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Journal of Economic Behavior and Organization

journal homepage: www.elsevier.com/locate/jebo

Editorial

Macroeconomic expectations: Formation, measurement, and consequences[☆]Zeno Enders^{a,b}, Stefan T. Trautmann^{a,*}, Dmitri V. Vinogradov^c^a Universität Heidelberg, Alfred Weber Institut für Wirtschaftswissenschaften, Bergheimer Straße 58, 69115 Heidelberg, Germany^b CESifo, Germany^c Adam Smith Business School, University of Glasgow, University Avenue, Glasgow, G12 8QQ, United Kingdom

ARTICLE INFO

JEL classification:

D84
E03
E27
E37
E71

Keywords:

Macroeconomic expectations
Inflation expectations
Survey design
Information frictions
Ambiguity
Behavioral macroeconomics

ABSTRACT

Subjective expectations about future macroeconomic developments are a core input to people's consumption and investment decisions. No commonly accepted model of the expectation-formation mechanism for macroeconomic variables has yet emerged. This special issue collects research that advances our understanding of how macroeconomic expectations are formed, how they can be measured, and how they shape economic behavior.

1. Introduction

Subjective expectations about future macroeconomic developments are a core input to people's consumption and investment decisions. A proper understanding of how these expectations are formed is essential both for building economic models that successfully replicate empirical data and for designing effective policy. Policy makers need to anticipate the impact of policy actions on expectations and account for the central role of communication and information dissemination; otherwise, the intended effects may not materialize as theory would predict. Recent evidence has documented systematic deviations from rational expectations that have a direct bearing on macroeconomic outcomes, yet the literature has not converged on a single, or even a small set of, commonly accepted models of the expectation-formation mechanism. Against this backdrop, the present special issue brings together papers that address three closely connected questions: how people form macroeconomic expectations; how these expectations can be measured; and how they affect downstream economic behavior. The contributions span survey experiments, large-scale household and firm surveys, laboratory experiments, and theoretical work on belief formation, elicitation, and identification. The remainder of this editorial introduction is organized accordingly. Section 2 reviews the literature on expectation formation and situates the contributions of this special issue within it. Section 3 turns to the measurement of macroeconomic expectations and the methodological advances proposed in the issue. Section 4 discusses how expectations translate into realized economic behavior. Section 5 concludes and points to open questions for future research.

[☆] This article is part of a Special issue entitled: 'Macroeconomic expectations' published in Journal of Economic Behavior and Organization.

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<https://doi.org/10.1016/j.jebo.2026.107620>

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2. Expectation formation

Macroeconomic research on expectation formation has evolved from adaptive expectations (AE), where agents adjust beliefs based on observation and past expectation errors (Cagan, 1954), and rational expectations (RE), where agents form unbiased forecasts using the true data-generating process and all available information (Muth, 1961). AE captured expectations inertia, provided a framework to explain persistence of inflation, and rationalized learning from past errors as a substitute for perfect recall. Yet it seemed too simplistic, and, in particular, was unable to accommodate policy regime changes (such as the end of Bretton Woods or the disinflation episodes of the 1980s, in which AE systematically under-reacts to the change in regime). While RE – and in particular its modern strong form, full-information rational expectations (FIRE) – became a standard tool for policy analysis and equilibrium modeling, empirical evidence revealed systematic deviations from the FIRE benchmark: expectations adjust sluggishly, display persistent biases, and show substantial disagreement across agents (Nordhaus, 1987; Ehrbeck and Waldmann, 1996; Lahiri and Sheng, 2008; Coibion and Gorodnichenko, 2012, 2015).¹ Sluggishness (expectations inertia) obtains in AE mechanically, by backward-looking adjustment of beliefs proportionally to past forecast errors, without any explicit role for information sets, while evidence suggested information sets are crucial for beliefs. In response, new models of expectation formation relaxed the strong informational and processing assumptions of FIRE by accounting for information frictions and behavioral departures. Sticky information implies infrequent updating (Mankiw and Reis, 2002), rational inattention treats the acquisition and processing of signals as costly (Sims, 2003), and noisy-information frameworks allow agents to observe imperfect signals and filter them over time (Woodford, 2003). Behavioral approaches capture systematic extrapolation of salient trends through diagnostic expectations (Bordalo et al., 2018) and lifelong experience as a determinant of priors in experience-based learning (Malmendier and Nagel, 2016). Complementary work on adaptive and recursive learning shows how agents converge (or fail to converge) to rational forecasts under model uncertainty (Evans and Honkapohja, 2001), while epidemiological diffusion models explain why expectations propagate slowly through social channels (Carroll, 2003). Taken together, this literature has established that beliefs are heterogeneous, subject to attention constraints, and filtered through social and cognitive mechanisms rather than formed by instantaneously and optimally processing a complete information set.

