What Determines Household Expectations?*

Anushka Mitra[1] and Aditi Singh[2]

[1] *Federal Reserve Board of Governors*
[2] *CAFRAL, Reserve Bank of India*

Abstract

Which macroeconomic signals shape household expectations? We develop a rational inattention model in which households optimally allocate limited attention across announcements, implying larger responses to signals that receive greater attention. Using daily microdata, we identify announcement-driven revisions and construct shock series under sophisticated and naive forecasting benchmarks. We demonstrate that labor market information significantly influences not only households' subjective expectations about the economy but also their inflation expectations. Even in periods when unemployment is declining and inflation is rising, shocks to unemployment lead to significant adjustments in households' subjective expectations. Most changes in inflation expectations are driven by shocks to unemployment rather than inflation. Finally, during negative supply and demand shocks, unemployment emerges as the primary driver of household expectations.

JEL Codes: E70, D84, E30

Keywords: Household expectations, macroeconomic data releases, high-frequency identification, survey data

*We sincerely thank Olivier Coibion, Gauti Eggertson, Stefano Eusepi, Amy Handlan, Pascal Michaillat, Andreas Mueller, Aysegul Sahin, and David Weil for their guidance and support. We are grateful to Anmol Bhandari, Saroj Bhattarai, Christoph Boehm, Jesse Bruhn, Arpita Chatterjee, Fernando Duarte, Yann Koby, Julio Ortiz, Marcel Peruffo, and, Neil Thakral for their feedback. We also thank seminar participants at Brown University, UT Austin, IIM, Bangalore, CAFRAL, SNU, IEG and conference participants at the FRBNY-ECB-BoC Conference on Expectations, DSE Winter School, IAES, ISI, IIT Delhi, Midwest Macro, NASMES, PAA and WEAI. The views expressed here are solely the responsibility of the author and should not be interpreted as reflecting the view of the Board of Governors of the Federal Reserve System or of any other person associated with the Federal Reserve System or the Reserve Bank of India.

1 Introduction

Household expectations are central to the transmission of macroeconomic policy. They shape consumption and saving decisions, influence wage bargaining, and determine responses to monetary and fiscal interventions (D'Acunto & Weber 2024, Coibion et al. 2023, Mueller et al. 2021). The centrality of expectations to policy effectiveness was articulated by Lucas Jr (1976), who warned that neglecting expectational effects would lead to systematically biased policy predictions. Despite the importance of expectations, we know surprisingly little about what information households actually use when forming these expectations. Households are exposed to a variety of economic signals, where some are more salient than others.[1] This paper investigates a fundamental question: information from which macroeconomic variables causes households to update their expectations?

We find that households primarily use the unemployment rate as a sufficient statistic for expectation formation. Households respond more strongly to unemployment announcements than to announcements about inflation, output growth, or housing starts. This finding is robust across surveys, time periods and economic environments—including periods of rising inflation when one might expect price signals to dominate. Even household inflation expectations respond significantly to unemployment shocks.

To arrive at these results, we develop a rational inattention model of household expectation formation following Sims (2003), Maćkowiak & Wiederholt (2015). In the model, households care about a payoff-relevant economic outcome that depends on multiple macroeconomic fundamentals, but face finite cognitive capacity to process information about these fundamentals. They optimally allocate attention across variables, and the model delivers a reduced-form prediction linking announcement surprises to expectation revisions. The key testable implication is that if households allocate more attention to unemployment than to inflation, then unemployment announcements should generate larger expectation revisions than CPI announcements.

A practical difficulty in taking the model to data is that households' true prior beliefs are unobserved. We address this by constructing announcement surprises under two polar benchmarks. Under the *sophisticated* benchmark, households form priors identical to professional forecasters, and the surprise is measured as the difference between the

[1] Moreover, household expectations are formed jointly over these signals (Andre et al. 2022, Kamdar & Ray 2024), which makes it imperative to understand which signals are most informative to households. This is because household expectations often reflect broader economic health, particularly in assessing household behavior during recessions. Understanding the drivers of household sentiment is valuable for policymakers to gauge general economic sentiment and respond effectively to downturns.

announced value and the Bloomberg consensus forecast. Under the *naive* benchmark, households simply extrapolate from the previous announcement, and the surprise is the change in the announced series. For plausible intermediate cases where household priors are a weighted average of these benchmarks, the true response coefficient is bounded by the estimates obtained under the two cases. Crucially, if unemployment announcements generate larger responses than inflation announcements under *both* benchmarks, unemployment dominates regardless of assumptions about household sophistication.

In testing these implications, we confront a fundamental identification challenge: macroeconomic announcements occur at discrete intervals, often clustered within short windows, while standard household surveys measure expectations only monthly.[2] This temporal mismatch makes it difficult to isolate the causal effect of any single announcement on beliefs. We address this challenge by exploiting daily variation in survey responses from the Gallup Daily Tracking Poll (2008–2017), which interviewed approximately 500 respondents per day with questions about economic expectations. This high-frequency data allows us to compare expectations formed immediately before and after specific announcements, isolating their causal impact within narrow event windows.

The empirical analysis proceeds in four steps. First, using the Gallup Daily Tracking Poll, we estimate local projections of expectation changes on announcement surprises for unemployment, CPI, GDP growth, and housing starts. Under both the sophisticated and naive shock measures, we find that unemployment announcements generate statistically significant revisions in household expectations, while announcements for other variables generally do not. A one-standard-deviation surprise in the unemployment rate reduces the share of households reporting optimism about the economy by 0.5 to 0.8 percentage points on impact. In contrast, CPI surprises, GDP surprises, and housing starts surprises have effects that are smaller in magnitude and rarely statistically distinguishable from zero.

Second, we extend the analysis using microdata from the Michigan Survey of Consumers (MSC), which spans 1980–2019 and includes recorded interview dates that permit high-frequency identification. The longer sample allows us to examine whether the stronger response to unemployment is specific to the post-Great Recession period covered by Gallup or reflects a more general pattern. We find that it does: across four decades and diverse macroeconomic environments, unemployment shocks consistently exert larger effects on household sentiment than inflation shocks. This remains true even when we restrict our

[2] The two most popular sources of expectations in the US are the University of Michigan's Survey of Consumers and the NY Fed's Survey of Consumer Expectations, both of which are monthly.

sample to periods of rising inflation.

Third, to form expectations, households can prioritize different variables at different points in time. For example, during periods of rapidly rising unemployment, such as the COVID-19 pandemic, unemployment likely becomes the dominant driver of expectations. Conversely, in periods of high inflation, such as the early 1980s, inflation likely takes precedence. We validate this dynamic by partitioning the MSC sample into four scenarios based on the direction of change in unemployment and inflation: (i) both rising (negative supply shock), (ii) both falling (positive supply shock), (iii) unemployment rising and inflation falling (negative demand shock), and (iv) unemployment falling and inflation rising (positive demand shock). In all four scenarios, unemployment shocks significantly affect household expectations.[3] It is interesting to note that even in periods of declining unemployment and rising inflation, it is shocks to unemployment that significantly affect households' sentiment. During negative shocks, typically associated with recessions, unemployment dominates completely.

Fourth, we analyze whether the same patterns hold for quantitative inflation expectations, as opposed to qualitative assessments of economic conditions. Using MSC's 12-month-ahead inflation expectations, we find that unemployment shocks affect inflation expectations at least as strongly as, and often more strongly than, CPI shocks. Under the sophisticated benchmark, unemployment shocks are the only significant driver of inflation expectations in scenarios conventionally associated with negative supply and demand shocks.

We also document significant asymmetries in household responses. Positive shocks to unemployment (announcements revealing worse-than-expected labor market conditions) generate larger expectation revisions than negative shocks of equal magnitude. This pattern is consistent with negativity bias: bad news about jobs generates larger belief revisions than good news.

We make three contributions relative to the existing literature. First, we conduct a systematic horse race across multiple macroeconomic announcements—unemployment, CPI, GDP, and housing starts—using a unified empirical framework. This allows us to directly compare which signals households attend to, rather than studying each announcement in isolation. Second, we construct announcement surprises under two polar benchmarks

[3]This is true regardless of whether households are assumed to be sophisticated or naive. The only scenario where the response to unemployment is insignificant is in the case of naive households when both unemployment and inflation are decreasing.

(naive and sophisticated) that together bound the true household response, allowing us to draw robust conclusions without taking a stand on household information sophistication. Third, we connect the reduced-form estimates to a microfounded rational inattention model, providing a structural interpretation: differences in response coefficients across announcements reflect differences in the attention households optimally allocate to each signal.

Our findings contribute to several strands of the literature. Most directly, we contribute to the growing body of work on survey-based expectations and their determinants (Malmendier & Nagel 2015, Kuchler & Zafar 2015, Mian et al. 2021, Bachmann et al. 2015, Armantier et al. 2015, Coibion et al. 2020, Lamla & Vinogradov 2019). While much of this literature focuses on inflation expectations and their anchoring properties, we show that labor market information plays an important role in shaping household beliefs, even beliefs about inflation itself. Recent work by Kamdar & Ray (2024), Andre et al. (2022), and Roth & Wohlfart (2019) emphasizes that households form joint expectations over multiple macroeconomic variables rather than tracking each in isolation. Our results suggest that the labor market is a key input to this joint expectation formation process.

Our paper is most closely related to Binder et al. (2024) and Mertens et al. (2020). In contrast to the daily event-study approach in Binder et al. (2024), which exploits the quasi-random timing of interview dates in the Survey of Consumer Expectations (SCE) to estimate average treatment effects of scheduled releases on inflation expectations, our design uses explicit surprise measures and local projections. Further, using expectations from the SCE, which was designed to be a monthly survey, at a daily level makes the analyses likely to suffer from small sample bias. As we document in the appendix, the daily SCE sample is only about 40 households,one-tenth the sample size of Gallup, and also has specially sparse sample around the BLS announcements. The Michigan microdata also suffers from this issue, however, we exploit the long time series dimension of the MSC rather than it's frequency.

Relative to Mertens et al. (2020), who apply a similar high-frequency Gallup/local-projection framework to monetary policy surprises, we broaden the scope to a systematic horse race across multiple macro announcements (labor market, inflation, output, housing) using harmonized shock construction.[4] We then discipline external validity by extending the analysis to Michigan microdata over 1980–2019, allowing us to study both economic

[4]While we have a similar baseline specification, our outcome variables are very different. Mertens et al. (2020) construct a weighted confidence index using current perception and future expectations, while we focus purely on the future expectation series.

sentiment and inflation expectations across markedly different macro regimes. Finally, we connect these reduced-form impulse responses to a microfounded attention allocation mechanism: differences in estimated coefficients across announcements are interpreted as differences in the welfare relevance and endogenously chosen attention weights placed on each signal, yielding a structural rationale for why labor-market news is a dominant driver of expectation revisions in both datasets.

We also contribute to the literature on the macroeconomic announcement premium. Prior research documents that announcements move spot exchange rates (Andersen et al. 2003, Evans & Lyons 2008), commodity prices (Caporale et al. 2016), bond yields (Balduzzi et al. 2001, Andersen et al. 2007, Gürkaynak et al. 2005*a*), global asset prices (Boehm & Kroner 2023), and effects of news shocks (Barsky et al. 2015). Our contribution is to show that this premium exists even for household expectations and is largest for labor market news.

The remainder of the paper is organized as follows. Section 2 develops the rational inattention model of expectation formation and derives testable predictions. Section 3 describes the Gallup Daily Tracking Poll, Michigan Survey of Consumers, and Bloomberg announcement data. Section 4 presents the empirical strategy, including the construction of shock measures and the local projection specification. Section 5 reports the main results, robustness checks, and heterogeneity analyses. Section 6 concludes.

2 A Rational Inattention Model of Expectation Formation

This section develops a theoretical framework to analyze how households form expectations about the macroeconomy in the presence of limited information processing capacity. The model builds on the rational inattention literature pioneered by Sims (2003) and extended by Maćkowiak & Wiederholt (2015).

The central insight is that households have finite cognitive resources and must optimally allocate attention across macroeconomic fundamentals. Because attention is scarce, households track some variables more closely than others, generating differential responses to announcements about unemployment, inflation, and other aggregates—even when all announcements are publicly available. The key testable prediction follows directly: announcements receiving greater attention generate larger expectation revisions. Comparing estimated coefficients across announcements thus reveals which macroeconomic signals households attend to most closely.

The section proceeds as follows. Sections 2.1 to 2.4 set up the environment, information structure, and optimal attention allocation problem. Section 2.5 derives the belief updating rule and the reduced-form coefficients. Section 2.6 states the key assumptions. Section 2.7 links the model to observable announcement surprises, and Section 2.8 develops two benchmark shock measures, corresponding to naive and sophisticated households, that allow us to bound the true household response without taking a stand on household information sophistication.

2.1 Environment

Consider a household that cares about an economic outcome Z_T that summarizes their future economic prospects between an initial date t and a finite horizon $T \geq t$. This outcome could represent, for example, future income growth, consumption possibilities, or a more general measure of economic welfare. The outcome depends on a vector of J macroeconomic fundamentals:

$$X_t = (X_{1t}, \ldots, X_{Jt}) \tag{1}$$

For example, suppose $J = 2$ and the outcome depends on unemployment and inflation, so that $X_t = (U_t, \pi_t)$, where U_t denotes the unemployment rate and π_t denotes inflation at time t. This example captures the two primary macroeconomic variables of interest in our empirical analysis, though the framework readily generalizes to include additional variables such as GDP growth or housing starts.

For tractability, we assume a simple linear structure for the payoff-relevant index:

$$Z_T = \sum_{\tau=t}^{T} \sum_{j=1}^{J} \theta_j X_{j\tau} + \sum_{\tau=t}^{T} \varepsilon_\tau \tag{2}$$

where θ_j measures how important fundamental j is for household welfare and ε_τ is an aggregate error term orthogonal to contemporaneous and past values of the fundamentals.

The welfare weight θ_j captures how sensitive household welfare is to movements in fundamental j. For instance, if labor income constitutes a large share of total household income, then θ_U (the welfare weight on unemployment) would be large in absolute value and negative, reflecting the fact that higher unemployment reduces expected income and welfare. Similarly, θ_π captures how inflation affects household welfare, potentially through its effect on real wages, real asset values, or the cost of consumption. We maintain the orthogonality condition:

$$\mathbb{E}_{t-1}[\varepsilon_\tau \mid \{X_s\}_{s\leq\tau}] = 0 \quad \text{for all } \tau > t-1 \tag{3}$$

This condition ensures that past and current fundamentals do not predict future aggregate shocks, a natural restriction given that ε_τ is meant to capture unpredictable variation in the payoff-relevant outcome that is orthogonal to the observable fundamentals.

Each fundamental follows a persistent autoregressive process:

$$X_{jt} = \rho_j X_{j,t-1} + \nu_{jt}, \quad \nu_{jt} \sim \mathcal{N}(0, \sigma^2_{\nu_j}) \tag{4}$$

with $|\rho_j| < 1$ to ensure stationarity.[5] The persistence parameter ρ_j plays a crucial role in determining the importance of current information about fundamental j. Highly persistent variables have innovations that affect the economy for many periods into the future, making current information about such variables particularly valuable to households.

Households are assumed to know the law of motion (4), the error distribution, and the parameters $(\rho_j, \sigma^2_{\nu,j})$. The friction in our model arises not from incorrect beliefs about how the economy works, but rather from limited capacity to process all available information in real time.

2.2 Timing and Information Sets

Time is discrete with periods indexed by $t = 0, 1, 2, \ldots$. We focus on new public information at date t and a planning horizon $T \geq t$. In the data, the release of new information will be measured by looking at announcements or data releases of macroeconomic variables. The timing of information revelation and belief updating is as follows:

Information sets. Let $\mathcal{I}_{t-1}$ and $\mathcal{I}_t$ denote the household's information set just before and after the new information release at date t, respectively. Expectations conditional on these information sets are defined as:

$$\mathbb{E}_{t-1}[\cdot] \equiv \mathbb{E}[\cdot \mid \mathcal{I}_{t-1}], \quad \mathbb{E}_t[\cdot] \equiv \mathbb{E}[\cdot \mid \mathcal{I}_t] \tag{5}$$

The distinction between these two information sets is central to our identification strategy.

[5] Under (4), the stationary variance of X_{jt} (if it exists) is $\sigma^2_j \equiv \frac{\sigma^2_{\nu,j}}{1-\rho^2_j}$, and in steady state $\mathrm{Var}(X_{jt}) = \sigma^2_j$.

By comparing expectations formed just before an announcement to those formed just after, we can isolate the causal effect of the announcement on beliefs.

Between announcements ($t-1$ to t). Between two consecutive announcements, households may observe noisy signals about the fundamentals from various sources such as news reports, personal experience, or informal communication. Rather than modeling this sub-period information structure explicitly, we summarize all pre-announcement information about X_{jt} by a Gaussian prior at time t:

$$X_{jt} \mid \mathcal{I}_{t-1} \sim \mathcal{N}(m_{j,t|t-1}, V_{j,t|t-1}) \tag{6}$$

where $m_{j,t|t-1} \equiv \mathbb{E}_{t-1}[X_{jt}]$ is the prior mean and $V_{j,t|t-1} \equiv \mathrm{Var}(X_{jt} \mid \mathcal{I}_{t-1})$ is the prior variance.[6]

At the announcement (t). At date t, an official macroeconomic statistic is released. We treat the released value as a signal s_{jt} observed at time t. Immediately after observing s_{jt}, households update their beliefs from $\mathbb{E}_{t-1}[X_{jt}]$ to $\mathbb{E}_t[X_{jt}]$ using Bayes' rule. The signal structure is described in detail below.

2.3 Information and the Capacity Constraint

Households do not observe the fundamentals X_{jt} perfectly. Instead, around macroeconomic announcement dates, they observe noisy signals of the form:

$$s_{jt} = X_{jt} + \eta_{jt}, \quad \eta_{jt} \sim \mathcal{N}(0, R_{jt}), \quad R_{jt} \equiv \gamma_{jt}^{-1} \tag{7}$$

with η_{jt} independent of X_{jt}. The scalar $\gamma_{jt} \geq 0$ is the precision chosen in the rational inattention problem.

The signal structure in (7) captures the idea that households observe macroeconomic announcements with some noise. The noise variance $R_{jt} = \gamma_{jt}^{-1}$ is inversely related to the precision γ_{jt} that the household chooses to allocate to tracking fundamental j. A higher precision (larger γ_{jt}) means the household pays closer attention to variable j, receiving a more accurate signal. A precision of zero ($\gamma_{jt} = 0$) corresponds to completely ignoring variable j. The key insight from information theory is that processing information is costly: reducing uncertainty about X_{jt} requires cognitive effort that is limited in supply. Note here

[6] The Gaussian assumption is maintained throughout for analytical tractability and because it delivers clean closed-form solutions for the optimal attention allocation problem.

that the noise in the signal is not due to any error in the announcement itself. Rather it reflects the fact that households allocate limited cognitive resources to tracking X_{jt}.

