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* Views expressed are those of the author and do not necessarily reflect official positions of De Nederlandsche Bank.

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Who's on FIRE?
Household characteristics and the formation of inflation expectations*

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We study how consumers form and revise inflation expectations using a unique, highly balanced monthly panel of Dutch households. We develop a Bayesian framework that nests Full-Information Rational Expectations (FIRE) alongside common forecasting heuristics and test it by recovering person-specific belief-updating rules from individual time-series regressions. Our novel individual-level design reveals substantial heterogeneity in how households process information over time. On average, consumers systematically overreact to current inflation, echoing patterns found for professional forecasters. Only 2.5 percent, predominantly wealthier, more educated men, behave consistently with FIRE. Most consumers rely on simple heuristics, especially adaptive expectations. Our results show that heuristic learning, not FIRE, characterizes expectation formation for the vast majority of households. Crucially, heterogeneity in belief updating is both large and systematic.

JEL Codes E31, E37, E70.
Keywords Household Inflation Expectations, FIRE, Heuristic Learning.

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1 Introduction

Household inflation expectations are central to understanding how individuals perceive real returns, make asset allocation decisions, and interpret nominal shocks. They influence key economic behaviors, including consumption, saving, investment, and portfolio choices (D'Acunto & Weber 2024), and thereby shape both monetary policy transmission (D'Acunto et al. 2024) and asset pricing (Vissing-Jorgensen 2003, Malmendier & Nagel 2016, Leombroni et al. 2020, Schnorpfeil et al. 2025). Their relevance has become particularly salient in the recent period of elevated inflation, during which households' information processing and belief formation play an even larger role.

A large literature documents that household inflation expectations differ markedly from the *Full Information Rational Expectations* (FIRE) benchmark. Surveys consistently reveal persistent heterogeneity and disagreement among consumers (Mankiw et al. 2004, Carroll 2003), with expectations that are right-skewed, sensitive to personal experience, and slow to adjust (Bachmann et al. 2015, Weber et al. 2022, D'Acunto et al. 2023). Beyond these distributional patterns, research has also highlighted systematic deviations in belief updating. At the aggregate level, forecast errors tend to rise with past forecast revisions, implying that expectations underreact to new information (Coibion & Gorodnichenko 2015). By contrast, individual forecasters frequently overreact to their own past revisions, especially for inflation (Bordalo et al. 2020). Additional evidence shows state-dependent attention: aggregate forecast errors co-move positively with actual inflation and unemployment, suggesting overreaction to salient macroeconomic conditions (Kohlhas & Walther 2021). These patterns are consistent with broader evidence on imperfect and state-dependent updating, including sluggish forecast adjustment followed by overshooting (Angeletos et al. 2021) and systematic biases arising from overconfidence in private signals (Adam et al. 2025).

Despite extensive evidence on the cross-sectional distribution of household inflation expectations and on the average time-series updating behavior of consumers, much less is known about how belief updating varies by consumer type. Randomized control trials (RCTs) provide valuable causal insights into how consumers respond to specific information (Armantier et al. 2016, Coibion et al. 2022, Coibion, Georgarakos, Gorodnichenko & Weber 2023, Haaland et al. 2023, Coibion & Gorodnichenko 2025), but by design they eliminate inattention and typically rely on single survey waves, offering limited guidance on how individuals update expectations in real time or how they evolve with macroeconomic conditions. Reduced-form approaches to studying systematic over- and underreaction (Bordalo et al.

2020, Angeletos et al. 2021, Kohlhas & Walther 2021, Chen et al. 2022, Broer & Kohlhas 2024, Adam et al. 2025, Gemmi & Valchev 2025) usually impose a common updating coefficient across agents, preventing an assessment of heterogeneity in belief formation. We address these gaps by estimating *person-specific* belief-updating dynamics, running separate time-series regressions for each respondent to recover individual sensitivities to past inflation and past forecasts. This design relaxes the usual homogeneity assumption and allows us to classify forecasting behavior at the consumer level.

Our analysis exploits the unique features of the DNB Household Survey (DHS) conducted in the Netherlands. Since December 2019, DHS respondents have been asked monthly to provide one-year-ahead inflation forecasts, yielding rich longitudinal microdata. Unlike other major surveys such as the Michigan Survey of Consumers or the New York Fed Survey of Consumer Expectations in the United States, or the ECB's Consumer Expectations Survey in the euro area, the DHS contains a highly balanced panel covering an extended period: 1,773 respondents participate for more than 36 consecutive months. Respondents are randomly assigned either to national (Dutch) or euro area inflation questions, and half of the sample receives regular information on the ECB's inflation target and recently realized inflation. This design allows us to study how information provision and the reference area shape forecasting rules. Moreover, the sample period spans both the pre-pandemic low-inflation regime and the sharp inflation surge during and after the Covid-19 pandemic, providing sufficient variation in inflation in our regressions. Covering the high inflation environment is important, as expectations matter most when inflation is high (Moessner 2024), attention increases (Link et al. 2024, Pfäuti 2023, Weber et al. 2025), information acquisition increases (Mikosch et al. 2024), and expectations behave differently than in low-inflation periods (Granziera et al. 2025).

To organize our empirical analysis, we embed all forecasting rules within a simple Bayesian updating framework. We assume inflation follows a stationary first-order autoregressive process, and households observe current inflation with noise. FIRE arises when agents possess complete information about the process and update rationally; noisy-information, sticky-information, and rational-inattention models (Woodford 2003, Carroll 2003, Sims 2003) correspond to rational but partial-information departures from FIRE. As shown by Coibion & Gorodnichenko (2015), these "noisy rational" models can be represented with a common reduced-form Bayesian updating parametrization, enabling direct tests for unbiasedness and efficiency at the individual level. Departures from FIRE may also re-

sult from model misperceptions or simplified forecasting rules. We focus on four prominent heuristic models (Pesaran & Weale 2006):

i A static model, **naive expectations**, where agents' inflation forecasts are given by the current realization (Lakonishok et al. 1994, Keynes 1937). In our framework, this implies that agents over-extrapolate from the signal they receive relative to their prior.

ii **Adaptive expectations**, where agents form a weighted average of the current realization and a previous forecast of the current period (Nerlove 1958, Sargent 1993). Agents thus update according to a Kalman filter, assuming inflation is fully persistent.

iii **Mean-reverting expectations**, which are given by a weighted average of current and lagged inflation realizations. In the framework, this arises if agents receive an additional signal about past values of inflation, and thus ignore their previous forecast.

iv **Fundamentalist** agents, who choose a constant anchor for inflation and ignore all new information. Thus, they perceive inflation to be constant and disregard all signals. Fundamentalists can have expectations anchored at an inflation target, although this does not need to be the case.

In our empirical analysis of forecasting behavior we provide results first at the aggregate level, and secondly at the individual level. We find that on average, individual consumers are overreacting to current inflation levels, a result that is consistent with the literature on professional forecaster, household and firm expectations but rejects the assumptions of FIRE on average (Born et al. 2025). Further, we find that consumers on average rely on current realizations of inflation, their own previous forecast and lagged realizations in equal parts when forming their predictions over the next 12 months. They do so in a way that is not substantially different from professional forecasters, and the coefficients yield a parametrization of our model that is close to the true model parameters under noisy information as estimated by a simple back-of-the-envelope calculation. However, these aggregate results hide a substantial heterogeneity in forecasting behavior.

When examining individual respondents, we find that only 2.5% of the sample follow 'Full Information Rational Expectations' (FIRE) or are consistent with data observations. These individuals are predominantly wealthier, highly educated men. This aligns with existing research showing upward biases in inflation expectations among women, lower-income, and less-educated individuals (D'Acunto, Malmendier & Weber 2021, D'Acunto et al. 2019,

Reiche 2025, Piccolo et al. 2025). We then explore alternative forecasting rules and find that the most prevalent are adaptive expectations with a positive inflation anchor (24%), mean-reverting with a positive inflation anchor (19%) and a fundamentalist rule (18%). Agents using adaptive expectations place less weight on their own past forecasts and more on current inflation, while mean-reverting types place more weight on past inflation than on current inflation. We confirm anchoring at the 2% inflation level for less than 1% of fundamentalists, a finding consistent with our sample period covering the high inflation period post-pandemic. Respondents that make use of these heuristics are more frequently female, have lower education and earn lower incomes. For approximately 50% of respondents, we cannot identify a simple heuristic, although we also reject FIRE for them. Aside from FIRE and data-consistent forecasts, these individuals tend to have the most accurate forecasts, possibly due to reliance on more forward looking behavior, unobserved heuristics, switching strategies, or the use of alternative information.

This paper is structured as follows. Section 2 introduces the Bayesian framework that nests the forecasting types; Section 3 describes the important features of the survey; Section 4 tests for FIRE and forecaster heuristics at the aggregate level, and Section 5 computes the same test at the individual level. Section 6 concludes.

2 Framework

We employ a simple Bayesian learning framework to illustrate how FIRE and alternative forecast heuristics shape individual-level inflation expectations. A representative agent at time t is asked to forecast inflation k periods ahead, denoted π_{t+k}. Inflation is assumed to follow a stationary AR(1) process,[1]

$$\pi_{t+1} = \mu + \rho\pi_t + u_{t+1}, \qquad u_t \sim \mathcal{N}(0, \sigma_u^2),\ \rho \in (0,1),$$

but agents do not observe the true current inflation rate. Instead, each agent i receives a noisy private[2] signal

$$s_{i,t} = \pi_t + \epsilon_{i,t}, \qquad \epsilon_{i,t} \sim iid.\ \mathcal{N}(0, \sigma_\epsilon^2).$$

[1] While this is a simplifying assumption standard in models of expectation formation, there is also empirical support for AR(1) dynamics in inflation Giacomini & Levin (2023).

[2] We assume that there are no strategic incentives in forecasting- unlike for professional forecasters (Gemmi & Valchev 2025, Broer & Kohlhas 2024)- and the private signal is just the true inflation plus noise.

