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

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Abstract

This paper explores the role of four behavioral biases in relation to overreaction to news in inflation expectations. While we highlight that the degree of overreaction is strikingly homogeneous across different types of economic agents—households, firms, professional forecasters, policymakers, and participants in experiments—, we find that their underlying behavioral foundations differ. Each group is associated with a distinct bias: representativeness heuristic for households and firms, salience of inflation news for policymakers, inflation memory for professional forecasters and recency bias for participants in experiments. These findings offer novel evidence that the apparent homogeneity in overreaction reflects different behavioral mechanisms.

Keywords: Forecast errors; Forecast revisions; Experimental forecasts; Survey forecasts; Central bank forecasts.

JEL classification: E3, E5, E7.

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Corresponding author: Camille Cornand, 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 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 on expectations from 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).

The predictability of forecast errors offers valuable insights into how economic agents form expectations. It can 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. Bordalo et al. (2019, 2020) assume revisions in individual forecasts measure the reaction to available news.[1] When the correlation between current forecast revision and future forecast error is negative, an upward revision predicts a lower realization relative to the revised forecast: this means the forecaster overreacts to information relative to FIRE (and vice versa, a positive correlation implies underreaction).

Overreaction is a well-established empirical pattern, extensively documented in the literature. Based on a large set of macroeconomic and financial variables, Bordalo et al. (2020) provide evidence of *overreaction* to information in *individual* forecast data. Other contributions have further established this fact across different datasets and types of agents (see Angeletos et al. 2021, Kohlhas and Walther 2021, Afrouzi et al. 2023, Broer and Kohlhas 2024). As a starting point in this paper, we revisit these findings and provide evidence that overreaction is a strikingly homogeneous pattern across five types of agents: households, firms, professional forecasters, policymakers, and participants in experiments. Despite differences in data sources, institutional contexts, and forecast frequencies, individuals consistently overreact to news. This robust pattern raises a fundamental question: what behavioral mechanisms might explain the striking homogeneity in outcomes across such highly diverse types of agents?

A large body of research has explored the role of behavioral biases in the expectation formation process, highlighting mechanisms such as recency bias (Nagel and Xu 2022, Gennaioli et al. 2024), inflation experience and memory (Malmendier and Nagel 2011, 2016), salience (Bordalo et al. 2022), and representativeness (Bordalo et al. 2018). While these behavioral forces have been studied in isolation and are often studied in the context of inflation expectation characteristics, their role in explaining overreaction to news across different types of agents has been much less explored. In this paper, we seek to connect the two by examining the potential behavioral underpinnings of individual overreaction to news. Specifically, we assess whether the observed homogeneity in overreaction across distinct types of agents may arise from homogeneous underlying behavioral biases.

To do so, we use inflation forecasts from US data (for households, firms, professional forecasters and policymakers) over a period ranging from 1948 to 2020 and from laboratory data (collected from five papers published in the 2010s). To enable comparison between types of economic agents, our paper focuses on a single, common, set of expectations, namely

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

inflation expectations. We acknowledge the heterogeneity across our five datasets in terms of frequency and sample period. This limitation is intrinsic to the nature of our research question and the use of multiple data sources. Relying on a single dataset would ensure homogeneity, but it would preclude the possibility of cross-group comparisons. To address these differences and enhance comparability, we conduct robustness checks using a common sample period across all datasets, as well as a comparable number of observations.[2]

Within this framework, we explore the role of four behavioral mechanisms in shaping overreaction: (i) recency bias, (ii) experience of inflation, (iii) salience of news, and (iv) representativeness heuristic. To identify the behavioral underpinnings of overreaction, we exploit variation across individuals within each dataset. Specifically, we estimate individual-level overreaction coefficients by regressing forecast errors on forecast revisions. We then relate these coefficients to individual-level measures of behavioral biases—such as the autocorrelation of forecasts (recency), average experienced inflation (memory), exposure to inflation volatility (salience), and the distance between current and one's experienced inflation (representativeness heuristic). This reduced-form approach allows us to isolate the behavioral correlates of overreaction without imposing structural assumptions. The identification stems from cross-sectional variation between individuals. By comparing across agent types, we assess whether the same behavioral mechanisms are at play or whether different groups rely on distinct heuristics when forming expectations.

Our analysis reveals that although the degree of overreaction is similar across groups, the underlying behavioral foundations are not. Each type of agents appears to rely on a distinct dominant bias. For households and firms, overreaction is primarily shaped by the representativeness heuristic, suggesting that these agents treat unusual inflation signals as outliers. Policymakers' overreaction is best explained by the salience of inflation news, consistent with heightened attention to volatile economic signals. For professional forecasters, inflation memory plays a central role, with those who have experienced higher inflation tending to moderate their reactions. Finally, recency bias emerges as the main driver of overreaction among participants in laboratory experiments, where more persistent forecasting behavior is associated with less responsiveness to new information. These findings suggest that the observed homogeneity in overreaction reflects a deeper heterogeneity in behavioral underpinnings.

These findings also underscore the importance of tailoring theoretical models and policy communication strategies to the specific cognitive profiles of different economic agents. They also have some implications for policymakers' communication. 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 central bankers whose task precisely consists in managing these expectations.[3]

This paper builds on a large literature documenting overreaction in expectations. Bordalo et al. (2020) show that professional forecasters systematically overreact to news, a finding

[2] However, we are not able to explore the demographic characteristics that may explain differences between groups, as such information is only available for one dataset (Michigan). A thorough investigation of this aspect would require access to comparable demographic data for all five types of agents.

[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.

extended to households and firms by Kohlhas and Walther (2021), and to experimental settings by Afrouzi et al. (2023). These studies establish overreaction across different agents (see also Angeletos et al. 2021 and Broer and Kohlhas 2024). Our contribution does not lie in further documenting this fact. Instead, we take overreaction as a starting point and revisit it across five types of agents using a unified empirical framework. The novel contribution of this paper is to investigate the potential behavioral underpinnings of overreaction and assess whether its apparent homogeneity across types of agents stems from shared or distinct underlying cognitive mechanisms.

The closest papers to ours are Granziera et al. (2025) and Cornand and Hubert (2020, 2022). The former leverages the harmonized design of the Norges Bank Expectations Survey (NBES) to compare inflation expectations across households, firms, social partners, and economists, examining level differences, disagreement, term structure, wage pass-through, and responses to energy price shocks. Cornand and Hubert (2020) assess the external validity of experimental inflation expectations by comparing forecast errors, deviations from FIRE, and their determinants across six types of agents, while Cornand and Hubert (2022) focus on the frequency of forecast revisions and cross-sectional disagreement. By contrast, these papers do not explore overreaction to news across these different types of economic agents, nor do they investigate its potential behavioral underpinnings.

