BEHAVIORAL UNDERPINNINGS OF OVERREACTION IN INFLATION EXPECTATIONS ACROSS ECONOMIC AGENTS

Camille Cornand

Paul Hubert

Rose Portier

SCIENCES PO OFCE WORKING PAPER n° 10/2025

CONTACT US

OFCE
10 place de Catalogne | 75014 Paris | France
Tél. +33 1 44 18 54 24
www.ofce.fr

WORKING PAPER CITATION

This Working Paper:
Camille Cornand, Paul Hubert and Rose Portier
Behavioral underpinnings of overreaction in inflation expectations across economic agents
Sciences Po OFCE Working Paper, n° 10/2025.
Downloaded from URL: www.ofce.sciences-po.fr/pdf/dtravail/WP2025-10.pdf
DOI - ISSN

ABOUT THE AUTHORS

Camille Cornand, Université de Lyon, CNRS, GATE
Email Address: cornand@gate.cnrs.fr
Paul Hubert, Banque de France, Sciences Po-OFCE
Email Address: paul.hubert@sciencespo.fr
Rose Portier, Banque de France, Paris 1
Email Address: rose.portier@banque-france.fr

ABSTRACT

This paper explores overreaction to news in agents' inflation expectations—households, firms, professional forecasters, policymakers, and participants to experiments—and examines the role of four behavioral factors: recency bias, memory of inflation, salience, and the representativeness heuristic. All agent categories show individual overreaction to news, with notable heterogeneity. Salience explains overreaction for most groups. Households exhibit a broad range of biases—recency bias, salience, and the representativeness heuristic—while firms are mainly influenced by salience. Finally, the paper offers insights on the generalizability of experimental inflation expectations.

KEYWORDS

Information frictions, Experimental forecasts, Survey forecasts, Central bank forecasts.

JEL

E3, E5, E7.

Behavioral underpinnings of overreaction in inflation expectations across economic agents*

Camille Cornand#
Univ Lyon, CNRS, GATE

Paul Hubert
Banque de France
Sciences Po – OFCE

Rose Portier
Banque de France
Paris 1

2 March 2025

Abstract

This paper explores overreaction to news in agents' inflation expectations—households, firms, professional forecasters, policymakers, and participants to experiments—and examines the role of four behavioral factors: recency bias, memory of inflation, salience, and the representativeness heuristic. All agent categories show individual overreaction to news, with notable heterogeneity. Salience explains overreaction for most groups. Households exhibit a broad range of biases—recency bias, salience, and the representativeness heuristic—while firms are mainly influenced by salience. Finally, the paper offers insights on the generalizability of experimental inflation expectations.

Keywords: Information frictions; Experimental forecasts; Survey forecasts; Central bank forecasts.

JEL classification: E3, E5, E7.

---

* We would like to thank Jérôme Creel, Pauline Gandré, Erwan Gautier and Sanjay Singh for helpful comments, and Michael Clements for a useful discussion at the early stage of this project. We are grateful to Cars Hommes, Domenico Massaro, Luba Petersen, Damjan Pfajfar, Matthias Weber and Blaz Žakelj for sharing their experimental data. A large part of this research was conducted while Paul Hubert was visiting Stanford University, whose hospitality is gratefully acknowledged. This paper presents the authors' views and should not be interpreted as necessarily reflecting the views of the Banque de France or the Eurosystem.
# Corresponding author: CNRS, Université Lumière Lyon 2, Université Jean Monnet Saint-Etienne, emlyon business school, GATE, 35 rue Raulin, 69007 Lyon, France. Email: cornand@gate.cnrs.fr.

1. Introduction

Expectations are critical for macroeconomics. The standard paradigm in macroeconomic theory has for long been the Full Information Rational Expectations (FIRE) hypothesis, according to which individuals form optimal forecasts based on their full information set. Under FIRE, agents form expectations about the future for which the forecast error should be unpredictable and the correlation between the forecast error and the past forecast revision should also be zero. A growing literature tests these hypotheses using survey data expectations for households, firm managers, financial analysts, professional forecasters or central bankers. The evidence points to systematic predictability of inflation forecast errors (Coibion and Gorodnichenko, 2012, 2015).

Predictability of forecast errors can teach us a lot about how market participants form expectations. It can in particular inform us about forecasters' over or underreaction to new information. Since the information set of forecasters cannot be directly fully observed by the econometrician, understanding whether departures from FIRE are due to over or underreaction is not an easy task. To get around this problem, Coibion and Gorodnichenko (2015) test whether errors of aggregate forecasts are predictable from revisions of aggregate forecasts, assuming that revisions measure the reaction to available news. When the correlation between current forecast revision and future forecast error is positive (respectively negative), upward revisions predict higher (respectively lower) realizations relative to the forecasts: the forecast underreacts (respectively overreacts) to information relative to FIRE.

While this test of departures from FIRE is applied to *aggregate* (consensus) inflation forecasts in Coibion and Gorodnichenko (2015) who find evidence of *underreaction* relative to FIRE, Bordalo et al. (2019, 2020) use this test on individual forecasts.[1] Studying expectations for a large set of macroeconomic and financial variables, Bordalo et al. (2020) provide evidence of *overreaction* to information in *individual* forecast data, but underreaction using consensus forecasts. Angeletos et al. (2020), Kohlhas and Walther (2021) and Broer and Kohlhas (2024) revisit these findings and provide evidence of overextrapolation and overconfidence. Afrouzi et al. (2023) find that forecasts display significant overreaction to the most recent observation and that overreaction is stronger for less persistent processes and for longer forecast horizons.

In this paper, we expand the literature by documenting the degree and dispersion of overreaction to news of various categories of agents (households, firms, professional forecasters, policymakers and participants to experiments) and by studying four potential behavioral underpinnings of this overreaction (recency bias, memory of inflation, salience, and representativeness heuristic).

Our paper uses inflation forecasts from US data (for households, firms, professional forecasters and policymakers) on a period ranging from 1948 to 2020 and from laboratory data (collected from five papers published in the 2010s). We first document over/underreaction to information in inflation forecasts across various categories of economic agents, both at the aggregate and individual levels. To make the comparison between categories possible, our paper focuses on a single, common, set of expectations, namely *inflation* expectations.[2] Second,

[1] See also D'Arienzo (2019) and Bouchaud et al. (2019).

[2] Based on the Survey of Professional Forecasters (SPF) and the Blue Chip Survey, Bordalo et al. (2020) expand the variables analyzed by Coibion and Gorodnichenko (2015) by considering various forecasts of real economic activity, consumption, investment, unemployment, housing starts, government expenditures, as well as multiple

we examine the potential behavioral underpinnings of individual overreaction to news. In terms of methodology, to determine the behavioral underpinnings of overreaction at the individual level, we consider four behavioral models. We look at whether there is a correlation between overreaction and: (i) recency bias, (ii) experience of inflation, (iii) salience of news, and (iv) representativeness heuristic. While these behavioral forces are often studied in the context of inflation expectation characteristics, their relationship with overreaction to news has been much less explored.

Our main results are the following. First, although we find evidence of underreaction to news at the aggregate level for professional forecasters, firms and participants to experiments (and not for households and policymakers), we confirm the results obtained in the literature of overreaction to news at the individual level for all categories of agents. We document further that overreaction at the individual level is robust to the inclusion of public signals (measured as the lagged aggregate forecast) and that individual forecasts overreact to such signals, suggesting a sort of beauty contest pattern. In terms of magnitude of the reaction, there is some heterogeneity, with policymakers responding strongly, followed by households, professional forecasters and firms. Participants to experiments stand at the end of the spectrum. The majority of individuals do overreact to news relative to FIRE for all categories of agents. The median overreaction across categories of agents is homogenous but there is some notable variation in the degree of overreaction to news across categories. Participants to experiments present the highest dispersion, followed by firms, policymakers, households and finally professional forecasters. Although there is a majority of individuals who overreact, there are still some individuals who underreact in all categories.

Second, we explore the role of four behavioral underpinnings of overreaction in inflation expectations at the individual level. We find that salience is a factor that explains overreaction for most categories of agents. Professional forecasters, firms, households and participants to experiments overreact less when inflation news is salient. The recency bias explains overreaction of professional forecasters, households and participants to experiments. Recency biased professional forecasters and households tend to overreact more to news while the opposite pattern is observed for participants to experiments. Memory of inflation operates for both policymakers and participants to experiments, with individuals who have experienced higher inflation being more likely to overreact to news. Finally, a link can be established between representativeness heuristic and overreaction for both policymakers and households. These two categories of agents are more likely to overreact to news when current inflation is far from the average inflation they have experienced. Overall, our results suggest that households combine the largest number of biases as explanations for individual overreaction—namely recency bias, salience and representativeness heuristic—while firms the lowest, as salience is the only relevant factor of overreaction for this category of agents.

These results have some implications for policymakers' communication. Indeed, the effectiveness of public, fiscal and monetary policies relies on the implicit assumption that economic agents optimally respond to news and form unbiased expectations that incorporate the relevant information in an appropriate manner. Understanding the formation and characteristics of economic agents' inflation expectations is thus of utmost importance for

interest rates. Coibion and Gorodnichenko (2015) focus their analysis on the SPF, but provide complementary evidence for households using the Michigan Survey of Consumers, firms in the Livingston Survey, and forecasts from financial market contracts.

central bankers whose task precisely consists in managing these expectations.[3] We develop upon these implications for central bank communication policy in the conclusion of the paper.

Third, our paper offers insights into the generalizability of experimental inflation expectations, contributing from a methodological perspective, following Cornand and Hubert (2020, 2022).[4] Macro-experiments—particularly Learning-to-Forecast Experiments (LtFE) (Hommes, 2011) focused on the formation of inflation expectations in laboratory settings—have become increasingly important for evaluating central bank policies, as they provide a controlled environment for testing competing policy actions and monetary rules.[5] However, the validity of policy recommendations derived from macro-experiments depends on whether experimental inflation expectations align statistically with real-world expectations. Despite this, only a limited number of studies have examined the external validity of experimental inflation expectations. By demonstrating that experimental data exhibit underreaction at the aggregate level and overreaction at the individual level, our paper further contributes to the evidence on the generalizability of these expectations. However, certain characteristics of experimental data constrain their external validity. Specifically, there is much greater homogeneity in the weak response to news within experimental inflation forecasts than is observed in any other category of field expectations. In addition, the behavioral underpinnings of overreaction to news of participants to experiments are somewhat specific to this category of agents. Section 5 discusses in more details how experimental data compare to field data.

Our paper relates to the large and growing body of literature that investigates the empirical drivers of the expectation formation process (e.g. D'Acunto et al. (2022), D'Acunto et al. (2023)) or that analyses the implications of introducing in macroeconomic models expectation formation process—such as diagnostic expectations, overconfidence, cognitive discounting, level-*k* and narrow thinking, strategic diversification—that departs from FIRE by relying on behavioral factors (e.g. Bianchi et al. (2023), L'Huillier et al. (2024), Broer and Kohlhas (2022), Angeletos et al. (2021), Gabaix (2020), García-Schmidt and Woodford (2019), Farhi and Werning (2019), Lian (2021), Gemmi and Valchev (2023)).

The paper is structured as follows. Section 2 presents the data. Section 3 provides evidence on under/overreaction to news in aggregate and individual forecasts. Section 4 explores four potential behavioral underpinnings of under/overreaction. Section 5 discusses the external validity and generalizability of experimental inflation forecasts. Section 6 concludes.

2. Data

We collect inflation expectation data from three types of measures (survey and policymaker data as well as experimental data), corresponding to five categories of agents (households, industry, professional forecasters, policymakers and participants to experiments).

---

[3] As Woodford (2003) states it, "*for [monetary policy to be most effective] not only do expectations about policy matter, but, at least under current conditions, very little else matters.*" Forward guidance is an illustration of such an instrument.

[4] Cornand and Hubert (2020) use aggregate data. Cornand and Hubert (2022) use individual data, but the research questions are very different. While Cornand and Hubert (2022) study how agents update their information and disagree in forming inflation expectations, the present paper focuses on the issue of over/underreaction to news.

