WORKING paper

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Information Frictions Across Various Types of Inflation Expectations*

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ABSTRACT

Understanding how the degree of information frictions varies among economic agents is of utmost importance for macroeconomic dynamics. We document and compare the frequency of forecast revisions and cross-sectional disagreement in inflation expectations among five categories of agents: households, firms, professional forecasters, policymakers and participants to laboratory experiments. First, we provide evidence of a heterogeneous frequency of forecast revisions across categories of agents, with policymakers revising more frequently their forecasts than firms and professional forecasters. Households revise less frequently. Second, all categories exhibit cross-sectional disagreement. There is however a strong heterogeneity: while policymakers and professional forecasters exhibit low disagreement, firms and households show strong disagreement. Our analysis suggests that the nature of information frictions is closer to noisy information model features. We also explore the external validity of experimental expectations.

Keywords: Disagreement, Forecast Revisions, Experimental Forecasts, Survey Forecasts, Central Bank Forecasts.

JEL Classification: E3, E5, E7.

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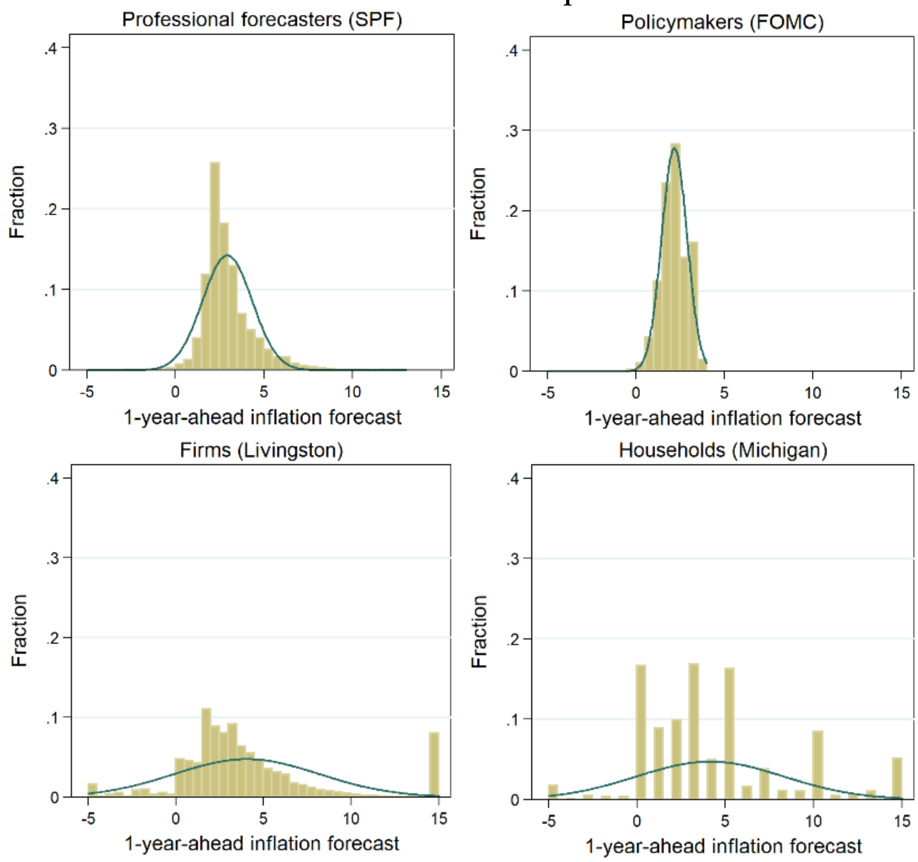
NON-TECHNICAL SUMMARY

Macroeconomic dynamics strongly depend on expectation processes. Monetary policy consists for a large part in managing inflation expectations of different agents (households, firms, professional forecasters). It is therefore of utmost importance for central bankers to know the strength of informational frictions that affect inflation expectations within and across different categories of economic agents.

These informational frictions are characterized by the frequency of revisions and disagreement in inflation expectations. Because the cost of collecting and processing information may be different for various categories of agents, the strength of information frictions within and across various categories may vary dramatically.

Distribution of inflation expectations



Note: These figures show the distribution of inflation forecasts for each dataset truncated at -5% and 15%, with the fraction that represents each bin on the y-axis. The blue line represents the normal density approximation.

We compare the frequency of inflation forecast revisions and disagreement in inflation expectations among five categories of agents: households, firms, professional forecasters, policymakers and participants to laboratory experiments. We document a heterogeneous frequency of forecast revisions across the five categories of agents, with policymakers revising more frequently than participants to experiments, firms and professional forecasters, who themselves revise much more frequently than households. We also provide evidence of disagreement within all categories of agents, although there is a strong heterogeneity across categories: while policymakers, professional forecasters and participants to experiments exhibit low disagreement, firms and households show strong disagreement.

Our results question the external validity of experimental inflation expectations: in terms of disagreement, the behavior of participants to experiments is closer to that of central bankers; in terms of frequency of forecast revisions, the behavior of participants to experiments is relatively close to that of professional forecasters or firms.

In terms of policy implications, our findings may inform central banks about the public they should target to improve their communication strategy in order to cope with information frictions, both within and across categories of economic agents. In particular, acknowledging the size of disagreement within and across each category of agents (implying that the information released by the central bank may not reach all categories of agents and also all agents within each category in the same manner), targeted communication towards each category and towards specific groups of agents (presenting the same characteristics) within each category might represent a useful tool.

Frictions informationnelles entre différents types d'anticipations d'inflation

RÉSUMÉ

Pour comprendre les dynamiques macroéconomiques, il est important d'évaluer la façon dont le degré de frictions informationnelles varie selon les agents économiques. Nous documentons et comparons la fréquence de révisions des prévisions et la dispersion dans les anticipations d'inflation de cinq catégories d'agents : les ménages, les entreprises, les prévisionnistes professionnels, les décideurs politiques et les participants aux expériences en laboratoire. Premièrement, nous mettons en évidence une fréquence hétérogène des révisions des prévisions entre les catégories d'agents, les décideurs politiques révisant plus fréquemment leurs prévisions que les entreprises et les prévisionnistes professionnels. Les ménages révisent moins fréquemment. Deuxièmement, nous mesurons la dispersion au sein de chaque catégorie. Il existe cependant une forte hétérogénéité : alors que les décideurs politiques et les prévisionnistes professionnels affichent une faible dispersion, les entreprises et les ménages affichent une forte dispersion. Notre analyse suggère que la nature des frictions informationnelles est plus proche des caractéristiques d'un modèle d'information bruitée. Nous explorons également la validité externe des prévisions expérimentales.

Mots-clés : dispersion, révisions des prévisions, prévisions expérimentales, prévisions d'enquête, prévisions de la banque centrale.

1. Introduction

Information frictions play a key role in various theories of expectations formation in macroeconomics. Models of sticky information (Mankiw and Reis, 2002), dispersed and heterogenous information (Angeletos and Lian, 2016), and rational inattention (Sims, 2003; Mackowiak and Wiederholt, 2009) exhibit disagreement in expectations among individuals. This disagreement is found to be key to macroeconomic dynamics (Mankiw et al., 2004). It may reflect heterogeneity in the rate at which agents update their information sets or differences in these information sets.[1] Because the cost of collecting and processing information may be different for various categories of agents, the strength of information frictions within and across various categories may vary dramatically. As macroeconomic dynamics strongly depend on expectation processes, understanding how the degree of information frictions varies among economic agents is of utmost importance.

While the recent empirical literature focuses on information frictions among households and firms (see e.g. Coibion and Gorodnichenko, 2018, Link et al., 2021, or Savignac et al. 2021), in this paper, we document and compare the frequency of forecast revisions and disagreement in inflation expectations among five categories of agents: households, firms, professional forecasters, policymakers, and participants to laboratory experiments. Disagreement is at the core of models with information frictions, and these models are compatible with agents updating their information sets infrequently or incompletely. Predictions from theoretical contributions could in principle be applied to any category of economic agents who form expectations. However, these five categories of agents exhibit different individual characteristics, are subject to different objectives and incentives and may collect and process information differently. These differences may impact their degree of information frictions. By considering these five categories of agents, our paper takes a broader view on information frictions and escapes from the magnifying glass effect associated with the opposition between firms and households. We emphasize the fact that differences in information frictions observed between households and firms should be considered relative to those with policymakers, professional forecasters and participants to experiments.

Our methodology follows in part Andrade and Le Bihan (2013) who quantify the disagreement among professional forecasters and the frequency at which they revise their forecasts. In contrast, we compare the degree of information frictions in inflation expectations *within* and *across* various categories of economic agents in the vein of Coibion and Gorodnichenko (2015).Another novelty relates to the inclusion of experimental data. We proceed in two steps. First, for each category of expectations, we measure the frequency with which economic agents revise their forecasts and document whether there is some heterogeneity in this frequency within and across the different categories of economic agents. Based on the predictions of the noisy information model, we assess whether this frequency is correlated with the time-varying variance of inflation dynamics. To do so, we estimate the conditional variance of inflation from a GARCH model. Second, we document disagreement in expectations within each category of agents and across these categories. We investigate whether disagreement is affected by inflation shocks, as predicted by the sticky information model. We use US data to perform this analysis: the Michigan and Livingston surveys, respectively for households and firms, the Survey of Professional Forecasters for professional forecasters, and the FOMC forecasts for

[1] Note that disagreement could also be driven by heterogeneity in beliefs about the underlying structure of the economy (Angeletos et al., 2021). Such heterogeneity generates disagreement in expectations even if all agents have the same information about previous realizations of macroeconomic variables and of shocks. See Andrade et al. (2016) and Andre et al. (2022) for an empirical analysis of heterogeneity in subjective models.

policymakers. We also use experimental data for participants to Learning-to-Forecast Experiments (LtFEs) from a series of papers (Petersen, 2014, Pfajfar and Žakelj, 2018; Cornand and M'baye, 2018a, b; and Hommes et al, 2019).[2] A methodological contribution of our paper consists in harmonizing the characteristics of structurally different surveys (horizon, time period, frequency, etc.) to make them as comparable as possible.

In tackling these issues, we are able to explore the external validity of experimental inflation expectations in terms of frequency of forecast revisions and disagreement relative to four categories of field expectations. Laboratory experiments are increasingly used to test the predictions of macroeconomic models or their assumptions (Duffy, 2008, 2016). Establishing the external validity of experimental inflation forecasts is essential if laboratory experiments are to be used as decision-making tools for monetary policy.[3] Conclusions that can be drawn from experiments would only be valid if the experimental expectations present similarities with those observed in field data – in particular regarding information frictions.[4]

Our main results can be summarized as follows. First, we observe a heterogeneous frequency of forecast revisions across categories of agents, with policymakers revising more frequently than participants to experiments, firms and professional forecasters, who themselves revise more frequently than households. Since an inflation shock has a positive and significant effect on the frequency of forecast revisions for all categories of agents, noisy information possibly explains the behavior of the different categories of agents. In terms of magnitude, the frequency of forecast revisions increases the least for households, firms, and professional forecasters. By contrast, participants to experiments revise more and policymakers even more. Second, we provide evidence of a strong heterogeneity in disagreement among the different categories of agents: while policymakers, professional forecasters and participants to experiments exhibit low disagreement, firms and households show strong disagreement. Since we find that an inflation shock does not have a positive and significant effect on disagreement for any of our categories of agents, sticky information may not be a good candidate model to explain their behavior.

Overall, our results qualify the view according to which firms and households have to be opposed in terms of information frictions. Especially regarding the frequency of revisions, policymakers and participants to experiments are the categories that stand in stark contrast to the others. When it comes to disagreement, there is more difference between two groups (one composed of policymakers, professional forecasters and participants to experiments and the other of households and firms) than within each of these two groups. Our analysis suggests that the nature of information frictions is closer to noisy information model features.

[2] In LtFEs, participants' task is to provide their expectations about an economic variable (say, inflation). Their payoffs depend negatively on their forecast error. The expectations that are formed by participants are aggregated (using the mean or median) and this summary statistic is introduced into the theoretical model as the aggregate expectation of agents. Most recent experiments have used variants of the standard 3-equation New-Keynesian model: IS curve, Phillips curve, and policy rule. This model is directly implemented via a computer program, except for the expectations determined by participants. The computer program then derives the current values of variables conditional on the model parameters. See Hommes (2011) for a survey.

