Attention-Dependent Monetary Transmission to Household Beliefs*

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Abstract

When do households listen to the Fed? We show the answer lies in a simple but powerful force: household attention to macroeconomic conditions. We develop a model where attention acts as a crucial gatekeeper for the pass-through of policy news to beliefs, and confirm its predictions using household survey data. We find that belief revisions to monetary policy surprises are concentrated among attentive individuals—particularly those with high financial stakes—and this effect strengthens dramatically during uncertain times. This implies the expectations channel is most potent when it matters most, suggesting policymakers should account for the time-varying and heterogeneous nature of public attention.

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. Four key results emerge: attention *gates* the individual-level impact of MP on beliefs; aggregate pass-through scales with the economy's average attentiveness; the effect strengthens in periods of elevated uncertainty; and the response is largest for households with higher payoffs to being informed.

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 gates 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 a predetermined attentiveness indicator by contrasting respondents' assessments of recent business conditions with an external benchmark. Monetary policy surprises are identified with high-frequency methods. Our empirical strategy tests each of the model's predictions: we begin with a micro event-study of the effect of conventional MP surprises on revisions in one-year-ahead inflation expectations, followed by a time-series regression that tests the scaling with aggregate attentiveness. We then analyze state dependence by interacting shocks with macro uncertainty and, finally, test the payoff-heterogeneity predictions using household characteristics including stockholding, homeownership, age, and income.

Four sets of findings align closely with the model's predictions. 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-gated 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). Fourth, consistent with the model's payoff logic, we find systematic heterogeneity in the response. Among attentive respondents, stockholders and homeowners exhibit an especially large pass-through, while younger and middle-aged individuals react more strongly than older ones. These patterns confirm the prediction that groups with a higher stake in the economy are endogenously more responsive to policy news. They also complement a growing body of evidence on firm attention heterogeneity and the efficacy of MP (*e.g.,* Afrouzi and Yang, 2021, Yang, 2022, Afrouzi, 2024, Wu, 2024). Our findings provide a household-level analogue: just as more complex firms pay closer attention, households with greater financial stakes are more attuned to policy news. For both firms and households, higher attention leads to expectations that 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:

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

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:

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

where $\mathbb{E}_t[\cdot]$ is the full-information conditional expectation.[2] Given the marginal benefit of being informed ω_i and attention costs κ_i, the agent chooses $m_{i,t}$ to minimize a standard quadratic loss function—which can be viewed as a second-order approximation to a more general problem—that balances forecast inaccuracy against mental costs:[3]

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

with closed-form solution

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

[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.

[2]For simplicity, we model the long-run anchor $\bar{\pi}$ as fixed. This assumption could be relaxed to a time-varying anchor, $\bar{\pi}_t$, to account for potential shifts in the inflation regime. Our model's core mechanism remains unchanged, as the household's behavioral expectation in Equation (2.2) would simply become $\mathbb{E}_{i,t}^B\left[\pi_{t+1}\right] = (1 - m_{i,t})\,\bar{\pi}_t + m_{i,t}\,\mathbb{E}_t\left[\pi_{t+1}^*\right]$. The key prediction—that the pass-through of a shock ε_t^{mp}, which represents news relative to the current anchor, is scaled by attention $m_{i,t}$—is robust to this extension.

[3]The payoff parameter ω_i can be micro-founded by linking it to household economic decisions. For instance, in a consumption-saving problem with utility depending on the perceived real interest rate, the loss from mis-forecasting inflation is larger for households with nominally exposed balance sheets (*e.g.*, net nominal assets or mortgage debt), making ω_i an endogenous function of those exposures. In a heterogeneous-agent rational-inattention model with homeowners and renters, Ahn, Xie and Yang (2024) show that the payoff parameter is closely linked to steady-state mortgage debt. For parsimony, we treat ω_i as a reduced-form parameter, which is sufficient for our comparative statics and testable implications.

Here

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

is the *payoff-relevant news variance* at the time attention is chosen.[4] Under the baseline normalization and orthogonality,

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

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 the household (higher ω_i, $\partial m^*_{i,t}/\partial \omega_i > 0$), and falls when attention is more costly (higher κ_i, $\partial m^*_{i,t}/\partial \kappa_i < 0$).[5]

2.2 Testable Implications

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

Proposition 2.1 (Attention gates MP pass-through)**.** *For household i, the impact change in inflation expectations in response to a contractionary MP surprise ($\varepsilon_t^{mp} > 0$ with $\theta < 0$) is*

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

Proof. See Appendix A.1. ■

Proposition 2.1 shows that the pass-through of policy news is scaled by the household's level of attention, a mechanism where attention mediates 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 2.2 (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)

[4]A key simplification in our framework is the use of a common, objective uncertainty measure, U_t. A richer model would feature individual-specific, subjective uncertainty ($U_{i,t}$), as each household's posterior beliefs depend on their unique information set and attention choices. Our setup is a reduced-form representation of this deeper mechanism: households face a payoff function that depends on objective uncertainty (U_t), and their endogenous choice of attention is therefore an increasing function of it. We focus on this common component of uncertainty because our empirical proxies for U_t, such as recessions and macroeconomic volatility, are chosen to capture the powerful public events that systematically drive these individual choices.

