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ABSTRACT

We present the case for the centrality of overreaction in expectations for addressing important challenges in finance and macroeconomics. First, non-rational expectations by market participants can be measured and modeled in ways that address some of the key challenges posed by the rational expectations revolution, most importantly the idea that economic agents are forward-looking. Second, belief overreaction can account for many long-standing empirical puzzles in macro and finance, which emphasize the extreme volatility and boom-bust dynamics of key time series, such as stock prices, credit, and investment. Third, overreaction relies on psychology and is disciplined by survey data on expectations. This suggests that relaxing the assumption of rational expectations is a promising strategy, helps theory and evidence go together, and offers a unified view of a great deal of data.

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Dynamic macroeconomics is one of the great accomplishments of 20th century social science. It recognizes the centrality of forward-looking behavior for investment, consumption, and other major decisions of consumers and firms. The bedrock assumption of this research program is that expectations are "rational," meaning that decision makers make optimal use of available information when making their forecasts. Indeed, this research program is often referred to as the "rational expectations revolution" (Lucas and Sargent 1981).

Despite the success of dynamic macroeconomics, growing evidence using surveys rejects any pure version of the rational expectations hypothesis (Souleles 2004, Vissing-Jorgensen 2003, Mankiw et al. 2004). To account for some of this evidence, early models maintained rational belief formation, but introduced costs of acquiring or processing information (Sims 2003, Woodford 2003). This approach has proved useful to explain sluggish price movements (Mankiw and Reis 2002). Recent evidence, however, points to deeper departures from rationality. The expectations of professional forecasters, corporate managers, consumers, and investors appear to be systematically biased in the direction of overreaction to news (Bordalo, Gennaioli, Ma, and Shleifer 2020). That is, beliefs are too optimistic in good times and too pessimistic in bad times, at the individual level and sometimes at the consensus level as well.

In this paper, we present the case for the centrality of overreaction in expectations for addressing important challenges in finance and macroeconomics. We begin with a brief overview of several formulations of expectations considered by economists. We then make three arguments. First, non-rational expectations by market participants can be measured and modeled in ways that address some of the key challenges posed by the rational expectations revolution, most importantly the idea that economic agents are forward-looking and form beliefs using their models of the economy (Muth 1961, Lucas 1976). We among others have constructed models of forward looking but overreacting expectations, such as "diagnostic expectations" (Bordalo, Gennaioli, and Shleifer 2018). These models can be integrated into dynamic macroeconomic analyses and estimated using survey data.

Second, belief overreaction can account for many long-standing empirical puzzles in macro and finance, which emphasize the extreme volatility and boom-bust dynamics of key time series, such as stock prices, credit, and investment, in a natural and empirically tractable way. In essence, excess volatility and predictable boom-bust cycles arise because expectations overreact to news and are subsequently systematically corrected. The mechanism of overreaction in beliefs links excess volatility of stocks to return predictability, credit market frothiness to increased risk of financial crises, and macro financial booms to subsequent recessions.

Third, overreaction has two important advantages over conventional mechanisms used in economic models to produce excess volatility: it relies on psychology and is disciplined by survey data on expectations. We briefly discuss frequently used mechanisms that maintain rational expectations, including exotic preferences and long run risk. We discuss the predictions of these models critically in light of the available survey evidence. Relaxing the assumption of rational expectations seems like a better research strategy, both theoretically and empirically.

A Very Brief History of Expectations Research

Before the rational expectations revolution, survey expectations were a central part of standard macroeconomic analysis. Starting in the 1940s, the National Bureau of Economic Research published several volumes on data on market participant forecasts, such as *The Quality and Significance of Anticipations Data* (1940). Although these early studies presented no systematic analysis of the structure of forecast errors, they were informed by a model of beliefs called adaptive expectations (Cagan 1956). This formulation was backward looking, with expectations modeled as a distributed lag of past changes, with fixed exogenous coefficients. This formalization yielded initial sluggishness of beliefs. After a long period of price stability in goods or financial markets, expectations of future prices would remain anchored, despite growing prices, so that beliefs would only slowly adjust to the new regime. In the presence of positive feedback mechanisms, such as wage renegotiations feeding back into higher goods' prices or growing asset demand feeding back into higher prices of financial assets, expectations would eventually catch up, potentially causing high inflation in goods or asset prices.

The rational expectations revolution put an end to this line of work. The key criticism is that adaptive expectations feature a particularly unrealistic kind of systematic error. According to what later became known as the Lucas critique (1976), adaptive expectations do not respond to regime changes. If a central bank tries to systematically inflate the economy to boost employment, this information itself, regardless of past price changes, will promote inflationary expectations. This mechanism was central to accounting for stagflation in the 70s. Likewise, if an economy is stuck in an inflationary spiral, but a central bank credibly announces its commitment to end inflation, this information itself, regardless of past price changes, will moderate expected inflation. The backward looking nature of adaptive expectations and their fixed coefficients do not allow for an immediate response of beliefs to news.

The rational expectations solution to this problem is to assume that beliefs are attuned to the key features of the economy, in the specific and extreme sense that expectations are fully dictated by the dynamic model of the economy itself. In the classic formulation of Muth (1961), the Rational Expectations Hypothesis holds that agents know the model that describes the evolution of the economy, observe the shocks that hit it, and based on this information form their expectations as statistically optimal forecasts. These rational forecasts may turn out to be incorrect ex-post, because news can unsettle previous forecasts. But they are correct on average because they are fully determined by the law that governs the evolution of the economy. A strong prediction follows: under rational expectations, forecast errors cannot be systematically predictable from any information available to the decision maker at the time the forecast is made.