[3] A recent growing macro-experimental literature (see Duffy, 2016 and Hommes, 2021, section 3) has considered inflation and/or output expectation formation in the laboratory. Laboratory experiments —particularly LtFEs— are used to validate expectation hypotheses and learning models and also serve as important tools for central bankers by providing a test bed for competing policy actions (Cornand and Heinemann, 2014, 2019).

[4] In addition, the comparison between experimental and field data can be valuable for experimenters to improve the design of their macro-experiments in order to mimic real world situations.

Regarding the external validity of experimental inflation expectations, while participants to experiments are not assigned a particular role in the economy (and can be asked to form expectations based on the behavior of firms, consumers or professional forecasters), we find that their behavior does not mimic much that of firms or households (consumers). It reproduces more closely the behavior of policymakers (and, to a lesser extent, of professional forecasters), which might be due to the salience of information and to the New-Keynesian (NK) data generating process enacted in LtFEs and the strong incentives faced by these participants.

Our paper relates to the empirical literature that documents disagreement in inflation expectations obtained from survey data, within and across different categories of economic agents. The closest paper to ours is Andrade and Le Bihan (2013). They show that forecasters do not systematically update their forecasts even when new information is released and that forecasters who update also disagree on their forecasts.[5] The main difference however is that they analyze one agent only (the ECB' Survey of Professional Forecasters). We apply and extend their methodology to five categories of agents. In this respect, we are close to Carroll (2003) who compares professional forecasters to consumers and Coibion and Gorodnichenko (2015) who consider forecasts from professional forecasters, firms, households and policymakers. Coibion and Gorodnichenko (2012) apply a different test of the expectation formation process to U.S. and international survey data from professional forecasters. Mankiw et al. (2004) document the extent of disagreement and show that it varies over time and with other aggregate variables. Finally, we complement this literature by including experimental data, allowing us to compare it to the four categories of field expectations and test the external validity of experimental inflation expectations as in Cornand and Hubert (2020).[6] While Coibion and Gorodnichenko (2012, 2015) and Cornand and Hubert (2020) consider aggregate data, our dataset exploits individual data to document the degree of information frictions.

The literature that compares experimental data to field data in macroeconomics is scarce. There is a recent literature on information-provision experiments in surveys.[7] This literature combines large-scale survey data of households and firms with Randomized Controlled Trial (RCT) experiments. RCT experiments provide a random subset of survey respondents with a piece of information and measure the corresponding effects on expectations. In particular, Link et al. (2021) study how information frictions (the dispersion of expectations and the learning rate from information, which can be comparable, to some extent, to the frequency of forecast revisions) vary between households and firms. They show that firms' expectations are less dispersed than those of households and more closely aligned with expert forecasts. Our research question is closely related to theirs, but our methodology is different. While RCT experiments allow for representative data of real-world expectations and actual decisions, most of them only permit collecting cross-sectional data. This does not allow to study how information frictions vary with the state of the economy. By contrast, we conduct a panel data analysis (enabling us to properly measure the frequency of forecast revisions[8]) and control for inflation dynamics.

[5] Clements (2020) complements this analysis by documenting whether inefficiencies in the use of information can explain the accuracy of forecasts and disagreement between forecasters. He provides evidence that the inefficient use of information is responsible for persistent differences in accuracy across forecasters.
[6] Compared to Cornand and Hubert (2020), the experimental data of Adam (2007) is excluded (for which only average expectations per group – and not individual ones – were available) because the focus here is on individual rather than aggregate data. For the same reason, we also exclude financial market expectations and Greenbook data from our field sample. Moreover, compared to the experimental dataset used by Cornand and Hubert (2020), we include an additional experimental paper (Petersen, 2014).
[7] Armantier et al. (2015), Armantier et al. (2016), Cavallo et al. (2017), Coibion et al. (2018) and Coibion et al. (2021) use this method to study inflation expectations.
[8] By contrast, in Link et al. (2021), the learning rate is based on an exogenous allocation of information.

In terms of policy implications, our findings may inform central banks about the public they should target to improve their communication strategy in order to cope with information frictions, both within and across categories of economic agents. In particular, acknowledging the size of disagreement within and across each category of agents (implying that the information released by the central bank may not reach all categories of agents and also all agents within each category in the same manner), targeted communication towards each category and towards specific groups of agents (presenting the same characteristics) within each category might represent a useful tool.

The paper is structured as follows. Section 2 presents the data. Section 3 depicts testable hypotheses. Sections 4 and 5 respectively describe the empirical results in terms of frequency of forecast revisions and disagreement for field expectations. Section 6 analyzes the external validity of experimental inflation expectations. Finally, Section 7 concludes the paper.

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).

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.[9]

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

[9] 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.

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 and real GDP growth twice per year in the Monetary Policy Report to the Congress since 1979. Since October 2007, their publication has been quarterly. We consider forecasts of the Consumer Price Index until 1999 and then the Personal Consumption Expenditures (PCE) measure of inflation following the focus of the FOMC. 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 only summary statistics or anonymous individual data are published in real-time, with an embargo of 10 years.[10]

2.3. Laboratory experiment data

We collect a sample of macro-experimental data on inflation expectation from five published papers.[11] The Learning-to-Forecast design, based on the NK reduced-form model, offers the incentives to form accurate inflation forecasts. 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. 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.

Pfajfar and Žakelj (2018) (henceforth PZ) 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. The computer program feeds the model with naïve output gap expectations: $E_t y_{t+1} = y_{t-1}$. The parameter values are standard: $\rho = 0.99$, $\lambda = 0.3$, $\varphi = 0.164$, and $\bar{\pi} = 3$. Since they investigate the targeting rule that

[10] We do not consider Greenbook data since our analysis of information frictions requires individual data.

[11] For a systematic comparison of the characteristics of experimental designs used in the five considered papers, see Table A1 in the Appendix.

best stabilizes the economy, they consider four treatments, corresponding to different policy rules: inflation forecast targeting, with three degrees of monetary policy aggressiveness: $\phi_y = 0$ and $\phi_\pi = 1.5$ or 1.35 or 4; and contemporaneous inflation targeting, with an intermediate degree of monetary policy aggressiveness: π_t is replaced by $E_t\pi_{t+1}$ in the monetary rule with $\phi_\pi = 1.5\%$. 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: $\varphi = 1$, $\bar{\pi} = 5$ 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.[12] CMb focus on the case in which the central bank stabilizes both inflation and the output gap ($\phi_\pi = 1.5$, $\phi_y = 0.5$) 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) (henceforth HMW) 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 ($\phi_\pi = 1.5$, $\phi_y = 0$), and one in which it additionally reacts to the output gap ($\phi_\pi = 1.5$, $\phi_y = 0.5$). Sessions have 50 periods; the number of observations amounts to 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 ($\rho = 0.989$, $\lambda = 0.13$, $\varphi = 1$, $\bar{\pi} = 0$, $\bar{y} = 0$, $\phi_\pi = 1.5$, $\phi_y = 0.5$, $\phi = 0.57$) 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.[13] 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; the number of observations amounts to 8 independent groups.

[12] More precisely, under strict IT, the sole objective of the central bank is to stabilize inflation ($\phi_\pi = 1.5$, $\phi_y = 0$). Under explicit strict IT, the central bank announces its 5% target, while under implicit strict IT, there is no announcement about the target value. Under a flexible IT, the central bank has both an inflation objective and an output gap stabilization objective ($\phi_\pi = 1.5$, $\phi_y = 0.5$). Depending on whether the flexible IT is made explicit or not, the central bank communicates its IT or not.

[13] While two treatments are considered, the data we managed to collect refer to a single information treatment, in which participants are also provided with forecast error information on their screen.

2.4. Macroeconomic data

Regarding experimental data, inflation is generated by a computer program that implements a model of the economy, conditional on the parameters and on 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)). For the observed inflation data, we use the monthly Consumer Price Index for All Urban Consumers (FRED mnemonic: CPI-AUCSL).

In order to characterize the type of information frictions faced by agents and differentiate sticky and noisy information models, we make use of two measures of inflation dynamics. First, we estimate a GARCH(1,1) model of the inflation rate to obtain the conditional variance of inflation. The GARCH model provides a parsimonious identification of the conditional variance combined with an agnostic statistical representation 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. In addition, assuming that individuals observe a noisy signal of the inflation state, for a constant variance of the noise, an increase in the conditional variance of inflation raises the signal-to-noise ratio and therefore raises the probability of forecast revisions. The GARCH model enables us to test for this possibility. The GARCH model is estimated with maximum likelihood and based on the following two – mean and variance – equations:

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

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 provides a time-varying measure of the variance of inflation shocks and enables us to examine whether the frequency of forecast revisions is state-dependent. In the case of homoscedastic inflation shocks (if inflation shocks have a constant variance), they may not shed light on the degree of inattention of individuals and their forecast updating behavior. Our analysis consists in investigating the link between the time-varying volatility of inflation shocks and the frequency of forecast revisions (see Section 3 for more details).

Second, we are interested in the level of inflation shocks, so we estimate a simple AR(1) model of the inflation rate. Our analysis then investigates the link between the level of inflation shocks to the cross-sectional forecast disagreement, another key relationship we aim to investigate for the question of information frictions. Inflation shocks are estimated with OLS as the residuals of the following equation:

$$\pi_t = \beta_0 + \beta_1 \pi_{t-1} + \epsilon_t^{\pi} \qquad (2)$$

where π_t is the year-over-year inflation rate. We estimate the conditional variance of inflation and inflation shocks at different frequencies – biannually and monthly – to match the characteristics of our datasets. Figure A1 in the Appendix shows the time series of the conditional variance of inflation while Figure A2 plots inflation shocks. These figures show episodes of large volatility and large shocks around the late 1970s, early 1980s and around the global financial crisis of 2008 consistent with the major macroeconomic crises of our sample.

2.5. Summary of inflation expectations across the five categories of agents

Table 1 presents the source, frequency and sample of inflation expectations 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, frequency is abstract. We therefore treat them separately and compare them to field forecasts to evaluate their external validity in Section 6. Regarding the sample period for field data, we complement, as robustness tests, our empirical analysis with tests performed on a common sample period, from 1992 to 2009, for comparability purposes between types of agents, as well as macroeconomic and structural environments (see Table A4 in Appendix).

Table 1 – Characteristics of inflation expectations data

	Source	Frequency	Sample	Resp./Wave	Nb Resp.	Nb Obs.	Measure
Professional F.	SPF	Quarterly	1981q2-2020q2	33.80	204	5 267	CPI
Policymakers	FOMC	6 months/Quarterly	1992m1-2009m11	16.93	49	474	CPI - PCE
Firms (Industry)	Livingston	6 months	1948h1-2020h1	44.05	376	6 387	CPI
Households	Michigan	6 months	1978m1-2020m5	505.51	91 390	257 307	CPI
Experiments	Experiments	Quarterly eq.	NA	7.02	736	42 016	CPI

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 the analysis of disagreement since they are not influenced by 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). We are therefore able to compare all forecasts on the same ground with a similar fixed-horizon (1-year) scheme. We provide alternative measures of disagreement and of the frequency of forecast revisions using the raw fixed-event data to ensure that our results are not driven by this transformation.

3. Theoretical predictions

In a framework with full information rational expectations (so in an economy without information frictions), information sets are revised continuously and there is no cross-sectional disagreement. By contrast, if the economy is subject to information frictions, economic agents may not update their information set continuously. This factor and the fact that they observe potentially different information sets would then generate some cross-sectional disagreement in their forecasts. These two consequences of information frictions apply to any category of economic agents who form inflation forecasts. In this work, our empirical proxy for the information set updating probability is the frequency of forecast revisions. We can then define the following two hypotheses about the characteristics of forecasts *within* each category of agents:

> *H1 - Frequency of forecast revisions.* Under the assumption of no information frictions, we expect a probability of forecast revisions equal to one. With information frictions, we expect a probability of forecast revisions strictly below one.
>
> *H2 – Cross-sectional disagreement.* Under the assumption of no information frictions, we expect no cross-sectional disagreement. By contrast, in the case of information frictions, we expect a non-null cross-sectional disagreement.

Should information frictions affect some categories of agents, we are interested in interpreting them in the light of two theories: sticky information and noisy information. In sticky information models (Mankiw and Reis, 2002), agents update their information set infrequently, with a given probability, and when they do they get full information. This probability is constant over time and exogenous, so unaffected by the state of the economy. Consequently, at each date, only a fraction of the population has access to up-to-date macroeconomic news and revises its expectations. By construction, the presence of economic shocks induces some cross-sectional disagreement between agents who update their information sets and the others, so the larger the shock, the higher disagreement. As long as some agents do not update their information set, the larger the proportion of agents who do update, the lower the disagreement. However, this relationship is not monotonic. Disagreement decreases more when the proportion of agents who update is large. Among agents who update their information set, cross-sectional disagreement should be null since they all get full information.