[5]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.

across households yields

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

where Λ_t is the average attentiveness *in the economy and υ_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.

Proposition 2.3 (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 ($\theta < 0$),*

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

so higher U_t makes the expectation decline more*. If group A is more attentive than group I at each U_t (i.e., $m_A(U_t) > m_I(U_t)$), 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 simple sufficient condition is if both groups' attention is below this peak, i.e., $0 \le m_I < m_A \le \frac{1}{2}$.

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 2.4 (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 simple behavior expectations 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 pass-through.

These core predictions hold under more general conditions. As shown in Appendix B.1, the results do not rely on a linear attention weight or quadratic attention costs; they require only that higher attention places more weight on the fully informed forecast and that the mental cost of attention is convex. Furthermore, the conclusions are robust to introducing a common, noisy public signal about future inflation that arrives before attention is chosen (Appendix B.2). While such a signal can synchronize attention choices and micro-found time variation in aggregate attentiveness, it does not alter the four main implications regarding individual gating, aggregate scaling, uncertainty amplification, or payoff heterogeneity. Because the signal is common, its level effect is absorbed by time controls in our empirical specifications.

In Section 3, we define the empirical attentiveness proxy and construct the aggregate attentiveness index used to verify these predictions. Section 4 then implements the corresponding micro and time-series tests.

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 2.1–2.4.

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. We focus on the one-year horizon because it is standard for near-term transmission, aligns with our six-month panel and identification window, and is the measure most responsive to contemporaneous macro and policy news in household data (e.g., Cavallo et al., 2017, Coibion et al., 2022, DAcunto, Malmendier and Weber, 2023). 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.[6]

Monetary policy shocks. Our baseline measure of monetary policy (MP) surprises uses the high-frequency series from Nakamura and Steinsson (2018), as extended by Bauer, Lakdawala and Mueller (2022). These surprises are identified from changes in federal funds futures prices in a narrow window around FOMC announcements and are standard in the literature. A potential concern with this approach is that it may capture not just pure policy actions but also a Fed "information effect." We retain this series as our baseline because its narrow identification window is crucial for precisely timing policy news relative to our survey's interview dates. To

[6]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 mitigate outliers.

ensure our results are not driven by information effects, we confirm our findings using alternative shocks from Bu, Rogers and Wu (2021) that are designed to purge such effects. For our time-series analysis of the Great Moderation (Section 4.2)), we also use the narrative-based shocks from Romer and Romer (2004).

To ensure consistent interpretation across all specifications, we normalize the shock series. First, we set the sign so that a positive value always represents a contractionary surprise (an unexpected policy tightening). Second, we scale the series so that a one-unit change corresponds to a one-percentage-point (100 basis point) tightening. This normalization allows our reported regression coefficients to be interpreted directly as the percentage-point response of inflation expectations to a one-percentage-point policy shock.[7] Our analysis uses all identified surprises, both contractionary and expansionary. For expositional clarity, we discuss the effects of a "contractionary" shock in the text, as the model's predictions are symmetric.

Other macro series. We obtain our macroeconomic data from the St. Louis Federal Reserve's FRED database. We use the unemployment rate, Industrial Production (IP), inflation, and the National Financial Conditions Index (NFCI) as either benchmarks for our attentiveness proxy or as contemporaneous controls. For our state-dependence analysis, we use the NBER-dated recession indicator and the CBOE Volatility Index (VIX).

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).

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

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 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:

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

We use a three-month window to smooth out high-frequency noise while still capturing the recent economic developments respondents were asked about ("in the last few months"). While we view this as a natural benchmark, our main findings are robust to using alternative horizons for this change, such as a one-month ($\text{Unrate}_t - \text{Unrate}_{t-1}$) or six-month ($\text{Unrate}_t - \text{Unrate}_{t-6}$) difference, as shown in Section 5. Furthermore, 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,

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

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

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. Table 1 reports respondent characteristics across the three groups. The groups are 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 ~ $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 accuracy 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, while *Accurate* and *Inaccurate* respondents are similar on observables. Section 4 will control for the full set of demographics in all specifications.

Discussion of the accuracy proxy. Our accuracy-based indicator is a noisy measure of the latent attention variable, $m_{i,t}$, in our model. To strengthen the theoretical justification for this proxy, we ground it directly through the lens of our model. Proposition 2.4 (part 3) provides a direct motivation to our empirical classification: $A_{i,t} = \mathbf{1}\{m^*_{i,t} \geq \tau\}$, where an agent is classified as "attentive" if their chosen attention level $m^*_{i,t}$ surpasses a certain threshold τ required for accurate perception.

From this perspective, our "Accuracy" indicator is not just a proxy for the continuous latent variable $m^*_{i,t}$, but an empirical implementation of this theoretical classification rule. An agent is classified as "Accurate" because their attention level was sufficiently high to correctly parse the direction of recent economic news. This approach still allows for misclassification—an attentive agent ($m^*_{i,t} \geq \tau$) might misread a specific signal, or an inattentive one ($m^*_{i,t} < \tau$) might guess correctly—which would induce attenuation bias and work against us finding significant results. Nonetheless, the robust alignment of our empirical results with all four of the model's predictions, as shown in Section 4, suggests that this proxy successfully captures this salient theoretical dimension of household attentiveness.