The rational expectations hypothesis turned out to be one of the most fruitful ideas in the history of economics, forming the foundation of modern macro as an internally coherent and consistent field. But it left several puzzling facts unexplained. In terms of economic outcomes, it had trouble accounting for the slow adjustment of some macroeconomic variables, such as wages or inflation, and for the excess volatility of other variables such as stock prices, interest rates or home prices. In addition, the assumption that expectations are rational in the sense of not displaying predictable errors was consistently rejected by survey data.

An early attempt to deal with slow adjustment included theories of rational inattention and information rigidities (Sims 2003, Woodford 2003, Mankiw and Reis 2002, Gabaix 2019), in which agents only partially update their beliefs as new information arrives, due to the cost of absorbing and processing news. Agents are rational, but thinking is costly. Because agents are rational, beliefs are attuned to the model of the economy. Because updating is costly, agents look forward but underreact to news. As a result, the reaction to a shock will be spread out over time, a result that helps a great deal with explaining rigidities in real variables.

The theories of rigid belief changes, however, do not help in a natural way to deal with puzzles related to volatility. In many instances adjustment to news is strong, and even if it is initially muted, it eventually speeds up as it gets going. In the next section, we show that this is indeed the case for important macroeconomic series. Such facts raise two important questions.

First, can we build theories of belief formation that can account for excess volatility in expectations, and perhaps even retain some useful features of adaptive expectations, while addressing the fundamental critiques of the ad hoc and backward looking models raised by Muth and Lucas? Second, can such theories explain expectations data and help account for important macro-finance puzzles? These are the key questions around which our discussion is organized.

Survey Expectations and Predictability of Forecast Errors

The central prediction of the theory of rational expectations is that forecast errors should not be predictable using information known when the forecast was made. A vast body of tests using survey data on the forecasts made by households, professional forecasters, corporate managers, and professional investors nearly universally rejects this prediction.

Souleles (2004) shows that forecast errors in the surveys of consumer confidence and expected inflation from the Michigan Index of Consumer Sentiment do not average out to zero over several decades and are correlated with demographic variables. Greenwood and Shleifer (2014) examine six different data sources for investor forecasts of stock market returns, and find that expectations of future stock returns are too optimistic after stock market booms.

Gennaioli, Ma, and Shleifer (2016) study forecasts of earnings growth in a Duke University quarterly survey of Chief Financial Officers, and find that errors can be predicted from past earnings and other factors. Bordalo, Gennaioli, Ma, and Shleifer (2020) consider expectations of 22 macro variables from the Survey of Professional Forecasters and the large-company business economists who participate in the Blue Chip Survey, and find that forecast errors are predictable based on revisions of previous forecasts. Gulen, Ion, and Rossi (2021) find broadly similar results using the same data, along with data from the Institutional Brokers

Estimate System (IBES). D'Arienzo (2020) looks at the Blue Chip data on expectations of one-quarter-ahead interest rates on bond yields, and again finds that forecast errors can be predicted based on revisions of previous forecasts. There are many more findings of this kind.

One critique of such findings is that true expectations are unobservable (Prescott 1977), and measured expectations are distorted by a misunderstanding of the survey questions or low incentives for accuracy. This argument is weak for three reasons. First, the evidence overwhelmingly shows that survey expectations are not noise. To begin, elicited beliefs are highly correlated across agents and surveys (e.g., Greenwood and Shleifer 2014). In addition, they typically correlate with economic decisions. In the Gennaioli, Ma, and Shleifer (2016) study, the expectations of Chief Financial Officers are highly predictive of corporate investment. Giglio et al. (2021) find a correlation between beliefs and portfolio choice in a Vanguard survey of large retail investors. Armona, Fuster, and Zafar (2019) append some questions to the Federal Reserve Bank of New York's Survey of Consumer Expectations, so that randomly selected groups of respondents receive different information, and find that expectations about home price growth have a causal effect on intended investment in housing. In short, the people in survey data do actually put their money where their mouths are.

Second, the livelihood of professional stock analysts, macroeconomic forecasters, and corporate managers depends in part on the accuracy of their forecasts. It is hard to maintain that their measured expectations are uninformative about their beliefs. Third, the forecast errors made by different agents often share a systematic overreaction component that cannot be explained by incentives, which differ sharply across agents (say, by demographic or income group, or job).

To incorporate survey expectations into macroeconomic analysis, we want to know not just whether forecast errors are systematic, but also whether these errors have meaningful macroeconomic implications. If agents overreact, so they are too optimistic in good times and too pessimistic in bad times, then beliefs are excessively volatile, which translates into excessive volatility in individual decisions. If instead agents underreact so that they are not optimistic enough in good times and not pessimistic enough in bad times, then sluggish belief adjustment translates into sluggish decisions. Different macroeconomic consequences follow in turn.

To detect whether beliefs over- or underreact, two main testing strategies for forecast error predictability have been developed. We describe these tests in turn and present some evidence of how each has been used. The first test correlates the future forecast error, defined as the actual future realization minus the current expectation of a variable, with measures of current conditions. For instance, one can correlate the future error in a manager's earnings growth forecast with the firm's current earnings level.

To see how this works, Figure 1, from Gennaioli, Ma, and Shleifer (2016), reports the results obtained when using the expectations of large US-listed companies for their firms' 12 months ahead earnings during the period 1998-2012. The data is from a Duke University survey of Chief Financial Officers. Panel A plots 12-month-ahead average forecast errors against average profits in the past 12 months. Panel B plots average earnings expectations and aggregate investment plans by these firms.

Figure 1: Panel A (left) – Panel B (right).