In models with dispersed and heterogenous information (Angeletos and Lian, 2016), agents update their information set continuously but the news they get is imperfect (subject to an idiosyncratic component, thus possibly different from one individual to the next), such that they partly integrate it in their forecast. In models of rational inattention (Sims, 2003), agents may rationally not account for new information because of processing costs. These latter two classes of models can be grouped into what the literature calls noisy information models. Under noisy information models, the frequency of forecast revisions is not set to be constant and can instead vary with the precision of signals observed or the variance of economic shocks. Note that theory and its empirical measurement can only partially meet. In theory, under the assumption that the observed signal is subject to non-zero shocks in every period, individuals revise their forecast every period. However, in practice, it is likely that individuals have some thresholds under which they do not revise their forecast because the observed change in the signal is too small. It is plausible that these thresholds differ across categories of agents: for instance, policymakers are more likely to revise their forecast than households in the face of a small change in the observed signal. In addition, there is cross-sectional disagreement among forecasters updating their forecasts since each has specific information due to the heterogeneous signals they observe. The magnitude of cross-sectional disagreement is independent of economic shocks.[14] We can summarize these theoretical predictions as follows:

H3 - Frequency of forecast revisions under sticky and noisy information:

(a) Under sticky information, the frequency of forecast revisions is constant over time, so is not a function of the conditional variance of inflation.

(b) Under noisy information, the frequency of forecast revisions is not set to be constant and is positively correlated with the conditional variance of inflation.

[14] The empirical literature shows that there is a correlation of disagreement and forecast revisions with macroeconomic variables and in particular inflation dynamics. Carlson and Valev (2003), Carroll (2003), Cukierman and Wachtel (1979), Mankiw et al. (2004) and Souleles (2004) provide evidence of a positive relationship between the cross-sectional dispersion in inflation expectations and the level of the inflation rate, Cukierman and Wachtel (1979) and Mankiw et al. (2004) document the link between the variance of measured inflation and the cross-sectional dispersion. Consistent with noisy information models, Coibion and Gorodnichencko (2015) cannot reject the hypothesis of no response of disagreement to shocks but can reject the hypothesis that disagreement responds in the manner predicted under sticky information. They conclude that noisy information models better render account for expectations of professional forecasters, consumers, firms and central bankers.

H4 – Cross-sectional disagreement under sticky and noisy information:

(a) Under sticky information, disagreement is strongly correlated to the frequency of forecast revisions, disagreement conditional on forecast revision is null and disagreement is positively correlated to an inflation shock.

(b) Under noisy information, disagreement is unrelated to the frequency of forecast revisions, disagreement conditional on forecast revision is positive and disagreement is independent of inflation shocks.

Focusing on the differences *across* categories of agents, each category may perceive high stakes in being informed about future inflation, but some may face lower costs of acquiring and processing information than others. Forecasting inflation accurately is obviously crucial for monetary policymakers. It is also central for firms to predict their future demand or their future financial constraints. Households have an interest in holding accurate expectations about changes in the cost of living. Professional forecasters have incentives, especially in terms of credibility. Finally, in LtFEs, participants have direct monetary incentives related to their tasks. As Andrade and Le Bihan (2013, p. 968), we conjecture that "*the extent of attention to news among professional forecasters [is] an upper bound for other agents' attention to aggregate conditions*". Another upper bound is policymakers, as both professional forecasters and them spent relatively more resources on analyzing signals about the state of the economy. Carroll (2003, 2006) show that the views of professional forecasters spread to households following an epidemiological model, so we conjecture that professional forecasts are the upper bound and households' forecasts are less regularly revised. The expectations formation process in an LtFE depends on the design features. The underlying structure of LtFEs is the reduced-form NK model, but participants – without being assigned a particular role in the economy – can be asked to form expectations based on the behavior of firms or households/consumers. They may also face incentives that are closely aligned with those of professional forecasters.[15] It is therefore an open empirical question to determine which category of agents laboratory participants behave like when forming inflation forecasts.

H5 - Frequency of forecast revisions and disagreement across categories of agents. We conjecture policymakers and professional forecasters to revise their forecast more frequently and disagree less than firms. We expect households to be the category of agents that revises the least frequently and disagrees the most. We are agnostic about the relative position of participants to experiments.

4. Frequency of inflation forecast revisions

In this section, we measure the frequency of forecast revisions for the four field categories of economic agents and proceed to comparisons across these categories of agents.

4.1. Descriptive statistics

To measure the frequency of forecast revisions, we look at whether forecasts in *t* differ from forecasts in *t*-1 and compute how many individuals revise their forecast for each category of agents. We consider the frequency of forecast revisions with respect to the time unit that corresponds to each dataset and compare these frequencies of revisions across our different categories of agents directly. The frequency of forecast revisions provides an indication about

[15] Pfajfar and Zakelj (2018) consider that participants rather play the role of professional forecasters who provide firms with their inflation forecasts.

the extent to which agents incorporate new information in their expectations. Following Andrade and Le Bihan (2013), the probability we estimate is:

$$P_i\left(f^{\pi}_{it,t+h} \neq f^{\pi}_{it-1,t+h}\right) \quad (3)$$

Table 2 presents the probability of forecast revisions for the four categories of agents, its standard deviation, the number N of observations, and for agents who revise their forecast, the average revision (Mean Rev.), the standard deviation of revisions (SD Rev.) and the number of agents who revised. The last two columns show the probability of forecast revisions if there was a revision in the preceding period and the probability of revision if there was no revision in the preceding period.

Table 2 - Descriptive statistics about frequency of forecast revisions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	P_{Mean}	P_{SD}	N	Mean Rev.	SD Rev.	N_{Rev}	Rev if Rev_{t-1}	Rev if $NoRev_{t-1}$	Quarterly-eq.
SPF	0.88	0.005	4 089	0.52	0.67	3 583	0.90	0.73	0.88
FOMC	0.94	0.012	421	0.39	0.35	394	0.96	0.72	0.85
Livingston	0.90	0.004	5 751	1.45	1.92	5 204	0.92	0.74	0.68
Michigan	0.75	0.001	91 390	4.58	5.44	68 500	0.79	0.61	0.50

Note: These statistics are computed over the subsample N for which we observe 2 consecutive forecasts of a same individual for each of the five datasets. The P_{Mean} is the average frequency of revisions for each dataset. The P_{SD} is the standard deviation of the frequency of revisions. The Mean Rev. is the average magnitude of the revision for individuals who revised their forecasts (the subsample N_{Rev}) while the SD Rev. is the standard deviation of the magnitude of these revisions. Column (9) shows the quarterly-equivalent frequency of forecast revisions.

Policymakers are those who show the highest frequency of revisions, but they are also those who revise the least (i.e. they have the lowest mean revision). Firms as well as professional forecasters are also revising frequently. The amount by which professional forecasters revise is lower than that of firms. Households are those who revise the least frequently (though with a larger heterogeneity – larger variance – than other categories), but present the highest mean revision (again with much variance). These results suggest that the category of households is the most subject to information frictions.

To complement the analysis of the frequency of forecast revisions, we consider the duration dependence in the probability of revision. We compute the probability of revising in *t* if individuals revised in *t*-1 or not (see columns (7) and (8)). For all categories of agents, the probability to revise their forecast in the current period is higher when they revised in the previous period than when they did not. This result suggests that some individuals seem to update quite regularly their forecasts while some others update less. Said differently, the frequency of forecast revisions does not appear homogeneous across individuals within each category. This result also provides some tentative evidence in favor of noisy information models rather than sticky information models in which the frequency of forecast revisions is common to individuals.

Recall that we make comparisons across the categories of agents by using the frequency of forecast revisions with respect to the time unit that corresponds to each dataset. The benefit of such an approach is to consider agents who revise their forecasts when they are asked for such forecasts. A drawback though is that agents may revise more frequently during the interval of time between two surveys, so our measure of the frequency of forecast revisions would be a lower bound. In addition, the comparison of a quarterly and semi-annual probability of forecast revisions is made more difficult by the different time periods and information flows. The fact that our four datasets have different frequencies of observation may thus bias our comparisons. In order to circumvent this issue, we can compute an adjusted frequency of forecast revisions in a comparable time unit. The common denominator is the quarterly frequency, so under the assumption of a constant quarterly rate of forecast revisions, we can translate the semi-annual frequency into a quarterly frequency. This means that the semi-annual frequency of 0.90 for firms corresponds to a quarterly frequency of 0.68, while the semi-annual frequency of 0.75 for households corresponds to a quarterly frequency of forecast revisions of 0.50. In the case of policymakers, the overall frequency of 0.94 is the average of a semi-annual frequency of 0.91 (over 181 observations) which translates to a quarterly frequency of 0.70, and of a quarterly frequency of 0.96 (over 240 observations), so a weighted average frequency of 0.85. Adjusting the frequency of forecast revisions to a comparable time unit suggests a slightly different ranking: professional forecasters remain in the group of those who update the most while households remain in the group of those who revise the least. However, firms – and, to a lesser extent, policymakers in the early period when they started producing forecasts – appear to move from the first to the second group.

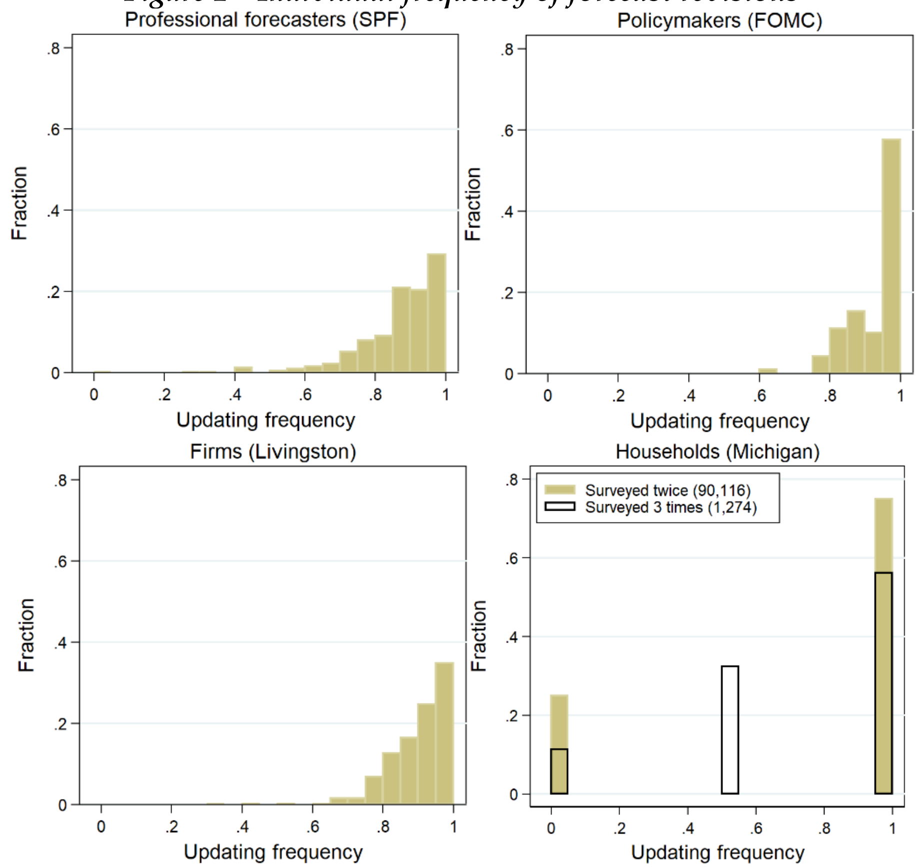
Another concern for the analysis of the frequency of forecast revisions relates to the nature of the underlying units of the inflation forecast. In the Michigan survey, households are requested to formulate their forecasts using integer values. The impossibility to use decimal points means that an observed revision in the forecast would require a much larger revision in the true underlying forecast than for other categories of agents. Professional forecasters can revise their forecast from 2.5 to 2.9, while this would show up as 3 in two waves of the Michigan survey. It is therefore possible that the nature of the survey contributes to the fact that households have less frequent and larger revisions. One possibility to investigate this issue is to standardize the threshold for a forecast revision to an integer value. We therefore round all forecasts of policymakers, professional forecasters and firms to the closest integer value and re-compute the frequency of forecast revisions. By construction, the frequency of forecast revisions for these three categories will mechanically drop. In order to explore more finely how important this bias is, we also re-compute the mean revision when individuals update their forecasts. Table A2 in the Appendix shows these statistics. The frequency of forecast revisions drops to 0.29 for professional forecasters, 0.24 for policymakers and 0.61 for firms, compared to the frequency of 0.75 for households. More interestingly, the mean revision is 1.28 for professional forecasters, 1.08 for policymakers and 2.12 for firms, compared to 4.58 for households. This suggests that although part of the reason for which households appear to revise less frequently is the integer value feature of their survey, they seem to be subject to larger information frictions than the three other categories of agents.