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). All entries are column percentages unless otherwise 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.

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, three pieces of evidence point toward an attention interpretation. First, 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, and it is less clear how these other factors would jointly explain this specific constellation of results. Second, regarding cognitive ability specifically, Table 1 shows that the Accurate and Inaccurate groups have nearly identical distributions of educational attainment and average income, suggesting the classification is not primarily driven by differences in cognitive ability. Third, the robustness of our main empirical 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. Finally, political composition is balanced across attentiveness groups suggesting that partisan bias is not the primary driver of the classification.[8] Taken together, these facts make it difficult for non-attention explanations to jointly account for the constellation of patterns we document.

3.3 Aggregate Attentiveness Index

To test Proposition 2.2 in time series, we construct an aggregate attentiveness measure as the cross-sectional share of attentive respondents at the first interview date t:

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

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 2.2.

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 $\Delta\pi^e_{t+h}$ (*e.g.*, median) are computed analogously across individuals interviewed in month t and re-interviewed in $t+h$.

[8]We classify political stance relative to the sitting U.S. president at the time of the first interview. *Supporters* are respondents who self-identify with the president's party; *Opponents* identify with the out-party; *Independents* include self-reported independents, other parties, and no preference. Among *Accurate* respondents, 32.5% are supporters, 30.3% opponents, and 36.7% independents, with similar shares for the *Inaccurate* group.

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 Gates Monetary Policy Pass-Through

We begin by testing Proposition 2.1 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, adapted from Coibion and Gorodnichenko (2015b), tests this attention-gating mechanism by interacting the policy shock with our attentiveness indicators:

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

where $\Delta\pi^e_{i,t+6}$ is the change in a household's one-year-ahead inflation expectation between the

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 quartiles, education, gender, homeownership, stockholding, marital status, region, and sentiment). Robust standard errors; t-statistics in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

two survey interviews, MPS_t is the normalized cumulative MP shock from t to $t+5$, $\mathbf{A}_{i,t}$ is our three-way vector of attentiveness indicators (Accurate / Inaccurate / Haven't heard), $\mathbf{Z}_t$ contains concurrent macro changes between interviews (IP growth and inflation), and $\mathbf{X}_{i,t}$ includes standard demographic controls including age and age^2, income quartiles, education, gender, homeownership, stockholding, marital status, region, and survey-mode controls.[9] Coefficients in $\beta_{M,A}$ are the group-specific pass-through slopes implied by Proposition 2.1.

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.[10] Quantitatively, the Accurate–Inaccurate

[9] 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. Cumulating the shocks over six months aligns the information set with the interview horizon and helps ensure the estimated interaction is not driven by within-month learning.

[10] One possible interpretation is that this group—which, as shown in Table 2, is observationally distinct—may engage 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.

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 2.1 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.

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 2.2 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 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 the aggregate attention index falls in the top 30% of its historical distribution. We measure this distribution using data only through June 2007 to ensure the classification is pre-determined relative to our full sample (Figure 1). This top-30% cutoff is a standard approach

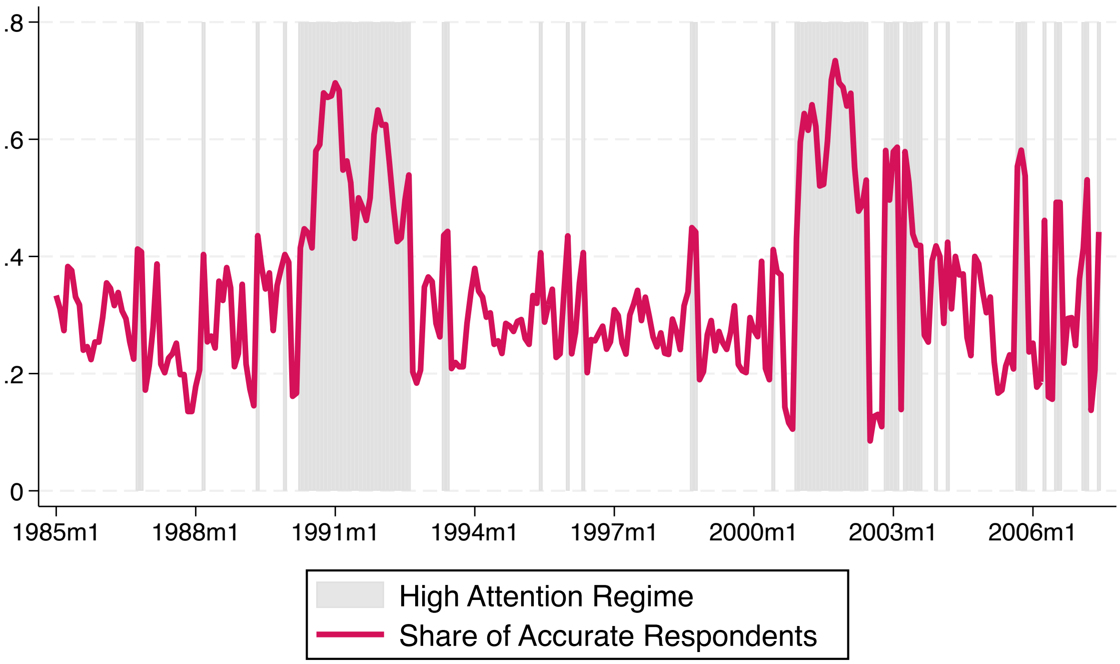

Figure 1: Aggregate Attentiveness: Share of Accurate Respondents (1985–2007)

