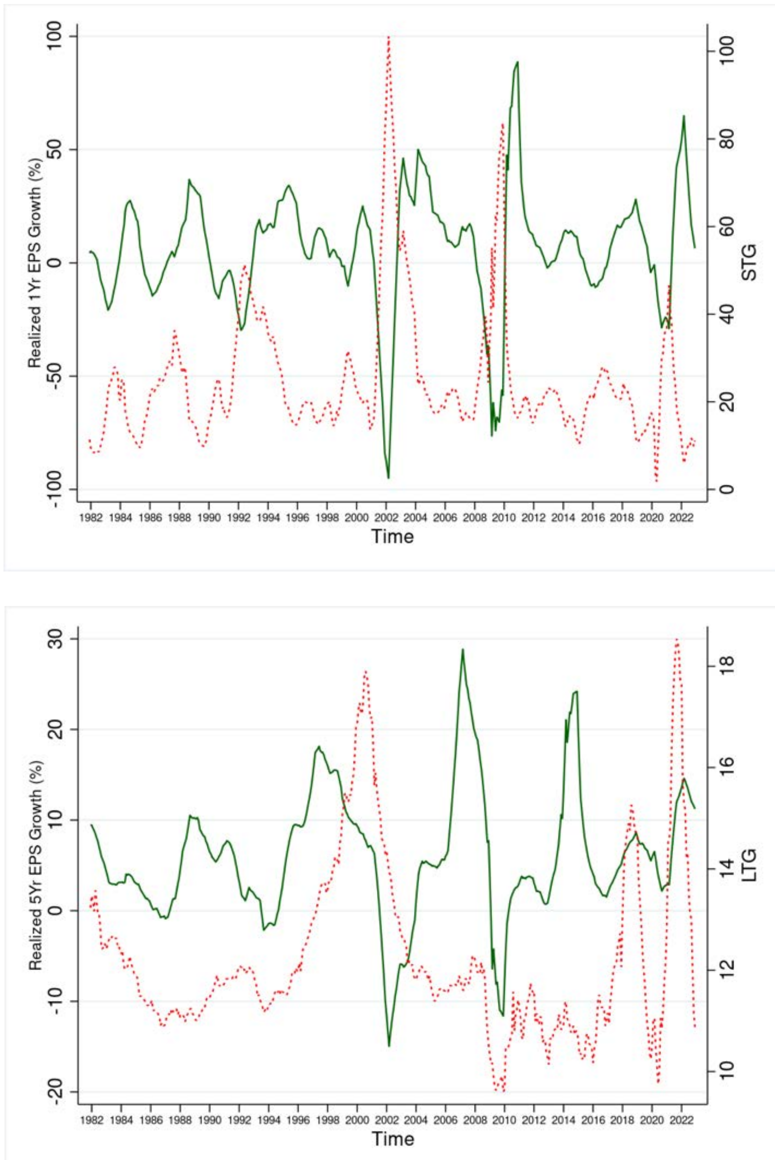
One concern is that analysts may distort their forecasts due to agency. For instance, sell-side analysists may choose to be more optimistic than buy-side ones. Such distortions are arguably stable and hence unlikely to materially affect the time series variation in forecasts. This is especially true for S&P 500 firms, which are followed by virtually all brokerage houses, so investment banking relationships or analyst sentiment are unlikely to influence the decision to cover firms in the index.[2] Our use of 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, BGLS (2019) show that LTG responds to news: firms that obtain a high LTG forecast do so after a sequence of positive surprises over two to three years.

Another concern is that analysts estimate expected earnings growth using stock prices themselves, while assuming constant required returns. BGLS (2022) 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 level. Thus, stock price changes are not mechanically incorporated into LTG. Second, LTG predicts future stock returns at both aggregate and firm-level 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

[2] For example, in December of 2018, nineteen analysts followed the median SP500 firm, while four analysts followed the median firm not in SP500. Analysts are also less likely to rate as "buy" firms in the SP500 index.

genuine variation in beliefs that in turn affects prices themselves. In sum, LTG offers a valuable proxy for market beliefs about future fundamentals.

Figure 2: Volatility of Earnings Growth and Expectations



Note: The figure plots 1-year earnings per share growth between $t-4$ and t against expectations for 4-quarter earnings growth between t and $t+4$ (STG, top panel) and 5-year earnings per share growth between $t-20$ and t against expectations for 5-year earnings growth between t and $t+20$ (LTG, bottom panel). LTG (resp. STG) is calculated by value weighting firm level forecasts for expected 1-year (resp. 5-year) growth in earnings per share.