[5] While the endogeneity of policy responses to macroeconomic issues complicates the analysis of real-world data and the drawing of valid inferences, laboratory experiments allow researchers to control all parameters of the tested model. This makes it possible to isolate and compare the effects of different policy regimes through various treatments, in a fast and cost-effective manner (Cornand and Heinemann, 2014, 2019).

2.1. Survey data

Households. The Michigan Survey of Consumer Attitudes and Behavior surveys a cross-section of the population about their expectations over the next year. Most papers using the Michigan survey cover only the period since 1978, during which these data have been collected monthly and on a quantitative basis: respondents were asked to state their precise quantitative inflation expectations. Before then, the Michigan survey was qualitative. It has been conducted quarterly since 1946, although for the first 20 years, the respondents were asked only whether they expected prices to rise, fall, or stay the same. Each month, a sample of approximately 500 households is interviewed, in which the sample is chosen to statistically represent households in the US, excluding Alaska and Hawaii. Survey respondents are questioned twice on average, sometimes thrice. The monthly phone call survey focuses on respondents' perceptions and expectations regarding personal finances, business conditions and news regarding the economy in general, as well as macroeconomic aggregates, such as unemployment, interest rates and inflation. Furthermore, the survey collects individual and household socioeconomic characteristics.[6]

Firms. The Livingston Survey was started in 1946 by the late columnist Joseph Livingston. It is the oldest continuous survey of firms' expectations. It summarizes the forecasts of analysts and economists working in the industry sector in the US. The Federal Reserve Bank of Philadelphia took responsibility for the survey in 1990. It is conducted twice per year, in June and December, so it has a semiannual frequency. It provides twelve-month Consumer Price Index (CPI) inflation forecasts from approximately 50 survey respondents. We consider that expectations collected via the Livingston survey represent firms' expectations. But, as these are expectations of firms' economists, we acknowledge that they could share the properties of that of professional forecasters. The subsequent results provided in Sections 4 and 5 suggest that Livingston expectations differ from those of professional forecasters in various respects.

Professional forecasters. The Survey of Professional Forecasters (SPF) is collected and published by the Federal Reserve Bank of Philadelphia. It focuses on professional forecasters mostly in the banking sector in the US. Surveys are sent to approximately 40 panelists at the end of the first month of the quarter, the deadline for submission is the second week of the second month of the quarter, and forecasts are published between the middle and end of February, May, August, and November. GDP price index forecasts (available since 1968) are fixed-horizon forecasts for the current and the next four quarters. They are provided as annualized quarter-over-quarter growth rates. We also perform our analysis with CPI forecasts provided since 1981. We consider the median of individual responses, rather than the mean, which could be affected by potential outliers.

2.2. Policymakers: Federal Open Market Committee (FOMC)

The FOMC has published forecasts for inflation twice per year in the Monetary Policy Report to the Congress since 1979. Since October 2007, their publication has been quarterly. The FOMC forecasted the Consumer Price Index until 1999 and then the Personal Consumption Expenditures (PCE) measure of inflation. These forecasts are fourth quarter-over-fourth quarter growth rates for the current and next calendar years. Until 2005, the forecast for the next year was published only once a year. Individual members' FOMC forecast are made

[6] We acknowledge that the Michigan survey includes questions formulated in a very broad manner rather than targeted on inflation, which could induce a bias toward more dispersion in inflation expectations.

public since 1992, but with an embargo of ten years. This embargo has been reduced to five years in 2016. This means that the 2014-2015 individual forecasts are not yet available in 2024, but those made in 2016 to 2018 are.[7]

2.3. Learning-to-Forecast (LtF) laboratory experiments

We collect a sample of macro-experimental data on inflation expectation from five published papers: Pfajfar and Žakelj (2018), Cornand and M'baye (2018a, b), Hommes et al. (2019), and Petersen (2014).[8] The Learning-to-Forecast design, based on the New Keynesian (NK) reduced-form model, offers the incentives to form accurate inflation forecasts. In LtFEs, the economy is qualitatively described to participants. Instructions include an explanation of the mechanisms that govern model equations. Participants observe the history of macroeconomic variables: at each period *t*, they observe inflation, the output gap and the interest rate up to period *t*-1. They play in groups (usually between 6 and 10 participants). They are asked to form a prediction of the *t*+1 period inflation (depending on the paper, they may also be asked to form output gap expectations, which we do not use in our study). The five papers respectively have about 70 periods with 24 independent groups, 50 periods with 32 independent groups, 60 periods with 32 independent groups, 50 periods with 43 independent groups, and 50 periods with 8 independent groups. Each period corresponds to one quarter. Appendix A provides a detailed description of the design of these LtF experimental papers.

2.4. Summary of inflation expectations data

Table 1 presents the source, frequency and sample characteristics of the inflation expectations data for our five categories of agents. We acknowledge the heterogeneity of the different datasets with respect to their frequency and the sample period considered. While frequency may differ from one set to the other, it is worth emphasizing that it corresponds to the frequency of usual economic decisions for each category of agents. For experimental forecasts, the frequency is abstract. The main limitation for our analysis relates to the Michigan data and the fact that most individuals are surveyed only twice and less than 2% are surveyed three times. For the analysis of how forecast revisions correlate with forecast errors, this means that we use a lot of variation across individuals but almost no within-individual variation.

Table 1 – Characteristics of inflation expectations data

	Policymakers	Professional F.	Firms (Industry)	Households	Experiments
Source	FOMC	SPF	Livingston	Michigan	LtF experiments
Frequency	6 months/Quarterly	Quarterly	6 months	6 months	Quarterly eq.
Measure	CPI/PCE	CPI	CPI	CPI	CPI
Sample	1992m1-2018m12	1981q3-2020q2	1948h1-2020h1	1980m7-2020m5	NA
Time Obs	70	156	145	479	5 989
Resp/Wave	17.03	36.54	47.69	384.25	7.02
Nb Resp	73	251	458	91 390	736
Nb Obs	1 192	5 701	6 915	184 054	42 016
Avg Length	16.33	22.71	15.10	2.01	57.09

Note: This table shows various characteristics of the five categories of inflation expectations data: the time series dimension, the average number of individuals surveyed in each wave, the total number of different individuals in each database, the total number of observations and the average length (number of waves) during which an individual is surveyed. For FOMC data, individual forecasts for the years 2014 and 2015 are still under embargo and are not in the dataset.

[7] For more details on FOMC forecast releases: www.federalreserve.gov/monetarypolicy/fomc_historical.htm.

[8] For a systematic comparison of the characteristics of experimental designs used in the five considered papers, see Cornand and Hubert (2022).

The various datasets that we consider provide two different forms of inflation forecasts: fixed-event or fixed-horizon forecasts. Fixed-horizon forecasts are preferable for our analysis of forecast errors since they are not influenced by a decreasing forecasting horizon. Following Dovern et al. (2012), we construct fixed-horizon forecasts (at the 1-year horizon) as a weighted average of fixed-event forecasts (using current-year and next-year forecasts as well as the number of months forecasted in each year) for the FOMC data. We are therefore able to compare all forecasts on the same ground with a similar fixed-horizon (1-year) scheme.

2.5. Other macroeconomic data

We use the monthly Consumer Price Index for All Urban Consumers (FRED mnemonic: CPI-AUCSL) and the Personal Consumption Expenditures: Chain-type Price Index (FRED mnemonic: PCEPI_PC1) for the computation of forecast errors. Regarding experimental data, inflation is generated by the computer program that implements a model of the economy, conditional on the parameters and the expectations that participants to the experiment are asked for (inflation expectations for all experiments considered in this paper as well as output gap expectations in Hommes et al. (2019) and Petersen (2014)).

3. Over/underreaction in aggregate and individual forecasts

3.1. Forecast errors and forecast revisions

We denote by $\pi_{t+h|t}$ the aggregate inflation forecast made at time *t* about the future value π_{t+h} of inflation at date *t*+*h*. We consider the median of individual inflation forecasts, $\pi^i_{t+h|t}$, where *i* denotes individual forecasters. Compared to the mean, it alleviates concerns about outliers. The *h*-periods ahead aggregate inflation forecast error $\mathrm{FE}_{\mathrm{agg},t}$ and forecast revision $\mathrm{FR}_{\mathrm{agg},t}$ at *t* are given by:

$$\mathrm{FE}_{\mathrm{agg},t} = \pi_{t+h} - \pi_{t+h|t} \tag{1}$$

$$\mathrm{FR}_{\mathrm{agg},t} = \pi_{t+h|t} - \pi_{t+h-1|t-1} \tag{2}$$

The individual forecast error and forecast revision are computed the same way with $\pi^i_{t+h|t}$. Table 2 presents the mean of the above-described measures of forecast errors (upper panel) and forecast revisions (lower panel) for the five categories of agents, both at the aggregate and individual levels. We also compute whether individuals revise their forecasts at each date to measure the forecast revision probability of each category of agents. This aims to be indicative of the extent to which agents update their information set from one period to another. This probability lies between 0.75 for households and 0.98 for both professional forecasters and firms. One caveat of this comparison is that the frequency of each survey is not identical, see Cornand and Hubert (2022) for a discussion of this issue and comparable measures of the updating probabilities.

Table 2 – Descriptive statistics for forecast errors and revisions

	FOMC	SPF	Livingston	Michigan	LtF Exp.
	Mean	Mean	Mean	Mean	Mean
$\lvert FE_{agg}\rvert$	0.75	0.95	1.48	1.10	0.19
$\lvert FE_{i}\rvert$	0.78	1.06	1.87	3.28	0.33
FE_{agg}	-0.03	-0.33	0.56	-0.24	0.00
FE_{i}	-0.05	-0.31	0.48	-0.92	-0.02
FR proba	0.94	0.98	0.98	0.75	0.84
$\lvert FR_{agg}\rvert$	0.24	0.16	0.44	0.27	0.30
$\lvert FR_{i}\rvert$	0.27	0.36	1.27	3.44	0.41
FR_{agg}	-0.02	-0.03	0.03	-0.02	0.00
FR_{i}	-0.02	-0.03	0.03	-0.43	0.00

Note: FE_{agg} is the aggregate forecast error, FE_i is the individual forecast error, FR_{agg} is the aggregate forecast revision, FR_i is the individual forecast revision. Prob FR is the probability of forecast revision.

Table 2 shows some interesting comparisons across the different categories of inflation expectations. The aggregate and individual forecast errors of participants to experiments are small compared to that of the four other categories of agents. The largest average aggregate forecast error is found for Livingston data (firms/industry), but the largest average individual forecast error is found for Michigan data (households). When focusing on biases in inflation expectations, Livingston expectations systematically underestimate future inflation whereas SPF and Michigan expectations systematically overestimate it. FOMC and LtF expectations exhibit no systematic bias. This is in line with the literature (Diebold and Mariano (1995), Romer and Romer (2000), and Ang et al. (2007), Cornand and Hubert (2020)).

The magnitude of the aggregate forecast revision is the most homogenous measure of this comparison. However, when looking at individual forecast revisions, Michigan data experience a much larger average revision than all four other categories. Individual forecast revisions are of comparable magnitude in FOMC, SPF and LtF data. There is no systematic bias in aggregate or individual forecast revisions, except for Michigan individual data. Between the first and second waves (or second and third), households tend to reduce their inflation expectations. This pattern can be explained by the inflation attention shock that being surveyed represents for households as evidenced by Gautier and Montornes (2022) and Kim and Binder (2023).