Another potential concern relates to the fact that, in the Livingston survey, participants form forecasts about the price level rather than its growth rate (i.e. the inflation rate). When it comes to exploring the frequency of *inflation* forecast revisions, the number of decimals in the computed growth rate matters. It is an open question whether two adjacent forecasts of 2.01 and 2.02 should be considered as true revisions of the state of the economy or as the consequence of growth rate computations. In order to exclude the potential upward bias in revisions induced by the decimals of computed growth rates, we consider a given forecast as unchanged if the change between two dates is less than 0.05 percentage point in our baseline statistics (see Clements, 2021, on forecasters' rounding behavior). We provide an alternative measure of the frequency of forecast revisions of firms using the raw computed growth rate (see Table A3 in the Appendix). With no rounding, the frequency of forecast revisions jumps to 0.98. Table A3 also provides statistics using alternative forecasts, in particular with different forecasting horizons and fixed-event forecasts. The ranking of the magnitude of information frictions across the different categories of agents holds.

Finally, one could argue that the differences in the frequency of forecast revisions reflect different states of the economy over different periods as our four datasets cover different sample periods. The Livingston survey captures various inflation regimes over the period 1948-2020 in contrast to FOMC forecasts that span over the period 1992-2009. We therefore provide the frequency of forecast revisions over a common sample period. Table A4 in the Appendix shows that the ranking of the magnitude of information frictions across the different categories of agents holds over the sample 1992-2009. All the subsequent tests performed in this paper are presented in Table A4 over this common sample period.

Figure 1 presents the distribution of individual frequency of forecast revisions for each category of agents. It complements previous results in specifying whether the overall frequency of revisions from Table 2 is reflecting individual behavior well (low heterogeneity within a category of agents) or not (large heterogeneity within a category of agents).

Figure 1 – Individual frequency of forecast revisions



Note: These subfigures show the distribution of the average, by individual, of his/her frequency of forecast revisions. For the Michigan survey, because we observe individuals only 2 or 3 times, they can only not revise (P=0), revise 1 over 2 times (P=0.5) or revise all the time (P=1). Figure A3 shows the frequency of forecast revisions for individual observed more than five times.

A vast majority of policymakers (around 60%) revise with probability 1, while only a few revise their forecast much less.[16] Regarding professional forecasters and firms about 30% revise

[16] This result raises the question of whether the frequency of forecast revisions for policymakers reflects the degree of information frictions. It is reasonable to think that policymakers do not endure information stickiness: they constantly update their information set. If the underlying outlook is unchanged, this leads to unchanged forecasts. Another specificity of policymakers relates to an optimal control issue. Policymakers by construction are likely to respond to inflation in a way that stabilizes inflation and hence requires fewer revisions later on.

with probability 1, while the large majority revises their forecast with a probability between 0.6 and 1. Our measures of the probability that professional forecasters revise their forecast are very comparable to the measure (between 0.6 and 0.9) of Andrade and Le Bihan (2013). Finally, a disclaimer applies to the Michigan survey. In this survey, households are only observed twice or thrice and then are dropped out of the sample, so no comparison can be made with other categories of agents. However, it is possible to compare within this category what happens when households are surveyed twice versus thrice. More than 20% of households who are observed twice do not revise their forecast, while a bit less than 80% revise with probability 1. Both proportions are smaller when households are observed thrice, as about 30% of them revise with probability 0.5. These estimates are consistent with Carroll (2003) who finds that about 27% of households have up-to-date forecasts. To summarize, there is some heterogeneity in the frequency of forecast revisions *across* the four categories of agents, but we find that, except for the households (and for the reason above-mentioned), there is a relative homogeneity in the frequency of revisions *within* each category of agents.

4.2. Frequency of forecast revisions and inflation dynamics

Andrade and Le Bihan (2013) study whether the frequency of forecast revisions depends on the state of the economy. Following their approach, we look at whether the frequency of forecast revisions depends on the time-varying variance of inflation shocks for each category of agents. We regress P_i over the conditional variance of inflation and control for the level of inflation:

$$P_i\left(f^{\pi}_{it,t+h} \neq f^{\pi}_{it-1,t+h}\right) = \Phi\left(\alpha_1 + \beta_1 v^{\pi}_t + \beta_2 \pi_{t-1}\right) \quad (4)$$

where Φ is the cumulative standard normal distribution function, β_1 (expected to be null under the assumption of no information frictions) and β_2 are the estimated coefficients. Equation (4) is estimated using a probit model and heteroskedasticity-robust standard errors.

Table 3 – Drivers of the frequency of forecast revisions

	(1)	(2)	(3)	(4)
	SPF	FOMC	Livingston	Michigan
	P_i	P_i	P_i	P_i
CondVar	0.095***	0.533***	0.081**	0.033***
	[3.11]	[2.89]	[2.41]	[7.46]
Level	-0.020	-0.041	0.417***	0.074***
	[-0.65]	[-0.54]	[10.62]	[10.25]
Constant	1.108***	1.189***	0.857***	0.565***
	[19.64]	[4.66]	[18.42]	[57.97]
AME CondVar	0.019***	0.063***	0.013**	0.011***
AME Level	-0.004	-0.005	0.067***	0.023***
N	4089	421	5751	91390
Pseudo R2	0.00	0.06	0.05	0.00

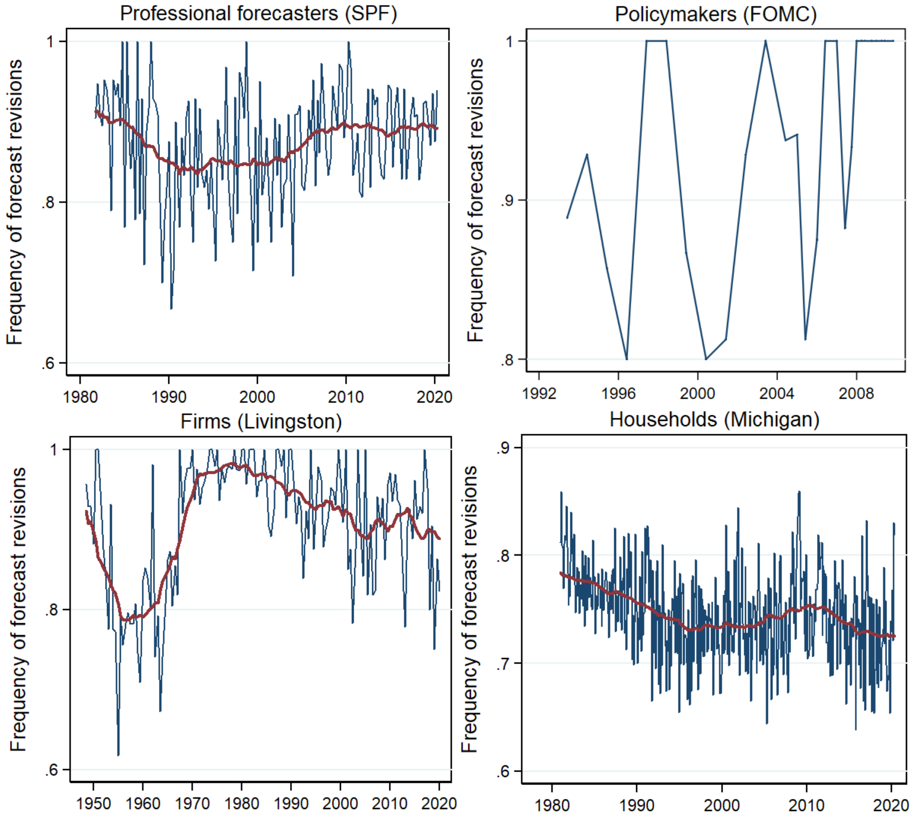
Note: t-statistics in brackets. * p < 0.10, ** p < 0.05, *** p < 0.01. Parameters are estimated with Equation (8) using a probit model. The conditional variance of inflation is estimated based on a GARCH(1,1) model and the inflation level is introduced with a lag. The dependent variable is a dummy variable that takes the value 1 when a given individual revise his/her forecasts.

Table 3 presents the results from the estimation of equation (4) for all categories of agents.[17] A robust result across our four categories of agents is that the conditional variance of inflation

[17] Table A5 in Appendix provides a robustness check (to collinearity issues) of these findings when regressions are conducted separately for the conditional variance of inflation and the level of inflation.

significantly and positively affects the frequency of forecast revisions. The bottom panel of Table 3 shows the Average Marginal Effect (AME) of the conditional variance and level of inflation. The magnitude with which the conditional variance of inflation affects the frequency of forecast revisions varies across the different categories. In particular, the effect is larger (0.06) for policymakers than for the three other categories. Households and firms are those who are the least affected. Figure A4 in the Appendix illustrates these findings by exhibiting the link between the conditional variance of inflation and whether individuals revise or not their forecasts. A higher conditional variance of inflation is associated with agents revising their forecasts. Finally, Table A4 in the Appendix shows that these findings are robust to considering a common time-sample, except for firms for which the conditional variance of inflation has no effect.

Figure 2 - Frequency of forecast revisions over time



Note: These subfigures show the time series of the average updating frequency across individuals by date. The low-frequency red line on the upper-left and bottom panels represents an 8-year centered moving average.

Equation (4) enables to shed light on the nature of information frictions: β_1 is expected to be null under sticky information whereas positive under noisy information. The results presented in Table 3 are therefore consistent with noisy information models. Moreover, recall that the probability of forecast revisions computed in equation (3) is supposed to be constant over time under sticky information, while not necessarily under noisy information. Figure 2 presents the frequency of forecast revisions over time for the four field categories of agents. In line with Andrade and Le Bihan (2013) for professional forecasters, it shows that this frequency evolves across time, in contrast with this feature of the sticky information model.

5. Cross-sectional disagreement

We measure the disagreement in expectations within the four categories of economic agents and proceed to comparisons across these categories of agents.

5.1. Descriptive statistics

Following Andrade and Le Bihan (2013), a natural measure of disagreement among economic agents about inflation is the cross-section standard deviation of inflation expectations for each category of agents:

$$SD^{f(\pi)} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(f_i^{\pi} - f^{\pi}\right)^2} \quad (5)$$

where f_i^{π} denotes individual i's fixed-horizon forecasts for inflation π on the whole sample (of the considered category of agents), one relevant period ahead (4 quarters for the considered categories), $f^{\pi} = \frac{1}{n}\sum_i^n f_i^{\pi}$ is the average (or consensus) inflation forecast, with n the number of respondents to the survey. The variable π denotes the year-on-year inflation rate. However, because the standard deviation is mechanically influenced by extreme values, we consider two measures of disagreement not subject to extreme values, and compute the interquartile (IQR) and interdecile (IDR) ranges:[18]

$$IQR^{f(\pi)} = p_{75}^{f(\pi)} - p_{25}^{f(\pi)} \quad (6)$$

$$IDR^{f(\pi)} = p_{90}^{f(\pi)} - p_{10}^{f(\pi)} \quad (7)$$

where $p_x^{f(\pi)}$ denotes the percentile x of inflation forecasts. Under information frictions, we expect a non-null disagreement, so positive values of $SD^{f(\pi)}$, $IQR^{f(\pi)}$, and $IDR^{f(\pi)}$, while we do not expect disagreement under no information frictions.

Table 4 - Descriptive statistics about cross-sectional disagreement

	(1) IQR	(2) IDR	(3) SD	(4) Mean	(5) Median	(6) IQR_N	(7) $Mean_{Avg}$	(8) IQR_{Avg}
SPF	1.30	3.02	1.40	2.92	2.60	0.45	3.08	1.23
FOMC	1.05	1.93	0.72	2.15	2.13	0.49	2.15	1.20
Livingston	2.94	6.51	3.04	3.10	2.93	0.95	2.95	2.88
Michigan	4.00	10.00	6.16	4.46	3.00	0.90	4.18	1.56

Note: These statistics are computed over the full sample for each of the five datasets. The IQR is the Inter Quantile Range. The IDR is the Inter Decile Range, the distance between the 90th and 10th percentiles. The SD is the standard deviation. The IQR_N is a normalized IQR by the level of inflation forecasts and corresponds to the ratio of the IQR divided by the mean.