II.2 The Expectations Based Stock Price Index

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

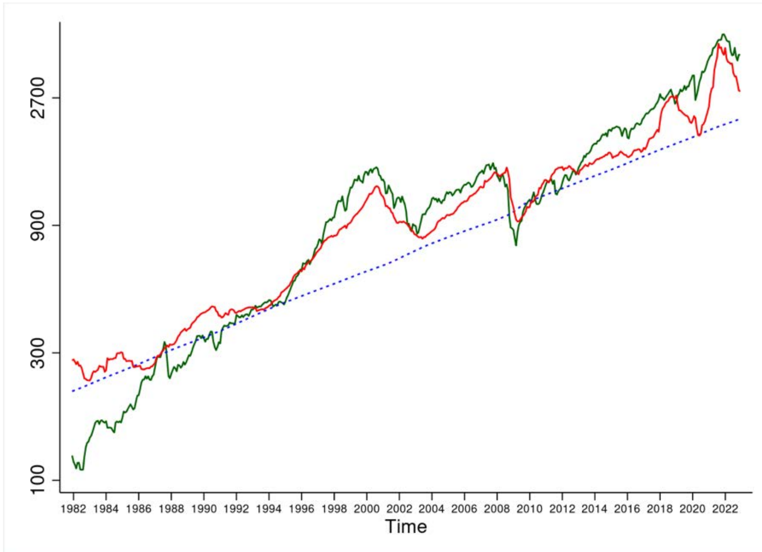
$$\tilde{p}_t = e_t + \frac{\tilde{k} - r}{1 - \alpha} + \ln\left(\frac{EPS_{t,t+1}}{EPS_t}\right) + \alpha \ln\left(\frac{EPS_{t,t+2}}{EPS_{t,t+1}}\right) + \sum_{s=2}^{10} \alpha^s \, LTG_t + \frac{\alpha^{10}}{1 - \alpha} \, g. \tag{4}$$

α and r are as before, and $\tilde{k} = k + (1 - \alpha) \, de = 0.0123$, 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 LTG_t to capture expected earnings growth at business cycle frequencies, specifically between $t + 3$ and $t + 10$. We employ 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 $\widetilde{p_t}$ matches the average stock price p_t in the sample.[3] 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 (Appendix A). 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.

[3] That is, g is the average of g_t, where the latter solves, at each t, the equation $p_t = e_t + \frac{\tilde{k}-r}{1-\alpha} + \alpha ln\left(\frac{\mathbb{E}_t^0 EPS_{t,t+2}}{\mathbb{E}_t^0 EPS_{t,t+1}}\right) + \sum_{s=2}^{10} \alpha^s \, LTG_t + \frac{\alpha^{10}}{1-\alpha} g_t$. Results are virtually identical if let LTG decay as observed cyclically adjusted earnings.

Figure 3: SP500 vs Shiller Index p^* and Expectations Based Index $\widetilde{p_t}$



Note: We plot in log scale the levels of the SP500 index (green line), the rational benchmark index (p^*_t, blue line, equation 3), and the price index based on earnings forecasts ($\tilde{p}_t$ red line, Equation 4).

Figure 3 adds our price index $\widetilde{p_t}$ to Figure 1 (red 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 80s 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, when actual earnings tanked, confirming that these beliefs are not mechanically inferred from prices.

To assess the quantitative ability of beliefs to deliver realistic price volatility, Table 1 reports the standard deviations of one-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 very realistic amount of price volatility, much higher than that obtained using the rational benchmark.

Table 1: Volatility of Log Price Changes

	Earnings Index		
	Δp	Δp^*	$\Delta \tilde{p}$
Variance	15.7%	0.7%	15.3%
Conf. interval	14.7-16.7%	0.6-0.7%	14.4-16.3%

Note: The table reports the standard deviation and 95th confidence interval of one-year change in: (a) the log of the price of the S&P500 index, Δp, (b) the rational benchmark index, Δp^* (equation 3), and (c) the price index based on earnings forecasts (equation 4), $\Delta \tilde{p}$. The sample period is 12/1982 to 12/2022.

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 to De La O and Myers (2021), our use of LTG proves critical for explaining a large range of anomalies. While much variation in short term earnings expectations reflects mechanical mean reversion, as already discussed, 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' 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, BGLS (2022) show that, while 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, predict disappointment of earnings growth expectations at a 3 to 5 year horizon. This finding contradicts rationality because statistically optimal forecasts should not exhibit predictable errors using a variable, current LTG, which is in the analyst's information set. BGLS (2022) also find that high current LTG predicts future low stock returns while short term earnings expectations do not, stressing the key role of long term expectations in explaining market inefficiency.