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.

for regime analysis, and our qualitative findings are robust to using alternative thresholds, such as the top quartile or tercile. Proposition 2.2 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 $I^A_{t-1} = \mathbf{1}\{\mathbf{A}^{\text{agg}}_{t-1} \text{ in top } 30\%\}$:

$$\Delta\pi^e_{t+6} = \alpha + \beta_M\left(RRshock_t \times I^A_{t-1}\right) + \beta'_{Z,A}\left(\mathbf{Z}_t \times I^A_{t-1}\right) + \varepsilon_t, \tag{4.2}$$

where $\mathbf{Z}_t$ contains contemporaneous IP growth and inflation changes between the two survey 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 2.2. 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

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. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

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 2.3 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,

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

where $\mathsf{State}_{t-1} \in$ {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.[11] During recessions, *Accurate* respondents revise down strongly on impact (-1.73 pp per 1 pp tightening; significant), while *Inaccurate* respondents do not respond.[12] 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.[13] 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

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

and the Accurate-Inaccurate wedge in high-uncertainty states is exactly the "stronger state dependence for attentive agents" in Proposition 2.3. In short, uncertainty raises attention, and higher 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*

[11] All regression coefficients are reported in Appendix Tables C.1–C.3 in Appendix C.1.

[12] 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. This point estimate is consistent with our model's core prediction that uncertainty and risk dramatically amplify the expectations channel for those who are paying attention.

[13] This core finding—that amplification is concentrated among the attentive—also holds when using a broad, text-based measure of Economic Policy Uncertainty, as shown in 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)
Controls	Yes		Yes		Yes	
Observations	37,445		37,445		37,445	
R^2	0.0170		0.0146		0.0182	

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

margin, with uncertainty inducing greater household attention and sharper belief updates to policy news. Relatedly, our findings can be reconciled with macro studies documenting weaker ultimate effects of policy on real activity in certain states (*e.g.*, deep recessions or high volatility). Our evidence points to a stronger initial impact through the expectations channel: in high-uncertainty states, attentive households align their inflation expectations more sharply with policy news. This leads to a larger adjustment in their perceived ex-ante real interest rates. This very alignment, however, can explain why the ultimate real effects on spending might be muted. If expectations adjust swiftly, there is less scope for policy surprises to generate real effects through informational frictions or misperceptions. In this view, a more potent expectations channel could lead to a more muted response in real activity, as well-informed agents have already incorporated the policy stance into their decisions.

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 2.4, 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 these higher payoff groups withr three charecteristics. First, we use asset exposure (stockholding and homeownership), as policy moves directly affect portfolio values and mortgage financing. Second, we examine age, where different life-cycle stages present distinct incentives: younger households' lifetime earnings are highly sensitive to the business cycle, while prime-age households (35-64) typically have the largest balance sheet exposure through assets and mortgages. Third, we use higher income, which correlates with both asset ownership and information use.

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:

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

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* × *demographic* cell. For contractionary shocks, the model predicts large negative slopes for *Accurate* × (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.[14]

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

Stockholding Proposition 2.4 predicts stronger monetary-policy (MP) pass-through among households for whom the payoff to paying attention is higher (larger ω_i). Stockholders are a

[14]All regression coefficients are reported in Appendix Tables C.5–C.6 in Appendix C.2.

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 2.1 (attention gates pass-through) and Proposition 2.4 (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 2.1. Quantitatively, this delivers a larger (more negative) slope for stockholders within the *Accurate* group, an empirical counterpart to Proposition 2.4 (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 proposed attention channel, rather than by selection on unobservable characteristics correlated with homeownership. The pattern mirrors Proposition 2.1—attention drives pass-through—and aligns with Proposition 2.4: 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 of Table 5, suggesting two complementary margins—portfolio exposure and mortgage-linked exposure—through which higher ω_i amplifies expectation responses when attention is present. Crucially, the prerequisite of *accuracy* remains central: absent 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 2.1: attention gates 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

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

$\boldsymbol{D}_{i,t} = \{\text{YTL1}, \ldots, \text{YTL4}\}$ and report results in Table 6.[15] 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 (-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.[16]

[15] All regression coefficients are reported in Appendix Table C.7 in Appendix C.2.

[16] Jaravel (2019) and Mangiante and Lauper (Forthcoming) investigate the link between monetary policy shocks and inflation inequality. They find that the inflation rates faced by households respond differently to policy, arguing that middle-income groups are most affected by contractionary shocks. This phenomenon is primarily driven by heterogeneous consumption bundles; sectors like gasoline and energy are more responsive to policy, and these goods make up a larger share of the consumption basket for low- and middle-income households.

