Attention-Dependent Monetary Transmission to Household Beliefs*

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Abstract

Household inflation expectations react unevenly to monetary policy. We model endogenous attention to inflation news and show that attention conditions pass-through to beliefs, scales aggregate pass-through with average attentiveness, intensifies in periods of elevated uncertainty, and is larger for groups with higher payoffs to information. Using household survey data, we confirm these predictions: revisions in inflation expectations concentrated among attentive respondents; aggregate pass-through is larger in high-attentive period; and uncertainty-driven amplification is stronger for the attentive households. Our findings suggest the expectations channel of monetary policy hinges on household attentiveness and how it varies across people and over time.

Keywords: Inflation expectations, Monetary policy, Rational inattention, Behavioral macroeconomics

JEL Codes: D83, D84, E31, E52

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1 Introduction

Central banks emphasize expectations as an important channel of monetary transmission. Yet when households actually update their inflation beliefs in response to policy news—and which households do so—has been hard to pin down empirically. This paper studies when households "listen" to the Fed. Our central claim is that attention to macroeconomic conditions is a key, heterogeneous, and time-varying determinant of the pass-through from conventional monetary policy (MP) surprises to household inflation expectations. We combine a simple model of endogenous attention with new micro and time-series evidence from a long-running U.S. household survey and externally identified policy shocks. Three results emerge: attention *mediates* the individual-level impact of MP on beliefs; aggregate pass-through scales with the economy's average attentiveness; and the effect strengthens in periods of elevated uncertainty, especially among already attentive households.

We begin with a minimal behavioral framework, following Gabaix (2020), in which each household chooses an attention level prior to the arrival of shocks and forms expectations as an attention-weighted combination of a long-run anchor and the fully informed forecast. Attention balances forecast-loss reductions against mental costs and is increasing in the *payoff-relevant news variance*—the volatility of monetary and non-monetary disturbances that would move the fully informed forecast. The model delivers four testable implications: (i) only the attentive component of beliefs loads on policy news (attention "mediates" pass-through); (ii) aggregate pass-through in time series is proportional to average attentiveness; (iii) higher uncertainty raises attention and therefore amplifies belief responses to policy; and (iv) pass-through is larger for households with higher payoffs to information (*e.g.*, stockholders and homeowners), consistent with a higher benefit parameter in the model.

We then take these predictions to the data using the Michigan Survey of Consumers (MSC). Exploiting its rotating panel, we construct an attentiveness indicator by contrasting respondents' assessments of recent business conditions with an external benchmark measured before the policy shock, ensuring predetermination. Monetary policy surprises are identified with high-frequency methods and standard external instruments. Our empirical strategy proceeds in three steps: a micro event-study of the impact effect of conventional MP surprises on revisions in one-year-ahead inflation expectations; a time-series regression that splits months by economy-wide attentiveness; and heterogeneity analyses that interact MP surprises with attentiveness and household characteristics (stockholding, homeownership, age, income), along with interactions with recession and real/financial uncertainty.

Three facts align closely with the model. First, in the micro data, a contractionary shock reduces one-year-ahead inflation expectations *only* among respondents classified as attentive; the estimate for inattentive respondents is small and statistically indistinguishable from zero. This individual-level pattern is the attention-mediated pass-through predicted by the model and directly links policy surprises to belief updates when attention is high. Second, in a time-series design that splits months by ex ante economy-wide attentiveness, the pass-through of a contractionary monetary policy shock is large and negative in high-attentiveness months and near zero otherwise, consistent with aggregate pass-through being proportional to average attention. Third, pass-through strengthens in more uncertain periods—during recessions and when real or financial uncertainty is elevated—and this amplification is concentrated among the attentive households. These facts match the comparative statics that optimal attention rises with payoff-relevant news variance and help reconcile why measured effects of MP on the economy could vary across environments (Vavra, 2014, Tenreyro and Thwaites, 2016, Alpanda, Granziera and Zubairy, 2021).

We also document systematic heterogeneity consistent with the model's payoff logic. Among attentive respondents, stockholders and homeowners exhibit especially large pass-through, while renters and non-stockholders do not respond significantly on impact; among inattentive respondents, no subgroup reacts. Younger and middle-aged attentive respondents react more than older ones, echoing experience-based and information-processing differences documented elsewhere (Malmendier and Nagel, 2016). These patterns resonate with recent work linking asset ownership to higher household attentiveness and more accurate macro beliefs (Ahn and Xie, 2024) and with evidence that homeownership shapes the salience of interest-rate movements for household decisions (Ahn, Xie and Yang, 2024). They also complement new evidence on firms' attention and the efficacy of MP (Afrouzi and Yang, 2021, Yang, 2022, Afrouzi, 2024, Song and Stern, 2024, Wu, 2024): when agents pay more attention, their expectations align more tightly with fundamentals and react more to policy news.

Our contribution is to show, in a single framework and dataset, that households' attention mediates how conventional monetary policy shocks pass through to inflation expectations, that average attentiveness organizes the strength of the expectations channel over time, and that the effect becomes stronger in more uncertain periods and for households with higher payoffs to information. Conceptually, the results underscore that the expectations channel is *attention sensitive*: the same policy action can have sharply different effects on beliefs depending on how much attention the audience endogenously devotes to macroeconomic news. In practice, they suggest that communication strategies and policy evaluations should account for variation in attentiveness across groups and over time.

This paper bridges theories of inattentive expectations with empirics on the monetary transmission of beliefs. On the theory side, our setup nests classic information frictions—sticky information and rational inattention (Mankiw and Reis, 2002, Sims, 2003, Maćkowiak and Wiederholt, 2009)—within the behavioral expectations operator of Gabaix (2020), and relates to broader bounded-rationality approaches (Angeletos and Lian, 2018, Bordalo, Gennaioli and Shleifer, 2018). On the empirical side, we connect to work on limited information and learning among households and firms (Coibion and Gorodnichenko, 2015a, Candia, Coibion and Gorodnichenko, 2024), the effects of central-bank communications on household beliefs (Carvalho and Nechio, 2014, Lamla and Vinogradov, 2019, Claus and Nguyen, 2020, Kryvtsov and Petersen, 2021, Coibion, Gorodnichenko and Weber, 2022, Bauer, Pflueger and Sunderam, 2024), and experience/salience in expectation formation (Malmendier and Nagel, 2016, Cavallo, Cruces and Perez-Truglia, 2017, DAcunto, Malmendier, Ospina and Weber, 2021). Our contribution is to fuse these strands by embedding classic information frictions within a behavioral expectations model that delivers sharp, state-contingent predictions for belief updating after externally identified MP shocks, and testing these predictions using a widely used household survey by measuring attentiveness prior to policy news and showing that it governs *who* updates, *by how much*, and *when*.

Household and firm attentiveness to inflation has been measured in several complementary ways. One strand uses "revealed attention" from search behavior and news supply, such as internet search for inflation-related queries and counts of inflation articles in major outlets (Kumar, Coibion, Afrouzi and Gorodnichenko, 2015, Marcellino and Stevanovic, 2022, Korenok, Munro and Chen, 2023). Pfäuti (2024) infers attention from updating behavior, estimating a time-varying attention parameter from how strongly short-run inflation expectations load on recent inflation and classifying "high-attention" regimes when this responsiveness exceeds an estimated threshold. Kroner (2025) introduces a complementary pre-announcement index of investor attention around CPI releases aggregates news coverage, mainstream media mentions, and Google search intensity for inflation into a CPI-attention measure used to predict market reactions. Micro-based approaches complement these aggregates by inferring attentiveness directly from survey behavior (*e.g.,* Braitsch and Mitchell, 2022, Song and Stern, 2024). In particular, Bracha and Tang (2024) proxy inattention from the MSC's two-step inflation module: among respondents who first say prices will "stay the same," low attention is flagged if they answer "don't know" at the numeric follow-up or, if they give a number, when it departs substantially from contemporaneous inflation. Relative to these papers, our contribution is to measure attentiveness at the respondent level before policy news and connect it to externally identified monetary policy shocks, showing that attention governs who updates, how much, and when—and that aggregate pass-through scales with independently measured attentiveness over time. This bridges aggregate search and news-based indicators and micro consistency-based measures by providing a direct, policy-linked mapping from attention to belief updating.

Recent evidence indicates that inattention itself is endogenous and varies with the environment: when inflation or macro risk is high, agents acquire more information and align beliefs more closely with fundamentals (Flynn and Sastry, 2024, Weber, Candia, Afrouzi, Ropele, Lluberas, Frache, Meyer, Kumar, Gorodnichenko, Georgarakos, Coibion, Kenny and Ponce, 2025). We build on these insights to provide a unified, micro-founded explanation of how attention shapes the MP expectations channel when policy shocks are identified externally and attentiveness is measured before the shock realizes. We also speak to state dependence in monetary policy. While prior explanations emphasize non-linear pricing (Vavra, 2014), and broader nonlinear propagation (Tenreyro and Thwaites, 2016), we highlight an informational channel: in more volatile or uncertain environments, agents endogenously raise attention, which amplifies the beliefs response to policy. This mechanism complements recent evidence on time-varying firm inattention and MP efficacy (Song and Stern, 2024).

The paper is organized as follows. Section 2 presents the behavioral expectations model and testable implications. Section 3 describes the data and the construction of the attentiveness proxy. Section 4 reports the main empirical results, and Section 5 provides robustness checks. Section 6 concludes.

2 Behavioral Expectations with Endogenous Attention

This section develops a minimal behavioral framework in which households choose how much attention to devote to inflation-relevant news. Building on the bounded-rational expectations operator of Gabaix (2020) and the endogenous-attention logic used in Dietrich (2024), we derive four testable implications that guide our empirical work in Sections 3 and 4: (i) *attention gates* the pass-through of monetary policy (MP) shocks to household inflation expectations; (ii) aggregate MP pass-through in time series scales with the economy's *average attentiveness*; (iii) state dependence is stronger for already-attentive agents, as higher payoff-relevant uncertainty raises attention and amplifies responses; and (iv) *payoff heterogeneity*: groups with a higher benefit of being informed (larger ω_i) or lower attention costs (smaller κ_i) choose more attention, are more likely to be classified as attentive, and exhibit larger pass-through. Section 3 introduces our empirical proxy for attentiveness; Section 4 implements the corresponding tests.

2.1 Setup

Timing. At the start of month t, household i chooses attention $m_{i,t} \in [0,1]$. Then the period-t shocks are realized, and the household forms a one-year-ahead inflation expectation using a behavioral operator. We study the *impact* change in expectations around the shock arrival (holding π_t fixed and varying only the news realized within t).

Inflation fundamentals. The fully informed (rational) forecast of next-period inflation is

$$\pi^*_{t+1} \;=\; \bar{\pi} + \rho\,(\pi_t - \bar{\pi}) + \theta\,\varepsilon^{mp}_t + \Gamma'\varepsilon^{o}_t, \tag{2.1}$$

where $\bar{\pi}$ is the steady-state anchor, $\rho \in (0,1)$, ε_t^{mp} is the MP surprise, and $\varepsilon_t^o \in \mathbb{R}^K$ stacks other contemporaneous disturbances (*e.g.*, markup, energy/import prices, wage growth, commodity, tax changes). The scalar θ and vector $\Gamma = (\gamma_1, \ldots, \gamma_K)'$ are *semi-elasticities* mapping standardized innovations into the fully informed forecast. We adopt the sign convention that contractionary monetary policy shocks lower the fully informed inflation forecast, implying $\theta < 0$.

Shock normalization and covariance. We normalize the shocks to be mean-zero Gaussian:

$$\varepsilon_t^{mp} \sim \mathcal{N}(0,1), \qquad \varepsilon_t^o \sim \mathcal{N}(0,\ \Sigma_{o,t}),$$

where $\Sigma_{o,t}$ is a $K \times K$ positive semidefinite covariance matrix with ones on the diagonal. Unless stated otherwise, we assume $\mathrm{Cov}_t(\varepsilon_t^{mp}, \varepsilon_t^o) = 0$ within the identification window; off-diagonal elements of $\Sigma_{o,t}$ allow contemporaneous correlation among non-MP shocks.[1]

Behavioral expectations and attention choice. Household i forms a behavioral expectation by blending a coarse anchor with the fully informed forecast:

$$\mathbb{E}_{i,t}^B[\pi_{t+1}] \;=\; (1 - m_{i,t})\,\bar{\pi} \;+\; m_{i,t}\,\mathbb{E}_t[\pi_{t+1}^*], \tag{2.2}$$

where $\mathbb{E}_t[\cdot]$ is the full-information conditional expectation. Given the marginal benefit of being informed ω_i and attention costs κ_i, the agent chooses $m_{i,t}$ to trade off forecast inaccuracy against mental costs:

$$m_{i,t} \;=\; \arg\min_{m \in [0,1]} \frac{1}{2}\,\omega_i\,U_t\,(1-m)^2 + \frac{\kappa_i}{2}\,m^2, \tag{2.3}$$

with closed-form solution

$$m_{i,t}^*(U_t) \;=\; \frac{\omega_i\,U_t}{\omega_i\,U_t + \kappa_i} \;\in\; [0,1]. \tag{2.4}$$

Here

$$U_t \;\equiv\; \mathrm{Var}_t(\pi_{t+1}^*) \;=\; \theta^2\,\mathrm{Var}_t(\varepsilon_t^{mp}) \;+\; \Gamma'\Sigma_{o,t}\Gamma \;+\; 2\,\theta\,\mathrm{Cov}_t(\varepsilon_t^{mp},\,\Gamma'\varepsilon_t^o), \tag{2.5}$$

is the *payoff-relevant news variance* at the time attention is chosen. Under the baseline normalization and orthogonality,

$$\mathrm{Var}_t(\varepsilon_t^{mp}) = 1, \qquad \mathrm{Cov}_t(\varepsilon_t^{mp}, \varepsilon_t^o) = 0 \;\Rightarrow\; U_t \;=\; \theta^2 + \Gamma'\Sigma_{o,t}\Gamma.$$

Intuition. Optimal attention $m_{i,t}^*$ rises when the incoming news that would move the fully informed forecast is more volatile (larger U_t, $\partial m_{i,t}^*/\partial U_t > 0$), when attention is more valuable for

[1] Any unconditional variances can be absorbed into (θ, Γ). Time variation in $\Sigma_{o,t}$ captures changing macro uncertainty across states of the world.

the household (higher ω_i, $\partial m^*_{i,t}/\partial\omega_i > 0$), and falls when attention is more costly (higher κ_i, $\partial m^*_{i,t}/\partial\kappa_i < 0$).[2]

2.2 Testable Implications

We now characterize individual and aggregate responses to a contractionary MP surprise ($\varepsilon^{mp}_t > 0$ with $\theta < 0$). Proofs are deferred to Appendix A.

Proposition 1 (Attention gates MP pass-through)**.** *For household i, the impact change in inflation expectations in response to a contractionary MP surprise ($\varepsilon^{mp}_t > 0$ with $\theta < 0$) is*

$$\Delta\pi_{i,t+1} \;\equiv\; \mathbb{E}^B_{i,t}[\pi_{t+1}] - \pi_{i,t} \;=\; \theta m^*_{i,t}(U_t)\varepsilon^{mp}_t.$$

Proof. See Appendix A.1. ■

Proposition 1 shows that the pass-through of policy news is scaled by the household's level of attention, a mechanism where attention conditions the response. In Section 4.1, we will test this mechanism by interacting MP surprises with an attentiveness proxy to show that the response is concentrated among agents we classify as attentive.