Consider the pattern of forecast errors in Panel A. If managers' expectations were rational, their future forecast error (black curve) would be uncorrelated with the firm's recent earnings (gray curve). In contrast, the average future forecast error of managers is strongly negatively correlated with their firms' recent earnings: if recent earnings have been high (the grey curve is high), managerial forecasts are systematically disappointed in the future (the black curve is low). This evidence is indicative of over-reaction: good current conditions prompt managers to be too optimistic about the future. Under-reaction would predict the opposite: good current conditions would prompt insufficient optimism, which is not the case in the data.

Overreaction in earnings expectations may shape stock market valuations and firms' investment decisions. The right panel shows that, consistent with this possibility, when the average manager is more optimistic, aggregate investment is higher. Gennaioli, Ma, and Shleifer (2016) show that these patterns are robust to controlling for aggregate shocks, and that managers' beliefs have a stronger explanatory power for firm level investment than standard factors such as financing constraints, stock market valuations (Tobin's q), and uncertainty.

The second test for over vs. under-reaction of beliefs to news was developed by Coibion and Gorodnichenko (2012, 2015). Their key innovation is to measure "news" by the extent to which the agent revises the forecast for a fixed future date. The test then consists in assessing whether such forecast revision predicts the agent's future forecast error. This test is conceptually cleaner than the first test, but it is harder to implement because only a few surveys have both a panel structure and the term structure of forecasts necessary to compute forecast revisions.

We illustrate the idea of the Coibion-Gorodnichenko test using expectations of stock market analysts of long-term earnings growth of listed firms, defined as expected earnings growth over a full business cycle horizon of 3-5 years (La Porta 1996). This data includes forecast revisions. Following Bordalo, Gennaioli, La Porta, and Shleifer (2022), for each firm in the S&P 500 stock index we take the median analyst forecast. We then average these forecasts across firms, obtaining a measure of consensus expectations of aggregate long term earnings growth, and then compute revisions in these consensus expectations. Figure 2 presents two plots using this measure of forecast revisions. Panel A plots the five-years-ahead forecast errors in long-term earnings growth against the revision in that variable for the S&P 500 index in the last quarter, over the period 1982-2018. Panel B plots aggregate investment against the current forecast revision for that same earnings growth of S&P 500 firms.

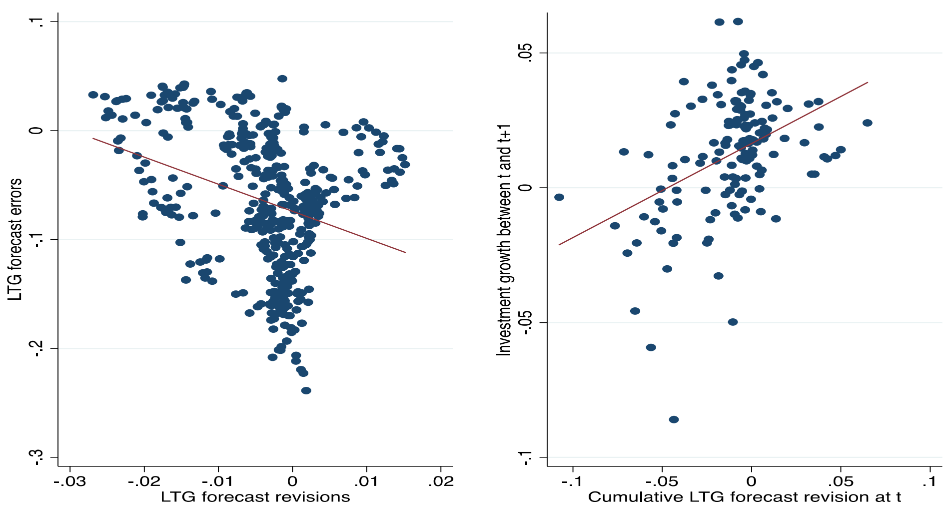

Figure 2: Panel A (left) – Panel B (right)

Panel A shows a strong negative correlation between the current forecast revision and the future forecast error. When analysts receive good news (they revise earnings growth forecasts up), their forecasts are systematically disappointed in the future (realized earnings growth is below expectations). This fact is inconsistent with rational expectations, and again points to over-reaction: when analysts receive good news their expectations are revised excessively up and become excessively optimistic about the future. Under-reaction here would predict a positive correlation between forecast revisions and forecast errors, which is not what we see in the data.

Panel B suggests that belief over-reaction can have significant economic consequences: current investment growth is strongly positively correlated with the current revision of the long-term growth variable. When the median analyst receives good news (and so do firm managers), current aggregate optimism increases and investment rises sharply, perhaps excessively so. Subsequent disappointment of overoptimistic beliefs may cause boom-bust investment cycles.

The Coibion and Gorodnichenko test was originally developed to assess rational inattention and information rigidity (Sims 2003, Woodford 2003, Mankiw and Reis 2002). In this theory, the errors of individual analysts should be unpredictable based on their own forecast revisions, but the consensus forecast errors should be positively correlated with the consensus revision. The reason is that individual analysts do not react to information of others, leading to aggregate sluggishness of forecasts. Bordalo, Gennaioli, Ma, and Shleifer (2020) perform the Coibion and Gorodnichenko test for individual forecasters using the Survey of Professional Forecasters and Blue Chip survey data on four quarters ahead forecasts for a large set of macroeconomic variables, including measures of economic activity, consumption, investment and interest rates. They find that, contrary to rational inattention, individual forecasters overreact for most time series. That is, individual analysts do not make optimal use of their own information, but rather overreact, which reveals a deeper problem than rational inattention.

Bordalo, Gennaioli, Ma, and Shleifer (2020) also show that, as long as the information possessed by individual forecasters is limited, which is certainly realistic, the consensus forecast may appear sluggish even when all individual forecasters overreact. The evidence in Figure 2 panel A shows that, for stock analysts, overreaction is so strong that it is detectable even at the level of the consensus forecast for the aggregate stock index.