We next further characterize LTG's non rationality and its ability to predict financial markets. Starting with non-rationality, 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 month 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 to 3 of Table 2 concern short term forecasts, i.e. 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 $h = 0, \dots 10$.

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 Appendix A). This finding strengthens the interpretation of excess sock 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 twelve months ahead stock returns. Higher current LTG predicts higher return expectations in the near term.[4] 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. LTG, 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
Dependent Variable	Panel B: Estimates From $y_{t+h} = B_h LTG_t + \varepsilon_{t+h}$ Independent Variable: LTG_t										
$y_{t+h} = STG1_{t+h} - \Delta_4 e_{t+h+4}$	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]
$y_{t+h} = STG2_{t+h} - \Delta_8 e_{t+h+8}/2$	5.36***	5.58***	5.53***	5.23***	4.18**	3.42	1.96	0.66	-0.36	-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]
$y_{t+h} = LTG_{t+h} - \Delta_{20} e_{t+h+20}/5$	3.69***	3.49***	3.04***	2.38***	1.53*	0.58	-0.33	-1.14	-1.63*	-1.81**	-1.69*
	[0.74]	[0.74]	[0.75]	[0.78]	[0.82]	[0.86]	[0.90]	[0.90]	[0.87]	[0.85]	[0.87]
Dependent Variable	Panel B: Estimates From $y_{t+h} = B_h LTG_t + \boldsymbol{X}_t + \varepsilon_{t+h}$ Independent Variable: LTG_t										
$y_{t+h} = Expected\ 1Y\ sp500$ $return\ (cfo)_{t+h}$	0.36	0.61**	0.45	0.43	0.34	0.25	-0.38	-0.75**	-0.61**	-0.19	0.09
	[0.25]	[0.25]	[0.31]	[0.34]	[0.37]	[0.43]	[0.25]	[0.28]	[0.27]	[0.30]	[0.27]

Note: The estimates measure the impact of a 1 standard deviation change in LTG_t on the dependent variable. Panel A: forecast errors $STG1_{t+h} - \Delta_4 e_{t+h+4}$ are the percentage point difference in 1 year forecasted growth in earnings at time $t + h$ and realized 1 year growth at $t + h + 4$. Forecast errors $STG2_{t+h} - \Delta_8 e_{t+h+8}$ are the percentage point difference in 2 year forecasted growth in earnings and realized 2-year growth at $t + h + 8$. Forecast errors $LTG_{t+h} - \Delta_{20} e_{t+h+20}/5$ is the percentage point difference in 5 year forecasted growth in earnings at t and realized 5-year earnings growth at $t + h + 20$. 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, $Expected\ 1Y\ sp500\ return\ (cfo)_{t+h}$ is the average expectation of 1-year returns on the SP500 of major US 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. Superscripts: *** significant at the 1% level, ** significant at the 5% level, and * significant at the 10% level.

[4] 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.

The finding that LTG captures waves of excess optimism and can account for stock price volatility suggests that excess volatility may be caused by non-rational 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, Gennaioli, Ma, and Shleifer 2020, Bordalo, Gennaioli, and Shleifer 2022, and BGLS 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.[5]

The key question is therefore whether the overreaction of LTG can account for macro-financial cycles. Supporting evidence comes from BGLS (2022). They show that higher LTG optimism, which is associated with high stock prices, predicts lower returns at a horizon of 3 to 5 years. Expectations of short-term earnings growth instead do not predict returns. In fact, BGLS (2022) show that the systematic disappointment of LTG accounts for most of the predictability of returns from the aggregate price to 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 (Section IV) and other business cycle indicators (Section V).

[5] Bordalo Gennaioli Ma and Shleifer (2020) show, for a broad range of macroeconomic outcomes, that while 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 (BGLS 2022).