In parallel, microeconomics developed a rich axiomatic foundation for the formation of individual expectations about utility from consumption, whereby the expectations operator is pinned down by basic assumptions (axioms) about how people make choices. Anchoring the analysis on utility is convenient because consumption, portfolio, and lottery choices are observable at the individual level, which makes the axioms testable. Classic expected utility (EU, von Neumann and Morgenstern, 1947; Savage, 1954) provided the axiomatic justification for using the mathematical expectation operator to represent rational choice under risk. This was revolutionary because it gave a behavioral foundation for representing uncertainty using probabilistic expectations, rather than treating the expectation operator as a purely formal mathematical object detached from choice behavior. The FIRE concept, introduced by Muth (1961), essentially imports this statistical apparatus, without re-deriving it axiomatically: economic agents are assumed to form expectations equal to the mathematical expectation of future variables conditional on all available information and the true model.

Formally, both the EU and FIRE frameworks employ the same mathematical expectation operator, $\mathbb{E}_t[\cdot]$, but differ in interpretation and epistemic assumptions. In the EU framework, the expectation refers to the subjective, probability-weighted evaluation of uncertain outcomes (consumption bundles or lotteries, converted into a utility value), showing that individuals can form expectations using a construct analogous to statistical expectation if they can specify a probability distribution:

$$U_t^e = \mathbb{E}_t[u(x_{t+1})].$$

By contrast, Muth's rational expectations model applies the same operator to outcomes understood as realizations of macroeconomic variables, but assumes that the probability distribution of the true underlying process is known and that expectations are conditional on the agent's information set:

$$E_t[x_{t+1}] = \mathbb{E}[x_{t+1} | \Omega_t].$$

While EU provides a benchmark for rational choice under risk, it fails to account for observed behaviors: people often switch preferences when a sure outcome is added to lotteries, showing a preference for certainty; they prefer bets with known probabilities over those with only subjective ("unknown") probabilities, even when the (subjective) expected value is the same; they are sensitive to framing and reference points, and limited in attention and computation. Alternatives and refinements separate distinct psychological and behavioral primitives, adding to our understanding of the formation of expectations and their impact on decisions.²

These microfoundations inform our choice of the appropriate expectation operator to use in place of the purely statistical expectation: they specify the probability distributions and distortions individuals employ in forming beliefs. In doing so, they clarify how micro-level distortions translate into systematic biases in expectations of macroeconomic variables. Expectations are

¹ See Born et al. (2025) for a survey of how the FIRE hypothesis was challenged empirically and theoretically.

² Rank-dependent utility (Quiggin, 1982) and prospect theory (Kahneman and Tversky, 1979, 1992) introduce non-linear probability weighting and pessimism/optimism, distorting the impact of beliefs on decisions. A different group of models distinguishes between risk (a unique probability distribution can be conceived to govern the expectations operator) and ambiguity (no unique probability distribution can be conceived, implying new forms for the expectation operator), as in Klibanoff et al. (2005), Chateauneuf et al. (2007), Abdellaoui et al. (2011), Dimmock et al. (2016). Maxmin expected utility (Gilboa and Schmeidler, 1989) models ambiguity aversion by evaluating payoffs under a set of priors and choosing the worst-case expectation, and has been adopted in macroeconomic modeling (Hansen and Sargent, 2008).

not merely statistical forecasts; they are filtered through ambiguity attitudes and cognitive weighting of evidence, producing heterogeneity that is both measurable and theoretically grounded. Macroeconomic expectation formation can thus be understood as Bayesian updating under information frictions, modified by non-Bayesian features originating at the micro-level. Rational inattention can be reinterpreted through salience and decision weighting, where limited processing capacity amplifies salient signals and underweights diffuse ones. Noisy information maps naturally to ambiguity attitudes: when signal realizations are imperfect and signal-to-noise ratios are uncertain across sources, ambiguity-sensitive agents place more weight on conservative priors and update cautiously, generating stickiness and underreaction that mirrors survey evidence. Experience-based learning translates micro-level belief formation through personal histories into macro-level heterogeneity of priors, consistent with persistent cross-sectional disagreement (Conrad et al., 2022). Given this background, the contributions to this special issue discuss aim to clarify how macroeconomic expectations are formed and what we can learn about their formation from survey data.