Following Sims (2003), we measure the value of information in signal s_{jt} by the reduction in uncertainty it produces—that is, by the difference between prior and posterior entropy. Under the Gaussian prior $X_{jt} \mid \mathcal{I}_{t-1} \sim \mathcal{N}(m_{j,t|t-1}, V_{j,t|t-1})$ and signal structure (7), the mutual information between X_{jt} and its signal s_{jt} takes the form:

$$I(X_{jt}; s_{jt} \mid \mathcal{I}_{t-1}) = \frac{1}{2}\log(1 + \gamma_{jt} V_{j,t|t-1}) \tag{8}$$

Equation (8) has an intuitive interpretation. Mutual information is higher when: (i) the signal is more precise (higher γ_{jt}), or (ii) there is more prior uncertainty to resolve (higher $V_{j,t|t-1}$). The logarithmic form reflects the decreasing marginal value of additional precision—there are diminishing returns to ever more precise tracking of a given variable.

Households face a constraint on total information processing capacity:

$$\sum_{j=1}^{J} I(X_{jt}; s_{jt} \mid \mathcal{I}_{t-1}) = \sum_{j=1}^{J} \frac{1}{2}\log(1 + \gamma_{jt} V_{j,t|t-1}) \leq \kappa \tag{9}$$

where $\kappa > 0$ measures the household's overall information processing capacity. The constraint (9) forces households to make trade-offs: paying more attention to one variable necessarily means paying less attention to others. This trade-off is at the heart of the rational inattention problem and generates predictions about which announcements should matter most for household expectations.

The parameter κ can be interpreted as the cognitive bandwidth available for processing macroeconomic information. It may vary across individuals (e.g., with education, cognitive ability, or experience) and across contexts (e.g., during periods of economic crisis when people devote more attention to economic news). For our purposes, we treat κ as fixed and focus on how a given capacity is optimally allocated across different fundamentals.

2.4 Optimal Attention Allocation

Households choose how precisely to track each fundamental by selecting the precision vector $\{\gamma_{jt}\}_{j=1}^{J}$. Their objective is to minimize the expected posterior variance of the horizon-T payoff Z_T subject to the information processing constraint. Formally, the household solves:

$$\min_{\{\gamma_{jt}\geq 0\}_{j=1}^{J}} \mathbb{E}_{t-1}\left[\mathrm{Var}(Z_T \mid \mathcal{I}_t) \mid \mathcal{I}_{t-1}\right] \tag{10}$$

$$\text{subject to} \quad \sum_{j=1}^{J} \frac{1}{2}\log(1+\gamma_{jt}V_{j,t|t-1}) \leq \kappa \tag{11}$$

This objective captures the idea that households dislike uncertainty about their future economic welfare. By acquiring more precise information about the fundamentals, they can reduce this uncertainty.

Horizon aggregation. To solve the problem (10)–(11), we first characterize how current beliefs about fundamentals translate into beliefs about the horizon-T payoff. Under the AR(1) law of motion (4), the forecast at any future date $\tau \geq t$ is:

$$\mathbb{E}_t[X_{j\tau}] = \rho_j^{\tau-t}\mathbb{E}_t[X_{jt}] \tag{12}$$

That is, forecasts of the future fundamental decay geometrically toward the unconditional mean. This motivates defining a *persistence multiplier*:

$$\Lambda_j(T-t) \equiv \sum_{\ell=0}^{T-t} \rho_j^{\ell} = \frac{1-\rho_j^{T-t+1}}{1-\rho_j} \tag{13}$$

The multiplier $\Lambda_j(T-t)$ captures the cumulative impact of a unit change in the current belief $\mathbb{E}_t[X_{jt}]$ on the expected cumulative value of the fundamental over the horizon $[t, T]$. For a highly persistent variable, the multiplier is approximately $T-t+1$; for a transitory variable, the multiplier is approximately 1. This persistence effect is economically important: it means that information about persistent fundamentals is more valuable because it helps forecast a longer sequence of future values.

Using the persistence multiplier, the horizon-T payoff can be written (up to terms independent of the precision choices) as:

$$Z_T = \sum_{j=1}^{J} \theta_j \Lambda_j(T-t) X_{jt} + (\text{terms independent of } \gamma) \tag{14}$$

Hence, by Assumption 2, the posterior variance decomposes additively across fundamentals:

$$\mathrm{Var}(Z_T \mid \mathcal{I}_t) = \sum_{j=1}^{J} \left[\theta_j \Lambda_j (T-t)\right]^2 \mathrm{Var}(X_{jt} \mid \mathcal{I}_t) + \mathrm{Var}\left(\sum_{\tau=t}^{T} \varepsilon_\tau\right) \tag{15}$$

where the final term involving ε does not depend on the precision choices $\{\gamma_{jt}\}$.

Posterior variance of X_{jt}. Under the Gaussian prior and signal structure, the posterior variance of X_{jt} after observing signal s_{jt} is given by the standard Bayesian updating formula:

$$\mathrm{Var}(X_{jt} \mid \mathcal{I}_t) = \frac{V_{j,t|t-1}}{1 + \gamma_{jt} V_{j,t|t-1}} \tag{16}$$

Higher precision γ_{jt} reduces the posterior variance, reflecting the value of attention in reducing uncertainty.

Substituting (16) into (15), the attention problem (10)–(11) reduces to:

$$\min_{\{\gamma_{jt} \geq 0\}} \mathbb{E}_{t-1} \left[\sum_{j=1}^{J} \left(\theta_j \Lambda_j (T-t)\right)^2 \frac{V_{j,t|t-1}}{1 + \gamma_{jt} V_{j,t|t-1}} \right] \quad \text{s.t.} \quad \sum_{j=1}^{J} \frac{1}{2} \log(1 + \gamma_{jt} V_{j,t|t-1}) \leq \kappa \tag{17}$$

The solution to this problem, following Sims (2003) and Maćkowiak & Wiederholt (2015), takes the form:

$$\gamma_{jt}^* = \max\left\{0, \frac{2\theta_j^2 \Lambda_j^2 (T-t)}{\lambda} - \frac{1}{V_{j,t|t-1}}\right\} \tag{18}$$

where $\lambda > 0$ is the Lagrange multiplier on the capacity constraint.

Equation (18) reveals the key forces determining optimal attention. Households allocate more precision to fundamental j when: (i) the welfare weight θ_j is large in absolute value (the fundamental matters more for welfare), (ii) the persistence multiplier $\Lambda_j(T-t)$ is large (current information helps forecast a longer horizon), and (iii) the prior variance $V_{j,t|t-1}$ is large (there is more uncertainty to resolve). The shadow cost of information λ pins down the overall scale of attention and ensures the constraint (9) binds.

The max operator in (18) reflects the possibility that some fundamentals receive zero attention. This occurs when the marginal benefit of tracking a fundamental (proportional to $\theta_j^2 \Lambda_j^2$) is sufficiently small relative to the marginal cost of information. In such cases, households rationally choose to ignore the fundamental entirely.

2.5 Belief Updating and Expectation Revisions

Given the optimally chosen precision γ_{jt}^*, we now characterize how beliefs are updated upon observing the signal. The posterior mean is a linear combination of the prior mean and the signal:

$$\mathbb{E}_t[X_{jt}] = (1-\omega_{jt})\mathbb{E}_{t-1}[X_{jt}] + \omega_{jt}s_{jt} \tag{19}$$

where the *Kalman gain* ω_{jt} is:

$$\omega_{jt} = \frac{V_{j,t|t-1}}{V_{j,t|t-1} + (\gamma_{jt}^*)^{-1}} = \frac{\gamma_{jt}^* V_{j,t|t-1}}{1+\gamma_{jt}^* V_{j,t|t-1}} \in [0,1] \tag{20}$$

The Kalman gain ω_{jt} measures the weight placed on the new signal relative to the prior. A higher gain (closer to 1) means households respond more strongly to new information; a lower gain (closer to 0) means households largely ignore the announcement and stick with their prior beliefs. The gain is increasing in the precision γ_{jt}^* allocated to fundamental j, establishing the link between attention and responsiveness to announcements.

Taking expectations of equation (14), we can compute the revision in beliefs about the horizon-T payoff:

$$\Delta\mathbb{E}_t^{HH}[Z_T] \equiv \mathbb{E}_t[Z_T] - \mathbb{E}_{t-1}[Z_T] = \sum_{j=1}^{J} \theta_j \Lambda_j(T-t) \left(\mathbb{E}_t[X_{jt}] - \mathbb{E}_{t-1}[X_{jt}]\right) \tag{21}$$

Substituting the updating rule (19) yields:

$$\Delta\mathbb{E}_t^{HH}[Z_T] = \sum_{j=1}^{J} \theta_j \Lambda_j(T-t)\omega_{jt} \left(s_{jt} - \mathbb{E}_{t-1}[X_{jt}]\right) \tag{22}$$

Let $S_{jt} \equiv s_{jt} - \mathbb{E}_{t-1}[X_{jt}]$ denote the household's *perceived shock*—the difference between the observed signal and the prior expectation. This is the surprise component of the announcement from the household's perspective. The reduced-form coefficient on this shock is:

$$\beta_{jt} \equiv \theta_j \Lambda_j(T-t)\omega_{jt} \tag{23}$$

The response of household expectations to announcement surprises depends on three components: (i) the welfare weight θ_j measuring how much fundamental j matters for household welfare, (ii) the persistence multiplier $\Lambda_j(T-t)$ capturing the horizon over which current information remains relevant, and (iii) the Kalman gain ω_{jt} reflecting the attention allocated to fundamental j.

2.6 Assumptions

Here we discuss the main assumptions underlying the model. These assumptions are sufficient to deliver closed-form solutions for the optimal attention allocation and the resulting belief dynamics.

Assumption 1 (Linearity and Normality) *The payoff Z_T is a linear function of the fundamentals as in (2). Each fundamental X_{jt} evolves according to (4), where ε_τ is independent of all past realizations $\{X_s\}_{s\leq\tau}$ and has mean zero. The innovations ν_{jt} are Gaussian with zero mean.*

The linear-Gaussian structure is the workhorse of the rational inattention literature. It ensures that the posterior distribution after observing a signal remains Gaussian, which greatly simplifies the computation of optimal attention.

Assumption 2 (Independence Across Fundamentals) *The innovations ν_{jt} are independent across j and over time, and ν_{jt} is independent of ε_τ for all j and τ.*

This independence assumption implies that the posterior variance of Z_T can be written as a sum of contributions from each fundamental separately. While potentially restrictive since unemployment and inflation may be correlated in practice, this assumption allows us to characterize how attention is allocated across individual fundamentals in a tractable way. We discuss how the model could be extended to accommodate correlated fundamentals in the online appendix .

Assumption 3 (Rational Expectations Given Information) *Households know the law of motion (4), the parameters $(\rho_j, \sigma^2_{\nu,j})$, and the distribution of ε_τ. Conditional on their (endogenously chosen) information set $\mathcal{I}_t$, they form Bayesian expectations.*

This assumption embodies the "rational" part of rational inattention. Households are sophisticated Bayesian updaters who correctly understand the structure of the economy. The friction in their expectation formation arises solely from limited information processing capacity, not from misunderstanding or behavioral biases.

Assumption 4 (Stationarity and Horizon) *The AR(1) processes in (4) are stationary ($|\rho_j| < 1$). The horizon T is finite and common across households. The welfare weight θ_j is constant over $\tau \in [t, T]$.*

Assumption 5 (Information Updating) *No other major news arrives in the short window* $[t-1, t]$. *Thus, the information set just after the announcement can be written as* $\mathcal{I}_t = \{s_{jt}, \mathcal{I}_{t-1}\}$.

Assumption 5 is the key identifying assumption that allows us to interpret expectation revisions around announcements as causal effects of the announcements themselves. It is most plausible when the window between $t-1$ and t is narrow, which is why we exploit daily survey data in our empirical analysis (Gürkaynak et al. 2005*b*).

2.7 Link to Announcement Surprises and Reduced-Form Coefficients

Empirically, we observe official macroeconomic releases (e.g., the published unemployment rate and CPI) and can construct announcement surprises using external forecasts (e.g., the Bloomberg consensus). To connect the model to the data, we treat the published series as the signal:

$$s_{jt} = X_{jt}^{\text{release}} \tag{24}$$

The release is measured without statistical error in the sense that it is the official published number. However, households may still perceive or ignore it depending on their attention choice, as captured by the gain ω_{jt} in equation (19).

The theoretical surprise for series X_j is:

$$\text{Shock}_{jt} \equiv X_{jt}^{\text{release}} - \mathbb{E}_{t-1}[X_{jt}] = s_{jt} - \mathbb{E}_{t-1}[X_{jt}] \tag{25}$$

If our empirical measure of Shock_{jt} is a good approximation to $s_{jt} - \mathbb{E}_{t-1}[X_{jt}]$, then equation (22) suggests the reduced-form relationship:

$$\Delta\mathbb{E}_{it}^{HH}[Z_T] = \beta_j \cdot \text{Shock}_{jt} + u_{it} \tag{26}$$

where i indexes individuals and t indexes event windows. Comparing (26) with (22), the reduced-form coefficient can be interpreted as:

$$\beta_j \approx \theta_j \Lambda_j (T-t)\omega_j \tag{27}$$

Survey timing. In our empirical application, we exploit variation in the timing of survey responses relative to macroeconomic announcements. Expectations measured on day $t-1$ are interpreted as $\mathbb{E}_{t-1}[Z_T]$ (prior to the announcement), while expectations measured on day t (after the release) correspond to $\mathbb{E}_t[Z_T]$. The change in expectations:

$$\Delta\mathbb{E}_t^{HH}[Z_T] \equiv \mathbb{E}_t[Z_T] - \mathbb{E}_{t-1}[Z_T] \tag{28}$$

captures the causal effect of the announcement on household expectations, under the identifying assumption that no other major news arrives in the short window between $t-1$ and t. This assumption is plausible when the window is narrow (for example, one day) and motivates our use of high-frequency survey data.

Main prediction. The model generates a clear testable prediction. If an announcement A is both more welfare-relevant (larger $|\theta_A|$) and more closely tracked (larger ω_A) than announcement B, the model implies:

$$|\beta_A| = |\theta_A \Lambda_A (T-t)\omega_A| > |\theta_B \Lambda_B (T-t)\omega_B| = |\beta_B| \tag{29}$$

so that the announcements of A should shift household expectations more than the announcements of B. This is precisely what we test empirically by estimating β_j for different series using local projections on high-frequency survey data.

2.8 Constructing Empirical Shock Measures

A practical challenge arises because households' true priors $\mathbb{E}_{t-1}[X_{jt}]$ are not directly observed. Different assumptions about household sophistication lead to different measures of the surprise component of announcements. We address this challenge by considering two polar benchmark cases that provide bounds on the true household response.

Naive benchmark. Under this benchmark, households pay little attention between announcements and simply extrapolate from the last release:

$$\mathbb{E}_{t-1}^{\text{naive}}[X_{jt}] = X_{j,t-1} \tag{30}$$

That is, naive households expect the current value of the fundamental to equal its previous announced value. The corresponding naive surprise is simply the change in the announced series:

$$\text{Shock}_{jt}^{\text{naive}} = X_{jt}^{\text{release}} - X_{j,t-1} \tag{31}$$

This measure is straightforward to construct from publicly available data and does not require access to professional forecasts.

Sophisticated benchmark. Under this benchmark, households process information efficiently and form expectations similar to professional forecasters:

$$\mathbb{E}_{t-1}^{\text{soph}}[X_{jt}] = \mathbb{E}_{t-1}^{PF}[X_{jt}] \tag{32}$$

where $\mathbb{E}_{t-1}^{PF}[X_{jt}]$ is the professional forecaster consensus (e.g., the Bloomberg median). The corresponding sophisticated surprise is:

$$\text{Shock}_{jt}^{\text{soph}} = X_{jt}^{\text{release}} - \mathbb{E}_{t-1}^{PF}[X_{jt}] \tag{33}$$

This is the standard measure of announcement surprise used in the asset pricing literature. It captures the unanticipated component of the release relative to market expectations.

For actual households, the true prior likely lies between these two extremes. A simple way to capture this is to write:

$$\mathbb{E}_{t-1}^{HH}[X_{jt}] = (1-\phi_j)X_{j,t-1} + \phi_j\mathbb{E}_{t-1}^{PF}[X_{jt}] \tag{34}$$

for some $\phi_j \in [0, 1]$. This formulation is consistent with the rational inattention model: higher attention (larger ϕ_j) leads to more sophisticated forecasts that incorporate more information beyond the last release.

Under (34), the true surprise is:

$$\begin{aligned}
\text{Shock}_{jt}^{HH} &= X_{jt}^{\text{release}} - \mathbb{E}_{t-1}^{HH}[X_{jt}] \\
&= \text{Shock}_{jt}^{\text{soph}} + (1-\phi_j)\left(\mathbb{E}_{t-1}^{PF}[X_{jt}] - X_{j,t-1}\right) && (35) \\
&= \text{Shock}_{jt}^{\text{naive}} - \phi_j\left(\mathbb{E}_{t-1}^{PF}[X_{jt}] - X_{j,t-1}\right) && (36)
\end{aligned}$$

If the professional forecast lies between the last period's value and the actual release, as is typically the case when forecasters correctly anticipate the direction of change, then Shock_{jt}^{HH} is bounded by $\text{Shock}_{jt}^{\text{naive}}$ and $\text{Shock}_{jt}^{\text{soph}}$. Combined with (27), this implies that the true response coefficient β_j lies between the coefficients estimated under the naive and sophisticated surprises:

$$\hat{\beta}_j^{\text{soph}} \leq \beta_j \leq \hat{\beta}_j^{\text{naive}} \tag{37}$$

This bounding result is important for our empirical strategy. If we observe that under *both* benchmarks the coefficient on a variable A dominates that on variable B:

$$|\hat{\beta}_A^{\text{naive}}| > |\hat{\beta}_B^{\text{naive}}| \quad \text{and} \quad |\hat{\beta}_A^{\text{soph}}| > |\hat{\beta}_B^{\text{soph}}| \tag{38}$$

then A dominates B in the true model regardless of the exact value of ϕ_j. This provides a robust test of the model's prediction that is invariant to assumptions about household sophistication.