III. LTG and the Financial Cycle

To link LTG to interest rates and spreads, we minimally modify a standard asset pricing model allowing for non-rational, 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) 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 ω_t summarizes the time-varying belief distortions. When $\omega_t > 0$ beliefs are excessively optimistic about future growth. The belief distortion ω_t – which we refer to as optimism at t – is persistent, and 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 μv_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 over-optimism followed by disappointment. BGLS (2022) 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, Ilut and Saijo (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 BGLS (2022). 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 BGST (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 CARA utility with risk aversion parameter γ. Asset prices are set according to the first order condition:

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

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 (8) the expectation is taken with respect to the possibly non-rational 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 to the present. Thus, he desires to consume more today, which pushes required returns up. 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 non-rational 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:

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

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

where σ_g^2 is the unconditional variance of consumption growth and σ_{rg} is the covariance between the asset return and consumption.

Consider the risk free rate in Equation (10). Here the new term is ω_t: during times of excessive optimism about future growth, the consumer is reluctant to save (he may actually want to borrow against future income). The risk-free rate is then higher. This yields two new predictions. Higher optimism ω_t, proxied by upward revisions of LTG_t, should be associated with: i) a higher current interest rate r_{t+1}^{f} , and ii) reversal of interest rates r_{t+s}^{f} in the future. Interest rate reversals are in part due to fundamental mean reversion in output growth (due to μ < 1) but they can also be due to the disappointment of excess optimism ω_t in the future, since $\rho < 1$. 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 ω_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 $\mathbb{E}_t(r_{t+s}) - r_{t+s}^{f}$ on the same assets in the future. In BGLS (2022) 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 for instance to higher than expected defaults).

We test these predictions by studying the association between the quarterly change in LTG_t and three contemporaneous and future outcomes: the one and the ten years interest rate, and the Baa credit spread. We perform quarterly local projections (Jorda, 2005) using as independent "shock" the yearly 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, ...10.

Following standard practice, we control for twelve 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 twelve lags in yearly changes in the policy rate, 12 lags of yearly cpi inflation, and twelve lags of the yearly log change in the SP 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 (10), reduces demand for funds by consumers and firms, reducing real interest rates.

Table 3: Estimate Of $\Delta_4 LTG_t$ On Asset Prices

	B_h Estimates From: $\Delta_4 y_{t+h} = B_h \Delta_4 LTG_t + \boldsymbol{X}_t + \varphi_{t+h}$ Time Horizon (h) of Dependent variable										
	0	1	2	3	4	5	6	7	8	9	10
	Panel A: dependent variable Δ_4 tbill $1y_{t+h}$										
$\Delta_4 LTG_t$	0.21***	0.40***	0.44***	0.39***	0.12	-0.19	-0.37***	-0.49***	-0.62***	-0.74***	-0.82***
	[0.07]	[0.07]	[0.09]	[0.12]	[0.13]	[0.13]	[0.13]	[0.12]	[0.13]	[0.15]	[0.17]
N	151	151	151	151	151	151	151	151	151	151	151
AR^2	0.85	0.66	0.48	0.25	0.17	0.24	0.33	0.38	0.35	0.30	0.24
	Panel B: dependent variable Δ_4 tbill $10y_{t+h}$										
$\Delta_4 LTG_t$	0.18**	0.35***	0.41***	0.40***	0.16	-0.09	-0.24**	-0.32***	-0.32***	-0.40***	-0.48***
	[0.07]	[0.08]	[0.08]	[0.09]	[0.12]	[0.12]	[0.10]	[0.11]	[0.12]	[0.12]	[0.13]
N	151	151	151	151	151	151	151	151	151	151	151
AR^2	0.77	0.60	0.49	0.37	0.25	0.27	0.30	0.29	0.24	0.20	0.16
	Panel C: dependent variable Δ_4 baa credit spread $10y_{t+h}$										
$\Delta_4 LTG_t$	-0.10	-0.13**	-0.12*	-0.08	0.08	0.19*	0.23**	0.22**	0.19**	0.16*	0.12
	[0.07]	[0.06]	[0.06]	[0.07]	[0.09]	[0.11]	[0.10]	[0.09]	[0.09]	[0.09]	[0.10]
N	151	151	151	151	151	151	151	151	151	151	151
AR^2	0.74	0.55	0.42	0.28	0.19	0.22	0.23	0.18	0.07	-0.03	-0.06

Note: the estimates measure the impact of a 1 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 SP500 return. Δ_4 tbill $1y_{t+h}$ is the 4-quarter percentage point change in the Federal Reserve's 1 year treasury bond (DGS1). Δ_4 tbill $10y_{t+h}$ is the 4-quarter percentage point change in the Federal Reserve's 10 year treasury bond (DGS10). Δ_4 baa credit spread $10y_{t+h}$ is the 4-quarter percentage point change in the percentage point change in the yield spread between Moody's 10y BAA bond (BAA) and the US 10-year Treasury Bond (DGS10). $\Delta_4 LTG_t$ is the 4-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. Superscripts: *** significant at the 1% level, ** significant at the 5% level, and * significant at the 10% level.