Table 4 presents the interquartile range, the interdecile range and the standard-deviation of inflation forecasts, as well as the mean and median forecasts, and the normalized values (over the mean of the whole sample) of the interquartile range (IQR_N). We also compute the average forecast by date and present the mean ($Mean_{Avg}$) and the interquartile range (IQR_{Avg}) of this metric.[19] In complement to Table 4, Figure 3 plots the distribution of inflation expectations for each category.[20]

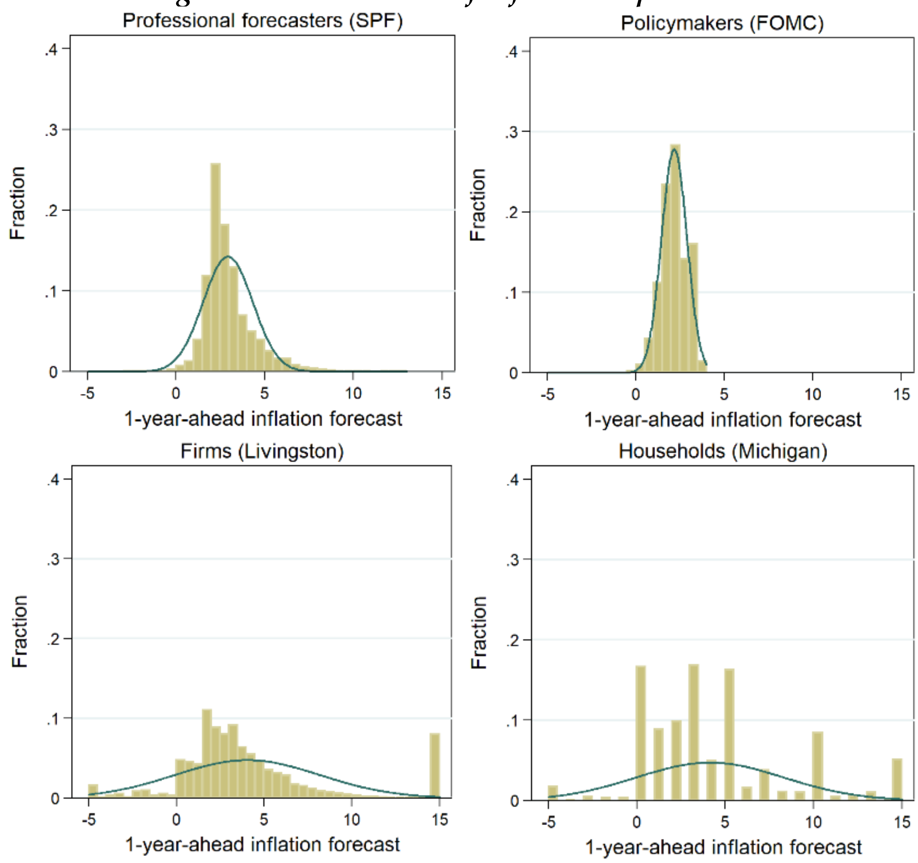
[18] For the FOMC data and experiments for which the number of respondents by period is relatively small, the concept of the IDR is akin to a min-max. However, the IDR computed with equation (7) encompasses the whole sample, so the IDR metric is not subject to this limit.

[19] This normalization allows us to consider the potential issue that may arise due to the mechanical link between the dispersion of forecasts and the level of the underlying variable. Indeed, a high level of inflation may mechanically increase the dispersion of inflation forecasts due to the larger span of possible values. We also acknowledge the potential asymmetric distribution of forecasts in the vicinity of zero, separating deflation and inflation, which can reduce forecast dispersion when inflation approaches zero.

[20] Figure A5 in the Appendix presents the cumulative density function.

We first document that cross-sectional disagreement is heterogeneous across the different categories of agents. While policymakers and professional forecasters exhibit low disagreement (with respective IQR of 1.05 and 1.30), firms and households are characterized by a stronger disagreement (with respective IQR of 2.94 and 4). As shown on Figure 3, the distribution of inflation expectations is flatter for these two categories of agents, which is also consistent with the larger spread between IQR and IDR for these two categories.[21] These comparisons across categories are robust to the normalization of disagreement by the level of the underlying variable forecasted, implying that this disagreement does not mechanically depend on the level of inflation. When computing the average forecast by date for each category, we are then able to document the disagreement across categories. Households' inflation forecasts are on average higher than that of firms and professional forecasters, while policymakers' inflation forecasts are the lowest. The average forecast by date also enables us to shed light on whether the overall disagreement for each category stems from the cross-sectional dispersion or from the volatility of inflation forecasts across time. The dispersion of the average forecast is thus much higher for firms than for the three other categories suggesting more volatile forecasts across time. However, this result seems driven by the longer sample considered for firms. Over a common sample, the dispersion of the average forecast of firms is lower (see Table A4 in the Appendix). The main result that the cross-sectional disagreement of households is larger than that of other categories holds.

Figure 3 - Distribution of inflation expectations



Note: These figures show the distribution of inflation forecasts for each dataset truncated at -5% and 15%, with the fraction that represents each bin on the y-axis. The blue line represents the normal density approximation.

[21] Note that Figure 3 reveals some specificities: firms are subject to threshold effects and professional forecasters and policymakers' forecasts exhibit distribution that are not fully symmetric.

The fact that firms and households disagree more is in line with Coibion et al. (2018). Nevertheless, our results put into perspective the findings of Link et al. (2021), according to whom firms' expectations are less dispersed than those of households and more closely aligned with expert forecasts: it seems that firms are further away from professional forecasters than professional forecasters are from policymakers. Moreover, we refine the result of Mankiw et al. (2004, p. 216), who show a "*correspondence between disagreement among policymakers and disagreement among professional economists*". While their study is based on the published range of FOMC forecasts, our results based on individual FOMC data confirm their findings.

5.2. Cross-sectional disagreement and inflation dynamics

We investigate whether disagreement is affected by inflation shocks. In this subsection, we compute for each category of agents the interquartile range for each date, labelled IQR_t. Contrary to equation (6), the measure of dispersion is computed for each date t, not over the whole sample of individual expectations. We then regress this measure of disagreement IQR_t on inflation shocks and control for the level of inflation to capture the potential mechanical link between the cross-sectional dispersion of forecasts and the level of the underlying variable:

$$IQR_t^{f(\pi)} = \alpha_2 + \beta_2 \epsilon_t^{\pi} + \beta_3 \pi_{t-1} + \eta_t \tag{8}$$

where ϵ_t^{π} is the estimated series of inflation shocks and β_2 (expected to be null under the assumption of no information frictions) and β_3 are the estimated coefficients. Equation (8) is estimated with OLS and heteroskedasticity-robust standard errors. The sample size N now corresponds to the time-series dimension of the sample for each category.

Table 5 presents the results from the estimation of equation (8) for all categories of agents.[22] Inflation shocks negatively and significantly affect disagreement for policymakers only. For the three other categories of agents, the inflation shock has no effect on cross-sectional disagreement. Tables A6, A8, A9, A10, and A4 in Appendix show that this finding is robust to considering respectively different forecasting horizons and fixed-event forecasts, IDR and SD as alternative measures of disagreement, controlling for the level of forecasts and considering a common time-sample for our four categories of agents.

Table 5 – Drivers of cross-sectional disagreement

	(1)	(2)	(3)	(4)
	SPF	FOMC	Livingston	Michigan
	IQR_t	IQR_t	IQR_t	IQR_t
Shocks	-0.009	-0.037**	-0.107	-0.009
	[-0.37]	[-2.14]	[-0.75]	[-0.14]
Level	0.180***	-0.026	0.341*	1.455***
	[6.57]	[-1.19]	[1.91]	[17.75]
Constant	0.492***	0.310***	1.029***	2.862***
	[10.50]	[5.77]	[5.67]	[31.23]
N	156	28	145	509
R2	0.28	0.18	0.07	0.55

Note: t-statistics in brackets. * p < 0.10, ** p < 0.05, *** p < 0.01. Parameters are estimated with Equation (6) using OLS. Inflation shocks are estimated based on a AR(1) model and the inflation level is introduced with a lag. The dependent variable is the IQR computed per period for each dataset.

[22] Table A7 in the Appendix provides a robustness check (to collinearity issues) of these findings when regressions are conducted separately for the CPI shock and the level of inflation.

We observe cross-sectional disagreement for all field categories of agents, which suggests the presence of information frictions for all categories. Firms and households seem to experience larger disagreement than policymakers and professional forecasters. In equation (8), β_1 is expected to be null under noisy information and positive under sticky information. Estimates in Table 5 appear to reject the prediction of the sticky information model, but would be consistent with the prediction of the noisy information model. The negative coefficient for policymakers is at odds with both theories. It looks like the inflation shocks act as an attention shock and instead reduce the cross-sectional disagreement among FOMC policymakers.

Looking at disagreement among forecasters who revise their forecasts allows us to evaluate further the empirical relevance of the sticky information model. Table 6 presents some relationships between the cross-sectional disagreement and the frequency of forecast revisions. The upper panel shows the mean of the cross-sectional disagreement by date conditional on whether individuals have revised or not their forecast, for each category. The bottom panel presents the correlation between the cross-sectional disagreement by date and the average frequency of forecast revisions by date.

Table 6 – Relation between disagreement and frequency of revisions

	SPF	FOMC	Livingston	Michigan
	IQR_t	IQR_t	IQR_t	IQR_t
If revised	0.78	0.27	1.36	4.02
If not	0.57	0.13	0.74	3.62
	Correlation disagreement & frequency of revision			
Corr w/updating	0.14	0.14	0.07	0.38

Table 6 shows that the cross-sectional disagreement is larger among individuals who revise their forecasts than among those who do not. This is true for all four categories of agents. This empirical feature goes against the prediction of the sticky information model and is consistent with the finding of Andrade et Le Bihan (2013) for professional forecasters. The positive correlation between the cross-sectional disagreement and the frequency of forecast revisions goes in the same direction, confirming the lack of empirical relevance of the sticky information model for professional forecasters, policymakers, firms and households.

6. External validity of experimental inflation expectations

To test the external validity of inflation forecasts formed by participants to experiments, we analyze both the frequency of forecast revisions and disagreement for this category of agents and compare them to those of field expectations. Table 7 synthetizes the empirical evidence about the frequency of forecast revisions and about the cross-sectional disagreement for participants to experiments.

The comparison between Table 2 and the left-part of Table 7 reveals that participants to laboratory experiments revise their forecasts frequently, with the same magnitude as firms and professional forecasters, but less than policymakers. Figure 4 presents the individual frequency of forecast revisions for participants to experiments and the distribution of inflation expectations.[23] Comparing Figure 4 to Figure 1, we observe that the distribution of the frequency of forecast revisions for participants to experiments has a shape that resembles that of professional forecasters and firms. Note that the frequency with which professional

[23] By construction, we cannot provide the frequency of inflation forecast revisions over time for experimental data.

forecasters revise their forecasts appears more dispersed than that of other categories of agents.

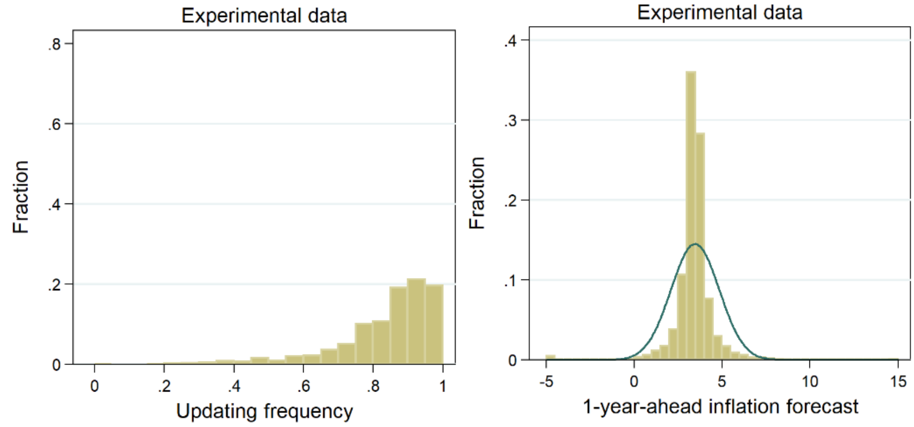
Table 7 – Evidence for laboratory experiments

Frequency of forecast revisions: P_i				**Disagreement: IQR_t**				
P_{Mean}	0.91	CondVar	0.189**	IQR	0.70	IQR_t if rev.	IQR_t if not	Corr IQR/P
P_{SD}	0.001		[2.02]	IDR	1.77	0.36	0.13	0.21
N	41 280	Level	0.013	SD	1.63	Shocks	-0.013	
Mean Rev.	1.06		[0.67]	Mean	3.45		[-0.40]	
SD Rev.	2.10	AME CondVar	0.028**	Median	3.43	Level	-0.015	
N_{Rev}	37 699	AME Level	0.002	IQR_N	0.20		[-0.33]	
Rev if Rev_{t-1}	0.93	N	40558	$Mean_{Avg}$	3.45	N	5882	
Rev if $NoRev_{t-1}$	0.71	Pseudo R2	0.08	IQR_{Avg}	0.63	R2	0.01	

The left-part of Table 7 also presents the results from the estimation of equation (4) for participants to experiments. Consistent with the noisy information model and in line with what is found for the four other categories of agents, the conditional variance of inflation significantly and positively affects the frequency of forecast revisions for participants to experiments. In terms of magnitude, the conditional variance of inflation has a larger effect on the frequency of forecast revisions for participants to experiments than for firms and households, but a smaller effect than for policymakers.