In summary, the rational inattention model developed in this section provides a structural interpretation of the reduced-form coefficients we estimate empirically. The model predicts that households should respond more strongly to announcements about variables that are more welfare-relevant, more persistent, and more closely tracked. By constructing shock measures under both naive and sophisticated benchmarks, we can bound the true response and test which announcements have the highest impact on household expectations —an exercise we take to the data in the following sections.

3 Data

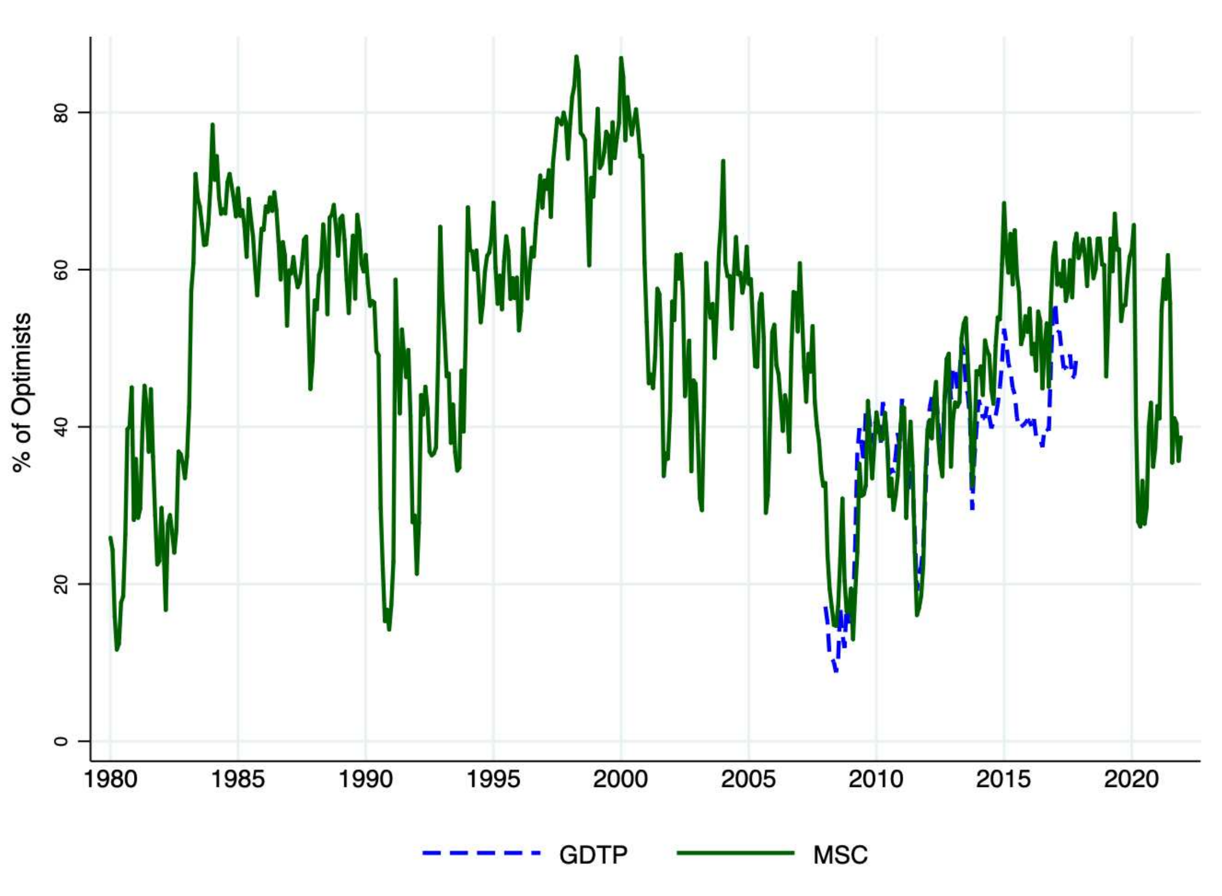
We use three main data sources. Our primary source is the Gallup Daily Tracking Poll, which provides daily data on household expectations. The high-frequency nature of this survey allows for clean identification of announcement effects within narrow windows. Our second source is the Michigan Survey of Consumers (MSC), a monthly survey that reports both qualitative sentiment measures and quantitative inflation expectations. The MSC microdata contain interview dates, enabling daily and weekly analysis over a longer time horizon (1980–2019). Our third source is Bloomberg's US Economic Calendar, which reports the median expectations of professional forecasters prior to each macroeconomic release. These forecasts allow us to construct the surprise component of announcements under the sophisticated benchmark.

3.1 Gallup's US Daily Tracking Poll

The US Daily Tracking Poll (Gallup Inc. 2017), henceforth GDTP, is a repeated cross-sectional survey conducted by Gallup. It was fielded to approximately 1,000 individuals per day from 2008 to 2013, and 500 individuals per day from 2013 to 2017. Figure 2b shows the average number of respondents each day of the month, consistently in the range of

450–500, giving us more than 1.7 million observations in total.[7] The data are representative at the daily level and match targets from the US Census Bureau by age, sex, region, gender, education, ethnicity, race, and population density of self-reported location. Appendix Table A3 displays summary statistics.[8]

Figure 1: Household Expectations Index



Notes: The GDTP Expectations Index is the fraction of respondents rating future economic conditions as "Getting better" (versus "Getting worse"). The MSC share of optimists is the fraction rating business conditions in the country as a whole during the next twelve months as "good times financially" (versus "bad times"). The correlation between these series is 0.86. Data from Gallup Inc. and Survey of Consumers, University of Michigan, Survey Research Center.

The main variable of interest is a measure of households' expectations about the future of the economy. Participants are asked:

[7]The survey is conducted for 350 days per year. Respondents are evenly divided between the Well-being track and the Politics and Economy track. Certain variables, such as employment indicators and key demographics, are asked on both tracks.

[8]We restrict our sample to individuals between the ages of 18 and 90.

"Right now, do you think that economic conditions in the country, as a whole, are getting better or getting worse?"

Participants choose between three options: getting better, staying the same, or getting worse. We denote this variable as our *Expectations Index*. The proportion of respondents answering "staying the same" is less than 5% throughout the sample, so we drop them. The resulting binary index takes value 1 when respondents are optimistic (reporting that the economy is "getting better") and 0 when pessimistic (reporting "getting worse"). Higher values indicate greater optimism about future economic conditions. Since the index is binary, it can be interpreted as the share of optimists in the population.

Figure 1 displays the evolution of the Expectations Index over time, along with the analogous series from the Michigan Survey of Consumers.[9] The two series exhibit high co-movement, with a correlation of 0.86, suggesting that both capture similar aspects of household economic expectations. Appendix Table 2 reports changes in the Expectations Index around major events during the sample period. For example, when Lehman Brothers filed for bankruptcy in September 2008, the Expectations Index fell by 0.22 points—a sharp decline in the share of optimistic households. We document substantial heterogeneity in expectations across demographic groups in the online appendix.

3.2 University of Michigan's Survey of Consumers

The Michigan Survey of Consumers (MSC) began in January 1978 and is the longest-running survey of household expectations in the United States. It interviews approximately 500 individuals per month, selected to be representative of the US population. Participants answer questions covering qualitative assessments of current and future economic conditions as well as quantitative forecasts, including point estimates of expected inflation.

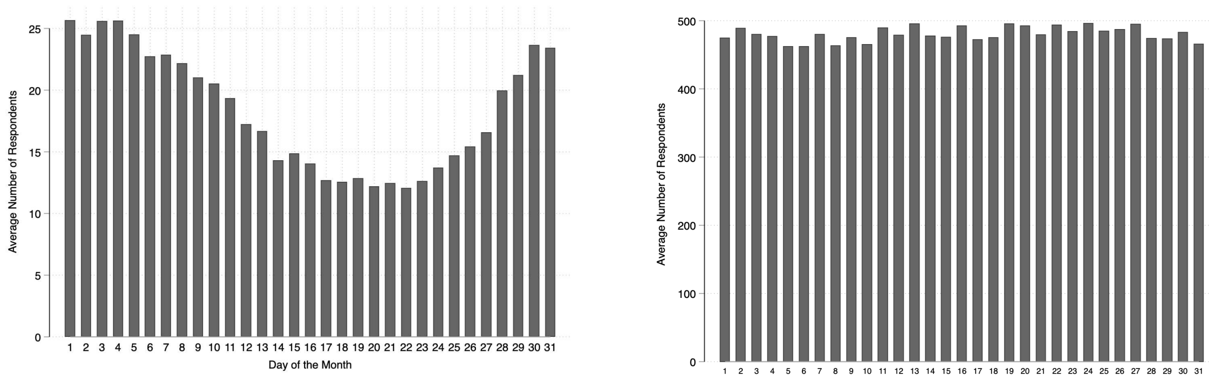
We use the MSC microdata because, since June 1979, interview dates have been recorded and made publicly available (York 2023). This allows for high-frequency identification at the daily and weekly level, complementing the Gallup analysis. Figure 2a reports the average number of respondents each day of the month. As seen from this figure, the Gallup survey has a significantly larger and more consistent sample each day, relative to the MSC, making it our choice for the baseline.[10] The Michigan microdata does suffer

[9] This corresponds to Question BUS12 in the MSC questionnaire.

[10] Note that this is true for other public surveys such as the NY Fed's Survey of Consumer Expectations (SCE). As we document in the online appendix, SCE also averages about 40-60 respondents each day, with a notably sparse sample around the BLS announcement windows. None of these daily samples are as consistent or large as the Gallup survey.

from a small-sample bias for the weekly window. However, we use the MSC for it's long time series.

Figure 2: Number of Respondents Each Day of the Month



(a) Michigan Survey of Consumers

(b) Gallup Daily Tracking Poll

Notes: Average number of respondents per day of the month in the Survey of Consumers, University of Michigan, Survey Research Center, and the Gallup Daily Tracking Poll.

We use two measures of expectations from MSC. The first is a qualitative measure of expected business conditions, chosen to match Gallup's Expectations Index as closely as possible.[11] The survey asks:

> *"Now turning to business conditions in the country as a whole—do you think that during the next twelve months we'll have good times financially, or bad times, or what?"*

As with Gallup, participants choose between "good times," "uncertain," or "bad times." The proportion answering "uncertain" is low, so we drop them, leaving a binary index comparable to Gallup's Expectations Index. Our sample covers January 1980 to November 2021.[12]

The second measure is quantitative: 12-month-ahead inflation expectations. The survey asks:

> *"By about what percent do you expect prices to go up/down on the average, during the next 12 months?"*

[11] For robustness, we also use the Index of Consumer Expectations, a composite index from MSC. Results are similar and reported in the Appendix.

[12] Although the survey started in 1978, interview dates are only available from June 1979. Moreover, interview dates are only available through November 2021.

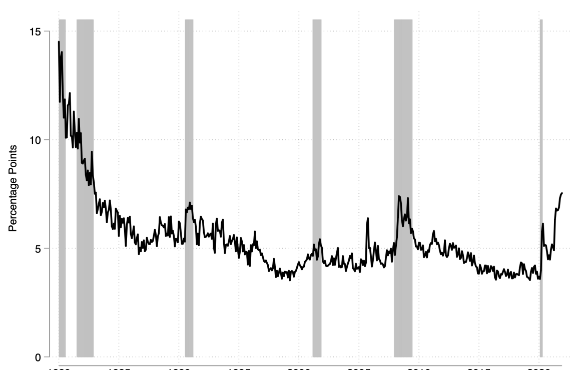
Respondents report a number from 0 to 100. Figure 3a shows the evolution of inflation expectations over time. Expectations were elevated in the early 1980s when realized inflation was high, declined as inflation fell, and have remained relatively stable since, with occasional increases around recessions. Figure 3b reports the distribution; most responses lie between 0% and 10%.

3.3 Bloomberg's US Economic Calendar

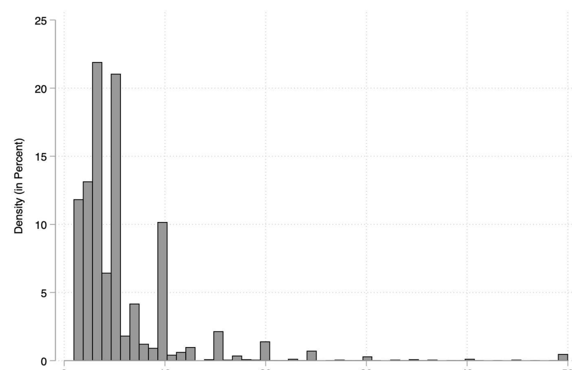
Bloomberg's US Economic Calendar reports data for major macroeconomic announcements along with the median forecast of professional forecasters (the "Consensus Forecast").[13] Before each announcement, Bloomberg surveys economists to elicit their expectations. We focus on four variables: the unemployment rate, GDP growth (Advance release), the month-on-month Consumer Price Index (CPI), and housing starts. Unemployment, CPI, and housing starts are released monthly; GDP is released quarterly. Table A3 reports summary statistics.

The Bloomberg forecasts allow us to construct the sophisticated shock measure: $\text{Shock}_{jt}^{\text{soph}} = X_{jt}^{\text{release}} - \mathbb{E}_{t-1}^{PF}[X_{jt}]$. Bloomberg Consensus Forecasts are available from 1996 onward, which determines the sample period for our sophisticated-household estimates (1997–2019 for MSC, 2008–2017 for Gallup).

Figure 3: 12-Month Ahead Inflation Expectations



(a) Time Series



(b) Distribution

Notes: Panel (a) shows the evolution of 12-month-ahead inflation expectations over time. Panel (b) shows the distribution of responses. Data from Survey of Consumers, University of Michigan, Survey Research Center.

[13]Bloomberg also reports revisions to initial releases. We use only the initial release, as this captures the new information available at the announcement.

4 Empirical Strategy

With the testable implications from the model, analyzing which macroeconomic variables affect household expectations is now straightforward. As discussed in 5 ,(Gürkaynak et al. 2005*a*, Mertens et al. 2020), we propose that if we estimate the change in expectations within a narrow window around the release date of a macroeconomic announcement, then we can assign a causal claim to it. In other words, by choosing a tight window, we assume that the only event occurring in that time frame is the macroeconomic announcement, and therefore any change in expectations in this window must be due to the announcement.[14]

To be precise, let the announcement occur on day t. We then consider the change in household expectations in the window $[t-1, t+h]$, where h denotes days from t. Since people may take some time to update their expectations, we vary the horizon h from one to five days. Let $E_t^i[Z]$ denote expectations of individual i on day t and $ShockX_t$ denote the shock coming from new information in the announcement. Then, following Jordà (2005), the effect of the announcement on expectations can be estimated using the following local projection:

$$E_{t+h}^i[Z] - \bar{E}_{t-1}[Z] = \alpha_h + \beta_h \cdot ShockX_t + D_{t+h}^i + \epsilon_{th}^i \tag{39}$$

This follows from Equation 26 in Section 2. D_t^i denotes demographic characteristics of person i at time t and include age, education, income, gender, occupation, job status and, state of residence. Note that since the Gallup poll is not a panel survey, we cannot track expectations of the same person over time. Thus, we average expectations for day $t-1$ and subtract them. Since Gallup is representative at the daily level, $\bar{E}_{t-1}[Z]$ denotes the expectations for a representative agent.

One of the benefits of the specification with first differences of the independent variable is that it allows us to parse out the anticipation effects (summarized in the day $t-1$ expectations) from the household expectations. This makes including lagged effects of the dependent variable as a control, which is a common practice in this literature, redundant, since they are already included in the day $t-1$ expectations. It also precludes the need to include other macroeconomic variables as controls, since they will also be subsumed in the day $t-1$ expectations about the economy in future.

[14] We check for overlaps of major events with macroeconomic releases and omit the days where any overlap occurs.

Although we do not observe the time at which a person is surveyed, Gallup only surveys people after 5 pm on weekdays. Since most announcements come out early in the morning, we feel that it is safe to include responses obtained on day t as coming after the announcement.[15] Our results, however, remain robust to the exclusion of day t.

It is also important to discuss the timeline of macroeconomic releases. The BLS jobs report is the first major macroeconomic release of every month, and it is released on the first Friday of every month. It is followed by CPI, which comes out in the middle of the month. Next is the housing report, which is released between the 15th and 20th of every month. Finally, the GDP report is released between the 27th and the last day of every month.

Since we use the timing of announcements for identification, it is crucial that our release dates not clash with other announcements. For this reason, we do not look at the Index of Industrial Production (IIP) because it is often released very close to the housing report. A similar issue is present with the BLS jobs report, which comes out on the first Friday of every month. It is preceded by the jobless claims numbers that are released every Thursday. Furthermore, ADP Research Institute also usually releases its employment report on the first Wednesday of every month. It could thus be argued that the correct prior to look at for the unemployment rate would be Tuesday, since Wednesday to Friday are filled with new information regarding the labor market. These results are summarized in the appendix Tables A5 and A10, and we find our results to be robust.

We are using unemployment to proxy for BLS's jobs report. However, several data is released in the jobs report, such as labor force participation, non-farm payroll etc. While labor force participation tends to be acyclical, non-farm payroll is very procyclical and could be another candidate with which to proxy the jobs report. However, ADP Research Institute also releases numbers on non-farm payroll in its report, which is highly correlated with the non-farm numbers in the BLS's report. Since ADP's report comes out before BLS's jobs report, we consider that non-farm payroll numbers are not actually new data and would already be incorporated in household's expectations at day $t-1$ prior to the jobs report. Therefore, we use unemployment rate to proxy the BLS's jobs report, not non-farm payroll.

Following the discussion in Subsection 2.8, the unanticipated component of each macroeconomic announcement can be summarized as follows:

[15]The survey occurs from 11 am on weekends, but no announcements are made on weekends.

$$ShockX_t = \begin{cases} \Delta X_t & \text{if naive} \\ SurpriseX_t & \text{if sophisticated} \end{cases}$$

5 Results

This section presents our main empirical findings. Recall that the model predicts households will respond more strongly to announcements about variables that receive greater attention. The model delivers a clear testable prediction: if $|\beta_A| > |\beta_B|$ under both the sophisticated and naive benchmarks, then release A announcements generate larger expectation revisions than release B announcements regardless of assumptions about household sophistication.

We begin with the Gallup Daily Tracking Poll, which provides the cleanest identification due to its daily frequency and large sample size. Section 5.1.1 presents baseline results showing that unemployment announcements generate significant expectation revisions while other announcements generally do not. Section 5.1.2 documents asymmetric responses, finding that bad labor market news moves expectations more than good news of equal magnitude

We then extend the analysis to the Michigan Survey of Consumers, which spans 1980–2019 and includes both qualitative sentiment measures and quantitative inflation expectations. Section 5.2.1 examines responses of business conditions expectations across four macroeconomic scenarios based on the co-movement of unemployment and inflation. Section 5.2.2 asks whether the dominance of unemployment extends to inflation expectations themselves—and finds that it does. Section 5.3 summarizes robustness checks, with detailed results in the Appendix.