Coibion et al. (2025) demonstrate that expectations respond strongly to real-world shocks like lockdowns. While most prior work focused on crises as aggregate shocks (financial crises, recessions), in their study policy interventions appear as localized expectation interventions. Income and wealth losses directly shape expectations when households extrapolate from personal hardship to macroeconomic pessimism. The timing of lockdowns acts as an informational cue. Households in early-lockdown counties adjusted expectations more sharply, showing that policy signals influence beliefs. The crisis increased perceived uncertainty, reinforcing the idea that shocks expand the distribution of possible outcomes in people's minds. Importantly, expectations translated into behavior: pessimistic macroeconomic views led to reduced spending, especially on durables.

The Coibion et al. (2025) study illustrates a broader methodological point about identifying how external events shape expectations. The randomized controlled trial (RCT) embedded in surveys, in which information is provided exogenously to a treatment group within a pre-existing survey panel, has become a workhorse design for this purpose. A complementary, more recently developed approach is the high-frequency survey (HFS) design, which exploits the timing of an exogenous, ex-ante scheduled real-world event – most often a monetary policy announcement – and schedules survey waves immediately before and after it, with random allocation of invitations ensuring exogeneity of treatment status. The term was coined by Refet Gürkaynak in his 2018 AEA discussion of Haldane and McMahon (2018), by analogy with high-frequency financial-market identification; the methodology was developed independently in a series of surveys starting in 2015 by Lamla and Vinogradov (2019). HFS shares the exogeneity benefits of an RCT but places respondents in a field environment where exposure to the event happens naturally, making it closer to a field experiment than to a natural experiment. Its main limitations are reliance on a scheduled event and a more restricted range of possible treatments than under an RCT. Day-of-the-week effects within the workweek are negligible (Binder, 2022).

Using monetary policy announcements as an exogenous inflow of macroeconomic information in the natural environment, Lamla and Vinogradov (2019) document a statistically nil absorption of new information in consumers' inflation expectations despite a significant causal effect on respondents' exposure to the news. Where daily survey data are available, an HFS-style analysis can be carried out on a sub-sample drawn from a narrow window around the event: Lewis et al. (2019) use Gallup data to study the effect of policy-rate changes on the economic sentiment reported by households, and De Fiore et al. (2022) use the daily incoming responses of the New York Fed Survey of Consumer Expectations to track the decay of households' assessments of saving-account rates around announcements, finding limited responsiveness of other expectations. Bottone and Rosolia (2019) cluster firm interviews from the Bank of Italy's Survey of Inflation and Growth Expectations around policy announcements and find that announcements shift firms' inflation point forecasts, while Di Pace et al. (2025) use the daily responses of the UK Decision Maker Panel to show that firms' pricing expectations react to policy announcements but not to high-frequency market-based measures.³

Benchimol et al. (2025) directly address the empirical measurement of one of the core deviations from FIRE: rational inattention and behavioral inattention. Their paper identifies and estimates both micro attention parameters (e.g., firms' attention to inflation, households' attention to interest rates) and the macro-level cognitive discounting parameter, highlighting substantial cross-country variation in attention and its positive association with macroeconomic volatility. This offers empirical support to the core premise of rational inattention theory: agents optimally allocate more attention when the cost of inattention (volatility) is higher. Attention levels turn out to be systematically influenced by macroeconomic surprises (sudden shocks) and institutional quality (government effectiveness). An important conclusion for our understanding of the formation of macroeconomic expectations is that attention is not a fixed behavioral parameter but a structural phenomenon that adapts to economic and institutional environments.

Gerotto et al. (2025) combine two established features, asymmetric valuation of over- and underpredictions and sticky information, in a model of expectation formation by households. Together, these two features imply a precise structural pattern in expectations that goes beyond mere sluggishness (implied by stickiness) and systematic bias (implied by the asymmetric loss function). The crucial implication is that the two features non-trivially interact: the sluggishness of the information set (inattentiveness) acts as a transmission mechanism that links the preference-driven bias (from the loss function) to the specific pattern of disagreement. This demonstrates that studying information frictions separately from a forecaster's personal loss function, or vice versa, would hide this important structural interaction effect in the expectation formation process.

Qiu and Deschamps (2025) demonstrate that forecasters are not purely independent information processors. Instead, their predictions are influenced by the forecasts of peers within the same professional environment. Using data from professional macroeconomic forecasts, the authors show that exposure to peers' predictions leads individuals to adjust their own forecasts closer to the group consensus. This is not just herding for reputational reasons (which has been studied before). The paper

³ Because endogenous timing of responses around an event is a natural concern, several of these studies formally test for randomness of response timing and find no evidence against it.

identifies peer information effects: forecasters treat peers' predictions as signals about the economy, integrating them into their own expectation formation. While herding (referring to reputational mimicry) and consensus effects (referring to convergent revisions absent reputational motives) are known, this paper isolates peer influence as an active driver of forecast revisions, rather than just correlated errors or reputational conformity.