3.2. Aggregate regressions

The predictability of forecast errors is assessed by estimating the classical Coibion and Gorodnichenko (2015) regression that computes the correlation between the forecast error and the forecast revision at the date when the former forecast is made:

$$\mathrm{FE}_{\mathrm{agg},t} = \alpha + \beta\ \mathrm{FR}_{\mathrm{agg},t} + \epsilon_t \tag{3}$$

Under FIRE, forecast errors should not be predictable from forecast revisions, then $\beta = 0$. By contrast, a positive coefficient β implies that when the aggregate forecast is revised upwards, $FR_{agg,t} > 0$: it predicts a higher realization relative to the forecast meaning that the aggregate forecast was not revised enough. Said differently, the forecast underreacts to information relative to FIRE. In contrast, a negative coefficient β implies that a positive aggregate forecast revision predicts a lower realized inflation compared to the forecast. It therefore indicates overreaction of aggregate forecasts relative to FIRE. Coibion and Gorodnichenko (2015) find

$\beta > 0$ for aggregate forecasts of professional forecasters. Their test enables them to reject the full information component of the FIRE assumption, but not necessarily rational expectations.[9]

Table 3 – Aggregate forecast regression

	FOMC	SPF	Livingston	Michigan	LtF Exp.
	(1)	(2)	(3)	(4)	(5)
	12m	12m	12m	12m	12m
FR_{agg}	-0.545	0.365	0.777	-0.428***	0.041**
	[-0.88]	[0.81]	[1.96]	[-3.39]	[2.44]
constant	-0.044	-0.281***	0.494***	-0.292***	0.004
	[-0.28]	[-3.04]	[2.91]	[-4.42]	[1.11]
N	56	155	144	478	5 882
R2	0.03	0.01	0.08	0.03	0.01

Note: *t*-statistics in brackets. ** $p < 0.05$, *** $p < 0.01$. Parameters are estimated with Eq. (3) using OLS and heteroskedasticity-robust standard errors. The dependent variable is the aggregate forecast error.

Table 3 shows the outcome of Equation (3) for the five categories of agents. We find that the β coefficient is positive, although not significant, for professional forecasters. This is consistent with Bordalo et al. (2020) who also use the SPF forecast of CPI inflation. Estimates suggest that aggregate forecasts of participants to laboratory experiments also underreact relative to FIRE ($\beta > 0$). However, while the coefficient is estimated with greater precision for this category of agents, its magnitude is considerably smaller. A larger underreaction pattern, though significant at the 10% level only, is observed for firms. In contrast, our estimates indicate overreaction of aggregate forecasts of households ($\beta < 0$), consistent with Angeletos et al. (2020). This suggests that upward forecast revisions are associated with lower realizations relative to households' forecasts. To some extent, policymakers' aggregate inflation forecasts also seem to overreact relative to FIRE, but the β coefficient is not significant. Finally, we find no evidence of a systematic bias for policymakers and participants to laboratory experiments. In contrast, while professional forecasters and household expectations display an upward bias (the conditional mean of aggregate forecast errors is negative, so forecasts are on average systematically larger than realizations), firm expectations exhibit a downward bias (a positive intercept).

Table A1 in Appendix B presents a robustness check on the same temporal sample as the one used for FOMC data (1992 to 2018) or, in the case of LtFEs, with a random draw of the same number of observations as for FOMC data. While the significant but small effect displayed for LtFEs is not robust to a smaller sample, the negative and significant relation documented for households is robust.

3.3. Panel regressions

As underlined by Bordalo et al. (2020), testing for the rationality of forecast updating requires unpredictability of forecast errors at the *individual* level. We adapt Equation (3) to analyze forecast error predictability with individual forecast revisions $\mathrm{FR}_{t,h}^{i} = \left(\pi_{t+h|t}^{i} - \pi_{t+h-1|t-1}^{i}\right)$ and individual forecast errors $\mathrm{FE}_{t,h}^{i} = (\pi_{t+h} - \pi_{t+h|t}^{i})$. The estimation consists in pooling all forecasters and estimating a common coefficient β_p from the following regression:

$$\mathrm{FE}_{i,t} = \kappa_i + \alpha_p + \beta_p \, \mathrm{FR}_{i,t} + \epsilon_{i,t} \tag{4}$$

[9] Coibion and Gorodnichenko (2015) demonstrate that $\beta > 0$ can arise in models where only the full-information assumption is relaxed, allowing individual forecasters to rationally update their predictions based on imperfect or noisy private signals.

Superscript p refers to the pooling of individual level data. $\beta_p > 0$ would indicate that the average forecaster underreacts to his own information. The rational expectations hypothesis implies that $\beta_p = 0$, even with information frictions. κ_i is an individual fixed effect that should capture individual-specific differences in systematic forecaster bias.

Table 4 shows the outcome of Equation (4). The main result is that individual forecasts overreact to news ($\beta_p < 0$) for all categories of economic agents. This is consistent with the main result of Bordalo et al. (2020) and extends it beyond professional forecasters. One potential explanation of this overreaction may be that individuals think current data is over-representative of what the future state of the economy will be. The overreaction coefficient is significant at the 1% level for all agents and the magnitude of the β_p coefficient is rather homogeneous across categories of agents ranging from -0.509 for policymakers to -0.357 for participants to laboratory experiments. For the Michigan survey, the result holds when considering either all households that are surveyed at least twice (Column 7) or those only surveyed thrice (Column 8). Additionally, we observe a systematic bias across all categories of agents. While firms exhibit a downward bias, we find evidence of a systematic upward bias for the other categories.

Table 4 – Individual forecast regressions

	FOMC		SPF		Livingston		Michigan			LtF Exp.	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	12m	12m	12m	12m	12m	12m	12m	12m	12m	12m	12m
FR_i	-0.509***	-1.247***	-0.453***	-0.506***	-0.378***	-0.396***	-0.405***	-0.453***	-0.445***	-0.357***	-0.370***
	[-10.43]	[-14.44]	[-14.92]	[-18.83]	[-18.32]	[-21.64]	[-58.36]	[-20.52]	[-21.12]	[-9.68]	[-10.50]
$F_{agg,t-1}$		-1.741***		-0.603***		-0.308***			-0.885***		-0.091***
		[-18.20]		[-12.93]		[-5.52]			[-13.07]		[-6.91]
constant	-0.065***	3.215***	-0.291***	1.356***	0.468***	1.390***	-0.934***	-0.781***	1.744***	-0.016***	0.295***
	[-80.13]	[17.87]	[-300.32]	[10.63]	[848.57]	[8.32]	[-63.42]	[-81.85]	[9.00]	[-172.82]	[6.55]
Ind. FE	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes
N	888	888	4 060	4 060	5 049	5 049	92 664	2 548	2 548	41 241	41 241
R2	0.10	0.48	0.21	0.27	0.32	0.35	0.24	0.88	0.90	0.27	0.29

Note: t-statistics in brackets. ** $p < 0.05$, *** $p < 0.01$. Parameters are estimated with Eq. (4) using individual-level pooled panel regressions and standard errors clustered at the forecaster level. The dependent variable is individual forecast error at time t. For the Michigan survey, Column (7) includes households that are surveyed at least twice, while Columns (8) and (9) focus on households that are surveyed thrice.

We then extend the analysis to the response to salient public signals in the vein of Broer and Kohlhas (2024). As a measure of a signal available to all individuals of each category, we include in Equation (4) the lagged aggregate forecast, denoted $F_{agg,t}$, of each category of inflation expectations. We find strong evidence of overreaction to lagged aggregate forecasts. The effect is very pronounced for policymakers at the FOMC. This result is suggestive of a beauty contest pattern, in which individuals look at each other and respond too much to what other individuals do. However, the effect is much smaller for laboratory participants to experiments. This small effect may indeed be due to the fact that the lagged aggregate forecast is not available to the participants in the experiments. Another message is that, for all types of agents, the overreaction to individual news is robust to the inclusion of a public signal, i.e. the lagged aggregate forecast.

Table A2 in Appendix B shows that the results presented in Table 4 are robust to a common sample. We use the same time sample as the one used for FOMC data for all categories of agents, and for LtFEs, we consider a random draw of the same number of observations as for FOMC data. Another concern relates to potential measurement errors when using survey forecasts. Juodis and Kucinskas (2023) document significant noise in these measures of expectations. Born et al. (2024) propose to set small errors to zero to address concerns about measurement error. We do so for both forecast errors and forecast revisions and set the threshold for each variable and for each category of agents to one-half of the standard deviation of the respective variable. Estimates are shown in Table A3 in the Appendix B for forecast errors and forecast revisions in isolation and both together. The result that each category of agent overreacts to news at the individual level holds with minimal variation in point estimates across the different specifications.

3.4. Regressions at the individual level

Following Bordalo et al. (2020), we then adapt Equation (4) to estimate forecaster-by-forecaster regressions. We therefore estimate N times the following Equation (5), N being the total number of individuals in each category of inflation expectations. This specification has the advantage that it does not impose the restriction of a common coefficient β_p as in Equation (4).

$$\text{FE}_{i,t} = \alpha_i + \beta_i \text{ FR}_{i,t} + \epsilon_{i,t} \qquad \text{with } i = 1, \dots, N \tag{5}$$

These N regressions for each category of agents yield a continuum of individual coefficients β_i. Rational expectations would here again imply that β_i = 0 for all i.

Table 5 – Forecaster-by-forecaster coefficients

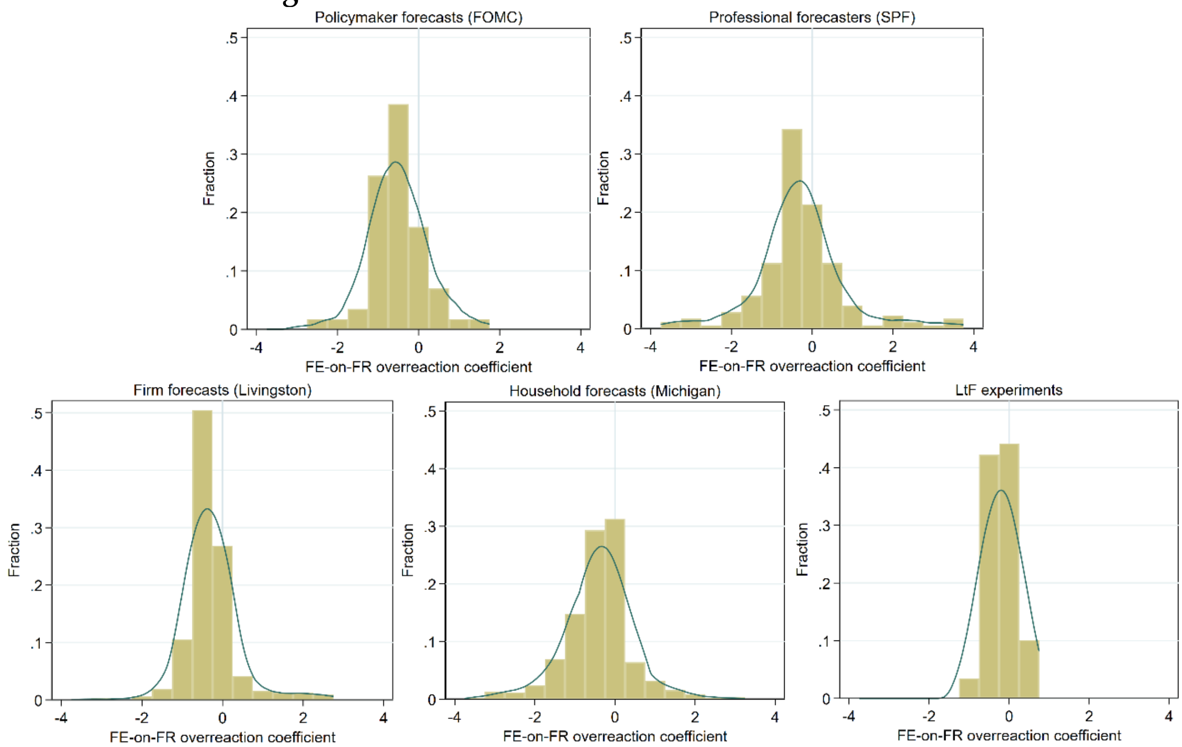
	FOMC	SPF	Livingston	Michigan	LtF Exp.
N	57	181	315	1 250	722
Mean	-0.51	-0.37	-0.33	-0.40	-0.20
SD	0.66	1.27	0.73	0.81	0.33
p10	-1.16	-1.64	-0.88	-1.36	-0.65
p25	-0.97	-0.72	-0.55	-0.79	-0.45
Median	-0.52	-0.38	-0.37	-0.38	-0.19
p75	-0.20	0.12	-0.12	0.00	0.03
p90	0.36	0.70	0.18	0.36	0.25

Note: Descriptive statistics of the individual overreaction coefficient β_i estimated with Eq. (5) for each individual. For the Michigan survey, only households that are surveyed thrice are considered. β_i is simply the slope of the relationship between $\text{FE}_{i,t}$ and $\text{FR}_{i,t}$, in a scatterplot of the two variables.