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

5 Robustness

We assess the robustness of our findings along several dimensions and report full details in Appendix C. First, to address concerns that high-frequency monetary policy surprises may contain a Fed information effect, we re-estimate our baseline specifications using the shock series from Bu et al. (2021) "BRW" shocks. The results, shown in Panel A of Table 7, confirm our main findings regarding the signs, cross-group ordering, and significance. The estimated magnitudes are somewhat larger, which is consistent with how the shocks are constructed. A one-unit shock from BRW is designed to move two-year bond yields nearly one-for-one, representing a more persistent policy signal than our baseline high-frequency surprises. This difference in scaling can naturally lead to larger estimated coefficients. We also verify our results using the reassessed high-frequency series from Bauer and Swanson (2023); the core patterns persist as shown in Panel B of Table 7.

Second, we vary the construction of *Accuracy*. Our benchmark measure uses the three-month change in the unemployment rate, chosen to smooth high-frequency noise while matching the survey's "last few months" phrasing. We confirm our results are robust to the precise construction of this benchmark: Appendix Table C.7 shows that using a one-month or six-month differencing horizon for the unemployment rate yields nearly identical baseline findings. Furthermore, to check that the results do not hinge on the unemployment rate itself, 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 C.3.2) or NFCI (Appendix Tables in Appendix C.3.3) instead of unemployment to define *Accuracy*.[17]

A more fundamental alternative is to proxy attention simply by whether respondents report hearing any news about business conditions without benchmarking against macroeconomic data. We test this simpler classification by re-estimating our baseline specification, Equation (4.1), replacing the accuracy indicators with dummies for "Have Heard" vs. "Haven't Heard" (Appendix Table C.18). While the "Have Heard" group shows a significant negative response (-0.208), the coefficient is considerably smaller than for our baseline "Accurate" group (-0.360). Furthermore, the "Haven't Heard" group also shows a marginally significant negative coefficient (-0.156) , unlike the clear null effect for our "Inaccurate" group. This comparison highlights the value of our accuracy-based measure. The sharper distinction between the "Accurate" and "Inaccurate" groups provides stronger support for the model's gating mechanism than the simpler "Heard News" proxy , reinforcing our choice of using accuracy to capture the relevant attention dimension.

Third, we evaluate representativeness by reweighting the micro regressions with household-head weights. Because the recontacted MSC panel in a given month contains at most about 250 respondents, weighting is a natural correction. Weighted regressions (Appendix Table C.19) 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 C.20), 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

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

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 C.21).

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) mediates 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 gates 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.

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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 2.1) , the scaling of aggregate pass-through with attention (Proposition 2.2), the state-dependent nature of the response to uncertainty (Proposition 2.3), and the cross-sectional predictions based on payoff heterogeneity (Proposition 2.4) .

A.1 Proof of Proposition 2.1.

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 2.2.

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 2.3.

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 2.4.

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 2.1. 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 Model Extension

This appendix shows that our four testable implications do not rely on the baseline choice of a linear attention weight or quadratic attention costs. The first subsection establishes a general comparative-statics result (Lemma B.1) for an arbitrary increasing attention mapping $\phi(\cdot)$ and strictly convex cost $\psi_i(\cdot)$: the optimal attention m_i^* is unique, increases with payoff-relevant news variance U_t and stakes ω_i, and decreases with costs κ_i. The linear/quadratic specification follows as a corollary. The second subsection introduces a common noisy public signal observed before attention is chosen and shows that it synchronizes attention choices—micro-founding time variation in the aggregate attentiveness index—while leaving the individual gating, aggregate scaling, uncertainty amplification, and payoff-heterogeneity predictions unchanged.

B.1 General attention mapping and convex costs

We show that the main comparative statics do not rely on a linear attention weight or quadratic costs.

Assumption B.1 (Information and costs)**.** *The expectations operator is* $E_i^B = \bar{\pi} + \phi(m_i)(E^* - \bar{\pi})$ *with* $\phi : [0,1] \to [0,1]$*,* $\phi'(m) > 0$*, and* $\phi''(m) \le 0$*. The attention cost is* $\psi_i(m)$*, where* ψ_i *is* C^1*, strictly convex on* $[0,1]$ *with* $\psi_i'(0) = 0$ *and* $\psi_i''(m) > 0$*. Benefits are scaled by* $\omega_i > 0$*, costs by* $\kappa_i > 0$ *(possibly via* $\psi_i(m) = \kappa_i \tilde{\psi}(m)$ *with* $\tilde{\psi}'(m) > 0$*). Let* $U_t \equiv Var(\Gamma' \varepsilon_{o,t} + \theta \varepsilon_t^{mp})$ *denote payoff-relevant news variance.*

With mean-squared forecast loss, the per-period objective can be written (up to a positive multiplicative constant) as

$$\mathscr{L}_i(m; U_t, \omega_i, \kappa_i) \;=\; \frac{1}{2}\omega_i U_t [1 - \phi(m)]^2 \;+\; \psi_i(m),$$

so the unique optimum $m_i^* \in (0,1)$ solves the first-order condition

$$\omega_i U_t \left(1 - \phi(m_i^*)\right)\phi'(m_i^*) \;=\; \psi_i'(m_i^*). \tag{B.1}$$