5.1 Gallup Daily Tracking Poll

5.1.1 Baseline Results

We estimate the local projection in Equation 39 to identify the causal effect of macroeconomic announcements on household expectations. The use of narrow windows—comparing expectations the day before an announcement to expectations immediately after—allows us to isolate the announcement effect from other contemporaneous news. We estimate β_j for each j and horizon h, where we vary the horizon h from 0 to 5 days to trace out the dynamic response. We report heteroskedasticity-consistent standard errors in parentheses. These results are summarized in Table 1. For detailed information on the results (including number of observations, R^2, controls) please refer to the online appendix.

Sophisticated Households. Panel A of Table 1 reports results under the assumption that households form priors consistent with professional forecasters, so that the shock is measured as $\text{Shock}_{jt}^{\text{soph}} = X_{jt}^{\text{release}} - \mathbb{E}_{t-1}^{PF}[X_{jt}]$. We find that unemployment surprises

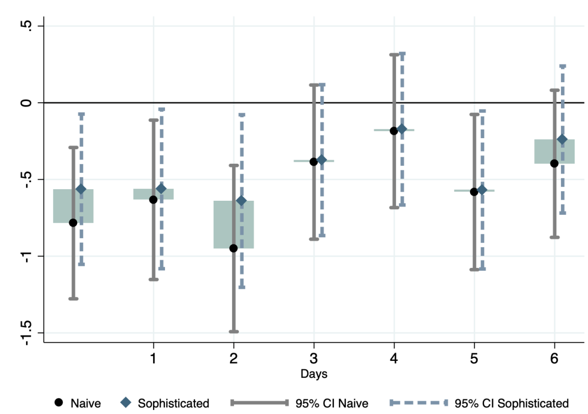
Table 1: Response of Household Expectations to Macroeconomic Announcements

Panel A: Sophisticated Households Model						
y_t : Δ(Expectations Index)$_t$	Day 0	Day 1	Day 2	Day 3	Day 4	Day 5
Surprise(Unemp)	-0.564*	-0.562*	-0.640*	-0.374	-0.173	-0.568*
	(0.298)	(0.316)	(0.342)	(0.299)	(0.300)	(0.313)
Surprise(CPI)	0.433	-0.173	0.396	-0.129	-0.419	0.108
	(0.290)	(0.306)	(0.308)	(0.282)	(0.288)	(0.295)
Surprise(GDP)	0.172	0.430	0.252	0.685**	-0.0762	0.189
	(0.324)	(0.325)	(0.324)	(0.323)	(0.341)	(0.327)
Surprise(Housing)	0.0103	-0.108	0.110	0.648**	-0.214	0.745**
	(0.321)	(0.331)	(0.331)	(0.328)	(0.343)	(0.337)
Panel B: Naive Households Model						
	Day 0	Day 1	Day 2	Day 3	Day 4	Day 5
$\Delta(Unemp)$	-0.785***	-0.633**	-0.950***	-0.387	-0.185	-0.582*
	(0.300)	(0.316)	(0.329)	(0.305)	(0.303)	(0.307)
$\Delta(CPI)$	0.0741	-0.0804	0.672**	0.306	0.667**	0.156
	(0.288)	(0.292)	(0.294)	(0.290)	(0.294)	(0.296)
$\Delta(GDP)$	0.791**	0.818**	0.625*	0.960***	0.395	0.203
	(0.343)	(0.345)	(0.351)	(0.344)	(0.352)	(0.356)
$\Delta(Housing)$	-0.485	-0.341	-0.171	0.569*	-0.128	0.376
	(0.337)	(0.352)	(0.350)	(0.343)	(0.344)	(0.349)

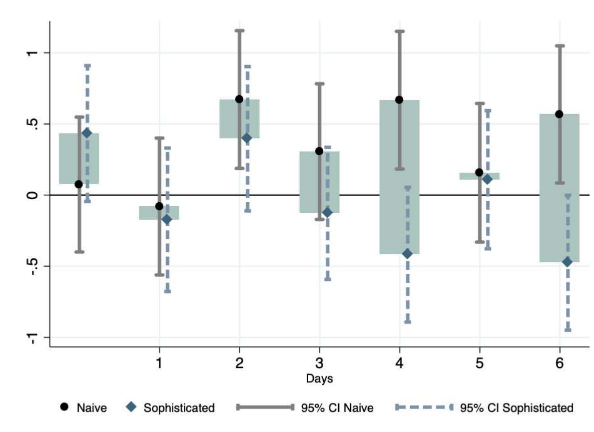
Notes: This table reports estimates of β_h from Equation 39. Each cell is the coefficient from a separate regression. We control for demographics including age, income, education, race, gender, political affiliation, and state of residence. Survey weights used. Standard errors in parentheses. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$. Data from Gallup Inc. and Bloomberg Finance LP.

generate statistically significant revisions in household expectations, while surprises in CPI, GDP, and housing starts do not. On the day of the announcement (Day 0), a one-standard-deviation unemployment surprise reduces the Expectations Index by 0.56 percentage points. This effect persists through Day 2, with a coefficient of –0.64. In contrast, none of the CPI coefficients are statistically significant at conventional levels. The point estimates are small and switch signs across horizons, suggesting no systematic response to inflation announcements. GDP and housing starts similarly fail to generate significant expectation revisions, with the exception of isolated coefficients at specific horizons that do not persist.

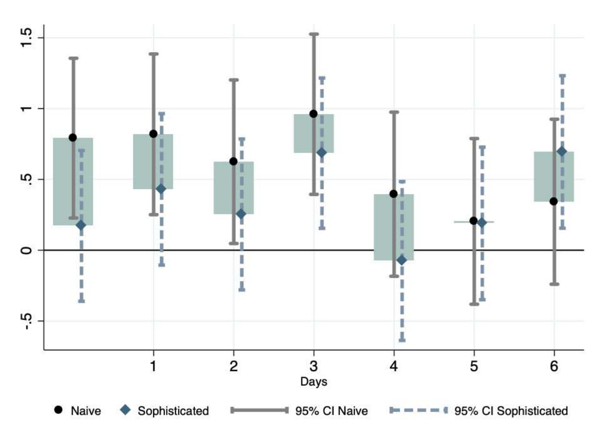
Figure 4: Dynamic Response of Household Expectations to Macroeconomic Announcements



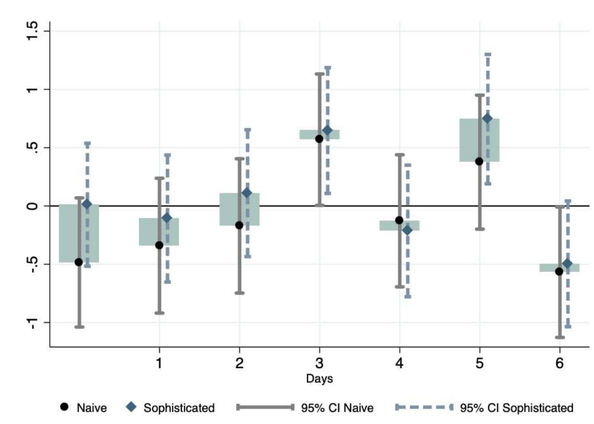
(a) Unemployment



(b) CPI



(c) GDP Advance



(d) Housing Starts

Notes: Coefficient plots for (a) Unemployment, (b) CPI, (c) GDP Advance, and (d) Housing Starts announcements. Naive model shown with black solid circles; Sophisticated model shown with blue solid diamonds. The shaded green region between coefficients indicates where the true coefficient lies. 95% confidence intervals shown for Naive (gray) and Sophisticated (light blue) models. Data from Gallup Inc. and Bloomberg Finance LP.

Naive Households. Panel B reports results under the assumption that households simply extrapolate from the previous announcement, so that the shock is $\text{Shock}_{jt}^{\text{naive}} = X_{jt}^{\text{release}} - X_{j,t-1}$. The pattern is similar but more pronounced. A one-standard-deviation increase in unemployment reduces the Expectations Index by 0.79 percentage points on impact, with effects remaining significant through Day 2 at −0.95.

Under this benchmark, GDP also generates a significant response: a one-standard-deviation increase raises expectations by 0.79 percentage points. However, this effect is not robust across horizons. CPI changes remain insignificant throughout.

Figure 4 displays the impulse responses with 95% confidence intervals. Across both benchmarks, the unemployment response is negative and significant in the short run, while the responses to other announcements are centered around zero throughout the horizon.

Bounding the True Response. The model in Section 2 establishes that the true household response lies between the sophisticated and naive estimates. For unemployment, combining the confidence intervals yields a bound of [−1.1%, −0.37%] for the true effect. Since this interval excludes zero, we conclude that unemployment announcements have a robust negative effect on household expectations.[16]

For GDP, the corresponding interval is [−0.16%, 1.1%], which includes zero. We therefore cannot conclude that GDP announcements systematically affect expectations. For CPI and housing starts, both benchmarks yield insignificant coefficients, providing no evidence that inflation announcements move household expectations in this sample.

5.1.2 Asymmetric Responses

The baseline estimates capture the average response to shocks of either sign. However, positive and negative shocks may convey different information and generate different

[16] Recall that $\beta_j = \theta_j \Lambda_j (T - t)\omega_{j,t}$. We do a back-of-the-envelope exercise using values of Λ and ω_j from the literature to decompose β_j into its components for each j. We find that the ratio of the welfare weights on inflation and unemployment is 2.4, implying that inflation is about 2.5 times more important than unemployment in the household's welfare. Thus, the higher response of households to unemployment ($\beta_U \geq \beta_\pi$) is driven by the higher persistence of unemployment relative to inflation ($\rho_U = 0.95 \geq \rho_\pi = 0.80$). The details of this exercise can be found in the online appendix.

responses. We therefore estimate separate regressions for positive and negative shocks:

$$E^i_{t+h}[Z] - \bar{E}_{t-1}[Z] = \alpha_{1h} + \beta_{1h} \times (\text{Shock } X_t \mid \text{Shock } X_t > 0) + D^i_{1t+h} + \epsilon_{1th} \tag{40}$$
$$E^i_{t+h}[Z] - \bar{E}_{t-1}[Z] = \alpha_{2h} + \beta_{2h} \times (\text{Shock } X_t \mid \text{Shock } X_t < 0) + D^i_{2t+h} + \epsilon_{2th} \tag{41}$$

where t is the day of the announcement, h indicates days from t, E^i_τ indicates expectations formed by person i on day τ, D^i_{t+h} denotes demographic controls, and Shock X_t denotes the shock to households' information set. In the sophisticated case, Shock X_t = Surprise X_t; in the naive case, Shock $X_t = \Delta X_t$.[17]

Table 2 reports the results. We find pronounced asymmetry in the response to unemployment announcements. Positive unemployment shocks—announcements indicating worse-than-expected labor market conditions—generate larger expectation revisions than negative shocks of equal magnitude. For naive households, a positive unemployment shock reduces expectations by 1.2 percentage points on impact, while a negative shock has no significant effect. The pattern is similar for sophisticated households, though the asymmetry is less pronounced.

This asymmetric response to unemployment shocks is consistent with negativity bias. Households appear to weigh negative labor market signs more heavily, perhaps reflecting greater concerns about downside risks to wage income and employment.[18] The asymmetry may also reflect the sample period (2008–2017), during which unemployment was generally declining from Great Recession peaks, making upward surprises particularly salient.

For CPI, we observe a different pattern. Sophisticated households respond only to positive CPI surprises (higher-than-expected inflation), while naive households respond to both directions. This suggests that inflation news may matter more when it signals rising prices.

5.1.3 Extending to the Michigan Survey of Consumers

The Gallup results establish that unemployment announcements generate larger expectation revisions than other macroeconomic news. However, two concerns about external validity remain. First, the sample period (2008–2017) was characterized by low and stable inflation, which may explain the non-response to CPI. Second, the Expectations Index is a

[17] Note that a positive surprise has different implications for different variables. A positive surprise in unemployment indicates worsening conditions, whereas a positive surprise in GDP indicates improvement.

[18] Within an extended rational inattention framework, this asymmetry could arise from asymmetric loss functions where households are more concerned about the downside risks to their welfare; or from a state dependent attention allocation problem.

Table 2: Asymmetric Response of Household Expectations to Macroeconomic Announcements

Panel A: Sophisticated Households Model

	Day 0	Day 1	Day 2	Day 3	Day 4	Day 5
$Surp(Unemp)_t > 0$	-0.457	-1.373**	-0.791	-0.0412	0.255	-0.147
	(0.588)	(0.571)	(0.579)	(0.562)	(0.568)	(0.583)
$Surp(Unemp)_t < 0$	-0.0543	0.262	-0.634	-1.489**	-0.518	-1.334*
	(0.728)	(0.795)	(0.938)	(0.739)	(0.716)	(0.747)
$Surp(CPI)_t > 0$	0.953**	0.325	1.028**	0.400	-0.0809	0.770*
	(0.458)	(0.510)	(0.523)	(0.446)	(0.449)	(0.451)
$Surp(CPI)_t < 0$	0.101	-0.703	-0.0379	-0.675*	-1.081***	-0.234
	(0.430)	(0.436)	(0.434)	(0.410)	(0.419)	(0.428)

Panel B: Naive Households Model

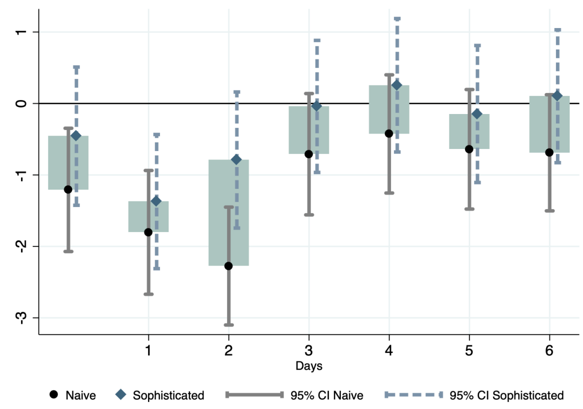
	Day 0	Day 1	Day 2	Day 3	Day 4	Day 5
$\Delta(Unemp)_t > 0$	-1.209**	-1.804***	-2.275***	-0.710	-0.426	-0.641
	(0.524)	(0.526)	(0.501)	(0.516)	(0.503)	(0.508)
$\Delta(Unemp)_t < 0$	0.630	2.546**	1.876	-1.038	0.720	-1.465
	(1.037)	(1.096)	(1.223)	(1.154)	(1.065)	(1.104)
$\Delta(CPI)_t > 0$	-1.386**	-1.885***	0.0382	-0.928	-0.0708	-0.0560
	(0.628)	(0.662)	(0.677)	(0.637)	(0.639)	(0.636)
$\Delta(CPI)_t < 0$	1.680***	0.859	3.078***	1.842***	1.173*	1.590***
	(0.609)	(0.620)	(0.606)	(0.586)	(0.602)	(0.616)

Notes: Estimates of β_h from Equations 40 and 41. β_h is the change in expectations due to positive or negative shock in the BLS jobs report and CPI announcement, in the window $[t-1, t+h]$ where t is the announcement day and $h = 0, 1, 2, 3, 4, 5$. Each cell is a separate regression. Controls include age, income, education, race, gender, political affiliation, and state. Survey weights used. Standard errors in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Data from Gallup Inc. and Bloomberg Finance LP.

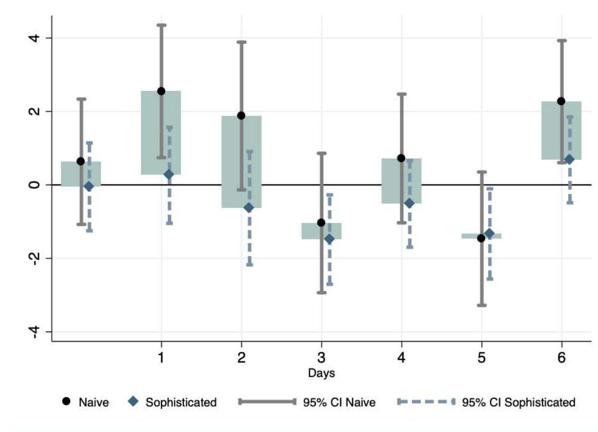
qualitative measure of sentiment; it is unclear whether quantitative inflation expectations would respond similarly.

To address these concerns, we turn to the Michigan Survey of Consumers, which spans 1980–2019 and includes both qualitative sentiment measures and point estimates of expected inflation. The longer time frame also provides more statistical power for subsample analyses.

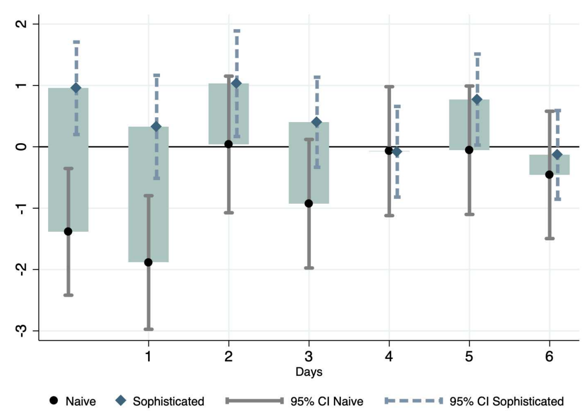
Figure 5: Asymmetric Response of Household Expectations to Macroeconomic Announcements



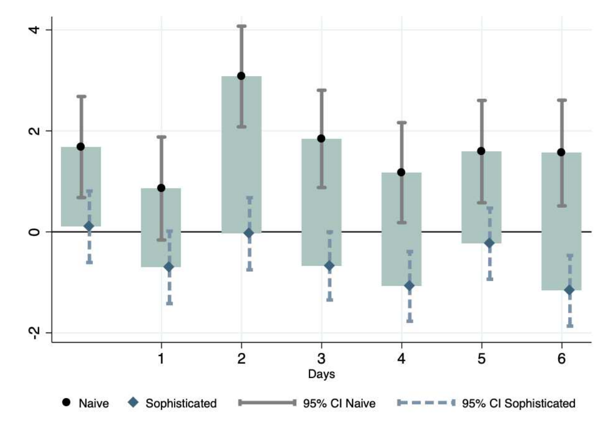
(a) Unemployment: Positive Shock



(b) Unemployment: Negative Shock



(c) CPI: Positive Shock



(d) CPI: Negative Shock

Notes: Coefficient plots for (a) positive unemployment shock, (b) negative unemployment shock, (c) positive CPI shock, and (d) negative CPI shock. Naive model shown with black solid circles; Sophisticated model shown with blue solid diamonds. The shaded green region indicates where the true coefficient lies. 95% confidence intervals shown for Naive (gray) and Sophisticated (light blue) models. Data from Gallup Inc. and Bloomberg Finance LP.