Table 5 reports the descriptive statistics of all individual coefficients β_i, truncated at the 1st and 99th percentiles, for the five datasets. The main message is that, consistent with the pooled specification of Equation (4), the mean and median β_i coefficients – that are very close and not statistically different one from the other – are negative, suggesting that the majority of individual forecasters do overreact to news relative to FIRE. This is true even for the Michigan data for which there is a very limited number of observations (only three) for each individual. In line with estimates in Table 4, the median across categories of agents is rather homogeneous. The differences in the standard deviation, however, suggest a larger amplitude across categories in the dispersion of overreaction coefficients.

Figure 1 plots the distribution of individual overreaction coefficients β_i for the five inflation expectations data. The distribution of overreaction coefficients is very dispersed for the SPF and at the opposite much tighter in LtFEs. Interestingly, for policymakers and firms more than 75% of the distribution of overreaction coefficients lies in negative territory, while this percentage is slightly smaller for professional forecasters, households, and participants to laboratory experiments. Financial literacy and socio-demographic variables could possibly explain the heterogeneity in reactions within and across categories.[10] Two messages are worth stressing. First, the distribution of overreaction coefficients for LtFEs appears different from those of the four other categories with much less dispersion, and a mode around zero. Overreaction to news seems less pronounced in this type of data. Second, although the mean, median and bulk of the distribution is in negative territory, a non-negligible part of individuals has a positive β_i coefficient, so underreacts to news. This raises the question of what determines whether individuals under or overreact to news.

Figure 1 – Distribution of overreaction coefficients



Note: These figures show the distribution of individual overreaction coefficients estimated with Eq. (5) for each dataset, truncated at the 1st and 99th percentiles. The blue line represents the Kernel density.

4. Behavioral underpinnings of over/underreaction

In this section, we relate over/underreaction to news at the individual level to four behavioral biases: recency bias (Kahneman and Tversky, 1973; for some application to inflation expectations, see e.g. Magud and Pienknagura, 2024), the inflation experience or memory (Malmendier and Nagel, 2011, 2016), salience (Bordalo et al., 2022), representativeness (Bordalo et al., 2018) that we apply to inflation expectations. While these biases are well-documented in the context of expectation formation, their association with overreaction to news remains unexplored. This section addresses this gap by examining whether and how these four biases correlate with forecasters' over/underreaction.

4.1. Recency bias

Recency bias is a cognitive bias that occurs when agents give more importance to recent events than to earlier ones, even when the more distant events may be more relevant or representative. In this subsection, we aim to explore the potential link between the recency

[10] Armantier et al. (2010) and Johannsen (2014) analyze how financial literacy and sociodemographic variables affect the characteristics of individual inflation expectations.

bias for each individual and his/her overreaction to news. We consider that a large autocorrelation of forecasts can render account for a recency bias, in the sense that more weight is attributed to recent observations.[11]

We compute the autocorrelation parameter of individual forecasts λ_i^{acfor} and we look at the correlation between λ_i^{acfor} and the overreaction parameter β_i. We assume that a high degree of persistence of forecasts (above the 75th percentile) for a given individual indicates that this individual is recency biased. The null hypothesis is that if agents have a strong recency bias, meaning that they give a large weight to more recent past events, they tend to underreact, or at least overreact less, to news. Said differently, an individual who overreaction has by definition large forecast revisions and should have a low autocorrelation of his/her forecasts. To test this null hypothesis, we first estimate the following forecaster-by-forecaster autoregressive specification to quantify the autocorrelation coefficient of each individual:

$$\mathrm{F}_{i,t} = \alpha_i + \lambda_i^{\text{acfor}}\, \mathrm{F}_{i,t-1} + \epsilon_{i,t} \tag{6}$$

In a second stage, we then regress overreaction coefficient on the coefficient:

$$\beta_i \ = \gamma_1 + \gamma_2\, \lambda_i^{\text{acfor}} + \gamma_3\, \lambda_i^{\text{acfor}} \cdot \mathbb{D}_i^{acfor} + \epsilon_i \tag{7}$$

where $\mathbb{D}_{\text{i}}^{\text{acfor}}$ equals one when λ_i^{acfor} is above the 75th percentile of the distribution for a given type of forecasts.

Table 6 – Individual autocorrelation of forecasts and overreaction

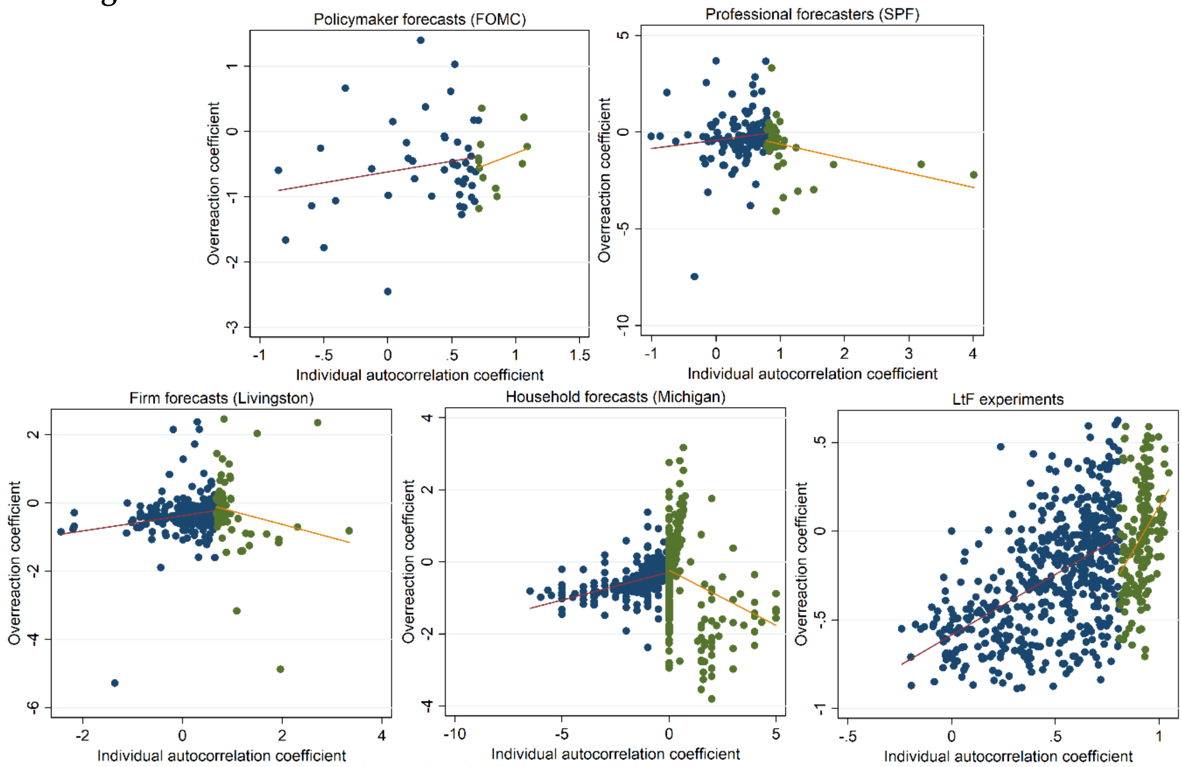
	FOMC	SPF	Livingston	Michigan	LtF Exp.
	(1)	(2)	(3)	(4)	(5)
	β_i	β_i	β_i	β_i	β_i
λ_i^{acfor}	0.332	0.437	0.222	**0.155*****	**0.684*****
	[1.42]	[1.04]	[1.93]	[10.79]	[15.97]
$\lambda_i^{\text{acfor}} \cdot \mathbb{D}_i^{\text{acfor}}$	0.445	**-1.182****	-0.613	**-0.459*****	**1.320*****
	[0.60]	[-2.58]	[-1.36]	[-10.02]	[3.64]
N	57	179	309	1 230	708
R2	0.05	0.07	0.04	0.08	0.31
Mean	0.43	0.57	0.30	-0.29	0.59
Median	0.56	0.61	0.37	0.00	0.65
p75	0.71	0.79	0.68	0.00	0.81

Note: t-statistics in brackets. ** p < 0.05, *** p < 0.01. Parameters are estimated with Eq. (7). λ_i^{acfor} is the individual autocorrelation coefficient of forecasts, truncated at the 1st and 99th percentiles; $\mathbb{D}_{\text{i}}^{\text{acfor}}$ equals one when λ_i^{acfor} is above the 75th percentile of the distribution for a given type of forecasts. The lower part of the Table shows the mean, median and 75th percentile of forecasts' autocorrelation coefficients for each category of agents. For the Michigan dataset, the autocorrelation parameter is computed on the subsample of individuals surveyed three times.

Table 6 shows the correlation between the autocorrelation coefficient in individual forecasts λ_i^{acfor}, truncated at the 1st and 99th percentiles, and the overreaction parameter β_i. It is worth noticing that the threshold defining strong autocorrelation is homogeneous for all categories (except for the special case of the Michigan dataset), and hovers around 0.7-0.8. To properly interpret this correlation (that is not trivial in particular when the correlation is positive and significant), we also consider in Figure 2 scatterplots relating the overreaction coefficient and the autocorrelation of forecasts for all categories of agents.

[11] Note that in Afrouzi et al. (2023) the recency bias is strong if autocorrelation of inflation is strong. Instead, we look at the perception of individuals by considering the autocorrelation of forecasts.

Figure 2 – Autocorrelation of individual forecasts and overreaction coefficient



Note: These scatterplots show the link between the overreaction parameter β_i (y-axis) and the autocorrelation coefficient of individual forecasts λ_i^{acfor} (x-axis) for the five categories of agents. Blue (green) dots represent individuals with a level of forecast autocorrelation below (above) the 75$^{\text{th}}$ percentile. The corresponding regression line is plotted in red (orange).

For LtFEs, the correlation between λ_i^{acfor} and β_i is positive and significant. The scatterplot shows that as the autocorrelation parameter increases, the overreaction parameter becomes less negative (from -0.6 to 0). This correlation is significantly larger for recency-biased participants, indicating a non-linear relationship between individual forecast autocorrelation and overreaction to news. This result supports the null hypothesis: recency-biased participants tend to either overreact less (with β_i approaching 0) or underreact more (when β_i is positive) to news. For households, a similar positive linear pattern is observed for low levels of forecast autocorrelation, an increase in autocorrelation being associated with a decrease in overreaction.[12] However, the sign of the non-linear relationship between λ_i^{acfor} and β_i is reversed compared to LtFEs: for recency-biased households, an increase in autocorrelation is associated with an increase in overreaction (β_i becomes more negative). A negative non-linear relationship is also observed for professional forecasters. Finally, for policymakers (FOMC) and firms (Livingston) the correlation coefficients are not significant. Overall, these results suggest that the recency bias is linked to individuals' overreaction for participants to LtFEs, professional forecasters, and households. For LtFEs, the results are consistent with the null hypothesis, while for professional forecasters and households, the relationship is reversed. For policymakers and firms, our results suggest no significant relationship between overreaction to news and individuals' recency bias.

[12] For the Michigan dataset, the autocorrelation parameter is computed on the subsample of individuals surveyed three times.

4.2. Memory of inflation

Malmendier and Nagel (2011, 2016) show that individuals overweight their personal experience of inflation. Indeed, agents tend to form their expectations about future inflation based on what they have personally experienced during their lifetime, particularly the periods of high or low inflation they have lived through. Malmendier and Nagel argue that agents who have experienced higher inflation in their past (for example, through price increases during their early adulthood) will perceive inflation as being higher than it actually is based on current data. On the other hand, individuals who have lived through periods of low inflation may underestimate future inflation. This effect is driven by personal memory, which is often more vivid for high-inflation periods.