By nature, this work builds on the flexibility of reduced-form approaches to permit comparison across datasets with different characteristics. In doing so, this paper complements the large and growing body of literature that investigates the drivers of the expectation formation process (e.g. D'Acunto et al. 2022, 2023) or that analyses the implications of introducing in macroeconomic models expectation formation processes that depart from FIRE by relying on behavioral factors, such as diagnostic expectations, overconfidence, cognitive discounting, level-*k* and narrow thinking, inattention or strategic diversification (e.g. Bianchi et al. 2023, L'Huillier et al. 2024, Broer and Kohlhas 2024, Angeletos et al. 2021, Gabaix 2020, García-Schmidt and Woodford 2019, Farhi and Werning 2019, Lian 2021, Gemmi and Valchev 2023, Boccanfuso and Neri, 2025).

The paper is structured as follows. Section 2 presents the data. Section 3 provides evidence on overreaction to news in individual forecasts. Section 4 explores four potential behavioral underpinnings of overreaction. Section 5 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 types of agents (households, industry, professional forecasters, policymakers and participants in experiments).

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.[4] Each month, a sample of approximately 500 households

[4] 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.

is interviewed. The sample is representative of households in the US. 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.[5]

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 Section 4 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. We perform our analysis with CPI forecasts provided since 1981. They are provided as annualized quarter-over-quarter growth rates and we construct year-over-year growth rates at the 12-month horizon.

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 public since 1992, but with an embargo of ten years. This embargo has been reduced to five years in 2016. This means that the 2015 individual forecasts are not yet available in 2025, but those made in 2016 to 2019 are.[6]

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).[7] 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

[5] 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.
[6] For more details on FOMC forecast releases: see www.federalreserve.gov/monetarypolicy/fomc_historical.htm.
[7] For a systematic comparison of the characteristics of experimental designs used in the five considered papers, see Cornand and Hubert (2022).

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 types 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 type of agents. For experimental forecasts, the frequency is artificial. 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 rely heavily on cross-sectional variation, with 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	1992m1-2019m12	1981q3-2020q2	1948h1-2020h1	1980m7-2020m5	NA
Nb Time Periods	78	156	145	479	5 989
Resp/Wave	17.0	36.5	47.7	384.2	7.0
Nb Resp	73	251	458	91 390	736
Nb Obs	1 326	5 701	6 915	184 054	42 016
Avg Length	18.16	22.71	15.10	2.01	57.09

Note: This table shows various characteristics of the five types 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 year 2015 are still under embargo and are not in the dataset.

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 in 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. Overreaction in individual inflation forecasts

3.1. Forecast errors and forecast revisions

We denote by $\pi^{i}_{t+h|t}$ the individual inflation forecast made at time t about the future value π_{t+h} of inflation at date $t+h$, where i denotes individual forecasters. The h-periods ahead individual inflation forecast error $\mathrm{FE}_{\mathrm{i},t}$ and forecast revision $\mathrm{FR}_{\mathrm{i},t}$ at t are given by:

$$\mathrm{FE}_{\mathrm{i},t} = \pi_{t+h} - \pi^{\mathrm{i}}_{t+h|t} \quad (1)$$

$$\mathrm{FR}_{\mathrm{i},t} = \pi^{\mathrm{i}}_{t+h|t} - \pi^{i}_{t+h-1|t-1} \quad (2)$$

Table 2 presents the mean of the above-described measures of individual forecast errors (upper panel) and forecast revisions (lower panel) for the five types of agents. We also compute whether individuals revise their forecasts at each date to measure the forecast revision probability of each type 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 (Cornand and Hubert 2022 discuss this issue and provide comparable measures of updating probabilities).

Table 2 – Descriptive statistics for forecast errors and revisions

	FOMC	SPF	Livingston	Michigan	LtF Exp.
	Mean	Mean	Mean	Mean	Mean
$\lvert \mathrm{FE}_{\mathrm{i},t} \rvert$	0.82	1.06	1.87	3.28	0.33
$\mathrm{FE}_{\mathrm{i},t}$	-0.16	-0.31	0.48	-0.92	-0.02
FR proba	0.94	0.98	0.98	0.75	0.84
$\lvert \mathrm{FR}_{\mathrm{i},t} \rvert$	0.25	0.36	1.27	3.44	0.41
$\mathrm{FR}_{\mathrm{i},t}$	-0.02	-0.03	0.03	-0.43	0.00

Note: $\lvert \mathrm{FE}_{\mathrm{i},t} \rvert$ is the individual absolute forecast error, $\mathrm{FE}_{\mathrm{i},t}$ is the individual forecast error, $\lvert \mathrm{FR}_{\mathrm{i},t} \rvert$ is the individual forecast revision, $\mathrm{FR}_{\mathrm{i},t}$ is the individual forecast revision. FR proba is the probability of forecast revision at each period.

Table 2 shows some interesting comparisons across the different types of inflation expectations. Individual forecast errors of participants in experiments are small compared to those of the four other types of agents. In contrast, 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 FOMC, SPF and Michigan expectations systematically overestimate it. LtF expectations exhibit no systematic bias. This is in line with the literature (Diebold and Mariano 1995, Romer and Romer 2000, Ang et al. 2007, Cornand and Hubert 2020).

Individual forecast revisions are of comparable magnitude in FOMC, SPF and LtF data. In contrast, Michigan data—and, to a lesser extent, Livingston data—experience a much larger average revision than the other types. There is no systematic bias in individual forecast revisions, except for Michigan data. Between the first and second (or second and third) waves, 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. Baseline panel regressions

Bordalo et al. (2020) underline that testing forecast rationality requires unpredictability of forecast errors at the individual level. We estimate Equation (3) to analyze forecast error predictability with individual forecast revisions $\mathrm{FR}_{\mathrm{i},t}$ and individual forecast errors $\mathrm{FE}_{\mathrm{i},t}$. The estimation consists in pooling all forecasters and estimating a common coefficient β_p from the following regression:

$$\mathrm{FE}_{i,t} = \kappa_i + \alpha_p + \beta_p \, \mathrm{FR}_{i,t} + \epsilon_{i,t} \tag{3}$$

Superscript p refers to the pooling of individual level data. $\beta_p > 0$ indicates 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 captures individual-specific differences in systematic forecaster bias.