Proposition B.1 (Comparative statics under general ϕ and ψ)**.** *Under Assumption B.1, there is a unique minimizer* $m_i^*(U_t, \omega_i, \kappa_i) \in (0,1)$ *satisfying Equation* (B.1)*. Moreover,*

$$\frac{\partial m_i^*}{\partial U_t} > 0, \qquad \frac{\partial m_i^*}{\partial \omega_i} > 0, \qquad \textit{and if } \psi_i(m) = \kappa_i \tilde{\psi}(m) \;\textit{ with }\; \tilde{\psi}'(m) > 0, \;\textit{ then }\; \frac{\partial m_i^*}{\partial \kappa_i} < 0.$$

Proof. Strict convexity of ψ_i implies a unique interior solution. Define $F(m; U, \omega, \kappa) \equiv \omega U (1 -$

$\phi(m))\phi'(m) - \psi_i'(m)$. Then

$$F_m = \omega U\{-(\phi'(m))^2 + (1-\phi(m))\phi''(m)\} - \psi_i''(m) < 0$$

because $\phi' > 0$, $\phi'' \leq 0$, $1-\phi \geq 0$, and $\psi_i'' > 0$. By the implicit function theorem,

$$\frac{\partial m^*}{\partial U} = -\frac{F_U}{F_m} = -\frac{\omega(1-\phi)\phi'}{F_m} > 0$$
$$\frac{\partial m^*}{\partial \omega} = -\frac{F_\omega}{F_m} = -\frac{U(1-\phi)\phi'}{F_m} > 0.$$

If $\psi_i(m) = \kappa_i \tilde{\psi}(m)$ with $\tilde{\psi}'(m) > 0$, then $F_\kappa = -\tilde{\psi}'(m) < 0$, so $\partial m^* / \partial \kappa = -F_\kappa / F_m < 0$. ■

Corollary B.1 (Linear weight/quadratic cost)**.** *If $\phi(m) = m$ and $\psi(m) = \frac{1}{2}\kappa m^2$, then Equation* (B.1) *reduces to $\omega U(1-m^*) = \kappa m^*$, hence the closed form*

$$m^*(U,\omega,\kappa) = \frac{\omega U}{\omega U + \kappa}, \qquad \phi(m^*) = m^*.$$

All four testable implications in the main text follow immediately.

Proof. We substitute the specific functional forms $\phi(m) = m$ and $\psi(m) = \frac{1}{2}\kappa m^2$. The derivatives are $\phi'(m) = 1$ and $\psi'(m) = \kappa m$. Plugging these into the FOC gives: $\omega U_t(1-m^*)(1) = \kappa m^*$. Rearranging yields $m^* = \frac{\omega U_t}{\omega U_t + \kappa}$. ■

Implications. Replacing m_i^* by $\phi(m_i^*)$ in the impact coefficient delivers the same four predictions: (i) individual *gating* (only attentive types load on policy news), (ii) aggregate scaling by $E[\phi(m_i^*)]$, (iii) amplification when U_t is higher, and (iv) larger pass-through for high-ω_i/low-κ_i groups.

B.2 Public Signal Extension

This appendix shows that introducing a common, noisy public signal s_t that arrives *before* attention choices does not alter the four testable implications in the main text: (i) individual gating; (ii) aggregate scaling; (iii) uncertainty amplification; and (iv) payoff heterogeneity. The public signal provides a simple micro-foundation for time-variation in aggregate attentiveness by synchronizing attention choices across households.

Suppose the public signal is about the fully informed forecast of next-period inflation π_{t+1}^* (e.g., a highly publicized data release or headline), observed before attention choice. Let s_t be informative about π^*_{t+1} so that the posterior variance

$$U_t^{\text{post}} \equiv Var(\pi^*_{t+1} \mid s_t)$$

is (weakly) smaller than the prior variance U_t and (weakly) decreasing in the signal's precision. Under quadratic forecast loss, the relevant loss component scales with U_t^{post}.

Assumption B.2. *The public signal about the inflation level yields a posterior variance $U_t^{post} = H(U_t, \tau_s)$ with $H_U > 0$ and $H_{\tau_s} < 0$, where τ_s is the signal precision. (For Gaussian-normal conjugacy, $U_t^{post} = (U_t^{-1} + \tau_s)^{-1}$, which does not depend on the realization of s_t.)*

Given s_t (and τ_s), the household chooses attention m to minimize the objective function based on the posterior variance U_t^{post}, using the same structure as in Appendix B.1:

$$\mathcal{L}_i(m; U_t^{\text{post}}, \omega_i, \kappa_i) = \frac{1}{2}\omega_i U_t^{\text{post}} [1 - \phi(m)]^2 + \psi_i(m),$$

where $\phi(m)$ is the attention mapping and $\psi_i(m)$ is the cost function (incorporating κ_i), satisfying Assumption B.1.