5.2 Michigan Survey of Consumers

We follow York (2023) in exploiting the interview dates recorded in the MSC microdata. Because daily response counts are low (approximately 20 per day), we construct weekly windows around each announcement and estimate:

$$E^i_w[Z] - \bar{E}_{w-1}[Z] = \alpha_w + \beta_w \cdot \text{Shock } X_t + D^i_w + \epsilon^i_{tw} \tag{42}$$

where $w = [t, t+6]$ denotes the week after the announcement and $w-1$ denotes the week before. In the sophisticated case, Shock X_t = Surprise X_t (available from 1997 when Bloomberg forecasts begin).[19] In the naive case, Shock $X_t = \Delta X_t$ (available from 1980).[20]

We consider two measures of expectations: (i) the fraction of optimists, based on the 12-month-ahead business conditions question (comparable to Gallup's Expectations Index), and (ii) point estimates of 12-month-ahead inflation expectations.

5.2.1 Business Conditions

Table 3 reports responses of the business conditions index. Panel A considers sophisticated households (1997–2019); Panel B considers naive households (1980–2019).[21]

Baseline. In the baseline specification, both unemployment and CPI surprises generate significant responses. For sophisticated households, a one-unit unemployment surprise reduces expectations by 1.2 points, while a one-unit CPI surprise reduces expectations by 1.6 points. For naive households, the corresponding numbers are –5 for unemployment and –1.7 for CPI. Thus, finding significant effects for both unemployment and CPI implies that households allocate attention to both signals and view both as informative for their broader economic prospects. The fact that pooled estimates are of similar magnitude does not, by itself, imply equal welfare relevance or equal attention across the two series: the coefficient is an average across states and shock realizations, and if belief updating is asymmetric for positive versus negative surprises, pooling them can have offsetting effects.[22]

Asymmetry. When we separate positive and negative shocks, a clearer pattern emerges. For sophisticated households, a positive unemployment surprise (bad news) reduces expectations by 13 points, while a negative surprise has no significant effect. For CPI, positive surprises reduce expectations by 6.5 points, while negative surprises are insignificant. For naive households, positive unemployment shocks reduce expectations by 7 points, versus –2.3 points for negative shocks. Positive CPI shocks reduce expectations by 8 points,

[19] Bloomberg Consensus Forecasts are available from 1996 onward.

[20] For naive shocks, we use initial release data where available. For older series (pre-1996), we use final revised data; results are similar when restricting to initial releases post-1997.

[21] We report results for the pre-COVID period. The COVID-19 pandemic generated shocks with standard deviations 13 times larger than average, which would dominate the estimates. Results including COVID are in the Appendix.

[22] Decomposing β_j into it's components reveals a similar story as before - while the implied welfare weight is higher for inflation than unemployment, it is unemployment's higher persistence that drives the larger β_j coefficient on it compared to CPI. Refer to the online appendix for further details of this exercise.

Table 3: Response of Business Conditions Index to Macroeconomic Announcements

y_t = Business Outlook		X_t = U	X_t =CPI
		(1)	(2)
Panel A: Sophisticated Households Model 1997-2019			
Baseline	Surp X_t	-1.2***	-1.6***
		(0.32)	(0.41)
Asymmetry	Surp $X_t > 0$	-13***	-6.5***
		(1.27)	(1.22)
	Surp $X_t < 0$	-0.8	0.6
		(0.84)	(1.34)
Scenarios	$\Delta U > 0, \Delta\pi > 0$	-3.8***	-1*
		(1.07)	(1.05)
	$\Delta U < 0, \Delta\pi < 0$	2.7***	-3.5***
		(0.96)	(1.11)
	$\Delta U > 0, \Delta\pi < 0$	-4.4**	-0.4
		(1.41)	(0.91)
	$\Delta U < 0, \Delta\pi > 0$	3.9***	-2.8***
		(1.14)	(0.94)
Panel B: Naive Households Model 1980-2019			
Baseline	Change X_t	-5***	-1.7***
		(0.24)	(0.32)
Asymmetry	Change $X_t > 0$	-7***	-8***
		(0.45)	(0.62)
	Change $X_t < 0$	-2.3***	4***
		(0.64)	(0.47)
Scenarios	$\Delta U > 0, \Delta\pi > 0$	-17***	0.5
		(0.94)	(0.56)
	$\Delta U < 0, \Delta\pi < 0$	-0.2	-3.5***
		(0.77)	(0.93)
	$\Delta U > 0, \Delta\pi < 0$	-5.7***	-3.2***
		(0.93)	(0.63)
	$\Delta U < 0, \Delta\pi > 0$	-6.1***	-2.8***
		(1.14)	(0.90)

Notes: Estimates of β_w from Equation 42. Controls include age, income, education, marital status, gender, and region. Survey weights used. Standard errors in parentheses. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$. Data from Survey of Consumers, University of Michigan, Survey Research Center. Surprises from Bloomberg Finance LP.

but negative CPI shocks actually *increase* expectations by 4 points. The key finding is that when economic conditions deteriorate (positive shocks to unemployment or CPI), unemployment news generates larger or comparable responses to CPI news.

Supply and Demand Scenarios. To further understand the behaviour of household expectations, we partition the sample into four scenarios based on the co-movement of unemployment and inflation: (i) both rising (negative supply shock), (ii) both falling (positive supply shock), (iii) unemployment rising and inflation falling (negative demand shock), and (iv) unemployment falling and inflation rising (positive demand shock). Appendix table **??** reports that these scenarios occur with roughly equal frequency.

The Scenarios section of Table 3 reveals a striking pattern:

- *Negative supply shocks* ($\Delta U > 0, \Delta\pi > 0$): Unemployment dominates. For sophisticated households, the unemployment coefficient is –3.8 while CPI is –1. For naive households, unemployment is –17 while CPI is insignificant.
- *Positive supply shocks* ($\Delta U < 0, \Delta\pi < 0$): CPI matters more. For sophisticated households, unemployment is 2.7 and CPI is –3.5. For naive households, only CPI is significant.
- *Negative demand shocks* ($\Delta U > 0, \Delta\pi < 0$): Unemployment dominates. The unemployment coefficient is –4.4 for sophisticated and –5.7 for naive households. CPI is insignificant.
- *Positive demand shocks* ($\Delta U < 0, \Delta\pi > 0$): Both matter, but unemployment remains significant. For sophisticated households, unemployment is 3.9 and CPI is –2.8.

Unemployment shocks significantly affect household expectations in all four scenarios. CPI shocks matter primarily during positive shocks—when economic conditions are improving. During negative shocks, typically associated with recessions, unemployment dominates.

5.2.2 Inflation Expectations

A natural question is whether the dominance of unemployment extends to inflation expectations themselves. If households form inflation expectations by tracking CPI, we would expect CPI announcements to dominate. Table 4 tests this hypothesis.

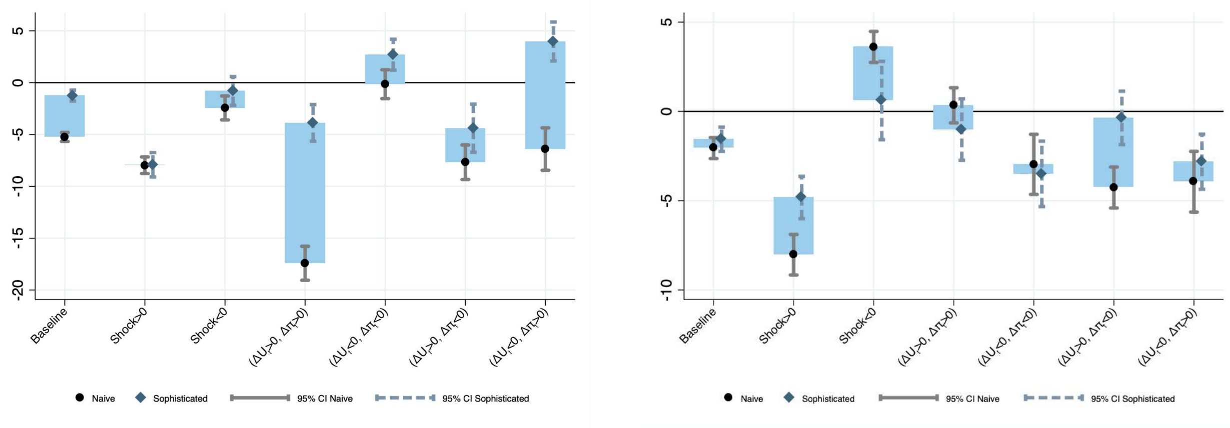
Baseline. For sophisticated households, unemployment surprises significantly affect 12-month-ahead inflation expectations (0.1), while CPI surprises do not (0.05). For naive

Table 4: Response of 12-Month-Ahead Inflation Expectations to Macroeconomic Announcements

$y_t = E_t\pi_{t+12}$		X_t = U (1)	X_t =CPI (2)
Panel A: Sophisticated Households Model 1997-2019			
Baseline	Surp X_t	0.1***	0.05
		(0.02)	(0.03)
Asymmetry	Surp $X_t > 0$	0.7***	0.3***
		(0.11)	(0.11)
	Surp $X_t < 0$	0.05	-0.07
		(0.06)	(0.11)
Scenarios	$\Delta U > 0, \Delta\pi > 0$	0.3***	-0.02
		(0.09)	(0.09)
	$\Delta U < 0, \Delta\pi < 0$	-0.03	0.1
		(0.07)	(0.08)
	$\Delta U > 0, \Delta\pi < 0$	0.3**	0.02
		(0.11)	(0.08)
	$\Delta U < 0, \Delta\pi > 0$	-0.1	0.2**
		(0.08)	(0.07)
Panel B: Naive Households Model 1980-2022			
Baseline	Change X_t	0.2***	0.3***
		(0.03)	(0.04)
Asymmetry	Change $X_t > 0$	0.5***	0.6***
		(0.06)	(0.08)
	Change $X_t < 0$	-0.3***	0.04
		(0.07)	(0.05)
Scenarios	$\Delta U > 0, \Delta\pi > 0$	0.6***	0.2***
		(0.13)	(0.07)
	$\Delta U < 0, \Delta\pi < 0$	-0.5***	0.05
		(0.09)	(0.08)
	$\Delta U > 0, \Delta\pi < 0$	0.7***	0.2***
		(0.12)	(0.07)
	$\Delta U < 0, \Delta\pi > 0$	0.1	0.5***
		(0.11)	(0.09)

Notes: Estimates of β_w from Equation 42. Controls include age, income, education, marital status, gender, and region. Survey weights used. Standard errors in parentheses. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$. Data from Survey of Consumers, University of Michigan, Survey Research Center. Surprises from Bloomberg Finance LP.

Figure 6: Response of Business Conditions Index to Macroeconomic Announcements



(a) Unemployment Shocks (b) CPI Shocks

Notes: Coefficient plots for response of business conditions index to (a) unemployment shocks and (b) CPI shocks. Naive model shown with black solid circles; Sophisticated model shown with blue solid diamonds. The shaded light blue region indicates where the true coefficient lies. 95% confidence intervals shown for Naive (solid lines) and Sophisticated (dashed lines) models. Data from Survey of Consumers, University of Michigan, Survey Research Center. Surprises from Bloomberg Finance LP.

households, both coefficients are significant: unemployment at 0.2 and CPI at 0.3.

Asymmetry. Positive unemployment shocks (bad labor market news) increase inflation expectations by 0.7 percentage points for sophisticated households and 0.5 points for naive households. Negative unemployment shocks have smaller or insignificant effects. For CPI, positive surprises increase inflation expectations by 0.3 points for sophisticated and 0.6 points for naive households. Negative CPI surprises are insignificant.

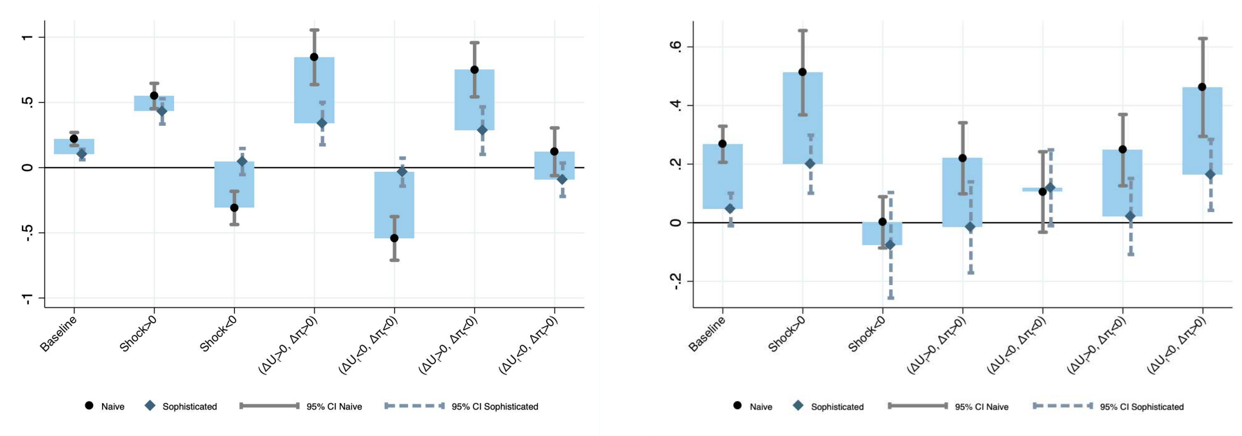
Supply and Demand Scenarios. The scenario analysis reveals that unemployment shocks drive inflation expectations in most economic environments:

- *Negative supply shocks*: The coefficient on unemployment is 0.3 for sophisticated households; CPI is insignificant.
- *Positive supply shocks*: Neither variable is significant for sophisticated households. For naive households, unemployment is –0.5.
- *Negative demand shocks*: Unemployment is 0.3 for sophisticated and 0.7 for naive households. CPI is insignificant.
- *Positive demand shocks*: CPI dominates. For sophisticated households, CPI is 0.2 while

unemployment is insignificant.

The finding that unemployment shocks affect inflation expectations, often more than CPI shocks, suggests that households do not form inflation expectations by directly tracking price indices. Instead, they may infer inflationary pressures from labor market conditions.

Figure 7: Response of 12-Month-Ahead Inflation Expectations to Macroeconomic Announcements



(a) Unemployment Shocks

(b) CPI Shocks

Notes: Coefficient plots for response of 12-month-ahead inflation expectations to (a) unemployment shocks and (b) CPI shocks. Naive model shown with black solid circles; Sophisticated model shown with blue solid diamonds. The shaded light blue region indicates where the true coefficient lies. 95% confidence intervals shown for Naive (solid lines) and Sophisticated (dashed lines) models. Data from Survey of Consumers, University of Michigan, Survey Research Center. Surprises from Bloomberg Finance LP.

Overall, these findings highlight the important role of unemployment news in shaping household expectations, not only about the general economy but also about inflation. Our results are consistent with Masolo (2022), who find that news about business cycle and labor market fluctuations are related, implying that people look at the labor market to infer movements in business conditions.

5.3 Robustness

We conduct several robustness checks, detailed in the Appendix.

Announcement Timing. The BLS employment report is released on the first Friday of each month, before CPI is announced. If households update expectations based on the first announcement regardless of content, our results could reflect timing rather than substance.

We address this by measuring expectation changes for subsequent announcements relative to pre-employment-report expectations ($E^i_{t+h}[Z] - \bar{E}^{\text{first}}_{t-1}[Z]$). Results are robust.

Pre-Announcement Information. Other labor market indicators (ADP employment, jobless claims) are released earlier in the week. We redefine the pre-announcement window to Tuesday ($E^i_{t+h}[Z] - \bar{E}^{\text{Tuesday}}_{t-1}[Z]$). Results remain significant, though naive household responses are attenuated, suggesting early releases provide partial information.

Local Labor Market. We test whether local labor market conditions influence households' attention. We find that households living in counties with high local unemployment respond more to shocks to unemployment, but not CPI.

Daily News Sentiment. Macroeconomic announcements often coincide with elevated news coverage about the economy, which could independently affect household sentiment. To isolate the the effect of the statistical release from contemporaneous news, we augment our baseline specification with the daily news sentiment index as described in Shapiro et al. (2020). The estimated responses are qualitatively similar to the baseline.

Financial Market Controls. Macroeconomic announcements move stock prices, which may independently affect household sentiment. Our estimates remain qualitatively robust to controlling for stock market returns.

Economic Conditions. Households may be more attentive during recessions or periods of high unemployment and inflation. We find stronger responses during such periods, consistent with state-dependent attention allocation.

Length of announcement window. We also test whether our results are driven by the length of window. Shorter windows might capture more volatile expectations by construction. We thus do robustness taking a weekly window for Gallup, and find our results to be broadly consistent. We also compute results at daily level windows in Michigan, so as to provide a direct comparison with the Gallup baseline table.

Michigan Survey: We conduct several robustness exercises with the Michigan survey as well, all of which are reported in the index. First, we report results for our baseline exercise assuming a daily rather than weekly window. Second, we report these results by restricting them to 2008 to 2017, to make them directly comparable to the Gallup results. Third, we check whether households are more attentive during recessions. Fourth, we report results using the Index of Consumer Expectations (ICE) as our outcome variable. This variable is constructed as an average of three forward looking questions based on personal conditions as well as economic conditions. Refer to the appendix for more details. Fifth, we categorize our four scenarios based on the level of unemployment and inflation, rather than the change.

Finally, we report the number of daily respondents in the Federal Reserve Bank of New York's Survey of Consumer Expectations (Armantier et al. 2017) to show why doing a daily event study with monthly survey data is likely to suffer from small sample bias.

6 Conclusion

This paper examines which macroeconomic signals households attend to when forming expectations. Using high-frequency data from the Gallup Daily Tracking Poll and the Michigan Survey of Consumers, we document that household expectations respond more strongly to unemployment announcements than to announcements about inflation, GDP, housing starts, among a wide array of other macroeconomic variables.

To interpret these patterns, we develop a rational inattention framework in which households allocate limited attention across macroeconomic signals. The model links reduced-form announcement responses to attention weights: a larger response to unemployment than to inflation implies a higher attention share devoted to labor market conditions. Because measured announcement "surprises" can depend on households' information and forecasting sophistication, we construct alternative shock measures corresponding to sophisticated and naive benchmarks, which together bound the response of expectations without requiring us to take a stand on the degree of sophistication.