Table 3 – Individual forecast regressions

	FOMC	**SPF**	**Livingston**	**Michigan**		**LtF Exp.**
	(1)	(2)	(3)	(4)	(5)	(6)
	12m	12m	12m	12m	12m	12m
FR_i	-0.466***	-0.453***	-0.378***	-0.405***	-0.453***	-0.357***
	[-10.03]	[-14.92]	[-18.32]	[-58.58]	[-20.52]	[-9.67]
constant	-0.183***	-0.291***	0.468***	-0.934***	-0.781***	-0.016***
	[-222.00]	[-300.32]	[848.57]	[-62.69]	[-81.85]	[-172.79]
Ind. FE	Yes	Yes	Yes	No	Yes	Yes*
N	1 006	4 060	5 049	92 664	2 548	41 241
R2	0.11	0.21	0.32	0.24	0.88	0.27

Note: *t*-statistics in brackets. ** $p < 0.05$, *** $p < 0.01$. Parameters are estimated with Eq. (3) 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 (4) includes households that are surveyed at least twice, while Columns (5) focuses on households that are surveyed thrice. We include individual forecasters fixed effects in all specifications together with database and treatment fixed effects for LtFEs.

Table 3 shows the outcome of Equation (3). The main result is that individual forecasts overreact to news ($\beta_p < 0$) for all types of economic agents. This is consistent with the main result of Bordalo et al. (2020) and extends it beyond professional forecasters. An important takeaway is that all types of economic agents not only overreact to news, but also do so in a highly homogeneous way. 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 statistically significant at the 1% level for all agents and the magnitude of the β_p coefficient is rather homogeneous across types of agents ranging from -0.466 for policymakers to -0.357 for participants in laboratory experiments. For the Michigan survey, estimates remain consistent across specifications, whether considering all households surveyed at least twice (Column 4) or only those surveyed three times (Column 5). This helps mitigate potential concerns about selection bias between the two groups of households. The precision of the estimates, together with the low dispersion of households' individual overreaction coefficients (see Figure 1), alleviates potential concerns about estimation noise arising from the data structure. Additionally, we observe a systematic conditional forecast error across all types of agents. While firms exhibit a pessimistic bias (forecasts are systematically below realizations), we find evidence of a systematic optimistic bias for the other types.

Table A1 in Appendix shows that the results presented in Table 3 are robust to using a common sample. We use the same sample period as the one used for FOMC data (1992 to

2019) for all types of agents except LtFEs, for which this test does not apply. In Appendix Table A2, we consider the same number of observations as for FOMC data to compare estimates on similar sample size. To do so, we perform random draws of around 1000 observations for each dataset. We find that the results are robust to a sample size common to all types of economic agents.

Table A3 in Appendix presents a robustness test for the omitted variable 'public information', following the approach by Broer and Kohlhas (2024). As a measure of a signal available to all individuals of each type, we include in Equation (3) the lagged aggregate forecast, denoted $F_{agg,t-1}$, of each type of inflation expectations. We find strong evidence of overreaction to lagged aggregate forecasts. For all types of agents, the overreaction to individual news is robust to the inclusion of the lagged aggregate forecast.

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 type of agents to one-half of the standard deviation of the respective variable. Estimates are shown in Table A4 in the Appendix for forecast errors and forecast revisions in isolation and both together. The result that each type of agent overreacts to news at the individual level holds with minimal variation in point estimates across the different specifications.

3.3. Regressions at the individual level

Following Bordalo et al. (2020), we then adapt Equation (3) to estimate forecaster-by-forecaster regressions. We therefore estimate N times the following Equation (4), 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 (3).

$$\mathrm{FE}_{i,t} = \alpha_i + \beta_i \, \mathrm{FR}_{i,t} + \epsilon_{i,t} \qquad \text{with } i = 1, \ldots, N \tag{4}$$

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

Table 4 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 (3), the mean and median β_i coefficients—that are very close and not statistically different from each 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 3, the median across the different types of economic agents is similar, around -0.35 for policymakers, professional forecasters, firms and households and about -0.20 for participants in LtFEs. This supports the view that overreaction is homogeneous across these economic agents. The differences in the standard deviation, however, suggest a larger amplitude in the dispersion of overreaction coefficients across types of economic agents.

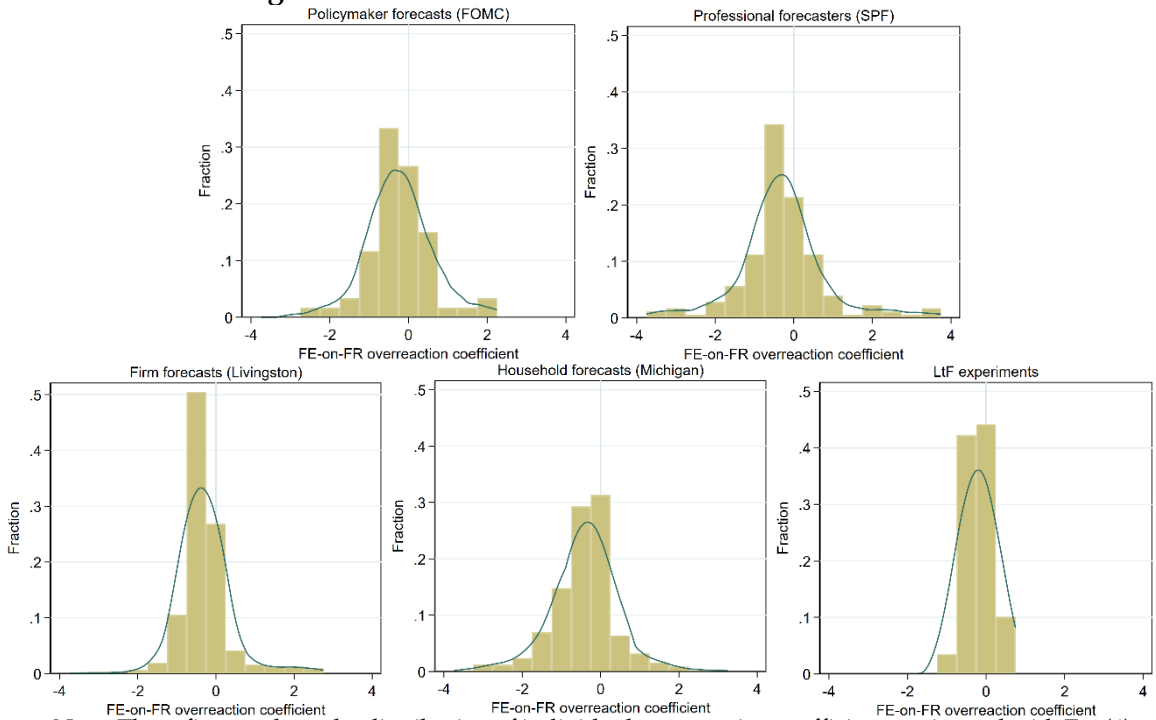
Table 4 – Forecaster-by-forecaster coefficients