Overall, departures from rational expectations and in particular belief overreaction appear necessary to make sense of the expectations data. Can belief overreaction be formalized and introduced into dynamic macroeconomic analysis? What puzzles in macroeconomics can belief overreaction help address? We address these questions in the next two sections.

Modeling and Estimating Diagnostic Expectations

In light of the previous discussion, one would like to have a model of belief formation in which expectations capture key features of the structure of the economy, so they have the forward-looking nature that addresses the Lucas critique. One would also want to have a model in which expectations overreact to information, which is a central fact in survey data.

Over the last several years, we have developed one such model, called diagnostic expectations. This model puts psychology, and in particular selective memory, center stage (Gennaioli and Shleifer 2010; Bordalo, Coffman, Gennaioli, and Shleifer 2016; Bordalo, Gennaioli, and Shleifer 2018). Doing so is key for two reasons. First, while in recent decades economists have mostly relied on preferences to explain challenging facts, psychologists have amassed a substantial body of evidence delineating situations in which beliefs over- or underreact to information (e.g. Kahneman and Tversky 1972). This evidence is extremely valuable to identify the key properties that a realistic theory of expectation formation should display. Second, memory research has unveiled robust regularities in selective recall (Kahana 2012). Because the information shaping beliefs often comes from memory, these regularities in recall can help build a theory of beliefs from first principles, based on deeper cognitive parameters. The resulting models of expectations can then be more flexible and less ad hoc than adaptive expectations, addressing the Lucas critique but also accounting for survey data.

To motivate the logic of diagnostic expectations, suppose that an agent must assess the future value of a random variable X conditional on data D. The agent has a memory database that contains past realizations of X and of D. Databases may differ across people, due to different experiences (Malmendier and Nagel 2011), but the main results are already obtained when the database stores the true distribution of events. Critically, when thinking about possible future realizations of X and the data D, the agent automatically and selectively retrieves states X that are most "similar" to the data D compared to other information in the database.[1] The agent who disproportionally samples such distinctive states then overweighs their probability in forming expectations.

Suppose for instance that an agent must guess the hair color of a person coming from Ireland, so $X \in \{red, light, dark\}$, and $D = Irish$. As the agent thinks about the possibility that the hair color is $X = red$, many examples of red-haired Irish come to mind. This occurs because Irish people are *more* similar to red hair than other populations, in the sense that red hair is relatively more frequent in Ireland than in the rest of the world. By contrast, as the agent thinks about the possibility that the hair color of an Irish is dark, $X = dark$, few examples of dark-haired Irish come to mind. Indeed, Irish people are much less similar to dark hair than other populations, in the sense that dark hair is relatively *less* frequent in Ireland than in the rest of the

[1] This assumption reflects the key fact that memory is associative, in the sense that a given event automatically prompts the retrieval of similar events experienced in the past (Kahana 2012). Crucially, similarity between events is measurable, e.g. in terms of frequency of co-occurrence (Tversky 1977, Bordalo, Coffman, Gennaioli, Shleifer, and Schwerter 2021) or at a more fundamental level in terms of feature overlap (Bordalo, Conlon, Gennaioli, Kwon, and Shleifer 2022). These measures predict not only subjective similarity assessments but also evidence on recall, probabilistic assessments, and related phenomena.

world. As a result, even though the dark-haired Irish outnumber the red-haired ones, the agent will oversample from memory the red hair color and overestimate its incidence.[2]

Likewise, when thinking about the health status of someone who tested $D = Positive$ on a medical test, memory oversamples $X = sick$ because this health status is more closely associated with (and hence more similar to) positive as opposed to negative test results. We then overestimate the probability that someone who tested positive has the disease.

This kind of mistakes can be especially pronounced when the data points to unlikely and extreme traits. Bordalo, Coffman, Gennaioli, and Shleifer (2016) show how this logic accounts for social stereotypes. For instance, people dramatically overstate the prevalence of criminals or terrorists in certain groups, even though an overwhelming majority of any group is honest and peaceful. This bad stereotype is formed automatically when a group contains even a few more criminals than a reference group, which leads to the trait coming to mind more easily.[3] Bordalo, Coffman, Gennaioli, and Shleifer (2019) show that this logic helps explain when and how beliefs about self and others are tainted by gender stereotypes. In a financial setting, this logic explains why investors are likelier to overreact to news that is diagnostic of rare and extreme outcomes (Bordalo, Gennaioli, La Porta, and Shleifer 2019, Kwon and Tang 2021).

The model of diagnostic expectations can be used to formalize expectation formation in dynamic settings, as shown formally by Bordalo, Gennaioli, and Shleifer (2018). In that model, forward-looking expectations about an economic variable are based on two components: one component anchored to the rational forecast, and a second component that overweighs news

[2] Bordalo, Conlon, Gennaioli, Kwon and Shleifer (2021) present a foundation for stereotypes on the basis of selective recall. Relatively to true frequency, it is harder to think about dark-haired Irish than about red-haired Irish because the former are more similar to other (dark-haired) Europeans. While other Europeans are irrelevant to the task at hand (which is to evaluate the Irish), they are similar to, and interfere with the retrieval of, dark-haired Irish. Red-haired Irish suffer less interference, and therefore are overestimated.

[3] Selective memory generates stereotypes that are not necessarily derogatory; they can be flattering if distinctive traits are good, like a stereotype that “Asians are good at math.”

received in the most recent few periods.[4] Anchoring to the rational forecast captures the dependence of memory retrieval on the full database, which includes all relevant empirical regularities the agent has experienced. Overweighting of recent news captures disproportionate retrieval of states that are associated with the observed news, which is again shaped by the news events that the agent has experienced in the past. This mechanism can help unify a great deal of evidence on belief overreaction in macro-financial settings.