Note that "expected inflation" itself is a macroeconomic variable. It is natural, therefore, to ask whether agents form expectations about others' expectations. Kieren et al. (2025) do exactly this by focusing on individual expectations about expectations of other economic agents (higher-order expectations). On the one hand, own beliefs and expectations about others' beliefs are quite similar in levels. On the other hand, cross-sectional disagreement regarding expectations about others' beliefs is larger than disagreement about beliefs themselves. Similarly, individual-level uncertainty about others' beliefs is greater than about the forecast variable itself. These results may be viewed from the perspective of information effects on expectations: there are various information channels through which people may learn about inflation (news, monetary policy announcements, own consumption experience, etc.), whereby much less is communicated about inflation expectations, let alone the likelihood of coming across others' expectations through own experience. If one is less informed about a variable, perceived uncertainty about it would increase, as in noisy-information models (e.g., in Lamla and Vinogradov, 2019, informed respondents have more precise expectations and are more confident in them). Theoretically, respondents should be able to infer others' behavior and expectations from one's own. Similarity of level beliefs and increased uncertainty about others' beliefs in Kieren et al. (2025) indicate respondents do see themselves as representative of an average belief (possibly due to anchoring higher-order beliefs on own belief), yet recognize heterogeneity of agents, which makes uncertainty amplify when moving from first-order beliefs to higher order.

Dietrich et al. (2024) focus on expectations related to climate change: survey respondents assign large probabilities to severely damaging natural disasters, and this is further aggravated by receiving news about disasters and by having experienced a disaster in respondents' regions. This direct evidence on the formation of probability distributions refines the micro-macro nexus of expectation formation by focusing on the distortion of the expectations operator itself. While traditional friction models focus on shifting the mean $\mathbb{E}[x]$ due to inattentiveness or linear bias, Dietrich et al. (2024) demonstrate that salient, extreme events (the tails) cause households to non-linearly overweight those outcomes, implying that the subjective probability distribution over future outcomes is systematically skewed. Consequently, the expectation about variables affected by climate change risks is formed by a psychologically contaminated operator, moving beyond the mean/median bias and inertia to explain the entire shape of subjective belief formation. Existing literature on probability weighting (e.g., in ambiguity aversion models) infers the distorted operator from observed choices, such as between lotteries. By contrast, Dietrich et al. (2024) offer direct survey evidence on belief formation itself, showing that the probability assigned to extreme tail events is systematically too large and is amplified by personal salience (experiencing a disaster or receiving news).

Expectation formation is neither mechanical nor uniform, but shaped by a rich interplay of forces: policy shocks, adaptive attention, structural interactions between frictions and preferences, peer influence, anchoring on personal beliefs and experiences, and probability distortions from salient extreme events. Each contribution highlights a distinct mechanism, yet collectively they reinforce the broader lesson that expectations emerge from the interaction of information, cognition, and social context.

3. Measurement and methodological contributions

A second group of papers in the special issue concerns methods for the empirical measurement of macroeconomic expectations, and the interpretation of the elicited data. There is already a rich literature on the elicitation of expectations in surveys, with many contributions studying the measurement of inflation expectations. The focus of this literature differs from the related experimental-economics literature on the measurement of beliefs, which is strongly concerned with the role of financial incentives for truthful revelation of subjective expectations, and with the empirical performance of different incentivization methods (Trautmann and van de Kuilen, 2015; Schlag et al., 2015). That literature typically works with data from a homogeneous pool of highly educated student participants in controlled laboratory environments. In contrast, the literature on measuring macroeconomic expectations is closely linked to applications in large population surveys with very heterogeneous participant pools, often managed by central banks. It is also less concerned about financial incentives because of practical reasons: first, many survey panels do not have a payment structure that would allow for an easy implementation of decision-dependent differentiated remuneration of participants; and second, the measured expectations typically concern uncertain future events of interest that materialize only several months or even years after the survey date, making it more difficult to condition participant payments on these.⁴

The focus of the literature on the elicitation of macroeconomic expectations has instead been on two broad topics. First, the wording of questions and the communication of potentially complex macroeconomic concepts that are of interest to policy makers, but may be confusing or unclear for many of the survey participants. Do people understand the questions asked, or do they interpret concepts possibly differently from the researchers analyzing and interpreting their data? Do they actually form the expectations they are asked for and use them in their daily economic decisions, even if only in a coarse and intuitive way? For example, when measuring expectations about future inflation rates, it is unclear whether participants typically form any such beliefs, let alone a full distribution of beliefs capturing their uncertainty about future rates (Hayo and Méon, 2023). It is unclear how they define inflation

