Investor Beliefs and Expectation Formation

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Abstract

This article reviews the literature that uses survey data to study expectation formation among investors. We begin by outlining methods for eliciting investor beliefs and summarizing key empirical patterns documented in recent work. Highlighting the persistent cross-sectional heterogeneity in expectations, we then review evidence on the determinants of beliefs, including a new analysis of belief reactions to the tariff announcement in April 2025. Next, we examine how expectations shape financial decision-making, emphasizing the systematic but muted sensitivity of outcomes to belief changes. We conclude by pointing to promising directions for future research on belief measurement, the determinants of expectations, and their implications for policymakers.

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1 Introduction

A growing body of research highlights the central role of beliefs in shaping economic outcomes. Nowhere is this more evident than in finance, where expectations influence asset prices, portfolio decisions, and responses to macroeconomic shocks. Belief dynamics are foundational to asset pricing, macro-finance, and behavioral finance, prompting increasing interest in understanding how beliefs are formed, how they evolve, and how they ultimately affect individual behavior in financial markets and the broader economy.

In parallel with these theoretical advances, the use of survey data has become an increasingly powerful tool in empirical finance and macroeconomics (Manski, 2004; Giglio et al., 2021a,b; Greenwood and Shleifer, 2014; Ameriks et al., 2020c,b; Shiller, 2000; Coibion and Gorodnichenko, 2012, 2015; Malmendier and Nagel, 2016). Surveys offer a unique window into the expectations of economic agents, providing several key advantages.

First, survey evidence has the potential to directly reveal beliefs about future outcomes—such as stock returns, inflation, and GDP growth—that are otherwise hard to observe. Because expectations are difficult to measure, survey responses provide critical data that would otherwise need to be inferred from behavior under strong structural assumptions.

Second, unlike market data, which typically reflect aggregate beliefs or equilibrium outcomes, surveys reveal the rich cross-sectional heterogeneity in expectations across individuals and investor types. This variation helps explain differences in economic behavior that representative-agent models overlook and provides essential input for calibrating heterogeneous agent frameworks (Moll, 2024).

Third, by linking survey expectations to administrative data—such as trading activity or portfolio allocations—researchers can more directly test and calibrate structural assumptions related to preferences, frictions, and belief formation. This allows for a sharper evaluation of how well theoretical models of investor beliefs align with observed economic behavior.

Despite early skepticism regarding the survey's reliability—concerns about measurement error, framing effects, and the link between stated and actual beliefs—recent empirical work has shown that survey data meaningfully correlate with real-world investment behavior and can distinguish between competing models of belief formation (Giglio et al., 2021a,b; Dominitz and Manski, 2010; Vissing-Jørgensen and Attanasio, 2003; Amromin and Sharpe, 2014; Greenwood and Shleifer, 2014; Cochrane, 2017). As a result, there is a growing theoretical literature that incorporates survey evidence into models of expectation formation and asset pricing, using it to discipline assumptions about beliefs in order to better match empirical patterns in investor behavior (see Barberis et al., 2015; Nagel and Xu, 2022; Adam et al., 2017, for examples).

In this review, we synthesize recent advances in the study of investor expectations, with particular attention to how survey data have been used to document belief dynamics, evaluate theoretical models, and refine frameworks in both behavioral and macro-finance. We begin by outlining approaches to measuring subjective expectations, highlighting early surveys such as Shiller (2000) and the Health and Retirement Study, which elicit expectations from investors and households, respectively. We also emphasize newer datasets that link survey responses to administrative data on financial portfolios and outcomes, enabling direct tests of belief-driven behavior.

We then turn to key empirical patterns uncovered in the literature, drawing on updated data from the GMSU-Vanguard survey used in Giglio et al. (2021a). A consistent finding is that cross-sectional heterogeneity in expectations far exceeds time-series variation. Individuals exhibit persistent differences in optimism or pessimism, raising a central question for theory: what determines this persistent belief heterogeneity? The following section addresses this by reviewing recent work on the origins of belief differences, including roles for personal experience, cognitive biases, and information frictions.

Subsequently, we examine the behavioral consequences of expectations, focusing on how beliefs shape individual decision-making in financial markets. While a systematic relationship exists between investor expectations and behaviors such as stock market participation, trading frequency, and portfolio risk-taking, the sensitivity of these decisions to beliefs is often modest in magnitude. We conclude by identifying open questions and promising directions for future research, including implications for policy design, model calibration, and the interpretation of survey-based measures of expectations.

2 Measuring Subjective Expectations

To study the patterns and determinants of beliefs, and their link to economic actions, researchers need reliable measures of investor expectations. Traditionally, economists inferred expectations from observed behavior, but this required strong assumptions about belief formation and the structure of preferences. Surveys now provide a more direct way to elicit expectations—intuitively, the most straightforward method of learning about investors' beliefs about future stock returns is simply to ask them (Manski, 2004).

2.1 Surveys about investor expectations

Early foundations. Shiller (2000) was one of the first to use survey questionnaires to elicit beliefs about financial markets. He administered a survey from 1989 to 1998 in order to measure investor confidence and bubble expectations in the U.S. stock market. There are two versions of the survey administered: one for wealthy individuals and one for institutional investors. The questions elicit beliefs about expected stock market returns from the Dow, higher order belief questions, and the probability of a stock market crash occurring. The survey continues to be administered by the Yale International Center for Finance (ICF).

The American Association of Individual Investors (AAII) conducts a weekly survey of its members, asking for their six-month outlook on the stock market. Respondents classify their views as "bullish," "neutral," or "bearish".

In addition to investor-focused surveys, some are administered to the broader household population. The RAND American Life Panel, a nationally representative, probability-based survey, covers a wide range of topics, including stock market expectations. One of its surveys asks respondents to assign probabilities that 1-year and 10-year stock returns will be around 0%, exceed 20%, or fall below –20%.

Another example of a household survey used in the early literature is the Health and Retirement Study (HRS), a biennial longitudinal panel survey that samples approximately 20,000 people in the

United States and is supported by the National Institute on Aging and the Social Security Administration. One of the questions on the survey, analyzed extensively in the current literature, asks about the probability of mutual fund shares increasing in value in a year's time.

The Michigan Survey of Consumer Attitudes, conducted by the Survey Research Center at the University of Michigan, is a household panel survey that also elicits expectations about stock market returns to households that report having at least $5,000 in stock or stock mutual fund holdings. The survey elicits information about expected average stock market returns over various horizons, the likelihood of realized outcomes, as well as the respondents' portfolio choices. The survey also elicits questions about other assets, including the expectations of housing market prices (see Kuchler et al., 2023, for more details).

The European Central Bank (ECB) administers both the Consumer Expectations Survey (CES) and the Survey of Professional Forecasters (SPF). The CES, fielded monthly, elicits household expectations in 11 EU countries regarding inflation, housing and credit markets, income and consumption, and labor market conditions and growth. The SPF, conducted quarterly, gathers point estimates and probability distributions from professional forecasters on inflation, unemployment, GDP, and other key macroeconomic variables.

While the surveys above focus on households and individual investors, the Duke (Graham–Harvey) CFO Survey is conducted quarterly among U.S. financial professionals, ranging from those at small firms to executives at Fortune 500 companies across major industries. Respondents—chief financial officers and other financial decision-makers—are asked about their expectations for 1-year stock returns.

Key features of survey data. Together, these early surveys highlight how researchers began to probe investors' and households' expectations about financial markets. Beyond asking questions about average stock market return expectations, an important strength of survey data is its ability to capture subjective probabilities that respondents assign to different macroeconomic scenarios. For instance, the Survey of Consumer Expectations (SCE) by the Federal Reserve Bank of New York directly elicits subjective probabilities on different ranges of 1-year inflation (see D'Acunto and Weber, 2024, for a review of the related literature on survey expectations of inflation). Similarly, the Shiller survey elicits subjective probabilities of a stock market disaster. Surveys can also include questions about returns on specific types of portfolios. For example, Giglio et al. (2025) ask investors to state the expected 10-year annualized return of a diversified U.S. ESG equity portfolio, along with their motivations for investing in ESG.

The recent literature has also included some additional key features that have further enhanced the understanding of belief formation. As opposed to the rotating nature of earlier surveys, more recent efforts have included a panel dimension to the survey population, which has enabled researchers to better understand changes in individual beliefs over time. For example, the GMSU-Vanguard survey features many investors who respond to multiple survey waves.

Another key feature of recent surveys is their ability to elicit expectations over different horizons. The GMSU-Vanguard survey asks respondents about their expectations for 1-year stock returns, 10-year stock returns, 3-year GDP growth, and 10-year GDP growth. The questions are directly about moments of interest for asset pricing, the mean and distribution of returns, rather than less quantitative in nature (e.g. the probability of the stock market "going up").

While most of the surveys above focus on higher-net-worth individuals—relevant for wealth-weighted asset pricing models—other surveys examine stock return expectations in the broader population of investors. The UBS/Gallup Survey is an example of a survey of the broader population that asks individual investors about their experiences in the economy and stock market, including their beliefs over the next 12 months.

Surveys in other domains. In addition to these household and higher net-worth retail investor surveys, there are other surveys that specifically target different stakeholders in financial markets. For example, the Federal Reserve Bank of Philadelphia conducts the Survey of Professional Forecasters, while IBES surveys equity analysts about stock market cash flow expectations. Wolters Kluwer conducts the Blue Chip Economic Indicators survey by polling top business economists in America to elicit their beliefs about U.S. economic growth, inflation, interest rates, and other macroeconomic indicators. Other papers have also collected the return expectations of institutional investors for different asset classes by using public reports on their websites (Dahlquist and Ibert, 2024).

2.2 Methodological challenges and innovations

The use of survey data in finance is relatively recent and was initially criticized for small, unrepresentative samples, measurement error, and doubts over whether reported beliefs reflect true expectations. Manski (2004), however, demonstrates that carefully designed surveys with probabilistic formats can mitigate these concerns by allowing respondents to express uncertainty rather than forcing point estimates. Contrary to early skepticism that individuals would only respond with 0, 50, or 100%, he shows that respondents make full use of the probability scale, providing informative distributions of beliefs. At the same time, Cochrane (2017) cautions that the everyday meaning of "expect" differs from its technical use in economics, and thus survey answers should not be taken uncritically as true conditional means (see also the recent discussion in Hartzmark and Sussman, 2024). Nonetheless, he emphasizes that such data remains valuable for disciplining and testing theoretical frameworks.