Our results are consistent across datasets and specifications. In Gallup, unemployment announcements generate economically and statistically significant revisions in sentiment, while CPI, GDP, and housing starts announcements typically do not. A one-standard-deviation unemployment surprise reduces the share of households reporting optimism about the economy by between 0.37 and 1.1 percentage points, depending on the benchmark for surprises, and this effect is robustly different from zero. In the Michigan Survey, which spans 1980–2019, unemployment shocks dominate CPI shocks across the four macroeconomic environments we consider (positive and negative demand and supply episodes). Inflation news matters primarily during periods of improving conditions; during recessions and other adverse episodes, labor market news is the primary driver of household expectation revisions.

A striking implication is that even inflation expectations respond more consistently to unemployment news than to CPI news. Under the sophisticated benchmark, unemployment is the only statistically reliable driver of inflation expectations during negative demand and supply episodes. This pattern suggests that households may infer inflation dynamics from labor market conditions—using unemployment as a salient summary statistic—rather than tracking price indices directly. Finally, we document pronounced asymmetries: bad labor market news generates larger revisions than equally sized good news, consistent with state-dependent attention and/or asymmetric updating.

Taken together, these findings have implications for understanding expectation formation and its role in macroeconomic dynamics. The dominance of unemployment in shaping household expectations, including inflation expectations, suggests that labor market conditions are central to how households perceive the state of the economy. Future research could explore the mechanisms underlying this pattern and its implications for policy transmission.

References

Andersen, T. G., Bollerslev, T., Diebold, F. X. & Vega, C. (2003), 'Micro effects of macro announcements: Real-time price discovery in foreign exchange', *American economic review* **93**(1), 38–62.

Andersen, T. G., Bollerslev, T., Diebold, F. X. & Vega, C. (2007), 'Real-time price discovery in global stock, bond and foreign exchange markets', *Journal of international Economics* **73**(2), 251–277.

Andre, P., Pizzinelli, C., Roth, C. & Wohlfart, J. (2022), 'Subjective models of the macroeconomy: Evidence from experts and a representative sample', *The Review of Economic Studies* .

Armantier, O., Bruine de Bruin, W., Topa, G., Van Der Klaauw, W. & Zafar, B. (2015), 'Inflation expectations and behavior: Do survey respondents act on their beliefs?', *International Economic Review* **56**(2), 505–536.

Armantier, O., Topa, G., Van der Klaauw, W. & Zafar, B. (2017), 'An overview of the survey of consumer expectations', *Economic Policy Review* (23-2), 51–72.

Bachmann, R., Berg, T. O. & Sims, E. R. (2015), 'Inflation expectations and readiness to spend: Cross-sectional evidence', *American Economic Journal: Economic Policy* **7**(1), 1–35.

Balduzzi, P., Elton, E. J. & Green, T. C. (2001), 'Economic news and bond prices: Evidence from the us treasury market', *Journal of financial and Quantitative analysis* **36**(4), 523–543.

Barsky, R. B., Basu, S. & Lee, K. (2015), 'Whither news shocks?', *NBER macroeconomics annual* **29**(1), 225–264.

Binder, C. C., Campbell, J. R. & Ryngaert, J. M. (2024), 'Consumer inflation expectations: Daily dynamics', *Journal of Monetary Economics* p. 103613.

Bloomberg Finance LP (1996-), 'Bloomberg terminals (open, anywhere, and disaster recovery licenses)'.

Boehm, C. E. & Kroner, T. N. (2023), The us, economic news, and the global financial cycle, Technical report, National Bureau of Economic Research.

Borgschulte, M. & Martorell, P. (2018), 'Paying to avoid recession: Using reenlistment to estimate the cost of unemployment', *American Economic Journal: Applied Economics* **10**(3), 101–27.

Caporale, G. M., Spagnolo, F. & Spagnolo, N. (2016), 'Macro news and stock returns in the euro area: a var-garch-in-mean analysis', *International Review of Financial Analysis* **45**, 180–188.

Coibion, O., Georgarakos, D., Gorodnichenko, Y. & van Rooij, M. (2023), 'How does consumption respond to news about inflation? field evidence from a randomized control trial', *American Economic Journal: Macroeconomics* **15**(3), 109–52.
URL: *https://www.aeaweb.org/articles?id=10.1257/mac.20200445*

Coibion, O., Gorodnichenko, Y., Kumar, S. & Pedemonte, M. (2020), 'Inflation expectations as a policy tool?', *Journal of International Economics* **124**, 103297.

D'Acunto, F. & Weber, M. (2024), 'Why survey-based subjective expectations are meaningful and important', *Annual Review of Economics* .

Evans, M. D. & Lyons, R. K. (2008), 'How is macro news transmitted to exchange rates?', *Journal of Financial Economics* **88**(1), 26–50.

Gallup Inc. (2017), 'Us daily tracking poll'. Retrieved from the Brown University Library.

Gürkaynak, R. S., Sack, B. & Swanson, E. (2005*a*), 'The sensitivity of long-term interest rates to economic news: Evidence and implications for macroeconomic models', *American economic review* **95**(1), 425–436.

Gürkaynak, R. S., Sack, B. & Swanson, E. T. (2005*b*), 'Do actions speak louder than words? the response of asset prices to monetary policy actions and statements', *International Journal of Central Banking* .

Jordà, Ò. (2005), 'Estimation and inference of impulse responses by local projections', *American economic review* **95**(1), 161–182.

Kamdar, R. & Ray, W. (2024), *Attention-Driven Sentiment and the Business Cycle*, CAEPR, Center for Applied Economics and Policy Research.

Kuchler, T. & Zafar, B. (2015), 'Personal experiences and expectations about aggregate outcomes', *The Journal of Finance* .

Lamla, M. J. & Vinogradov, D. V. (2019), 'Central bank announcements: Big news for little people?', *Journal of Monetary Economics* **108**, 21–38.

Lucas Jr, R. E. (1976), Econometric policy evaluation: A critique, *in* 'Carnegie-Rochester conference series on public policy', Vol. 1, North-Holland, pp. 19–46.

Maćkowiak, B. & Wiederholt, M. (2015), 'Business cycle dynamics under rational inattention', *The Review of Economic Studies* **82**(4), 1502–1532.

Malmendier, U. & Nagel, S. (2015), 'Learning from inflation experiences', *The Quarterly Journal of Economics* **131**(1), 53–87.

Masolo, R. (2022), 'Mainly employment: survey-based news and the business cycle'.

Mertens, K., Lewis, D. J. & Makridis, C. (2020), 'Do monetary policy announcements shift household expectations?'.

Mian, A., Sufi, A. & Khoshkhou, N. (2021), 'Partisan bias, economic expectations, and household spending', *The Review of Economics and Statistics* pp. 1–46.

Mueller, A. I., Spinnewijn, J. & Topa, G. (2021), 'Job seekers' perceptions and employment prospects: Heterogeneity, duration dependence, and bias', *American Economic Review* **111**(1), 324–63.

Roth, C. & Wohlfart, J. (2019), 'How do expectations about the macroeconomy affect personal expectations and behavior?', *Review of Economics and Statistics* pp. 1–45.

Shapiro, A. H., Sudhof, M. & Wilson, D. J. (2020), 'Measuring news sentiment', *Journal of Econometrics* .

Sims, C. A. (2003), 'Implications of rational inattention', *Journal of monetary Economics* **50**(3), 665–690.

University of Michigan. Survey Research Center (n.d.), 'Survey of Consumers'.
URL: *http://new.sca.isr.umich.edu/*

York, J. (2023), 'Do household inflation expectations respond to macroeconomic data releases?', *Available at SSRN 4648451* .

A Appendix

In this Appendix, we first derive several features of the quantitative model. We then describe the data used in the empirical exercise by providing summary statistics. We then discuss various robustness exercises.

A.1 Detailed derivation of the model

In this section we provide detailed derivation of the quantitative model discussed in Section 2. We first discuss the minimization exercise for the household's optimal attention allocation problem. We then discuss the properties of some structural parameters. Finally, we discuss two potential extensions.

A.1.1 Derivation of the Optimal Precision γ^*_{jt} (Horizon T)

Here we derive the optimal attention allocation in the Gaussian–linear environment used above, explicitly incorporating the horizon T and the persistence factor $\Lambda_j(T-t)$.

A.1.1.1 Setup. Households care about the payoff-relevant outcome

$$Z_T = \sum_{\tau=t}^{T}\sum_{j=1}^{J}\theta_j X_{j\tau} + \sum_{\tau=t}^{T}\varepsilon_\tau,$$

with θ_j measuring how important fundamental X_{jt} is for Z_T.

As argued in the main text, under the AR(1) law of motion and the Markov property, the contribution of fundamental j to the forecast-error variance of Z_T can be written as

$$\left(\theta_j\Lambda_j(T-t)\right)^2 \operatorname{Var}\left(X_{jt} - E[X_{jt} \mid s_{jt}]\right).$$

If the prior variance of X_{jt} is σ_j^2 and the signal is

$$s_{jt} = X_{jt} + \eta_{jt}, \qquad \eta_{jt} \sim \mathcal{N}(0, \gamma_{jt}^{-1}),$$

then the posterior variance of X_{jt} is

$$\operatorname{Var}(X_{jt} \mid s_{jt}) = \frac{\sigma_j^2}{1+\sigma_j^2\gamma_{jt}}.$$

Hence the contribution of variable j to the forecast error of Z_T is

$$\left(\theta_j \Lambda_j(T-t)\right)^2 \frac{\sigma_j^2}{1+\sigma_j^2 \gamma_{jt}} + \text{other terms independent of } \gamma_j$$

Following Sims (2003), information processing capacity is limited:

$$\sum_{j=1}^{J} I(X_{jt}; s_{jt}) \;\leq\; \kappa,$$

where, in the scalar Gaussian case,

$$I(X_{jt}; s_{jt}) = \frac{1}{2} \log\left(1+\sigma_j^2 \gamma_{jt}\right).$$

The household's problem is therefore

$$\min_{\{\gamma_{jt} \geq 0\}} \sum_{j=1}^{J} \left(\theta_j \Lambda_j(T-t)\right)^2 \frac{\sigma_j^2}{1+\sigma_j^2 \gamma_{jt}} \quad \text{s.t.} \quad \sum_{j=1}^{J} \frac{1}{2} \log\left(1+\sigma_j^2 \gamma_{jt}\right) \leq \kappa. \tag{43}$$

A.1.1.2 Lagrangian. Let $\lambda \geq 0$ be the multiplier on the capacity constraint and $\mu_j \geq 0$ the multipliers on $\gamma_{jt} \geq 0$. The Lagrangian is

$$\mathcal{L}(\{\gamma_{jt}\}, \lambda, \{\mu_j\}) = \sum_{j=1}^{J} \left(\theta_j \Lambda_j(T-t)\right)^2 \frac{\sigma_j^2}{1+\sigma_j^2 \gamma_{jt}} + \lambda \left(\sum_{j=1}^{J} \frac{1}{2} \log\left(1+\sigma_j^2 \gamma_{jt}\right) - \kappa \right) - \sum_{j=1}^{J} \mu_j \gamma_{jt}. \tag{44}$$

A.1.1.3 First-order condition for γ_{jt} (interior case). For a variable j with strictly positive attention ($\gamma_{jt}^* > 0$), the Kuhn–Tucker multiplier satisfies $\mu_j = 0$, and the FOC is

$$\frac{\partial \mathcal{L}}{\partial \gamma_{jt}} = 0.$$

Compute the derivative term by term.

(i) Cost term.

$$\frac{\partial}{\partial \gamma_{jt}} \left[\left(\theta_j \Lambda_j(T-t)\right)^2 \frac{\sigma_j^2}{1+\sigma_j^2 \gamma_{jt}} \right] = -\left(\theta_j \Lambda_j(T-t)\right)^2 \frac{\sigma_j^4}{(1+\sigma_j^2 \gamma_{jt})^2}.$$

(ii) Information constraint term.

$$\frac{\partial}{\partial \gamma_{jt}} \left[\lambda \cdot \frac{1}{2} \log(1 + \sigma_j^2 \gamma_{jt}) \right] = \lambda \cdot \frac{1}{2} \cdot \frac{\sigma_j^2}{1 + \sigma_j^2 \gamma_{jt}}.$$

Adding these and setting the derivative to zero (and using $\mu_j = 0$) gives

$$-\left(\theta_j \Lambda_j (T - t)\right)^2 \frac{\sigma_j^4}{(1 + \sigma_j^2 \gamma_{jt})^2} + \lambda \cdot \frac{1}{2} \cdot \frac{\sigma_j^2}{1 + \sigma_j^2 \gamma_{jt}} = 0.$$

Multiply both sides by $(1 + \sigma_j^2 \gamma_{jt})^2$:

$$-\left(\theta_j \Lambda_j (T - t)\right)^2 \sigma_j^4 + \lambda \cdot \frac{1}{2} \sigma_j^2 (1 + \sigma_j^2 \gamma_{jt}) = 0.$$

Rearrange:

$$\lambda \cdot \frac{1}{2} \sigma_j^2 (1 + \sigma_j^2 \gamma_{jt}) = \left(\theta_j \Lambda_j (T - t)\right)^2 \sigma_j^4.$$

Divide both sides by σ_j^2:

$$\lambda \cdot \frac{1}{2} (1 + \sigma_j^2 \gamma_{jt}) = \left(\theta_j \Lambda_j (T - t)\right)^2 \sigma_j^2.$$

Solve for $(1 + \sigma_j^2 \gamma_{jt})$:

$$1 + \sigma_j^2 \gamma_{jt} = \frac{2\left(\theta_j \Lambda_j (T - t)\right)^2 \sigma_j^2}{\lambda}.$$

Therefore

$$\sigma_j^2 \gamma_{jt} = \frac{2\left(\theta_j \Lambda_j (T - t)\right)^2 \sigma_j^2}{\lambda} - 1 \quad \Rightarrow \quad \gamma_{jt} = \frac{2\theta_j^2 (\Lambda_j (T - t))^2}{\lambda} - \frac{1}{\sigma_j^2}.$$

Imposing the non–negativity constraint $\gamma_{jt} \geq 0$ yields the optimal precision

$$\gamma_{jt}^* = \max \left\{ 0, \ \frac{2\theta_j^2 (\Lambda_j (T - t))^2}{\lambda} - \frac{1}{\sigma_j^2} \right\}, \tag{45}$$

which is the horizon-T version of (18) in the main text.

Thus attention to fundamental j is strictly positive only if its horizon-weighted welfare–variance term $\theta_j^2\Lambda_j^2(T-t)\sigma_j^2$ is large enough relative to the shadow cost of information λ; otherwise, $\gamma_{jt}^* = 0$.

A.1.2 Derivation of the Kalman Gain ω_j

For completeness, we derive the gain ω_j used in equation (20) in the simple scalar case for a given variable j (we suppress the index j to simplify notation).

A.1.2.1 Setup.

Consider a latent state X and a noisy signal s:

- Prior (just before the announcement at time t):

$$X \sim \mathcal{N}\left(m_{t-1}, P_{t-1}\right),$$

  where $m_{t-1} = E_{t-1}[X]$ and $P_{t-1} = \mathrm{Var}(X \mid \mathcal{I}_{t-1})$.

- Signal observed at time t:

$$s = X + \varepsilon, \qquad \varepsilon \sim \mathcal{N}(0, R), \qquad R = \gamma^{*-1},$$

  where γ^* is the chosen precision of the signal.

Because (X, s) are jointly normal, the posterior distribution $X \mid s$ is normal with mean and variance given by standard formulas for the conditional distribution of a bivariate normal.

A.1.2.2 Joint moments.

We first compute the mean, variance, and covariance implied by the prior and signal equations:

$$E[X] = m_{t-1}, \qquad E[s] = E[X+\varepsilon] = m_{t-1},$$
$$\mathrm{Var}(X) = P_{t-1}, \qquad \mathrm{Var}(s) = \mathrm{Var}(X+\varepsilon) = P_{t-1} + R,$$
$$\mathrm{Cov}(X, s) = \mathrm{Cov}(X, X+\varepsilon) = \mathrm{Var}(X) = P_{t-1},$$

since ε is independent of X.

A.1.2.3 Conditional mean.

For any jointly normal (X, s), the conditional expectation is

$$E[X \mid s] = E[X] + \frac{\mathrm{Cov}(X, s)}{\mathrm{Var}(s)}\left(s - E[s]\right).$$

Substituting the expressions above,

$$\begin{aligned}E[X \mid s] &= m_{t-1} + \frac{P_{t-1}}{P_{t-1}+R}\left(s - m_{t-1}\right)\\ &= m_{t-1} + \frac{P_{t-1}}{P_{t-1}+R}\, s - \frac{P_{t-1}}{P_{t-1}+R}\, m_{t-1}.\end{aligned}$$

Define the Kalman gain

$$K \equiv \frac{P_{t-1}}{P_{t-1}+R}.$$

Then we can write

$$E[X \mid s] = (1-K)\, m_{t-1} + K\, s.$$

Identifying $E_t[X] \equiv E[X \mid s]$ and $E_{t-1}[X] \equiv m_{t-1}$, this becomes

$$E_t[X] = (1-K)E_{t-1}[X] + Ks.$$

Comparing with the updating rule in equation (**??**),

$$E_t[X_{jt}] = (1-\omega_j)E_{t-1}[X_{jt}] + \omega_j s_{jt},$$

we see that the gain ω_j is exactly the Kalman gain:

$$\omega_j = K = \frac{P_{t-1}}{P_{t-1}+R}. \tag{46}$$

A.1.2.4 Expressing ω_j in terms of precision γ^*_{jt}.

Using $R = \gamma^{*-1}_{jt}$ in (46), we obtain

$$\omega_j = \frac{P_{t-1}}{P_{t-1}+\gamma^{*-1}_{jt}} = \frac{P_{t-1}\,\gamma^*_{jt}}{1+P_{t-1}\,\gamma^*_{jt}}.$$

Under the AR(1) process for X_{jt} in equation (4), the prior variance converges in steady state to a constant $P_{t-1} \to \sigma_j^2$. In that case,

$$\omega_j = \frac{\sigma_j^2\gamma^*_{jt}}{1+\sigma_j^2\gamma^*_{jt}},$$

A.1.2.5 Properties.

Since $\gamma_{jt}^* \geq 0$ and $\sigma_j^2 > 0$, the gain satisfies

$$0 \leq \omega_j = \frac{\sigma_j^2 \gamma_{jt}^*}{1 + \sigma_j^2 \gamma_{jt}^*} < 1.$$

As $\gamma_{jt}^* \to 0$ (very imprecise signal), $\omega_j \to 0$ and the posterior puts almost all weight on the prior. As $\gamma_{jt}^* \to \infty$ (very precise signal), $\omega_j \to 1$ and the posterior puts almost all weight on the signal. Thus ω_j is a convenient scalar measure of how much attention (precision) households allocate to announcements about variable j.