⁴ That said, there has been a recent interest in testing the effects of financial incentives in this context. For example, Drobot et al. (2025) find that incentivizing inflation expectations with a simple but not incentive-compatible method reduces the often observed upward bias in inflation expectations, especially for women. It also makes participants more sensitive to information and leads to a stronger association between expectations and spending decisions.

and come to a quantitative answer when asked about it. They may simply construe the question in terms of the increase in the prices of a few salient products instead of the general price level based on a broad bundle of different goods (Bruine de Bruin et al., 2010, 2012). These problems regard the more general issue of framing effects in surveys. If participants have only a vague idea about the concepts they are asked to report on, seemingly minor differences in the wording and the structure of the questions (e.g., open questions versus selecting from a pre-defined set of answers) can have a major impact on the elicited values (Bruine de Bruin et al., 2010, 2012; Hayo and Méon, 2023).

The second prominent focus of the literature on the elicitation of macroeconomic expectations is the measurement of the full distribution of the, typically, uncertain expectations. A survey may ask participants to state their expected rate of unemployment a year from now: such questions are called point predictions or point forecasts. However, it is unclear what an answer of “3%” would in fact mean. It is possible, but unlikely, that the survey participant is certain that the rate will be 3% a year from now. More typically, they will consider several rates possible, and potentially attach different likelihoods to each. In particular, different participants may differ in how wide the range of possible unemployment rates is that they consider. While one person may see the rate somewhere between 2.5% and 3.5%, another person may be more uncertain and believe that the rate may end up somewhere between 2% and 5%. If participants hold such a distribution of possible outcomes, it is unclear what statistic their point prediction actually entails. It may be a modal, i.e., most likely outcome, or the mean or the median of the underlying belief distribution. The literature does not provide a conclusive answer to this question yet (e.g., Zhao, 2023).

To overcome the problems in interpreting the point forecast and its low information content, it became standard practice to elicit the full distribution of expectations for each participant (Armantier et al., 2013). From the distribution the researcher can then derive important statistics like the mean forecast or the standard deviation of the forecast, capturing the uncertainty of the participants at the individual level. Different methods have been used to elicit the distribution of expectations. The most popular and widely used method asks participants to directly allocate 100% probability mass into a set of mutually exclusive ranges for the variable of interest, so-called bins (Delavande and Rohwedder, 2008). For example, in the case of inflation expectations, many surveys follow the design by the Survey of Consumer Expectations (SCE; Armantier et al., 2013) that asks participants to allocate probability mass in ten bins ranging from an open bin of “–12% or lower” to an open bin “+12% or larger”. The bin structure is centered at 0, and provides smaller ranges of 2 percentage-points for central bins close to the target rate, and larger 4 percentage-point ranges for the outer bins. Participants allocate probability mass into these bins according to their beliefs how likely it is that the true inflation rate will end up in each range. The data elicited through this probability density forecast directly provides a histogram of the distribution of expectations. It can subsequently also be fitted to a parametric density function if that is considered of interest.

Because of its popularity, the density forecast method has received much scrutiny. Especially in the context of inflation expectations during the hike in rates in 2022–2024, several problems with the approach have become apparent (Becker et al., 2023; Goldfayn-Frank et al., 2026). In particular, as Becker et al. (2023) have shown, the bin structure chosen by the researcher exerts a strong framing effect on the answers provided by the participants. The location of the scale centered close to the target rate provides a possible signal which rates are considered reasonable by the researcher, and the structure itself with smaller and larger bin ranges directly influences the probability mass allocated to some interval of rates. Both effects may bias the participants’ reported expectations. With inflation rates above 6% and increasing, a substantial amount of probability mass was also allocated to the outer open bins, reducing the information content of the data. That is, the method does not allow for a good comparison of data over time if the level of the elicited variable is going to change substantially over time. The same is true for comparisons between different countries with very different levels of a variable (like inflation in the Euro area versus Türkiye). Moreover, the task requires participants to explicitly form probabilistic judgments. It may therefore be complicated for participants with low education, and prone to noise due to confusion with the concept of probability.

Several papers in the current collection on macroeconomic expectations consider methodological advances falling into these two broad topics in the literature. The papers by Chin et al. (2025) and Beckmann et al. (2026) speak to the first topic, showing how the presentation of survey questions affects the elicited expectations. Chin et al. (2025) start from the observation that stock market expectations in surveys appear too pessimistic when compared to the true developments of the market. They argue that the typical question is framed such that participants are asked to indicate their subjective probability of an increase in the market, and conjecture that people may bias their report downward to zero. Indeed, they show that if asked about the complementary probability of a decrease in the stock market, this probability seems to be biased downwards as well, leading to a wedge between the complementary probabilities. Chin et al. (2025) go on to show that a lack of confidence on the side of the participants with the topic they are surveyed about is positively associated with, and probably causing, the downward bias. Importantly, while a lack of knowledge or confidence has often been associated with an excessive use of 50%-options, here a lack of confidence is observed to bias answers downwards, towards zero. This leads to systematically biased reported expectations at the population level.