The agent's forecast follows a *Recursive Forecast Equation*, which generalizes the Kalman filter. The idea is that when forming expectations, agents combine their prior belief about current inflation (formed at time $t-1$, denoted $f_{i,t-1}(\pi_t)$) with the new information contained in the signal $s_{i,t}$. Two parameters govern how this combination occurs. The parameter $\lambda \in [0,1]$ determines how strongly the agent relies on the prior forecast of inflation, while the gain parameter g measures how responsive the agent is to the new signal relative to the prior. Higher values of g imply that new information is given substantial weight, whereas lower values imply a sluggish adjustment in which past beliefs matter more.

Given these assumptions, the agent's forecast after observing $s_{i,t}$ is

$$\begin{aligned} f_{i,t}(\pi_{t+k}) &= \sum_{j=0}^{k} \rho^j \mu + \rho^k \left[\lambda f_{i,t-1}(\pi_t) + g(s_{i,t} - \lambda f_{i,t-1}(\pi_t))\right] \\ &= \sum_{j=0}^{k} \rho^j \mu + \rho^k \lambda (1-g) f_{i,t-1}(\pi_t) + \rho^k g \pi_t + \rho^k g \epsilon_{i,t} \\ &= \sum_{j=0}^{k} \rho^j \mu + \rho \lambda (1-g) f_{i,t-1}(\pi_{t+k-1}) + \rho^k g \pi_t + \rho^k g \epsilon_{i,t}. \end{aligned}$$

The first term on the right hand side, $\sum_{j=0}^{k} \rho^j \mu$, represents the deterministic component implied by the AR(1) process. The remaining terms describe how the agent forms a belief about current inflation, which is then projected k periods into the future. These terms correspond respectively to the persistence of past beliefs, the adjustment toward the true current inflation rate, and the influence of noise in the signal. The expression is recursive because yesterday's forecast of the current period (unobserved in the data) is linked to yesterday's (k)-step-ahead forecast (measured) through the identity

$$f_{i,t-1}(\pi_t) = \frac{1}{\rho^{k-1}} f_{i,t-1}(\pi_{t+k-1}).$$

Hence, past expectations enter the forecast only insofar as they inform the agent's belief about current inflation.

We also consider a second information environment in which the agent receives accurate and costless information about lagged inflation, as in one of our survey treatments. In this case the signal vector is $(s_{i,t}, y_t)$, where $y_t = \pi_{t-1}$. Observing π_{t-1} perfectly implies that the prior for current inflation need not rely on lagged expectations; instead, it is given

by the model-implied projection. Intuitively, having access to the true value of π_{t-1} removes the need to substitute the agent's own past forecast (Bordalo et al. 2020). Applying the same recursive rule then yields

$$\begin{aligned} f_{i,t}(\pi_{t+k}) &= \sum_{j=0}^{k} \rho^j \mu + \rho^k \left[\lambda\rho\pi_{t-1} + g(s_{i,t} - \lambda\rho\pi_{t-1})\right] \\ &= \sum_{j=0}^{k} \rho^j \mu + \rho^{k+1}\lambda(1-g)\pi_{t-1} + \rho^k g\pi_t + \rho^k g\epsilon_{i,t}. \end{aligned}$$

Combining the two informational environments gives the general form of the agent's forecast:

$$f_{i,t}(\pi_{t+k}) = \underbrace{\sum_{j=0}^{k} \rho^j \mu}_{\beta_0} + \underbrace{\rho\lambda(1-g)}_{\beta_1}(1-\mathbb{I}_i) f_{i,t-1}(\pi_{t+k-1}) + \underbrace{\rho^k g}_{\beta_2}\pi_t + \underbrace{\rho^{k+1}\lambda(1-g)}_{\beta_3}\mathbb{I}_i\pi_{t-1} + \rho^k g\epsilon_{i,t}, \tag{1}$$

where $\mathbb{I}_i = 1$ if agent i receives information about lagged inflation and $\mathbb{I}_i = 0$ otherwise. When $\mathbb{I}_i = 0$, the agent's forecast depends on her past forecast, and β_1 captures the persistence of beliefs. When $\mathbb{I}_i = 1$, the agent instead conditions on the true value of π_{t-1}, and β_3 captures how this information feeds into the forecast. Correspondingly, β_1 is identified only for observations with $\mathbb{I}_i = 0$, and β_3 only for those with $\mathbb{I}_i = 1$.

Equation 1 nests different forecasting types. Under rational expectations, the parameters of the model are known, and agents' forecasts are equal to their conditional expectations: $f_{i,t}(\pi_{t+k}) = \mathbb{E}[\pi_{t+k}|s_{i,t}]$. Hence, the gain parameter is given by the Kalman filter, $g = \frac{\sigma_u^2}{\sigma_\epsilon^2+\sigma_u^2}$ and $\lambda = 1$. The most restrictive case is where the agents have complete information (FIRE). In this case, the noise of their signal is zero ($\sigma_\epsilon^2 = 0$), such that the gain parameter $g = 1$, and the forecasts are given by $f_{i,t}(\pi_{t+k}) = \sum_{j=0}^{k} \rho^j \mu + \rho^k \pi_t$. We estimate values for these parameters from the historical values of CPI inflation the Netherlands and the euro area by imposing a first-order stationary autoregressive process (Appendix Table 7). The results suggest values of around $\hat{\mu}_{NL} = 0.08$, $\hat{\rho}_{NL} = 0.96$, $\hat{\mu}_{EA} = 0.06$ and $\hat{\rho}_{EA} = 0.96$. Under bounded rationality, the true parameters of the model are unknown to the agents, and the beliefs about parameters may be heterogeneous across individuals. We denote perceived coefficients with a tilde, and consider a range of extrapolative models discussed in Pesaran & Weale (2006).

Under *naive* expectations, agents disregard prior beliefs and instead rely fully on the signal they receive about current inflation for their forecasts, such that $\tilde{g} = 1$. Under naive expectations, any value of $\tilde{\lambda}$ is permissible. At the same time, naive agents assume that the true data generating process is a random walk ($\tilde{\mu} = 0$ and $\tilde{\rho} = 1$). The latter assumption is also true for *mean-reverting* and *adaptive* forecasters, for whom $\tilde{g} \in (0, 1)$ and $\tilde{\lambda} = 1$. Both types have the same beliefs about the parameters, but receive a different set of signals. Adaptive agents form their forecast using a weighted average of the current realization and a previous forecast of the current period. Mean-reverting agents form their forecasts using a weighted average of current and lagged inflation realizations. Finally, we include a *fundamentalist* type who perceives inflation to be constant ($\tilde{\sigma}_u$), such that $\tilde{g} = 0$. In addition, $\tilde{\lambda} = 0$ so that the signals are ignored. That is, they choose a constant anchor for inflation and ignore all new information, so that they perceive inflation to be constant and disregard all signals. For fundamentalists, we can test whether their expectations are anchored at the inflation target set by the central bank. All forecasting heuristics and their parameter restrictions are summarized in Table 1.

Table 1: Forecaster types in the framework

		β_0	β_1	β_2	β_3
Rational					
FIRE		$\sum_{j=0}^{k} \rho^j \mu$	0	ρ^k	0
95% for k=12, NL		[0.05,1.93]		[0.40,0.89]	
95% for k=12, EA		[-0.06,1.66]		[0.50,1.28]	
Noisy RE		$\sum_{j=0}^{k} \rho^j \mu$	$\rho(1-g)$	$\rho^k g$	$\rho^{k+1}(1-g)$
Boundedly Rational					
Extrapolative					
	Naive	0	0	1	0
	Mean-reverting	0		$\tilde{g}$	$1-\tilde{g}$
	Adaptive	0	$1-\tilde{g}$	$\tilde{g}$	
Fundamentalist		$\sum_{j=0}^{k} \tilde{\rho}^j \tilde{\mu}$	0	0	0

Estimated values for the 95% confidence interval for FIRE with k=12 can be found in Table 7.

Our four forecasting types span the principal dimensions of heterogeneity emphasized in the broader expectations literature. Equation 1 shows that differences in the gain parameter $\tilde{g}$ and the prior-weighting parameter $\tilde{\lambda}$ capture the degree of attention and memory in agents' learning rules. Varying these two parameters nests several well-known extensions.

First, models of sticky information (Mankiw & Reis 2002, Carroll 2003) can be viewed as a probabilistic mixture of our Bayesian-updating agents. In those models, only a fraction of agents update their information set in any period, while the remainder retain prior forecasts. This corresponds to agents with $\tilde{\lambda} = 1$ who occasionally set $\tilde{g} = 0$. Thus, the mean-reverting type in our framework represents the continuous-time analogue of sticky expectations, where the speed of updating is governed by $\tilde{g}$. Second, rational inattention models (Sims 2003, Woodford 2003, Maćkowiak & Wiederholt 2009) imply that agents optimally choose $g < 1$ because processing information is costly. In our framework, rational inattention corresponds to the noisy-information benchmark where agents rationally filter signals but underreact to news. The adaptive and mean-reverting heuristics approximate this behavior when updating is partial but systematic. Third, diagnostic expectations (Bordalo et al. 2020) generate overreaction to recent inflation surprises. In our model this corresponds to $\tilde{g} > 1$, so that agents overweight the current signal relative to prior beliefs. Fourth, experience-based learning (Malmendier & Nagel 2016) implies that prior beliefs are shaped by personal inflation histories. In our notation, this corresponds to heterogeneity in the perceived persistence $\tilde{\rho}$ and in the weight placed on past signals when forming $f_{i,t-1}(\pi_t)$. Demographic variation in $(\tilde{g}, \tilde{\lambda}, \tilde{\rho})$ thus provides a microfoundation for the experience effects documented in the literature. While the model features a representative agent, we relate heuristics back to demographics showing that these do play a role in the choice of updating parameters. Finally, models with heuristic switching (Brazier et al. 2008, Anufriev & Hommes 2012) allow agents to move endogenously between rules depending on past forecast performance. In our panel setting, such switching would appear as time variation in the estimated parameters g or λ across survey waves. While we treat forecasting types as fixed within individuals, the Bayesian structure of (1) provides a foundation for interpreting such state-dependent transitions in future work.