A.1.3 Potential Extensions

A.1.3.1 Extension 1: Mapping to Gallup Optimism

To map the continuous payoff–relevant index to a binary Gallup response, consider a latent variable Z_{iT}^* that depends on the *expected* payoff–relevant outcome:

$$Z_{iT}^* \equiv E_t[Z_T] + \zeta_{it}, \tag{47}$$

where ζ_{it} captures idiosyncratic determinants of respondent i's survey answer at time t, which we assume to be orthogonal to macro announcements and to the common component $E_t[Z_T]$.

The observed Gallup outcome (indicator for being optimistic about the economy over the next year) is

$$y_{it} \equiv \mathbf{1}\{Z_{iT}^* \geq 0\} = \mathbf{1}\{E_t[Z_T] + \zeta_{it} \geq 0\}. \tag{48}$$

If ζ_{it} has CDF F_ζ and density f_ζ, then conditional on the information set $\mathcal{I}_t$,

$$\Pr(y_{it} = 1 \mid \mathcal{I}_t) = \Pr(\zeta_{it} \geq -E_t[Z_T] \mid \mathcal{I}_t) = 1 - F_\zeta\big(-E_t[Z_T]\big).$$

Now, consider a small announcement–induced change in beliefs about Z_T between $t-1$ and t. Using a first–order Taylor expansion around a reference belief $\bar{Z}_T$,

$$\Delta \Pr(y_{it} = 1) \;\equiv\; \Pr_t(y_{it} = 1) - \Pr_{t-1}(y_{it} = 1) \;\approx\; f_\zeta\big(-\bar{Z}_T\big)\, \Delta E_t^{HH}[Z_T], \tag{49}$$

where $\Delta E_t^{HH}[Z_T]$ is given by equation (**??**).

Thus, up to the positive scaling factor $f_\zeta(-\bar{Z}_T)$, the change in the fraction of respondents who report being optimistic inherits the same structure as the underlying expectation revision in the RI model. In particular, all comparative statics and cross–series rankings based on $\beta_j = \tilde{\theta}_j \omega_j$ carry over to the binary Gallup outcome.

A.1.3.2 Extension 2: correlated fundamentals and cross-updating.

The baseline model imposes independence across fundamentals (Assumption **??**), which rules out cross-updating effects (e.g., unemployment news shifting inflation expectations). A simple extension replaces **??** with a joint linear system:

$$\mathbf{X}_t = A\mathbf{X}_{t-1} + \boldsymbol{\nu}_t, \qquad \boldsymbol{\nu}_t \sim \mathcal{N}(\mathbf{0}, \Sigma_\nu), \tag{50}$$

and allows signals about linear combinations of $\mathbf{X}_t$,

$$s_t = H\mathbf{X}_t + \boldsymbol{\eta}_t, \qquad \boldsymbol{\eta}_t \sim \mathcal{N}(\mathbf{0}, R), \tag{51}$$

where H selects (or loads on) announced series and R is a noise covariance matrix. In this environment, observing a precise signal about U_t can rationally move beliefs about π_t whenever A and Σ_ν imply that unemployment helps forecast inflation under (50).

A parsimonious alternative is the following representation

$$\mathbf{X}_t = bF_t + \mathbf{e}_t, \qquad F_t = \rho_F F_{t-1} + \upsilon_t, \tag{52}$$

with $\mathbf{e}_t$ idiosyncratic and independent of F_t. In this case, paying attention to unemployment is valuable if U_t has a large factor loading b_U and relatively low idiosyncratic noise, so that U_t is an informative proxy for the common factor F_t that drives the payoff-relevant index.

In either formulation, optimal attention is directed not necessarily to each payoff-relevant variable separately, but to those linear combinations of $\mathbf{X}_t$ that span the payoff-relevant component of the state vector. As a result, the model generically generates cross-series belief revisions: a precise signal about unemployment leads to updating of beliefs about other series like inflation whenever they share common dynamics or common factors.

In this section, we report several results from robustness checks as well as some statistics to better understand the data in our study.

A.2 Gallup

A.2.1 Summary Statistics

Table 1: General Summary Statistics

Variable	GDTP	MSC
Age	47 years	49 years
Female	51%	54%
Low Income	38%	43%
Middle Income	47%	33%
High Income	15%	25%
White	73%	NA
Black	12%	NA
< High School	11%	4%
High School	35%	6%
Some College	31%	28%
N	1,705,158	277,160

This table records summary statistics for demographic variables for both GDTP and MSC. Survey weights used.

Table 2: ΔE around Major Events

Date	**Event**	**E_{t+1} - E_{t-1}**
15 Sep 2008	Lehman Bankruptcy	-0.22
4 Nov 2008	US Election 2008	0.27
25 Nov 2008	Quantitative Easing	-0.03
23 Mar 2010	Affordable Care Act	-0.06
9 Aug 2011	Forward Guidance	0.04
6 Nov 2012	US Election 2012	0.11
1-17 Oct 2013	Congress Shutdown	-0.13
Nov 2016	US Election 2016	0.05

This table summarizes the changes in household expectations around some major events during the sample period 2008–17.

Table A3: Summary Statistics: Expectations

Variable	Total Obs (1)	Mean (2)	Std. Dev. (3)	Frequency (4)
Michigan Survey of Consumers				
Index of Consumer Expectations (ICE)	277,160	79.8	45.8	Daily
12-month ahead Inflation Expectations	209,744	5.4	5.5	Daily
Fraction of Optimists	231,304	51.9	50.0	Daily
Change in Fraction of Optimists	12,227	-0.03	22	Daily
Gallup Daily Tracking Poll				
Fraction of Optimists	1,705,161	0.4	0.5	Daily
Change in Fraction of Optimists	3387	-0.009	3.8	Daily
Bloomberg Economic News (1996-2019)				
Surprise(Unemployment)	273	-0.03	0.14	Monthly
Surprise(CPI)	276	-0.01	0.12	Monthly
Surprise(Housing)	257	1.67	78.63	Monthly
Surprise (GDP)	84	0.01	0.71	Quarterly
Actual Economic Variables (1980-2019)				
Change(Unemployment)	480	-0.005	0.17	Monthly
Change(CPI)	480	0.38	0.47	Monthly
Change(Housing)	257	0.16	183	Monthly
Change (GDP)	84	-0.04	2.1	Quarterly

Notes: This table reports summary statistics for household expectations from GDTP and MSC, as well as surprises and actual values from Bloomberg Finance LP. Housing and GDP data are available from 1997–2019. Survey weights used. Data from Gallup Inc. and Survey of Consumers, University of Michigan, Survey Research Center.

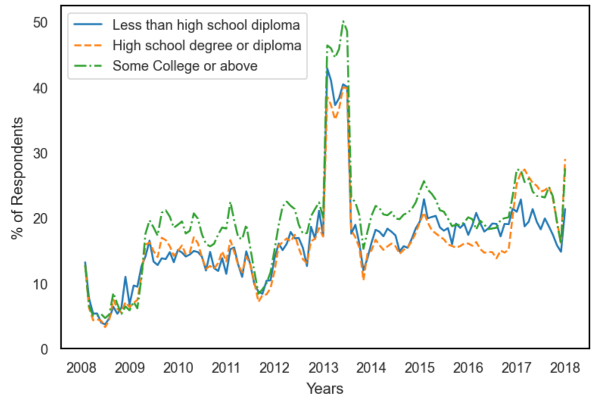
A.2.1.1 Heterogeneity in Household Expectations

We observe substantial heterogeneity in household expectations across demographic groups. In Figure 8a, we find that college graduates were systematically the most optimistic over time. This can be linked to job status, since college graduates tend to have the highest employment rates and thus tend to be consistently more optimistic than the unemployed (Figure 8b). Looking across age groups in Figure 8c, we find that younger respondents are consistently more optimistic than middle-aged and older respondents. While little difference in optimism exists across genders in most years (Figure 8d), there seems to be a sharp increase among men post 2016.

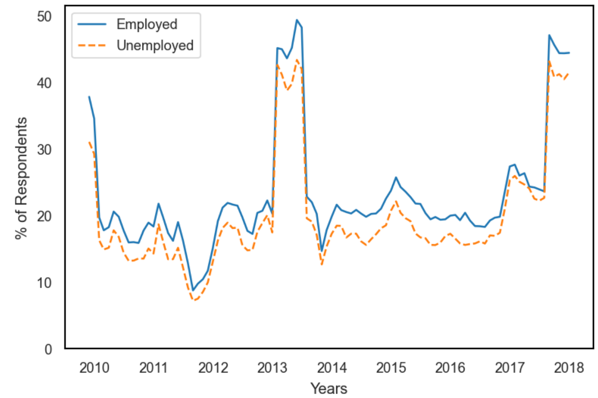
Interestingly, we find a reversal when looking at heterogeneity across political affiliation and race. As Figure 8f demonstrates, households' optimism is proportional to their party affiliation, and changes depending on the ruling party (Mian et al. 2021).[23] This reversal is also present when looking at heterogeneity by race (Figure 8e).[24]

[23]At the start of 2008, when the Republican party is in power, we observe that households affiliated with the Republican party are more optimistic than those affiliated with the Democratic party. In the 2008 elections, when the Democrats win, we see that expectations of households affiliated with them increase, while those of households affiliated with the Republicans decline. Democrats stay consistently more optimistic than Republicans after winning the 2012 election, but become pessimistic after losing in 2016.

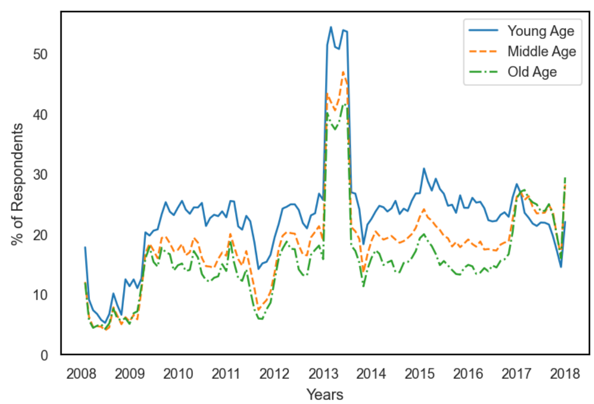
[24]After the 2008 Presidential election when Barack Obama is elected as the first Black president of the United States, Black households become significantly more optimistic, even exceeding the proportion of white households who are optimistic. In contrast, after the 2016 election which brought Donald Trump to power, the reverse occurs and Black households become more pessimistic than White households.



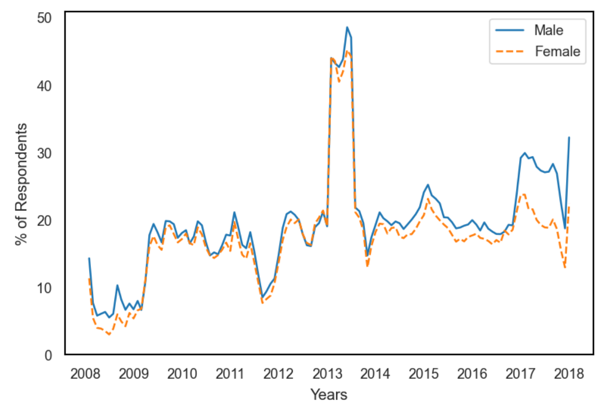
(a) Education



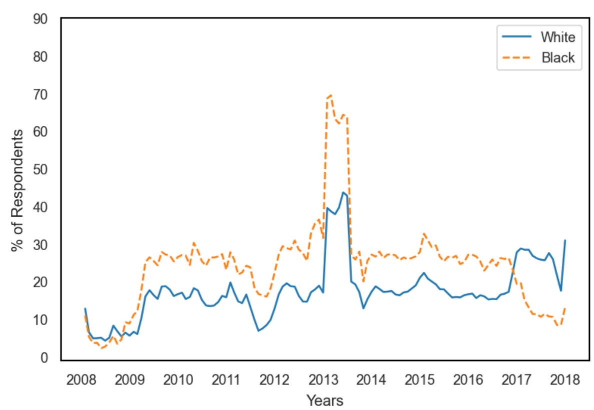
(b) Job Status



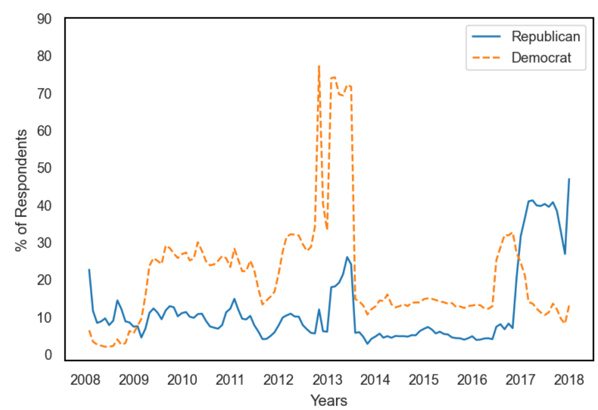
(c) Age



(d) Gender



(e) Race



(f) Party Affiliation

Figure 8: Heterogeneity in Household Expectations

A.2.2 Detailed Regression Tables for GDTP

Table 4a: Baseline: Sophisticated Households

Panel A: Sophisticated Households	Day 0	Day 1	Day 2	Day 3	Day 4	Day 5
Surprise(Unemp)	-0.568*	-0.565*	-0.642*	-0.377	-0.170	-0.578*
	(0.298)	(0.316)	(0.341)	(0.299)	(0.300)	(0.313)
Observations	33363	32657	30264	32826	33950	31544
R^2	0.051	0.049	0.045	0.052	0.049	0.048
Surprise(CPI)	0.434	-0.168	0.391	-0.123	-0.419	0.111
	(0.290)	(0.306)	(0.308)	(0.282)	(0.288)	(0.295)
Observations	32697	31409	31836	33342	33528	32386
R^2	0.049	0.047	0.051	0.051	0.055	0.055
Surprise(GDP)	0.168	0.427	0.252	0.690**	-0.0763	0.189
	(0.324)	(0.325)	(0.324)	(0.323)	(0.341)	(0.327)
Observations	32112	31029	29208	30264	29008	30338
R^2	0.056	0.051	0.049	0.048	0.045	0.057
Surprise(Housing)	0.0147	-0.107	0.115	0.650**	-0.216	0.749**
	(0.321)	(0.331)	(0.331)	(0.328)	(0.343)	(0.337)
Observations	34746	32693	33347	33745	32740	31851
R^2	0.053	0.044	0.049	0.045	0.054	0.051
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table reports estimates of β_h from Equation 39 for sophisticated expectations model. Here each cell is the coefficient from a separate regression equation. We control for demographics such as age, income, education, race, gender, political affiliation, and state of residence of the respondent. Survey weights are used. Standard errors are presented in parentheses. *$p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Surprises from Bloomberg Finance LP.

Table 4b: Baseline: Naive Households

Panel B: Naive Households						
	Day 0	Day 1	Day 2	Day 3	Day 4	Day 5
$\Delta(Unemp)$	-0.790***	-0.640**	-0.951***	-0.392	-0.184	-0.591*
	(0.300)	(0.315)	(0.329)	(0.305)	(0.303)	(0.307)
Observations	32657	31955	29556	32156	33276	30858
R^2	0.053	0.051	0.047	0.053	0.050	0.050
$\Delta(CPI)$	0.0657	-0.0737	0.663**	0.308	0.666**	0.157
	(0.288)	(0.293)	(0.294)	(0.289)	(0.294)	(0.296)
Observations	32003	30699	31113	32589	32834	32386
R^2	0.049	0.048	0.053	0.052	0.056	0.055
$\Delta(GDP)$	0.787**	0.817**	0.625*	0.963***	0.397	0.204
	(0.343)	(0.345)	(0.351)	(0.344)	(0.352)	(0.356)
Observations	31690	30593	28761	29814	28569	29890
R^2	0.058	0.052	0.050	0.049	0.046	0.058
$\Delta(Housing)$	-0.484	-0.339	-0.167	0.571*	-0.131	0.378
	(0.337)	(0.352)	(0.350)	(0.343)	(0.344)	(0.349)
Observations	33937	31857	32493	32937	32617	31379
R^2	0.054	0.045	0.050	0.046	0.053	0.051
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table reports estimates of β_h from Equation 39 for the naive expectations model. Here each cell is the coefficient from a separate regression equation. We control for demographics such as age, income, education, race, gender, political affiliation, and state of residence of the respondent. Survey weights are used. Standard errors are presented in parentheses. *$p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Surprises from Bloomberg Finance LP.

A.2.3 Robustness Exercises

This section reports various robustness exercises in the Gallup sample. We show our results are robust to taking $t-1$ expectations, local labor markets, taking weekly horizons, and different sample periods. We report these results below.

A.2.3.1 Taking $t-1$ expectations for all announcements as the expectations the day before the first announcement in the month, i.e. the unemployment announcement

Table A5: GDTP: $E^i_{t+h}[Z] - \bar{E}^{first}_{t-1}[Z] = \alpha_h + \beta^{first}_h \cdot ShockX_t + D^i_{t+h} + \epsilon^i_{th}$

	Day 0	Day 1	Day 2	Day 3	Day 4	Day 5
Panel A: Sophisticated Households						
Surprise(CPI)	0.501*	-0.000281	0.426	-0.0285	-0.224	0.384
	(0.292)	(0.307)	(0.309)	(0.272)	(0.276)	(0.283)
Surprise(GDP)	0.0357	-0.0171	-0.183	0.350	-0.390	0.148
	(0.412)	(0.417)	(0.363)	(0.364)	(0.387)	(0.603)
Surprise(Housing)	0.593*	0.341	0.818**	1.169***	0.209	1.496***
	(0.321)	(0.332)	(0.331)	(0.328)	(0.343)	(0.337)
Panel B: Naive Households						
$\Delta(CPI)$	-0.163	-0.121	0.507*	0.150	0.482*	0.0631
	(0.289)	(0.293)	(0.294)	(0.288)	(0.291)	(0.293)
$\Delta(GDP)$	1.030*	0.868	0.785*	0.961**	0.737	0.132
	(0.566)	(0.563)	(0.456)	(0.453)	(0.491)	(0.710)
$\Delta(Housing)$	0.345	0.337	0.685*	1.357***	0.637*	1.338***
	(0.337)	(0.353)	(0.351)	(0.342)	(0.344)	(0.349)

This table shows the estimates from computing the change in expectations as as $E^i_{t+h}[Z] - \bar{E}^{first}_{t-1}[Z]$, where $\bar{E}^{first}_{t-1}[Z]$ is the average expectations before the employment situation release each month. This exercise allows us to calculate changes in expectation around each release relative to the expectations set before the first announcement of the month. Standard errors are presented in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Surprises from Bloomberg Finance LP.