	FOMC	SPF	Livingston	Michigan	LtF Exp.
N	60	181	315	1 250	722
Mean	-0.22	-0.37	-0.33	-0.40	-0.20
SD	0.79	1.27	0.73	0.81	0.33
p10	-1.05	-1.64	-0.88	-1.36	-0.65
p25	-0.60	-0.72	-0.55	-0.79	-0.45
Median	**-0.34**	**-0.38**	**-0.37**	**-0.38**	**-0.19**
p75	0.19	0.12	-0.12	0.00	0.03
p90	0.64	0.70	0.18	0.36	0.25

Note: Descriptive statistics of the individual overreaction coefficient β_i estimated with Eq. (4) 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 $FE_{i,t}$ and $FR_{i,t}$, in a scatterplot of the two variables.

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, more than 75% of the distribution of overreaction coefficients lies in negative territory for firms, while this percentage is slightly smaller for policymakers, professional forecasters, households, and participants in laboratory experiments. Financial literacy and sociodemographic factors can possibly explain the heterogeneity within and across types, but this question is beyond the scope of this paper as the common denominator across datasets do not allow exploring this issue.[8]

Figure 1 – Distribution of overreaction coefficients



Note: These figures show the distribution of individual overreaction coefficients estimated with Eq. (4) for each dataset, truncated at the 1st and 99th percentiles. The blue line represents the Kernel density.

Two messages are worth stressing. First, the distribution of overreaction coefficients for LtFEs appears different from that of the four other types with much less dispersion, and a mode around zero. Overreaction to news seems less pronounced in this type of data. Second, a small

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

share of individuals has a positive β_i coefficient and therefore underreacts to news. Still, the mean, median and bulk of the distribution is in negative territory, suggesting that overreaction is a widespread feature across the majority of economic agents. This raises the question of what determines overreaction and what may shape the homogeneous nature of this pattern. In Section 4, we explore the role of four behavioral factors and assess whether shared underlying biases may account for the observed homogeneity in overreaction.

4. Behavioral underpinnings of overreaction to news

In this section, we relate overreaction to news at the individual level to four behavioral biases: recency bias (Nagel and Xu 2022, Gennaioli et al. 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. Although these biases are well-documented in the context of expectation formation, their association with overreaction to news remains underexplored. This section addresses this gap by examining whether and how these four biases correlate with forecasters' overreaction.

While we document robust associations between individual-level overreaction coefficients and proxies for behavioral biases, we emphasize that our analysis is correlational. Our identification strategy relies on cross-sectional variation across individuals within each dataset and does not permit causal inference. As such, we cannot rule out the possibility that unobserved factors—such as cognitive ability, financial literacy, or attention—may influence both the behavioral bias proxies and the degree of overreaction. Moreover, measurement error in the behavioral proxies (e.g., autocorrelation as a proxy for recency bias) may be noisy and attenuate estimated relationships. Reverse causality cannot be excluded in some cases (especially the fact that frequent forecast revisions might reduce autocorrelation). Therefore, we interpret our findings as indicative of how behavioral mechanisms correlate with individual overreaction to news.

4.1. Recency bias

Recency bias is a cognitive bias that occurs when agents place greater weight on recent events than on earlier ones, even when the more distant events may be more relevant or representative (see for instance, Gandré 2020). In this subsection, we aim to explore the potential link between the recency bias for each individual and his/her overreaction to news. We consider that a large autocorrelation of forecasts can account for a recency bias, in the sense that more weight is attributed to recent observations.[9] While the individual inflation forecast autocorrelation is likely related to the persistence of the underlying inflation process, our identification strategy exploits cross-sectional variation across individuals. Since inflation persistence is not individual-specific but common to all individuals, it is unlikely to account for differences in individual forecast autocorrelation. In contrast, cross-sectional idiosyncratic differences in individual forecast autocorrelation primarily reflect heterogeneity in individuals' behavior.

We compute the autocorrelation parameter of individual forecasts λ_i^{Rec} and we look at the correlation between λ_i^{Rec} and the overreaction parameter β_i. We assume that a high degree of persistence of forecasts for a given individual indicates that this individual exhibits recency bias. The null hypothesis is that if agents have a strong recency bias, meaning that they place

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

substantial weight to more recent past events, they tend to underreact, or at least overreact less, to news. Said differently, an individual who overreacts 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:

$$\pi^{\mathrm{i}}_{t+h|t} = \alpha_i + \lambda_i^{\mathrm{Rec}}\, \pi^{i}_{t+h-1|t-1} + \epsilon_{i,t} \tag{5}$$

In a second stage, we then regress the overreaction coefficient on the autocorrelation coefficient. There is no time dimension in this regression and the identification comes only from variation between individuals:

$$\beta_i \ = \gamma_1 + \gamma_2\, \lambda_i^{\mathrm{Rec}} + \epsilon_i \tag{6}$$

where β_i is the overreaction parameter estimated in Equation (4), truncated at the 1st and 99th percentiles, and λ_i^{Rec} is the autocorrelation parameter estimated in Equation (5). Table 5 shows the correlation between these two coefficients. It is worth noting that the distribution of the autocorrelation parameter across the different types of agents is quite homogeneous (except for the case of Michigan data).[10] For these types of economic agents, most of the individual autocorrelation parameters lies in positive territory. The mean of these parameters ranges around 0.4-0.6 suggesting a homogeneous recency bias across agents.

Table 5 – 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^{Rec}	0.372	**-0.363****	0.004	0.004	**0.389*****
	[1.38]	[-2.05]	[0.20]	[0.38]	[9.34]
N	60	181	315	1 250	722
R2	0.04	0.03	0.00	0.00	0.56
Mean	0.44	0.58	0.35	-0.35	0.58
p25	0.19	0.34	-0.02	-1.00	0.40
Median	0.59	0.61	0.37	0.00	0.65
p75	0.71	0.80	0.68	0.00	0.81

Note: Robust *t*-statistics in brackets. ** $p < 0.05$, *** $p < 0.01$. Parameters are estimated with Eq. (6) using individual-level regressions. λ_i^{Rec} is the individual autocorrelation coefficient of forecasts, while β_i is the individual overreaction parameter, truncated at the 1st and 99th percentiles. The lower part of the Table shows the mean, 25th percentile, median and 75th percentile of forecasts' autocorrelation coefficients for each type of economic agents. For the Michigan dataset, the autocorrelation parameter is computed on the subsample of individuals surveyed three times.