First, it can produce neglect or overweighting of tail-end downside risk depending on whether incoming news is good or bad. In good times, good states of the world come to mind and crowd out bad ones, leading to the neglect of tail risk. After a bad shock, bad states of the world come to mind and crowd out the retrieval of good states, leading to exaggerated tail risk.

Second, it produces a foundation for extrapolative expectations. As good news causes good outcomes to disproportionally come to mind, and interferes with the retrieval of bad outcomes, the entire distribution of beliefs shifts to the right, causing average excess optimism. The reverse occurs when bad news is received, which causes average excess pessimism. Critically, the extent of extrapolation depends on the data generating process. For a series with low persistence, news causes a small update in beliefs, because they are less associated with changing future conditions in memory. This prediction is consistent with the evidence from survey data: survey expectations track salient features of the data generating process. In

[4] In formal terms, in such a model an agent's beliefs are captured by the probability density function:

$$f^{\theta}(X|D) \propto f(X|D)\left[\frac{f(X|D)}{f(X|-D)}\right]^{\theta},$$

where $f(X|D)$ is the true density, which captures the memory database, and the likelihood ratio captures oversampling of realizations that are relatively more likely given the data D. The strength of oversampling is regulated by $\theta \geq 0$. For $\theta = 0$, beliefs are rational. Bordalo, Gennaioli, and Shleifer (2018) show that when forming beliefs about a Gaussian AR(n) variable, the diagnostic expectation of future value X_{t+1} obeys $\mathbb{E}_t^{\theta}(X_{t+1}) = \mathbb{E}_t(X_{t+1}) + \theta[\mathbb{E}_t(X_{t+1}) - \mathbb{E}_{t-k}(X_{t+1})]$. In this formula, $\mathbb{E}_t(X_{t+1})$ is the rational forecast, and θ overweights the rational news received in the last k periods. The time period k and the magnitude of overstatement θ can be estimated given appropriate data.

particular, belief revisions are larger for more persistent series (Bordalo, Gennaioli, Ma, and Shleifer 2020). Unlike for adaptive expectations, updating coefficients are not fixed but rather depend on the underlying reality and have a forward-looking component, addressing the Lucas critique.

Third, the same mechanism produces systematic reversals in beliefs. Consider the case of an over-optimistic agent. When good news ceases to come in, the agent is no longer cued to oversample good outcomes from memory. As a result, beliefs cool down even in the absence of bad news, causing a sharp reversal that is not driven by bad fundamental news. Diagnostic expectations can generate large movements in beliefs and choices on the basis of small shocks, as well as sudden reversals in beliefs on the basis of past, but not contemporaneous, shocks.

Our model of expectations is surely not the final formulation, but it offers two advantages relative to alternative theories. First, diagnostic expectations are forward looking, and respond to changes in the environment using a model of the world. This occurs due to a fundamental feature of human memory: it affects beliefs by causing selective sampling of real-world regularities that are stored in the memory database. As a result, belief distortions depend on the true features of the data-generating process. This feature is not shared by models in which agents mechanically assume a specific data generating process, such as one with high persistence (Angeletos, Huo, and Sastry 2021) or without long-term mean reversion (Fuster, Laibson, and Mendel 2010).

Second, the model of diagnostic expectations can be and has been estimated from empirical data. Critically, due to the model's flexibility, its parameters can be compared across different datasets and series/data generating processes. Several studies have now estimated the parameter controlling the strength of overreaction and found in the survey data on expectations that the reaction to news is about twice what would be warranted under rational expectations

(Bordalo, Gennaioli, Ma, and Shleifer 2020, D'Arienzo 2020). These estimates help discipline the ballpark magnitude of overreaction to be used in macroeconomic models.

Belief Overreaction and Macro-financial Volatility

Overreacting beliefs can help shed light on three central phenomena in finance and macroeconomics: 1) excess stock market volatility, 2) financial crises, 3) regular fluctuations in credit markets and economic activity. They do so in a way that offers hope for a unified approach to economic volatility.

Overreaction and Excess Volatility in the Stock Market

The first, most direct, and perhaps most dramatic evidence of excess volatility comes from the aggregate stock market. Shiller (1981) famously showed that stock prices are much more volatile than warranted by the volatility of future dividends. Campbell and Shiller (1988) further showed that time variation in the price dividend ratio cannot be explained by future dividend growth, but rather by future realized stock returns, which tend to be systematically low after periods in which the price to dividend ratio is high.

A growing body of work using survey expectations shows the promise of explaining stock market and more generally financial volatility using overreacting beliefs. One strand of this work is connected to the evidence in Section 2, and argues that stock prices are excessively volatile because beliefs about future dividends or earnings are themselves excessively volatile.[5]

[5] Another strand of work focuses on extrapolative beliefs about future stock returns. Greenwood and Shleifer (2014) show that investor expectations of one year ahead stock returns are too optimistic in good times and too pessimistic in bad times, consistent with overreaction. This may lead to upward price spirals and hence to an overvalued stock

La Porta (1996) first documented that LTG, the measure of expected long term earnings growth we used in Section 2, accounts for boom bust dynamics in the stock price of individual firms: firms which analysts are most optimistic about have lower future stock returns than do firms which analysts are least optimistic about. Bordalo, Gennaioli, La Porta, and Shleifer (2019) show that belief overreaction can account for this phenomenon: a firm's high recent earnings growth fuels excess optimism about its future earnings, which leads to an overvaluation and a future stock price correction as earnings expectations are disappointed. They show that a diagnostic expectations model with the reaction to news at about twice the rational level, can generate quantitatively realistic boom-bust cycles in expectations and stock prices at the firm level with a realistic process for actual earnings growth. Interestingly, about the same level of distortion is found in a variety of datasets, including analysts' expectations of earnings growth (Bordalo, Gennaioli, La Porta, and Shleifer 2019), CFOs' expectations of profits (Bordalo, Gennaioli, Shleifer, and Terry 2022), and expectations of interest rates (d'Arienzo 2020).