3 The Dutch Household Satellite Survey

We use data from the DHS Satellite Survey.[3] The survey has been conducted since December 2019, and we use data until December 2024, i.e. 61 survey waves. In contrast to all other household surveys we are aware of, our satellite survey provides a more balanced panel: We observe 1773 individuals more than 36 periods consecutively.

[3]The DHS is a longitudinal database of economic and psychological aspects of financial behavior of Dutch households (since 1993), conducted by CentERdata, Tilburg University and sponsored by De Nederlandsche Bank. More information can be found in Teppa & Vis (2012). The satellite survey is described in more detail in Galati et al. (2023).

Participants in the survey are randomly assigned to one of four treatment groups. The first two groups are asked about inflation in the Netherlands. This is in line with other surveys in the European Union, such as the Consumer Expectations Survey (CES) or the European Commission survey, in which participants are asked about their respective national inflation. In contrast, the latter two groups of our survey are asked about inflation in the euro area. We will show our results both pooled and disaggregated by target geography. Further, treatment groups two and four are provided information about the ECB's price stability aim as well as the latest realization (i.e., for respondents in December 2019 the latest realization is November 2019) of HICP inflation and historical values since 1999 in the respective location. Coibion, Georgarakos, Gorodnichenko & van Rooij (2023) show that this produces an exogenous variation in the level of inflation expectations that can significantly affect durable goods spending, as high inflation surprises are associated with lower aggregate spending and real income. Here, the information is used to differentiate between agents who must rely on their own imprecise estimates of perceptions to form their inflation forecasts, and those who can make use of cost-free precise inflation signals of the past period. The receipt of information has a significantly negative effect on the level of inflation expectations for both regions, specifically at the peak of the inflation surge in the fourth quarter of 2022 (Minina et al. 2024).[4] Since 2023, the series diverged between Dutch and euro area inflation, with participants who receive information about inflation in the Netherlands having the lowest expectations.

As in other surveys, the DHS satellite survey shows significant heterogeneity in responses by demographic groups. Average expectations pooled over the sample period can be found in Table 8 in the Appendix. The differences between men and women, and across different ages, education and income levels have been documented before for other surveys (Weber et al. 2022, D'Acunto et al. 2024).

4 The Average Consumer

Before exploiting the long time dimension of the panel, we can test how forecasts are formed on average. We start by testing if FIRE holds on average and if not, how agents form expectations instead.

[4] An exception is May 2022, when the information provision significantly increased euro area expectations, presumably due to a shock to actual inflation at the time.

4.1 Is the average consumer on FIRE?

The framework can be used to test whether agents align with FIRE. Since a forecast under FIRE is given by $f_{i,t}(\pi_{t+k}) = \sum_{j=0}^{k} \rho^j \mu + \rho^k \pi_t$, the forecast error should be unpredictable since $u_t \sim \mathcal{N}(0, \sigma_u^2)$:

$$\pi_{t+k} - f_{i,t}(\pi_{t+k}) = \sum_{j=0}^{k} \rho^j u_{t+k-j}. \tag{2}$$

A common test of this assumption is to see if forecast errors can be predicted by forecast revisions (Coibion & Gorodnichenko 2015). For household surveys, forecast revisions cannot be easily used, since households are not asked to forecast inflation at different horizons. Instead, we employ an implementation by Kohlhas & Walther (2021) and Angeletos et al. (2021) who argue that similarly, the current level of inflation should not contain any information about forecast errors:

$$\pi_{t+k} - f_{i,t}(\pi_{t+k}) = \gamma_i + \alpha_0 + \alpha_1 \pi_t + \zeta_{i,t}, \tag{3}$$

where γ_i captures individual fixed effects, α_0 is a constant and $\zeta_{i,t}$ is an error term.[5] Under FIRE, $\alpha_0 = \alpha_1 = 0$, since no variable that is observable at time t should be correlated with the forecast error. In fact, FIRE here implies that forecasts are on average unbiased and efficient, where $\alpha_0 = 0$ is required for unbiasedness and $\alpha_1 = 0$ is required for efficiency. On the aggregate level we can only observe $\alpha_{0,i} = \alpha_0 + \gamma_i$ and therefore cannot test for unbiasedness directly. However, as common in the literature cited above we test for $\alpha_1 = 0$ which is equally required for FIRE. In addition, we report $\hat{c} = \alpha_0 + \frac{1}{N} \sum_{i=1}^{N} \hat{\gamma}_i$. Using the DHS satellite survey we test FIRE for 12-month-ahead inflation ($k = 12$) using monthly data. The survey contains two groups, one group of agents is asked about euro area inflation, hence the forecast error is constructed using euro area HICP (all items). The other group is asked about inflation in the Netherlands, where we use the corresponding Dutch inflation measure.

Table 2 summarizes the results for the regression in Equation 3. Column (1) pools all observations, and shows that on average consumers overreact to current realizations of inflation. Columns (2) to (5) show that the effect of local inflation seems to dominate. When separated, both samples overreact to recent realizations of the variable forecasted, but more so when asked about Dutch inflation. This finding also underscores the importance of our

[5] We must assume cross-sectional independence but do not require the error term to be serially uncorrelated.

Table 2: Test of FIRE on the aggregate

	$\pi_{t+k} - f_{i,t}(\pi_{t+k})$						
	Dutch Households					SPF	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
π_t	-0.596***	-0.602***	-0.630***	-0.593***	-0.532***	-0.0655*	0.0215
	(0.008)	(0.013)	(0.013)	(0.023)	(0.021)	(0.035)	(0.031)
c	1.713***	2.120***	2.923***	0.660***	1.081***	0.239***	1.571***
	(0.034)	(0.058)	(0.060)	(0.088)	(0.080)	(0.062)	(0.103)
Region	All	NL	NL	EA	EA	EA	EA
Info Treatment	All	No	Yes	No	Yes		
Period	2019-2024	2019-2024	2019-2024	2019-2024	2019-2024	1999-2019	2019-2024
Observations	134765	33618	33099	32907	35141	1591	351
N	4505	1092	1155	1134	1125	57	57
R^2	0.110	0.131	0.148	0.0872	0.0673	0.00461	0.000437
Average Forecast Error	-0.773	-0.620	0.0674	-1.602	-0.934	0.123	1.642

Cluster-robust standard errors (CRSE) clustered at the individual forecaster level in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

$f_{i,t}(\pi_{t+12})$ is winsorized at the 1% and 99% level for households.

survey asking questions about euro area inflation rather than only on domestic inflation expectations. Further, the parameters are similar for those who receive the information treatment and for those who do not. Finally, $\hat{c}$ is significantly positive for households. We reject FIRE and conclude that either households on average are not fully rational *or* have imperfect information about the current level of inflation. This is in line with evidence for professional forecasters (Kohlhas & Walther 2021, Angeletos et al. 2021). In addition, in column (6) and (7) we include for comparison results from the Survey of Professional Forecasters (SPF) for euro area inflation. Interestingly, we find that professional forecasters overreacted to current realizations only until the end of 2019 (in line with evidence cited above) but neither over- nor undereacted in our sample period. This is driven by the high-inflation period initially falsely interpreted as transitory by many professional economists (Hartmann & Schepens 2021, PrincetonEconomics 2021, BCF 2022). By contrast, households in the DHS satellite survey already interpreted the inflationary shock in the wake of the pandemic as more persistent initially, including in the first year, as reflected in an increase in their median long-term inflation expectations in the second half of 2021 (Galati et al. forthcoming).

4.2 How does the average consumer forecast inflation?

Further, we can test how respondents forecast inflation on average. We run the regression model as derived from the framework in Equation 1 for $k = 12$,

$$f_{i,t}(\pi_{t+k}) = \gamma_i + \beta_0 + \beta_1(1 - \mathbb{I}_i)f_{i,t-1}(\pi_{t+k-1}) + \beta_2\pi_t + \beta_3\mathbb{I}_i\pi_{t-1} + \zeta_{i,t}. \tag{4}$$

As before, we cannot estimate β_0 in the fixed effects regression. Instead, we report $\hat{c} = \beta_0 + \frac{1}{N}\sum_{i=1}^{N}\hat{\gamma}_i$. Because the panel is long (>27 waves on average), Nickell bias (Nickell 1981) from the lagged expectation term is negligible, and the fixed-effects estimator remains appropriate. The results can be found in Table 3. We find that on average, households have a positive inflation anchor and rely on current realizations of inflation, as well as their previous forecast, or the previous inflation realization when it was provided. The estimated coefficients allow us to solve for the parameters of the underlying model for both groups of agents, those who receive no information treatment ($\mathbb{I} = 0$), and those who receive information about the past realization of inflation ($\mathbb{I} = 1$) when assuming non-fundamentalist behavior ($\lambda = 1$). The results for both groups are summarized in Table 3.

We find that the coefficients for both models are very similar. The largest difference arises between the estimated gain parameter $\hat{g}$ in the two models. The difference may arise because households who receive information also see historical values of inflation and thus may perceive the variance of the inflation process to be lower (and thus have a smaller gain parameter). Further, we find that the perceived autocorrelation of inflation is lower for Dutch inflation than for euro area inflation, which is in line with historical evidence (see Table 7 in the appendix). In fact, the average perceived values align closely with the true historical autocorrelation. They also align closely with the parameters estimated for professional forecasters when using their mean point forecast on the left-hand side in a corresponding regression (column (4)).

In sum, the evidence suggests that on average, households do not have full information but may be rational given the noisy information they have. The average perceived parameters are close to historical estimates of the true data generating process. However, the aggregation masks large heterogeneity among individuals in the sample. In the next section we show how the coefficients are dispersed and allocate individuals to forecasting types.