About the cross-sectional disagreement, comparing Table 4 and the right-part of Table 7, we observe that participants to experiments exhibit a disagreement in forming inflation expectations that is close to the one of policymakers and professional forecasters, showing low disagreement (the IQR for participants to experiment is 0.70 in Table 7, which compares more to the IQR for policymakers and professional forecasters (respectively: 1.05 and 1.30 in Table 4) than to that of firms and households). The right panel of Figure 4 also shows that the distribution of inflation expectations of participants to experiments is more consistent with that of policymakers and professional forecasters than with that of firms and households as depicted on Figure 3.

Figure 4 - Individual frequency of forecast revisions & Distribution of inflation expectations



Note: The left-hand side figure shows the distribution of the average, by individual, of his/her frequency of forecast revisions. The right-hand side figure shows the distribution of inflation forecasts at -5% and 15%, with the fraction that represents each bin on the y-axis. The blue line represents the normal density approximation.

The fact that experimental data do not well reproduce the forecasting behavior of firms and households/consumers could be surprising. Intuitively, laboratory participants outside of the laboratory seem similar to households. However, participants to the considered laboratory experiments are usually undergraduate students mainly studying economics and business (see Table A1 in Appendix), who thus have a higher level of education on these subjects than a representative survey. Instead, experimental expectations could be comparable to firms' expectations due to a relatively more comparable level of education. Nevertheless, the fact that the expectations of participants to experiments rather mimic the expectations of professional forecasters or policymakers may be due to the incentivized forecasting tasks (consistent with survey of professional forecasters' or policymakers' forecasting tasks, whose incentives to form accurate forecasts are either financial or reputational) and to the nature of the data generating process (the NK model) that frames the forecasts of participants to experiments and that central banks use themselves to understand the working of the economy.

The right-part of Table 7 also presents the results from the estimation of equation (8) for participants to experiments. As for the other categories of agents (except policymakers), the inflation shock does not significantly affect disagreement for participants to experiments, in contrast to the prediction of the sticky information model. Rejection of the sticky information model based on experimental data is also confirmed by the non-null cross-sectional disagreement conditional on forecast revision and the positive correlation between disagreement and the frequency of forecast revisions.

Overall, our results question the external validity of experimental inflation expectations. The reason why the behavior of participants to experiments seems more aligned with those of central bankers and professional forecasters might find its roots in the incentives (closely aligned with those of professional forecasters) participants to experiments are faced with, the salience of the information they receive and the NK data generating process. This study could be used by experimenters to design experiments that mimic real-world features. More precisely, experimenters should insure that when stating their expectations, participants to experiment reach, on average, the disagreement and forecast revision properties found on firms' data. Similarly, if they intend to reproduce the expectations of households, professional forecasters or central bankers, the properties found for each category using field data should be mimicked. This would help reproduce stylized facts in the laboratory as a precondition for simulating the impact of alternative policy measures. While we do not expect usual undergraduate student participants to experiments to achieve the same forecasting performance as highly qualified professional central bankers, a way to mimic their performance in the laboratory could be to provide an appropriate training to participants, in addition to providing the correct incentives. While simulating a macroeconomic environment that mimics real-world data is important for the external validity of experiments dealing with monetary policy issues, we have to acknowledge that using a pool of participants that resembles household or firms' decision makers is equally crucial in terms of external validity. This issue is however beyond the scope of the present paper.

7. Concluding remarks

Understanding the strength of information frictions in inflation expectations within and across different categories of economic agents is of particular importance for central banks whose aim is to manage inflation expectations. In this paper, we compare the frequency of inflation forecast revisions and disagreement in inflation expectations among five categories of agents: households, firms, professional forecasters, policymakers and participants to laboratory experiments. We have documented a heterogeneous frequency of forecast revisions across the five categories of agents, with policymakers revising more frequently than participants to experiments, firms and professional forecasters, who themselves revise much more frequently than households. Inflation shocks are found to be an important driver of forecast revision, suggesting that a shock on inflation plays the role of an attention shock. We have also provided evidence of disagreement among all categories of agents, although there is a strong heterogeneity across categories: while policymakers, professional forecasters and participants to experiments exhibit low disagreement, firms and households show strong disagreement. Inflation shocks play a key role on disagreement within all field categories, except for policymakers.

While a frictionless model would predict no disagreement and a continuous frequency of forecast revisions for all agents, we provide evidence of limited probability adjustment and disagreement, which plaids in favor of models of information friction. In terms of interpretation of our results, our paper allows us to shed light on the quantitative relevance of two theories of information friction. First, we reject the sticky information model, on the grounds that we find (i) a frequency of forecast revisions that evolves over time, (ii) this frequency is affected by the variance of inflation, (iii) disagreement among forecasters who update their forecast is non-null, and (iv) disagreement is not positively affected by inflation shocks. By contrast, these elements are compatible with the noisy information model, for which we find some elements in its favor, especially that the frequency of forecast revisions is affected by the conditional variance of inflation.

By considering five categories of agents, our paper gives a broader view on information frictions than the sole comparison between firms and households on which the literature recently focused. Avoiding the magnifying glass effect associated with the opposition between firms and households, we observe that there is more difference between firms and households on the one hand and policymakers, professional forecasters, and participants to experiments on the other, than between firms and households themselves.

We acknowledge the existence of other theories of inflation expectations formation, e.g. endogenous attention to inflation (i.e., agents update more and more precisely in times in which they perceive inflation to be important, or if communications from the central bank pushed them to update, see e.g. Fuster et al., 2020), subjective models (i.e., agents may observe shocks perfectly but have limited or selective understanding of how shocks propagate to inflation, see e.g. Andre et al., 2022), and learning (i.e., agents not only need to derive inflation from shocks but also need to know the structural parameters of the economy, see e.g. Evans and Honkapohja, 2012). The survey data considered in this paper do not allow to test for these alternative theories, as they neither measure attention, nor agents' knowledge of the data generating process or of the structure of the economy. The fact that we do not account for these theories might bias the comparison between sticky versus noisy information models. We leave to future research a quantitative comparison of these alternative theories owing to alternative surveys of inflation expectations.

Our results provide useful insights in terms of macroeconomic theory, survey design, external validity of macroeconomic experiments, and central bank communication. First, our results suggest some heterogeneity in information frictions across different field groups that has to be accounted for in macroeconomic models, as different categories of agents may respond to shocks, monetary policy or fiscal policy in a different manner. Moreover, it is particularly important to account for heterogeneity within categories of field agents in macroeconomic models, especially for households, but also professional forecasters. Second, the challenges we encountered in our attempt to compare different datasets of inflation expectations can serve as a basis to design surveys that allow to more properly test and quantify the two theories of information frictions we focused on in this paper. In particular, individuals should be interviewed repeatedly (at least more than twice), the inflation rate (rather than the CPI level) should be elicited directly, and decimal-point precision levels should be asked for. Finally, it is also important to harmonize the frequency at which surveys are conducted. Third, while crucial for laboratory experiments to be useful for policymakers, the issue of the external validity of experimental inflation expectations has not been much studied. Our results question this external validity: in terms of disagreement, the behavior of participants to experiments is closer to that of central bankers; in terms of frequency of forecast revisions, the behavior of participants to experiments is relatively close to that of professional forecasters or firms. Fourth, we can derive some policy prescriptions from our results, in terms of central bank communication. Indeed, which category of agents is more likely to be reached by central bank communication depends on the frequency of forecast revisions of each category. Those categories of agents whose frequency of forecast revisions reacts most to inflation dynamics are likely to respond more to communication about monetary policy. Since we find a strong disagreement within each category, the information released by the central bank may not reach all agents in the same manner. Targeted communication towards groups of economic agents presenting the same characteristics (e.g. for firms, in terms of size or sector) might represent a useful tool.

References

Adam K. (2007). "Experimental Evidence on the Persistence of Output and Inflation", *Economic Journal,* 117, 603-635.

Andrade, P., O. Coibion, E. Gautier and Y. Gorodnichenko (2022). “No Firm Is an Island? How Industry Conditions Shape Firms’ Expectations”, *Journal of Monetary Economics*, 125, 40-56.

Andrade P., R. Crump, S. Eusepi and E. Moench (2016). "Fundamental Disagreement", *Journal of Monetary Economics*, 83, 106-128.

Andrade P. and H. Le Bihan (2013). "Inattentive professional forecasters", *Journal of Monetary Economics,* 60(8), 967-982.

Andre P., C. Pizzinelli, C. Roth, and J. Wohlfart (2022). "Subjective Models of the Macroeconomy: Evidence from Experts and Representative Samples", *Review of Economic Studies*, forthcoming.

Angeletos G.-M., Z. Huo and K. Sastry (2021). "Imperfect Macroeconomic Expectations: Evidence and Theory", *NBER Macroeconomics Annual 2020*, 35(1), 1-86.

Angeletos G.-M. and C. Lian, (2016). "Incomplete Information in Macroeconomics: Accommodating Frictions in Coordination", *Handbook of Macroeconomics 2.*

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., 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.

Carlson J. and N. Valev (2003). "Sources of dispersion in consumer inflation forecasts", *Applied Economic Letters,* 10, 77-81.

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.

Carroll C.D. (2003). "Macroeconomic Expectations of Households and Professional Forecasters", *Quarterly Journal of Economics,* 118(1), 269-298.

Carroll C.D. (2006). “The epidemiology of macroeconomic expectations”, L. Blume, S. Durlauf (Eds.), The Economy as an Evolving Complex System. III, Oxford University Press.

Clements M. (2020). "Forecaster Efficiency, Accuracy and Disagreement: Evidence using Individual-Level Survey Data", *Journal of Money, Credit and Banking*, forthcoming.

Clements M. (2021). "Rounding behaviour of professional macro-forecasters", *International Journal of Forecasting*, forthcoming.

Coibion O. and Y. Gorodnichenko (2012). "What Can Survey Forecasts Tell Us About Informational Rigidities?", *Journal of Political Economy,* 120(1), 116-159.

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, S. Kumar and J. Ryngaert (2021). "Do You Know That I Know That You Know...? Higher-order Beliefs in Survey Data", *Quarterly Journal of Economics*, 136, 1387–1446.

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

Cornand C. and F. Heinemann (2019). "Experiments on macroeconomics: methods and applications", in *Handbook of Research Methods and Applications in Experimental Economics*, A. Schram and A. Ule (eds.), Edward Elgar Publishing, 269-294.

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 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.

Cukierman A. and P. Wachtel (1979). "Differential inflationary expectations and the variability of the rate of inflation: theory and evidence", *American Economic Review,* 69, 595-609.

Dovern, J., U. Fritsche and J. Slacalek (2012). "Disagreement among Forecasters in G7 Countries", *Review of Economics and Statistics*, 94, 1081–96.

Duffy J. (2008). "Experimental Macroeconomics", in S. Durlauf and L. Blume (Eds.), *New Palgrave Dictionary of Economics*, 2nd Ed., New York: Palgrave Macmillan.

Duffy J. (2016). "Macroeconomics: A Survey of Laboratory Research", in J. Kagel and A. Roth (eds.), *Handbook of Experimental Economics* 2, Princeton University Press, 1-90.

Evans, G., and S. Honkapohja (2012). *Learning and Expectations in Macroeconomics* (Princeton and Oxford: Princeton University Press).