Can expectations of future fundamentals also account for aggregate stock market volatility? Yes. De la O and Myers (2021) show that time variation in analyst expectations about the market's short-term earnings growth explains a sizable chunk of dividend-price ratio variation. Nagel and Xu (2019) show that high past aggregate earnings growth correlates with expectations of higher future earnings growth and low future stock returns. These papers do not, however, focus on systematic errors in measured growth expectations or on their ability to predict future returns, so they cannot assess whether overreaction drives excess stock market volatility and return predictability.

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market (Barberis et al. 2015). Bordalo, Gennaioli, La Porta, and Shleifer (2019) show that controlling for expectations of future stock returns leaves the explanatory power of expectations of fundamentals (LTG) unaffected.

Bordalo, Gennaioli, La Porta, and Shleifer (2022) take up this challenge. They show that, in line with Section 2, expectations of aggregate long-term earnings growth indeed overreact, and that such overreaction can account for three leading stock market puzzles. First, volatility in LTG fully accounts for Shiller's (1981) excess volatility puzzle. Second, overreaction of beliefs about future aggregate earnings growth explains a large share of return predictability in the data. It does so in the aggregate market, accounting for systematically low (high) stock returns after good (bad) times. But it does so also in the cross section: overreaction of forecasts of aggregate earnings growth accounts for a significant chunk of cross-sectional return spreads typically attributed to risk factors (Fama and French 1992). In this analysis, overreaction of long term expectations outperforms conventional measures of time varying risk premia, emerging as a key and parsimonious driver of key stock market puzzles.

Excess volatility has been documented in the bond market as well. Consider the term structure of interest rates, in which long-term interest rates are an average of short-term rates. Shiller (1979) showed that, from this perspective, long-term interest rates on bonds co-move too much with short-term rates relative to standard benchmarks, a finding he called "excess sensitivity" (Mankiw and Summers 1984, Gürkaynak et al. 2005). Giglio and Kelly (2018) show that long-term rates are excessively volatile relative to short-term ones, again compared to standard term structure models. They argue that non-rational expectations are needed to explain the evidence. D'Arienzo (2020) directly addresses the role of expectations. Using both survey forecasts from Blue Chip and beliefs extracted from bond prices, he shows that when news arrives, expectations about long-term interest rates overreact compared to those for short-term rates (see also Wang 2021). D'Arienzo (2020) offers a formulation of diagnostic expectations that produces this finding with quantitatively reasonable parametrization. Using a standard term structure model, he shows that such a degree of belief overreaction accounts not only for the bulk of the Giglio and Kelley (2018) excess volatility puzzle, but also for the excess sensitivity of long-term rates and for bond return predictability (Cochrane and Piazzesi 2009).

In sum, overreaction to news helps account for and unify the evidence of excess volatility and return predictability in the stock and bond markets. Quantitatively, the volatility in measured expectations does a good job accounting for the excess volatility in asset prices.

Overreaction and Financial Crises

Financial crises, defined as episodes of major distress in a country's banking system that are often associated with deep and prolonged recessions, are another leading example of macro-financial volatility. There are two broad rational expectations theories of such crises. In the "bolt from the sky" theories, crises come as a surprise, such as a large adverse productivity shock, an uncertainty shock (Bloom et al 2018, Arellano, Bai, and Kehoe 2019), or a "financial shock", which may be a sudden increase in risk aversion or a bank run (Diamond and Dybvig 1983). In the "house of cards" theories, shocks can be small, but hit a financial system that has already been rendered fragile by high leverage. In both cases, the trigger of crises is an exogenous shock, which gets amplified by fire sales, agency problems, or adverse selection (Sufi and Taylor 2021).

Overreacting beliefs suggest a different account, consistent with the informal hypothesis of Minsky (1977) and Kindleberger (1978), as well as with Reinhart and Rogoff (2009). In the boom phase, excessive optimism and neglect of risk fuel asset price bubbles and an overexpansion of credit. When beliefs are systematically disappointed, this causes falling asset values, unsustainable liabilities, fire sales, and panics. As with stock market volatility, a single controlling parameter, the extent of overreaction, accounts for both the boom and the bust.

Large scale financial crises are sporadic events, many of which occurred a long time ago, so there is no readily available historical data on expectations. This makes it hard to compare theories using measured beliefs. But rational expectations theories make two strong and testable predictions. Under the "bolt from the sky" theories, crises are not predictable. Under "house of cards" theories, crises are predictable with indicators such as high leverage or asset valuations, but markets should show awareness of building up risks since they appreciate the fragility of the system. If in contrast crises are due to belief overreaction, they should be predictable – again, say, based on leverage and valuations – but the pre-crisis period should be associated with euphoria and the neglect of risk (Gennaioli, Shleifer, and Vishny 2015). Data on the predictability of crises as well as on the ex-ante perception of risk can thus distinguish alternative theories.

It is by now well established that the data reject the "bolts from the sky" view: crises are systematically predictable using asset price and quantity information.[6] Critically for the current purposes, it also appears that prior to crises markets do not exhibit an awareness of heightened risks, as they instead should in the "house of cards" theories. In fact, available evidence suggests that markets exhibit euphoria and dampened risk perceptions before crises.