Lemma B.1 (Optimal attention with a public level signal)**.** *Under Assumption B.2 and the properties of ϕ and ψ_i from Assumption B.1, the unique optimal attention $m_i^* = m_i^*(U_t^{post}, \omega_i, \kappa_i)$ is (weakly) increasing in U_t^{post} and in ω_i, and (weakly) decreasing in κ_i and in the signal precision τ_s (via U_t^{post}).*

Proof. The FOC defining the unique optimum $m_i^* = m_i^*(U_t^{post}, \omega_i, \kappa_i)$ is:

$$\omega_i U_t^{post} (1 - \phi(m_i^*))\phi'(m_i^*) = \psi_i'(m_i^*)$$

This FOC has the exact same structure as Equation (B.1), with U_t^{post} replacing U_t. The comparative statics with respect to U_t^{post}, ω_i, and κ_i therefore follow directly from the proof of Proposition B.1. For the effect of signal precision τ_s, we use Assumption B.2 ($U_t^{post} = H(U_t, \tau_s)$ with $\frac{\partial H}{\partial \tau_s} < 0$) and the chain rule:

$$\frac{\partial m_i^*}{\partial \tau_s} = \frac{\partial m_i^*}{\partial U_t^{post}} \frac{\partial U_t^{post}}{\partial \tau_s} = \frac{\partial m_i^*}{\partial U_t^{post}} \frac{\partial H}{\partial \tau_s} < 0$$

since $\frac{\partial m_i^*}{\partial U_t^{post}} > 0$ and $\frac{\partial H}{\partial \tau_s} < 0$. ■

Proposition B.2 (Robustness of implications: level signal)**.** *Replacing U_t by U_t^{post} leaves all four* *implications intact:*

1. ***Individual gating****: the impact coefficient remains proportional to* $\phi(m_i^*)\theta$ *with* $m_i^* = m_i^*(U_t^{post}, \omega_i, \kappa_i)$.

2. ***Aggregate scaling****:* $\beta_t^{agg} = \theta\, E[\phi(m_i^*)]$ *scales with average attention; a more precise public signal reduces* U_t^{post} *and thus lowers average attention, but does not alter the gating logic.*

3. ***Uncertainty amplification****: when residual uncertainty* U_t^{post} *is higher (e.g., the public signal is imprecise or absent), optimal attention is higher and pass-through is stronger.*

4. ***Payoff heterogeneity****: for any* U_t^{post}*, higher* ω_i */ lower* κ_i *types choose more attention and exhibit larger pass-through.*

Proof. The logic follows directly from substituting U_t^{post} for U_t in the derivations underpinning the four main implications and using the comparative statics established in Lemma B.1.

1. **Individual Gating**: The pass-through coefficient is $\frac{\partial \mathbb{E}_{i,t}^B[\pi_{t+1}]}{\partial \epsilon_t^{mp}} = \phi(m_i^*)\theta$, where m_i^* now depends on U_t^{post}. The form is identical.

2. **Aggregate Scaling**: The aggregate coefficient is $\Lambda_t^{post}\theta$, where $\Lambda_t^{post} = \mathbb{E}_i[\phi(m_i^*(U_t^{post}))]$. It still scales with the (now potentially lower) average attention.

3. **Uncertainty Amplification**: The sensitivity to uncertainty is $\frac{\partial(\phi(m_i^*)\theta)}{\partial U_t^{post}} = \theta\phi'(m_i^*)\frac{\partial m_i^*}{\partial U_t^{post}} < 0$. Higher U_t^{post} implies stronger pass-through.

4. **Payoff Heterogeneity**: Since $\frac{\partial m_i^*}{\partial \omega_i} > 0$, $\frac{\partial m_i^*}{\partial \kappa_i} < 0$, and $\phi' > 0$, the pass-through magnitude $|\phi(m_i^*)\theta|$ remains larger for higher ω_i / lower κ_i types, given U_t^{post}. ■

Discussion. A *level* signal reduces residual uncertainty and thereby lowers the marginal value of costly attention, but conditional on the chosen attention, the pass-through of monetary policy news is still multiplied by the attention weight. Since s_t is common, its *level* effect on beliefs is absorbed by time variation (e.g., month fixed effects) in our empirical designs; the estimated slope with respect to policy surprises is therefore unaffected.

C 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.

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

C.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 C.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 C.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 C.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) $[18-34] \times \Delta \mathrm{IP}_t$	0.110**	0.031	0.004
	(2.43)	(0.72)	(0.10)
(5) $[35-64] \times \Delta \mathrm{IP}_t$	0.059***	-0.019	0.015
	(2.95)	(-0.84)	(0.57)
(6) $[65+] \times \Delta \mathrm{IP}_t$	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 C.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) $YTL1 \times \Delta \mathrm{IP}_t$	0.024	-0.043	-0.059
	(0.48)	(-0.93)	(-1.37)
(6) $YTL2 \times \Delta \mathrm{IP}_t$	0.142***	-0.062	0.017
	(3.43)	(-1.49)	(0.49)
(7) $YTL3 \times \Delta \mathrm{IP}_t$	0.024	-0.018	0.020
	(0.82)	(-0.59)	(0.56)
(8) $YTL4 \times \Delta \mathrm{IP}_t$	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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

C.3 Alternative Measures

This section tests the robustness of our baseline Accuracy proxy to its precise construction. Our main analysis relies on a 3-month change in the unemployment rate as the benchmark for "business conditions." Here, we show that this specific choice is not critical to our findings. First, we re-estimate our baseline using 1-month and 6-month differencing horizons for the unemployment rate to show the results are not sensitive to the 3-month window. Second and third, we replace the unemployment benchmark entirely with two alternative indicators—one for real activity and one for financial conditions—to demonstrate that our results are robust to the choice of macroeconomic data series.