Proposition 2 (Aggregate attentiveness raises time-series pass-through)**.** *Let $\Delta\pi^e_{t+1}$ denote the aggregate (e.g., mean or median) revision in inflation expectations. Aggregating Equation* (2.2) *across households yields*

$$\Delta\pi^e_{t+1} \;=\; \underbrace{\Lambda_t}_{\in[0,1]}\,\theta\,\varepsilon^{mp}_t \;+\; v_t, \qquad \Lambda_t \;\equiv\; \int m^*_{i,t}di, \tag{2.6}$$

where Λ_t is the average attentiveness *in the economy and v_t collects aggregation residuals orthogonal to ε^{mp}_t.*

Proof. See Appendix A.2. ■

The time-series impact of conventional MP on aggregate belief revisions scales with the economy's *average* attention. In Section 4.2, we will sort months by aggregate attentiveness and show that the MP slope is large and negative in high-attentive regimes and negligible in low-attentive regimes.

[2] ω_i scales the marginal loss from forecast errors ("benefit of being informed") while κ_i captures cognitive/opportunity costs. Heterogeneity in (ω_i, κ_i) will map into cross-sectional differences in pass-through.

Proposition 3 (State dependence is stronger for more attentive households)**.** *Let U_t be the payoff-relevant news variance in Equation* (2.5)*. For a contractionary MP surprise ($\theta < 0$),*

$$\frac{\partial \Delta \pi_{i,t+1}}{\partial U_t} = \theta \, \varepsilon_t^{mp} \, \frac{m^*_{i,t}(U_t)\big(1 - m^*_{i,t}(U_t)\big)}{U_t} \;<\; 0,$$

so higher U_t makes the expectation decline more. *If group A is more attentive than group I at each U_t ($m_A(U_t) > m_I(U_t)$), then*

$$\Big|\partial\big(m_A(U_t)\theta\big)/\partial U_t\Big| \;>\; \Big|\partial\big(m_I(U_t)\theta\big)/\partial U_t\Big|$$

whenever $m_A(U_t)\big(1 - m_A(U_t)\big) > m_I(U_t)\big(1 - m_I(U_t)\big)$; a sufficient condition is $m_A \in (\frac{1}{2}, 1)$ and $m_I \in (0, \frac{1}{2})$.

Proof. See Appendix A.3. ■

Endogenous attention creates *state dependence*: when the environment is more uncertain (larger U_t), attentive agents reduce their inflation expectations by more after a contractionary MP shock, and the sensitivity to U_t is itself stronger for the already-attentive group.

Proposition 4 (Payoff heterogeneity and cross-sectional pass-through)**.** *Fix $U_t > 0$. Let households differ only in (ω_i, κ_i) in Equation* (2.3)*–Equation* (2.4)*. Then:*

1. ***Attention ordering.*** *$m^*_{i,t}(U_t)$ is strictly increasing in ω_i and strictly decreasing in κ_i (i.e., $\partial m^*_{i,t}/\partial \omega_i > 0$ and $\partial m^*_{i,t}/\partial \kappa_i < 0$).*

2. ***Pass-through ordering.*** *The individual MP pass-through magnitude,*

$$\left|\frac{\partial \Delta \pi_{i,t+1}}{\partial \varepsilon_t^{mp}}\right| = |\theta| \, m^*_{i,t}(U_t),$$

   is strictly increasing in ω_i and strictly decreasing in κ_i.

3. ***Selection into "attentive/accurate".*** *For any threshold $\tau \in (0,1)$, the probability of being classified as attentive (accurate) $A_{i,t} = \mathbf{1}\{m^*_{i,t} \geq \tau\}$ is weakly increasing in ω_i and weakly decreasing in κ_i.*

4. ***Conditional ordering within the attentive group.*** *Among agents with $A_{i,t} = 1$, the conditional pass-through $|\theta| \, \mathbb{E}[m^*_{i,t} \mid A_{i,t} = 1]$ is larger for groups with higher ω and/or lower κ (whenever the support of $m^*_{i,t}$ has positive measure above τ).*

Proof. See Appendix A.4. ■

Groups for whom reducing forecast errors is more valuable (higher ω_i) or less costly (lower κ_i) choose higher attention, are more likely to be classified as attentive under any fixed threshold, and, crucially, display larger MP pass-through *and* stronger state dependence. In Section 4.4, we will treat homeowners, stockholders, prime-age, and higher-income households as empirical counterparts of higher-ω (and/or lower-κ) groups, and test the corresponding cross-sectional predictions.

In sum, the model delivers four testable implications: (i) *attention gates* the impact of MP shocks on individual expectations; (ii) aggregate MP pass-through scales with the economy's *average attentiveness*; (iii) higher payoff-relevant uncertainty strengthens pass-through—especially for already-attentive agents; and (iv) groups with higher payoff from information (larger ω_i) or lower attention costs (smaller κ_i) choose more attention and exhibit larger. In Section 3, we defines the empirical attentiveness proxy and the aggregate attentiveness index used to verify these predictions. Section 4 implements the corresponding micro and time-series analysis.

3 Data

This section describes the datasets and the construction of our empirical *attentiveness proxy*, which we will take to the tests implied by Section 2. We first outline sources and sample definitions, then construct an individual-level *accuracy* indicator (our proxy for attention in the model), and finally define an aggregate attentiveness index used in our time-series exercises. Section 4 will bring these measures to the micro and aggregate regressions implied by Propositions 1–4.

3.1 Sources and Samples

Micro survey and demographics. Our micro data come from the *Michigan Survey of Consumers* (MSC), which interviews a nationally representative sample monthly and re-interviews a rotating panel of respondents roughly six months later. We use the rotating-panel structure to construct revisions in expectations at the individual level and to control for observed heterogeneity (age, income, education, homeownership, stock ownership, gender, region). The MSC provides one-year-ahead inflation expectations and a rich set of qualitative questions on recent business conditions. Our analysis centers on this one-year-ahead horizon, as it is the most relevant for the near-term expectations channel of monetary policy and typically exhibits the highest signal-to-noise ratio in household survey data. Our baseline micro sample spans September 1998 to March 2020, which is the intersection of MSC availability for the necessary items and the availability of our high-frequency monetary policy shocks.[3]

[3]We drop November 2002 and May 2003 due to missing stock-ownership information. Following Bachmann, Berg and Sims (2015), we trim observations with absolute one-year (or five-year) inflation expectations above 20% to

Monetary policy shocks. For conventional (non-ZLB) periods, we use high-frequency MP surprises identified in narrow windows around FOMC announcements: the series of Nakamura and Steinsson (2018), extended by Bauer, Lakdawala and Mueller (2022). These measures capture unexpected policy news using futures prices and are standard in the literature. A potential concern with high-frequency surprises is that they may compound pure policy shocks with a Fed "information effect". We use the high-frequency series as our baseline because its narrow identification window is crucial for precisely timing policy news relative to individual survey interview dates. To ensure our results are not driven by such effects, we also use alternative shock measures specifically designed to purge these information effects, including the series from Bu, Rogers and Wu (2021). In the Great Moderation time-series analysis (Section 4.2), we additionally use the exogenous shocks of Romer and Romer (2004). Throughout, we code *contractionary* surprises as positive and scale horizons so that a one-percentage-point tightening corresponds to our reported coefficients.[4]

Other macro series. We obtain unemployment, Industrial Production (IP), inflation, and the National Financial Conditions Index (NFCI) from FRED. These series are used either to define the objective macro comparator in our attentiveness proxy (unemployment) or as contemporaneous controls between the two MSC interviews in some specifications.

3.2 Measuring Attentiveness: An Accuracy Proxy

Section 2 formalizes attention as a latent weight $m^*_{i,t} \in [0,1]$. In the data, we proxy attentiveness with a *pre-determined* indicator based on each respondent's qualitative assessment of recent business conditions, recorded at the first interview.

Step 1: Perceived business conditions (favorable / unfavorable / no news). At the first interview in month t, each respondent reports whether they have heard favorable or unfavorable changes in business conditions in "the last few months," or have not heard of changes. We code a three-way categorical variable

$$\text{News}_{i,t} \in \{\text{Fav},\ \text{Unfav},\ \text{Haven't heard}\},$$

which records the *sign* of the respondent's perceived business news at time t (or lack of exposure).

Step 2: Benchmark for business conditions. To construct our accuracy benchmark, we seek a macroeconomic indicator that is canonical, widely reported, and maps closely to the survey's

mitigate outliers.

[4] In panel specifications we cumulate the announcement-window shocks from t to $t+5$ to match the six-month interview horizon.

phrasing of "changes in business conditions." The unemployment rate is arguably the most salient and easily understood measure of real economic health for the general public. Specifically, we compare perceived favorability with the three-month change in the unemployment rate to smooth out high-frequency noise while still capturing the recent economic developments respondents were asked about:

$$\Delta\text{Unrate}_t \equiv \text{Unrate}_t - \text{Unrate}_{t-3}.$$

While we view this as the most natural benchmark, we confirm the robustness of our findings using alternative real and financial indicators in Section 5.

Accuracy classification. We define three mutually exclusive groups at the first interview date t:

$$\text{Accuracy}_{i,t} = \begin{cases} \text{Accurate} & \text{if Fav \& } \Delta\text{Unrate}_t < 0, \text{ or Unfav \& } \Delta\text{Unrate}_t \geq 0, \\ \text{Inaccurate} & \text{if Unfav \& } \Delta\text{Unrate}_t < 0, \text{ or Fav \& } \Delta\text{Unrate}_t \geq 0, \\ \text{Haven't heard} & \text{otherwise.} \end{cases}$$

For estimation, we encode attentiveness using a *three-way* set of mutually exclusive indicators,

$$\mathbf{A}_{i,t} = \big(\mathbf{1}\{\text{Accurate}_{i,t}\},\ \mathbf{1}\{\text{Inaccurate}_{i,t}\},\ \mathbf{1}\{\text{Haven't heard}_{i,t}\}\big),$$

and use the corresponding group dummies in our specifications (with one category omitted as the reference group).

Discussion of the accuracy proxy. Our accuracy-based indicator is a noisy measure of the latent attention variable, $m_{i,t}$, in our model. Attentive respondents can misread the news, and inattentive respondents can guess correctly. Such misclassification induces attenuation, biasing interaction coefficients toward zero. Despite this, we argue that on average, respondents who have devoted more attention to macroeconomic conditions are more likely to correctly assess the direction of a canonical indicator like the unemployment rate. The robust alignment of our empirical results with all four of the model's predictions, as shown in Section 4, suggests that this proxy, while noisy, successfully captures a salient dimension of household attentiveness.

One might be concerned that our "Accuracy" proxy captures factors other than attention, such as cognitive ability or political bias. While we cannot rule these channels out entirely, our framework provides a unified explanation for the full set of our findings: the scaling of aggregate pass-through, the amplification during uncertain times, and the stronger response among high-payoff groups like stockholders and homeowners. It is less clear how these other factors would jointly explain this specific constellation of results. Furthermore, the robustness of our findings to using different macro indicators, as shown in Section 5, mitigates concerns that the results are driven by a specific political narrative tied to unemployment.

Timing and identification. Crucially, the attentiveness indicators, $\mathbf{A}_{i,t}$, are measured at the *first* interview in month t, *prior* to the FOMC announcement window that defines the monetary policy surprise ε_t^{mp}. Hence they are pre-determined with respect to the shock. Under our high-frequency identification,

$$\mathbb{E}\left[\varepsilon_t^{mp} \,\middle|\, \mathbf{A}_{i,t}, \mathbf{X}_{i,t}, \alpha_t\right] = 0,$$

where $\mathbf{X}_{i,t}$ collects observed covariates (age bins, education, income, homeownership, stockholding, gender, region, marital status, and survey-mode controls) and α_t are month-year fixed effects that absorb common macro/news variation. This timing, combined with the exogeneity of high-frequency surprises, forms our key identifying assumption, allowing us to interpret the coefficients on the interaction terms as the differential pass-through of policy news, ruling out reverse causality or within-month information acquisition.

Descriptive statistics by accuracy group. This table reports demographics across the three groups. The groups are sizable and balanced in the sample (Accurate: 37.2%, Inaccurate: 29.7%, Haven't heard: 33.1%). *Accurate* and *Inaccurate* respondents look strikingly similar on observables: homeownership (83.2% vs. 81.9%), stockholding (76.4% vs. 75.6%), education (about 56% vs. 55% with a college degree), age (35-64: 63.4% vs. 61.7%; 65+: 22.0% vs. 23.3%), gender, region, marital status, and average income (both $\sim$ \$94k). By contrast, the *Haven't heard* group differs systematically: lower homeownership (76.9%), lower stockholding (60.8%), lower educational attainment (36.4% with a college degree; 5.6% less than high school), younger on average (18-34: 22.8%), less likely to be married/partnered (60.0%), and lower average income (\$71.2k). These patterns are consistent with interpreting our binary indicator $\mathbf{A}_{i,t}$ as an *attentiveness* proxy rather than a proxy for fixed traits; observable composition differences are concentrated in the "haven't heard" category. Section 4 will control for these demographics in all specifications.

3.3 Aggregate Attentiveness Index

To test Proposition 2 in time series, we construct an aggregate attentiveness measure as the cross-sectional share of attentive respondents at the first interview date t:

$$\mathbf{A}_t^{\text{agg}} \;\equiv\; \frac{1}{N_t}\sum_{i=1}^{N_t} \mathbf{A}_{i,t} \in [0, 1],$$

Table 1: Demographic and Socioeconomic Characteristics by Attentiveness Group

	Accurate	Inaccurate	Haven't Heard
Panel A: Homeownership			
(1) Homeowner (%)	83.2	81.9	76.9
(2) Renter (%)	16.8	18.1	23.1
Panel B: Stockownership			
(3) Stockholder (%)	76.4	75.6	60.8
(4) Non-stockholder (%)	23.6	24.4	39.2
Panel C: Education level			
(4) Grade 0-8 no hs diploma (%)	0.5	0.6	1.5
(5) Grade 9-12 no hs diploma (%)	1.6	1.3	4.1
(6) Grade 0-12 w/ hs diploma (%)	16.1	16.3	28.0
(7) Grade 13-17 no col degree (%)	25.7	26.7	29.8
(8) Grade 13-16 w/col degree (%)	30.7	29.3	22.8
(9) Grade 17 w/ col degree (%)	25.2	25.5	13.6
Panel D: Age			
(10) 18-34 (%)	14.4	14.8	22.8
(11) 35-64 (%)	63.4	61.7	53.3
(12) 65+ (%)	22.0	23.3	23.7
Panel E: Gender			
(13) Male (%)	56.3	56.2	53.1
(14) Female (%)	43.6	43.7	46.8
Panel F: Region			
(15) West (%)	22.3	22.2	20.5
(16) North Central (%)	27.0	27.0	27.8
(17) Northeast (%)	17.4	17.4	16.3
(18) South (%)	33.2	33.2	35.2
Panel G: Marital status			
(19) Married/partner (%)	67.2	67.0	60.0
(20) Divorced (%)	13.5	13.5	13.9
(21) Widowed (%)	6.3	6.3	8.4
(22) Never married (%)	12.8	13.0	17.4
Panel H: Average income			
(23) Average income	93,911.9	93,886.0	71177.6
Total (%)	37.2	29.7	33.1

Notes: Table 1 reports respondent characteristics by attentiveness group (Accurate, Inaccurate, Haven't Heard). Entries are column percentages unless noted; "Average income" is mean nominal household income (USD). Demographic categories include housing tenure, stockholding, education, age, gender, region, marital status, and income. Sample covers first interviews from 1998m09–2020m03. See Section 3 for the construction of the attentiveness measure and variable definitions.

where N_t is the number of respondents with non-missing $\mathbf{A}_{i,t}$. We use $\mathbf{A}_t^{\text{agg}}$ directly as a continuous index and, for regime analyses, define *high-attentive* months as those in the upper quantile of $\mathbf{A}_t^{\text{agg}}$

(*e.g.*, top 30% in the Great Moderation subsample) and *low-attentive* months as the complement. By construction, $\mathbf{A}_t^{\text{agg}}$ is the empirical counterpart to the model's average attention $\Lambda_t = \mathbb{E}_i[m_{i,t}^*]$ in Proposition 2.