Beckmann et al. (2026) study the effect of varying the presentation format in information provision experiments on the elicited expectations. In particular, they vary the reliability of the presented forecast, captured by the quality of past forecasts of the same professional forecaster, and the complexity of the presentation (graphical only versus graphical and numerical, compounded annually or quarterly). They argue that a complex presentation mode leads to cognitive noise on the side of the participants, and predict that it reduces updates and increases ex-post uncertainty in the participants’ forecasts. In a survey experiment, they find evidence for the effect on forecast revisions, but no direct effect on uncertainty. Their results show that cognitive noise is a potential factor reducing the impact of information interventions if information is relatively complex, as is often the case simply because of the nature of the variables studied. Moreover, the same problem obtains if a regulator aims to influence consumers’ expectations by disseminating information. The degree of complexity will then affect how strongly consumers will actually revise their prior views on the topic.

Three contributions to the special issue deal with the elicitation of the full distribution of beliefs, all in the context of inflation expectations, proposing new elicitation methods and discussing related framing issues. The article by [Becker et al. \(2025\)](#) observes that a fixed bin structure for density forecasts does not work well if the underlying variable is volatile. As discussed above, for the example of inflation expectations, a structure that is centered at zero and has smaller bin ranges close to the central banks' target leads to a downward bias and substantial probability mass in open bins if inflation and consumers' inflation expectations become large relative to the target. They propose two alternative approaches. First, shifting the bin structure for all participants according to the current level of the variable of interest, or maybe the researcher's belief about its development. Second, shifting the bin structure to center it at each participant's own previously elicited point forecast. [Becker et al. \(2025\)](#) compare these different approaches according to several quality criteria. They find that shifting at the survey level (i.e., same shift for all respondents) improves the quality of the elicited expectations compared to the structure centered at zero in an environment with inflation in the range of 6% and higher. However, because inflation was in fact higher at the time of the survey compared to the planned shift of 4%, the improvements were limited. This is also true because of the substantial individual heterogeneity in expectations. The condition with a bin structure that shifts according to the participants' own point forecasts led to stronger improvements. In an auxiliary experiment, [Becker et al. \(2025\)](#) consider a related question. In the individually shifted bin structure it is ex-ante unknown which bins are associated with deflation, i.e., negative inflation. And, depending on the point forecast, it may also be the case that a bin contains both positive and negative inflation rates (e.g., ranging from -1.5% to $+0.5\%$). Therefore, an explicit reference to deflation is not possible in this structure. In contrast, in the widely used bin format of the NY Fed's Survey of Consumer Expectations, deflation is explicitly mentioned. [Becker et al. \(2025\)](#) therefore compare a standard SCE structure with and without mentioning deflation explicitly, and show that this difference in wording has an effect on the elicited expectations, with lower histogram means if deflation is mentioned. They conjecture that respondents may be induced to provide expectations conditional on there being inflation or deflation, respectively. The result is consistent with [Goldfayn-Frank et al. \(2026\)](#)'s result that use of extreme deflation bins by an individual is associated with poor overall quality of the elicited expectations.

[Pavlova \(2025\)](#) also introduces an alternative to density forecasts for inflation expectations, based on three more simple questions. Her method asks participants about the minimum and maximum rate of inflation that they consider possible over the next year, and the rate they consider most likely. She then fits a triangular distribution to the support endpoints and mode. She also considers a framing aspect, namely wording in terms of "inflation" or wording in terms of "prices in general". She finds that elicitation using the support and the modal expectation leads to overall lower incidence of deflation expectations, higher mean expectations and reduced uncertainty at the individual level, compared to density forecasts.⁵ In terms of several quality criteria, the method performs similar to the bins-based elicitation. It is therefore a viable alternative in situations where asking for explicit probability judgments is not considered feasible. In terms of the wording differences, [Pavlova \(2025\)](#) finds that with a framing in terms of prices in general, both the mean expectation and uncertainty increase. Possibly, the participants construed the prices-in-general question in terms of a few salient products that were especially affected by price increases and were relatively volatile (e.g., certain food items).