Linking surveyed beliefs to administrative or transaction data. Recent innovations in the literature have established systematic links between subjective beliefs and economic outcomes. For instance, Ameriks et al. (2017, 2020c,b) connect survey evidence to retirement choices and to the sensitivity of equity investment to stock market expectations. Similarly, Manski (2004), Hurd (2009), and Greenwood and Shleifer (2014) show that investor beliefs vary systematically with individual behavior. Building on this approach, Giglio et al. (2021a) use the GMSU-Vanguard Survey to link investors' expectations about stock and bond returns to their actual trades and portfolio allocations, while Dahlquist and Ibert (2024) relate institutional investors' reported return expectations to equity allocations observed in Morningstar data.

This body of work demonstrates the central insight of modern survey-based research: subjective expectations, though noisy, serve as informative proxies for agents' beliefs and can be used to uncover systematic patterns in investor behavior.

3 Empirical Patterns of Beliefs

Using the survey data described above, a large literature has emerged on understanding how investor beliefs vary both across individuals and within individual over time. We now proceed by discussing the empirical patterns of individual beliefs documented in the literature.

3.1 Time-series variation

We first document the time-series variation in stock market expectations. Figure 1 presents the time-series variation of cross-sectional average beliefs using updated results from the GMSU-Vanguard survey data from Giglio et al. (2021a,b). Panels (*a*) and (*b*) of Figure 1 highlight the time-series of average expected 1-year and 10-year stock returns by survey wave. Panels (*c*) and (*d*) show the time-series of average expected 3-year real GDP growth and 10-year GDP growth (annualized). Panels (*e*) and (*f*) show the time-series of average subjective probabilities of a stock market disaster and a GDP disaster, defined as the probability of a return lower than -30% within 1 year and an annual GDP growth below -3% over 3 years, respectively. The shaded areas in each panel mark major downturns: the COVID-19 stock market crash in March 2020,[1] when 1-year return expectations dropped to 1%, and the global tariff announcement on April 2, 2025, when 1-year return expectations fell below 0% for the first time in the survey's history.

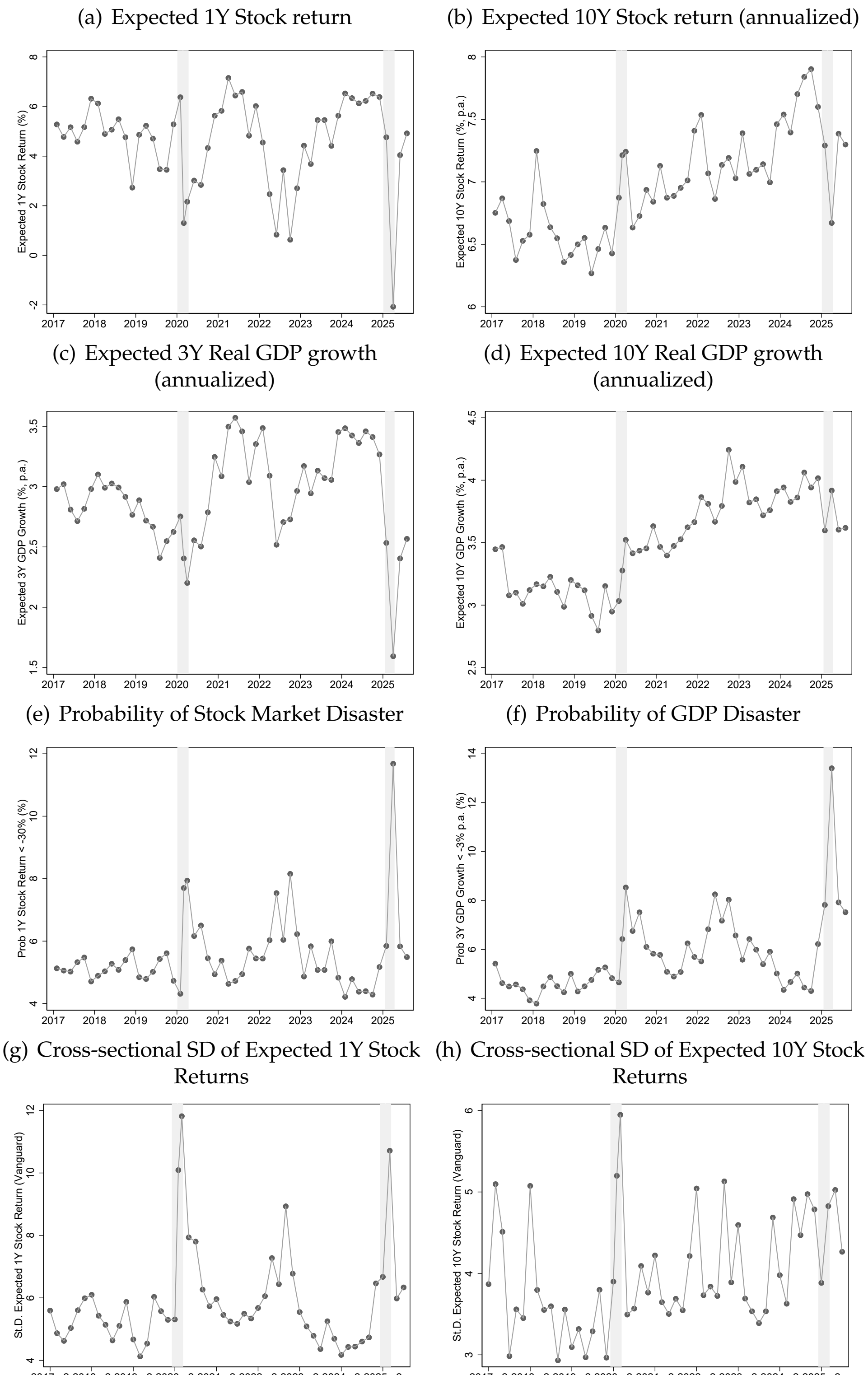
Generally, we find that short-term expectations fall significantly during downturns, consistent with the return-extrapolation in Greenwood and Shleifer (2014). Expected 1-year returns and expected 3-year GDP growth fell significantly after the COVID-19 stock market crash and the tariff announcements. Conversely, the patterns of long-term expectations are less clear. Although both expected 10-year stock returns and expected 10-year GDP growth rose modestly during the COVID-19 crash, their trajectories diverged after the tariff announcement: expected 10-year returns declined, while expected 10-year GDP growth continued to edge upward. The subjective probabilities of disasters both generally increase after a crash. We further discuss the implications of these results in later sections.

Another key area of interest to financial economists is the correlation between the time-series average of survey expectations of returns and model-based expected returns (ERs) from the theoretical literature. Ideally, survey expectations of returns should be a noisy approximation of ERs and, therefore, should have a positive correlation. However, using different survey data and measures of ERs such as the dividend price ratio, Greenwood and Shleifer (2014) find that these values are negatively correlated with each other.

Notably, the behavior of institutional investors' expectations over time is different from retail investors. A related literature describes the subjective expectations of institutional investors (focusing on expected *excess* returns). The evidence on the patterns of excess returns tends to be mixed, as noted by Nagel and Xu (2023). Using the Yale ICF survey of institutional investors in the U.S., Bacchetta

[1] The GMSU-Vanguard survey is normally fielded bimonthly starting in February. During the March 2020 crash, however, an unscheduled flash wave was conducted. See Giglio et al. (2021b) for details.

Figure 1: Time Series of Average Responses to GMSU-Vanguard Survey



Note: Time series plots of average across respondents within a survey wave between February 2017 and August 2025 of (*a*) Expected 1Y stock return, (*b*) Expected 10Y stock return (annualized), (*c*) Expected 3Y real GDP growth (annualized), (*d*) Expected 10Y real GDP growth (annualized), (*e*) Perceived probability of a stock market disaster ($< -30\%$ returns within 1Y), (*f*) Perceived probability of a GDP disaster (avg. annual growth $< -3\%$ over 3Y), (*g*) Cross-sectional standard deviation of expected 1Y stock return, (*h*) Cross-sectional standard deviation of expected 10Y stock return. Shaded regions mark the COVID-19 flash wave in March 2020 and the wave immediately after the announcement of tariffs in April 2025.

et al. (2009) find that subjective excess returns are acyclical; they have no relationship with variables that capture the valuation cycles of the stock market such as the price-dividend ratio and interest rates. However, Renxuan (2020) and Dahlquist and Ibert (2024) find that subjective expected excess returns are countercyclical (although the latter shows this for a one-year horizon only). In other words, asset managers' implied subjective equity premium expectations mirror the objective equity premium expectations, which is the opposite of the results for retail investors in Greenwood and Shleifer (2014); Amromin and Sharpe (2014).

3.2 Cross-sectional disagreement

Panels (*g*) and (*h*) of Figure 1 show the time series of cross-sectional standard deviations in expected 1- and 10-year stock returns across respondents in each survey wave. The figures show that there is substantial cross-sectional disagreement relative to time-series variation. The pattern could arise from two distinct sources. At one extreme, individual beliefs may fluctuate significantly over time, with the same person expressing different views at different points in time. At the other extreme, the cross-sectional variation may reflect persistent heterogeneity, whereby certain individuals are consistently optimistic or pessimistic across periods.

Giglio et al. (2021a) conduct a variance decomposition to analyze the source of this cross-sectional dispersion. They find that this heterogeneity reflects persistent individual fixed effects—the same people are consistently optimistic or pessimistic—rather than massive shifts in each individual's beliefs over time. Furthermore, observable demographic characteristics explain only a small part of individual fixed effects, with the R^2 only ranging between 2-7% across different survey questions. This suggests that there are important persistent differences in beliefs across investors that we cannot explain using observable individual characteristics, which represents a promising area of study for future research.

These results are consistent even across different domains explored in the literature. Dahlquist and Ibert (2024) find similar results for institutional investors: manager fixed effects explain 78% of the variation in subjective expectations. Using a panel of New Zealand firms, Coibion et al. (2018) also show that there is significant disagreement among firms in their past and future macroeconomic expectations, such as inflation, unemployment, and GDP growth. Kuchler et al. (2023) also demonstrate similar results for housing market beliefs; there is large cross-sectional dispersion, but relatively small time series variation in house price expectations, with demographics playing a systematic but quantitatively muted explanatory role. Importantly, they find that observable demographic characteristics such as age, wealth, and gender explain only a small portion of this panel variation (Das et al., 2020; Malmendier and Nagel, 2011; Kuchler and Zafar, 2019; Bailey et al., 2018, also find similar results).