3.4 Variable Alignment and Construction Notes

Expectation revisions. For individual i, we compute the revision in one-year-ahead inflation expectations over the six-month panel window, aligning the timing so that the first interview (where $A_{i,t}$ is measured) precedes the MP shock and the second interview falls at $t+h$ (typically $h = 6$ months). Aggregate revisions $\Delta\pi_{t+h}^e$ (*e.g.*, median) are computed analogously across individuals interviewed in month t and re-interviewed in $t+h$.

Controls and scaling. When used, contemporaneous macro controls are measured between the first and second interviews (*e.g.*, ΔIP and $\Delta\pi$ from t to $t+h$). Monetary shocks are cumulated from t through $t+h-1$ to match the survey horizon when appropriate; Section 4 reports the exact horizon choice and robustness to alternatives.

4 Empirical Results

This section brings the model's predictions to the data. We test four implications from Section 2 using the measures defined in Section 3. First, at the micro level, *attention gates* the pass-through of contractionary monetary policy surprises to one-year-ahead inflation expectations: only attentive (accurate) respondents revise down on impact. Second, in time series, the aggregate pass-through scales with the economy's *average attentiveness*. Third, pass-through is *state dependent* and strengthens when uncertainty is high, especially among the attentive. Fourth, cross-sectional heterogeneity lines up with payoff differences: groups for whom information is more valuable—homeowners, stockholders, prime-age, and higher-income households—display larger responses when they are accurate. Throughout, identification exploits exogenously identified monetary policy shocks and the fact that accuracy is measured *before* the shock window; we report robustness to alternative shock measures, controls, and samples.

4.1 Attention Shapes Monetary Policy Pass-Through

We begin by testing Proposition 1 in the micro data: only attentive (accurate) respondents should load on contractionary monetary policy (MP) news on impact. Identification rests on two timing features. First, attentiveness is measured at the *first* interview in month t and is therefore predetermined with respect to the FOMC announcement window that generates the MP surprise in month t. Second, the

MP shock is measured in high frequency around the announcement and then *cumulated* from t to $t+5$ so that the information set between the two interviews (typically six months apart) aligns with the survey horizon. Under this timing, and conditional on observables, the surprise component of MPS_t is orthogonal to respondents' pre-shock attentiveness and demographics, so the interaction coefficients below identify differential pass-through rather than reverse causality or within-month information acquisition.

Our baseline specification is a slight modification of Coibion and Gorodnichenko (2015b):

$$\Delta\pi^e_{i,t+6} = \alpha + \beta'_{M,A}\big(MPS_t \times \mathbf{A}_{i,t}\big) + \beta'_{Z,A}\big(\mathbf{Z}_t \times \mathbf{A}_{i,t}\big) + \Gamma'\mathbf{X}_{i,t} + \varepsilon_{i,t}, \tag{4.1}$$

where $\Delta\pi^e_{i,t+6}$ is the revision in one-year-ahead inflation expectations between interviews, MPS_t is the normalized cumulative MP shock from t to $t+5$, $\mathbf{A}_{i,t}$ is the three-way accuracy vector (Accurate / Inaccurate / Haven't heard), $\mathbf{Z}_t$ contains concurrent macro changes between interviews (IP growth and inflation), and $\mathbf{X}_{i,t}$ includes demographics (age and age^2, income and quartiles, education, gender, homeownership, stockholding, marital status, region, and survey-mode controls).[5] Coefficients in $\beta_{M,A}$ are the group-specific pass-through slopes implied by Proposition 1.

Table 2 reports the estimates. The results line up closely with the gating prediction. For the *Accurate* group, a 1 pp tightening in the shadow policy rate lowers one-year-ahead expected inflation by -0.359 percentage points $(t = -4.56)$. For the *Inaccurate* group, the slope is small and statistically indistinguishable from zero $(0.088,\ t = 0.81)$. The *Haven't heard* group shows a modest negative and only marginally significant coefficient $(-0.155,\ t = -1.66)$, an effect much smaller in magnitude than that of the Accurate group.[6] Quantitatively, the Accurate–Inaccurate wedge is large: accurate respondents revise down by roughly one third of a percentage point per 1 pp tightening, while inaccurate respondents do not react on impact. This pattern is exactly what Proposition 1 implies when attentive agents have $m^*_{i,t} > 0$ and inattentive agents have $m^*_{i,t} \approx 0$.

Beyond statistical significance, our estimates imply that attention has an economically meaningful impact on the monetary transmission mechanism. Our baseline micro-level estimate indicates that for attentive ("Accurate") individuals, a standard 25-basis-point contractionary policy surprise lowers one-year-ahead inflation expectations by approximately 9 basis points. For a given path of the nominal interest rate, this revision directly amplifies the intended policy tightening by raising the perceived short-term real interest rate for this group.

[5] Our attentiveness measure is recorded at the first interview in month t, prior to the narrow FOMC announcement window used to form MPS_t; accuracy is therefore predetermined with respect to the identified surprise. The six-month cumulation aligns the information set between interviews and rules out within-month learning as a driver of the $MPS_t \times \mathbf{A}_{i,t}$ interaction.

[6] One possible interpretation is that this group, which Table 2 shows is observationally distinct, engages in indirect or passive belief updating. For example, they might react to highly salient signals like changes in gasoline prices or absorb broad economic sentiment from media headlines, even if they do not follow specific news about business conditions.

Table 2: Attention Shapes Monetary Policy Effects on Inflation Expectations

	(1) Accurate	(2) Inaccurate	(3) Haven't Heard
(1) MPS_t	-0.360***	0.088	-0.155*
	(-4.56)	(0.81)	(-1.66)
(2) ΔIP_t	0.060***	-0.008	0.013
	(3.60)	(-0.49)	(0.70)
(3)$\Delta\pi_t$	0.370***	0.272***	0.325***
	(9.81)	(6.41)	(7.21)
Controls		Yes	
Observations		37,445	
R^2		0.0138	

Notes: This table shows the baseline regression results of Equation (4.1). Dependent variable is the revision in one-year-ahead inflation expectations between the first and second MSC interviews (t to t+6). MPS_t is the high-frequency monetary policy surprise cumulated from t to t+5 and normalized so that one unit corresponds to a 1 pp change in the shadow policy rate over that window. ΔIP_t is the log change in industrial production and $\Delta\pi_t$ is the change in inflation. Columns report coefficients from interactions with the three attentiveness groups (Accurate, Inaccurate, Haven't Heard) defined at the first interview in month t. All specifications include individual controls (age and age^2, income and quartiles, education, gender, homeownership, stockholding, marital status, region, and sentiment). Robust standard errors; t-statistics in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

The controls behave sensibly. IP growth between interviews is positively associated with revisions only for the *Accurate* group (consistent with real-side news being processed by attentive respondents), while contemporaneous inflation changes load positively and significantly for all groups, reflecting the salience of price changes in household belief formation. Crucially, the primary empirical support for our mechanism comes from the sharp contrast between the "Accurate" and "Inaccurate" groups. As shown in Table 1, these two groups are nearly identical across a wide range of demographic and socioeconomic characteristics. Their divergent responses to monetary policy shocks therefore cannot be easily attributed to observable heterogeneity, lending strong support to our interpretation that pre-shock accuracy—our proxy for attention—is the key mediating factor. Taken together, the specification, timing, and magnitudes support a "attention gates pass-through" interpretation at the micro level: contractionary MP news lowers expected inflation primarily among respondents who accurately perceived recent business conditions before the policy news arrived.

4.2 Aggregate Pass-Through Scales with Attentiveness

We now test Proposition 2 in aggregate time series: the impact of a conventional monetary policy (MP) surprise on revisions in inflation expectations should be proportional to the economy's *average attentiveness* Λ_t. To leverage a longer time series and focus squarely on conventional policy actions prior to the zero lower bound, we focus on the Great Moderation (1985m1–2007m12) and use

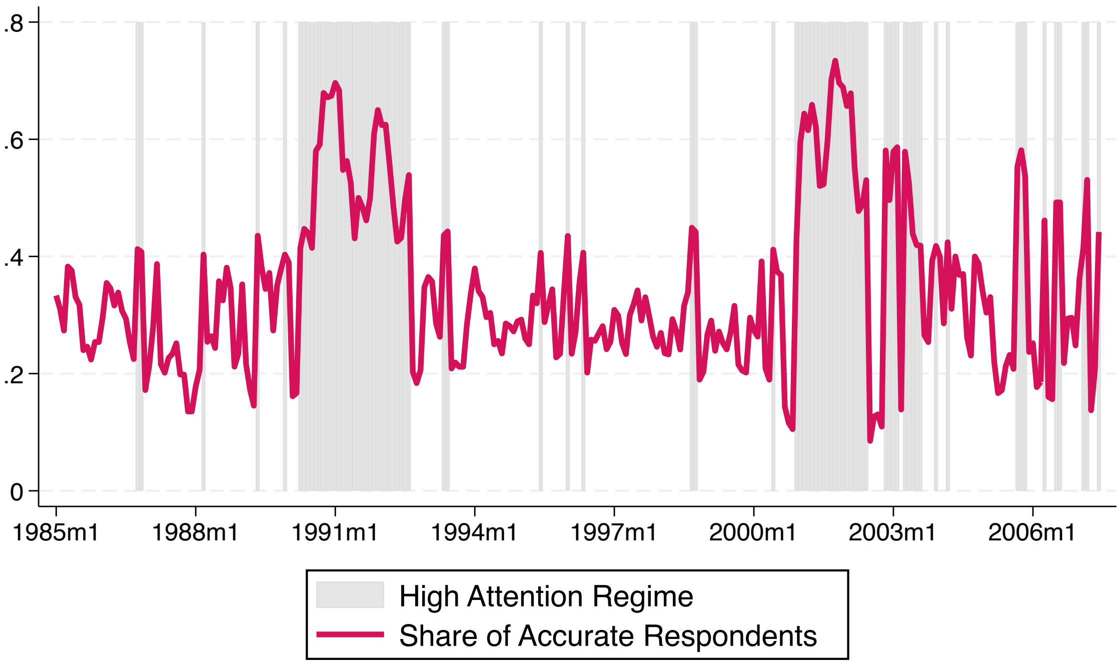

Figure 1: Aggregate Attentiveness: Share of Accurate Respondents (1985–2007)

Notes: This figure represents the monthly aggregate attentiveness (accuracy) rate from January 1985 to December 2007, defined as the share of respondents at the first interview in month t whose assessment of recent business conditions aligns with the sign of the three-month change in the unemployment rate (see Section 3 for construction). We use data through 2007m6 to define the "high-attentive" regime as the top 30% of the distribution employed in the time-series analysis.

the narrative-based shocks Romer-Romer shock series, $RRshock_t$ (Romer and Romer, 2004). We construct an aggregate attentiveness index $\mathbf{A}_t^{\text{agg}}$ as the cross-sectional share classified *Accurate* at the first interview (Section 3.3). To define our policy regimes, we classify months as "high-attentive" if they fall in the top 30% of the historical distribution of this index, which we measure using data only through June 2007 to ensure the classification is pre-determined relative to our full sample (Figure 1). This 30% threshold aligns with the average share of accurate respondents in the sample, and our qualitative findings are robust to using alternative common cutoffs like the top quartile or tercile. Proposition 2 implies a larger (more negative) policy slope in these months: $\beta^H = \theta\,\mathbb{E}[\Lambda_t \,|\, \text{High}]$ vs. $\beta^L = \theta\,\mathbb{E}[\Lambda_t \,|\, \text{Low}]$ with $|\beta^H| > |\beta^L|$ for contractionary MP shocks ($\theta < 0$).

Our time-series regression mirrors the micro design but aggregates the dependent variable to the monthly median revision, and splits months by $I_{t-1}^A = \mathbf{1}\{\mathbf{A}_{t-1}^{\text{agg}} \text{ in top } 30\%\}$:

$$\Delta\pi_{t+6}^e = \alpha + \beta_M \left(RRshock_t \times I_{t-1}^A\right) + \beta_{Z,A}' \left(\mathbf{Z}_t \times I_{t-1}^A\right) + \varepsilon_t, \tag{4.2}$$

where $\mathbf{Z}_t$ contains contemporaneous IP growth and inflation changes between the two survey

Table 3: Aggregate Pass-Through Scales with Attentiveness

Accuracy Regime	(1) High	(2) Low
(1) $RRshock_t$	-0.620***	-0.009
	(-3.17)	(-0.09)
(2) ΔIP_t	0.183***	-0.032
	(2.82)	(-1.54)
(3) $\Delta\pi_t$	0.333***	0.223***
	(3.01)	(4.66)
Observations	269	
R^2	0.394	

Notes: This table shows the regression results of Equation (4.2). Dependent variable is the median revision in 1-year-ahead inflation expectations. $RRshock_t$ is the the cumulative Romer and Romer (2004) monetary policy shocks from period t to $t+5$. ΔIP_t is the log change in industrial production and $\Delta\pi_t$ is the change in inflation. Columns report regime-specific coefficients where high-attentive months are those with the aggregate attentiveness index $\mathbf{A}_{t-1}^{\text{agg}}$ in the top 30% of its 1985m1–2007m6 distribution (Figure 1) and low-attentive months are the complement. Newey-west standard errors with 6 lags are used for the inference; t-statistics in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

interviews. Newey-West standard errors (6 lags) account for serial correlation at the six-month horizon.