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, while its tightening is predictable and associated to economic and financial reversals (Lopez-Salido et al. 2017, Krishnamurthy and Muir 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 long term earnings growth.

IV. LTG and Boom-Bust Investment Cycles

The explanatory power of LTG for boom-bust financial dynamics is consistent with Keynes' 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 level. 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.

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&P500 return. Our main shock is again the yearly change in LTG. The results are reported in Table 4, Panel A, first row. A one standard deviation increase in LTG 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.

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
	Panel A: Estimates From Δ_4 investment-to-capital$_t = B_h \Delta_4 LTG_t + \boldsymbol{X}_t + \varepsilon_t$										
$\Delta_4 LTG_t$	0.70***	1.83***	2.65***	3.21***	2.45***	0.57	-1.27	-2.58***	-2.63***	-1.83***	-0.68
	[0.20]	[0.42]	[0.50]	[0.53]	[0.60]	[0.79]	[0.81]	[0.74]	[0.64]	[0.63]	[0.60]
AR^2	0.94	0.85	0.75	0.59	0.36	0.13	0.11	0.17	0.22	0.19	0.15
N	150	150	150	150	150	150	150	150	150	150	150
	Panel B: Estimates from Δ_4 investment-to-capital$_t = B_h \Delta_4 LTG_t + \delta_h \widehat{FE}_t + \boldsymbol{X}_t + \varepsilon_t$ First Stage: $LTG_t - \Delta_{20} e_{t+20}/5 = \Phi LTG_t + \varepsilon_t \rightarrow \widehat{FE}_t$										
$\Delta_4 LTG_t$	0.85***	1.67***	2.20***	2.80***	2.47***	1.47*	0.55	-0.24	-0.84	-0.75	-0.24
	[0.31]	[0.49]	[0.64]	[0.86]	[0.89]	[0.88]	[0.84]	[0.76]	[0.69]	[0.73]	[0.82]
$\widehat{FE}_t$	0.13	0.30	0.29	0.07	-0.44	-1.15**	-1.70***	-2.02***	-1.98***	-1.80***	-1.61***
	[0.14]	[0.24]	[0.33]	[0.43]	[0.46]	[0.47]	[0.44]	[0.39]	[0.36]	[0.37]	[0.42]
AR^2	0.95	0.87	0.75	0.57	0.37	0.17	0.15	0.20	0.25	0.25	0.20
N	138	138	138	138	138	138	138	138	138	138	138

Note: The estimates measure the impact of a 1 standard deviation change in $\Delta_4 LTG_t$ and $\widehat{FE}_t$ on the 4-quarter log growth in investment-to-capital, Δ_4 investment-to-capital. The set of controls include 12 lags of dependent variable, 12 lags of 4-quarter percentage point changes in the policy interest rate, 12 lags of yearly cpi inflation, and 12 lags of the log 4-quarter SP500 return. $\Delta_4$investment-to-capital is the 4-quarter log change in the ratio of non-residential investment (PNFI) to the previous year's cost of capital (K1NTOTL1ES000). $\Delta_4 LTG_t$ is the 4-quarter percentage point change in aggregate market expectation for 5-year earnings per share growth, calculated by value weighting firm level forecasts. FE_t is defined as the difference between (a) aggregate market expectation for 5-year earnings per share growth, LTG_t, and (b) the average annual growth in aggregate earnings per share between quarter t and $t+20$, $\Delta_{20}e_{t+20}/5$. $\widehat{FE}_t$ are fitted values from the regression of FE_t on LTG_t. Heteroskedasticity-consistent asymptotic standard errors reported in parentheses are computed according to Huber-White. Superscripts: *** significant at the 1% level, ** significant at the 5% level, and * significant at the 10% level.

This behaviour is consistent with a mechanism in which excess optimism about long-term earnings growth 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 BGST (2023), 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" than to new investment plans.[6] The ability of changes in LTG to jointly shift the demand and supply of capital can help account for aggregate co-movement, which is otherwise hard to explain based solely on investment shocks or news (Jaimovich and Rebelo 2009, Christiano, Motto, and Rostagno 2014).