3.3 Correlation across macroeconomic beliefs

Another key dimension of belief formation concerns how expectations about different economic outcomes co-move. That is, beyond understanding how individuals differ in their beliefs, it is also interesting to ask how beliefs across various processes—such as stock returns, GDP growth, and bond yields—are correlated within and across individuals. These correlations provide critical insight into how individuals perceive macroeconomic linkages and, ultimately, how those joint beliefs influence decision-making and asset prices.

Table 1: Correlation of Survey Responses

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1) Expected 1Y Stock Return (%)	1.000								
(2) Expected 10Y Stock Return (% p.a.)	0.307	1.000							
(3) Probability 1Y Stock Return < -30% (%)	-0.272	-0.064	1.000						
(4) St.D. Expected 1Y Stock Return (%)	-0.065	0.011	0.460	1.000					
(5) Expected 3Y GDP Growth (% p.a.)	0.276	0.212	-0.084	0.044	1.000				
(6) Expected 10Y GDP Growth (% p.a.)	0.106	0.280	0.005	0.060	0.631	1.000			
(7) Probability p.a. 3Y GDP Growth < -3% (%)	-0.217	-0.076	0.431	0.276	-0.170	-0.012	1.000		
(8) St.D. Expected 3Y GDP Growth (% p.a.)	0.033	0.069	0.217	0.572	0.218	0.221	0.325	1.000	
(9) Expected 1Y Return of 10Y Zero Coupon Bond (%)	0.145	0.133	-0.022	0.004	0.161	0.161	-0.019	0.067	1.000

Note: Table presents within-survey wave unconditional correlations across questions which elicit beliefs about various macroeconomic outcomes. The survey covers the period from February 2017 to August 2025.

Table 1 updates Appendix Table A.3 in Giglio et al. (2021a), reporting correlations across responses to different belief questions in the GMSU–Vanguard survey and highlighting the key relationships showed in Giglio et al. (2021a).[2]

The empirical relationship between expected cash flows and expected returns. First, a variable of interest to financial economists is the subjective expectation of future cash flows. Although return expectations play a pivotal role in asset pricing, they do not fully capture the nuanced relationship between investor sentiment and asset prices (Nagel and Xu, 2023). Instead, the interplay between expected cash flows and returns can offer a richer explanation of market dynamics.

Table 1 highlights the positive relationship between investor expectations of 3-year GDP growth and 1-year stock returns, with an unconditional correlation of 0.274. There is a similarly strong correlation between expected 10-year GDP growth and expected 10-year stock returns at 0.28. Thus, investors who expect higher GDP growth tend to also expect higher stock returns over both the short and long run. Giglio et al. (2021a) show that these results hold even after controlling for respondent demographics and survey wave fixed effects.

Implications from the Campbell-Shiller decomposition. The documented correlation between expected stock returns and GDP growth is particularly relevant for asset pricing models, due to their link through the Campbell-Shiller approximate identity. These empirical findings highlight a critical gap in traditional macro-finance models.

The Campbell-Shiller decomposition implies that, everything else equal, that rising expected cash flows should drive up asset prices. Similarly, an increase in expected returns (implying a higher discount rate), should lower prices. If both expectations move in the same direction, the effects on prices offset each other. The survey data shows that empirically, these two expectations are positively correlated. Asset pricing models that only focus on modeling cash flow expectations will ignore the correlated

[2]Note that Giglio et al. (2021a) focuses on the conditional relationships between these outcomes, controlling for survey wave fixed effects and demographics. Nevertheless, the same general trends hold.

variation in discount rates, which has a first-order effect on prices, and may lead to overestimating the explanatory power of cash flow expectations alone.[3]

Additionally, under the Campbell–Shiller identity, expectations of cash flows and returns are expected to be positively related not only in the time series, but also in the cross-section. Thus, cross-sectional disagreement about returns should be correlated with disagreement about cash flows. However, the identity is silent about the horizon at which these correlations apply (because the decomposition depends on the aggregation of all horizons). Giglio et al. (2021a) provide evidence on these relationships, documenting cross-sectional correlations of cash-flow and return expectations at short-run and long-run horizons.

Perceived probabilities of disasters and expected returns. Another area of interest is the relationship between probabilities of stock market disasters and GDP disasters. We define stock market disasters and GDP disasters as the probability of 1-year stock market returns falling below -30% and per-annum 3Y GDP growth falling below -3% respectively.

Table 1 shows a negative correlation between perceived probabilities of stock market disasters and short-run stock returns, an estimated value of -0.269. Giglio et al. (2021a) further show that, even after controlling for demographics, outlier responses, and survey wave fixed effects, higher perceived probabilities of stock market disasters are consistently associated with lower expected stock returns—both within and across individuals.

Implications for models of disagreement. The cross-sectional results for perceived stock market disaster probabilities and stock market returns support models where agents "agree to disagree" about the probability of stock market disasters, such as in Chen et al. (2012). In their model, the optimistic agents are those who expect both higher returns and a lower probability of disasters.

However, the results *within* individuals complicate the findings of time-varying rare-disaster models with representative agents as in Gabaix (2012) and Wachter (2013). In these models, an increase in disaster probability leads investors to demand higher risk premia, thereby raising equilibrium expected returns. In contrast, we find that individual investors' return expectations decline as their perceived probability of a stock market disaster rises—a fact that suggests the importance of disagreement across agents and provides useful guidance for calibrating future rare-disaster models, particularly those with heterogeneous agents.

4 Determinants of Beliefs

As we reviewed in the previous section, the cross-section of beliefs is rich and difficult to explain; cross-sectional variation across individuals explains the variation in beliefs far more than time-series variation. This poses the question: what drives this cross-sectional variation? In recent years, there has been a growing literature that, more generally, examines what factors impact investor belief formation.

[3] Some papers, most prominently, De La O and Myers (2021), have studied the time-series relation between expectations and prices empirically, attributing the variation in the price-dividend ratio to the various components of the Campbell-Shiller decomposition.

4.1 The extrapolative component of beliefs

The literature on expectation formation across various asset classes and financial market participants has found that individuals over-extrapolate from recent information signals when forming expectations about the future (Barsky and De Long, 1993; Greenwood and Shleifer, 2014; Barberis et al., 2015; Giglio et al., 2021a).

Lakonishok et al. (1994) analyze differences in returns for glamour and value stocks through a variety of classification schemes (e.g., book-to-market ratio, earnings-to-price ratio, etc.). Ultimately, they show that these value strategies, especially those that bet against extrapolative investors, produce higher returns than glamour stocks.

Additional evidence about the prevalence of extrapolative expectations can be found directly in survey expectations data. Using different sources of survey data, Greenwood and Shleifer (2014) analyze the relationship between investor expectations and the past 12-month returns. They find that, generally, investor expectations of future returns are higher when recent past returns are high. Quantitatively, an increase in the price level of 20% increases expectations by 1.80 percentage points in the Gallup survey. They further show that these survey expectations negatively forecast future returns—consistent with extrapolative beliefs—although the explanatory power is small. In related work, Barberis et al. (2015) incorporate extrapolative expectations in a consumption-based asset pricing model with heterogeneous agents. They show that this model captures many features of returns and stock prices.

Building on this existing literature, Cassella and Gulen (2018) present a recursive model that quantifies the relative weight extrapolators assign to recent versus distant past returns when forming their beliefs—a metric they term the "degree of extrapolative weighting" (DOX). They find that the DOX has significant time variation and that market return predictability is only significant when extrapolators place greater weight on recent returns (i.e., when the DOX is high).

4.2 Personal experiences

While recent information shapes expectations, a related literature emphasizes the role of personal experiences in belief formation.

Malmendier and Nagel (2011) use SCF and UBS/Gallup data to show that personal macroeconomic experiences strongly shape beliefs. Individuals overweight events from their lifetimes: those who lived through low stock returns report lower risk tolerance and expectations, and younger investors are more sensitive to recent returns than older ones. Overall, people place greater weight on recent outcomes. Malmendier and Nagel (2016) find a similar pattern for inflation, with individuals over-weighting lifetime inflation when forming expectations.

Personal experiences also shape macroeconomic expectations across asset classes and dimensions beyond time. For example, Kuchler and Zafar (2019) use SCE data to show that local housing price changes affect national house price expectations: a 1-point increase in local prices raises 1-year national expectations by 0.1 points. They also find that greater local price volatility increases cross-sectional disagreement, and that unemployment experiences make individuals more pessimistic about future unemployment.

It is important to note that extrapolation from recent information and personal experiences are not necessarily mutually exclusive. Broadly speaking, both cases are a result of the over-weighting of recent, personal information when formulating macroeconomic expectations. Since the intake of recent information and personal experiences are largely heterogeneous across individuals (partially due to variations in geography and demographics), this can lead to the large cross-sectional heterogeneity observed in the empirical data.

Finally, although recent returns systematically shape short-run expectations, they, along with extrapolative patterns and observable characteristics, explain relatively little of the overall variation in beliefs, as discussed in detail in Giglio et al. (2021a).

4.3 Macroeconomic shocks

Another factor shaping beliefs is exposure to rare macroeconomic shocks. This is especially relevant for the rare-disaster literature, which studies how return expectations and perceived disaster probabilities adjust following the realization of such events (Rietz, 1988; Barro, 2006).

Giglio et al. (2021b) investigate the short-term changes in investor expectations in response to the COVID-19 stock market crash. They observe that the dispersion in expected 1-year returns and the perceived probability of stock market disasters increased substantially after the crash, persisting even through part of the market recovery. Panel (*g*) of Figure 1 highlights this pattern: the cross-sectional disagreement significantly increased in the first shaded area during the COVID-19 flash wave.

Moreover, the average investor became more pessimistic about 1-year stock market returns and 3-year real GDP growth while also expecting higher probabilities for further extreme declines in stock market and real economic activity. Panels (*a*) and (*c*) of Figure 1 show that 1-year expected returns and 3-year expected GDP growth fell to approximately 1.8% and 2.4% respectively. Panels(*e*) and (*f*) highlight that the probability of disasters increased from 4.3% to 7.9% for the stock market, and from 4.6% to 8.5% for GDP growth. However, expectations about long-run real GDP growth and stock market returns remain mostly unchanged. Giglio et al. (2021b) also decompose investor reactions by the relative level of optimism just before the crash. Analyzing changes in equity allocation by relative optimism, they show that the most optimistic respondents saw the largest fall in expectations and sold the most equity, while the most pessimistic respondents mostly left their portfolios unchanged during and after the crash.