Table 3: Test of forecasting rules on the aggregate

	$f_{i,t}(\pi_{t+k})$				
	Dutch Households			SPF	
	(1)	(2)	(3)	(4)	(5)
$f_{i,t-1}(\pi_{t+11})$	0.327***	0.311***	0.331***	0.500***	0.447***
	(0.019)	(0.023)	(0.030)	(0.035)	(0.130)
π_t	0.343***	0.293***	0.447***	0.217***	0.216***
	(0.011)	(0.013)	(0.021)	(0.022)	(0.053)
π_{t-1}	0.209***	0.207***	0.186***	-0.0738***	-0.0742
	(0.016)	(0.018)	(0.031)	(0.020)	(0.068)
c	2.580***	2.584***	2.488***	0.586***	0.617***
	(0.048)	(0.057)	(0.073)	(0.044)	(0.156)
Region	All	NL	EA	EA	EA
Period	2019-2024	2019-2024	2019-2024	1999-2019	2019-2024
Observations	123669	60840	62829	1306	291
N	4505	2247	2248	57	57
R^2	0.184	0.192	0.183	0.562	0.630
$\bar{f}_t\pi_{t+12}$	5.313	5.222	5.400	1.683	1.984
$\hat{\mu}_{\mathbb{I}=0}$	0.269	0.290	0.231	0.0643	0.0709
$\hat{g}_{\mathbb{I}=0}$	0.654	0.666	0.658	0.467	0.519
$\hat{\rho}_{\mathbb{I}=0}$	0.948	0.934	0.968	0.938	0.930
$\hat{\mu}_{\mathbb{I}=1}$	0.261	0.272	0.237	0.103	0.109
$\hat{g}_{\mathbb{I}=1}$	0.610	0.572	0.699	1.676	1.688
$\hat{\rho}_{\mathbb{I}=1}$	0.953	0.946	0.963	0.843	0.842

Cluster-robust standard errors (CRSE) clustered at the individual forecaster level in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

$f_{i,t}(\pi_{t+12})$ is winsorized at the 1% and 99% level for households.

5 Analysis at the Individual Level

The long time dimension of our panel (monthly since December 2019) allows us to test forecasting types at the micro level. In total we have 4505 individuals. However, to maximize the power of our exercise (individual-specific regressions) we focus on the 1773 individuals who participated in the survey for at least 36 months.

As before, we start by testing the FIRE hypothesis, and then extrapolative forecasting types. We test FIRE both, according to the standard tests in the literature (Kohlhas & Walther 2021), as well as by using the confidence intervals computed for the historical values of inflation. Finally, we test how forecasting types correlate with demographics and the level of inflation expectations.

5.1 Who is on FIRE?

We start by deciding if an individual forecasts according to FIRE. To test this hypothesis, we run a similar test as before, but now at the level of the individual consumer, which has the advantage of not imposing a common α_0 and α_1 (Bordalo et al. 2020) for individuals.

$$\pi_{t+k} - f_{i,t}(\pi_{t+k}) = \alpha_{i,0} + \alpha_{i,1}\pi_t + \zeta_{i,t}. \tag{5}$$

Equation 5 tests whether a given respondent systematically over- or under-reports inflation. Unbiasedness requires that $\alpha_{i,0} = 0$. Equation 5 additionally tests for efficiency, which requires that $\alpha_{i,1} = 0$. FIRE is rejected whenever a forecast is either biased or inefficient. As we are running these regressions for all individuals insteap of a panel regression we can now estimate $\alpha_{i,0}$ as the constant in a standard time-series regression. Panel A of Table 4 summarizes the average coefficients α_0 and α_1. As indicated by the panel regression, the average coefficient for α_1 is negative; in fact, 96.5% of participants overreact to current inflation realizations. Figure 1a summarizes the distribution of the coefficients across the sample.

For consumers on FIRE, we begin with the null hypothesis $H_0 : \alpha_{i,0} = \alpha_{i,1} = 0$. A standard t-test allows us to reject this hypothesis for about 94% of consumers (at 90% confidence). However, for those individuals where we fail to reject the null, this does not provide sufficient evidence to conclude that they are on FIRE. To address this, we use an equivalence testing framework. Specifically, we apply the two one-sided tests (TOST) procedure (Schuirmann 1987, Lakens 2017), testing whether each coefficient $\alpha_{i,j}$ for $j \in \{0, 1\}$

lies within a symmetric equivalence bound defined as

$$d = 0.2 \times \hat{\sigma}_{\text{resid},i},$$

where $\hat{\sigma}_{\text{resid},i}$ is the estimated residual standard deviation from the regression for consumer i.[6] Formally, the composite null hypotheses are

$$H_{0,1} : \alpha_{i,j} \leq -d \quad \text{and} \quad H_{0,2} : \alpha_{i,j} \geq d,$$

with the alternative that the effect is practically equivalent to zero, i.e.

$$H_1 : -d < \alpha_{i,j} < d.$$

Equivalence is concluded when both one-sided tests are rejected at the 90% confidence level, which is equivalent to verifying that the 80% confidence interval lies entirely within $[-d, d]$. Under this criterion, only 15 observations (less than 1%) pass the equivalence test.

Table 9 shows the sensitivity of the FIRE acceptance to the choice of confidence level for both hypothesis tests, non-rejection of FIRE (i.e. a Wald test) and rejection of non-FIRE (TOST). Fot the remainder of this analysis we focus on the results of the TOST procedure. However, we show the results for non-rejection in the appendix.

We conclude that only a small proportion of the population is on FIRE. For less than 1% of the population we confidently accept FIRE. In the next section we therefore investigate which forecasting heuristics consumers alternatively employ.

5.2 Alternative forecasting types

We attempt to allocate consumers to one of the forecasting heuristics as discussed in Section 2. In addition, we also test for model-consistent FIRE expectations where we calibrate the parameters from the framework to historical estimates for Dutch and Euro area CPI inflation (see Appendix Table 7). We run the following time-series specification for each participant,

$$f_{i,t}(\pi_{t+k}) = \beta_{i,0} + \beta_{i,1}(1 - \mathbb{I}_i) f_{i,t-1}(\pi_{t+k-1}) + \beta_{i,2}\pi_t + \beta_{i,3}\mathbb{I}_i\pi_{t-1} + v_{i,t}. \tag{6}$$

[6] The factor of 0.2 corresponds to a "small" effect size in Cohen's terms and follows common practice in equivalence testing.

Panel B of Table 4 summarizes the mean, standard deviation and extreme values of the four estimated coefficients. We find that the averages of β_1 to β_3 approximately sum up to 1. β_1 is estimated with the lowest standard deviation. The distribution of the coefficients is also visualized in Figure 1b which shows that in contrast to the other coefficient there is a lower tail to either side for the coefficient on the past forecast. β_1 and β_3 can each only be identified for half of the sample, since an individual either received the information treatment such that β_3 is identified, or did not receive the information treatment such that β_1 is identified.

Table 4: Summary statistics of the regression coefficients

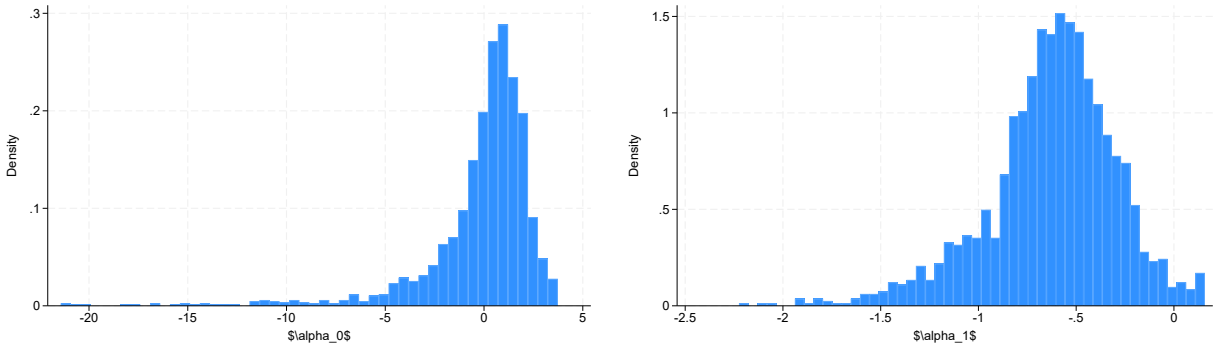
	Mean	SD	Min	Max	N
α_0	2.20	3.16	-16.64	6.23	1773
α_1	-0.60	0.37	-2.18	0.23	1773
β_0	2.28	2.47	-0.36	15.58	1773
β_1	0.29	0.23	-0.21	0.78	865
β_2	0.29	0.58	-2.25	2.30	1773
β_3	0.39	0.97	-2.08	5.94	907

Coefficients are winsorized at the 1% and 99% level.