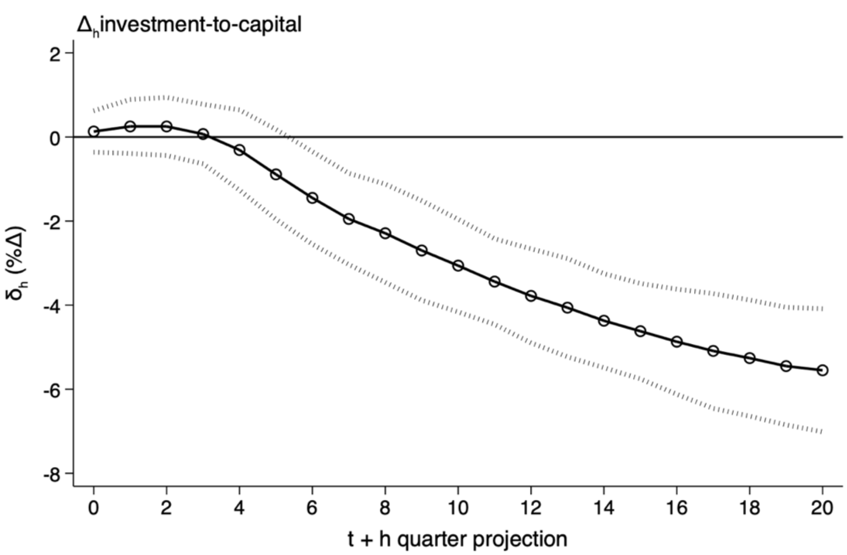
One important question is whether the long run investment decline estimated in Table 4 is connected to the disappointment of optimistic expectations (again, this decline is unlikely to be due to fundamental mean reversion given the 12 investment lags in Table 4). We add to the specification of Panel 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, predicts 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 5 quarters ahead. As before, the effects are large in magnitude, with 1 standard deviation increase in $\widehat{FE}_t$ leading to a 0.27 standard deviation drop in investment growth 2

[6] It may also be the case that firm managers update expectations earlier than analysts.

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 5, we take this analysis one step further to show that over-optimism 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 to 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).

Figure 5: Impulse Response of Cumulative Investment Growth to Predictable Forecast Errors



The figure shows the cumulative impact of a 1 standard deviation change in $\widehat{FE}_t$ on Δ_h investment-to-capital$_{t+h}$. The regressiong specification is: Δ_h investment-to-capital$_{t+h}$ = $B_h \Delta_4 LTG_t + \boldsymbol{\delta}_h \widehat{FE}_t + \boldsymbol{X}_t + \varepsilon_{t+h}$. 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 SP500 return. is the 4-quarter percentage point change in annual cpi inflation (CPIAUCSL). LTG_t is the aggregate market expectation for 5-year earnings per share growth, calculated by value weighting firm level forecasts. FE_t is defined as the difference between (a) aggregate market expectation for 5-year earnings per share growth, LTG_t, and (b) the average annual growth in earnings per share between quarter t and t+20, $\Delta_{20} e_{t+20}/5$. $\widehat{FE}_t$ are fitted values from the regression of FE_t on LTG_t. Heteroskedasticity-consistent asymptotic standard errors reported in parentheses are computed according to Huber-White. Superscripts: *** significant at the 1% level, ** significant at the 5% level, and * significant at the 10% level.

Once 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 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 over-optimism 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.[7]

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 5. LTG and Investment at the Firm Level

	(1)	(2)	(3)	(4)	(5)	(6)
	FE_{it}			Estimates From:		

[7] 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.