Table 3 shows that the results align tightly with Proposition 2. In high-attentive months, a 1 pp conventional tightening reduces one-year-ahead expected inflation by about -0.62 pp (significant), whereas in low-attentive months the slope is small and statistically indistinguishable from zero. Controls also behave sensibly: real activity and inflation changes load positively in the high-attentive regime and are muted otherwise. The difference in slopes is consistent with a higher average attentiveness Λ_t in high-attentive months: $\widehat{\beta}^H \approx \theta\,\widehat{\Lambda}^H$ vs. $\widehat{\beta}^L \approx \theta\,\widehat{\Lambda}^L \approx 0$. Quantitatively, in high-attentive months, a 25-basis-point tightening reduces median inflation expectations by a substantial 16 basis points. This suggests that during such periods, the expectations channel can amplify the effect of a policy surprise on ex-ante real rates by more than 60%. Conversely, the absence of this effect in low-attentive periods demonstrates how a crucial channel of monetary transmission can become dormant, highlighting that the state of household attentiveness is a key determinant of the overall potency of monetary policy.

Our results imply that *belief pass-through* is state-dependent and scales with an independently measured attentiveness index. This complements micro evidence on information frictions in expectations formation (*e.g.*, Coibion and Gorodnichenko, 2015a; Gabaix, 2020) by providing a clean time-series counterpart: when more households are attentive, aggregate expectations respond strongly to policy news; when fewer are attentive, pass-through is weak.

4.3 State Dependence: Uncertainty Raises Attention and Amplifies Expectation Responses

Proposition 3 predicts that when payoff-relevant uncertainty U_t is higher, optimal attention $m^*_{i,t}$ rises and the impact of a contractionary MP shock on expectations becomes more negative, with a stronger sensitivity among already-attentive agents. We bring this to the data by interacting MP surprises with (i) our accuracy indicators and (ii) proxies for U_t measured at $t-1$: NBER recessions, the Ludvigson, Ma and Ng (2021) real-uncertainty index (LMN), and financial-market volatility (VIX). We select these three measures to span canonical business cycle, real, and financial uncertainty, ensuring our findings are not specific to one domain. For the LMN and VIX indices, our definition of a high-uncertainty state is based on their cyclical component to isolate deviations from the recent trend in uncertainty, which may be more salient to households than the absolute level. The estimating equation extends Equation (4.1) with a triple interaction,

$$\Delta\pi^e_{i,t+6} = \alpha + \beta'_{M,A,C}\left(MPS_t \times \mathbf{A}_{i,t} \times \mathsf{State}_{t-1}\right) + \beta'_{Z,A,C}\left(\mathbf{Z}_t \times \mathbf{A}_{i,t} \times \mathsf{State}_{t-1}\right) + \Gamma'\mathbf{X}_{i,t} + \varepsilon_{i,t}, \tag{4.3}$$

where $\mathsf{State}_{t-1} \in \{\text{Recession, High LMN, High VIX}\}$; coefficients on $MPS_t \times \mathbf{A}_{i,t} \times \mathsf{State}_{t-1}$ recover how the policy slope varies with uncertainty for the attentive group, while the corresponding "Inaccurate" terms benchmark the inattention case.

The results, reported in Table 4, closely match the theory.[7] During recessions, *Accurate* respondents revise down strongly on impact (-1.73 pp per 1 pp tightening; significant), while *Inaccurate* respondents do not respond.[8] In High-LMN and High-VIX months, the same qualitative pattern holds: Accurate households reduce expected inflation by ≈ -0.5 pp; Inaccurate households again show no significant reaction.[9] In Low-uncertainty or Normal states, policy slopes are small and statistically indistinguishable from zero or weakly significant for all groups. This cross-state contrast is the empirical counterpart of

$$\frac{\partial}{\partial U_t}\left(m^*_{i,t}(U_t)\,\theta\right) = \theta\frac{m^*_{i,t}(1-m^*_{i,t})}{U_t} < 0 \quad \text{(for contractionary MP shocks)},$$

and the Accurate-Inaccurate wedge in high-uncertainty states is exactly the "stronger state dependence for attentive agents" in Proposition 3. In short, uncertainty raises attention, and higher

[7] All regression coefficients are reported in Appendix Tables B.1–B.3 in Appendix B.1.

[8] The estimated effect for accurate respondents during NBER-dated recessions is economically very large. This substantial magnitude may reflect the nature of recessions as periods of heightened macro-financial risk and policy scrutiny. During such critical periods, attentive households may become hyper-responsive to Fed actions, perceiving them as crucial signals about the future state of the economy. The point estimate is consistent with our model's core prediction: uncertainty and risk dramatically amplify the expectations channel for those who are paying attention.

[9] The core finding that amplification is concentrated among the attentive also holds when using a broad, text-based measure of Economic Policy Uncertainty (see Section 5).

Table 4: Uncertainty Raises Attention and Amplifies Expectation Responses

	(1) Accurate	(2) Inaccurate	(3) Accurate	(4) Inaccurate	(5) Accurate	(6) Inaccurate
Panel A: NBER						
(1) $Recession \times MPS_t$	-1.730***	-1.125				
	(-4.01)	(-1.00)				
(2) $Normal \times MPS_t$	-0.039	0.115				
	(-0.49)	(1.12)				
Panel B: LMN Real Uncertainty						
(3) $High \times MPS_t$			-0.539***	0.048		
			(-5.51)	(0.35)		
(4) $Low \times MPS_t$			-0.269*	0.250		
			(-1.77)	(1.33)		
Panel C: VIX						
(5) $High \times MPS_t$					-0.456***	0.040
					(-4.06)	(0.22)
(6) $Low \times MPS_t$					-0.007	0.100
					(-0.07)	(0.79)
R^2	0.0170		0.0146		0.0182	
Controls	Yes		Yes		Yes	
Observations	37,445		37,445		37,445	

Notes: This table shows regime- and group-specific policy coefficients from the triple-interaction regression in Equation (4.3). The dependent variable is the revision in 1-year-ahead inflation expectations between interviews, $\Delta\pi^e_{i,t+6}$. MPS_t is the normalized cumulative monetary policy shock from t to t+5. $\mathbf{A}_{i,t}$ is the three-way accuracy indicator (Accurate / Inaccurate / Haven't heard) measured at the first interview in month t. $\mathtt{State}_{t-1}$ is (i) the NBER recession dummy (Panel A); (ii) High LMN real-uncertainty (Panel B) and (iii) High VIX financial volatility (Panel C), each defined at $t-1$; "Normal/Low" are the complementary regimes (see Section 4.3 for construction). We include concurrent IP growth and inflation changes between t and $t+6$. We use individual information about age, income, homeownership, stockownership, gender, education level, region, marital status and sentiment as controls. Robust standard errors are used for the inference; t-statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

attention scales the expectations response to policy news.

These findings complement existing state-dependence evidence obtained from prices and quantities. Vavra (2014) shows that time-varying volatility changes firms' adjustment behavior and thereby alters aggregate inflation dynamics; our mechanism works on the *expectations* margin, with uncertainty inducing greater household attention and sharper belief updates to policy news. Relatedly, macro studies documenting weaker real effects of policy in certain states (*e.g.*, deep recessions or high volatility) can be reconciled with our evidence if higher uncertainty leads agents to pay closer attention and align expectations more tightly with policy intentions—leaving less scope for misperceptions to generate real effects through the expectations channel. On the producer side, recent work on firm information choice (*e.g.*, Song and Stern, 2024) similarly finds that attention is state dependent; our results provide a household analogue: when the environment is noisy or risky, agents endogenously process more information, and policy news is more swiftly incorporated into beliefs.

Two additional patterns are worth noting. First, the state dependence we uncover does not require time variation in the volatility of the MP shock itself; increases in $\Gamma'\Sigma_{o,t}\Gamma$ (*e.g.*, energy or markup volatility) suffice to raise U_t and, therefore, attention. Second, controls behave sensibly across states: real-side changes (IP) load more in high-uncertainty states for the Accurate group, while contemporaneous inflation changes remain salient across groups. Together, the micro evidence supports a simple message: the expectations pass-through of monetary policy shocks is *attention weighted* and therefore *state dependent*.

4.4 Payoff Heterogeneity and Accuracy: Who Reacts to Policy News?

Guided by Proposition 4, in this section, we ask whether groups for whom being informed is more valuable (higher ω) or less costly (lower κ) display larger monetary-policy pass-through *when* they are accurate. We proxy higher ω/lower κ with (i) asset exposure—stockholding and homeownership—because policy moves affect portfolio values and mortgage financing; (ii) prime working age (35-64), for whom labor-market stakes are larger; and (iii) higher income, which correlates with information use and policy sensitivity.

Empirically, we extend Equation (4.1) by interacting MPS_t with the accuracy indicators and each demographic partition, controlling for group means and the full set of covariates. Let $\boldsymbol{D}_{i,t}$ be a mutually exclusive demographic partition (*e.g.*, Stockholder/Non-stockholder; Homeowner/Renter; Young/Middle/Old; Income quartiles), with one category omitted in estimation. Our general specification replaces the demographic block as needed:

$$\Delta\pi^e_{i,t+6} = \alpha + \underbrace{\beta'_{M,A,D}\big(MPS_t \times \mathbf{A}_{i,t} \times \boldsymbol{D}_{i,t}\big)}_{\text{group- and accuracy-specific MP pass-through}} + \beta'_{Z,A,D}\big(\mathbf{Z}_t \times \mathbf{A}_{i,t} \times \boldsymbol{D}_{i,t}\big) + \Gamma'\mathbf{X}_{i,t} + \varepsilon_{i,t}, \tag{4.4}$$

where MPS_t is the normalized cumulative MP surprise between interviews, $\mathbf{Z}_t$ collects concurrent macro changes (IP growth, inflation) between the two interviews, and $\mathbf{X}_{i,t}$ includes the full set of demographics and survey controls; all lower-order terms and fixed effects are included. The coefficients in $\beta_{M,A,D}$ deliver the impact slopes by *accuracy* $\times$ *demographic* cell. For contractionary shocks, the model predicts large negative slopes for *Accurate* $\times$ (high-ω/low-κ) groups (*e.g.*, stockholders, homeowners, prime-age, higher-income) and slopes near zero for *Inaccurate* cells. We estimate Equation (4.4) separately for each partition $\boldsymbol{D}_{i,t}$ and Table 5 report the $\beta_{M,A,D}$ blocks.[10]

[10] All regression coefficients are reported in Appendix Tables B.5–B.6 in Appendix B.2.

Stockholding Proposition 4 predicts stronger monetary-policy (MP) pass-through among households for whom the payoff to paying attention is higher (larger ω_i). Stockholders are a natural candidate: the value of their portfolios is more exposed to macro and policy news, which raises the marginal benefit of tracking and interpreting such news.

Panel A of Table 5 estimates Equation (4.4) with interactions between MP shocks and (i) our pre-determined attentiveness proxy and (ii) stockholding status. We find a large and statistically significant response only for *accurate stockholders*: a 1 pp contractionary MP surprise lowers their one-year-ahead inflation expectations on impact by about -0.41 pp $(t = -4.57)$. In contrast, the coefficient is smaller and statistically indistinguishable from zero for *accurate non-stockholders*, and all coefficients are near zero for the *inaccurate* groups. The absence of any response among inaccurate stockholders, alongside the strong effect for accurate ones, points to attention—rather than simple selection on unobservable traits—as the operative channel. This pattern maps tightly to Proposition 1 (attention mediates pass-through) and Proposition 4 (higher-ω types exhibit stronger pass-through).

Ahn and Xie (2024) independently document that stock-market participation is associated with greater household attentiveness and more accurate inflation beliefs. Using MSC micro data, they show that stockholders are more attentive and hold more accurate inflation beliefs; they update more to macro news than non-holders, and the attention gap widens when uncertainty is high (consistent with a risk-hedging motive). Our finding is complementary along the MP margin: conditioning on a *pre-determined* attentiveness proxy, the *impact* pass-through of conventional MP surprises is concentrated among *accurate stockholders*, whereas inaccurate stockholders do not react—exactly the attention-gating logic of Proposition 1. Quantitatively, this delivers a larger (more negative) slope for stockholders within the *Accurate* group, an empirical counterpart to Proposition 4 (higher ω).

Homeownership For homeowners, interest-rate movements are directly salient via mortgage payments, refinancing options, and housing wealth, raising the marginal benefit of tracking policy news and plausibly increasing optimal attention m_i^*. This mechanism complements evidence that homeowners are especially sensitive to rate changes through refinancing/payment channels (*e.g.*, Ahn et al., 2024).

Estimating Equation (4.4) with interactions between MP surprises, our pre-determined accuracy indicators, and homeownership status supports these predictions. Panel B of Table 5 shows that, among *accurate* respondents, a 1 pp contractionary MP surprise reduces one-year-ahead expected inflation by about -0.434 pp for *homeowners* ($t = -5.08$), whereas *renters* exhibit no detectable impact response; for the *inaccurate* groups, coefficients are small and statistically indistinguishable from zero. This sharp contrast provides evidence that the results are driven by the

Table 5: Attention and Demographic Heterogeneity in Monetary Policy Pass-Through

	(1) Accurate	(2) Inaccurate	(3) Accurate	(4) Inaccurate	(5) Accurate	(6) Inaccurate
Panel A: Stockholding						
(1) $Stock \times MPS_t$	-0.410***	0.150				
	(-4.57)	(1.20)				
(2) $NonStock \times MPS_t$	-0.228	-0.047				
	(-1.42)	(-0.21)				
Panel B: Homeownership						
(1) $Homeowner \times MPS_t$			-0.436***	0.063		
			(-5.08)	(0.54)		
(2) $Renter \times MPS_t$			0.026	0.214		
			(0.13)	(0.76)		
Panel C: Age						
(1) $Young \times MPS_t$					-0.613***	0.260
					(-3.22)	(0.82)
(2) $Middle \times MPS_t$					-0.350***	0.140
					(-3.68)	(1.12)
(3) $Old \times MPS_t$					-0.234	-0.264
					(-1.22)	(-0.98)
Interaction	Stockownership		Homeownership		Age Group	
Controls	Yes		Yes		Yes	
Observations	37,445		37,445		37,445	
R^2	0.0142		0.0144		0.0150	

Notes: This table report group- and accuracy-specific policy coefficients from the interacted specification in Equation (4.4). The dependent variable is the revision in 1-year-ahead inflation expectations between interviews, $\Delta\pi^e_{i,t+6}$. MPS_t is the normalized cumulative monetary policy surprise from t to $t+5$ (mapped to a 1 pp change in the shadow rate). $\mathbf{A}_{i,t}$ is the three-way accuracy indicator (Accurate / Inaccurate / Haven't heard) measured at the first interview in month t. $\boldsymbol{D}_{i,t}$ denotes the demographic partition used in each panel: (A) Stockholder vs. Non-stockholder; (B) Homeowner vs. Renter; (C) Age groups (Young 18-34, Middle 35-64, Old 65+). We include concurrent macro changes between interviews (IP growth and inflation) as well as the full set of demographics and survey controls. All lower-order terms and group means are included. Reported coefficients are on $MPS_t \times \mathbf{A}_{i,t} \times \boldsymbol{D}_{i,t}$. Robust standard errors are used for the inference; t-statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

proposed attention channel, rather than by selection on unobservable characteristics correlated with homeownership. The pattern mirrors Proposition 1—attention drives pass-through—and aligns with Proposition 4: conditional on being attentive, the homeowner group (a high-payoff-to-information margin) transmits policy news more strongly into expectations.