These results relate to the theoretical literature on heterogeneous beliefs and trading. These models identify optimists who expect high returns and hold larger positions in equity, as well as pessimists who expect low/negative returns. When a crash occurs, optimists tend to lose more wealth; the changes in beliefs between the two groups helps in generating trading activity, which is in line with the empirical findings of Giglio et al. (2021b).

A more recent example of an aggregate shock is the U.S. announcement of wide-ranging tariffs on April 2nd, 2025. Following this announcement, the GMSU-Vanguard survey was fielded on its regular schedule on April 8, 2025. Panels (*a*) and (*g*) of Figure 1 highlight some patterns similar to those discussed above for the COVID period: expected 1-year returns dropped significantly (below 0%), while disagreement significantly increased at a comparable magnitude to the COVID-19 shock. Panel (*c*) also highlights that expected 3-year GDP growth significantly fell from 2.5% to roughly 1.6%.

Panels (*e*) and (*f*) document similar patterns in the average perceived probabilities of disasters as in the COVID-19 stock market crash. However, the magnitude of the increases is much larger, with the average perceived probabilities of stock market crashes doubling from 6% to 12% and the perceived probabilities of a 3-year GDP crash increasing from 8% to 13.8%.

Long-term expectations did not move uniformly during these two macroeconomic events. Panel (*d*) of Figure 1 shows that expected 10-year GDP growth rose modestly in both cases, whereas panel (*b*) shows that expected 10-year stock returns fell after the tariffs announcement but remained stable during the COVID-19 crash. One possible explanation is that tariffs were interpreted as a structural drag on long-run prospects because of a change in the policy environment, whereas COVID was perceived as a temporary shock with limited impact on long-term returns.

5 The Effects of Beliefs on Individual Behavior

In the previous sections we have reviewed the growing literature on expectation formation, documenting patterns in investor and household beliefs and their determinants. A key conclusion is that beliefs are heterogeneous and difficult to explain based on simple observables. Still, financial economists remain interested in how these beliefs affect asset pricing variables to assess which models best capture investors' empirical behavior.

As discussed earlier, a growing body of work links survey measures of expectations to administrative data on trading and portfolio positions. These datasets allow researchers to directly observe how individual beliefs map into investment choices, providing valuable discipline for calibrating portfolio choice models in asset pricing. In this section, we build on this literature to document the relationship between beliefs and behavior in greater detail.

5.1 Beliefs and Stock Market Participation

A first strand of the literature examines whether return expectations influence equity market participation. If beliefs meaningfully drive participation, then subjective expectations play a direct role in determining who sets prices and how risks are shared.

The literature has generally documented low stock market participation rates (Mankiw and Zeldes, 1991; Haliassos and Bertaut, 1995; Favilukis, 2013; Heaton and Lucas, 2000; Duraj et al., 2024). Nevertheless, beliefs play a systematic role in stock market participation.

Dominitz and Manski (2010) survey elderly respondents in the 2004 Health and Retirement Study and show that a 1% increase in the perceived probability of positive stock returns raises the probability of stock ownership by 0.4%. Hurd et al. (2011) corroborate these findings using Dutch investor surveys, where a 1% increase in expected 1-year gains raises the probability of stock ownership by 0.29% in 2004 and 0.49% in 2006. Similarly, Kézdi and Willis (2011) use the same Health and Retirement Study to show that a 1% higher expected return corresponds to 0.3% more equity in portfolios.

Beyond return expectations, both optimism and literacy in one's beliefs shape stock market participation. Merkoulova and Veld (2022) survey U.S. investors and find that overly optimistic individuals are more likely to enter the stock market, while those unable to provide point estimates of expected returns or return distributions are less likely to participate. Similarly, van Rooij et al. (2011) show that in the Netherlands, individuals with lower financial literacy are less likely to invest in stocks.

5.2 Beliefs and Portfolio Allocation Decisions

A related strand of literature studies the relationship between beliefs and equity allocation in an investor's portfolio. Asset pricing models predict that individuals change their portfolio positions and trading activity based on their beliefs, but an important quantitative question arises: *how much* do investors change their trading activity and portfolio positions following a change in their beliefs?

Giglio et al. (2021a) investigate the relationship between survey-elicited beliefs and investors' actions using the survey respondents and administrative data of Vanguard investors. In order to estimate the sensitivity, they run the following regression:

$$\text{EquityShare}_{i,t} = \alpha + \beta E_{i,t}[R_{1y}] + \gamma X_{i,t} + \psi_t + \epsilon_{i,t} \tag{1}$$

The dependent variable $\text{EquityShare}_{i,t}$ represents the equity share in the individual's Vanguard portfolio at time t, while β captures the increase in an individual's equity share for each percentage point increase in 1-year expected returns ($E_{i,t}[R_{1y}]$). They also control for time fixed effects ψ_t and demographics $X_{i,t}$ in different specifications of the regression.

Table 2: Updated Portfolio Sensitivity Table from Giglio et al. (2021a)

	Equity share (%)					
	(1)	(2)	(3)	(4)	(5)	(6)
Expected 1Y stock return (percent)	0.647***	0.685***	1.125***	0.619***	0.816***	1.102***
	(0.022)	(0.023)	(0.042)	(0.030)	(0.041)	(0.040)
Expected 1Y stock return (percent) $\times$ assets $>$ median assets				0.103**		
				(0.042)		
Controls	N	Y	Y	Y	Y	Y
ORIV	N	N	N	N	N	Y
Sample			E(return) 0-15 percent		Feb 2017 - Feb 2020 (Pre-COVID)	
Observations	109506	109295	95943	109295	39797	108712

Note: Table shows results from Equation 1 for survey data from Feb 2017 to Jun 2025. The unit of observation is a survey response. The dependent variable is equity share of individual i at wave t. Columns 2-6 control for age, gender, region, wealth, and survey wave. Standard errors are in parentheses and are clustered at the respondent level. Significance levels: * ($p<0.10$), ** ($p<0.05$), *** ($p<0.01$).

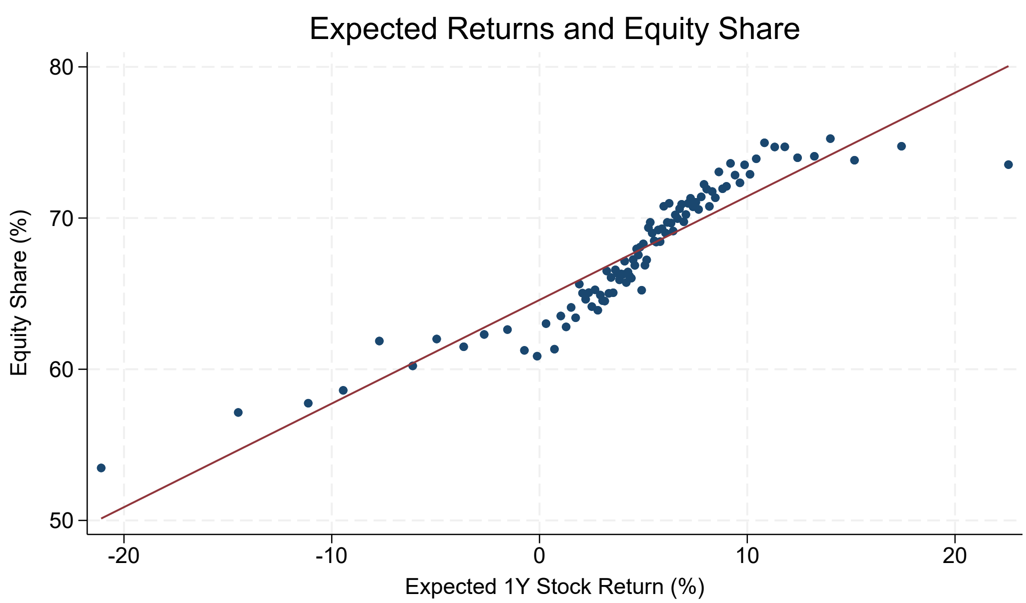


Figure 2: Expected 1-year Stock Returns and Equity Share

Note: Figure shows conditional binscatter of expected 1-year stock returns vs. equity share, controlling for age, gender, wealth, and survey wave (Feb 2017–Jun 2025).

Table 2 presents updated results from Table 3 of Giglio et al. (2021a). Column 1 shows estimates from the regression without controlling for any additional covariates. Quantitatively, a 1% increase in expected 1-year stock returns is associated with a 0.65% increase in respondents' equity shares. Column 2 of Table 2 controls for demographic characteristics such as age, gender, wealth, region of residence, and survey-wave fixed effects.

Figure 2 shows the binscatter plot of the equity share against the expected returns, controlling for age, gender, wealth and survey wave. The figure highlights the possibility that the estimates of the slope is affected by individuals with more extreme beliefs. Thus, we next run regression 1 on a sample of respondents that report expected returns between 0-15%, which drops around 13% of our responses. Column 3 of Table 2 shows that the sensitivity estimate is around 65% higher, which suggests that outliers in beliefs mute the sensitivity of the beliefs-portfolio relationship.

The results of columns 1 and 2, however, are an order of magnitude smaller than estimates of this sensitivity implied by a standard frictionless Merton (1969) model, which implies $\beta = 4.25$.[4]

We next explore whether the sensitivity of portfolios to beliefs is different for wealthier individuals—a group of particular interest for the theoretical literature, where asset prices are driven by wealth-weighted beliefs. Column 4 of Table 2 suggests that respondents in the top 50% of assets in the sample have a sensitivity marginally larger than that of individuals with lower wealth—though still unable to match the sensitivity implied by the Merton (1969) model.

The outliers appearing in Figure 2 also highlight the possibility that measurement error in the elicited expectations might be driving the low sensitivity estimates: classical measurement error would induce attenuation bias in the β estimates. In order to mitigate this measurement error, we exploit the fact that our survey produces two different estimates of $E_{i,t}[R_{1y}]$: the expected 1-year returns reported directly by survey respondents, and the *implied* mean of 1-year expected returns, constructed from the distribution of probabilities that respondents assign across 1-year return intervals. The two measures are strongly positively correlated with a correlation of 0.5041, allowing us to exploit recent advancements from the econometrics literature on instrumental variables for measurement error correction.

In particular, we employ the Obviously Related Instrumental Variables (ORIV) approach proposed by Gillen et al. (2019), an IV estimator that specifically exploits the availability of multiple measurements of the same variable, yielding a more efficient estimator than traditional IV approaches. Column 6 shows the results of the ORIV regression, finding that the estimated sensitivity increases by 70% from column 2, to $\beta = 1.102$. These findings highlight the importance of including different methods to measure the same beliefs. Nevertheless, even accounting for classical measurement error, the β estimate still falls far below the sensitivity implied by the Merton (1969) model.