Table 7 – Average inflation rate experienced and overreaction

	FOMC	SPF	Livingston	Michigan	LtF Exp.
	(1)	(2)	(3)	(4)	(5)
	β_i	β_i	β_i	β_i	β_i
π_i^{Exp}	0.873***	0.366	-0.023	0.059	0.054
	[3.88]	[1.11]	[-0.56]	[0.39]	[1.02]
$\pi_i^{Exp} \cdot \mathbb{D}_i^{\pi}$	**-1.521*****	-0.339	0.103	-0.234	**-0.159****
	[-3.36]	[-0.93]	[0.85]	[-1.27]	[-2.03]
N	57	181	315	1 250	722
R2	0.21	0.05	0.04	0.00	0.49
Mean	2.33	2.75	3.65	3.22	3.43
Median	2.31	2.41	3.12	3.22	3.32
p75	2.57	3.20	4.73	3.22	4.37

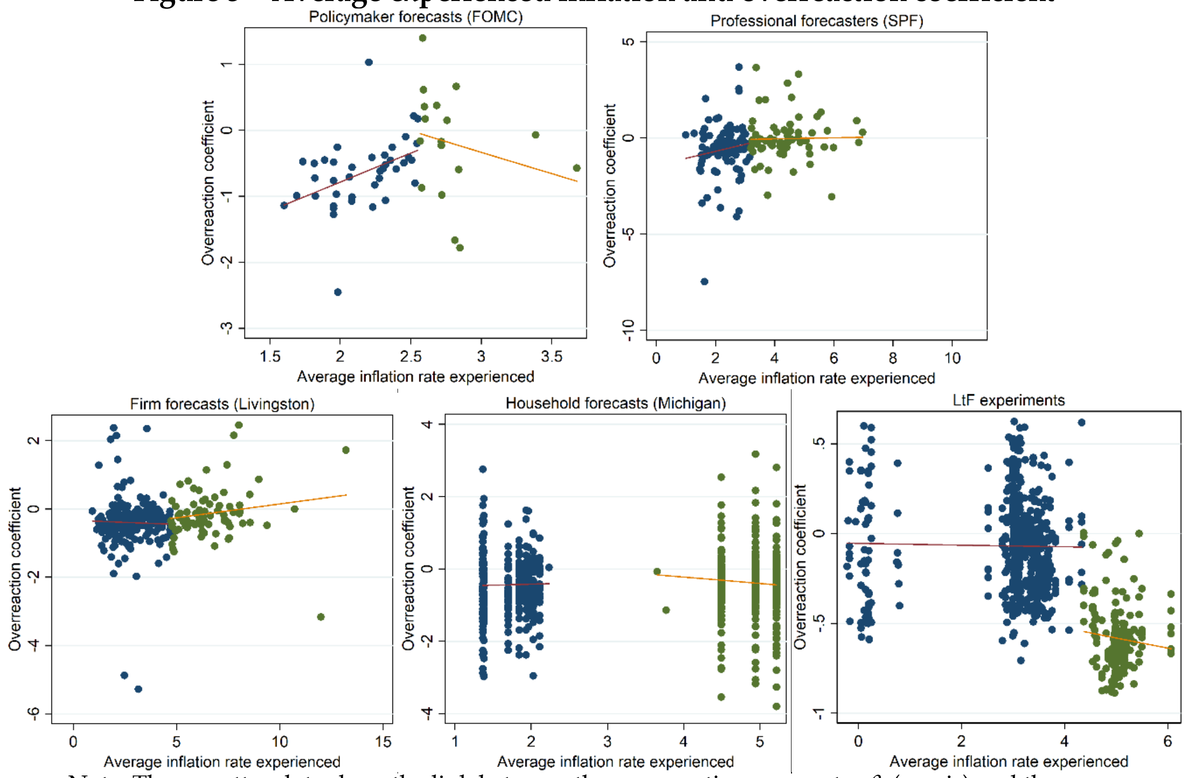
Note: *t*-statistics in brackets. ** $p < 0.05$, *** $p < 0.01$. Parameters are estimated with Eq. (8). π_i^{Exp} is the average inflation rate experienced by each forecaster i when present in the sample. $\mathbb{D}_i^{acfor}$ equals one when π_i^{Exp} is above the 75th percentile of the distribution for a given type of forecasts. The lower part of the Table shows the mean, median and 75th percentile of the average inflation rate experienced for each category of agents. For the Michigan dataset, the analysis is based on the subsample of individuals surveyed three times.

In this subsection, we complement this approach by analyzing whether individual inflation experience contributes to forecasters' overreaction. The considered null hypothesis is that individuals who have experienced high inflation are more likely to overreact to news when forecasting inflation. To explore this question, we compute the average of inflation rate experienced by each forecaster when they did forecast inflation in our sample, denoted $\bar{\pi}_i$. One drawback of this choice is that we do not observe the inflation rate experienced when forecasters are not in the sample (especially in their early years). However, one advantage of our measure is the consistency of the inflation experience metric with the actual inflation forecasts that are used to compute the overreaction coefficient. In a second stage, we then regress the individual overreaction coefficient on the individual inflation experience measure:

$$\beta_i = \gamma_1 + \gamma_2 \, \pi_i^{Exp} + \gamma_3 \, \pi_i^{Exp} \cdot \mathbb{D}_i^{\pi} + \epsilon_i \tag{8}$$

where π_i^{Exp} is the average inflation rate experienced by each forecaster i when present in the sample. Table 7 shows the correlation between the average experienced inflation π_i^{Exp} and the overreaction parameter β_i. Figure 3 complements Table 7 with scatterplots relating the two measures for all categories of agents. The threshold above which the average experienced inflation is considered to be high varies from 2.57% for policymakers to 4.73% for firms. We observe a positive and significant correlation for policymakers who have experienced relatively low levels of inflation, suggesting that an increase in the average experienced inflation is associated with less overreaction. However, for high levels of experienced inflation, the conclusion is reversed, an increase in the average experienced inflation being associated with more overreaction. A similar, though smaller, non-linear pattern is observed for participants to LtFEs. This means that if participants to experiments see a higher inflation than what they are used to on their screen, they overreact to news that they subsequently receive. These findings support the null hypothesis. However, for professional forecasters, firms and households, the coefficients are not significant, suggesting no link between individual inflation experience and overreaction for these agents. Overall, the null hypothesis linking inflation experience to overreaction is validated for policymakers and participants to experiments.

Figure 3 – Average experienced inflation and overreaction coefficient



Note: These scatterplots show the link between the overreaction parameter β_i (y-axis) and the average inflation rate experienced by each forecaster i when present in the sample π_i^{Exp} (x-axis) for the five categories of agents. Blue (green) dots represent individuals with an average experienced inflation rate below (above) the 75th percentile. The corresponding regression line is plotted in red (orange).

4.3. Salience

Salience theory (Bordalo et al., 2022) focuses on how individuals perceive and make decisions based on the relative prominence of certain features. Agents tend to overweight the most noticeable or striking features, even if they are not necessarily the most relevant, leading to biases in decision-making, where individuals may ignore less noticeable but more important information. In this subsection, we look at whether over/underreaction to news may be related to salience. Salience influences reactions to news by making certain details stand out. We thus state our third null hypothesis: when inflation news is salient, individuals overreact.

To capture salient inflation news, we consider the stochastic volatility of inflation. To do so, we estimate a GARCH(1,1) model of the inflation rate to obtain the conditional variance of inflation. Although the GARCH model has been criticized for its ability to capture inflation uncertainty (see Giordani and Soderlind, 2003), it provides a parsimonious identification of the conditional variance of the inflation process, and it fits very well data-generating processes in which the volatility of a series varies over time. It captures this time-varying volatility as a function of observed prior volatility and appears relevant to capture inflation news. The GARCH model is estimated with maximum likelihood and is based on the following two—mean and variance—equations:

$$\begin{aligned} \pi_t &= \beta_0 + \beta_1\,\pi_{t-1} + \epsilon_t\,,\ \ \epsilon_t \sim (0, \sigma_t^2) && \text{Mean equation} \\ \sigma_t^2 &= \gamma_0 + \gamma_1\,\epsilon_{t-1}^2 + \gamma_2\,\sigma_{t-1}^2 && \text{Variance equation} \end{aligned} \tag{9}$$

where π_t is the year-over-year inflation rate and ϵ_t is the error term. The number of lags in the mean equation and in the variance equation for both the error term and its variance is set to one. The conditional variance of inflation, σ_t^2, provides a (monthly or quarterly) time-varying measure of the variance of inflation (see Figure A1 in Appendix B). We consider that inflation news are particularly salient when the variance of inflation is above its 75th percentile and denote it by the following dummy $\mathbb{D}_t^{\sigma}$.

In contrast with the previous two tests for the recency bias and inflation experience for which we computed measures at the individual level (and therefore estimated Equations (7) and (8) at the individual level), the measure of salient inflation news is an aggregate time-series. We therefore resort to Equation (4) that we previously used to estimate the overreaction coefficient. We augment this equation with an interaction term between forecast revisions and the dummy capturing when inflation news are salient.

$$\mathrm{FE}_{i,t} = \kappa_i + \alpha_p + \beta_p\,\mathrm{FR}_{i,t} + \beta_S\,\mathrm{FR}_{i,t}\cdot\mathbb{D}_t^{\sigma} + \epsilon_{i,t} \tag{10}$$

The coefficient β_p then captures the overreaction coefficient for each type of forecasters in normal times (that could be compared to the overreaction estimates in Table 4), while the coefficient β_S reflects the marginal overreaction effect when the conditional variance of inflation is large.

Table 8 shows the result of Equation (10). It provides the correlation between forecast errors and forecast revisions, taking into account the size of inflation shocks. The threshold above which inflation news is considered salient varies from 0.69 for firms to 1.26 for households. For small inflation shocks, our results are consistent with Table 4: individual forecasts overreact to news ($\beta_p < 0$) for the five categories of agents. However, for professional forecasters, firms, households and participants to LtFEs, the relationship between forecast errors and forecast revisions is non-linear. When inflation shocks are large, so that salience is high, overreaction decreases. Thus, although the results contradict the direction predicted by the null hypothesis, salience appears as a widespread bias correlated with overreaction across most categories of agents. This suggests that when inflation news is big, agents pay more attention to the inflation process and overreact less (by paying more attention to inflation, they react in line with the information content of the news but do not overreact), as also found in the literature on inflation attention (e.g. Korenok et al., 2024 and Bracha and Tang, 2024).

Table 8 – Salience of inflation news and overreaction

	FOMC	SPF	Livingston	Michigan	LtF Exp.
	(1)	(2)	(3)	(4)	(5)
	12m	12m	12m	12m	12m
$FR_{i,t}$	**-0.520*****	**-0.546*****	**-0.436*****	**-0.598*****	**-0.475*****
	[-4.26]	[-13.57]	[-16.55]	[-24.40]	[-36.08]
$FR_{i,t} \cdot \mathbb{D}_t^{\sigma}$	-0.014	**0.163*****	**0.106*****	**0.169*****	**0.224*****
	[-0.10]	[2.65]	[2.80]	[4.75]	[4.09]
Ind. FE	Yes	Yes	Yes	Yes	Yes
N	888	4 060	5 049	2 548	41 239
R2	0.14	0.22	0.32	0.89	0.29
Mean	0.85	0.87	0.68	1.03	0.20
Median	0.49	0.53	0.34	0.70	0.03
p75	0.90	0.93	0.69	1.26	0.08

Note: t-statistics in brackets. ** p < 0.05, *** p < 0.01. Parameters are estimated with Eq. (10) using individual-level pooled panel regressions and standard errors clustered at the forecaster level. $\mathbb{D}_t^{\sigma}$ equals one when the variance of inflation is above its 75th percentile. The lower part of the Table shows the mean, median and 75th percentile of the variance of inflation for each category of agents. For the Michigan dataset, the analysis is based on the subsample of individuals surveyed three times.