In magnitude, the homeowner effect is comparable to the stockholder effect in Panel A, suggesting two complementary margins—portfolio exposure and mortgage-linked exposure—through which higher ω_i amplifies expectation responses when attention is present. Crucially, the *accuracy* prerequisite remains central: without pre-shock attentiveness, neither homeowners nor renters transmit policy news into expected inflation on impact.

Age Group Age offers another natural partition for the attention sensitivity. Younger and prime-age households have greater labor-market exposure and more high-frequency economic decisions, which plausibly raises ω_i; they may also face lower information costs (lower κ_i). Moreover, the *personal-experience* framework of Malmendier and Nagel (2016) implies that younger individuals place more weight on recent macro information and thus update beliefs more strongly, whereas older individuals rely more on longer-horizon experience and update less on impact.

Estimating Equation (4.4) with interactions between monetary policy (MP) surprises, our pre-determined accuracy indicators, and age-group status (Young 18-34, Middle 35-64, Old 65+) yields a clear gradient within the *accurate* group (Panel C of Table 5). Accurate *young* respondents revise one-year-ahead inflation expectations the most after a 1 pp contractionary MP surprise (-0.611, $t = -3.23$), accurate *middle*-aged respondents respond less but still significantly (-0.349, $t = -3.68$), and accurate *older* respondents show a smaller, statistically insignificant coefficient (-0.234, $t = -1.22$). For *inaccurate* respondents, coefficients are small and indistinguishable from zero across all age groups.

This pattern mirrors Proposition 1: attention conditions pass-through, with virtually no impact among the inaccurate. Conditional on being attentive, the magnitude ordering (Young $>$ Middle $>$ Old) is consistent with higher ω_i and/or lower κ_i for younger/prime-age households, and with the experience-based updating of Malmendier and Nagel (2016), whereby younger individuals place greater weight on recent policy-relevant information. In sum, the age gradient in impact responses provides an additional cross-sectional validation of the model's payoff-based heterogeneity.

Income Quartile Lastly, income offers another natural partition: relative to the bottom quartile, middle- and higher-income households typically have more policy-exposed stakes (labor-market risk, asset portfolios, mortgage/credit margins), which raises ω_i and, in turn, the attention-scaled response $|\theta\, m_i^*|$.

Using the MSC income quartiles, we estimate Equation (4.4) with the demographic partition $\boldsymbol{D}_{i,t} = \{\text{YTL1}, \dots, \text{YTL4}\}$ and report results in Table 6.[11] The *accuracy prerequisite* remains first-order: across all quartiles, inaccurate respondents do not react on impact. Within the *accurate* group, we find a clear gradient: middle-income households (YTL2, YTL3) display the largest and most precisely estimated declines in 1-year-ahead expectations after a 1 pp contractionary MP surprise (-0.667 and -0.360, respectively), high-income households (YTL4) react moderately

[11] All regression coefficients are reported in Appendix Table B.7 in Appendix B.2.

Table 6: Attention and Income Quartile in Monetary Policy Pass-Through

	(1) Accurate	(2) Inaccurate
(1) $YTL1 \times MPS_t$	0.048	-0.192
	(0.18)	(-0.58)
(2) $YTL2 \times MPS_t$	-0.669***	0.046
	(-3.90)	(0.19)
(3) $YTL3 \times MPS_t$	-0.361***	0.201
	(-2.58)	(1.04)
(4) $YTL4 \times MPS_t$	-0.298**	0.132
	(-2.47)	(0.77)
Interaction	Income Quartile	
Controls	Yes	
Observations	37,445	
R^2	0.0153	

Notes: This table report group- and accuracy-specific policy coefficients from the interacted specification in Equation (4.4). The dependent variable is the revision in 1-year-ahead inflation expectations between interviews, $\Delta\pi^e_{i,t+6}$. MPS_t is the normalized cumulative monetary policy surprise from t to t+5 (mapped to a 1 pp change in the shadow rate). $\mathbf{A}_{i,t}$ is the three-way accuracy indicator (Accurate / Inaccurate / Haven't heard) measured at the first interview in month t. The demographic partition used in this talbe is income level. We use YTL4 variable from MSC to define consumers' income quartile. We include concurrent macro changes between interviews (IP growth and inflation) as well as the full set of demographics and survey controls. All lower-order terms and group means are included. Reported coefficients are on $MPS_t \times \mathbf{A}_{i,t} \times \boldsymbol{D}_{i,t}$. Robust standard errors are used for the inference; t-statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

(-0.297), and the lowest-income quartile (YTL1) shows no detectable impact response. This pattern is consistent with our payoff-based mechanism (higher ω_i outside the bottom quartile) and with the idea that groups whose expenditure baskets load more on energy and other policy-sensitive categories anticipate larger near-term disinflation following a tightening.[12]

5 Robustness

We assess the robustness of our findings along five dimensions and report full details and tables in Appendix Section B. First, we address concerns that high-frequency (HF) monetary policy surprises may bundle a Fed information-effect component. We therefore re-estimate our baseline specifications using the Bu et al. (2021) "BRW" shocks (Panel A of Table 7). The signs, cross-group ordering, and significance mirror the HF results; magnitudes are somewhat larger under BRW,

[12] Jaravel (2019) and Mangiante and Lauper (Forthcoming) investigated the relationship between monetary policy shocks and inflation inequality. Their main finding is that the household *faced* inflation may respond differently to monetary policy. More specifically, they argue that the inflation rate faced by middle income group reacts more toward the contractionary shocks. The main driven factor of this phenomenon comes from the heterogeneous consumption bundles across income-level group. They investigated gasoline, water and energy sectors might show strong response to contractionary monetary policy shocks and figured out middle- and low-income group relatively consume more weight on these sectors than high-income group.

Table 7: Alternative Monetary Shock Measure

	(1) Accurate	(2) Inaccurate	(3) Haven't Heard	(4) Accurate	(5) Inaccurate	(6) Haven't Heard
Panel A: Bu et al. (2021)						
(1) MPS_t	-1.411***	-0.256	-0.505**			
	(-6.66)	(-1.19)	(-2.14)			
(2) ΔIP_t	0.043***	-0.001	0.004			
	(2.77)	(-0.10)	(0.24)			
(3)$\Delta\pi_t$	0.349***	0.268***	0.319***			
	(9.29)	(6.33)	(7.04)			
Panel B: Bauer and Swanson (2023)						
(1) MPS_t				-1.343***	-0.535	-0.898***
				(-4.46)	(-1.57)	(-2.79)
(2) ΔIP_t				0.079***	0.056**	0.056***
				(3.97)	(1.97)	(2.16)
(3)$\Delta\pi_t$				0.275***	0.268***	0.275***
				(7.45)	(6.32)	(6.11)
Controls		Yes			Yes	
Observations		37,445			35,592	
R^2		0.0148			0.0168	

Notes: This table replaces the high-frequency MPS_t series with the Bu et al. (2021) monetary policy shocks (Panel A) and Bauer and Swanson (2023) (Panel B) and re-estimates the baseline micro specification Equation (4.1). The dependent variable is the revision in one-year-ahead inflation expectations. Shocks are cumulated from t to $t+5$ to align with the six-month survey horizon. Accuracy is measured at the first interview. We include contemporaneous IP growth and inflation changes between interviews; demographics and survey controls are included. Robust standard errors; t-statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

which is consistent with differences in the mapping from shocks to rates (BRW innovations move 2-year yields nearly one-for-one, whereas HF factors need not). We also verified robustness to the reassessed HF series in Bauer and Swanson (2023); because that sample ends in 2019:M7, we do not tabulate it, but the core patterns persist (Panel B of Table 7).

Second, we vary the construction of *Accuracy*. Our benchmark measure uses recent changes in the unemployment rate; to check that results do not hinge on this choice, we reclassify *Accuracy* using two alternative aggregate signals that proxy the real and financial sides of the macro environment: Industrial Production (IP) and the National Financial Conditions Index (NFCI). The baseline gating and heterogeneity patterns are unchanged when we use IP (Appendix Tables in Appendix B.3) or NFCI (Appendix Tables in Appendix B.4) instead of unemployment to define *Accuracy*.[13]

Third, we evaluate representativeness by reweighting the micro regressions with household-head

[13] We also replace IP with its year-over-year growth rate to remove trend; results are essentially identical.

weights (*wt*). Because the recontacted MSC panel in a given month contains at most about 250 respondents, weighting is a natural correction. Weighted regressions (Appendix Table B.18) yield coefficients that are statistically and economically indistinguishable from our baseline, suggesting that small-sample composition does not drive our results.

Fourth, we augment the macro controls to account for the salience of gasoline prices in household belief formation. We add the log change in *U.S. Regular All Formulations Gas Price* between the two interviews (from FRED) to the baseline controls (replacing crude oil prices used elsewhere). The gating and heterogeneity results are robust to this addition (Appendix Table B.19), indicating that our findings are not an artifact of omitted gasoline-price movements.

Finally, we revisit the state-dependence analysis using an alternative uncertainty proxy. We construct the volatility state from the Economic Policy Uncertainty (EPU) index (Baker, Bloom and Davis, 2016a)—a text-based measure that captures policy-relevant uncertainty spanning both real and financial sources. Defining high-uncertainty months by the cyclical component of EPU and re-estimating the triple-interaction design reproduces our baseline pattern: Accurate respondents load more strongly on contractionary policy news in high-uncertainty states, while Inaccurate respondents do not (Appendix Table B.20).

Across all checks—alternative Accuracy definitions (IP, NFCI), alternative shock measures (BRW, reassessed HF), population weighting, richer price controls, and alternative uncertainty splits (EPU)—the core results remain: attention (Accuracy) conditions pass-through on impact, aggregate pass-through scales with attentiveness, state dependence is stronger for the attentive, and high-payoff groups (stock-holders, homeowners, prime-age, higher-income) display larger effects when accurate.

6 Conclusion

We develop a minimal behavioral framework in which households optimally choose attention to inflation-relevant news and derive four predictions: attention drives the pass-through of monetary policy to inflation expectations; aggregate pass-through scales with the economy's average attentiveness; pass-through is *state dependent* and rises with payoff-relevant uncertainty; and, conditional on being attentive, groups with a higher payoff from being informed display stronger effects. Using pre-determined *Accuracy*, high-frequency identified MP surprises, and both micro and aggregate designs, the data align closely with these predictions. On impact, attentive households revise down expected inflation after contractionary shocks, the aggregate response is larger in high-attentive months, state dependence is concentrated among the attentive, and stockholders, homeowners, prime-age, and higher-income households react more when accurate.

These findings have clear policy and macro implications. Attention acts as an *expectations* *multiplier*: when attention is low, policy news barely reaches household beliefs; when high, the same news moves expectations strongly. This provides a microfoundation for why broad-based communications can have limited effects, as a large share of the audience may be in a low-attention state. Our results suggest that the expectations channel is most potent when communications are timed to coincide with periods of high uncertainty or targeted toward high-payoff groups—like homeowners and stockholders—who are endogenously more attentive. The effectiveness of tools like forward guidance is therefore not constant but is likely amplified during turbulent economic times. This uneven transmission, while useful for fast-acting policy, means central banks may confront distributional asymmetries in how expectations are updated. From a macro lens, stronger belief pass-through amplifies the short-run real-rate effect of a given nominal tightening, potentially making conventional MP more powerful in disinflating while sharpening near-term trade-offs.

Our analysis focuses on impact revisions and leaves longer-horizon dynamics and general-equilibrium propagation to future work. Natural next steps include causal manipulation of attention (e.g., information treatments), linking belief updates to spending/refinancing/portfolio behavior, and integrating household and firm attention in a structural model, and studying optimal communication under attention constraints. While our work focuses on monetary policy, the model implies that attention conditions responses to any inflation-relevant news; investigating this mechanism for other disturbances, like fiscal or energy shocks, is a fruitful avenue for future research. A companion agenda is to connect time variation in *attention inequality* to the changing effectiveness of policy over the business cycle.

References

Afrouzi, Hassan, "Strategic Inattention, Inflation Dynamics, and the Nonneutrality of Money," *Journal of Political Economy*, 2024, *132* (10), 3378–3420.

— **and Choongryul Yang**, "Dynamic rational inattention and the Phillips curve," Working Paper 8840, CESifo 2021.

Ahn, Hie Joo and Shihan Xie, "Stock-driven Household Attention," 2024.

— **, — , and Choongryul Yang**, "Effects of monetary policy on household expectations: The role of homeownership," *Journal of Monetary Economics*, 2024, *147*, 103599.

Alpanda, Sami, Eleonora Granziera, and Sarah Zubairy, "State dependence of monetary policy across business, credit and interest rate cycles," *European Economic Review*, 2021, *140*, 103936.

Angeletos, George-Marios and Chen Lian, "Forward Guidance without Common Knowledge," *American Economic Review*, 2018, *108* (9), 2477–2512.

Bachmann, Rudiger, Tim O Berg, and Eric R Sims, "Inflation expectations and readiness to spend: Cross-sectional evidence," *American Economic Journal: Economic Policy*, 2015, *7* (1), 1–35.

Baker, Scott R., Nicholas Bloom, and Steven J. Davis, "Measuring Economic Policy Uncertainty," *Quarterly Journal of Economics*, 2016, *131* (4), 1593–1636.

Baker, Scott R, Nicholas Bloom, and Steven J Davis, "Measuring economic policy uncertainty," *The quarterly journal of economics*, 2016, *131* (4), 1593–1636.

Bauer, Michael D, Aeimit Lakdawala, and Philippe Mueller, "Market-based monetary policy uncertainty," *The Economic Journal*, 2022, *132* (644), 1290–1308.

_ **and Eric T Swanson**, "A reassessment of monetary policy surprises and high-frequency identification," *NBER Macroeconomics Annual*, 2023, *37* (1), 87–155.

_ **, Carolin E Pflueger, and Adi Sunderam**, "Perceptions About Monetary Policy," *The Quarterly Journal of Economics*, 06 2024, *139* (4), 2227–2278.

Bordalo, Pedro, Nicola Gennaioli, and Andrei Shleifer, "Diagnostic Expectations and Credit Cycles," *Journal of Finance*, 2018, *73* (1), 199–227.

Bracha, Anat and Jenny Tang, "Inflation Levels and (In)Attention," *The Review of Economic Studies*, 06 2024, *92* (3), 1564–1594.

Braitsch, Hana and James Mitchell, "A New Measure of Consumersï¿œï¿œ (In)Attention to Inflation," *Economic Commentary*, October 2022, *2022* (14), 1–7.

Bu, Chunya, John Rogers, and Wenbin Wu, "A unified measure of Fed monetary policy shocks," *Journal of Monetary Economics*, 2021, *118*, 331–349.

Candia, Bernardo, Olivier Coibion, and Yuriy Gorodnichenko, "The Inflation Expectations of U.S. Firms: Evidence from a New Survey," *Journal of Monetary Economics*, 2024, *145*. Supplement issue.

Carvalho, Carlos and Fernanda Nechio, "Do people understand monetary policy?," *Journal of Monetary Economics*, 2014, *66*, 108–123.