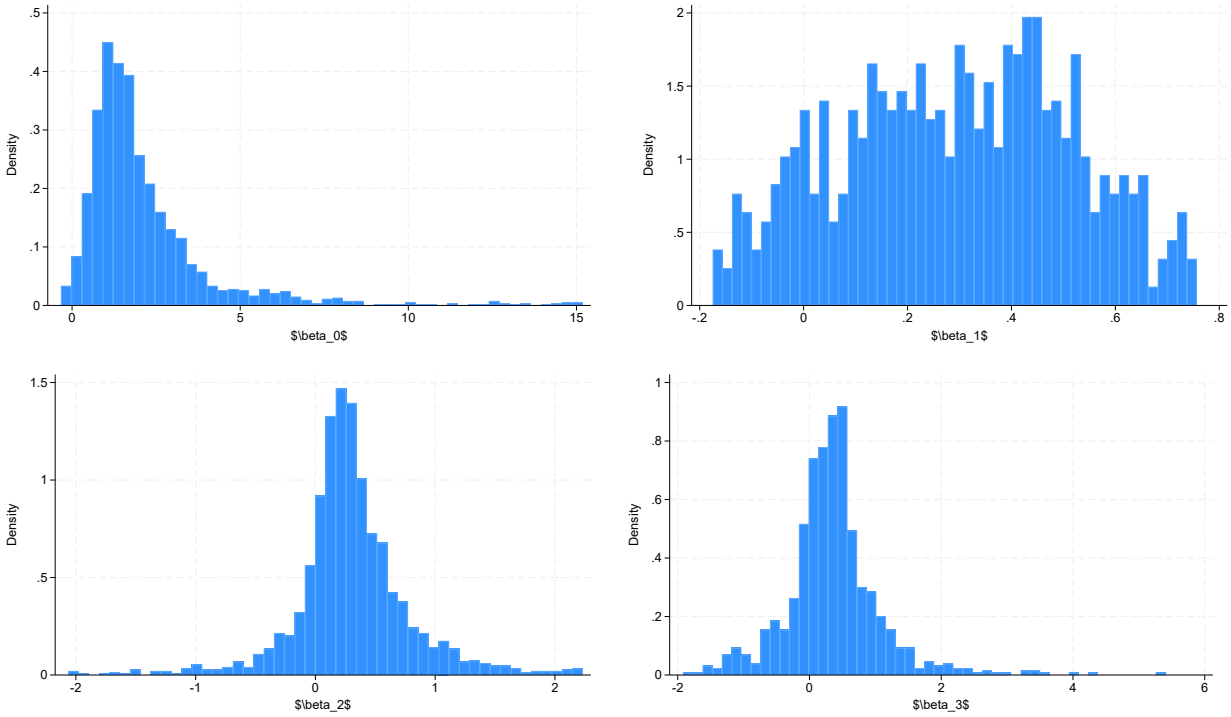
We assign an individual to the naive type when $\beta_0 = \beta_1(\text{or } \beta_3) = 0$ and $\beta_2 = 1$. Similarly, we assign an individual to the fundamentalist type when $\beta_1(\text{or } \beta_3) = \beta_2 = 0$ and simultaneously reject that $\beta_0 = 0$. For adaptive types, we require that β_1 and β_2 be nonzero and that we do not reject $\beta_0 = 0$ and $\beta_1 + \beta_2 = 1$. The same is true for mean-reverting types, replacing β_1 with β_3. Further, we include a weaker variant of the naive, adaptive and mean-reverting types where we allow for $\beta_0 \neq 0$.

As discussed above, we apply the TOST procedure with symmetric equivalence bounds. Since the bounds are individual specific, we can have individuals being assigned to more than one heuristic. Of course, those that satisfy the strict definitions of naive, adaptive and mean-reverting will always satisfy the weak definition. For model consistent FIRE expectations, we use the bounds on β_0 and β_2 computed in Appendix Table 7. Model consistent FIRE expectations partially overlap with the bounds on naive.

While strict FIRE is rejected for more than 99% of consumers, we find that approximately 2% have model consistent forecasts using parameters that are within our calibration using historical values. We find that when applying the strict definitions, none of the heuristics captures more than 1% of consumers. This is because for most individuals $\beta_0 > 0$ as



(a) $\pi_{t+k} - f_{i,t}(\pi_{t+k}) = \alpha_{i,0} + \alpha_{i,1}\pi_t + \zeta_{i,t}$



(b) $f_{i,t}(\pi_{t+k}) = \beta_{i,0} + \beta_{i,1}(1 - \mathbb{I}_i)f_{i,t-1}(\pi_{t+k-1}) + \beta_{i,2}\pi_t + \beta_{i,3}\mathbb{I}_i\pi_{t-1} + v_{i,t}$

Figure 1: Histograms of the estimated coefficients

shown in Figure 1b. However, when allowing for weaker definitions with positive anchors, about 50% can be assigned to at least one category. The most prevalent are adaptive expectations with a positive anchor (24%), mean-reverting with a positive anchor (19%) and a fundamentalist rule (18%).

5.3 Characterizing the forecasting types

The analysis of the DHS satellite survey allows us to show the demographic characteristics of the different forecasting types. Panel A of Table 5[7] shows the demographic characteristics, namely the share of women, the average birth year and the share of high education and of high net household income for each forecasting type. Panel B summarizes the average inflation perceptions and short- and long-term inflation expectations of the different forecasting types. Panel C summarizes the survey feedback respondents gave about whether the questions were difficult, clear, thought-provoking or interesting. Finally, panel D features some statistics from the estimation.

For further analysis, we merge the categories *FIRE* and *Consistent* into one group, as both represent model-consistent forecasts with relatively low bias and variance. Further we merge the stricter and weaker definitions of naive, adaptive and mean-reverting forecasts together (i.e. allowing each to anchored at some non-zero value). Figure 2 shows that there is some overlap between the groups such that categories are non-exclusive. In particular, we find a large overlap between adaptive, naive and fundamental expectations. The evidence in Table 5 Panel D suggests that the types successfully capture the forecasting types. For the strict definitions of naive, adaptive and mean-reverting we find average β_0-coefficients close to zero. Column (2) also shows that this is not consistent with the data where it is closer to 0.9 in line with the evidence from historical values of inflation (Table 7). Additionally, data-consistent forecasts put more weight on β_2 but little weight on β_1 or β_3. Hence, they are similar to naive forecasts, which explains the overlap described above. Further, the table shows that the length of survey participation does not predict forecaster type (as it should).

We now turn analyze the specific characteristics of each type. In Table 6,[8] we analyze the characteristics of the different types using a logistic regression which predicts the binary variable of membership to a certain type using demographic variables, forecasting characteristics, and survey evaluation.

[7] For non-rejection Table 10
[8] For non-rejection Table 11

FIRE/Consistent forecasters. This combined group is small (46 respondents, $\approx 2.5\%$ of the sample). Unsurprisingly, the consistent group displays the most accurate forecasts, with the lowest mean squared forecast errors (MSE ≈ 4.7). Their long-run forecasts are on average higher. While FIRE forecasts have a substantially lower R^2 (as they shouldn't be systematically predicable) we find a larger R^2 for consistent forecasts. The latter group stands out for being slightly older and higher educated than the rest of the sample. However, FIRE forecasters find that forecasting is less thought-provoking than other households. These characteristics resemble "expert-like" households in the population

Naive forecasters. Naive types (238 respondents, $\approx 13\%$) predominantly extrapolate directly from current inflation, often with an upward bias ($\beta_0 > 0$). Their one-year-ahead forecasts are high (around 11% for biased subgroup) though there is a lot of noise in forecast of this group. Regressions show that female respondents are significantly more likely to be naive ($\beta = 0.57, p < 0.01$), while high education and high income reduce the likelihood of being naive. They illustrate the common tendency of households to overreact to current inflation.

Adaptive forecasters. Adaptive expectations are the most common identifiable rule (425 respondents, $\approx 49\%$ of those without info-treatment). These households combine past forecasts and current realizations, placing substantial weight on past forecasts ($\beta_1 \approx 0.33$) with a slight positive bias. Forecasts tend to overshoot realized values, with one-year-ahead expectations around 8% (for positively anchored subgroup). Forecast errors are lower than naive types on average but still elevated (MSE ≈ 9.8) and significantly different from the overall sample. Regression results indicate similar demographics for adaptive as for naive forecasting. Survey feedback shows no difference to the overall sample.

Mean-reverting forecasters. Mean-reverting types (335 respondents, $\approx 37\%$ of those with info-treatment) rely more on lagged inflation than on current realizations. Their forecasts average 8.5% at a one-year horizon, but longer-horizon expectations vary substantially (one-year MSE ≈ 11.5, 10-year forecast highly volatile). Females are significantly more likely to be mean-reverting ($\beta = 0.46, p < 0.01$), while higher education and high income decrease the likelihood. These respondents appear to expect inflation to revert toward a perceived mean, though forecasts are inaccurate.

Fundamentalists. Fundamentalists (316 respondents, $\approx 18\%$) anchor expectations on a constant value, often ignoring new information, for 3 respondents aligning with the ECB 2% target. Given the high inflation episode captured by our sample period, this is of little surprise. Instead, their forecasts cluster around 6–9% during the high-inflation period, with MSE ≈ 11. Females are significantly more likely to be fundamentalists ($\beta = 0.65, p < 0.01$), while higher education and high income reduce the likelihood. By design, those that do not change their forecasts across several waves have lower R^2 as their forecasts are less predicted by time varying variables. They show moderate survey engagement, on average rating the questionnaire as more thought-provoking.

Unclassified (None). The largest group (880 respondents, $\approx 50\%$) cannot be matched to a simple heuristic. Yet, they display the highest accuracy after FIRE/Consistent types (MSE ≈ 4.75) in line with lower 1-year ahead forecasts than other forecasters. Regression results indicate males, highly educated, and higher-income respondents are more likely to be unclassified (female $\beta = -0.67, p < 0.01$; high education $\beta = 0.47, p < 0.01$; high income $\beta = 0.40, p < 0.01$). This heterogeneous group may reflect switching between heuristics, reliance on external information, or forward-looking strategies not captured by simple rules.

Overall, the results reveal substantial heterogeneity in household inflation expectations and forecasting behavior. A small share of "expert-like" respondents (FIRE/Consistent types) form the most accurate and stable expectations, consistent with rational or model-based updating. These are disproportionately older, wealthier, and male. In contrast, women, those with lower education and those on lower incomes are more likely to employ simple heuristics: Naive, adaptive and mean-reverting forecasters extrapolate from current or recent inflation (forecasts) and systematically overpredict future inflation. By contrast, males and higher-educated, higher-income individuals are overrepresented among the unclassified group, which shows the second-highest forecast accuracy. These patterns suggest that information processing ability, attention, and experience play a central role in shaping expectation formation among households.