Fuster, A., R. Perez-Truglia, M. Wiederholt and B. Zafar (2020), "Expectations with Endogenous Information Acquisition: An Experimental Investigation", *Review of Economics and Statistics*, forthcoming.

Hommes C. (2011). "The Heterogeneous Expectations Hypothesis: Some Evidence from the Lab", *Journal of Economic Dynamics and Control*, 35(1), 1-24.

Hommes C. (2021). "Behavioral and Experimental Macroeconomics and Policy Analysis: A Complex Systems Approach", *Journal of Economic Literature,* 59(1), 149-219.

Hommes C., D. Massaro and M. Weber (2019). "Monetary Policy under Behavioral Expectations: Theory and Experiment", *European Economic Review,* 118, 193-212.

Kryvtsov O. and L. Petersen (2021). "Central Bank Communication That Works: Lessons from Lab Experiments", *Journal of Monetary Economics,* 117, 760-780.

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

Mankiw G. and R. Reis (2002). "Sticky information versus sticky prices: A proposal to replace the new Keynesian Phillips curve", *Quarterly Journal of Economics,* 117(4), 1295-328.

Mackowiak B. and M. Wiederholt (2009). "Optimal Sticky Prices under Rational Inattention", *American Economic Review,* 99(3), 769-803.

Mankiw G., R. Reis, and J. Wolfers (2004). "Disagreement about Inflation Expectations", in *NBER Macroeconomics Annual 2003*, M. Gertler and K. Rogoff (eds.), 209-248, Cambridge, MA: MIT Press.

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

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

Savignac F., E. Gautier, Y. Gorodnichenko and O. Coibion (2021). "Firms' Inflation Expectations: New Evidence from France", *NBER WP* 29376, *WP BDF* 840.

Sims C. (2003). "Implications of rational inattention", *Journal of Monetary Economics,* 50, 665-90.

Souleles N. (2004). "Expectations, heterogeneous forecast errors, and consumption: micro evidence from the Michigan Consumer Sentiment Surveys", *Journal of Money, Credit and Banking,* 36, 39-72.

Appendix

A. Experimental designs

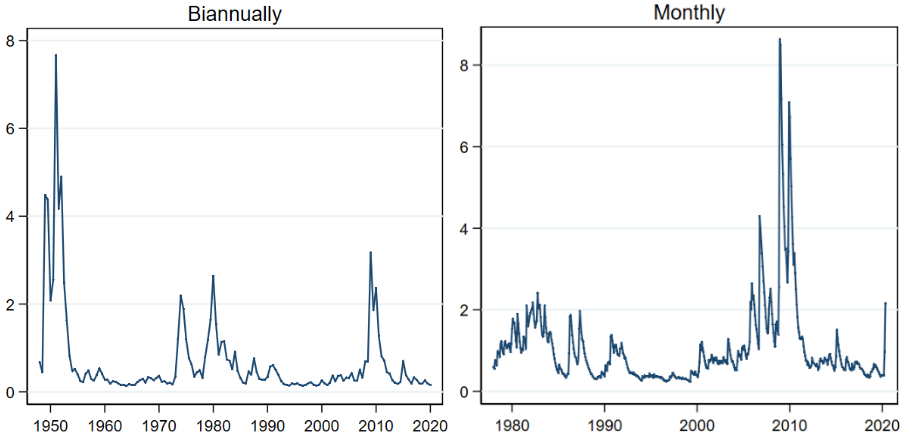
Table A1 summarizes the experimental designs of the five considered experimental papers, in terms of data-generating processes, tasks of participants, incentives, information sets and characteristics of participants.

Table A1 - Characteristics of experimental designs

	Data generating process: Model	Data generating process: Output gap expectations	Data generating process: Shocks	Participants' task	Incentives in ECU, F: absolute forecast error	Information set at date t: history of variables up to period t-1	Participants: undergraduate students
PZ	Qualitative description of the same NK model structure with relatively standard and comparable parameter values	Pre-programmed naïve	AR-1 process	Inflation forecasts in t for t+1	$max\left\{\frac{100}{1+F} - 20, 0\right\}$	Inflation, Output gap, Interest rate, profits from forecasts	Group size: 9 Majors: economics, business
CMa			iid distributions variances may differ		$max\left\{\frac{160}{1+F} - 40, 0\right\}$	In most treatments, information about the inflation target	Group size: 6 Majors: economics, business
CMb							Group size: 6 Majors: engineering, business
HMW		Part of participants' task		Inflation and output gap forecasts in t for t+1	$\frac{100}{1+F}$		Group size: 6 Majors: economics, business
Petersen					$0.3(e^{-0.01\,F} + e^{-0.01\,FX})$, where FX is the absolute output gap forecast error	Information on forecast error, Period t's interest rate and shock to the natural rate of interest, Expected shock size in t+1	Group size: 9 Students and non-students.

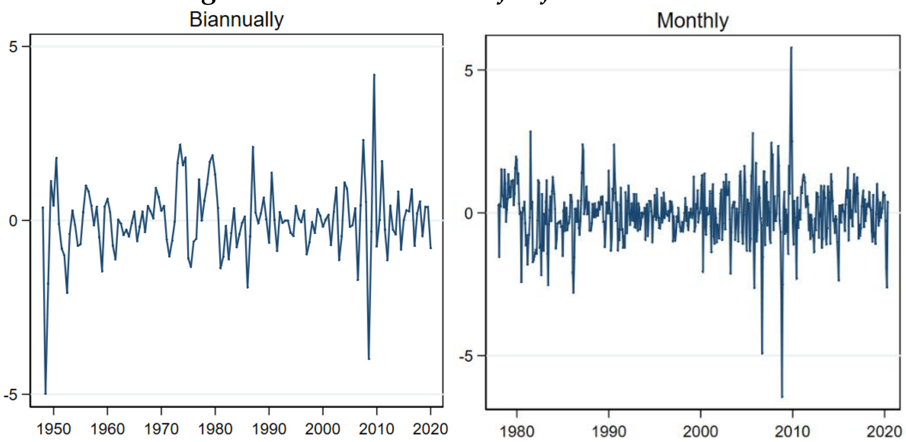
B. Further evidence

Figure A1 – Time series of the conditional variance of inflation



Note: The conditional variance of inflation is estimated based on a GARCH(1,1) model for each frequency.

Figure A2 – Time series of inflation shocks



Note: Inflation shocks are estimated based on a AR(1) model.

Table A2 – Rounding inflation forecasts to integer values

	(1)	(2)	(3)	(4)	(5)	(6)
	P_{Mean}	P_{SD}	N	Mean Rev.	SD Rev.	N_{Rev}
SPF	0.29	0.007	4 089	1.28	0.82	1 204
FOMC	0.24	0.021	421	1.08	0.27	101
Livingston	0.61	0.006	5 751	2.12	2.07	3 521
Michigan	0.75	0.001	91 390	4.58	5.44	68 500
Experiments	0.44	0.002	41 280	2.08	2.72	17 993

Note: These statistics are computed over the subsample N for which we observe 2 consecutive forecasts of a same individual for each of the five datasets. The P_{Mean} is the average frequency of revisions for each dataset. The P_{SD} is the standard deviation of the frequency of revisions. The Mean Rev. is the average magnitude of the revision for individuals who revised their forecasts (the subsample N_{Rev}) while the SD Rev. is the standard deviation of the magnitude of these revisions.

Table A3 – Alternative forecasts: Descriptive statistics about frequency of forecast revisions

		P_{Mean}	P_{SD}	N	Mean Rev.	SD Rev.	N_{Rev}
SPF	Fixed event	0.85	0.006	3 265	0.39	0.56	2 774
FOMC	Current year	0.84	0.015	643	0.47	0.34	538
FOMC	Next year	0.76	0.034	158	0.32	0.26	118
Livingston	Fixed event	0.91	0.006	2 238	0.76	1.00	2 044
Livingston	No rounding	0.98	0.002	5 751	1.34	1.88	5 637
Michigan	Lag forecast	0.71	0.013	1 274	5.02	5.90	909

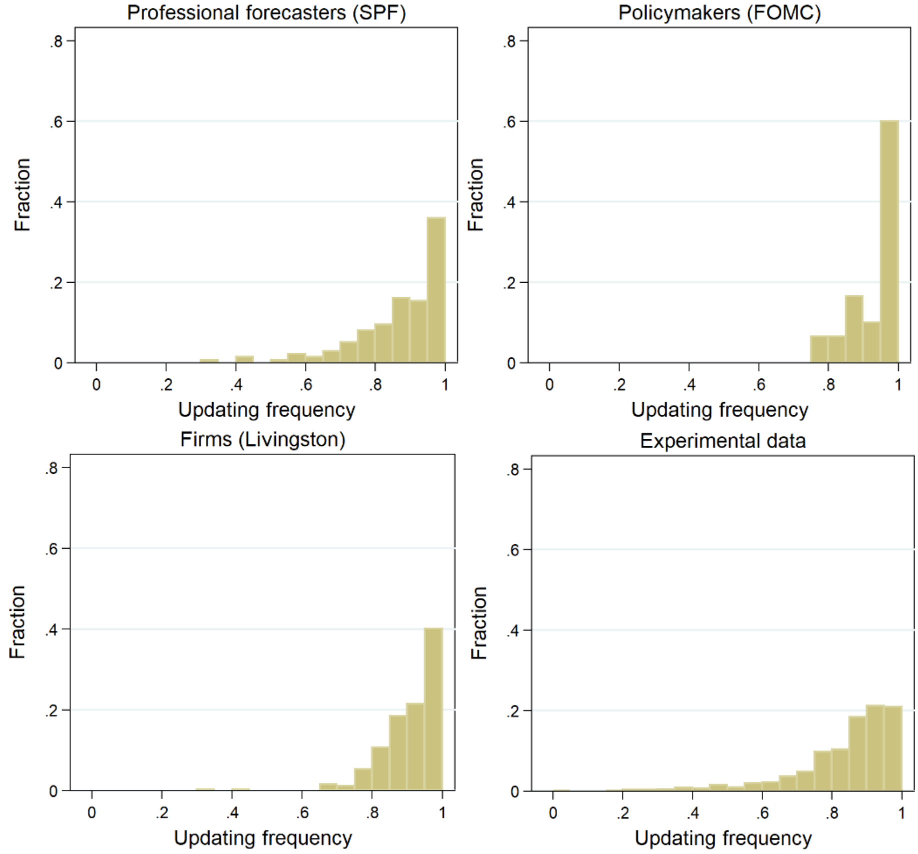
Note: These statistics are computed over the subsample N for which we observe 2 consecutive forecasts of a same individual for each of the five datasets. The P_{Mean} is the average frequency of revisions for each dataset. The P_{SD} is the standard deviation of the frequency of revisions. The Mean Rev. is the average magnitude of the revision for individuals who revised their forecasts (the subsample N_{Rev}) while the SD Rev. is the standard deviation of the magnitude of these revisions.

Table A4 - Common sample period: 1992-2009

	(1)	(2)	(3)	(4)
	Updating - Descriptive statistics			
	P_{Mean}	P_{SD}	Mean Rev.	Rev if Rev_{t-1}
SPF	0.86	0.008	0.46	0.89
FOMC	0.94	0.012	0.39	0.96
Livingston	0.91	0.008	0.85	0.92
Michigan	0.74	0.002	4.20	.
	Updating drivers			
	SPF	FOMC	Livingston	Michigan
	P_i	P_i	P_i	P_i
CondVar	0.099**	0.533***	-0.145	0.035***
	[2.22]	[2.89]	[-1.36]	[6.07]
Level	0.012	-0.041	-0.174	-0.008
	[0.17]	[-0.54]	[-1.12]	[-0.40]
AME CondVar	0.021**	0.063***	-0.023	0.011***
AME Level	0.003	-0.005	-0.027	-0.003
N	2019	421	1107	37886
Pseudo R2	0.01	0.06	0.00	0.00
	Disagreement - Descriptive statistics			
	IQR	Mean	IQR_N	IQR_{Avg}
SPF	0.90	2.65	0.34	0.75
FOMC	1.05	2.15	0.49	1.20
Livingston	1.18	2.74	0.43	0.81
Michigan	4.00	3.46	1.16	0.89
	Disagreement drivers			
	SPF	FOMC	Livingston	Michigan
	IQR_t	IQR_t	IQR_t	IQR_t
Shocks	-0.024	-0.037**	-0.017	0.013
	[-0.80]	[-2.14]	[-0.48]	[0.19]
Level	-0.032	-0.026	-0.03	-0.320
	[-0.40]	[-1.19]	[-0.25]	[-1.53]
N	72	28	36	216
R2	0.02	0.18	0.01	0.02

Note: t-statistics in brackets. * p < 0.10, ** p < 0.05, *** p < 0.01. Parameters are estimated with Equation (6) using OLS. The estimation is performed on common sample for all datasets, from 1992m1 to 2009m11. The conditional variance of inflation is estimated based on a GARCH(1,1) model, inflation shocks are estimated based on a AR(1) model and the inflation level is introduced with a lag. The dependent variable is the IQR computed per period for each dataset.