Cavallo, Alberto, Guillermo Cruces, and Ricardo Perez-Truglia, "Inflation expectations, learning, and supermarket prices: Evidence from survey experiments," *American Economic Journal: Macroeconomics*, 2017, *9* (3), 1–35.

Claus, Edda and Viet Hoang Nguyen, "Monetary policy shocks from the consumer perspective," *Journal of Monetary Economics*, 2020, *114*, 159–173.

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

_ and _ , "Is the Phillips curve alive and well after all? Inflation expectations and the missing disinflation," *American Economic Journal: Macroeconomics*, 2015, *7* (1), 197–232.

_ , _ , and Michael Weber, "Monetary policy communications and their effects on household inflation expectations," *Journal of Political Economy*, 2022, *130* (6), 1537–1584.

DAcunto, Francesco, Ulrike Malmendier, Juan Ospina, and Michael Weber, "Exposure to grocery prices and inflation expectations," *Journal of Political Economy*, 2021, *129* (5), 1615–1639.

Dietrich, Alexander M., "Consumption categories, household attention, and inflation expectations: Implications for optimal monetary policy," *Journal of Monetary Economics*, 2024, *147*, 103594.

Flynn, Joel P and Karthik Sastry, "Attention Cycles," Working Paper 32553, National Bureau of Economic Research June 2024.

Gabaix, Xavier, "A Behavioral New Keynesian Model," *American Economic Review*, 2020, *110* (8), 2271–2327.

Jaravel, Xavier, "The unequal gains from product innovations: Evidence from the us retail sector," *The Quarterly Journal of Economics*, 2019, *134* (2), 715–783.

Korenok, Oleg, David Munro, and Jiayi Chen, "Inflation and Attention Thresholds," *The Review of Economics and Statistics*, 11 2023, pp. 1–28.

Kroner, Niklas, "How Markets Process Macro News: The Importance of Investor Attention," Finance and Economics Discussion Series 2025-022, Board of Governors of the Federal Reserve System Mar 2025.

Kryvtsov, Oleksiy and Luba Petersen, "Central bank communication that works: Lessons from lab experiments," *Journal of Monetary Economics*, 2021, *117*, 760–780.

Kumar, Saten, Olivier Coibion, Hassan Afrouzi, and Yuriy Gorodnichenko, "Inflation Targeting Does Not Anchor Inflation Expectations: Evidence from Firms in New Zealand," *Brookings Papers on Economic Activity*, 2015, pp. 151–208.

Lamla, Michael J and Dmitri V Vinogradov, "Central bank announcements: Big news for little people?," *Journal of Monetary Economics*, 2019, *108*, 21–38.

Ludvigson, Sydney C, Sai Ma, and Serena Ng, "Uncertainty and business cycles: exogenous impulse or endogenous response?," *American Economic Journal: Macroeconomics*, 2021, *13* (4), 369–410.

Maćkowiak, Bartosz and Mirko Wiederholt, "Optimal Sticky Prices under Rational Inattention," *American Economic Review*, 2009, *99* (3), 769–803.

Malmendier, Ulrike and Stefan Nagel, "Learning from inflation experiences," *The Quarterly Journal of Economics*, 2016, *131* (1), 53–87.

Mangiante, Giacomo and Christoph Lauper, "Monetary policy shocks and inflation inequality," *International Journal of Central Banking*, Forthcoming.

Mankiw, N. Gregory and Ricardo Reis, "Sticky Information versus Sticky Prices: A Proposal to Replace the New Keynesian Phillips Curve," *Quarterly Journal of Economics*, 2002, *117* (4), 1295–1328.

Marcellino, Massimiliano and Dalibor Stevanovic, "The demand and supply of information about inflation," Working Papers 22-06, University of Quebec in Montreal's School of Management Aug 2022.

Nakamura, Emi and Jon Steinsson, "High-frequency identification of monetary non-neutrality: the information effect," *The Quarterly Journal of Economics*, 2018, *133* (3), 1283–1330.

Pfäuti, Oliver, "The Inflation Attention Threshold and Inflation Surgers," Working Papers 2024-02, EMPCT Working Paper Series 2024.

Romer, Christina D and David H Romer, "A new measure of monetary shocks: Derivation and implications," *American economic review*, 2004, *94* (4), 1055–1084.

Sims, Christopher A., "Implications of Rational Inattention," *Journal of Monetary Economics*, 2003, *50* (3), 665–690.

Song, Wenting and Samuel Stern, "Firm Inattention and the Efficacy of Monetary Policy: A Text-Based Approach," *The Review of Economic Studies*, 10 2024, p. rdae102.

Tenreyro, Silvana and Gregory Thwaites, "Pushing on a String: US Monetary Policy Is Less Powerful in Recessions," *American Economic Journal: Macroeconomics*, 2016, *8* (4), 43–74.

Vavra, Joseph, "Inflation Dynamics and Time-Varying Volatility: New Evidence and an Ss Interpretation," *The Quarterly Journal of Economics*, None 2014, *129* (1), 215–258.

Weber, Michael, Bernardo Candia, Hassan Afrouzi, Tiziano Ropele, Rodrigo Lluberas, Serafin Frache, Brent Meyer, Saten Kumar, Yuriy Gorodnichenko, Dimitris Georgarakos, Olivier Coibion, Geoff Kenny, and Jorge Ponce, "Tell Me Something I Don't Already Know: Learning in Low- and High-Inflation Settings," *Econometrica*, 2025, *93* (1), 229–264.

Wu, Edson, "Rationally Inattentive Seller: The Geographic Dispersion of U.S. Retail Chains and its Aggregate Implications," Technical Report, Kilts Center at Chicago Booth Marketing Data Center 2024.

Yang, Choongryul, "Rational inattention, menu costs, and multi-product firms: Micro evidence and aggregate implications," *Journal of Monetary Economics*, 2022, *128*, 105–123.

APPENDIX

A Proofs

This appendix provides the formal mathematical derivations for the four main propositions presented in the theoretical framework of Section 2. It details the steps for deriving the impact of monetary policy on individual expectations (Proposition 1) , the scaling of aggregate pass-through with attention (Proposition 2), the state-dependent nature of the response to uncertainty (Proposition 3), and the cross-sectional predictions based on payoff heterogeneity (Proposition 4) .

A.1 Proof of Proposition 1.

Combine Equation (2.1)–Equation (2.2) evaluated at the optimum $m^*_{i,t}(U_t)$:

$$E^B_{i,t}\pi_{t+1} = (1 - m^*_{i,t})\bar{\pi} + m^*_{i,t}\left[\bar{\pi} + \rho(\pi_t - \bar{\pi}) + \theta\,\varepsilon^{mp}_t + \Gamma'\varepsilon^o_t\right].$$

Holding π_t fixed at impact and differentiating w.r.t. ε^{mp}_t yields $\partial E^B_{i,t}\pi_{t+1}/\partial\varepsilon^{mp}_t = m^*_{i,t}\theta$. The impact change is $\Delta\pi_{i,t+1} = m^*_{i,t}\theta\,\varepsilon^{mp}_t$.

A.2 Proof of Proposition 2.

Start from the individual impact change,

$$\Delta\pi_{i,t+1} = \mathbb{E}^B_{i,t}[\pi_{t+1}] - \pi_{i,t} = m^*_{i,t}(U_t)\left(\theta\,\varepsilon^{mp}_t + \Gamma'\varepsilon^o_t\right),$$

which follows by substituting Equation (2.1) into Equation (2.2) and evaluating at impact (holding π_t fixed). Let the aggregate revision be the cross-sectional average:

$$\Delta\pi^e_{t+1} \equiv \mathbb{E}_i[\Delta\pi_{i,t+1}] = \underbrace{\mathbb{E}_i[m^*_{i,t}(U_t)]}_{\Lambda_t}\,\theta\,\varepsilon^{mp}_t + \underbrace{\mathbb{E}_i[m^*_{i,t}(U_t)]\,\Gamma'\varepsilon^o_t}_{v_t}.$$

By construction $\Lambda_t \in [0,1]$. Under the baseline orthogonality within the identification window, $\mathrm{Cov}_t(\varepsilon^{mp}_t, \varepsilon^o_t) = 0$, and since $m^*_{i,t}(U_t)$ is predetermined at the time the shocks are realized, we have $\mathbb{E}\left[\varepsilon^{mp}_t\,v_t\right] = 0$, so the regression coefficient of $\Delta\pi^e_{t+1}$ on ε^{mp}_t equals $\theta\,\Lambda_t$, yielding Equation (2.6). ■

A.3 Proof of Proposition 3.

Let $S_g(U) \equiv \partial[m_g(U)\theta]/\partial U = \theta \cdot \frac{m_g(U)[1-m_g(U)]}{U}$ for group g. For any $U > 0$, if $m_A(1 - m_A) > m_I(1 - m_I)$, then $|S_A(U)| > |S_I(U)|$ because $|\theta|$ and U cancel in the comparison. A sufficient condition is $m_A \in (\frac{1}{2}, 1)$ and $m_I \in (0, \frac{1}{2})$ since $f(m) = m(1 - m)$ is strictly increasing on $[0, \frac{1}{2}]$ and strictly decreasing on $[\frac{1}{2}, 1]$ with maximum at $m = \frac{1}{2}$.

A.4 Proof of Proposition 4.

Fix $U_t > 0$. From Equation (2.4),

$$m^*_{i,t}(U_t) = \frac{\omega_i U_t}{\omega_i U_t + \kappa_i}.$$

(i) Attention ordering. A direct calculation gives $\partial m^*_{i,t}/\partial\omega_i = \frac{U_t \kappa_i}{(\omega_i U_t + \kappa_i)^2} > 0$ and $\partial m^*_{i,t}/\partial\kappa_i = -\frac{\omega_i U_t}{(\omega_i U_t + \kappa_i)^2} < 0$, so $m^*_{i,t}$ is strictly increasing in ω_i and strictly decreasing in κ_i.

(ii) Pass-through ordering. The individual MP pass-through magnitude is $\left|\partial\,\Delta\pi_{i,t+1}/\partial\varepsilon^{mp}_t\right| = |\theta|\, m^*_{i,t}(U_t)$ by Proposition 1. Monotonicity then follows from part (i).

(iii) Selection into "attentive/accurate". For any threshold $\tau \in (0, 1)$, $A_{i,t} = \mathbf{1}\{m^*_{i,t} \geq \tau\}$ is nondecreasing in ω_i and nonincreasing in κ_i because $m^*_{i,t}$ is monotone in those parameters.

(iv) Conditional ordering within the attentive group. On $\{A_{i,t} = 1\}$ we have $m^*_{i,t} \geq \tau$. Since $m^*_{i,t}$ is increasing in ω_i and decreasing in κ_i pointwise, any upward (first-order) shift in ω or downward shift in κ raises $m^*_{i,t}$ for every individual, and thus raises $\mathbb{E}[m^*_{i,t} \mid A_{i,t} = 1]$ whenever the support above τ has positive measure. ■

B Robustness

This appendix contains the complete regression tables that support the robustness analysis discussed in Section 5 . It includes detailed output from the state-dependence and demographic heterogeneity analyses, as well as a comprehensive set of checks using alternative definitions for the accuracy proxy (based on Industrial Production and the NFCI), alternative monetary policy shock measures, population weighting, and additional controls.

B.1 Full Reports: State Dependent Analysis

This section provides the complete regression output for the state-dependence analysis presented in Section 4.3. The tables report the full set of coefficients, including those for the "Haven't Heard" group and contemporaneous macro controls, for specifications using NBER recessions , the LMN real uncertainty index , and the VIX to define high- and low-uncertainty states.

Appendix Table B.1: Attention with NBER Business Cycle Indicator

NBER Recession	(1) Accurate	(2) Inaccurate	(3) Haven't Heard
Panel A: NBER Recession			
(1) $Recession \times MPS_t$	-1.701***	-1.125	-0.988
	(-4.01)	(-1.00)	(-1.29)
(2) $Recession \times \Delta\text{IP}_t$	0.200***	0.084	0.120*
	(5.19)	(0.87)	(1.68)
(3) $Recession \times \Delta\pi_t$	0.303***	0.258	0.243
	(3.29)	(1.32)	(1.52)
Panel B: Normal			
(4) $Normal \times MPS_t$	-0.039	0.115	-0.123
	(-0.49)	(1.12)	(-1.43)
(5) $Normal \times \Delta\text{IP}_t$	-0.028	-0.018	-0.021
	(-1.41)	(-1.00)	(-1.09)
(6) $Normal \times \Delta\pi_t$	0.332***	0.269***	0.275***
	(8.17)	(6.17)	(5.86)
Interaction		NBER	
Controls		Yes	
Observations		37,445	
R^2		0.0170	

Notes: This table reports the state-dependent regression in Equation (4.3) using the NBER recession indicator as $\texttt{State}_{t-1}$. The dependent variable is the revision in one-year-ahead inflation expectations between interviews. MPS_t denotes the normalized cumulative high-frequency monetary policy shocks from month t to $t+5$. $\mathbf{A}_{i,t}$ is the three-way accuracy vector (Accurate / Inaccurate / Haven't heard) measured at the first interview. We include contemporaneous Industrial Production growth and inflation changes between interviews; all lower-order terms and the full set of demographics and survey controls are included. Robust standard errors are reported; t-statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Appendix Table B.2: Attention with Real Uncertainty Indicator

LMN Real Uncertainty	(1) Accurate	(2) Inaccurate	(3) Haven't Heard
Panel A: High Uncertainty			
(1) $High \times MPS_t$	-0.539***	0.048	-0.137
	(-5.51)	(0.35)	(-1.18)
(2) $High \times \Delta \text{IP}_t$	0.130***	-0.003	0.022
	(4.37)	(-0.09)	(0.66)
(3) $High \times \Delta\pi_t$	0.304***	0.137*	0.324***
	(5.29)	(1.95)	(4.38)
Panel B: Low Uncertainty			
(4) $Low \times MPS_t$	-0.269*	0.250	-0.248
	(-1.77)	(1.33)	(-1.49)
(5) $Low \times \Delta \text{IP}_t$	0.034	-0.012	0.008
	(1.62)	(-0.63)	(0.37)
(6) $Low \times \Delta\pi_t$	0.381***	0.397***	0.310***
	(7.54)	(7.73)	(5.76)
Interaction		LMN real uncertainty	
Controls		Yes	
Observations		37,445	
R^2		0.0146	

Notes: This table reports the state-dependent regression in Equation (4.3) using the Ludvigson et al. (2021) real uncertainty index (LMN) to define State_{t-1} ("High" when the HP-detrended index is above trend at $t-1$). The dependent variable is the revision in one-year-ahead inflation expectations. MPS_t is the normalized cumulative high-frequency monetary policy shocks from t to $t+5$. Accuracy is measured at the first interview; We include contemporaneous Industrial Production growth and inflation changes between interviews. All lower-order interactions, demographics, and survey controls are included. Robust standard errors; t-statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Appendix Table B.3: Attention with the VIX

VIX	(1) Accurate	(2) Inaccurate	(3) Haven't Heard
Panel A: High Volatility			
(1) $High \times MPS_t$	-0.456***	0.040	-0.098
	(-4.06)	(0.22)	(-0.70)
(2) $High \times \Delta \text{IP}_t$	0.078***	0.074**	-0.000
	(2.73)	(1.96)	(-0.01)
(3) $High \times \Delta \pi_t$	-0.011	0.141*	0.137*
	(-0.17)	(1.92)	(1.83)
Panel B: Low Volatility			
(4) $Low \times MPS_t$	-0.007	0.100	-0.179
	(-0.07)	(0.79)	(-1.45)
(5) $Low \times \Delta \text{IP}_t$	0.020	-0.027	0.007
	(0.97)	(-1.40)	(0.35)
(6) $Low \times \Delta \pi_t$	0.538***	0.338***	0.413***
	(11.82)	(6.51)	(7.37)
Interaction		VIX	
Controls		Yes	
Observations		37,445	
R^2		0.0182	

Notes: This table reports the state-dependent regression in Equation (4.3) using financial-market volatility (VIX) to define $\texttt{State}_{t-1}$ ("High" when the HP-detrended log VIX is above trend at $t-1$). The dependent variable is the revision in one-year-ahead inflation expectations. MPS_t denotes the normalized cumulative high-frequency monetary policy shocks from t to $t+5$. Accuracy is measured at the first interview. We include contemporaneous Industrial Production growth and inflation changes between interviews. All lower-order interactions, demographics, and survey controls are included. Robust standard errors. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

B.2 Full Reports: Demographic Heterogeneity

This section presents the full regression tables corresponding to the demographic heterogeneity analysis in Section 4.4. Each table details the complete set of interaction coefficients for the partitions based on stockholding, homeownership, age group, and income quartile, including results for all three accuracy groups and macro control variables.