A large body of evidence suggests that households systematically overextrapolate recent inflation developments when forming expectations. Survey studies (e.g., Coibion & Gorodnichenko 2015, Cavallo et al. 2017) show that households' forecasts respond disproportionately to recent price changes, implying adaptive or backward-looking expectations. Experimental and microdata evidence further indicate that individuals anchor beliefs on

Table 5: Average characteristics of forecasting types

	FIRE	Consistent	Naive		Adaptive		Mean-Reverting		Fundamentalist		None
			$\beta_0 = 0$	$\beta_0 \neq 0$	$\beta_0 = 0$	$\beta_0 \neq 0$	$\beta_0 = 0$	$\beta_0 \neq 0$	$\beta_0 \neq 0$	$\beta_0 = 2$	
Panel A: Demographics											
Female	0.40	0.42	1.00	0.59	0.80	0.55	0.00	0.52	0.59	0.67	0.36
	(0.51)	(0.50)	(0.00)	(0.49)	(0.45)	(0.50)		(0.50)	(0.49)	(0.58)	(0.48)
Birth year	1959	1955	1960	1961	1956	1961	1935	1959	1961	1948	1961
	(13.50)	(9.58)	(9.64)	(14.63)	(8.23)	(14.98)		(14.75)	(15.99)	(7.94)	(14.79)
High educ	0.27	0.29	0.33	0.26	0.20	0.33	0.00	0.28	0.29	0.33	0.45
	(0.46)	(0.46)	(0.58)	(0.44)	(0.45)	(0.47)		(0.45)	(0.46)	(0.58)	(0.50)
High income	0.33	0.65	1.00	0.43	1.00	0.47	0.00	0.44	0.44	0.33	0.60
	(0.49)	(0.49)	(0.00)	(0.50)	(0.00)	(0.50)		(0.50)	(0.50)	(0.58)	(0.49)
Panel B: Inflation forecasts											
$f_{i,t}\pi_t$	6.78	4.32	4.50	9.74	4.19	7.41			8.97	5.35	4.40
	(2.33)	(0.60)	(0.09)	(14.94)	(0.44)	(10.73)			(14.18)	(0.38)	(1.59)
$f_{i,t}\pi_{t+12}$	8.01	3.98	4.92	10.85	4.14	7.99	5.84	8.49	8.58	6.03	3.67
	(2.59)	(0.90)	(0.31)	(12.35)	(1.09)	(9.25)		(10.15)	(11.24)	(0.35)	(1.83)
$f_{i,t}\pi_{t+120}$	13.72	7.51	9.58	19.56	6.89	13.67	6.66	20.85	14.04	8.42	4.76
	(9.98)	(12.02)	(6.73)	(22.20)	(6.02)	(16.97)		(112.82)	(15.42)	(2.57)	(6.46)
$(\pi_{t+12} - f_{i,t}\pi_{t+12})^2$	9.40	4.71	9.14	14.24	7.15	9.83	19.03	11.50	11.71	11.05	4.75
	(4.27)	(1.18)	(2.71)	(14.04)	(3.33)	(10.76)		(14.61)	(12.77)	(1.93)	(2.04)
Panel C: Survey Feedback											
Difficult?	2.22	2.53	1.96	2.50	2.24	2.52	1.70	2.46	2.58	3.93	2.46
	(1.42)	(1.26)	(0.83)	(1.29)	(0.71)	(1.30)		(1.31)	(1.30)	(0.97)	(1.25)
Clear?	4.18	4.42	4.48	4.20	4.68	4.23	4.67	4.26	4.19	3.76	4.20
	(0.92)	(0.57)	(0.61)	(0.78)	(0.51)	(0.77)		(0.77)	(0.81)	(0.91)	(0.74)
Make you think?	2.22	3.20	3.10	3.05	3.24	3.05	3.15	3.15	3.21	2.72	2.96
	(1.11)	(1.07)	(0.96)	(1.16)	(0.71)	(1.13)		(1.21)	(1.17)	(0.84)	(1.02)
Interesting?	2.74	3.40	3.72	3.32	3.44	3.26	2.95	3.35	3.35	2.11	3.22
	(1.36)	(0.97)	(1.08)	(1.08)	(0.85)	(1.08)		(1.11)	(1.11)	(0.86)	(1.02)
Panel D: Estimation details											
Survey waves	54.87	54.94	53.33	52.71	56.00	53.12	58.00	52.78	52.59	56.67	53.06
	(5.63)	(5.87)	(5.03)	(7.17)	(5.10)	(7.01)		(7.26)	(7.35)	(5.77)	(7.13)
β_0	4.05	0.93	0.02	3.97	0.01	2.49	-0.23	3.51	3.92	1.99	1.67
	(2.07)	(0.29)	(0.03)	(3.69)	(0.02)	(2.81)		(3.88)	(3.33)	(0.13)	(1.07)
β_1	0.44	0.11	0.25	0.18	0.36	0.33			0.21	0.02	0.31
	(0.24)	(0.16)	(0.27)	(0.22)	(0.24)	(0.24)			(0.22)	(0.13)	(0.21)
β_2	0.29	0.64	0.84	0.71	0.65	0.53	2.30	0.19	0.31	0.77	0.24
	(0.71)	(0.10)	(0.35)	(0.44)	(0.36)	(0.38)		(1.04)	(0.37)	(0.16)	(0.40)
β_3	0.34	0.03		-0.01			-1.60	0.70	0.22	0.17	0.22
	(0.87)	(0.12)		(0.67)				(1.40)	(0.32)		(0.52)
R2	0.34	0.63	0.58	0.35	0.66	0.51	0.33	0.46	0.22	0.22	0.57
	(0.24)	(0.13)	(0.24)	(0.22)	(0.20)	(0.24)		(0.29)	(0.17)	(0.08)	(0.23)
Observations	15	31	3	235	5	425	1	334	316	3	880

Table 6: Predicting forecasting types using observables

	Fire	Data Consistent	Naive	Adaptive	Mean Revert	Fundamental	Anchor 2%	Nonallocated
Panel A: Demographics								
Female	-0.29	-0.00	0.57***	0.73***	0.46***	0.65***	1.02	-0.67***
	(0.53)	(0.38)	(0.14)	(0.14)	(0.14)	(0.13)	(1.26)	(0.10)
Birth year	-0.00	-0.03**	0.00	0.00	-0.01*	0.00	-0.08	0.00
	(0.02)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.06)	(0.00)
High educ	-0.34	-0.55	-0.51***	-0.32**	-0.51***	-0.35**	0.16	0.47***
	(0.61)	(0.41)	(0.16)	(0.15)	(0.16)	(0.14)	(1.28)	(0.10)
High income	-0.78	0.69*	-0.32**	-0.44***	-0.34**	-0.30**	-0.50	0.40***
	(0.57)	(0.39)	(0.15)	(0.14)	(0.15)	(0.13)	(1.29)	(0.10)
Observations	1769	1768	1768	865	903	1768	1768	1768
Panel B: Inflation forecasts & Estimation details								
$f_{i,t}\pi_{t+12}$	0.12	-0.12	0.07	0.00	0.01	0.05	-0.01	-0.01***
	(0.08)	(0.11)	(0.05)	(0.01)	(0.01)	(0.03)	(0.07)	(0.00)
$f_{i,t}\pi_{t+120}$	0.00	0.03***	-0.00	0.01**	-0.00	-0.00	-0.04	0.00
	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.05)	(0.00)
$(\pi_{t+12} - f_{i,t}\pi_{t+12})^2$	-0.11	-0.36**	0.03	0.01***	0.01**	-0.01	0.04**	-0.00**
	(0.08)	(0.16)	(0.03)	(0.00)	(0.01)	(0.02)	(0.02)	(0.00)
Survey waves	0.05	0.03	-0.00	0.00	-0.00	0.00	0.11	-0.00
	(0.04)	(0.03)	(0.01)	(0.00)	(0.00)	(0.01)	(0.11)	(0.00)
R2	-2.89***	1.56***	-2.17***	0.08	-0.03	-6.33***	-4.57***	0.36***
	(0.91)	(0.50)	(0.27)	(0.07)	(0.06)	(0.35)	(0.75)	(0.04)
Observations	1771	1770	1770	863	907	1770	1770	1770
Panel C: Survey Feedback								
Difficult?	-0.15	0.10	0.02	0.00	0.02	0.05	0.53	-0.05
	(0.24)	(0.15)	(0.06)	(0.06)	(0.06)	(0.05)	(0.57)	(0.04)
Clear?	0.02	0.46	-0.10	0.08	0.05	-0.12	-0.11	-0.06
	(0.36)	(0.32)	(0.11)	(0.10)	(0.11)	(0.10)	(0.73)	(0.07)
Make you think?	-0.65**	0.06	-0.08	0.04	0.08	0.18**	0.74	-0.14**
	(0.31)	(0.23)	(0.09)	(0.09)	(0.09)	(0.09)	(0.77)	(0.06)
Interesting?	-0.11	-0.01	0.16	-0.04	0.04	0.03	-1.47*	0.02
	(0.30)	(0.26)	(0.10)	(0.10)	(0.10)	(0.10)	(0.87)	(0.07)
Observations	1773	1772	1772	865	907	1772	1772	1772

Standard errors in parentheses

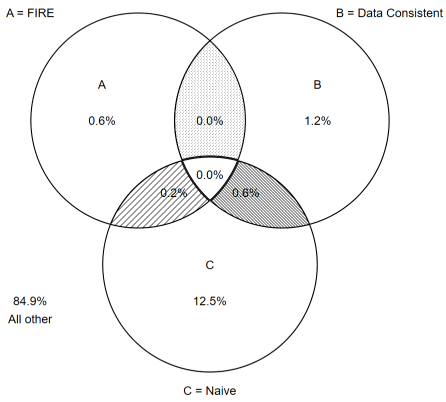
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

salient, recent price experiences (e.g., fuel or food prices) and are affected by lifetime experiences (D'Acunto, Malmendier, Ospina & Weber 2021, Malmendier & Nagel 2016). Such behavior leads to upward-biased forecasts after inflationary shocks and delayed downward revisions, consistent with models of overextrapolation or noisy information updating (Bordalo et al. 2020, Angeletos et al. 2021). Overall, the literature converges on the view that household expectations are excessively influenced by recent inflation rather than long-run fundamentals. Our evidence suggests that this is driven by a largely female population with lower education and lower income. This finding supports the theory in D'Acunto, Malmendier & Weber (2021), who argue that women's exposure to grocery prices makes them overestimate inflation. In contrast, there is also a share of the population for whom we cannot assign a consistent heuristic but who forecast with lower forecast errors. This share is more male, of higher income and higher education. It is likely, that they employ more sophisticated forecasting rules that we cannot measure.