4.4. Representativeness heuristic

The representativeness heuristic is a mental shortcut or cognitive bias that agents use to judge the likelihood of an event based on how similar it is to a prototype, rather than considering statistical information or more relevant data. Diagnostic expectations (Bordalo et al., 2018) are based on representativeness heuristic. Agents tend to weigh information based on how strongly they believe it provides evidence about an underlying characteristic. They make biased inferences based on the diagnosticity of available information rather than considering all relevant data. Therefore, they may consider information that fits their expectations about a particular scenario and disregard less obvious or contradictory data. The consequence is that the representativeness heuristic causes agents to overreact less to news that fit a familiar pattern.

Our fourth null hypothesis is that if today's inflation is close to the level of inflation an individual has known, this individual tends to overreact less. Conversely, if the distance between these two measures—current inflation and the average inflation experienced—is large, this individual would be more likely to overreact. To test this hypothesis, we use the average inflation rate experienced by each forecaster, $\overline{\pi_i}$, and compute the distance between the current inflation rate at the date when a forecast is formed and the average inflation rate experienced by each forecaster.[13] We then isolate when this distance is large with the dummy $\mathbb{D}_{i,t}^{d}$ that equals one when the distance reaches the 75th percentile. The average experienced inflation by each individual is determined based on the entire sample. Although this measure is not restricted to the set of information available to forecasters at the time of their forecast, it has the advantage of characterizing each individual's type based on their inflation experience.

We again augment Equation (4) with an interaction term between forecast revisions and the dummy capturing when this distance is large.

$$\mathrm{FE}_{i,t} = \kappa_i + \alpha_p + \beta_p \,\mathrm{FR}_{i,t} + \beta_D \,\mathrm{FR}_{i,t} \cdot \mathbb{D}_{i,t}^{d} + \epsilon_{i,t} \tag{11}$$

[13] Observe that we make a strong assumption as we consider the inflation rate experienced as a forecaster in the sample. This is experienced inflation for the same set of forecasts. In comparison to Malmendier and Nagel (2011, 2016), our measure is sub-optimal but it is consistent with the set of forecasts. We measure a sub-sample of agents' experienced inflation. This corresponds to inflation as a forecaster and not as an individual.

The coefficient β_p captures the overreaction coefficient for each type of forecasters in normal times, while the coefficient β_D reflects the marginal overreaction effect when the distance between current inflation and the individual inflation experienced is large.

Table 9 – Representativeness heuristics and overreaction

	FOMC	SPF	Livingston	Michigan	LtF Exp.
	(1)	(2)	(3)	(4)	(5)
	12m	12m	12m	12m	12m
$FR_{i,t}$	**-0.364*****	**-0.427*****	**-0.415*****	**-0.419*****	**-0.287*****
	[-3.62]	[-10.55]	[-16.13]	[-16.68]	[-4.45]
$FR_{i,t} \cdot \mathbb{D}_{i,t}^{d}$	**-0.325****	-0.063	0.082	**-0.394*****	-0.122
	[-2.59]	[-0.75]	[1.93]	[-5.49]	[-0.93]
Ind. FE	Yes	Yes	Yes	Yes	Yes
N	888	4 060	5 049	2 548	41 241
R2	0.15	0.22	0.32	0.89	0.28
Mean	0.74	0.91	1.65	1.43	0.61
Median	0.53	0.65	1.12	1.06	0.29
p75	1.06	1.20	2.28	1.67	0.62

Note: *t*-statistics in brackets. ** $p < 0.05$, *** $p < 0.01$. Parameters are estimated with Eq. (11) using individual-level pooled panel regressions and standard errors clustered at the forecaster level. $\mathbb{D}_{i,t}^{d}$ equals one when the distance between the current inflation rate and the average inflation rate experienced by each forecaster is above its 75th percentile. The lower part of the Table shows the mean, median and 75th percentile of this distance measure for each category of agents. For the Michigan dataset, the analysis is based on the subsample of individuals surveyed three times.

Table 9 presents the outcome of Equation (11). It shows the correlation between forecast errors and forecast revisions accounting for the distance between current inflation and experienced inflation. The threshold above which this distance is considered as large varies from 0.62 percentage points (pp) for participants to LtFEs to 2.28pp for firms. Consistent with Table 4, when this distance is small, individual forecasts overreact to news for all categories of agents. However, for policymakers and households, when the distance between current inflation and the average inflation experienced is large, overreaction is even larger. This validates the null hypothesis for these two categories of agents. For professional forecasters, firms and participants to LtFEs, our results suggest no link between the representativeness heuristic bias and overreaction to news.

5. Discussion about the generalizability of experimental forecasts

Although it is crucial for laboratory experiments to be relevant for policymakers, the issue of the external validity of experimental inflation expectations has received limited attention. We identify three different approaches in the literature that compare experimental and field data. The first one consists in comparing survey to lab-in-the-field data on the *same* (category of) *agents* and ask whether experiments are comparable to surveys. Armantier et al. (2015) present a study in which they compared consumers' survey data on inflation expectations to the behavior of the same subjects in a financially incentivized investment experiment. They show that stated beliefs in the survey and experimental decisions are highly correlated and conform to theoretical predictions. Recently, Salle et al. (2023) explore how individuals' memories of inflation influence their expectations about future inflation in both surveys and laboratory experiments. They specifically demonstrate that experiencing periods of rising inflation or disinflation in an inflation forecasting game can create an experience similar to actual lifetime exposure to inflation. These findings represent an important step toward comparing survey and experimental data.

A second approach consists in comparing exactly the *same task* on two different categories of agents, namely agents from the field versus agents in the lab.[14] Coibion et al. (2021) study higher-order macroeconomic expectations of firm managers in New Zealand. In contrast to previous surveys, they ask managers not only about their own expectations over macroeconomic variables (first-order expectations), but also about *what they think other managers expect* for inflation, i.e. their higher-order beliefs. To this aim, survey respondents participate in a guessing game (Nagel, 1995). Coibion et al. (2021) find that 37 percent of managers are level-0 thinkers—that is play randomly—, as opposed to around 25 percent in experimental studies. Their sample is also more heavily weighted towards higher than level-3 thinker (about a quarter of respondents performing such higher levels of reasoning), which is above what is usually found in other papers.

Finally, a third approach—that we follow in the present paper—is to conduct a meta-analysis and compare experimental data to various categories of field inflation expectations in spite of the considerable heterogeneity among the different data sets and see whether they exhibit common features. Cornand and Hubert (2020) and (2022) compare inflation expectations of different categories of agents (participants to laboratory experiments, households, industry, professional forecasters and central bankers) and confirm the comparability of experimental inflation forecasts to field inflation forecasts in terms of forecast accuracy and to a lesser extent in terms of information frictions. More precisely, Cornand and Hubert (2020) find that, excluding central bank forecasts (which demonstrate clear superiority), the accuracy of forecasts is generally comparable.[15] Cornand and Hubert (2022) delve further into information frictions at the individual level by comparing the disagreement in expectations and the frequency of forecast revisions across different categories of agents. They observe greater heterogeneity among their datasets than in their previous work on forecast accuracy using aggregate data.[16]

Complementing these studies on the generalizability of experimental forecasts, our current paper shows that experimental data share some common patterns with other categories of data but also present some particular patterns. As all other categories of data, individual experimental inflation forecasts exhibit overreaction. At the aggregate level, experimental forecasts underreact to new information as professional forecasts and firms forecasts and consistently with the results found in the literature. Finally, in terms of behavioral underpinnings, salience explains overreaction to news for participants to experiments, as for most other categories of agents.

Two peculiarities are worth mentioning. First, participants to LtFEs overreact less to news than other categories of agents. In this respect, while participants to experiments are not assigned a particular role in the economy (and can be asked to form expectations based on the

[14] A complementary approach to the elicitation of inflation expectations in the laboratory is the use of Randomized Controlled Trial (RCT) experiments in large-scale surveys, see Haaland et al. (2023). Armantier et al. (2016), Armantier et al. (2022), Binder and Rodrigue (2018), Cavallo et al. (2017), Coibion et al. (2018), Coibion et al. (2020), Coibion et al. (2021), D'Acunto et al. (2020), Humziker et al. (2018) and Link et al. (2021) apply this method to inflation forecasts. Salle (2022) provides a comparison between laboratory and survey approaches.

[15] Forecast errors are substantial and exhibit similar biases, with the exception of industry forecasts. Both forecast errors and revisions are predictable. Experimental data resemble households and professional forecasters data in terms of autocorrelation of forecast errors and predictability of forecast revisions, while it is more similar to financial market data in terms of errors in forecast revisions.

[16] While policymakers, professional forecasters, and LtFE participants exhibit low levels of disagreement, firms and households show much stronger disagreement. In terms of forecast revision frequency, they also find notable variation across the five categories of agents. Policymakers revise their forecasts more frequently than participants to experiment, firms, and professional forecasters, who in turn revise much more often than households.

behavior of firms, consumers or professional forecasters), they behave relatively close to firms when it comes to the magnitude of overreaction to news. There are also less individuals who underreact in this category of agents. Their behavior is less dispersed than that of other categories. The homogenous behavior of this category of agents may be due to the very controlled experimental set-up, that includes a qualitative description of a simple economy, with only a limited number of economic variables and a rather simple task (predicting inflation for the next period(s) and possibly additionally predicting output gap).

Second, in addition to salience that affects overreaction for most categories of agents, we have identified two biases that explain under/overreaction to news for participants to experiments: recency bias (causing underreaction, rather than overreaction as is the case for professional forecasters and households) and memory of inflation (causing overreaction). Instead, representativeness heuristic is not relevant for this category of agents.

Overall, experimenters should ensure that, when stating their expectations, participants in the experiment exhibit, on average, the same key characteristics as the field data they aim to replicate. Specifically, this means a sufficiently high level of overreaction to news and a notable degree of heterogeneity in reactions (with adequate dispersion between overreaction and underreaction). Additionally, the same biases that drive under/overreaction in real-world data should be present in experimental data. Currently, this does not seem to be the case. Enhancing the design of experiments to better replicate the expectations observed in the field would be crucial for reproducing stylized facts in the laboratory, thus enabling more accurate simulations of the effects of alternative policy measures.

6. Conclusion

The literature has shown that inflation consensus forecasts exhibit underreaction, while individual forecasts exhibit overreaction to news. In this paper, we document these facts for various categories of agents' *inflation expectations*: households, firms, professional forecasters, policymakers and participants to laboratory experiments. While we find—in line with the literature—mixed evidence of underreaction at the aggregate level—with professional forecasters, firms and participants to experiments underreacting and households and policymakers overreacting to news—, at the individual level, we provide evidence of overreaction for all categories of agents with some heterogeneity in the magnitude of the reaction across categories. The strongest overreaction is observed for policymakers, then for households, followed by professional forecasters, firms and participants to experiments. The majority of individuals do overreact to news relative to FIRE and the median of individual overreaction across categories of agents is similar. There is however a larger amplitude in individual overreaction across categories. The category that presents the largest amplitude is that of professional forecasters, followed by households, policymakers and firms. Participants to experiments represent a much more homogenous category.

Apart from extending the analysis to a variety of categories of economic agents, another main contribution of our paper consists in analyzing the potential behavioral foundations of under/overreaction. We find that salience is the primary bias driving overreaction across the five categories of agents studied. Professional forecasters, firms, households, and participants to experiments exhibit less overreaction when inflation news is salient. Our findings also indicate that households and participants to experiments display a broader range of biases, while firms tend to rely on fewer biases to explain overreaction. Recency bias is associated with over/underreaction among professional forecasters, households, and experimental participants. More precisely, professionals and households influenced by recency bias tend to overreact more to news, while this effect is reversed for participants to experiments. Additionally, we observe an inflation-experience bias among both policymakers and participants to experiments: those with more direct experience of higher inflation are more prone to overreact. Finally, we find a connection between the representativeness heuristic and overreaction for policymakers and households, as both groups are more likely to overreact when current inflation significantly deviates from their average inflation experience.