Giglio et al. (2021a) find that the sensitivity of portfolio allocations to beliefs is higher in tax-advantaged retail accounts and increases in wealth, trading frequency, attention and confidence. Importantly, when focusing on respondents who are most similar to the frictionless benchmark, they find that the sensitivity estimates are significantly closer to the implied parameter estimates from the Merton (1969) model. These results suggest that differences in attention, adjustment costs, capital gains taxes, and confidence play key roles in shaping how beliefs translate into portfolio choices. In other words, these factors influence how responsive an investor is to their own beliefs when making allocation decisions.

This key finding—that beliefs systematically but weakly vary with portfolio allocation—is consistent with previous studies in the literature that link equity market participation and equity share allocation to expected stock market returns (Vissing-Jørgensen and Attanasio, 2003; Ameriks et al., 2020a; Amromin and Sharpe, 2014). Vissing-Jørgensen and Attanasio (2003) analyze survey and portfolio allocation data from the Survey of Consumer Attitudes and Behavior and also find that investors with higher expected

[4]See Giglio et al. (2021a) for the full back-of-the-envelope calculation.

stock returns also had higher portfolio allocations. Ameriks et al. (2020a) explore the survey data from the Vanguard Research Initiative and, using a structural model, find that an increase in expected returns by 1% leads to an increase in equity share by 0.48%, which is a comparable magnitude of sensitivity as implied by Giglio et al. (2021a). They also map their findings to a simple Merton (1969) model and find that their estimated parameters associated with the risk and belief parameters is substantially smaller in magnitude than suggested from benchmark theories.

Similar results also hold for institutional investors. Dahlquist and Ibert (2024) collect data on the return expectations of institutional investors and investment consultants at a one-year horizon across asset classes based on public reports on their websites or by directly requesting them. They show a similar magnitude of sensitivity. Quantitatively, a one percentage point increase in the long-term U.S. equity premium expectation is associated with a 2–4 percentage point greater allocation in U.S. equities in the cross-section of funds. They conclude that internal investment mandates constrain institutional investors, dampening the effect of return expectations on portfolio allocations. This aligns with the theoretical framework of Gabaix and Koijen (2021), which models institutional investors as having lower elasticity to demand shocks.

5.3 Beliefs and Trading

While the previous section focused on work studying how changes in beliefs impact an individual's portfolio choices, another related area of interest is understanding the relationship between beliefs and trading activity. There is a large theoretical literature that models trading volume in financial markets as a result of changes in beliefs and overconfidence (Hong and Stein, 2007; Scheinkman and Xiong, 2003).

Giglio et al. (2021a) analyze whether a change in beliefs impacts trading activity on the extensive margin—that is, whether a change in beliefs increases the probability of trading in either direction. They find that a change in beliefs does not impact the probability of an individual trading. However, they show that there is an intensive margin channel through which beliefs impact trading. Conditional on a trade occurring, a change in beliefs influences both the direction and the magnitude of the trade. Quantitatively, an investor who expects future 1-year stock returns to be 1 percentage point higher at the time of responding is roughly 1.5 percentage points more likely to buy equities in a given time window. Additionally, a 1 percentage point increase in expected 1-year stock returns corresponds to a 0.4 percentage point increase in equity share.

These results, particularly the lack of predictive power at the extensive margin, also further confirm that infrequent trading plays an important role in the low sensitivity of beliefs to portfolio allocations.

In assessing the impact of beliefs on trading activity during large macroeconomic shocks, Giglio et al. (2021b) find that, on average, respondents sold little equity; the optimists—those in the top tercile of beliefs—sold the most equity, actively decreasing their share by 1.05%. However, the intensive margin effects are more pronounced; optimists moved their equity allocation from a high of 68% to a low of 64%, and bought back part of their equity after the market rebounded at the end of March 2020. These findings are consistent with the previous discussion on the systematic, yet muted sensitivity of beliefs to portfolio allocation relative to benchmark frictionless models.

5.4 Firm expectations

Beyond the beliefs of retail and institutional investors, firm expectations are a crucial, yet sometimes overlooked aspect of financial markets. Unlike retail investors or professional forecasters, firms—through the judgments of their CFOs and other executives—shape real economic decisions, such as capital spending and investment in growth projects. These decisions have far-reaching effects on market dynamics and economic outcomes. For instance, when corporate managers anticipate strong future earnings growth, they tend to increase investment, which can drive broader economic expansion and, ultimately, influence market valuations. Some firms are also large investors in public security markets via their treasury departments, so that their portfolio allocations are also of direct interest.

Empirical evidence supports the significance of firm expectations. Gennaioli et al. (2016) focus specifically on firm expectations by looking at a quarterly survey of CFOs. They show that expectations of earnings growth are a key determinant of investment plans and of actual capital spending. Quantitatively, a 1 percentage point increase in CFO earnings growth expectations predicts a 0.6 percentage point increase in actual investment growth in the next 12 months. They further find that CFOs are systematically overoptimistic in good times and overpessimistic in bad times: future realized earnings growth falls below CFO expectations when past earnings are high, and vice versa. Gormsen and Huber (2025) construct a dataset of earnings calls, investor conferences, and similar events, and measure discount rate wedges—the gap between perceived cost of capital and discount rates, where the latter are defined as managers' required minimum rates of return on projects. They find that a 1 percentage point increase in the wedge reduces investment in the subsequent year by about 0.8 percentage points. Using the same dataset, Gormsen and Huber (2024) show that firms with a higher perceived cost of capital achieve higher returns on invested capital but invest less in the long run.

Conversely, some macroeconomic variables are seen by firms as relatively unimportant, yet shifts in these expectations can still influence their decisions. Coibion et al. (2018) show that few New Zealand managers actively track inflation, yet when randomly informed of the central bank's target, firms revised down their inflation expectations and reduced planned investment and employment; in fact, firms with high prior beliefs cut investment by 2% and employment growth by 3% relative to the control group (Coibion et al., 2021, also show similar results for higher-order inflation beliefs). In related work, Kumar et al. (2015) show that 75% of managers would change wages when they change their inflation expectations. Crucially, Coibion et al. (2020) provide causal evidence from Italian firms: randomly informing a subset of firms about recent (publicly available) inflation persistently shifted their inflation expectations and led them to raise prices, increase credit utilization, and reduce employment and capital. In the periods when the main ECB refinancing rate was near the zero lower bound (from late 2014 to mid 2018), price effects were larger and employment reductions disappeared.

Additionally, survey-based measures of firm expectations provide valuable insight into forecast uncertainty. Bachmann et al. (2013) evaluate survey expectations data from the German IFO Business Climate Survey and show that ex ante disagreement between managers in manufacturing firms about domestic production activities is unconditionally positively correlated with ex post forecast errors, which highlights the value of using survey disagreement as a proxy for forecast uncertainty.

6 Areas for Further Research

Despite substantial progress, the study of economic agents' expectations remains a dynamic field with many open questions. Survey data has deepened our understanding of how individuals and institutions form, update, and act on their beliefs. However, key challenges remain: particularly in explaining belief heterogeneity, broadening the scope and precision of measurement, and embedding expectations more fully into behavioral models and policy analysis. We outline several directions for future research across these fronts. We also briefly discuss the implications of large language models (LLMs), which, though not yet mature for beliefs research, raise important concerns about measurement contamination and the representativeness of synthetic belief data.

6.1 LLMs and expectations data

The rapid advancement of large language models (LLMs) introduces two distinct implications for the expectations-data literature. First, LLMs may contaminate survey responses if participants consult them while answering. Second, researchers may leverage LLMs to simulate synthetic belief offering a scalable tool for studying heterogeneity when human data is limited or costly. For example, there is recent evidence that LLMs can replicate human-like behavior under structured prompts (e.g. Horton, 2023).

Because LLMs are trained on vast text corpora, they have the potential to function as implicit models of human cognition and social reasoning. Yet, there are valid concerns that these models perform poorly in hard to predict ways, and that good performance in one domain does not necessarily imply likely good performance in other domains the same way it would occur in a human mind. Horton (2023) show that endowing LLMs with different social preferences reproduces classic results from behavioral experiments, underscoring their potential for modeling belief formation. This potential extends naturally to survey data and subjective expectations.

On the generative side, recent work illustrates how LLMs could be used to simulate belief distributions. For example, Fedyk et al. (2025) compare AI- and human-generated investment attitudes across stocks, bonds, and cash. LLMs initially skew toward the preferences of young, high-income individuals. However, when demographic attributes are seeded into the prompt (e.g., gender, age, income), this bias is reduced: AI–human average ratings correlate at roughly 0.7 across eight demographic cells. The model reproduces well-known patterns (e.g., men favor stocks; older respondents prefer cash), and the factor structure of qualitative justifications closely mirrors that of human free-text responses. In both human and AI data, higher perceived returns improve the perception of an investment option, while greater perceived risk worsens it. Moreover, younger individuals and men tend to report more positive past experiences with the stock market, which the LLM is able to replicate in its own responses. In related work, Bybee (2025) uses news-conditioned prompts to recover aggregate expectations consistent with benchmark survey data, suggesting that LLMs can also imitate patterns in aggregate expectations from common information sets. On the contamination margin, LLM-assisted responses may increase measurement error and introduce self-fulfilling bias if respondents default to model-typical beliefs and models are trained on data and text that analyzes the survey outcomes.

When it comes to measurement, reliance on LLMs by survey respondents may lead to a homogenization of answers, pulling individual responses toward the model's internal weights—often resembling the beliefs of young, high-income individuals. This can introduce bias into the cross-sectional data and obscure the meaningful cross-sectional heterogeneity across respondents documented in the literature (while this may have been already happening with information publicly available on the web, the possibility of asking the LLM the exact question may make the problem more severe). On the generative side, LLMs—when guided with carefully crafted prompts and seeded with demographic attributes—offer an intriguing possibility to generate data. Still, researchers must proceed with caution. Although it may be possible to simulate a cross-section of expectations, it is an exercise fraught with problems that the literature is yet to sort out. It is difficult to control for potential contaminants such as look-ahead bias and training-leakage where models inadvertently incorporate information from their training dataset that would not have been available at the time or to that person (see Ludwig et al., 2025, for formalized conditions of prediction problems with LLMs).