Figure A3 – Individual frequency of forecast revisions - Individuals observed 5 times or more



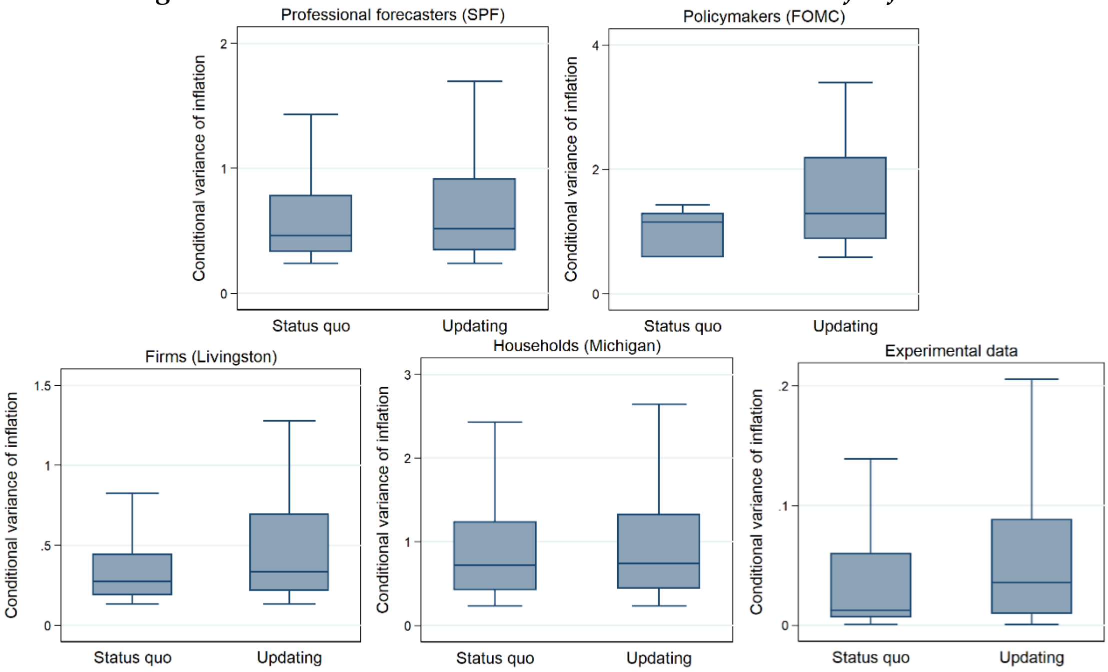
Note: These subfigures show the distribution of the average, by individual, of his/her frequency of forecast revisions, for individuals observed 5 times or more

Table A5 - Estimation of equation (4) for each covariate separately

	SPF		FOMC		Livingston		Michigan		Experiments	
	P_i	P_i	P_i	P_i	P_i	P_i	P_i	P_i	P_i	P_i
CondVar	0.096***		0.552**		0.126***		0.032***		0.182**	
	[3.17]		[2.34]		[3.67]		[7.11]		[2.06]	
Level		-0.028		-0.107***		0.414***		0.072***		0.013
		[-0.96]		[-3.48]		[11.45]		[10.12]		[1.19]
Constant	1.163***	1.153***	1.092***	2.019***	1.234***	0.905***	0.639***	0.601***	1.585***	1.608***
	[45.70]	[45.40]	[3.61]	[13.46]	[41.47]	[23.28]	[98.12]	[71.89]	[43.45]	[44.66]
N	4089	4089	241	241	5751	5751	91390	91390	41278	40559
Pseudo R2	0.00	0.00	0.07	0.01	0.01	0.05	0.00	0.00	0.08	0.08

Note: t-statistics in brackets. * p < 0.10, ** p < 0.05, *** p < 0.01. Parameters are estimated with a reduced version of Equation (8) using a probit model. The conditional variance of inflation is estimated based on a GARCH(1,1) model and the inflation level is introduced with a lag. The dependent variable is a dummy variable that takes the value 1 when a given individual revise his/her forecasts.

Figure A4 - Forecast revision & Conditional variance of inflation



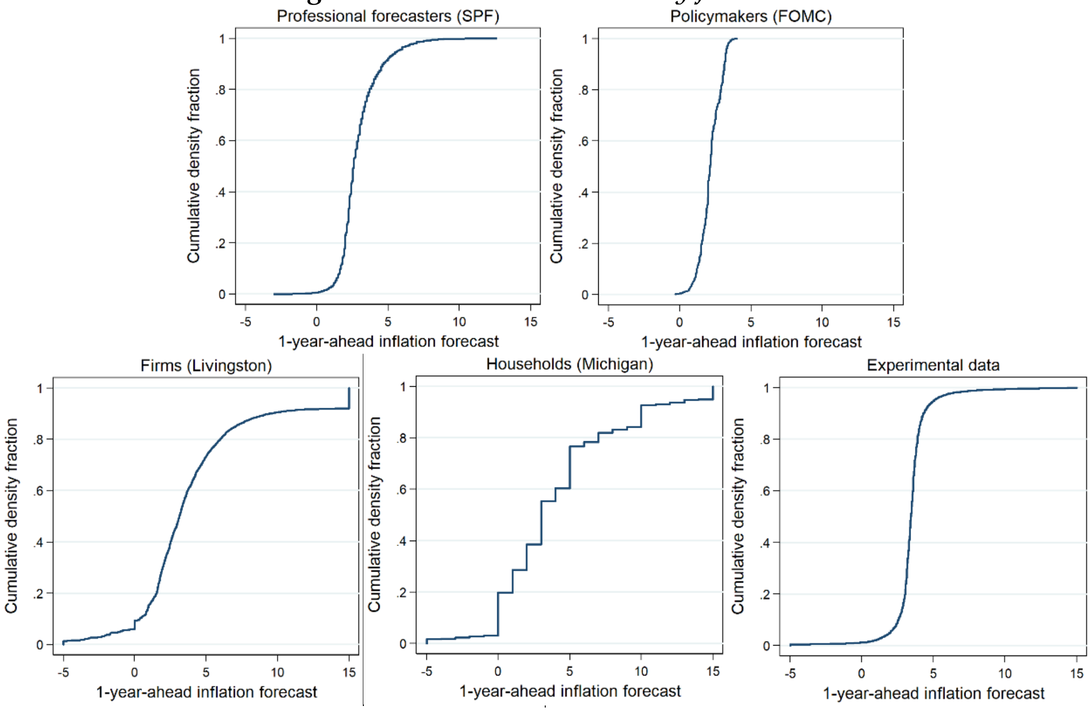
Note: These boxplot figures show the distribution of the conditional variance of inflation when individuals revise or not their inflation forecasts.

Table A6 – Alternative forecasts: Descriptive statistics about disagreement

		IQR	IDR	SD	Mean	Median	IQR_N
SPF	Fixed event	1.20	2.90	1.37	2.88	2.54	0.42
FOMC	Current year	1.25	2.00	0.81	2.27	2.25	0.55
FOMC	Next year	0.80	1.70	0.66	2.09	2.00	0.38
Livingston	Fixed event	2.09	4.65	2.05	3.54	2.97	0.59
Michigan	Lag forecast	5.00	18.00	26.25	10.70	3.00	0.47

Note: These statistics are computed over the full sample for each of the five datasets. The IQR is the Inter Quantile Ratio. The IDR is the Inter Decile Ratio, the distance between the 90th and 10th percentiles. The SD is the standard deviation. The IQR_N is a normalized IQR by the level of inflation forecasts and corresponds to the ratio of the IQR divided by the mean.

Figure A5 - Cumulative density function



Note: These figures show the cumulative density function of all individual inflation forecasts for each dataset.

Table A7 – Estimation of equation (8) for each covariate separately

	SPF		FOMC		Livingston		Michigan		Experiments	
	IQR_t	IQR_t	IQR_t	IQR_t	IQR_t	IQR_t	IQR_t	IQR_t	IQR_t	IQR_t
Shocks	-0.050*		-0.029*		-0.114		-0.046		-0.013	
	[-1.98]		[-1.86]		[-0.74]		[-0.51]		[-0.40]	
Level		0.182***		-0.016		0.343*		1.455***		-0.015
		[6.86]		[-0.68]		[1.93]		[17.72]		[-0.33]
Constant	0.770***	0.488***	0.256***	0.283***	1.427***	1.027***	4.493***	2.862***	0.398***	0.400***
	[31.12]	[10.85]	[12.93]	[5.37]	[12.59]	[5.72]	[58.02]	[31.22]	[27.58]	[26.29]
N	156	156	28	28	145	145	509	509	5882	5882
R2	0.02	0.28	0.10	0.03	0.01	0.06	0.00	0.55	0.01	0.01

Note: t-statistics in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Parameters are estimated with a reduced version of Equation (6) using OLS. Inflation shocks are estimated based on a AR(1) model and the inflation level is introduced with a lag. The dependent variable is the IQR computed per period for each dataset.

Table A8 - IDR measure as a dependent variable in equation (8)

	(1)	(2)	(3)	(4)	(5)
	SPF	FOMC	Livingston	Michigan	Experiments
	IDR_t	IDR_t	IDR_t	IDR_t	IDR_t
Shocks	0.017	-0.026	-0.209	0.226*	0.071
	[0.22]	[-0.86]	[-0.80]	[1.72]	[0.63]
Level	0.610***	-0.071	0.915***	2.778***	-0.07
	[3.08]	[-1.65]	[3.64]	[19.80]	[-0.59]
Constant	0.799***	0.745***	2.093***	6.489***	2.948***
	[2.86]	[7.01]	[6.74]	[34.23]	[8.30]
N	156	28	145	509	5882
R2	0.31	0.16	0.16	0.59	0.05

Note: t-statistics in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Parameters are estimated with Equation (6) using OLS. Inflation shocks are estimated based on a AR(1) model and the inflation level is introduced with a lag. The dependent variable is the IDR computed per period for each dataset.

Table A9 – SD measure as a dependent variable in equation (8)

	(1)	(2)	(3)	(4)	(5)
	SPF	FOMC	Livingston	Michigan	Experiments
	SD_t	SD_t	SD_t	SD_t	SD_t
Shocks	0.019	-0.010	-0.008	0.010	0.024
	[0.70]	[-0.93]	[-0.08]	[0.18]	[0.64]
Level	0.228***	-0.022	0.464***	1.633***	-0.026
	[4.58]	[-1.32]	[4.67]	[30.29]	[-0.67]
Constant	0.398***	0.270***	0.969***	3.342***	0.955***
	[5.21]	[6.45]	[7.49]	[37.46]	[8.19]
N	156	28	145	509	5882
R2	0.31	0.10	0.21	0.57	0.04

Note: t-statistics in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Parameters are estimated with Equation (6) using OLS. Inflation shocks are estimated based on a AR(1) model and the inflation level is introduced with a lag. The dependent variable is the SD computed per period for each dataset.

Table A10 – Controlling for the level of forecasts in equation (8)

	(1)	(2)	(3)	(4)	(5)
	SPF	FOMC	Livingston	Michigan	Experiments
	IQR_t	IQR_t	IQR_t	IQR_t	IQR_t
Shocks	-0.033	-0.031**	-0.003	-0.228***	-0.012
	[-1.59]	[-2.19]	[-0.02]	[-3.03]	[-0.35]
Forecast Level	0.164***	-0.060*	-0.185*	0.687***	-0.002
	[9.60]	[-1.85]	[-1.80]	[15.31]	[-0.09]
Constant	0.265***	0.385***	1.972***	1.617***	0.405***
	[5.31]	[4.75]	[5.15]	[9.59]	[5.03]
N	156	28	145	509	5882
R2	0.42	0.25	0.11	0.46	0.01

Note: t-statistics in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Parameters are estimated with Equation (6) using OLS. Inflation shocks are estimated based on a AR(1) model and the forecast level is introduced with a lag. The dependent variable is the IQR computed per period for each dataset.