Our paper also addresses the external validity of experimental inflation expectations, an issue that, despite its importance for ensuring the relevance of laboratory experiments to policymakers, has received limited attention. We argue that researchers should ensure that expectations formed in the laboratory display a sufficiently high and heterogeneous degree of overreaction to news, along with the same biases that drive under/overreaction in real-world data. Replicating key characteristics of field expectations is essential for conducting meaningful policy experiments in the laboratory.

Finally, understanding whether economic agents over or underreact to new information in forming their inflation expectations is crucial for central banks. The effectiveness of their monetary policy relies on a proper management of inflation expectations, which is made possible by an appropriate communication policy. When some categories of economic agents overreact more than others—as we found in this paper—, the central bank should adjust its communication strategy to account for these differences and deliver messages tailored to the characteristics of each audience.

References

Afrouzi, H., S. Kwon, A. Landier, Y. Ma and D. Thesmar (2023). Overreaction in Expectations: Evidence and Theory, *The Quarterly Journal of Economics*, 138(3), 1713-1764.

Andre P., I. Haaland, C. Roth and J. Wohlfart (2022). Narratives About the Macroeconomy, *CEPR Discussion Paper* DP17305.

Ang, A., G. Bekaert and M. Wei (2007). Do macro variables, asset markets, or surveys forecast inflation better?, *Journal of Monetary Economics*, 54 (4), 1163-1212.

Angeletos, G.-M., Z. Huo and K. Sastry (2020). Imperfect Macroeconomic Expectations: Evidence and Theory, *NBER Macroeconomics Annual 2020*, vol. 35.

Armantier, O., W. Bruine de Bruine, W. van der Klauw, J. Downs, B. Fischoff and G. Topa (2010). Expectations of Inflation: The Role of Financial Literacy and Demographic Variables, *Journal of Consumer Affairs*, 44(2), 381-402.

Armantier, O., W. Bruine de Bruin, G. Topa, W. van der Klaauw and B. Zafar (2015). Inflation expectations and behavior: do survey respondents act on their beliefs?, *International Economic Review*, 56, 505-536.

Armantier, O., A. Sbordone, G. Topa, W. van der Klauw and J. Williams (2022). A new Approach to Assess Inflation Expectations Anchoring Using Strategic Surveys, *Journal of Monetary Economics*, 129.

Armantier, O., W. van der Klauw, G. Topa and B. Zafar, (2016). The price is right: Updating inflation expectations in a randomized price information experiment, *Review of Economics and Statistics*, 98(3), 503-523.

Bianchi, F., C. Ilut, and H. Saijo (2023). Diagnostic Business Cycles, *Review of Economic Studies*, 91(1), 129-162.

Binder, C, and A. Rodrigue (2018). Household Informedness and Long-Run Inflation Expectations: Experimental Evidence, *Southern Economic Journal*, 85(2), 580-598.

Bordalo P., N. Gennaioli, R. La Porta and A. Shleifer (2019). Diagnostic Expectations and Stock Returns, *Journal of Finance,* 74(6), 2839-2874.

Bordalo, P., N. Gennaioli and A. Shleifer (2018). Diagnostic Expectations and Credit Cycles, *Journal of Finance,* 73(1), 199-227.

Bordalo, P., N. Gennaioli, Y. Ma and A. Shleifer (2020). Over-Reaction in Macroeconomic Expectations, *American Economic Review,* 110, 2748-2782.

Bordalo, P., N. Gennaioli and A. Shleifer (2022). Salience, *Annual Review of Economics*, 14: 521-544.

Born, B., Z. Enders, G. J. Müller and K. Niemann (2023). Chapter 12 - Firm expectations about production and prices: Facts, determinants, and effects, R. Bachmann, G. Topa, W. van der Klaauw (eds.), *Handbook of Economic Expectations*, Academic Press, 355-383

Born, B., Z. Enders, M. Menkhoff, G. J. Müller and K. Niemann (2024). Firm expectations and news: micro v macro, *mimeo*.

Bouchaud, J.-P., P. Krueger, A. Landier and D. Thesmar (2019). Sticky Expectations and the Profitability Anomaly, *Journal of Finance,* 74(2), 639-674.

Bracha, A. and J. Tang (2024). Inflation Levels and (In)Attention, *The Review of Economic Studies*, forthcoming.

Broer, T. and A. Kohlhas (2024). Forecaster (Mis-)Behavior, *Review of Economics and Statistics*, forthcoming.

Capistrán, C. and A. Timmermannn (2009). Disagreement and Biases in Inflation Expectations, *Journal of Money, Credit and Banking*, 41(2-3), 365-396.

Carstensen, K. and R. Bachmann (2023). Chapter 2 - Firm surveys, R. Bachmann, G. Topa, W. van der Klaauw (eds.), *Handbook of Economic Expectations*, Academic Press, 33-70.

Cavallo, A., G. Cruces and R. Perez-Truglia (2017). Inflation Expectations, Learning and Supermarket Prices: Evidence from Survey Experiments, *American Economic Journal: Macroeconomics*, 9(3), 1-35.

Coibion, O. and Y. Gorodnichenko (2015). Information Rigidity and the Expectations Formation Process: A Simple Framework and New Facts, *American Economic Review,* 105(8), 2644-2678.

Coibion, O., Y. Gorodnichenko and S. Kumar (2018). How Do Firms Form Their Expectations? New Survey Evidence, *American Economic Review*, 108(9), 2671-2713.

Coibion, O., Y. Gorodnichenko and T. Ropele (2020). Inflation Expectations and Firm Decisions: New Causal Evidence, *The Quarterly Journal of Economics*, 135(1), 165-219.

Coibion, O., Y. Gorodnichenko, S. Kumar and J. Ryngaert (2021). Do you know that I know that you know…? Higher order beliefs in survey data, *The Quarterly Journal of Economics*, 136(3), 1387-1446.

Cornand, C. and P. Hubert (2020). On the external validity of experimental inflation forecasts: A comparison with five categories of field expectations, *Journal of Economic Dynamics and Control,* 110, 103746.

Cornand, C. and P. Hubert (2022). Information frictions in inflation expectations: a comparison among five categories of economic agents, *European Economic Review*, 146, 104175.

Cornand, C. and C. K. M'baye (2018a). Does inflation targeting matter? An experimental investigation, *Macroeconomic Dynamics,* 22(2), 362-401.

Cornand, C. and C. K. M'baye (2018b). Band or Point Target? An Experimental Study, *Journal of Economic Interaction and Coordination,* 13(2), 283-309.

Cornand, C. and F. Heinemann (2014). Experiments on monetary policy and central banking, In "Experiments in Macroeconomics", J. Duffy (eds.), *Research in Experimental Economics*, 17, Emerald Group Publishing.

Cornand, C. and F. Heinemann (2019). Experiments in macroeconomics: methods and applications. In A. Schram and A. Ule (eds), *Handbook of Research Methods and Applications in Experimental Economics*, Edward Elgar Publishing, 269-294.
D'Acunto, F., D. Hoang, M. Paloviita and M. Weber (2020). Effective Policy Communication: Targets versus Instruments, manuscript.
D'Acunto, F., Y. Gorodnichenko, O. Coibion and M. Weber (2022). The Subjective Inflation Expectations of Households and Firms: Measurement, Determinants, and Implications, *Journal of Economic Perspectives*, 36(3), 157-184.
D'Acunto, F., U. Malmendier and M. Weber (2023). What Do the Data Tell Us About Inflation Expectations?, *Handbook of Subjective Expectations*, chapter 5, 133-161.
D'Arienzo, D. (2019). Excess Volatility with Increasing Over-reaction, University of Bocconi Mimeo.
Diebold, F. and R. Mariano (1995). Comparing predictive accuracy, *Journal of Business and Economic Statistics*, 13, 253-263.
Dovern, J., U. Fritsche and J. Slacalek (2012). Disagreement among Forecasters in G7 Countries, *Review of Economics and Statistics*, 94(4), 1081-1096.
Enders, Z., F. Hünnekes and G. Müller (2022). Firm expectations and economic activity, *Journal of the European Economic Association*, 20(6), 2396-2439.
Farhi, E. and I. Werning (2019). Monetary Policy, Bounded Rationality, and Incomplete Markets, *American Economic Review*, 109(11), 3887-3928.
Gabaix, X. (2020). A Behavioral New Keynesian Model, *American Economic Review*, 110(8), 2271-2327.
Garcia-Schmidt, M. and M. Woodford (2019). Are Low Interest Rates Deflationary? A Paradox of Perfect-Foresight Analysis, *The American Economic Review*, 109(1), 86-120.
Gautier, E. and J. Montornes (2022). Household Inflation Expectations in France: Lessons from a New Survey and the COVID-19 Crisis, *Economics and Statistics*, 534-535, 3-19.
Gemmi, L. and R. Valchev (2023). Biased Surveys, Working Paper 31607, National Bureau of Economic Research, August.
Giordani, P. and P. Soderlind (2003), Inflation Forecast Uncertainty, *European Economic Review*, 47(6), 1037-1059.
Haaland, I., C. Roth and J. Wohlfart (2023). Designing Information Provision Experiments, *Journal of Economic Literature*, 61(1), 3-40.
Hommes, C. H. (2011). The heterogeneous expectations hypothesis: some evidence from the lab, *Journal of Economic Dynamics and Control*, 35 (1), 1-24.
Hommes, C. H., D. Massaro and M. Weber (2019). Monetary Policy under Behavioral Expectations: Theory and Experiment, *European Economic Review,* 118, 193-212.
Humziker, H.-U., C. Raggi and R. Rosenblatt-Wisch (2018). The impact of guidance, short-term dynamics and individual characteristics on firms' long-term inflation expectations, manuscript.
Johannsen, B. K. (2014). Inflation experience and inflation expectations: Dispersion and disagreement within demographic groups, *FEDS Working Paper*, 2014-89.
Juodis, A. and S. Kucinskas (2023), Quantifying noise in survey expectations, *Quantitative Economics*, 14(2), 609-650.
Kim, G. and C. Binder (2023). Learning-through-Survey in Inflation Expectations, *American Economic Journal: Macroeconomics*, 15(2), 254-278.
Kohlhas, A. and A. Walther (2021). Asymmetric Attention, *American Economic Review,* 111(9), 2879-2925.
Korenok, O., D. Munro and J. Chen (2024). Inflation and Attention Thresholds. *The Review of Economics and Statistics*, forthcoming.
L'Huillier, J.-P., S. Singh and D. Yoo (2024). Incorporating Diagnostic Expectations into the New Keynesian Framework, *Review of Economic Studies*, 91(5), 3013-3046.

Lian, C. (2021). A Theory of Narrow Thinking, *Review of Economic Studies*, 88 (5), 2344-2374.

Link S., A. Peichl, C. Roth and J. Wohlfart (2021). Information Frictions Among Firms and Households, *CESifo Working Paper*, No. 8969.

Magud, N., and S. Pienknagura (2024). Inflated Concerns: Exposure to Past Inflationary Episodes and Preferences for Price Stability, *IMF Working Paper*, *2024*(040), A001.

Malmendier, U. and S. Nagel (2011). Depression Babies: Do Macroeconomic Experiences Affect Risk Taking?, *The Quarterly Journal of Economics*, 126(1), 373-416.

Malmendier, U. and S. Nagel (2016). Learning from Inflation Experiences, *The Quarterly Journal of Economics*, 131(1), 53-87.

Nagel, R. (1995). Unraveling in Guessing Games: An Experimental Study, *American Economic Review*, 85(5), 1313-1326.

Ottaviani, M. and P. Sørensen (2006). The Strategy of Professional Forecasting, *Journal of Financial Economics*, 81(2), 441-466.

Petersen, L. (2014). Forecast Error Information and Heterogenous Expectations in Learning to Forecast Macroeconomic Experiments, *Experiments in Macroeconomics*, In J. Duffy (eds.), *Research in Experimental Economics,* 17, Emerald Group Publishing.