A first takeaway from these estimates is that the recency behavior is not related to overreaction for policymakers (FOMC), firms (Livingston) and households (Michigan). The correlation is either null or non-significant. For professional forecasters, the correlation between λ_i^{Rec} and β_i is negative and significant. These analysts who display stronger persistence in their own forecasts (a stronger autocorrelation parameter that we interpret as a stronger recency behavior) tend to have a more negative overreaction parameter (i.e., a larger overreaction to news). The opposite pattern is observed for LtFEs, with the overreaction and autocorrelation parameters being positively correlated. This indicates that more recency-biased participants tend to overreact less to news.

[10] For Michigan data, the autocorrelation parameter is computed on the sample of individuals surveyed three times.

Overall, these results indicate that recency-biased behavior does not explain the observed homogeneity in overreaction across the five types of economic agents. While it appears to play a role for professional forecasters and participants in LtFEs, it operates in opposite directions for these two groups. The counter-intuitive negative correlation for professional forecasts suggests that those who rely strongly on their latest forecast are prone to larger-than-warranted revisions when new data become available. One possible explanation is that these forecasters, by over-relying on recent data, interpret even small shocks—thus amplifying new signals. In contrast, in a laboratory environment, the recency bias induces inertia: subjects who rely closely on the previous period forecast are more reluctant to revise their forecasts when given new signals. Hence, stronger persistence translates into dampened overreaction. In sum, the recency bias plays a differentiated role across the different types of agents.

4.2. Memory of inflation

Malmendier and Nagel (2011, 2016) and Kuchler and Zafar (2019) 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. These authors 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 (see also Magud and Pienknagura 2024). Cenzon (2025) provides evidence of such a mechanism with credit rejections triggering pessimistic expectations. 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.

In this subsection, we assess 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 inflation rate experienced by each forecaster when they did forecast inflation in our sample, denoted π_i^{Exp}. 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 regress the individual overreaction coefficient on the individual inflation experience measure:

$$\beta_i = \gamma_1 + \gamma_2 \pi_i^{Exp} + \epsilon_i \quad (7)$$

Table 6 shows the correlation between the average experienced inflation π_i^{Exp} and the overreaction parameter β_i. The lower part of Table 6 shows that firms and participants in LtFEs have faced higher levels of inflation during their forecaster experience. For these two groups, the median average experienced inflation exceeds 3%, while it is slightly above 2% for the other types of economic agents.

Table 6 – 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}	-0.154	**0.224*** **	0.058	0.015	0.039
	[-0.69]	[2.78]	[1.85]	[0.97]	[0.89]
N	60	181	315	1 250	722
R2	0.01	0.04	0.03	0.00	0.50
Mean	2.27	2.75	3.65	3.29	3.43
p25	1.99	2.17	2.19	1.84	3.02
Median	2.24	2.41	3.12	2.11	3.32
p75	2.55	3.20	4.73	4.94	4.37

Note: Robust *t*-statistics in brackets. ** $p < 0.05$, *** $p < 0.01$. Parameters are estimated with Eq. (7) using individual-level regressions. π_i^{Exp} is the average inflation rate experienced by each forecaster i when present in the sample. The lower part of the Table shows the mean, 25th percentile, median and 75th percentile of the average inflation rate experienced for each type of economic agents. For the Michigan dataset, the analysis is based on the subsample of individuals surveyed three times.

Whereas inflation experience has been found to be a strong predictor of the level of inflation expectations in the literature (Malmendier and Nagel 2011, 2016), it is not correlated with overreaction to news for most types of economic agents. For policymakers, households, firms and participants in LtFEs, the coefficients are not significant, suggesting no link between individual inflation experience and overreaction for these agents. In other words, those who have experienced higher or lower inflation themselves do not systematically overreact more to news than those with a different inflation background. For professional forecasters however, we find a positive and significant correlation, such that a higher personal inflation experience is associated with less overreaction. While these findings diverge from the stated null hypothesis, they are consistent with professional forecasters displaying a memory effect—increased understanding of high-inflation regimes appears to dampen their tendency to overreact. Overall, these findings suggest that individual inflation experience does not explain the homogeneity of overreaction to news across economic agents.

4.3. Salience

The salience theory (Bordalo et al. 2022) focuses on how individuals 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 overreaction to news may be related to salience. Salience influences reactions to news by making certain details stand out. We thus state this 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 for 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 based on the following two—mean and variance—equations:

$$\begin{aligned} \pi_t &= \beta_0 + \beta_1 \pi_{t-1} + \epsilon_t\,,\ \epsilon_t \sim (0, \sigma_t^2) && \text{Mean equation} \\ \sigma_t^2 &= \gamma_0 + \gamma_1 \epsilon_{t-1}^2 + \gamma_2 \sigma_{t-1}^2 && \text{Variance equation} \end{aligned} \quad (8)$$

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 then compute the mean of σ_t^2 for each individual (σ_i^{Sal}), which represents the average volatility of inflation to which they are exposed as forecasters. The larger the value of σ_i^{Sal}, the more salient the inflation news an individual has experienced. In Equation (9), we estimate the relationship between the individual overreaction coefficient and the average salience of news measured at the individual level.

$$\beta_i = \gamma_1 + \gamma_2 \, \sigma_i^{Sal} + \epsilon_i \tag{9}$$

Table 7 shows the estimates of Equation (9). It provides the correlation between the average volatility of inflation σ_i^{Sal} and the overreaction parameter β_i. The median volatility of inflation which individuals have been exposed to is very heterogeneous, ranging from 0.05 for participants in LtFEs to 1 for households.

Table 7 – Salience of inflation news and overreaction

	FOMC	**SPF**	**Livingston**	**Michigan**	**LtF Exp.**
	(1)	(2)	(3)	(4)	(5)
	β_i	β_i	β_i	β_i	β_i
σ_i^{Sal}	**-0.565*****	0.099	**0.146****	0.039	**-0.054*****
	[-3.33]	[0.37]	[2.13]	[1.12]	[-3.49]
N	60	181	315	1 250	722
R2	0.11	0.00	0.02	0.00	0.51
Mean	0.84	0.87	0.68	1.16	0.20
p25	0.40	0.64	0.42	0.48	0.01
Median	0.90	0.87	0.57	1.00	0.05
p75	1.12	1.06	0.88	1.70	0.09

Note: Robust *t*-statistics in brackets. ** $p < 0.05$, *** $p < 0.01$. Parameters are estimated with Eq. (9) using individual-level regressions. σ_i^{Sal} is the average volatility of inflation individuals are exposed to as forecasters. The lower part of the Table shows the mean, 25th percentile, median and 75th percentile of this measure for each type of economic agents. For the Michigan dataset, the analysis is based on the subsample of individuals surveyed three times.