6.2 The measurement of beliefs

With the growing use of surveys to elicit beliefs, there is significant potential to expand and refine the set of features included in future survey designs. Although the existing literature has largely focused on quantitative questions—such as point forecasts or probabilistic distributions of stock market expectations—to discipline economic models, there is considerable scope for broadening this approach. In particular, incorporating qualitative questions and open-ended responses can capture richer dimensions of belief formation, including reasoning, sentiment, and perceived uncertainty that are often difficult to quantify. Duraj et al. (2024) use open-ended qualitative interviews analyzed with large language models (LLMs) to elicit German investors' beliefs about money and stock market participation, showing that non-investors perceive high attention costs and substantial knowledge requirements as barriers to entry (see also Ke, 2024, for an example of analyzing belief formation through analysts' written reports and quantitative forecasts).

Advances in natural language processing (NLP), specifically the development of LLMs, have made it increasingly feasible to analyze unstructured textual data at scale, offering new opportunities to extract economically meaningful features from brief qualitative inputs. These could include sentiment scores, thematic categorizations (e.g., macroeconomic vs. firm-specific concerns), or narratives underlying belief updates. As such, we see value in the inclusion of textual responses (even if short) as a supplement to the quantitative questions already used in the literature. This hybrid approach could enhance both model calibration and the interpretation of belief heterogeneity, paving the way for more behaviorally-informed theories of expectation formation.

Another area of beliefs with ample scope for research is an investor's higher order beliefs—beliefs about other people's beliefs. These beliefs can be important determinants of trading activity (Gorodnichenko and Yin, 2024; Schmidt-Engelbertz and Vasudevan, 2025). While macroeconomic news plays a key role in shaping higher-order beliefs (Schmidt-Engelbertz and Vasudevan, 2025), many other potential determinants remain to be explored in empirical work.

6.3 The determinants of the cross-section of beliefs

As mentioned in the previous section, there is significant scope for future research in understanding the determinants of investor beliefs; much of the cross-sectional variation in expectations of returns and cash flows remains unexplained. We anticipate that, instead of a few factors explaining most of the cross-sectional variation in expectations, researchers might keep discovering many variables that each explain only a small portion of belief heterogeneity. In this context, there is ample scope for the use of structural models in understanding belief formulation (see Kézdi and Willis, 2011, for an example). In addition, similar to the work in Bailey et al. (2018), we see ample opportunities to utilize the growing electronic trace and administrative data as a means to identify additional determinants of beliefs.

6.4 Implications for Policymakers

Much of the recent literature has leveraged high-quality expectations data to study how different agents formulate beliefs. These datasets are typically characterized by several key features.

First, they often include panel structures with repeat respondents, allowing researchers to track how individual beliefs evolve over time and disentangle persistent heterogeneity from transitory noise. Second, they often provide additional information, including demographic, financial, and behavioral variables that enable detailed heterogeneity analysis across different subpopulations. Third, high-frequency collection ensures that the data can be meaningfully aligned with macroeconomic or financial events. Fourth, they include question modules that elicit both point forecasts and probabilistic beliefs, which are crucial for understanding subjective distributions, uncertainty, and perceived disaster probabilities. Finally, they exploit the ability to link survey responses to administrative or transactional data on actual behavior. This linkage enables researchers to study not just what people believe, but also how those beliefs translate into real-world decisions—allowing for more precise tests of economic models.

In addition to shaping theoretical models, high-quality data on investor expectations offer valuable guidance for policymakers[5].

Policy effectiveness and uncertainty. Investor expectations data provides valuable guidance for policymakers in assessing the *ex post* effectiveness of their communication. Comparing time-series expectations before and after policy announcements, such as the earlier discussion about tariffs, reveals whether investors updated their growth- and return-expectations in the intended direction. Furthermore, analyzing the cross-sectional dispersion of these responses also provides useful information on the state of uncertainty after policy implementation.

Fiscal and monetary policy design. Policymakers can also use aggregate expectations data as *ex ante* inputs to policy formulation and forecasting. For instance, central banks may calibrate interest rate decisions not only based on realized inflation, but also on expected inflation and the degree of cross-sectional disagreement, which serves as a proxy for uncertainty. Likewise, expectations about fiscal policy—such as anticipated tax or spending changes, as measured by the New York Fed's Survey of

[5] See the Supplemental Materials section for a plot of the aggregate time series of various belief indices.

Consumer Expectations (SCE)—can influence household consumption and firm investment, providing a forward-looking foundation for fiscal policy analysis.

Stress testing and financial stability. The subjective probabilistic component of expectations data is especially valuable for the design of stress tests. For instance, data on the perceived likelihood of rare disasters—such as stock market or GDP crashes—can help regulators construct more realistic tail-risk scenarios. More broadly, expectations data offer insight into risk sentiment and can reveal early signs of systemic vulnerabilities, such as the formation of speculative bubbles. By tracking these beliefs—especially when they appear detached from fundamentals—policymakers can intervene before a tail-risk scenario materializes. For example, large and persistent divergences between expected and realized returns, as well as abrupt spikes in cross-sectional disagreements, may precede the materialization of tail-risk events.

7 Conclusion

Through the use of survey expectations data, there has been significant progress in understanding the behavior of various economic agents—especially investors and other financial market participants. As Giglio et al. (2021a) note, survey-based evidence is "here to stay, and.. the theoretical work has to continue to confront such evidence."

The current literature on survey data and beliefs has documented several key patterns of beliefs. First, individuals are persistently pessimistic and optimistic—even across different contexts and stakeholders. This cross-sectional variation in beliefs explains most of the panel variation, with observable demographic characteristics only explaining a small portion of the cross-sectional variation. Second, expected stock returns and GDP growth are positively correlated. Third, perceived tail-risk probabilities are negatively correlated with their respective beliefs. These results are particularly informative for macro-finance models like the rare disaster models documented by Rietz (1988); Barro (2006) and heterogeneous beliefs models such as in Chen et al. (2012).

While existing research on belief formation has attributed some cross-sectional variation to factors such as extrapolative beliefs, recent experiences, and tail-risk shocks, much remains to be understood about the broader determinants of expectation formation. Research on this front can be expanded through improvements in belief measurement (especially with qualitative text data), as well as through exploring their links to digital activity and administrative data.

These patterns and determinants of beliefs shape how expectations translate into economic outcomes of interest. There is growing evidence of the relatively weak sensitivity of portfolios, trading, and stock market participation to belief changes. However, this responsiveness of beliefs is increasing in wealth, trading frequency, attention, and confidence.

More broadly, expectations data offer a powerful lens for testing and refining economic models. The incorporation of subjective expectations into macro-finance has already disciplined classes of models in asset pricing and portfolio choice. However, there is a proliferation of data sources and techniques such as text analysis, experimental survey design, and potentially LLMs. These, combined with the growing availability of linked administrative data, open up many possibilities for deepening our understanding of expectations and economic behavior—which thereby enhance clarity for policymakers when analyzing the state of the economy and evaluating policy impacts.

Ultimately, survey expectations data have reshaped the study of belief formation and its economic implications. As new data sources and empirical strategies continue to emerge, they offer a promising path toward models that more accurately capture behavior and better inform economic policy.

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Investor Beliefs and Expectation Formation: Supplemental Materials

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A Figures and Belief Indices

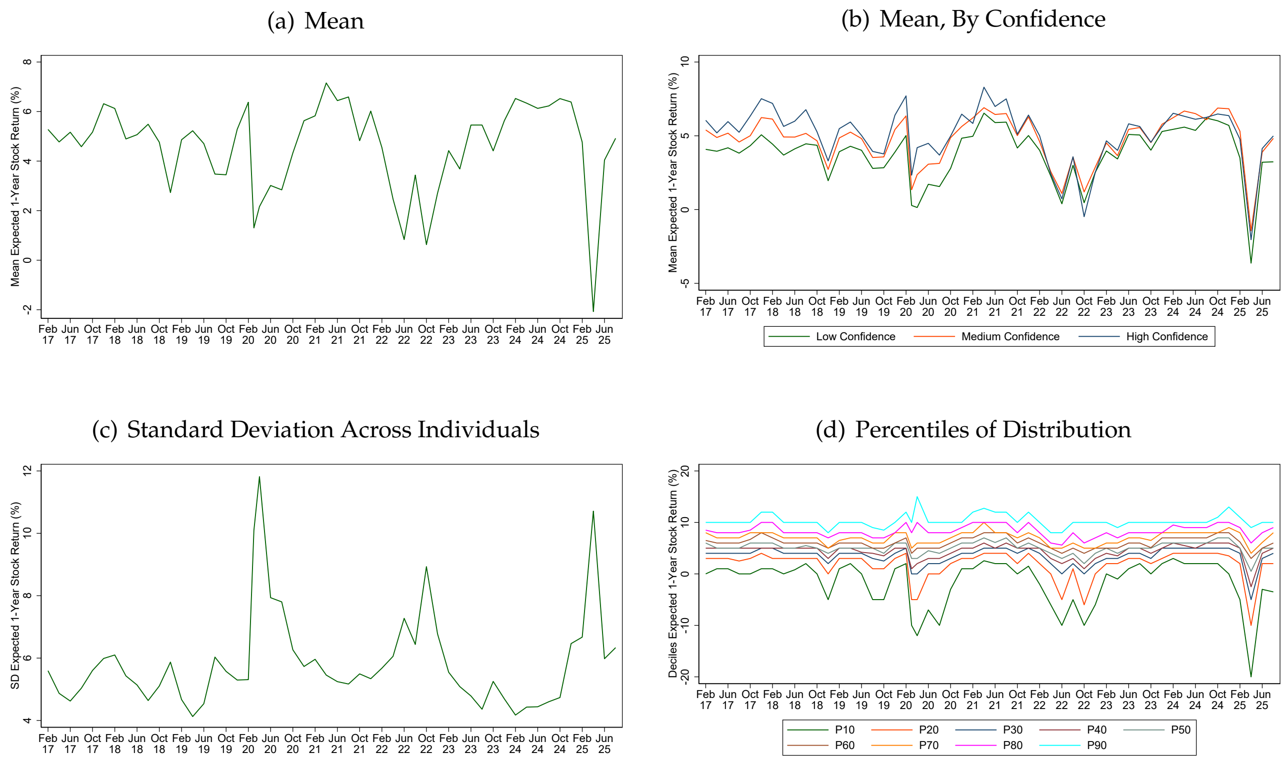
In this Appendix, we present additional figures documenting aggregate expectations for major questions in the GMSU-Vanguard Investor Expectations Survey. The survey elicits beliefs central to macro-finance, including expected stock returns, expected GDP growth in the short and long run, and perceived probabilities of economic and stock market disasters. Conducted bimonthly since February 2017, the survey samples U.S.-based Vanguard clients, with 80% drawn from retail investors and 20% from participants in defined contribution plans. Eligible respondents are at least 21 years old and must hold Vanguard assets of $10,000 or more. This sampling design captures a financially relevant population, with the contact pool representing approximately $2.5 trillion in Vanguard assets under management (see Giglio et al., 2021a, for further details about the survey design).