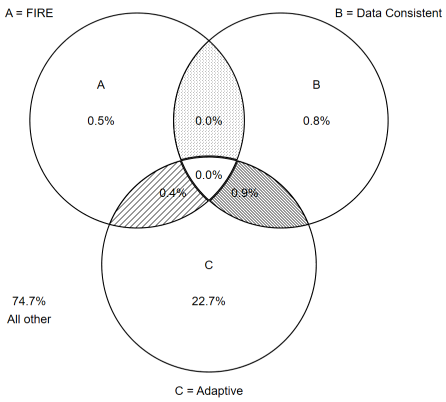
6 Conclusion

In this paper, we study how Dutch households form and revise inflation expectations using a rich monthly panel since December 2019. Our Bayesian framework nests Full Information Rational Expectations (FIRE) within a range of behavioral forecasting heuristics, allowing individual-level tests of model-consistent learning. We reject FIRE both in the aggregate and for almost all respondents—only 2.5% behave as FIRE or data consistent forecasters, typically wealthier, highly educated men, consistent with previous evidence on expectation biases (D'Acunto et al. 2023).

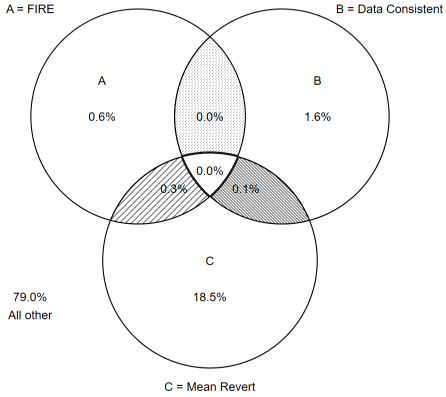
On aggregate we confirm the evidence of Bordalo et al. (2020) that consumers, just as professional forecasters, overreact to recent inflation events. However, the aggregate hides substantial heterogeneity. Almost half of consumers employ simple heuristics such as naive, adaptive, mean-reverting or fundamentalist rules. The most common heuristic is adaptive expectations, a finding that aligns with models of sticky, noisy or costly information (Carroll 2003, Mankiw & Reis 2002, Coibion & Gorodnichenko 2015, Sims 2003, Maćkowiak & Wiederholt 2015), where agents update beliefs gradually rather than fully incorporating new data. Adaptive forecasters in our sample—predominantly women and lower-income households—appear to overweight recent inflation relative to past beliefs. This gradual adjustment mirrors findings from laboratory and survey studies suggesting that consumers learn about inflation through experience rather than through model-consistent inference



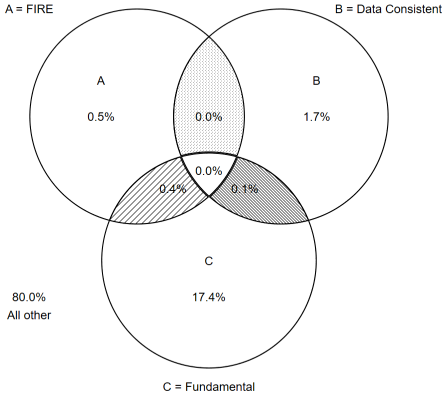
(a) FIRE/Consistent & Naive



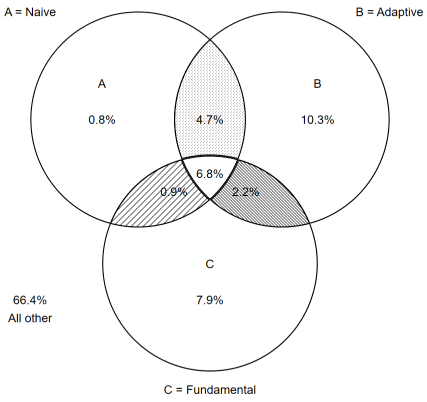
(b) FIRE/Consistent & Adaptive



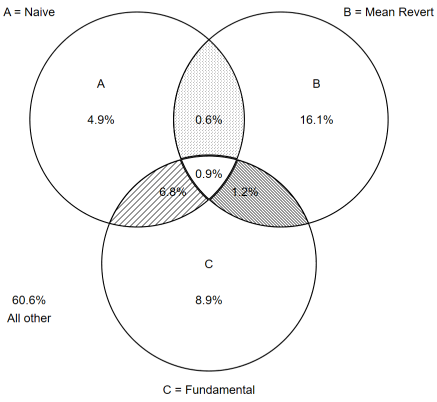
(c) FIRE/Consistent & Mean Revert



(d) FIRE/Consistent & Fundament



(e) Naive, Adaptive, Fundament



(f) Naive, Mean Revert, Fundament

Figure 2: Overlap of TOST Groups

(Malmendier & Nagel 2016, D'Acunto et al. 2024). Roughly half of all respondents cannot be assigned to any single heuristic, suggesting either switching behavior across regimes (Brazier et al. 2008, Anufriev & Hommes 2012) or the use of more complex updating rules. These respondents achieve lower forecast errors, demonstrating that the use of simple heuristics may harm forecast accuracy.

Future work should use longer panels to test for regime-dependent or switching heuristics, and to identify how communication strategies can shift households toward more informed updating. Understanding when and why households move from fundamentalist to adaptive or extrapolative behavior can provide valuable insight for central banks seeking to stabilize expectations in volatile environments.

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A Appendix

Table 7: Autocorrelation of Inflation

	π_t^{NL}		π_t^{EA}	
	1997-2019	1997-2025	1997-2019	1997-2025
π_{t-1}^{NL}	0.959***	0.951***		
	(0.016)	(0.054)		
π_{t-1}^{EA}			0.961***	0.982***
			(0.019)	(0.019)
Constant	0.0814**	0.121	0.0611*	0.0366
	(0.039)	(0.106)	(0.035)	(0.035)
Observations	274	339	274	338
R^2	0.917	0.904	0.923	0.965
$\bar{\pi}_t$	1.890	2.387	1.666	2.051
σ_u^2	0.514	0.514	0.107	0.106
$\hat{\beta}_0\_FIRE$	0.831	1.187	0.633	0.429
$\hat{\beta}_0\_FIRE\_lb$	0.0487	-0.501	-0.0597	-0.308
$\hat{\beta}_0\_FIRE\_ub$	1.930	6.111	1.659	1.560
$\hat{\beta}_2\_FIRE$	0.602	0.547	0.622	0.808
$\hat{\beta}_2\_FIRE\_lb$	0.401	0.132	0.390	0.503
$\hat{\beta}_2\_FIRE\_ub$	0.892	1.945	0.976	1.276

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

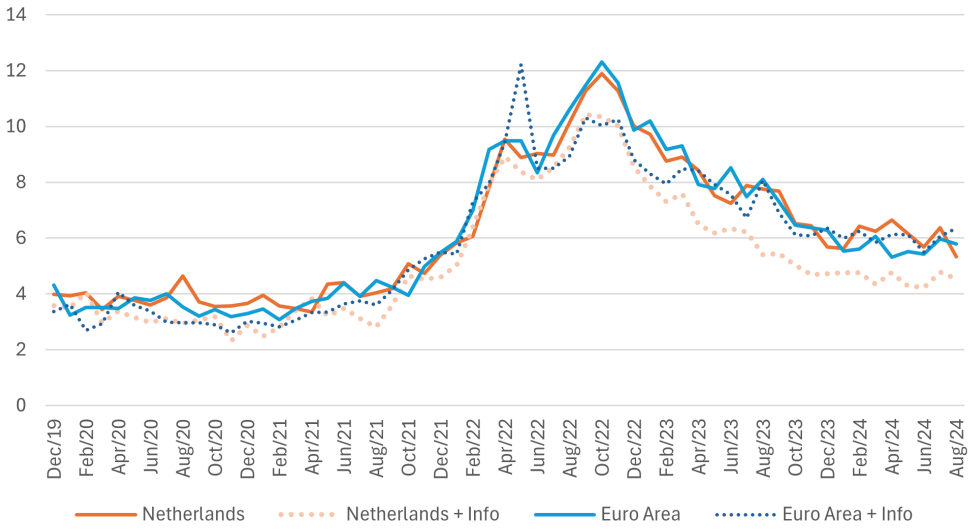

Figure A.1: Average inflation point forecast (12 months ahead) of Dutch households

Table 8: Summary statistics of 12 months ahead inflation expectations

	NL				EA			
Information	No		Yes		No		Yes	
	mean	sd	mean	sd	mean	sd	mean	sd
Sex								
Men	5.36	6.63	4.89	5.86	5.24	6.48	5.02	7.31
Women	6.04	7.95	4.97	6.81	6.48	8.39	5.34	8.11
Age								
Young	6.54	9.64	4.96	6.71	6.93	9.76	5.45	9.17
Middle	5.70	7.18	5.10	6.87	5.82	7.26	5.46	8.05
Old	5.02	5.27	4.65	5.22	4.96	5.25	4.64	6.07
Education								
Low	6.54	8.49	5.03	6.73	6.68	8.91	6.07	9.63
Middle	5.86	7.63	5.37	7.39	5.87	7.43	5.40	8.25
Higher	6.10	7.90	5.32	7.21	6.45	8.06	5.23	7.61
Income								
Low	5.34	6.74	4.58	5.35	5.32	6.91	5.10	7.80
High	5.69	7.30	4.93	6.32	5.83	7.48	5.18	7.72