We find mixed evidence regarding how the salience of inflation news relates to individuals' overreaction parameter. The role of salience in shaping individuals' overreaction to inflation news is heterogeneous across types of economic agents. First, it is uncorrelated with professional forecasters' and households' overreaction to news. Second, while it is linked with overreaction to news for policymakers, firms and participants in LtFEs, it operates in different directions. For policymakers—and, to a lesser extent, participants in LtFEs—, larger inflation shocks (i.e., higher salience) are associated with greater overreaction (β_i becomes more negative). For these two types of agents, the findings are in line with the null hypothesis: the more salient the inflation news, the greater the overreaction in individual forecasts to news. Volatile inflation reports trigger disproportionately large forecast jumps, perhaps reflecting a heightened "attention-for-risk" channel when deciding policy. The salience of inflation dynamics captures attention and induces excessive updating. We find the opposite pattern for firms, with more volatile inflation shocks being associated with less overreaction. Although this finding contradicts the direction predicted by the null hypothesis, it may indicate that when inflation news is large, firms pay more attention to inflation (Korenok et al. 2024, Bracha

and Tang 2025). In this case, they overreact less (by paying more attention to inflation, they react in line with the information content of the news but do not overreact).

Overall, the salience of inflation news appears to influence individuals' overreaction for three of the five types of economic agents. Yet it operates in opposite ways, suggesting that it does not account for the observed homogeneity in overreaction.

4.4. Representativeness heuristic

The representativeness heuristic is a 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.

In contrast to the original concept of representativeness heuristic, we adopt a slightly modified measure that allows us to extract meaningful insights given the constraints of our different datasets. Unlike the more individualized and experience-based extrapolation studied in D'Acunto et al. (2020), where individuals project based on their frequent purchases, our approach captures extrapolation based on past experiences or observations.[11] Importantly, our empirical setup spans five distinct datasets, enabling cross-dataset comparisons that are essential to our analysis but also require a degree of abstraction from the original concept to ensure consistency across data sources.

Therefore, the null hypothesis is that if today's inflation is close to the level of inflation an individual has usually observed, 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 is more likely to overreact. To test this hypothesis, we use the average inflation rate experienced by each forecaster, π_i^{Exp}, and compute the distance between the current inflation rate at the date when a forecast is formed and this average rate.[12] For each individual, we then compute the average of these distances (d_i^{Rep}), which captures how different current inflation is from what individuals are used to observing. The average inflation experienced 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 behavior based on their inflation experience. In Equation (10), we regress the individual overreaction parameter on the average distance between current and experienced inflation.

$$\beta_i = \gamma_1 + \gamma_2 \, d_i^{Rep} + \epsilon_i \tag{10}$$

[11] The setting of D'Acunto et al. (2020) is closer to a natural experiment. They provide evidence that consumers extrapolate inflation expectations from the prices of frequently purchased goods.

[12] 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 experienced as a forecaster and not as an individual.

Table 8 presents the outcome of Equation (10). It shows the correlation between the individual overreaction parameter and the average distance between current and experienced inflation measured at the forecaster level. On average, this distance is homogeneous across policymakers, professional forecasters, households, and participants in LtFEs, around 0.6-0.9 percentage points (pp). However, it is substantially larger for firms, reaching 1.65 pp.

Table 8 – Representativeness heuristics and overreaction

	FOMC	**SPF**	**Livingston**	**Michigan**	**LtF Exp.**
	(1)	(2)	(3)	(4)	(5)
	β_i	β_i	β_i	β_i	β_i
d_i^{Rep}	-0.674	0.253	**0.162*****	**0.072****	**-0.038****
	[-1.69]	[1.01]	[3.80]	[1.99]	[-2.22]
N	60	181	315	1 250	722
R2	0.06	0.01	0.04	0.00	0.51
Mean	0.71	0.91	1.65	0.86	0.61
p25	0.46	0.79	0.85	0.31	0.21
Median	0.76	0.87	1.58	0.76	0.34
p75	0.92	1.02	2.55	1.31	0.60

Note: Robust *t*-statistics in brackets. ** $p < 0.05$, *** $p < 0.01$. Parameters are estimated with Eq. (10) using individual-level regressions. d_i^{Rep} is the average distance between current and experienced inflation measured at the forecaster level. The lower part of the Table shows the mean, 25th percentile, median and 75th percentile of this measure for each type of economic agents. For the Michigan dataset, the analysis is based on the subsample of individuals surveyed three times.

A key result is that the distance between current and one's experienced inflation is significantly correlated with overreaction for three of the five types of economic agents. For firms and households, an increase in this distance is associated with less overreaction (β_i becomes more positive). Although this finding contrasts with the stated hypothesis, one interpretation is that firms and households respond more cautiously to new signals when inflation diverges from what they have experienced, making them less likely to overreact. This behavior is consistent with the theory of cautious expectations of Kohlhas and Robertson (2025). For participants in LtFEs, the relationship is reversed: an increase in the average distance between current and experienced inflation is associated with more overreaction, consistent with a pure representativeness heuristic where any "atypical" outcome is seen as diagnostic of a new state of the world. For policymakers and professional forecasters, our results suggest no significant link between this distance and overreaction to news. Overall, these results imply that the representativeness heuristic does not explain the homogeneity of the degree of overreaction to news across types of agents.

4.5. Comparing behavioral biases for each type of economic agents

The preceding subsections have investigated the role of a given bias in isolation in explaining overreaction to news across the different types of economic agents. In this subsection, we estimate a multivariate regression to assess the relative importance of each of the four considered bias for each type of economic agents and to determine whether a common behavioral mechanism underlies the observed homogeneity in overreaction.

$$\beta_i = \gamma_1 + \gamma_2 \lambda_i^{Rec} + \gamma_3 \pi_i^{Exp} + \gamma_4 \sigma_i^{Sal} + \gamma_5 d_i^{Rep} + \epsilon_i \quad (11)$$

Equation (11) is estimated for each type of agents separately and only includes the significant bias highlighted in Tables 5 to 8. It is also important to acknowledge a key limitation of our empirical approach: the proxies we use to capture behavioral biases are subject to measurement error and conceptual overlap. Each proxy—forecast autocorrelation for recency

bias, average experienced inflation for memory, inflation volatility for salience, and the distance between current and experienced inflation for representativeness—offers only an indirect and partial representation of the underlying cognitive mechanism. These measures may also reflect more than one behavioral trait. For instance, exposure to volatile inflation could simultaneously affect salience and representativeness. Equation (11) aims at addressing this concern. This allows us to assess the relative importance of each behavioral mechanism while controlling for the others, thereby mitigating this mismeasurement risk.