We cover the following belief indices:

1. 1-Year Expected Stock Returns
2. Subjective Probability that 1-Year Stock Returns < -10%
3. 10-Year Expected Stock Return
4. 3-Year Expected GDP Growth
5. Subjective Probability that 3-Year GDP Growth < 0%
6. 10-Year Expected GDP Growth
7. 1-Year Expected Bond Returns

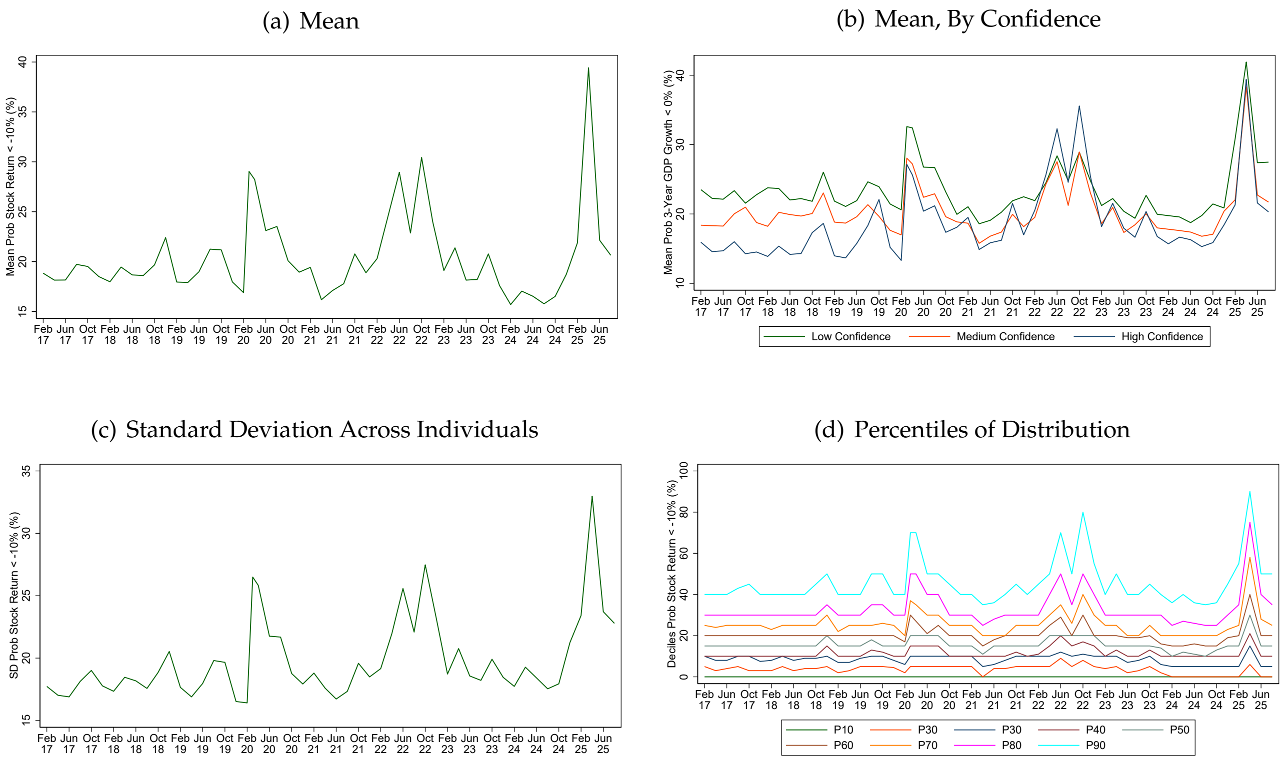
We plot the mean for each survey wave, the means separately by investor confidence, the across-individual standard deviation, and the deciles of the across-individual distribution. We also include average confidence in answers for the stock, GDP, and bond questions.

Figure A.1: 1-year expected stock returns



Note: Panel (A) shows the time series of average expected 1-year stock returns. Panel (B) shows the time series of average expected 1-year stock returns, split by confidence levels. Panel (C) shows the across-individual standard deviation of expectations by wave. Panel (D) shows the deciles of the expectations distribution by wave. The data span from February 2017 to August 2025. Source: GMSU-Vanguard Investor Expectations Survey.

Figure A.2: Prob 1-Year Stock Returns < -10%



(a) Mean

(b) Mean, By Confidence

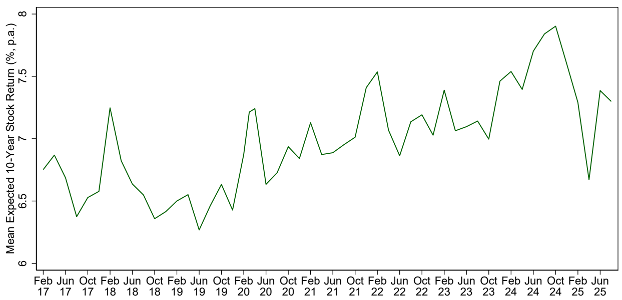
(c) Standard Deviation Across Individuals

(d) Percentiles of Distribution

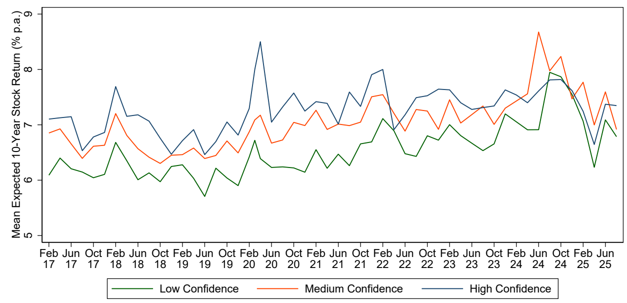
Note: Panel (A) shows the time series of the average subjective probability of stock returns falling below -10%. Panel (B) shows the time series of average subjective probability of stock returns falling below -10%, split by confidence levels. Panel (C) shows the across-individual standard deviation of subjective probabilities by wave. Panel (D) shows the deciles of the subjective probabilities by wave. The data span from February 2017 to August 2025. Source: GMSU-Vanguard Investor Expectations Survey.

Figure A.3: 10-Year Expected Stock Return

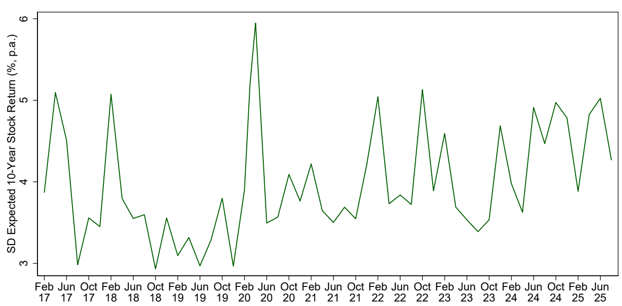
(a) Mean



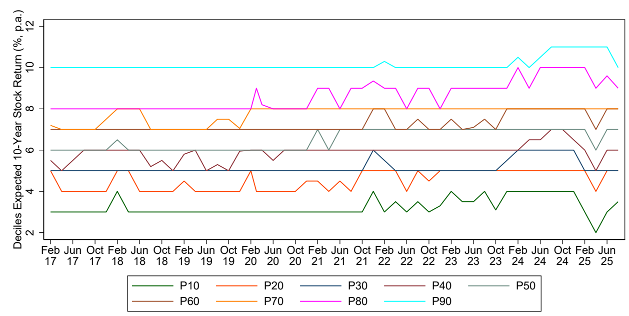
(b) Mean, By Confidence



(c) Standard Deviation Across Individuals



(d) Percentiles of Distribution



Note: Panel (A) shows the time series of average expected 10-year stock returns (annualized). Panel (B) shows the time series of average expected 10-year stock returns, split by confidence levels. Panel (C) shows the across-individual standard deviation of expectations by wave. Panel (D) shows the deciles of the expectations distribution by wave. The data span from February 2017 to August 2025. Source: GMSU-Vanguard Investor Expectations Survey.

Figure A.4: 3-Year Expected GDP Growth

(a) Mean

(b) Mean, By Confidence

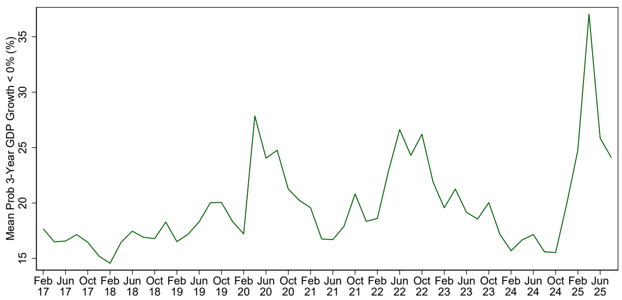
(c) Standard Deviation Across Individuals

(d) Percentiles of Distribution

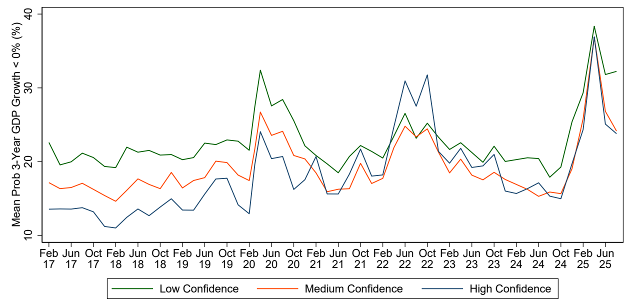
Note: Panel (A) shows the time series of average expected 3-year GDP growth (annualized). Panel (B) shows the time series of average expected 3-year GDP growth, split by confidence levels. Panel (C) shows the across-individual standard deviation of expectations by wave. Panel (D) shows the deciles of the expectations distribution by wave. The data span from February 2017 to August 2025. Source: GMSU-Vanguard Investor Expectations Survey.