Table 9: Sensitivity analysis

	$H_0 : \alpha_0 = \alpha_1 = 0$			$H_0 : \lvert\alpha_0\rvert \geq 0.5$ and $\lvert\alpha_1\rvert \geq 0.5$		
	80%	90%	95%	80%	90%	95%
FIRE	66	111	160	124	15	0
Data consistent	266	378	481	117	31	6
Naive	396	530	655	361	238	194
Adaptive	228	329	428	506	430	371
Mean-reverting	136	177	221	391	335	305
Fundamentalist	543	651	722	481	316	231
Nonallocated	467	585	755	1004	880	698

Table 10: Average characteristics of forecasting types (based on non-rejection)

	FIRE	Consistent	Naive		Adaptive		Mean-Reverting		Fundamentalist		None
			$\beta_0 = 0$	$\beta_0 \neq 0$	$\beta_0 = 0$	$\beta_0 \neq 0$	$\beta_0 = 0$	$\beta_0 \neq 0$	$\beta_0 \neq 0$	$\beta_0 = 2$	
Panel A: Demographics											
Female	0.54	0.54	0.61	0.56	0.59	0.62	0.62	0.57	0.45	0.48	0.36
	(0.50)	(0.50)	(0.49)	(0.50)	(0.49)	(0.49)	(0.49)	(0.50)	(0.50)	(0.50)	(0.48)
Birth year	1962.86	1959.15	1961.18	1959.24	1964.72	1962.60	1957.52	1959.43	1961.96	1960.79	1960.08
	(17.80)	(13.81)	(14.28)	(14.68)	(14.56)	(14.15)	(13.26)	(14.53)	(15.17)	(14.55)	(14.97)
High educ	0.31	0.35	0.32	0.31	0.44	0.32	0.31	0.24	0.39	0.38	0.41
	(0.46)	(0.48)	(0.47)	(0.46)	(0.50)	(0.47)	(0.47)	(0.43)	(0.49)	(0.49)	(0.49)
High income	0.46	0.47	0.43	0.42	0.55	0.46	0.60	0.50	0.51	0.50	0.59
	(0.50)	(0.50)	(0.50)	(0.49)	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)	(0.49)
Panel B: Inflation forecasts											
$f_{i,t}\pi_t$	7.75	6.26	8.81	10.70	6.50	9.02			9.89	5.95	4.63
	(19.71)	(10.37)	(16.90)	(17.44)	(13.24)	(14.50)			(15.82)	(3.83)	(1.59)
$f_{i,t}\pi_{t+12}$	4.99	5.35	6.69	8.42	5.75	9.56	5.21	9.73	6.13	4.89	4.41
	(1.85)	(3.72)	(5.99)	(10.87)	(3.59)	(11.95)	(1.80)	(11.10)	(8.80)	(3.40)	(3.82)
$f_{i,t}\pi_{t+120}$	7.53	14.68	26.38	19.85	8.07	15.06	8.04	32.30	12.38	12.28	6.81
	(4.82)	(104.76)	(169.83)	(104.36)	(6.06)	(15.65)	(4.92)	(175.01)	(80.50)	(100.20)	(16.62)
$(\pi_{t+12} - f_{i,t}\pi_{t+12})^2$	8.74	8.26	11.44	11.30	8.81	11.32	9.67	13.92	8.02	7.37	5.69
	(9.06)	(10.50)	(14.62)	(14.83)	(7.59)	(12.77)	(5.21)	(18.83)	(11.29)	(9.34)	(5.35)
Panel C: Survey Feedback											
Difficult?	2.60	2.66	2.68	2.49	2.50	2.50	2.58	2.45	2.41	2.47	2.49
	(1.22)	(1.31)	(1.29)	(1.31)	(1.21)	(1.25)	(1.25)	(1.33)	(1.24)	(1.26)	(1.31)
Clear?	3.99	4.21	4.09	4.22	4.17	4.23	4.11	4.30	4.22	4.20	4.22
	(0.83)	(0.75)	(0.76)	(0.76)	(0.72)	(0.76)	(0.71)	(0.73)	(0.76)	(0.74)	(0.75)
Make you think?	3.11	3.15	3.04	3.05	3.14	3.03	2.91	3.20	3.04	3.05	3.00
	(0.98)	(1.14)	(1.11)	(1.19)	(1.07)	(1.12)	(0.96)	(1.21)	(1.12)	(1.10)	(1.06)
Interesting?	3.19	3.31	3.21	3.30	3.22	3.21	2.94	3.30	3.23	3.18	3.28
	(0.95)	(1.04)	(1.06)	(1.12)	(1.05)	(1.03)	(0.99)	(1.16)	(1.07)	(1.06)	(1.05)
Panel D: Estimation details											
Survey waves	52.55	51.54	50.71	52.69	50.84	52.46	51.69	52.01	52.66	52.07	54.05
	(7.16)	(7.48)	(7.92)	(7.30)	(7.71)	(7.33)	(8.10)	(7.79)	(7.28)	(7.69)	(6.64)
β_0	3.41	1.42	1.29	3.26	1.04	2.66	1.07	3.64	3.12	2.26	1.76
	(1.85)	(1.28)	(1.61)	(3.66)	(1.12)	(3.25)	(1.20)	(4.17)	(2.89)	(1.19)	(1.71)
β_1	0.20	0.26	0.22	0.18	0.41	0.36			0.25	0.41	0.29
	(0.28)	(0.22)	(0.25)	(0.21)	(0.26)	(0.23)			(0.26)	(0.26)	(0.22)
β_2	0.04	0.59	0.84	0.74	0.45	0.59	0.93	0.25	0.06	0.12	0.24
	(0.64)	(0.51)	(0.67)	(0.72)	(0.28)	(0.29)	(1.09)	(1.20)	(0.48)	(0.52)	(0.49)
β_3	0.30	0.11	-0.00	-0.04			-0.07	0.81	0.44	0.39	0.73
	(0.79)	(0.80)	(1.04)	(0.92)			(1.21)	(1.58)	(0.60)	(0.65)	(1.41)
(mean) type_R2	0.19	0.50	0.45	0.39	0.58	0.53	0.43	0.46	0.43	0.42	0.57
	(0.22)	(0.26)	(0.24)	(0.26)	(0.23)	(0.23)	(0.25)	(0.29)	(0.29)	(0.26)	(0.22)
Observations	111	378	143	387	111	281	42	135	651	412	585

Table 11: Predicting forecasting types (based on non-rejection) using observeables

	Fire	Data Consistent	Naive	Adaptive	Mean Revert	Fundamental	Anchor 2%	Nonallocated
Panel A: Demographics								
Female	0.32	0.50***	0.52***	0.88***	0.57***	-0.02	0.16	-0.45***
	(0.20)	(0.12)	(0.12)	(0.16)	(0.19)	(0.10)	(0.11)	(0.11)
Birth year	0.01	-0.01***	-0.01**	0.01*	-0.01	0.01**	-0.00	-0.00
	(0.01)	(0.00)	(0.00)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)
High educ	-0.27	-0.02	-0.19	-0.25	-0.75***	0.12	0.06	0.06
	(0.22)	(0.13)	(0.13)	(0.17)	(0.22)	(0.11)	(0.12)	(0.11)
High income	-0.22	-0.21*	-0.43***	-0.30*	0.13	-0.18*	-0.14	0.31***
	(0.20)	(0.12)	(0.12)	(0.16)	(0.20)	(0.10)	(0.12)	(0.11)
Observations	1769	1769	1769	865	903	1769	1769	1769
Panel B: Inflation forecasts & Estimation details								
$f_{i,t}\pi_{t+12}$	-0.04	-0.17***	0.01	0.38***	-0.10**	0.03*	-0.10***	-0.10***
	(0.05)	(0.03)	(0.02)	(0.05)	(0.04)	(0.02)	(0.02)	(0.03)
$f_{i,t}\pi_{t+120}$	-0.03	0.01*	0.02***	-0.02**	0.03***	0.00	0.00	0.00
	(0.02)	(0.00)	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)
$(\pi_{t+12} - f_{i,t}\pi_{t+12})^2$	0.02	0.12***	0.02	-0.00	0.12***	-0.03*	0.03**	-0.00
	(0.02)	(0.02)	(0.02)	(0.02)	(0.04)	(0.02)	(0.02)	(0.02)
Survey waves	0.00	-0.03***	-0.00	-0.02	-0.02	-0.01	-0.02***	0.03***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
R2	-5.90***	0.47*	-1.76***	1.59***	0.82**	-1.91***	-1.65***	1.16***
	(0.55)	(0.25)	(0.25)	(0.41)	(0.41)	(0.21)	(0.23)	(0.22)
Observations	1771	1771	1771	863	907	1771	1771	1771
Panel C: Survey Feedback								
Difficult?	-0.05	0.13***	0.01	-0.04	-0.00	-0.10**	-0.06	0.03
	(0.09)	(0.05)	(0.05)	(0.07)	(0.08)	(0.04)	(0.05)	(0.04)
Clear?	-0.47***	0.02	-0.02	0.07	0.19	-0.00	-0.01	-0.01
	(0.14)	(0.09)	(0.09)	(0.12)	(0.15)	(0.08)	(0.09)	(0.08)
Make you think?	0.26*	0.11	-0.05	0.08	0.28**	0.09	0.18**	-0.15**
	(0.15)	(0.08)	(0.07)	(0.10)	(0.14)	(0.07)	(0.08)	(0.06)
Interesting?	-0.11	0.01	0.09	-0.13	-0.24	-0.13*	-0.25***	0.15**
	(0.17)	(0.09)	(0.08)	(0.11)	(0.15)	(0.07)	(0.09)	(0.07)
Observations	1773	1773	1773	865	907	1773	1773	1773

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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