Appendix Table B.4: Full reports for Stockholding

	(1) Accurate	(2) Inaccurate	(3) Haven't Heard
(1) $Stock \times MPS_t$	-0.410***	0.150	-0.299**
	(-4.57)	(1.20)	(-2.38)
(2) $NonStock \times MPS_t$	-0.228	-0.047	0.034
	(-1.42)	(-0.21)	(0.24)
(3) $Stock \times \Delta \text{IP}_t$	0.053***	0.001	0.020
	(2.84)	(0.09)	(0.91)
(4) $NonStock \times \Delta \text{IP}_t$	0.090***	-0.049	0.004
	(2.35)	(-1.22)	(0.11)
(5) $Stock \times \Delta \pi_t$	0.394***	0.258***	0.377***
	(9.67)	(5.92)	(6.89)
(6) $NonStock \times \Delta \pi_t$	0.292***	0.318***	0.241***
	(3.18)	(2.86)	(3.06)
Interaction		Stockholding	
Controls		Yes	
Observations		37,445	
R^2		0.0142	

Notes: This table reports the full set of coefficients for the homeownership specification of Equation (4.4). The dependent variable is the revision in one-year-ahead inflation expectations. MPS_t denotes the normalized cumulative high-frequency monetary policy shocks from t to $t+5$. We interact MPS_t with the three-way accuracy vector (measured at the first interview) and homeownership status (Homeowner / Renter). We include contemporaneous Industrial Production growth and inflation changes between interviews; We include age and age^2, income and quartiles, education, gender, homeownership, stockholding, marital status, region, and sentiment as controls; all lower-order terms are included. Robust standard errors; t-statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Appendix Table B.5: Full reports for Homeownership

	(1) Accurate	(2) Inaccurate	(3) Haven't Heard
(1) $Homeowner \times MPS_t$	-0.436***	0.063	-0.148
	(-5.08)	(0.54)	(-1.40)
(2) $Renter \times MPS_t$	0.026	0.214	-0.181
	(0.13)	(0.76)	(-0.91)
(3) $Homeowner \times \Delta\text{IP}_t$	0.057***	-0.0000	0.027
	(3.11)	(-0.00)	(1.22)
(4) $Renter \times \Delta\text{IP}_t$	0.075*	-0.032	-0.024
	(1.88)	(-0.81)	(-0.67)
(5) $Homeowner \times \Delta\pi_t$	0.386***	0.286***	0.334***
	(9.61)	(6.43)	(6.61)
(6) $Renter \times \Delta\pi_t$	0.297***	0.166	0.276***
	(2.67)	(1.30)	(2.73)
Interaction		Homeownership	
Controls		Yes	
Observations		37,445	
R^2		0.0144	

Notes: This table reports the full set of coefficients for the homeownership specification of Equation (4.4). The dependent variable is the revision in one-year-ahead inflation expectations. MPS_t denotes the normalized cumulative high-frequency monetary policy shocks from t to $t+5$. We interact MPS_t with the three-way accuracy vector (measured at the first interview) and homeownership status (Homeowner / Renter). We include contemporaneous Industrial Production growth and inflation changes between interviews; We include age and age^2, income and quartiles, education, gender, homeownership, stockholding, marital status, region, and sentiment as controls; all lower-order terms are included. Robust standard errors; t-statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Appendix Table B.6: Full reports for Age Group

	(1) Accurate	(2) Inaccurate	(3) Haven't Heard
(1) $[18-34] \times MPS_t$	-0.613***	0.260	-0.006
	(-3.22)	(0.82)	(-0.03)
(2) $[35-64] \times MPS_t$	-0.350***	0.140	-0.145
	(-3.68)	(1.12)	(-1.16)
(3) $[65+] \times MPS_t$	-0.234	-0.264	-0.338*
	(-1.22)	(-0.98)	(-1.66)
(4) $[18-34] \times \Delta \text{IP}_t$	0.110**	0.031	0.004
	(2.43)	(0.72)	(0.10)
(5) $[35-64] \times \Delta \text{IP}_t$	0.059***	-0.019	0.015
	(2.95)	(-0.84)	(0.57)
(6) $[65+] \times \Delta \text{IP}_t$	0.038	0.004	0.022
	(1.01)	(0.13)	(0.60)
(7) $[18-34] \times \Delta \pi_t$	0.381***	0.033	0.206**
	(3.68)	(0.27)	(2.07)
(8) $[35-64] \times \Delta \pi_t$	0.435***	0.328***	0.373***
	(9.41)	(6.17)	(5.94)
(9) $[65+] \times \Delta \pi_t$	0.179**	0.243***	0.311***
	(2.20)	(2.92)	(3.66)
Interaction		Age Group	
Controls		Yes	
Observations		37,445	
R^2		0.0150	

Notes: This table reports the full set of coefficients for the age-group specification of Equation (4.4). The dependent variable is the revision in one-year-ahead inflation expectations. MPS_t is the normalized cumulative high-frequency monetary policy shocks from t to $t+5$. We interact MPS_t with the three-way accuracy vector and age groups (Young 18-34, Middle 35-64, Old 65+). We include contemporaneous Industrial Production growth and inflation changes between interviews; We include age and age^2, income and quartiles, education, gender, homeownership, stockholding, marital status, region, and sentiment as controls; all lower-order terms are included. Robust standard errors; t-statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Appendix Table B.7: Full Reports for Income Quartile

	(1) Accurate	(2) Inaccurate	(3) Haven't Heard
(1) $YTL1 \times MPS_t$	0.048	-0.192	0.149
	(0.18)	(-0.58)	(0.71)
(2) $YTL2 \times MPS_t$	-0.669***	0.046	-0.212
	(-3.90)	(0.19)	(-1.12)
(3) $YTL3 \times MPS_t$	-0.361***	0.201	-0.119
	(-2.58)	(1.04)	(-0.77)
(4) $YTL4 \times MPS_t$	-0.298**	0.132	-0.416**
	(-2.47)	(0.77)	(-2.07)
(5) $YTL1 \times \Delta \text{IP}_t$	0.024	-0.043	-0.059
	(0.48)	(-0.93)	(-1.37)
(6) $YTL2 \times \Delta \text{IP}_t$	0.142***	-0.062	0.017
	(3.43)	(-1.49)	(0.49)
(7) $YTL3 \times \Delta \text{IP}_t$	0.024	-0.018	0.020
	(0.82)	(-0.59)	(0.56)
(8) $YTL4 \times \Delta \text{IP}_t$	0.054**	0.047*	0.069*
	(2.26)	(1.80)	(1.93)
(9) $YTL1 \times \Delta \pi_t$	0.427***	0.220	0.282***
	(3.30)	(1.47)	(2.68)
(10) $YTL2 \times \Delta \pi_t$	0.265***	0.313***	0.271***
	(3.16)	(3.12)	(3.12)
(11) $YTL3 \times \Delta \pi_t$	0.438***	0.307***	0.414***
	(6.51)	(4.35)	(5.37)
(12) $YTL4 \times \Delta \pi_t$	0.352***	0.238***	0.329***
	(6.16)	(3.88)	(3.51)
Interaction		Income Quartile	
Controls		Yes	
Observations		37,445	
R^2		0.0153	

Notes: This table reports the full set of coefficients for the income-quartile specification of Equation (4.4). The dependent variable is the revision in one-year-ahead inflation expectations. MPS_t denotes the normalized cumulative high-frequency monetary policy shocks from t to $t+5$. We interact MPS_t with the three-way accuracy vector and income quartiles (YTL1–YTL4). We include contemporaneous Industrial Production growth and inflation changes between interviews; We include age and age^2, income and quartiles, education, gender, homeownership, stockholding, marital status, region, and sentiment as controls; all lower-order terms are included. Robust standard errors; t-statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

B.3 Accuracy Measure with IP

This section tests the robustness of our findings to an alternative definition of the accuracy proxy. Here, we reconstruct the "Accurate" and "Inaccurate" classifications using the three-month change in Industrial Production (IP) instead of the unemployment rate.

Appendix Table B.8: Accuracy Measure with Industrial Production

	(1) Accurate	(2) Inaccurate	(3) Haven't Heard
(1) MPS_t	-0.334***	-0.044	-0.156*
	(-3.84)	(-0.47)	(-1.67)
(2) $\Delta \mathrm{IP}_t$	0.053***	-0.003	0.013
	(3.32)	(-0.16)	(0.71)
(3)$\Delta\pi_t$	0.336***	0.351***	0.325***
	(8.26)	(8.90)	(7.20)
Controls		Yes	
Observations		37,445	
R^2		0.0135	

Notes: This table reconstructs the accuracy measure using IP as the objective comparator. A respondent is "Accurate" if the sign of their reported business condition news aligns with the sign of the three-month change in IP between the two interview months; "Inaccurate" if it does not; "Haven't heard" otherwise. We re-estimate the baseline specification Equation (4.1) using this IP-based accuracy. The dependent variable is the revision in one-year-ahead inflation expectations. MPS_t is the normalized cumulative high-frequency monetary policy shocks from t to $t+5$. We include contemporaneous IP growth and inflation changes between interviews; demographics and survey controls are included. Robust standard errors; t-statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Appendix Table B.9: IP Specification for Stockholding

	(1) Accurate	(2) Inaccurate	(3) Haven't Heard
(1) $Stock \times MPS_t$	-0.398***	-0.002	-0.299**
	(-4.02)	(-0.02)	(-2.38)
(2) $NonStock \times MPS_t$	-0.158	-0.154	0.033
	(-0.89)	(-0.80)	(0.23)
(3) Stock$\times\Delta \mathrm{IP}_t$	0.053***	0.0007	0.020
	(3.07)	(0.03)	(0.93)
(4) Non-stock$\times\Delta \mathrm{IP}_t$	0.055	-0.018	0.004
	(1.47)	(-0.45)	(0.11)
(5) Stock$\times\Delta\pi_t$	0.352***	0.351***	0.377***
	(8.10)	(8.50)	(6.89)
(6) Non-stock$\times\Delta\pi_t$	0.284***	0.351***	0.241***
	(2.79)	(3.54)	(3.06)
Interaction		Stockownership	
Controls		Yes	
Observations		37,445	
R^2		0.0138	

Notes: This table re-estimates Equation (4.4) with the IP-based accuracy measure and the Stockholding partition (Stockholder/Non-stockholder). The dependent variable is the revision in one-year-ahead inflation expectations. MPS_t denotes the normalized cumulative high-frequency monetary policy shocks from t to $t+5$. We include contemporaneous IP growth and inflation changes between interviews; demographics and survey controls are included; all lower-order terms are included. Robust standard errors; t-statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Appendix Table B.10: IP Specification for Homeownership

	(1) Accurate	(2) Inaccurate	(3) Haven't Heard
(1) $Homeowner \times MPS_t$	-0.361***	-0.186*	-0.149
	(-3.79)	(-1.83)	(-1.40)
(2) $Renter \times MPS_t$	-0.185	0.660**	-0.182
	(-0.89)	(2.56)	(-0.91)
(3) $Homeowner \times \Delta \text{IP}_t$	0.051***	0.009	0.027
	(2.95)	(0.43)	(1.23)
(4) $Renter \times \Delta \text{IP}_t$	0.061	-0.060	-0.024
	(1.64)	(-1.47)	(-0.67)
(5) $Homeowner \times \Delta \pi_t$	0.353***	0.347***	0.334***
	(8.31)	(8.12)	(6.61)
(6) $Renter \times \Delta \pi_t$	0.246*	0.369***	0.275***
	(1.89)	(3.56)	(2.73)
Interaction		Homeownership	
Controls		Yes	
Observations		37,445	
R^2		0.0142	

Notes: This table re-estimates Equation (4.4) with the IP-based accuracy measure (see Table B.7) and the Homeownership partition (Homeowner / Renter). The dependent variable is the revision in one-year-ahead inflation expectations. MPS_t is the normalized cumulative high-frequency monetary policy shocks from t to $t+5$. We include contemporaneous IP growth and inflation changes between interviews; the full set of demographics and survey controls is included; all lower-order terms are included. Robust standard errors; t-statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Appendix Table B.11: IP Specification for Age Group

	(1) Accurate	(2) Inaccurate	(3) Haven't Heard
(1) $[18-34] \times MPS_t$	-0.439**	-0.236	-0.007
	(-1.99)	(-0.95)	(-0.04)
(2) $[35-64] \times MPS_t$	-0.327***	0.003	-0.145
	(-3.14)	(0.03)	(-1.16)
(3) $[65+] \times MPS_t$	-0.322	-0.032	-0.338*
	(-1.53)	(-0.14)	(-1.66)
(4) $[18-34] \times \Delta \mathrm{IP}_t$	0.106**	0.018	0.004
	(2.52)	(0.42)	(0.11)
(5) $[35-64] \times \Delta \mathrm{IP}_t$	0.057***	-0.020	0.015
	(2.84)	(-0.87)	(0.58)
(6) $[65+] \times \Delta \mathrm{IP}_t$	0.015	0.022	0.023
	(0.48)	(0.53)	(0.61)
(7) $[18-34] \times \Delta \pi_t$	0.304***	0.201*	0.206**
	(2.70)	(1.74)	(2.07)
(8) $[35-64] \times \Delta \pi_t$	0.386***	0.426***	0.373***
	(7.68)	(8.73)	(5.94)
(9) $[65+] \times \Delta \pi_t$	0.212**	0.227***	0.311***
	(2.49)	(2.83)	(3.65)
Interaction		Age Group	
Controls		Yes	
Observations		37,445	
R^2		0.0144	