Table 9 – A multivariate regression of significant behavioral bias

	FOMC	**SPF**	**Livingston**	**Michigan**	**LtF Exp.**
	(1)	(2)	(3)	(4)	(5)
	β_i	β_i	β_i	β_i	β_i
λ_i^{Rec}	.	-0.343	.	.	**0.384*****
		[-1.90]			[9.15]
π_i^{Exp}	.	**0.215****	.	.	
		[2.58]			
σ_i^{Sal}	**-0.565*****	.	0.011	.	-0.031
	[-3.33]		[0.12]		[-0.98]
d_i^{Rep}	.	.	**0.158*****	**0.072****	-0.015
			[2.77]	[1.99]	[-0.44]
N	60	181	315	1250	722
R2	0.11	0.07	0.04	0.00	0.56

Note: Robust *t*-statistics in brackets. ** $p < 0.05$, *** $p < 0.01$. Parameters are estimated with Eq. (11) using individual-level regressions. Column 5 includes paper and treatment fixed effects. For the Michigan dataset, the analysis is based on the subsample of individuals surveyed three times.

Table 9 presents the results of this comparison. The main takeaway is that there is a strong heterogeneity in how behavioral biases shape overreaction to news across economic agents. Specifically, each type of agents appears to be associated with one particular bias. First, representativeness heuristic shapes overreaction for firms and households, with less overreaction in the presence of unusual inflation signals. This is consistent with the literature that shows the importance of firm idiosyncratic conditions —rather than aggregate signals— in explaining their aggregate expectations (Born et al. 2023, Born et al. 2024, Carstensen and Bachmann 2023, Enders et al. 2022, and Vermeulen et al. 2012). Second, the salience of inflation news matters for policymakers' overreaction. Third, inflation experience is related to overreaction for professional forecasters. Potential strategic forecasting considerations (as suggested by Ottaviani and Sørensen 2006, and Capistrán and Timmermann 2009) would explain the expectation formation process of these analysts and why the inflation experienced affects the degree to which these individuals overreact to news. Finally, the recency-biased behavior emerges as the main factor for participants in LtFEs. Overall, our results suggest that although overreaction is strinkingly homogeneous across economic agents, it is related to different behavioral biases for each type of agents. This finding highlights the importance of tailoring theoretical models to each type of economic agents and its specific behavioral bias.

4.6. Discussion about the external validity of experimental forecasts

The literature follows different approaches to compare experimental and field data. The first approach is to compare survey to lab-in-the-field data on the *same* (type of) *agents* and examine whether experiments are comparable to surveys. Armantier et al. (2015) present a study in which they compared consumers' survey expectations to the behavior of the same subjects in an experiment. They show a strong correlation between stated survey beliefs and experimental decisions. Salle et al. (2023) explore how individuals' memories of inflation influence their expectations about future inflation in both surveys and laboratory

experiments. They show that experiencing periods of rising inflation or disinflation in a forecasting game can create an experience similar to actual exposure to inflation.

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.[13] Coibion et al. (2021) study higher-order macroeconomic expectations of firm managers in New Zealand. 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.

Complementing these studies on the external validity of experimental forecasts, this 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. However, in terms of behavioral underpinnings, recency explains overreaction to news for participants in experiments, in contrast to other types of economic agents.

Two peculiarities are worth mentioning. First, participants in LtFEs overreact somehow less to news than other types of agents and there are also fewer individuals who underreact in this category of agents. Their behavior is less dispersed than that of other types. This more homogenous behavior may stem from the very controlled experimental set-up that includes a qualitative description of a simple economy, with a limited number of economic variables and a rather simple task (predicting inflation for the next periods). Second, the role of the recency bias in explaining overreaction to news could also be related to the experimental set-up. While survey forecasts are elicited at a low frequency, participants in experiments provide multiple forecasts in a very short time span. This might induce a recency bias and the fact that subjects who rely closely on the previous period forecast are less likely to revise their forecasts when given new signals.

5. Conclusion

This paper revisits the well-documented phenomenon of overreaction in inflation expectations and extends it across five distinct types of economic agents. We provide evidence of a very homogeneous degree of overreaction to news across households, firms, professional forecasters, policymakers, and experimental participants. Most individuals do overreact to news relative to FIRE and the median of individual overreaction across types of agents is similar. This consistency holds across sample size, time periods, and robustness checks.

However, our main contribution lies in uncovering the behavioral foundations of this overreaction. Despite the homogeneity in outcomes, the behavioral mechanisms driving overreaction to news differ markedly across agent types. Each type of agents appears to rely on a distinct dominant bias. For households and firms, overreaction is primarily shaped by the representativeness heuristic, suggesting that these agents treat unusual inflation signals as outliers. Policymakers' overreaction is best explained by the salience of inflation news, consistent with heightened attention to volatile economic signals. For professional forecasters,

[13] 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.

inflation memory plays a central role, with those who have experienced higher inflation tending to moderate their reactions. Finally, recency bias emerges as the main driver of overreaction among participants in laboratory experiments, where more persistent forecasting behavior is associated with less responsiveness to new information. These findings underscore the importance of tailoring theoretical models and policy communication strategies to the specific behavior of each type of economic agents.

These findings challenge the notion that similar macro-level patterns stem from similar micro-level behaviors. Instead, they underscore the importance of agent-specific behavioral models in macroeconomic analysis. These findings also carry practical implications for central banks: effective communication strategies must account for the distinct behavioral biases that shape how different audiences process economic news.

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 (2021). 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.

Boccanfuso, J. and L. Neri (2025). Uncovering attention heterogeneity, *Manuscript*.

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 (2025). Inflation Levels and (In)Attention, *The Review of Economic Studies*, 92(3), 1564-1594.

Broer, T. and A. Kohlhas (2024). Forecaster (Mis-)Behavior, *Review of Economics and Statistics*, 106(5), 1334–1351.

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.

Cenzon, J. (2025). Credit Market Experiences and Macroeconomic Expectations: Evidence and Theory, *Manuscript*.