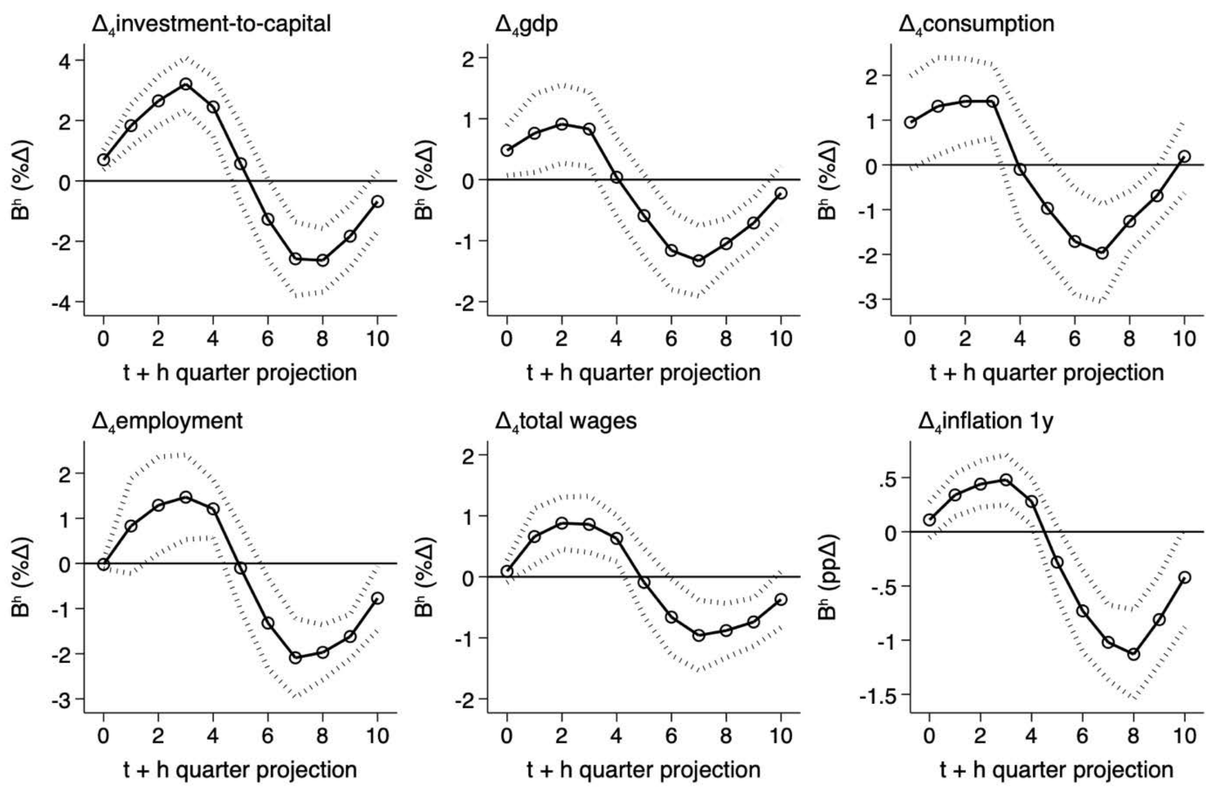
		$\Delta_4 i_{i,t+h} = B_h \Delta_4 LTG_{it} + \delta_h \widehat{FE}_{it} + \varepsilon_{t+h}$				
		$h = 0$	$h = 6$	$h = 12$	$h = 18$	$h = 24$
LTG_{it}	0.7770***					
	(0.0477)					
$\Delta_4 LTG_{it}$		0.3134***	0.2066***	0.0775*	0.0544***	0.0038
		(0.0582)	(0.0625)	(0.0432)	(0.0183)	(0.0251)
$\widehat{FE}_{it}$		-0.1021***	-0.1218***	-0.1963***	-0.2081***	-0.1514***
		(0.0195)	(0.0323)	(0.0384)	(0.0395)	(0.0375)
AR^2	0.02	-0.03	-0.03	-0.03	-0.03	-0.03
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 IBES sample. We define firm-level forecast errors as the difference between (a) the expected long-term growth in firm *i*'s earnings, $LTG_{i,t}$, and (b) the average annual growth in firm *i*'s earnings per share between quarters t and $t + 20$, $\Delta_{20} e_{i,t+20}/5$. $\Delta_4 i_{i,t+h}$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 OLS regression of the error in forecasting the firm's five-year earnings growth on $LTG_{i,t}$. 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 one-year revision of the forecast of firm *i*'s long-term earnings growth, $\Delta_4 LTG_{i,t}$. Regressions include time- and firm-fixed effects, 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. Superscripts: *** significant at the 1% level, ** significant at the 5% level, and * significant at the 10% level.

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 6 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) to the predicted responses of year on year growth in gdp, aggregate consumption, employment, wages and inflation (see Appendix B 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 one standard deviation increase in LTG is associated with a 0.31 std increase for gdp growth, a 0.47 std increase for consumption, a 0.67 std increase for employment growth, a 0.30 std increase for wages, as well as a 0.43pp 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.