Some of this evidence takes the form of unusually high stock valuation and low credit spreads right before crises.[7] More recent data allow for a closer look at expectations. For the

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[6] Borio and Lowe (2002) show that rapid credit and asset price growth predict banking crises in 34 countries between 1970 and 1999. Schularick and Taylor (2012) show that rapid credit expansions in a sample of 14 developed economies predict financial fragility and bad macroeconomic performance. Mian et al. (2017) show that growth in household debt predicts low GDP growth in a panel of 30 countries. Most recently, Greenwood et al. (2022) build a predictive index for postwar financial crises using past credit and asset price growth. In a sample of 42 countries over the period 1950-2016, the authors find that a combination of rapid asset price growth and rapid buildup in debt can predict a financial crisis within three years with an over 40 percent probability.

[7] Baron and Xiong (2017) show that, in the run up of bank lending expansions, bank stock returns are unusually high, not low, suggesting neglect of mounting risks. To a similar effect, Krishnamurthy and Muir (2017) shows that crises are typically preceded by unusually low credit spreads.

2007-8 crisis, Jarrow, Mesler, and van Deventer (2006) and Coval, Jurek, and Stafford (2009a, 2009b) show that investors were too optimistic about the returns of securitized assets due to their reliance on incorrect valuation models. Gennaioli and Shleifer (2018) document widespread excessive optimism prior to the Lehman crisis, evidenced by home buyer expectations about future home price growth, investor expectations about the risk of home price declines, and forecasts of economic activity made by both private forecasters and the Federal Reserve. The evidence points to neglect of downside risk in the boom, in line with overreacting expectations.

Overreacting beliefs offer a way to trace the origin of financial crises to a three stages mechanism reminiscent of Kindleberger (1978). In the first stage, a positive "displacement" such as a technological/financial innovation, or a surge in investor demand, improves an asset's fundamental value. Due to overreaction, expectations become too optimistic, creating an asset price bubble. In the second phase, leverage expands. This effect is amplified by a key byproduct of overreacting beliefs: the neglect of downside tail risk (Gennaioli and Shleifer 2018; Gennaioli, Shleifer, and Vishny 2012, 2013). As a result, even typically risk-averse investors such as banks start to over-expand. In the third phase, beliefs are disappointed, which causes excessive optimism to wane and the asset price bubble to deflate. As risk perception rises, excessive leverage becomes evident, igniting a crisis. In this model, credit spreads are low before the crisis, consistent with the evidence, and the event triggering the crisis is not a negative shock, but the unwinding of the excess optimism created by overreaction to the original, positive shock.[8]

In sum, overreaction to good times and the resulting neglect of downside tail risk help account for financial crises, including the facts that such crises are predictable and begin in what

[8] Recent work has started to model these mechanisms by incorporating diagnostic expectations into a standard model of asset pricing (Bordalo, Gennaioli, Kwon, and Shleifer 2021), or into continuous time general equilibrium model of intermediary based asset pricing (Maxted 2022, Krishnamurthy and Li 2020, Chodorow-Reich et al. 2021).

otherwise seem to be good times. Introducing the overreaction to news with diagnostic expectations enables otherwise standard dynamic macro models to account for these events.

Business Cycles

The belief formation mechanism may also play a role in regular business cycle fluctuations. Current business cycle research, whether in the New Keynesian or real business cycle model, is almost exclusively built on rational expectations: fluctuations are triggered by demand or supply shocks, which are transmitted via intertemporal substitution and frictions in investment, financing, and price setting. Belief overreaction opens the possibility to connect macroeconomic expansions and recessions to each other via the dynamics of expectations and the systematic winding up and unwinding of optimism.

Business cycles are recurrent events, so the analysis of overreaction can make use of expectations data, which are increasingly available at both aggregate and firm levels. Using postwar US data, López-Salido et al. (2017) find that low credit spreads predict low GDP growth and investment over the next two years. [9] Gulen, Ion, and Rossi (2021) tie these dynamics to expectations data: periods of excess optimism, measured as in Section 2, are followed by low investment and credit spread reversals.[10]

Can the magnitude of belief overreaction observed in survey data help account for significant business cycle fluctuations? Bordalo, Gennaioli, Shleifer, and Terry (2021) address this question by incorporating diagnostic expectations into an otherwise standard real business

[9] Relatedly, Greenwood and Hanson (2013) show, using US data, that periods in which credit spreads are low, or where a large share of issued bonds are risky, predict disappointing and even negative bond excess returns. Sørensen (2021) shows that periods in which investors accept a low incremental yield for higher default risk in corporate bonds are followed by extremely low returns on risky bonds.

[10] Greenwood and Hanson (2015) document boom-bust cycles in shipbuilding: strong increases in the price of ships lead to excessive investment in shipbuilding and low realized marginal product of investment.

cycle model with financial frictions. The model is structurally estimated using firm level data, which crucially includes data on managers' expectations about their firms' profitability. This approach delivers three key results. First, managers' expectations overreact, and the estimated degree of overreaction is similar to that found in other datasets (i.e., two-fold). Second, the real business cycle model augmented by diagnostic expectations can match successfully untargeted firm-level, as well as sectoral cycles. Periods when expectations about a firm (or a sector) are over-optimistic, and firm level (sector level) investment is high, are systematically followed by reversals in which: i) credit spreads rise, ii) realized bond returns are low, and iii) investment growth is low. Third, the estimated model delivers large increases in aggregate credit spreads, such as the one observed in 2008, from mild reductions in aggregate productivity. The rational version of the same model generates neither systematic boom bust cycles nor realistic macro-financial volatility without large negative productivity shocks. In this sense, diagnostic expectations offer a belief-based foundation for the "financial shocks" evident in macro-financial data (Jermann and Quadrini 2012, Gilchrist and Zakrajšek 2012).[11]

This is only the beginning of the systematic assessment of the role of non-rational beliefs in business cycles fluctuations. One important step, for instance, is to connect beliefs with standard mechanisms for demand driven business cycles such as price rigidity. Bianchi, Ilut, and Saijo (2021) and L'Huillier, Singh, and Yoo (2021) address this question by developing methods to incorporate diagnostic expectations into workhorse New Keynesian models.