Pfajfar, D. and B. Žakelj (2018). Inflation Expectations and Monetary Policy Design: Evidence from the Laboratory, *Macroeconomic Dynamics,* 22(4), 1035-1075.

Romer, C. and D. Romer (2000). Federal reserve information and the behavior of interest rates, *American Economic Review*, 90, 429-457.

Salle, I. (2022). Comment on `No Firm is an Island? How Industry Conditions Shape Firms' Aggregate Expectations, by P. Andrade, O. Coibion, E. Gautier, and Y. Gorodnichenko. *Journal of Monetary Economics*, 125, 57-61.

Salle, I., O. Coibion and Y. Gorodnichenko (2023). Lifetime Memories of Inflation: Evidence from Surveys and the Lab, *NBER Working Paper,* No. 31996.

Vermeulen, P., D. Dias, M. Dossche, E. Gautier, I. Hernando, R. Sabbatini and H. Stahl (2012). Price Setting in the Euro Area: Some Stylised Facts from Individual Producer Price Data, *Journal of Money, Credit and Banking*, 44(8), 1631-1650.

Woodford, M. (2003). *Interest and Prices: Foundations of a Theory of Monetary Policy*, Princeton University Press.

APPENDIX

Appendix A – Details on LtF experimental papers

Four out of five considered experimental papers implement variants of the standard NK three equation model, with the IS curve, Phillips curve, and policy rule:

$$y_t = E_t y_{t+1} - \varphi(i_t - E_t \pi_{t+1}) + g_t$$
$$\pi_t = \lambda y_t + \rho E_t \pi_{t+1} + u_t$$
$$i_t = \bar{\pi} + \phi_\pi(\pi_t - \bar{\pi}) + \phi_y(y_t - \bar{y})$$

where π_t and y_t are the inflation rate and output gap in period t, $\bar{\pi}$ and $\bar{y}$ are their steady state values, i_t is the nominal interest rate, g_t and u_t are exogenous disturbances, $E_t \pi_{t+1}$ is the average expected inflation, $E_t y_{t+1}$ is the average expected output gap, φ, λ, ρ, ϕ_π, and ϕ_y are positive parameters.

Pfajfar and Žakelj (2018) present an LtFE conducted at the Universities of Pompeu Fabra in Spain and Tilburg in the Netherlands, based on the above-presented model. They ask participants to form a prediction of the t+1 period inflation. Since they investigate the targeting rule that best stabilizes the economy, they consider four treatments, corresponding to different policy rules: inflation forecast targeting, with three degrees of monetary policy aggressiveness; and contemporaneous inflation targeting. There are 70 periods, each corresponding to one quarter. The number of observations amounts to 24 independent groups.

Cornand and M'baye (2018a, b) (henceforth CMa and CMb) focus on a very close design: they rely on the same model with slightly different parameter values and also ask participants to state only inflation expectations. CMa study the role of the central bank's Inflation Target (IT) communication by comparing treatments in which the central bank explicitly announces its IT to treatments in which it does not announce it. CMb focus on the case in which the central bank stabilizes both inflation and the output gap and consider four treatments differing with respect to whether the central bank implements a band or point IT and also by the size of shocks. There are 50 periods in CMa and 60 periods in CMb, with a total of 32 independent groups. Both experiments were conducted at the GATE-Lab of the University of Lyon in France.

Hommes et al. (2019) present an LtFE conducted at the CREED lab at the University of Amsterdam in the Netherlands. The parameter values are the same as in CMa, except for $\bar{\pi} = 3.5$. A main difference is that participants' task consists in forming *both* inflation and output gap expectations in period t for period t+1. They consider two treatments: one in which the central bank reacts to inflation only and one in which it additionally reacts to the output gap. Sessions have 50 periods with 43 independent groups.

Petersen (2014) presents an LtFE conducted in Montreal, Quebec (with both students and non-students), based on a slightly modified four equation version of the above NK economy where households and firms make optimal decisions given their expectations:

$$y_t = E_t y_{t+1} - \varphi(i_t - E_t \pi_{t+1} - r_t^n)$$
$$\pi_t = \lambda y_t + \rho E_t \pi_{t+1}$$
$$i_t = \bar{\pi} + \phi_\pi(E_{t-1}\pi_t - \bar{\pi}) + \phi_y(E_{t-1} y_t - \bar{y})$$
$$r_t^n = \phi r_{t-1}^n + \epsilon_t$$

where r_t^n is the natural rate of interest and parameter values are intended to mimic the Canadian economy. Each period, participants are provided information about the current period's interest rate, shock to the natural rate of interest, and the expected shock size in the following period. Participants are asked to provide forecasts for next period's inflation and output gap. The current period's inflation and output and the next period's nominal interest rate are then computed using the median (rather than the mean) forecasts for inflation and output. There are approximately 50 periods and 8 independent groups.

Appendix B – Additional tables and figures

Table A1 - Aggregate forecast regression - FOMC sample (or random draws for LtFEs)

	FOMC	SPF	Livingston	Michigan	LtF Exp.
	(1)	(2)	(3)	(4)	(5)
	12m	12m	12m	12m	12m
FR_{agg}	-0.545	-0.478	-0.323	-0.451***	0.183
	[-0.88]	[-0.73]	[-0.70]	[-2.67]	[1.20]
constant	-0.044	-0.146	-0.215	-0.583***	0.004
	[-0.28]	[-1.39]	[-1.39]	[-7.56]	[0.06]
N	56	107	53	323	55
R2	0.03	0.01	0.01	0.03	0.19

Note: *t*-statistics in brackets. ** $p < 0.05$, *** $p < 0.01$. Parameters are estimated with Eq. (3) using OLS and heteroskedasticity-robust standard errors. The dependent variable is the aggregate forecast error.

Table A2 - Individual forecast regressions - FOMC sample (or random draws for LtFEs)

	FOMC		SPF		Livingston		Michigan			LtF Exp.	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	12m	12m	12m	12m	12m	12m	12m	12m	12m	12m	12m
FR_i	-0.509***	-1.247***	-0.462***	-0.516***	-0.471***	-0.488***	-0.417***	-0.573***	-0.578***	-0.229***	-0.301***
	[-10.43]	[-14.44]	[-13.92]	[-16.36]	[-12.37]	[-13.18]	[-46.90]	[-4.95]	[-5.06]	[-3.26]	[-4.17]
$F_{agg,t-1}$		-1.741***		-0.664***		-0.483***			-1.029***		-0.160***
		[-18.20]		[-9.54]		[-3.59]			[-2.75]		[-4.52]
constant	-0.065***	3.215***	-0.172***	1.399***	-0.327***	0.888***	-1.085***	-1.504***	1.410	-0.015***	0.548***
	[-80.13]	[17.87]	[-490.20]	[8.50]	[-275.77]	[2.62]	[-70.94]	[-5.41]	[1.30]	[-11.94]	[4.40]
Ind. FE	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes
N	888	888	3 199	3 199	1 359	1 359	54 786	148	148	892	892
R2	0.10	0.48	0.17	0.21	0.31	0.32	0.26	0.41	0.43	0.41	0.48

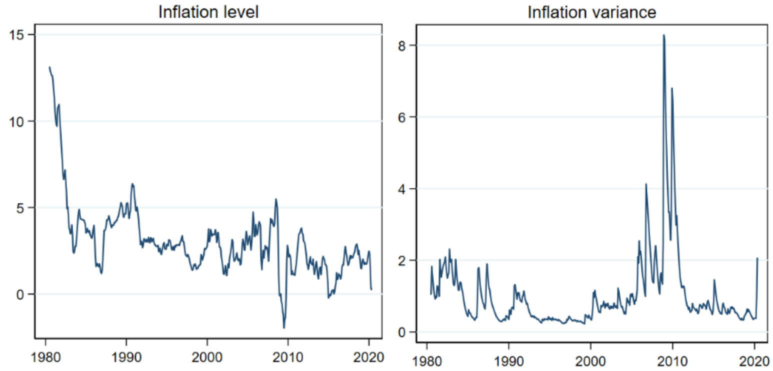
Note: *t*-statistics in brackets. ** $p < 0.05$, *** $p < 0.01$. Parameters are estimated with Eq. (4) using individual-level pooled panel regressions and standard errors clustered at the forecaster level. The dependent variable is individual forecast error at time *t*. For the Michigan survey, Column (7) includes households that are surveyed at least twice, while Columns (8) and (9) focus on households that are surveyed thrice.

Table A3 - Individual forecast regressions – Measurement error tests

	FOMC			SPF			Livingston			Michigan			LtF Exp.		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
	FE	FR	Both	FE	FR	Both	FE	FR	Both	FE	FR	Both	FE	FR	Both
FR_i	-0.498***	-0.480***	-0.469***	-0.432***	-0.448***	-0.430***	-0.366***	-0.384***	-0.375***	-0.442***	-0.453***	-0.445***	-0.356***	-0.364***	-0.363***
	[-9.62]	[-10.38]	[-9.47]	[-14.02]	[-13.90]	[-13.21]	[-16.93]	[-18.26]	[-17.20]	[-19.91]	[-19.58]	[-19.13]	[-9.55]	[-9.86]	[-9.83]
constant	-0.063***	-0.066***	-0.064***	-0.248***	-0.292***	-0.249***	0.479***	0.466***	0.477***	-0.641***	-0.764***	-0.625***	-0.021***	-0.017***	-0.021***
	[-73.2]	[-72.8]	[-65.8]	[-251.9]	[-264.0]	[-223.1]	[829]	[1045]	[1032]	[-66.8]	[-83.8]	[-68.2]	[-221]	[-666]	[-849]
Ind. FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	888	888	888	4 060	4 060	4 060	5 049	5 049	5 049	2 548	2 548	2 548	41 241	41 241	41 241
R2	0.09	0.10	0.09	0.21	0.21	0.20	0.30	0.32	0.30	0.87	0.87	0.87	0.27	0.27	0.28

Note: *t*-statistics in brackets. ** $p < 0.05$, *** $p < 0.01$. Parameters are estimated with Eq. (4) using individual-level pooled panel regressions and standard errors clustered at the forecaster level. The dependent variable is individual forecast error at time *t*. For the Michigan survey, Column (7) includes households that are surveyed at least twice, while Columns (8) and (9) focus on households that are surveyed thrice. The forecast error and forecast revisions are set to zero when below one half of the standard deviation. For each category, we first estimate Eq. (4) with the updated series for forecast errors, then for forecast revisions, and finally using both updated series.

Figure A1 – Time series of inflation level and variance and shocks



Note: These figures show the time series of inflation level, and the conditional variance of inflation at the monthly frequency.

ABOUT OFCE

The Paris-based Observatoire français des conjonctures économiques (OFCE), or French Economic Observatory is an independent and publicly-funded centre whose activities focus on economic research, forecasting and the evaluation of public policy.

Its 1981 founding charter established it as part of the French Fondation nationale des sciences politiques (Sciences Po) and gave it the mission is to "ensure that the fruits of scientific rigour and academic independence serve the public debate about the economy". The OFCE fulfils this mission by conducting theoretical and empirical studies, taking part in international scientific networks, and assuring a regular presence in the media through close cooperation with the French and European public authorities. The work of the OFCE covers most fields of economic analysis, from macroeconomics, growth, social welfare programmes, taxation and employment policy to sustainable development, competition, innovation and regulatory affairs.

ABOUT SCIENCES PO

Sciences Po is an institution of higher education and research in the humanities and social sciences. Its work in law, economics, history, political science and sociology is pursued through ten research units and several crosscutting programmes.
Its research community includes over two hundred twenty members and three hundred fifty PhD candidates. Recognized internationally, their work covers a wide range of topics including education, democracies, urban development, globalization and public health.
One of Sciences Po's key objectives is to make a significant contribution to methodological, epistemological and theoretical advances in the humanities and social sciences. Sciences Po's mission is also to share the results of its research with the international research community, students, and more broadly, society as a whole.

PARTNERSHIP