Figure 6. Impulse Projections of Business Cycle Variables



Note: The figure shows the impulse response of business cycle variables to the 4-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. $\Delta_4$investment-to-capital is the 4-quarter log change in the ratio of non-residential investment (PNFI) to the previous year's cost of capital (K1NTOTL1ES000). $\Delta_4 gdp$ is the 4-quarter log change in gdp (GDP). $\Delta_4 consumption$ is the 4-quarter log change in consumption (PCE). $\Delta_4 employment$ is the 4-quarter log change in total employment (CE16OV). $\Delta_4 total\ wages$ is the 4-quarter log change in total wage and salary disbursements (A576RC1). $\Delta_4 inflation$ is the 4-quarter percentage point change in yearly cpi inflation (CPIAUCSL). The set of controls include 12 lags of dependent variable, 12 lags of 4-quarter percentage point changes in the policy interest rate, 12 lags of yearly cpi inflation, and 12 lags of the log 4-quarter SP500 return. 95% confidence interval shown, computed with Huber-White standard errors.

The Figure also shows that, in the long run, a current increase in LTG is associated with reversals whose magnitude is comparable to that of the initial boom. These dynamics mimic those of real investment and financial 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. We find that, in a Granger sense, LTG causes investment gorwth, gdp growth, consumption growth, employment growth, wage growth and inflation, while the reverse is almost never the case, especially at four and eight quarter lags. While 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 co-movement 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 co-movement 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 "Marginal Efficiency of Investment" (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 to 85% of US post-war 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' 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.

We ask: 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, since 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 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), and ii) current LTG over-optimism (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. 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: $mei_{t+h} = B_h \Delta_4 LTG_t + \emptyset_h BaaSpread_{t+h} + \delta_h \widehat{FE}_t + \varepsilon_{t+h}$ No Controls										
$\Delta_4 LTG_t$	0.19***	0.22***	0.13	0.07	0.06	0.02	0.06	-0.01	-0.03	-0.05	-0.08
	[0.07]	[0.07]	[0.08]	[0.07]	[0.06]	[0.07]	[0.06]	[0.07]	[0.07]	[0.07]	[0.09]
$BaaSpread_{t+h}$	0.03	0.19*	0.14	0.06	0.10	-0.01	0.08	0.00	-0.00	0.01	-0.03
	[0.11]	[0.11]	[0.09]	[0.08]	[0.09]	[0.09]	[0.08]	[0.08]	[0.07]	[0.07]	[0.07]

$\widehat{FE}_t$	-0.11**	-0.15***	-0.15***	-0.13***	-0.14***	-0.11**	-0.12***	-0.10**	-0.08*	-0.08*	-0.05
	[0.05]	[0.05]	[0.05]	[0.05]	[0.05]	[0.05]	[0.05]	[0.05]	[0.05]	[0.04]	[0.05]
AR^2	0.02	0.06	0.04	0.03	0.04	0.02	0.03	0.01	0.01	0.01	0.00
N	95	95	95	95	95	95	95	95	95	95	95

Notes: The estimates measure the impact of a 1 standard deviation change in $\Delta_4 LTG_t$ and $\widehat{FE}_t$ on mei_{t+h}. The regressions are unconditional (no controls). $\Delta_4 LTG_t$ is the 4-quarter percentage point change in aggregate market expectation for 5-year earnings per share growth, calculated by value weighting firm level forecasts. FE_t is defined as the difference between (a) aggregate market expectation for 5-year earnings per share growth, LTG_t, and (b) the average annual growth in earnings per share between quarter t and $t+20$, $\Delta_{20} e_t - e_{t+20}/5$. $\widehat{FE}_t$ are fitted values from the regression of FE_t on LGT_t (Table 5 Column 1). $BaaSpread_{t+h}$ is the yield spread between Moody's 10y 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. Superscripts: *** significant at the 1% level, ** significant at the 5% level, and * significant at the 10% level.

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 co-movement.

Christiano, Motto, and Rostagno (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 co-movement. 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, as well as firms' investment policies, as our empirical analysis show. In line with this possibility, in Appendix B we show that a current increase in LTG optimism predicts good news shock informing markets about low risk in the near term (up to 8 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 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.

VI. Conclusion

Using analyst expectations of long-term earnings growth 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 non-rational expectations on both. In line with Keynes' intuition, long term expectations exhibit excess volatility, which in turn correlates with movements of stock prices and returns, interest rates, credit spreads, as well as with the cyclical behaviour 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, non-rational 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 (Angeletos et al. 2020, BGST 2023, Bianchi et al. 2023, Ilut and Schneider 2014, 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, while Bastianello and Fontanier (2022) 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 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, Gennaioli, Ma, and Shleifer (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, Conlon, Gennaioli, Kwon, and Shleifer 2023). 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, while 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 her 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 over reaction 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 micro-foundations, deeper "parameters", and the ability to incorporate as well as explain a larger body of data.

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