Notes: This table re-estimates Equation (4.4) with the IP-based accuracy measure and the Age partition (Young 18-34, Middle 35-64, Old 65+). The dependent variable is the revision in one-year-ahead inflation expectations. MPS_t denotes the normalized cumulative high-frequency monetary policy shocks from t to $t+5$. We include contemporaneous IP growth and inflation changes between interviews; demographics and survey controls are included; all lower-order terms are included. Robust standard errors; t-statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Appendix Table B.12: IP Specification for Income Quartile

	(1) Accurate	(2) Inaccurate	(3) Haven't Heard
(1) $YTL1 \times MPS_t$	0.009	0.018	0.148
	(0.03)	(0.06)	(0.71)
(2) $YTL2 \times MPS_t$	-0.595***	-0.227	-0.213
	(-3.18)	(-1.03)	(-1.13)
(3) $YTL3 \times MPS_t$	-0.248	-0.145	-0.119
	(-1.59)	(-0.88)	(-0.77)
(4) $YTL4 \times MPS_t$	-0.358***	0.131	-0.416**
	(-2.69)	(0.89)	(-2.08)
(5) $YTL1 \times \Delta\text{IP}_t$	0.008	-0.066	-0.059
	(0.19)	(-1.27)	(-1.37)
(6) $YTL2 \times \Delta\text{IP}_t$	0.084**	0.014	0.017
	(2.25)	(0.30)	(0.50)
(7) $YTL3 \times \Delta\text{IP}_t$	0.031	-0.023	0.020
	(1.08)	(-0.70)	(0.56)
(8) $YTL4 \times \Delta\text{IP}_t$	0.068***	0.031	0.069*
	(2.93)	(1.10)	(1.93)
(9) $YTL1 \times \Delta\pi_t$	0.313**	0.424***	0.282***
	(2.11)	(3.33)	(2.68)
(10) $YTL2 \times \Delta\pi_t$	0.297***	0.345***	0.271***
	(3.25)	(3.75)	(3.12)
(11) $YTL3 \times \Delta\pi_t$	0.375***	0.389***	0.414***
	(5.31)	(5.60)	(5.36)
(12) $YTL4 \times \Delta\pi_t$	0.333***	0.295***	0.329***
	(5.45)	(5.15)	(3.51)
Interaction		Income Quartile	
Controls		Yes	
Observations		37,445	
R^2		0.0148	

Notes: This table re-estimates Equation (4.4) with the IP-based accuracy measure and the Income partition (YTL1–YTL4). The dependent variable is the revision in one-year-ahead inflation expectations. MPS_t is the normalized cumulative high-frequency monetary policy shocks from t to $t+5$. We include contemporaneous IP growth and inflation changes between interviews; demographics and survey controls are included; all lower-order terms are included. Robust standard errors; t-statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

B.4 Accuracy measure with NFCI

This section provides a further robustness check on the construction of our accuracy proxy. We redefine accuracy using the three-month change in the National Financial Conditions Index (NFCI) as the benchmark, where a rising index signals unfavorable conditions.

Appendix Table B.13: Accuracy Measure with NFCI

	(1) Accurate	(2) Inaccurate	(3) Haven't Heard
(1) MPS_t	-0.336***	-0.002	-0.155*
	(-3.88)	(-0.03)	(-1.66)
(2) ΔIP_t	0.039**	0.021	0.013
	(2.46)	(1.14)	(0.70)
(3)$\Delta \pi_t$	0.315***	0.375***	0.325***
	(7.98)	(8.95)	(7.21)
Controls		Yes	
Observations		37,445	
R^2		0.0135	

Notes: This table reconstructs the accuracy measure using the NFCI as the objective comparator for business conditions. A respondent is "Accurate" if the sign of their reported news aligns with the sign of the three-month change in NFCI (with higher NFCI interpreted as tighter, i.e., unfavorable, financial conditions); "Inaccurate" if not; "Haven't heard" otherwise. We re-estimate the baseline specification Equation (4.1) with this NFCI-based accuracy. The dependent variable is the revision in one-year-ahead inflation expectations. MPS_t is the normalized cumulative high-frequency monetary policy shocks from t to $t+5$. We include contemporaneous IP growth and inflation changes between interviews; demographics and survey controls are included. Robust standard errors; t-statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Appendix Table B.14: NFCI Specification for Stockholding

	(1) Accurate	(2) Inaccurate	(3) Haven't Heard
(1) $Stock \times MPS_t$	-0.340***	-0.028	-0.299**
	(-3.51)	(-0.26)	(-2.38)
(2) $NonStock \times MPS_t$	-0.336*	0.069	0.033
	(-1.74)	(0.40)	(0.24)
(3) Stock$\times \Delta \text{IP}_t$	0.038**	0.026	0.020
	(2.20)	(1.23)	(0.92)
(4) Non-stock$\times \Delta \text{IP}_t$	0.046	0.003	0.004
	(1.17)	(0.09)	(0.11)
(5) Stock$\times \Delta \pi_t$	0.308***	0.390***	0.377***
	(7.43)	(8.62)	(6.89)
(6) Non-stock$\times \Delta \pi_t$	0.341***	0.329***	0.241***
	(3.28)	(3.33)	(3.06)
Interaction		Stockownership	
Controls		Yes	
Observations		37,445	
R^2		0.0137	

Notes: This table re-estimates Equation (4.4) with the NFCI-based accuracy measure and the Stockholding partition. The dependent variable is the revision in one-year-ahead inflation expectations. MPS_t denotes the normalized cumulative high-frequency monetary policy shocks from t to $t+5$. We include contemporaneous IP growth and inflation changes between interviews; demographics and survey controls are included; all lower-order terms are included. Robust standard errors; t-statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Appendix Table B.15: NFCI Specification for Homeownership

	(1) Accurate	(2) Inaccurate	(3) Haven't Heard
(1) $Homeowner \times MPS_t$	-0.430***	-0.020	-0.148
	(-4.65)	(-0.20)	(-1.40)
(2) $Renter \times MPS_t$	0.170	0.086	-0.181
	(0.71)	(0.43)	(-0.91)
(3) $Homeowner \times \Delta \mathrm{IP}_t$	0.046***	0.021	0.027
	(2.71)	(1.02)	(1.22)
(4) $Renter \times \Delta \mathrm{IP}_t$	0.005	0.024	-0.024
	(0.15)	(0.64)	(-0.67)
(5) $Homeowner \times \Delta \pi_t$	0.317***	0.395***	0.334***
	(7.84)	(8.73)	(6.61)
(6) $Renter \times \Delta \pi_t$	0.296**	0.258**	0.275***
	(2.19)	(2.32)	(2.73)
Interaction		Homeownership	
Controls		Yes	
Observations		37,445	
R^2		0.0141	

Notes: This table re-estimates Equation (4.4) with the NFCI-based accuracy measure and the Homeownership partition (Homeowner/Renter). The dependent variable is the revision in one-year-ahead inflation expectations. MPS_t is the normalized cumulative high-frequency monetary policy shocks from t to $t+5$. We include contemporaneous IP growth and inflation changes between interviews; the full set of demographics and survey controls is included; all lower-order terms are included. Robust standard errors; t-statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Appendix Table B.16: NFCI Specification for Age Group

	(1) Accurate	(2) Inaccurate	(3) Haven't Heard
(1) $[18-34] \times MPS_t$	-0.167	-0.379*	-0.006
	(-0.68)	(-1.83)	(-0.04)
(2) $[35-64] \times MPS_t$	-0.363***	0.068	-0.145
	(-3.50)	(0.34)	(-1.16)
(3) $[65+] \times MPS_t$	-0.372*	0.079	-0.338*
	(-1.81)	(0.34)	(-1.66)
(4) $[18-34] \times \Delta \text{IP}_t$	0.059	0.084*	0.004
	(1.40)	(1.86)	(0.10)
(5) $[35-64] \times \Delta \text{IP}_t$	0.031	0.026	0.015
	(1.57)	(1.14)	(0.57)
(6) $[65+] \times \Delta \text{IP}_t$	0.056*	-0.024	0.022
	(1.72)	(-0.61)	(0.60)
(7) $[18-34] \times \Delta \pi_t$	0.046	0.440***	0.206**
	(0.41)	(3.84)	(2.07)
(8) $[35-64] \times \Delta \pi_t$	0.418***	0.391***	0.373***
	(8.34)	(7.72)	(5.94)
(9) $[65+] \times \Delta \pi_t$	0.145**	0.287***	0.311***
	(1.96)	(3.12)	(3.65)
Interaction		Age Group	
Controls		Yes	
Observations		37,445	
R^2		0.0147	

Notes: This table re-estimates Equation (4.4) with the NFCI-based accuracy measure and the Age partition (Young 18-34, Middle 35-64, Old 65+). The dependent variable is the revision in one-year-ahead inflation expectations. MPS_t denotes the normalized cumulative high-frequency monetary policy shocks from t to $t+5$. We include contemporaneous IP growth and inflation changes between interviews; demographics and survey controls are included; all lower-order terms are included. Robust standard errors; t-statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Appendix Table B.17: NFCI Specification for Income Quartile

	(1) Accurate	(2) Inaccurate	(3) Haven't Heard
(1) $YTL1 \times MPS_t$	0.118	-0.155	0.148
	(0.40)	(-0.54)	(0.71)
(2) $YTL2 \times MPS_t$	-0.563***	-0.271	-0.212
	(-2.81)	(-1.40)	(-1.13)
(3) $YTL3 \times MPS_t$	-0.418***	0.240	-0.119
	(-2.75)	(1.44)	(-0.77)
(4) $YTL4 \times MPS_t$	-0.271**	0.024	-0.416**
	(-2.03)	(0.17)	(-2.07)
(5) $YTL1 \times \Delta \text{IP}_t$	-0.003	-0.025	-0.059
	(-0.08)	(-0.49)	(-1.37)
(6) $YTL2 \times \Delta \text{IP}_t$	0.040	0.067	0.017
	(1.14)	(1.36)	(0.49)
(7) $YTL3 \times \Delta \text{IP}_t$	0.013	0.003	0.020
	(0.43)	(0.10)	(0.56)
(8) $YTL4 \times \Delta \text{IP}_t$	0.076***	0.026	0.069*
	(3.11)	(1.00)	(1.92)
(9) $YTL1 \times \Delta \pi_t$	0.490***	0.273**	0.282***
	(3.14)	(2.17)	(2.68)
(10) $YTL2 \times \Delta \pi_t$	0.268***	0.343***	0.271***
	(3.16)	(3.51)	(3.11)
(11) $YTL3 \times \Delta \pi_t$	0.319***	0.464***	0.414***
	(4.94)	(6.09)	(5.37)
(12) $YTL4 \times \Delta \pi_t$	0.277***	0.352***	0.329***
	(4.64)	(5.66)	(3.51)
Interaction		Income Quartile	
Controls		Yes	
Observations		37,445	
R^2		0.0151	

Notes: This table re-estimates Equation (4.4) with the NFCI-based accuracy measure and the Income partition (YTL1–YTL4). The dependent variable is the revision in one-year-ahead inflation expectations. MPS_t is the normalized cumulative high-frequency monetary policy shocks from t to $t+5$. We include contemporaneous IP growth and inflation changes between interviews; demographics and survey controls are included; all lower-order terms are included. Robust standard errors; t-statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

B.5 Others

This section contains a set of robustness checks. We re-estimate our baseline micro-level specification using household-head weights to ensure population representativeness, add controls for gasoline price changes to account for their salience, and use the Economic Policy Uncertainty (EPU) index as an alternative measure for the state-dependence analysis.

Appendix Table B.18: Household Head Weight

	(1) Accurate	(2) Inaccurate	(3) Haven't Heard
(1) MPS_t	-0.298***	0.097	-0.154
	(-3.56)	(0.81)	(-1.52)
(2) ΔIP_t	0.061***	-0.014	0.008
	(3.50)	(-0.76)	(0.40)
(3)$\Delta\pi_t$	0.357***	0.266***	0.300***
	(8.85)	(5.73)	(6.20)
Controls		Yes	
Observations		36,565	
R^2		0.0130	

Notes: This table re-estimates the baseline micro specification Equation (4.1) using household-head weights provided by the survey to improve population representativeness of the recontact sample. The dependent variable is the revision in one-year-ahead inflation expectations. MPS_t denotes the normalized cumulative high-frequency monetary policy shocks from t to $t+5$. Accuracy is measured at the first interview; We include contemporaneous IP growth and inflation changes between interviews; the full set of demographics and survey controls is included. Weighted least squares with robust standard errors; t-statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Appendix Table B.19: Including Gasoline Price Controls

	(1) Accurate	(2) Inaccurate	(3) Haven't Heard
(1) MPS_t	-0.193**	0.170	-0.088
	(-2.49)	(1.55)	(-0.94)
(2) ΔIP_t	-0.001	-0.063***	-0.030
	(-0.09)	(-3.45)	(-1.51)
(3)$\Delta\pi_t$	0.035	0.061	0.112**
	(0.83)	(1.27)	(2.21)
(4)ΔGas_t	0.042***	0.033***	0.026***
	(14.62)	(10.84)	(8.18)
Controls		Yes	
Observations		37,445	
R^2		0.0283	

Notes: This table augments the baseline micro specification Equation (4.1) by adding the log change in U.S. Regular All Formulations Gasoline Price between the two interview months (from FRED) to control for salient price movements. The dependent variable is the revision in one-year-ahead inflation expectations. MPS_t denotes the normalized cumulative high-frequency monetary policy shocks from t to $t+5$. Accuracy is measured at the first interview; We include contemporaneous IP growth and inflation changes between interviews; demographics and survey controls are included. Robust standard errors; t-statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Appendix Table B.20: Attention with Economic Policy Uncertainty

EPU	(1) Accurate	(2) Inaccurate	(3) Haven't Heard
High Uncertainty			
(1) MPS_t	-0.651***	-0.242	-0.267
	(-5.69)	(-1.29)	(-1.81)
(2) ΔIP_t	0.056**	0.011	0.010
	(2.53)	(0.50)	(0.38)
(3) $\Delta \pi_t$	0.324***	0.383***	0.292***
	(5.08)	(5.91)	(4.26)
Low Uncertainty			
(4) MPS_t	0.168	0.276**	-0.007
	(1.58)	(2.17)	(-0.07)
(5) ΔIP_t	0.051**	-0.025	0.009
	(1.98)	(-0.98)	(0.37)
(6) $\Delta \pi_t$	0.373***	0.223***	0.342***
	(7.79)	(3.98)	(5.75)
Interaction		EPU	
Controls		Yes	
Observations		37,445	
R^2		0.0167	

Notes: This table estimates Equation (4.3) using the Economic Policy Uncertainty (EPU) index (Baker et al., 2016b) to define State_{t-1} ("High EPU" when the HP-detrended EPU is above trend at $t-1$). The dependent variable is the revision in one-year-ahead inflation expectations. MPS_t is the normalized cumulative high-frequency monetary policy shocks from t to $t+5$. Accuracy is measured at the first interview. We include contemporaneous IP growth and inflation changes between interviews; the full set of demographics and survey controls is included; all lower-order terms are included. Robust standard errors; t-statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.