In sum, diverse phenomena such as excess stock market volatility, financial crises, and macroeconomic fluctuations may have a common underpinning rooted in overreacting expectations. Two broad messages emerge from the existing work. First, diagnostic expectations

[11] These results are due to the fact that diagnostic expectations entail overleveraging in good times, making the economy vulnerable to even small adverse productivity shocks. The explanatory power of the model thus comes from a single parameter controlling overreaction, which is matched using expectations data at the micro level.

enable researchers to incorporate an empirically realistic belief overreaction mechanism into standard dynamic macroeconomic models. Second, the ability of overreaction to produce macro-financial volatility relies on directly measurable expectations.

Alternative Approaches to Macro-Financial Volatility

Economists have grappled with the phenomena of excess financial and economic volatility for decades. Under rational expectations, expectations must on average equal realizations. As a consequence, rational explanations of excess volatility must introduce exogenous variation in preferences or in risk (i.e. in required returns) to explain the data.

One standard approach, which we call *exotic preferences*, stresses the role of time varying risk aversion. A prominent example in this class is the idea that preferences are habit forming, so that the marginal utility of consumption of a representative consumer is very sensitive to even small changes in consumption (Campbell and Cochrane 1999). In good times, when consumption is unusually high, the marginal utility of consumption is very low, and investors accept low expected returns to hold financial instruments to delay consumption. This means, in turn, that valuations are very high. In bad times, when consumption is below trend and the marginal utility of consumption is very high, investors require high returns to hold financial assets, and therefore valuations are very low. The volatility of valuations, and of real variables such as investment, derives from volatility in the marginal utility of consumption.

Another classical approach, which we call *time varying risk*, introduces high volatility of future risks. In theories of long run risk (Bansal and Yaron 2004), when investors expect a higher probability of a bad outcome in the distant future, they avoid risky assets and valuations are low. Fluctuations in expectations about long run risk can lead to substantial fluctuations in required returns and valuations. A related mechanism focuses on beliefs about the risk of a rare disaster (Barro 2006, Gabaix 2012, Wachter 2013).

These two approaches to resolving the volatility puzzles face closely related problems. First, neither marginal utilities nor long run or rare disaster risk can be measured in the data. These models are driven by unobservables, which can only be inferred from other market outcomes. Second, and more importantly, if we use survey expectations data to evaluate these theories, the evidence rejects both exotic preferences and time varying risk approaches.

Consider exotic preferences. This approach makes one key prediction about expectations of returns: valuations are high in good times because required (and therefore rationally expected) returns are low. This prediction can be tested using survey evidence on expectations of returns. Greenwood and Shleifer (2014) show, using a variety of investor surveys, that when market valuations are high, expected returns are high, not low. Investors drive up stock prices because they think they will do well, not because they are willing to do poorly. If one takes expectations data seriously, the fundamental premise of exotic preference theories is rejected.

The long run risk theories do no better. These theories also predict that when risk is high, required (and hence rationally expected) returns should be high. Again, expectations data reject this prediction. Giglio et al. (2021) run a large survey of sophisticated individual investors, and ask them both about their perception of long run risks, and their expectations of stock returns. The paper finds, in a cross section, that investors who expect higher long run risk also expect lower returns. This of course is exactly the opposite of the prediction of long run risk theory.

The basic problem of rational models based on exotic preferences or time varying risk is their inability to account for expectations data and systematic forecast errors, which are indicative of departures from rational updating. A literature on Bayesian learning tries to reconcile the evidence on measured beliefs with rational updating. It shows that systematic forecast errors may arise within a Bayesian framework, provided: i) priors are wrong, and ii) learning is slow relative to the frequency of changes in fundamental parameters, such as persistence (Singleton 2021, Farmer, Nakamura, and Steinsson 2021).

This approach also stresses the centrality of beliefs and their departure from rationality, which takes the form of wrong priors as opposed to non-Bayesian updating. Despite this similarity, we see two main problems with learning. First, the evidence of overreaction is common across variables and datasets. It indicates that recent conditions and news exert an undue influence on beliefs. This seems difficult to reconcile with learning. On the one hand, rational updating would arguably predict dampened reaction to news as agents progressively learn. On the other hand, due to different data generating processes in different variables and time periods, it would seem that different “wrong priors” would have to be reverse engineered in order to account for systematic overreaction across datasets. Overreaction explains a wide range of data by adding just one psychologically founded parameter to the rational expectations model.

Diagnostic expectations are one formulation of forward-looking overreaction, and future work should refine this model, in particular bringing in underreaction. Bordalo, Conlon, Gennaioli, Kwon, and Shleifer (2021) show that well established regularities in human recall, similarity and interference (Kahana 2012), offer a foundation for the overreaction in diagnostic expectations but also reconcile it with underreaction to data. The logic of this approach could be used to develop a portable model of belief formation usable in dynamic macroeconomic analysis.

Dynamic macroeconomics, for all its amazing achievements, has resisted taking non-rational expectations seriously. This may be due to a view described by Sargent (2001), paraphrasing Sims (1980), that once we abandon rational expectations, we are in the "wilderness." To us, reality seems to be the reverse: we are in the wilderness if we abandon survey expectations, resorting to unmeasurable mechanisms to account for the data. In contrast, expectations are measurable, understandable from basic psychological principles, disciplined by empirical analysis, and informative about macroeconomics and finance. Departures from rational expectations can be incorporated into models, and the theories can be tested. Unlike in the rational expectations alternatives, theory and evidence go together, and promise a unified view of a great deal of data.

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