The third paper proposing alternatives to the density forecast format argues that instead of eliciting a histogram of expectations and then fitting a beta distribution, as often done, researchers may as well directly elicit the distribution ([Gonzalez-Fernandez et al., 2025](#)). [Gonzalez-Fernandez et al. \(2025\)](#) provide an easy-to-use graphical tool where participants directly choose the mean expectation and the degree of uncertainty, and are shown the implications in terms of a distribution graph and a table mimicking the density forecast ranges. Applying their method to inflation forecasts, they compare it to the SCE bin structure density forecast, and to a shifted-bins method similar to [Becker et al. \(2025\)](#), but shifting in terms of the minimum-to-maximum range instead of the point prediction. They find that the tool is perceived as very easy to use by participants, and as easier compared to the bin-based methods. Consistent with [Pavlova \(2025\)](#) and [Goldfayn-Frank et al. \(2026\)](#), they find that their direct elicitation method yields higher mean expectations and lower uncertainty than the SCE density forecasts, and similar mean expectations but lower uncertainty compared to the shifted bins method. They find that the elicited expectations fulfill desirable quality criteria (e.g., correlating with the respondents' assessments of the likelihood of some specific inflation scenarios in a separate task, and the correlation with point predictions).

The final paper concerned with methodological issues in the elicitation of macroeconomic expectations in this collection deals with the often-observed inconsistency between point forecasts and central tendencies of the density forecasts ([Clements, 2025](#)). Using data from predictions of professional forecasters, [Clements \(2025\)](#) aims to find out whether inconsistencies are caused by biases in the point or the density forecasts. First, he demonstrates that density forecasts are sensitive to the complexity of the bin structure. Changes in the bin structure due to changes in the macroeconomic environment affected the incidence of inconsistencies, and do so in a way that is not consistent with changes in the macroeconomic uncertainty. Second, he looks at forecast revisions in point and histogram forecasts, and finds that larger histogram revisions are associated with larger inconsistencies between the two methods. For inflation, there is over-reaction for both point and density forecasts, but density forecasts are less accurate as measured by forecast errors. That is, the inconsistencies are driven by lower performance of the histogram forecasts. In light of these results, it would be of interest to see how the alternative approaches for the measurement of the full distribution of expectations proposed in this special issue perform in terms of consistency with the point prediction over longer forecast horizons.

⁵ These results are consistent with findings in [Goldfayn-Frank et al. \(2026\)](#), who also use a method based on the support of the individual's expectations, and then split it into quartiles.

4. Consequences

Understanding how expectations translate into realized economic behavior is central to both positive and normative economics. While expectations are a core component of virtually all forward-looking models – from consumption and investment decisions to price-setting and labor supply – their empirical relevance ultimately hinges on whether and how they shape actual actions. Including a view on realized behavior, rather than on expectations alone, is therefore essential for assessing the economic significance of beliefs and for informing policy interventions aimed at managing or influencing expectations.

A growing body of empirical literature has addressed this challenge by combining direct measures of expectations with observed individual or firm-level actions. In the household context, a few studies exploit survey data that elicit subjective expectations and link them to administrative records (Vellekoop and Wiederholt, 2019), to self-reported behavior in subsequent survey waves (Roth and Wohlfart, 2020; Coibion et al., 2023), or to transaction-level datasets such as home-scanner data (Chopra et al., 2025). These approaches enable researchers to jointly observe beliefs and detailed consumption or savings choices, thereby providing a more direct assessment of the behavioral implications of expectations. The resulting evidence consistently shows that expectations exert a significant influence on household behavior, although the magnitude and underlying transmission channels vary substantially across individuals. For traders, Schnorpfeil et al. (2025) make use of confidential bank data to show that providing information about past returns during phases of high inflation changes return expectations and actual trading.

At the firm level, recent contributions have made substantial progress by exploiting survey data that directly link expectations to realized outcomes. Enders et al. (2022) use a large panel of German manufacturing firms to identify the causal effect of expectations on (self-reported) firm behavior. They show that firms expecting higher future production are significantly more likely to increase current production and prices. Notably, these effects persist even when expectations turn out to be incorrect, indicating that expectations operate not only as carriers of information about future fundamentals but also as independent drivers of economic activity. Complementary evidence is provided by Born et al. (2022), who survey the relevant literature and document a number of robust stylized facts, among them the fact that expectations systematically affect firms' production, pricing, and investment decisions. Together, these contributions underscore the value of datasets that jointly measure expectations and actions at the micro level, enabling a more precise identification of the role of beliefs in shaping economic outcomes. Alternatively, Bartscher et al. (2026) merge survey data with credit register and balance sheet data and find that information about the central bank policy rate changes firms' expectations of future interest rates and reduces their uncertainty thereof. A reduction of expectations raises credit demand and investment of small firms in particular.