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.
Gandré, P. (2020). US stock prices and recency-biased learning in the run-up to the Global Financial Crisis and its aftermath, *Journal of International Money and Finance*, 104, 102165.
García-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, *NBER Working Paper*, No. 31607.
Gennaioli, N., M. Leva, R. Schoenle and A. Shleifer (2024). How inflation expectations de-anchor: The role of selective memory cues, *NBER Working Paper*, No. 32633.
Giordani, P. and P. Soderlind (2003), Inflation Forecast Uncertainty, *European Economic Review*, 47(6), 1037-1059.
Granziera, E., Reiche, L., Maffei-Faccioli, N., Weber, M., and T. Fastbø (2025). Five Facts About Inflation Expectations: Evidence from Four Different Groups of Agents, *Norges Bank Working Paper*, No. 7/2025.
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 D. Robertson (2025). Cautious expectations, *Journal of Monetary Economics*, forthcoming.
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.
Kuchler, T., and B. Zafar (2019). Personal Experiences and Expectations about Aggregate Outcomes, *Journal of Finance*, 74(5), 2491–2542.

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.
Nagel, S., and Z. Xu (2022). Asset Pricing with Fading Memory, *Review of Financial Studies*, 35(5), 2190–2245.
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 - Individual forecast regressions - FOMC period sample

	FOMC	SPF	Livingston	Michigan		LtF Exp.
	(1)	(2)	(3)	(4)	(5)	(6)
	12m	12m	12m	12m	12m	12m
FR_i	-0.466***	-0.454***	-0.473***	-0.418***	-0.499***	.
	[-10.03]	[-13.51]	[-12.42]	[-48.15]	[-15.32]	
constant	-0.183***	-0.199***	-0.348***	-1.117***	-2.029***	.
	[-222.00]	[-481.49]	[-283.72]	[-75.80]	[-411.50]	
Ind. FE	Yes	Yes	Yes	Yes	Yes	.
N	1 006	3 316	1 393	57 739	370	.
R2	0.11	0.17	0.30	0.26	0.90	.

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 estimation is conducted on the same sample period as the one used for FOMC data (1992-2019) for all types of economic agents except LtFEs for which this test does not apply. The dependent variable is individual forecast error at time *t*. For the Michigan survey, Column (4) includes households that are surveyed at least twice, while Column (5) focuses on households that are surveyed thrice.

Table A2 - Individual forecast regressions - FOMC sample size

	FOMC	**SPF**	**Livingston**	**Michigan**	**LtF Exp.**
	(1)	(2)	(3)	(5)	(6)
	12m	12m	12m	12m	12m
FR_i	-0.466***	-0.489***	-0.410***	-0.435***	-0.735***
	[-10.03]	[-4.15]	[-6.48]	[-13.23]	[-3.78]
constant	-0.183***	-0.334***	0.497***	-0.745***	-0.040**
	[-222.00]	[-120.56]	[411.75]	[-47.14]	[-2.06]
Ind. FE	Yes	Yes	Yes	Yes	Yes*
N	1 006	1 023	1 029	1 022	1 054
R2	0.11	0.28	0.40	0.87	0.76

Note: *t*-statistics in brackets. ** $p < 0.05$, *** $p < 0.01$. Parameters are estimated with Eq. (3) using OLS and heteroskedasticity-robust standard errors. For each dataset, the estimation is conducted using a similar number of observations as for FOMC data obtained from random draws of around 1000 observations. The dependent variable is individual forecast error at time *t*. For the Michigan survey, Column (4) includes households that are surveyed at least twice, while Column (5) focuses on households that are surveyed thrice.

Table A3 - Individual forecast regressions – Including lagged aggregate forecasts

	FOMC	SPF	Livingston	Michigan	LtF Exp.
	(1)	(2)	(3)	(4)	(5)
	12m	12m	12m	12m	12m
FR_i	-1.161***	-0.506***	-0.396***	-0.445***	-0.370***
	[-14.05]	[-18.83]	[-21.64]	[-21.12]	[-10.50]
$F_{agg,t-1}$	-1.652***	-0.603***	-0.308***	-0.885***	-0.091***
	[-17.96]	[-12.93]	[-5.52]	[-13.07]	[-6.91]
constant	2.888***	1.356***	1.390***	1.744***	0.295***
	[16.93]	[10.63]	[8.32]	[9.00]	[6.55]
Ind. FE	Yes	Yes	Yes	Yes	Yes*
N	1 006	4 060	5 049	2 548	41 241
R2	0.43	0.27	0.35	0.90	0.29

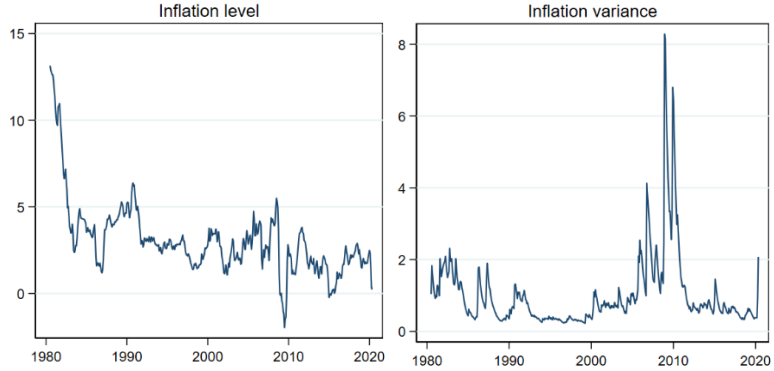
Note: *t*-statistics in brackets. ** $p < 0.05$, *** $p < 0.01$. Parameters are estimated with Eq. (3) using individual-level pooled panel regressions and standard errors clustered at the forecaster level. The dependent variable is individual forecast error at time *t*. For the Michigan survey, Column (4) includes households that are surveyed thrice.

Table A4 - 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	-0.46***	-0.44***	-0.43***	-0.43***	-0.45***	-0.43***	-0.37***	-0.38***	-0.38***	-0.44***	-0.45***	-0.45***	-0.36***	-0.36***	-0.36***
	[-9.0]	[-9.7]	[-8.8]	[-14.0]	[-13.9]	[-13.2]	[-16.9]	[-18.3]	[-17.2]	[-19.9]	[-19.6]	[-19.1]	[-9.6]	[-9.9]	[-9.8]
constant	-0.18***	-0.18***	-0.18***	-0.25***	-0.29***	-0.25***	0.48***	0.47***	0.48***	-0.64***	-0.76***	-0.63***	-0.02***	-0.02***	-0.02***
	[-195]	[-194]	[-172]	[-251]	[-264]	[-223]	[829]	[1045]	[1032]	[-66]	[-83]	[-68]	[-220]	[-665]	[-848]
Ind. FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes*	Yes*	Yes*
N	1 006	1 006	1 006	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	0.10	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. (3) 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, Columns (10) to (12) 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 type, 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.