Figure A.5: Prob 3-Year GDP Growth < 0%

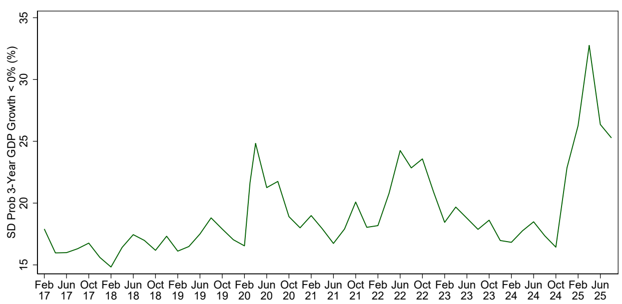
(a) Mean



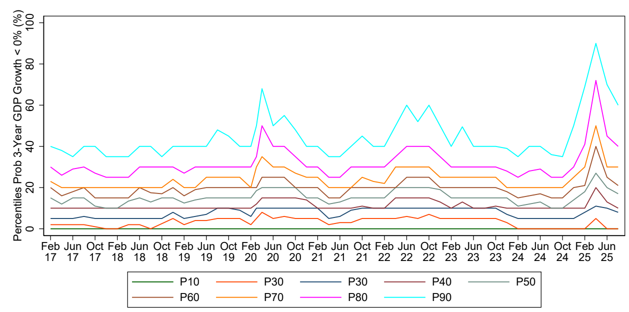
(b) Mean, By Confidence



(c) Standard Deviation Across Individuals

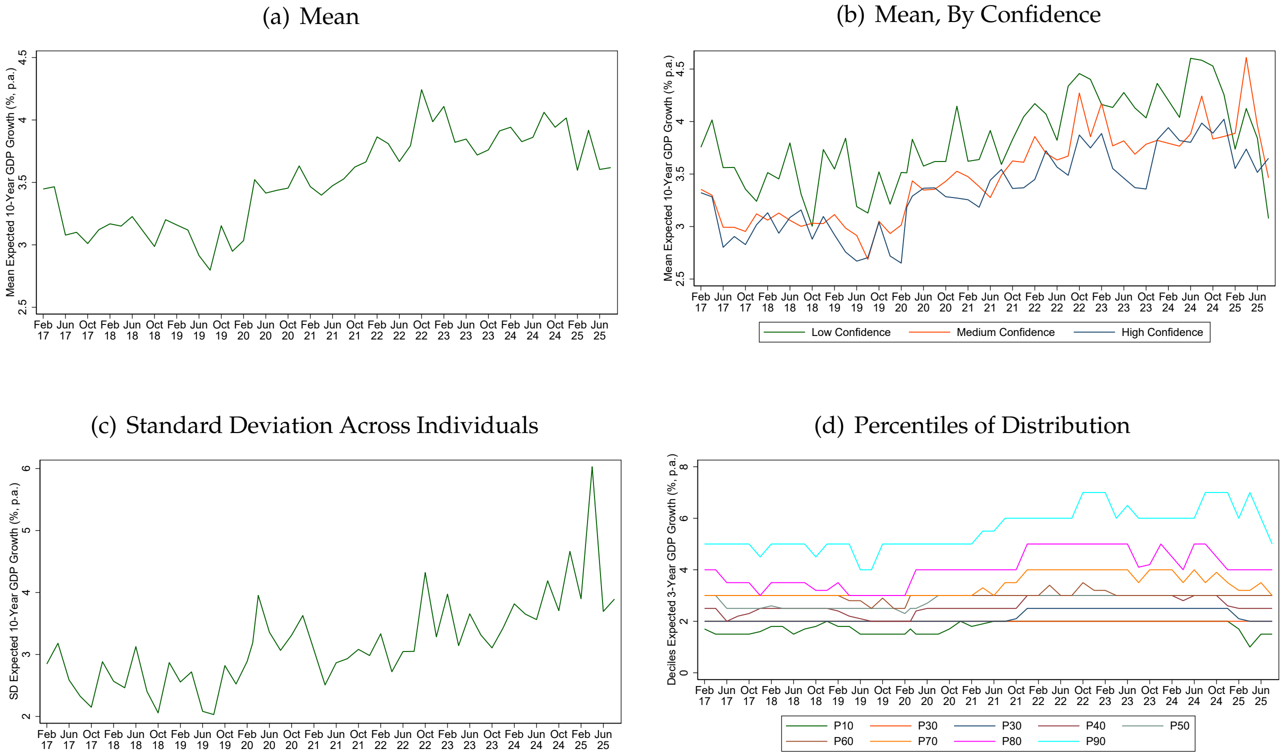


(d) Percentiles of Distribution



Note: Panel (A) shows the time series of the average subjective probability of annualized GDP growth falling below 0%. Panel (B) shows the time series of average subjective probability of annualized GDP growth falling below 0%, split by confidence levels. Panel (C) shows the across-individual standard deviation of subjective probabilities by wave. Panel (D) shows the deciles of the subjective probabilities by wave. The data span from February 2017 to August 2025. Source: GMSU-Vanguard Investor Expectations Survey.

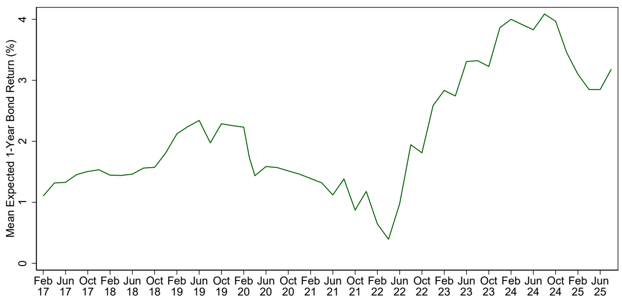
Figure A.6: 10-Year Expected GDP Growth



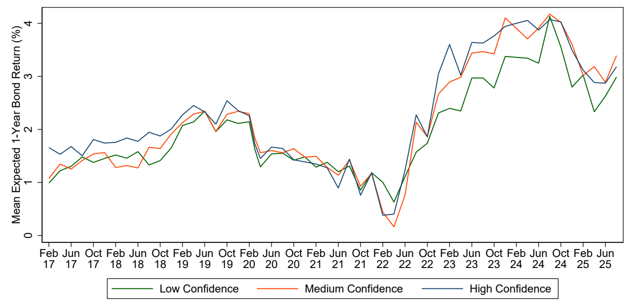
Note: Panel (A) shows the time series of average expected 10-year GDP growth (annualized). Panel (B) shows the time series of average expected 10-year GDP growth, split by confidence levels. Panel (C) shows the across-individual standard deviation of expectations by wave. Panel (D) shows the deciles of the expectations distribution by wave. The data span from February 2017 to August 2025. Source: GMSU-Vanguard Investor Expectations Survey.

Figure A.7: 1-Year Expected Bond Returns

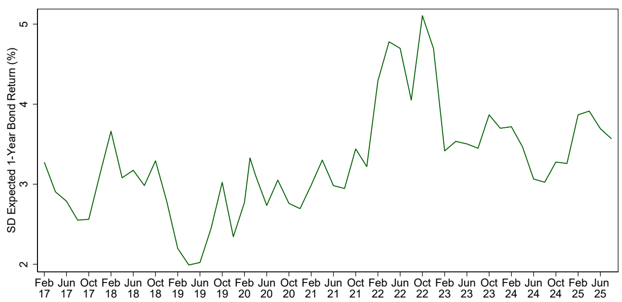
(a) Mean



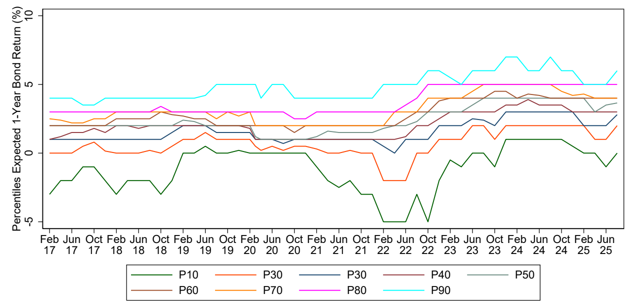
(b) Mean, By Confidence



(c) Standard Deviation Across Individuals



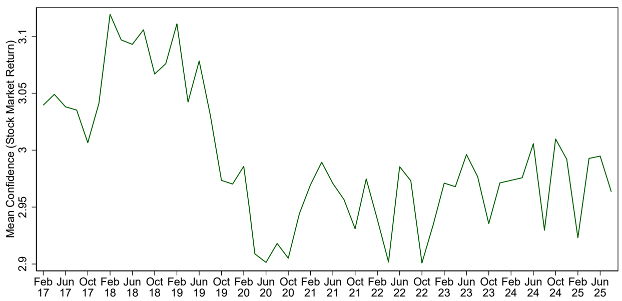
(d) Percentiles of Distribution



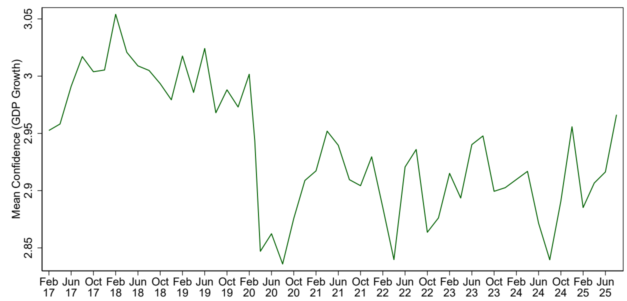
Note: Panel (A) shows the time series of average expected 1-year bond returns. Panel (B) shows the time series of average expected 1-year bond returns, split by confidence levels. Panel (C) shows the across-individual standard deviation of expectations by wave. Panel (D) shows the deciles of the expectations distribution by wave. The data span from February 2017 to August 2025. Source: GMSU-Vanguard Investor Expectations Survey.

Figure A.8: Average Confidence in Beliefs

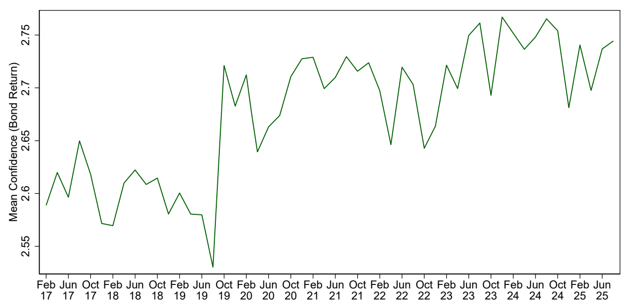
(a) Mean Stock Confidence



(b) Mean GDP Confidence



(c) Mean Bond Confidence



Note: Panel (A) shows the time series of average confidence levels for the stock market questions. Panel (B) shows the time series of average confidence levels for the GDP questions. Panel (C) shows the average confidence levels for the bond questions. The data span from February 2017 to August 2025. Source: GMSU-Vanguard Investor Expectations Survey.