Despite these advances, measuring the effects of expectations on actual behavior remains empirically challenging. The ideal data – where expectations and subsequent actions are observed for the same units over time – are relatively scarce. Many surveys elicit expectations but do not track realized behavior, or they lack sufficiently detailed behavioral measures. Panel surveys can, in principle, overcome this limitation, but they often suffer from attrition, implying that the individuals or firms surveyed in later waves are not always identical to those who reported expectations initially. This complicates the identification of expectation–behavior linkages. Moreover, even when both expectations and actions are observed, issues such as measurement error, timing mismatches, and endogeneity pose additional challenges.

In the absence of ideal data, researchers have developed alternative empirical strategies to study the impact of expectations on behavior. The contributions in this special issue illustrate several such approaches, each leveraging different types of data and identification strategies.

One approach consists of measuring expectations and incorporating them into structural or semi-structural model simulations. Dietrich et al. (2024) combine a large-scale survey of U.S. households with a calibrated New Keynesian model featuring rare disasters. Using detailed data on climate-related expectations, they show that households assign substantial probability to adverse future events and that these beliefs are systematically related to reported behavioral adjustments (such as avoiding products made from plastic) because of climate change concerns. When embedded in a structural model, higher disaster expectations act as adverse demand shocks, leading to declines in consumption, investment, and inflation, thereby exerting quantitatively meaningful effects on aggregate dynamics.

A second approach relies on survey measures of intended behavior as a proxy for realized actions. Qian (2025) implements a randomized information experiment within a household survey to identify the causal effect of house price expectations on consumption plans. By exogenously shifting expectations through the provision of alternative forecasts, the study shows that higher expected house price growth leads to a significant increase in intended spending, with particularly strong effects among financially constrained households. These findings highlight that expectations influence economic behavior through wealth and borrowing channels, even when actual behavior is not directly observed. A similar strategy is followed by D'Acunto et al. (2021), who find that higher inflation expectations increase households' consumption plans.

A third strategy exploits controlled laboratory environments to observe behavior in response to elicited expectations. Akiyama et al. (2025) conduct an asset market experiment in which participants' beliefs about future prices are measured in an incentivized manner and, in part, made public. The results show that while the public disclosure of expectations does not significantly affect trading volume, it substantially improves price efficiency by reducing mispricing. This evidence underscores that expectations shape economic outcomes through informational and coordination channels, even when their impact on observable actions such as trading intensity is limited.

Taken together, the contributions in this special issue convey a consistent message: expectations matter for economic behavior, but identifying their effects requires careful empirical design and, often, innovative use of available data. While ideal datasets linking expectations to realized actions remain scarce, a combination of survey-based evidence, experimental methods, and model-based approaches provides a coherent and complementary body of evidence. These approaches jointly advance our understanding of how expectations influence economic decisions and highlight the importance of incorporating empirically grounded expectation formation into both theoretical and applied work.

5. Conclusions

The contributions assembled in this special issue cut across the three thematic strands of formation, measurement, and consequences of expectations, but they speak to one another in ways that suggest a more integrated agenda. On the formation side, the new evidence reinforces the picture of expectations as the joint product of information frictions, cognitive limitations, social influences, and salient personal experiences, rather than the output of a single canonical mechanism. On the measurement side, the papers in the issue show that the apparent properties of expectations – their level, dispersion, and uncertainty – depend systematically on how questions are framed, on which response format is used, and on how the elicited distributions are summarized; methodological choices are not innocuous, and the comparability of results across surveys and over time hinges on them. On the consequences side, the evidence confirms that expectations influence behavior across households, firms, and asset markets, but also that detecting these effects depends on careful identification strategies, structural model integration, randomized information experiments, and laboratory designs, each with its own strengths and limitations.

Several open questions emerge for future research. First, the choice between elicitation methods has direct implications for what can be inferred about expectation formation: a method that produces lower estimated uncertainty or different estimated tail probabilities will tend to produce different conclusions about underreaction, ambiguity, and the salience of extreme outcomes. Cross-walks between the elicitation methods proposed in this issue – bin-based, support-based, choice-based, and direct distributional elicitation – are needed before findings can be confidently aggregated across studies. Second, the micro-foundations of expectation formation, in particular the role of ambiguity attitudes and probability weighting in macroeconomic beliefs, remain only partially mapped to the canonical macro models of information frictions. Bridging this gap promises a richer theoretical account of why beliefs are heterogeneous and respond asymmetrically to news. Third, while randomized information experiments and high-frequency survey designs have made the identification of information effects on expectations far more credible, the next frontier is to track these effects through to realized behavior using linked panel data – ideally combining incentivized expectation elicitation, exogenous information variation, and administrative or transaction-level outcomes. The contributions in this special issue, taken together, mark substantial progress along all three of these fronts, and we hope they will encourage further work that continues to integrate the formation, measurement, and consequences of macroeconomic expectations into a single coherent research program.

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