C.3.1 Alternative Differencing Horizons

We reconstruct the attention measure using the one-month and six-month changes in unemployment rate, instead of the three-month change in unemployment rate.

Appendix Table C.7: Alternative Differencing Horizons for Unemployment

	(1) Accurate	(2) Inaccurate	(3) Haven't Heard	(4) Accurate	(5) Inaccurate	(6) Haven't Heard
Panel A: 1 month ($\Delta\text{Unrate}_t \equiv \text{Unrate}_t - \text{Unrate}_{t-1}$)						
(1) MPS_t	-0.360***	0.094	-0.156*			
	(-4.48)	(0.90)	(-1.67)			
(2) ΔIP_t	0.049***	0.001	0.013			
	(3.17)	(0.07)	(0.71)			
(3)$\Delta\pi_t$	0.376***	0.282***	0.325***			
	(9.95)	(6.69)	(7.21)			
Panel B: 6 months ($\Delta\text{Unrate}_t \equiv \text{Unrate}_t - \text{Unrate}_{t-6}$)						
(1) MPS_t				-0.336***	0.090	-0.155***
				(-4.05)	(0.86)	(-1.66)
(2) ΔIP_t				0.068***	-0.026	0.013
				(4.36)	(-1.42)	(0.70)
(3)$\Delta\pi_t$				0.338***	0.328***	0.325***
				(8.87)	(7.79)	(7.21)
Controls		Yes			Yes	
Observations		37,445			37,445	
R^2		0.0136			0.0139	

Notes: This table replaces the differencing horizons in unemployment rate that is used to define *Accuracy* measure with 1 month (Panel A) and 6 months (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. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

C.3.2 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 C.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) ΔIP_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 C.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×ΔIP_t	0.053***	0.0007	0.020
	(3.07)	(0.03)	(0.93)
(4) Non-stock×ΔIP_t	0.055	-0.018	0.004
	(1.47)	(-0.45)	(0.11)
(5) Stock×$\Delta\pi_t$	0.352***	0.351***	0.377***
	(8.10)	(8.50)	(6.89)
(6) Non-stock×$\Delta\pi_t$	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 C.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) $Homeowner \times \Delta \mathrm{IP}_t$	0.051***	0.009	0.027
	(2.95)	(0.43)	(1.23)
(4) $Renter \times \Delta \mathrm{IP}_t$	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 C.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) $[18-34] \times \Delta \text{IP}_t$	0.106**	0.018	0.004
	(2.52)	(0.42)	(0.11)
(5) $[35-64] \times \Delta \text{IP}_t$	0.057***	-0.020	0.015
	(2.84)	(-0.87)	(0.58)
(6) $[65+] \times \Delta \text{IP}_t$	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 C.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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

C.3.3 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 C.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) $\Delta \mathrm{IP}_t$	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 C.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×$\Delta \mathrm{IP}_t$	0.038**	0.026	0.020
	(2.20)	(1.23)	(0.92)
(4) Non-stock×$\Delta \mathrm{IP}_t$	0.046	0.003	0.004
	(1.17)	(0.09)	(0.11)
(5) Stock×$\Delta\pi_t$	0.308***	0.390***	0.377***
	(7.43)	(8.62)	(6.89)
(6) Non-stock×$\Delta\pi_t$	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 C.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) $Homeowner \times \Delta \text{IP}_t$	0.046***	0.021	0.027
	(2.71)	(1.02)	(1.22)
(4) $Renter \times \Delta \text{IP}_t$	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 C.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) $[18-34] \times \Delta \mathrm{IP}_t$	0.059	0.084*	0.004
	(1.40)	(1.86)	(0.10)
(5) $[35-64] \times \Delta \mathrm{IP}_t$	0.031	0.026	0.015
	(1.57)	(1.14)	(0.57)
(6) $[65+] \times \Delta \mathrm{IP}_t$	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 C.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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

C.4 Others

This section provides additional robustness checks. First, we re-estimate our baseline using a simpler “Heard News” proxy to evaluate the specific contribution of accuracy to our attention measure. Second, we apply household-head weights to ensure population representativeness. Third, we include gasoline price changes as controls to account for their unique salience. Finally, we use the Economic Policy Uncertainty (EPU) index to confirm the state-dependence results with an alternative uncertainty measure.

Appendix Table C.18: Classification Based on News Heard

	(1) Have Heard	(2) Haven’t Heard
(1) MPS_t	-0.208***	-0.156*
	(-3.26)	(-1.67)
(2) ΔIP_t	0.032**	0.013
	(2.68)	(0.71)
(3) $\Delta\pi_t$	0.342***	0.325***
	(11.97)	(7.21)
Controls	Yes	
Observations	37,445	
R^2	0.0131	

Notes: This table shows regression results of Equation (4.1) with replacing *Accuracy* measure with *News Heard* measure. 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 quartiles, education, gender, homeownership, stockholding, marital status, region, and sentiment). Robust standard errors; t-statistics in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Appendix Table C.19: 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 C.20: 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 C.21: 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 $\texttt{State}_{t-1}$ ("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. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.