A.2.3.2 Taking $t-3$ expectations for the unemployment announcement instead of $t-1$

Table A6

Panel A: Sophisticated Households						
	Day 0	Day 1	Day 2	Day 3	Day 4	Day 5
Surprise(Unemp)	-0.00519*	-0.00600*	-0.00683*	-0.00588*	-0.000968	-0.00425
	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)
Observations	30407	29659	27281	29719	30921	29203
R^2	0.052	0.049	0.044	0.054	0.048	0.047

Panel B: Naive Households						
	Day 0	Day 1	Day 2	Day 3	Day 4	Day 5
$\Delta(Unemp)_t$	-0.00480	-0.00381	-0.00701**	-0.00296	0.000810	-0.00153
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Observations	30407	29659	27281	29719	30921	29203
R^2	0.052	0.049	0.044	0.054	0.048	0.047

This table reports estimates for Equation 39 taking the prior expectation to be 3 days before the announcement, instead of one day before. Robust (heteroscedasticity-consistent) standard errors are presented in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Surprises from Bloomberg Finance LP.

A.2.3.3 Local unemployment

We now test whether people change their expectations differently depending on their local economic conditions. Both personal as well as local conditions can influence an individual's expectations.[25] People living in areas with traditionally higher unemployment could be more sensitive to movements in the unemployment rate. It could also be that when unemployment increases, the shock is greatest to people in areas with traditionally lower unemployment, so they respond more. We examine these hypotheses empirically by estimating:

$$E^i_{t+h}[Z] - \bar{E}_{t-1}[Z] = \alpha_{1h} + \beta_{1h} \times (ShockX_t | LocalU_t > median(LocalU_t)) + D^i_{1t+h} + \epsilon_{1th} \tag{53}$$

$$E^i_{t+h}[Z] - \bar{E}_{t-1}[Z] = \alpha_{2h} + +\beta_{2h} \times (ShockX_t | LocalU_t > p75(LocalU_t)) + D^i_{2t+h} + \epsilon_{2th} \tag{54}$$

where t is the day of the announcement, h indicates days from t, E_τ indicates expectations formed by agent i on day τ, D^i_{t+h} denotes demographic information for person i, $ShockX_t$ denotes the shock in information due to the announcement, $LocalU_t$ denotes the local unemployment rate of the fipscode that agent i lives in. We cluster standard errors by state. We find the median and the 75th percentile local unemployment rate for all fipscode every month, and split areas according to that value. We find that people living in areas with high local unemployment pay more attention to shocks to the national unemployment rate. This result, however, does not hold for shocks to CPI.

[25] Borgschulte & Martorell (2018) use data on military personnel records and they find that service members would forgo 1.5% in reenlistment earnings to avoid a 1 percentage point increase in local unemployment rate.

Table A7: Response of Household Expectations to Unemployment Shocks Depending on Local Area Unemployment

Panel A: Sophisticated Households						
	Day 0	Day 1	Day 2	Day 3	Day 4	Day 5
Surp(U)$_t$, *High*50	-0.678**	-0.630**	-0.649	-0.357	-0.201	-0.691**
	(0.259)	(0.260)	(0.421)	(0.329)	(0.323)	(0.287)
Surp(U)$_t$, *Low*50	0.0875	-0.637	-0.565	-0.00299	-0.0558	0.668
	(0.909)	(0.583)	(0.899)	(1.002)	(0.851)	(0.740)
Surp(U)$_t$, *High*75	-0.650**	-0.633**	-0.516	-0.313	-0.327	-0.675**
	(0.308)	(0.271)	(0.458)	(0.385)	(0.329)	(0.268)
Surp(U)$_t$, *Low*75	-0.104	-0.610	-1.237	-0.690	0.577	-0.0739
	(0.912)	(0.455)	(0.708)	(0.785)	(0.808)	(0.650)
Panel B: Naive Households						
	Day 0	Day 1	Day 2	Day 3	Day 4	Day 5
$\Delta(Unemp)_t$, *High*50	-0.753***	-0.682**	-0.893**	-0.364	-0.135	-0.602**
	(0.278)	(0.284)	(0.388)	(0.349)	(0.399)	(0.297)
$\Delta(Unemp)_t$, *Low*50	-0.721	-0.708	-1.420	-0.363	-0.669	-0.168
	(0.676)	(0.732)	(0.970)	(0.856)	(0.810)	(0.797)
$\Delta(Unemp)_t$, *High*75	-0.715**	-0.742**	-0.759*	-0.255	-0.255	-0.623**
	(0.316)	(0.320)	(0.411)	(0.384)	(0.428)	(0.306)
$\Delta(Unemp)_t$, *Low*75	-0.805	-0.562	-1.894**	-0.953	0.107	-0.489
	(0.678)	(0.459)	(0.704)	(0.678)	(0.738)	(0.638)

This table reports the estimates of β_h from Equation 53 for shocks to unemployment. Here, β_h is change in the expectations due to a shock in the unemployment rate in the BLS jobs report interacted with the state's unemployment rate, in the window $[t-1, t+h]$ where t is the day of the announcement and $h = 0, 1, 2, 3, 4$. In both panels, rows 1 and 2 indicate areas with high and low local unemployment depending on median county level unemployment, and rows 2 and 4 indicate areas with high and low local unemployment depending on 75% percentile county level unemployment. Standard errors are presented in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Surprises from Bloomberg Finance LP.

Table A8: Response of Household Expectations to CPI Shocks Depending on Local Area Unemployment

Panel A: Sophisticated Households						
	Day 0	Day 1	Day 2	Day 3	Day 4	Day 5
Surp(CPI)$_t$, *High*50	0.578*	-0.0716	0.424	0.00657	-0.264	0.213
	(0.316)	(0.333)	(0.335)	(0.307)	(0.313)	(0.323)
Surp(CPI)$_t$, *Low*50	-0.395	-0.587	0.451	-0.958	-1.169	-0.375
	(0.750)	(0.803)	(0.829)	(0.748)	(0.773)	(0.756)
Surp(CPI)$_t$, *High*75	0.441	0.0685	0.369	0.110	-0.0578	0.267
	(0.329)	(0.345)	(0.348)	(0.318)	(0.327)	(0.337)
Surp(CPI)$_t$, *Low*75	0.242	-0.937	0.224	-0.808	-1.505**	-0.282
	(0.615)	(0.662)	(0.667)	(0.615)	(0.608)	(0.620)

Panel B: Naive Households						
	Day 0	Day 1	Day 2	Day 3	Day 4	Day 5
$\Delta(CPI)_t$, *High*50	0.120	-0.0258	0.535**	0.245	0.535	0.432
	(0.326)	(0.327)	(0.261)	(0.222)	(0.348)	(0.349)
$\Delta(CPI)_t$, *Low*50	-0.0491	0.116	1.720	0.595	1.264*	-1.238
	(0.678)	(0.886)	(1.031)	(0.596)	(0.701)	(0.898)
$\Delta(CPI)_t$, *High*75	-0.0687	0.190	0.534*	0.331	0.707*	0.406
	(0.353)	(0.266)	(0.285)	(0.244)	(0.362)	(0.338)
$\Delta(CPI)_t$, *Low*75	0.690	-0.938	1.220**	0.405	0.638	-0.465
	(0.489)	(0.780)	(0.564)	(0.529)	(0.707)	(0.903)

This table reports the estimates of β_h from Equation 53 for shocks to CPI. Here, β_h is change in the expectations due to a shock in the unemployment rate in the BLS jobs report interacted with the state's unemployment rate, in the window $[t-1, t+h]$ where t is the day of the announcement and $h = 0, 1, 2, 3, 4$. In both panels, rows 1 and 2 indicate areas with high and low local unemployment depending on median county level unemployment, and rows 2 and 4 indicate areas with high and low local unemployment depending on 75% percentile county level unemployment. Standard errors are presented in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Surprises from Bloomberg Finance LP.

A.2.3.4 Including News Sentiment as control

Table A9

Panel A: Sophisticated Households						
	Day 0	Day 1	Day 2	Day 3	Day 4	Day 5
Surprise(Unemp)	-0.00611***	-0.00413*	-0.00890***	-0.00286	-0.00506**	-0.00679***
	(0.002)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)
Surprise(CPI)	0.0829**	0.110**	0.100**	-0.0109	-0.0603*	0.00167
	(0.037)	(0.050)	(0.041)	(0.039)	(0.034)	(0.040)
Panel B: Naive Households						
	Day 0	Day 1	Day 2	Day 3	Day 4	Day 5
$\Delta(Unemp)$	-0.00804***	-0.00509**	-0.0120***	-0.00395	-0.00577**	-0.00850***
	(0.002)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)
$\Delta(CPI)$	0.00154	0.00101	0.00452*	0.00146	0.00721***	0.000503
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)

This table reports estimates for Equation 39 modified to include the change in the Federal Reserve Bank of San Francisco's Daily News Sentiment Index as a control. Robust (heteroscedasticity-consistent) standard errors are presented in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Surprises from Bloomberg Finance LP.

A.2.3.5 Including Stock Market as control

Table A10

	Day 0	Day 1	Day 2	Day 3	Day 4	Day 5
Panel A: Sophisticated Households						
Surprise(Unemp)	-0.00597**	-0.00594**	-0.00790***	-0.00357	-0.00462*	-0.00690***
	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)
Surprise(CPI)	0.00396*	-0.00281	0.00382	-0.00248	-0.00225	-0.000995
	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)
Panel B: Naive Households						
$\Delta(Unemp)$	-0.00876***	-0.00846***	-0.0114***	-0.00420*	-0.00624***	-0.00787***
	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)
$\Delta(CPI)$	0.00136	0.000904	0.00629***	0.00164	0.00660***	0.000290
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)

This table reports estimates for Equation 39 modified to include the change in NASDAQ as a control. Robust (heteroscedasticity-consistent) standard errors are presented in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Surprises from Bloomberg Finance LP.

A.2.3.6 Pre vs post 2012

Table A11: Response of Expectations in Recession versus Non-recession Years

Panel A: Sophisticated Households						
	Day 0	Day 1	Day 2	Day 3	Day 4	Day 5
Surp(U)_t, $Pre2012$	-0.00269	-0.00893**	-0.0104***	-0.00570	-0.00324	-0.00762**
	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Surp(U)_t, $Post2012$	-0.0111*	0.000518	-0.000430	-0.00192	0.00201	0.00209
	(0.006)	(0.007)	(0.007)	(0.006)	(0.006)	(0.006)
Surp(CPI)_t, $Pre2012$	0.00280	-0.00192	0.00126	-0.00285	-0.00943***	-0.00230
	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)
Surp(CPI)_t, $Post2012$	0.00961*	0.000798	0.00988	0.00115	0.00491	0.00930*
	(0.006)	(0.006)	(0.006)	(0.006)	(0.005)	(0.006)
Panel B: Naive Households						
	Day 0	Day 1	Day 2	Day 3	Day 4	Day 5
$\Delta(Unemp)_t$, $Pre2012$	-0.00697**	-0.0109***	-0.0153***	-0.00776**	-0.00526	-0.00587
	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
$\Delta(Unemp)_t$, $Post2012$	-0.0125*	0.00137	-0.000297	-0.00339	0.00801	-0.00122
	(0.007)	(0.008)	(0.008)	(0.007)	(0.007)	(0.008)
$\Delta(CPI)_t$, $Pre2012$	-0.00191	-0.00259	0.00521	0.00470	0.00536	0.00394
	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)
$\Delta(CPI)_t$, $Post2012$	0.00445	0.00180	0.00858	-0.000261	0.00922*	-0.00203
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)

This table reports estimates for two subsamples for GDTP - the period of the Great Recession (2008-2011), and the non-recession period (2012-2017). Standard errors are presented in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Surprises from Bloomberg Finance LP.

A.2.3.7 Gallup weekly results

Table A12: GDTP Weekly Estimates

	X_t =	X_t = CPI	X_t = GDP	X_t = Housing
	1	2	3	4
Panel A: Sophisticated Households				
Surp X_t	-3***	-2***	0.07	-0.03
	(0.12)	(0.12)	(0.13)	(0.13)
N	222644	227598	215142	229071
R^2	0.047	0.046	0.043	0.045
Controls	Yes	Yes	Yes	Yes
Panel B: Naive Households				
Change X_t	-4.5***	-0.3**	1.8	2***
	(0.12)	(0.12)	(0.14)	(0.14)
N	217823	223661	212041	224846
R^2	0.053	0.045	0.045	0.047
Controls	Yes	Yes	Yes	Yes

This table shows the estimates from a weekly window around each announcement in the GDTP, equivalent to the weekly windows in the MSC. Standard errors are presented in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Surprises from Bloomberg Finance LP.

A.3 Michigan Survey of Consumers

In this subsection we describe robustness exercises done on the MSC sample. We discuss different horizons, account for recessions, different measures of expectations, and inclusion of level of macro variables.

A.3.1 Daily results

Table 13a: MSC Daily Estimates

Panel A: Sophisticated Households 1997-2019						
	Day 0	Day 1	Day 2	Day 3	Day 4	Day 5
Surprise(Unemp)	0.438	0.189	0.273	-0.257	-0.459	0.700
	(0.860)	(0.858)	(0.862)	(0.766)	(0.806)	(0.822)
N	3208	3711	3302	4470	4295	3918
R^2	0.027	0.022	0.033	0.019	0.023	0.024
Surprise(CPI)	-0.637	2.361**	-2.049*	4.313***	-2.255**	1.651
	(1.048)	(1.076)	(1.184)	(1.093)	(0.999)	(1.037)
N	2284	2233	1941	2146	2280	2352
R^2	0.028	0.019	0.023	0.030	0.031	0.020
Panel B: Naive Households 1980-2019						
	Day 0	Day 1	Day 2	Day 3	Day 4	Day 5
$\Delta(Unemp)$	-0.0389	0.373	0.711	-0.166	-1.288**	1.145*
	(0.635)	(0.654)	(0.647)	(0.563)	(0.604)	(0.613)
N	6357	6845	6315	8557	8468	7936
R^2	0.024	0.022	0.026	0.020	0.023	0.018
$\Delta(CPI)$	-1.380*	1.925**	-0.663	1.571**	-1.248*	2.589***
	(0.746)	(0.773)	(0.806)	(0.707)	(0.715)	(0.843)
N	4561	4228	3715	4026	4238	4408
R^2	0.026	0.016	0.023	0.019	0.025	0.024

This table shows the estimates from a daily window around each announcement in the MSC for the full sample: 1980-2019. Standard errors are presented in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Data from Survey of Consumers, University of Michigan. Survey Research Center. Surprises from Bloomberg Finance LP.

A.3.2 Daily results for Gallup subsample

Table 13b: MSC Daily Estimates: 2008 to 2017

Panel A: Sophisticated Households

	Day 0	Day 1	Day 2	Day 3	Day 4	Day 5
Surprise(Unemp)	-1.476	1.204	-0.756	0.997	-2.839***	3.499***
	(0.964)	(0.981)	(1.038)	(0.868)	(0.875)	(1.116)
N	1459	1479	1262	1861	1773	1603
R^2	0.026	0.040	0.058	0.016	0.026	0.045
Surprise(CPI)	-3.625**	2.620	-0.370	3.196*	-4.093***	4.153***
	(1.649)	(1.802)	(1.869)	(1.811)	(1.444)	(1.579)
N	986	925	891	973	1020	1035
R^2	0.042	0.034	0.050	0.030	0.042	0.049

Panel B: Naive Households

	Day 0	Day 1	Day 2	Day 3	Day 4	Day 5
$\Delta(Unemp)$	-0.162	3.109***	0.0219	-1.894*	-0.437	0.162
	(1.015)	(1.099)	(1.153)	(0.975)	(1.033)	(1.081)
N	1681	1698	1434	2103	2040	1832
R^2	0.027	0.036	0.045	0.016	0.019	0.037
$\Delta(CPI)$	-2.212**	1.535	-0.528	0.638	-2.691***	3.519***
	(1.008)	(1.066)	(1.094)	(0.979)	(0.924)	(1.194)
N	1132	1086	1034	1095	1111	1132
R^2	0.031	0.024	0.056	0.022	0.034	0.037

This table shows the estimates from a daily window around each announcement in the MSC, equivalent to the daily window in the GDTP for 2008-17. Standard errors are presented in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Data from Survey of Consumers, University of Michigan. Survey Research Center. Surprises from Bloomberg Finance LP.

A.3.3 Response of Expectations during US Recessions

In this section we estimate

$$E^i_{t+h}[Z] - \bar{E}_{t-1}[Z] = \alpha_h + \beta_{1h} \times ShockX_t + \beta_{2h} \times \mathbb{1}(Recession) + \beta_{3h} \times (ShockX_t \times \mathbb{1}(Recession)) + D^i_{t+h} + \epsilon_{th}$$

Table A14: Share of Optimists in Recessions

y_t = Share of Optimists	X_t = U	X_t =CPI
	1	2
Panel A: Sophisticated Households		
Surprise(X_t)	1***	-1.6*
	(0.36)	(0.46)
Recession Year	-23***	-24***
	(1.13)	(1.33)
Surprise(X_t)× Recession Year	-3.5***	1.2
	(0.86)	(0.92)
Panel B: Naive Households		
ΔX_t	-1***	-0.8*
	(0.41)	(0.48)
Recession Year	-21***	-24***
	(1.40)	(1.32)
ΔX_t× Recession Year	-1	0.3
	(0.83)	(0.87)

This table shows the estimates for change in share of optimists during US Recessions. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Data from Survey of Consumers, University of Michigan. Survey Research Center. Surprises from Bloomberg Finance LP.

Table A15: Response of Household Inflation Expectations in Recessions

$y_t = E_t\pi_{t+12}$	X_t = U	X_t =CPI
	1	2
Panel A: Sophisticated Households		
Surprise(X_t)	0.003	0.05
	(0.025)	(0.04)
Recession Year	1.2***	-1.6***
	(0.10)	(0.14)
Surprise(X_t)$\times$ Recession Year	0.18**	-0.05
	(0.08)	(0.09)
Panel B: Naive Households		
ΔX_t	0.06**	0.03
	(0.03)	(0.04)
Recession Year	1.1***	1.6***
	(0.13)	(0.14)
$\Delta X_t\times$ Recession Year	0.03	0.1
	(0.08)	(0.09)

This table shows the estimates for change in household inflation expectations during US Recessions. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Data from Survey of Consumers, University of Michigan. Survey Research Center. Surprises from Bloomberg Finance LP.

A.3.4 Index of Consumer Expectations (ICE)

ICE is a composite index of three forward looking survey questions:

1. *Now looking ahead–do you think that a year from now you (and your family living there) will be better off financially, or worse off, or just about the same as now?*

2. *Now turning to business conditions in the country as a whole–do you think that during the next twelve months we'll have good times financially, or bad times, or what?*

3. *Looking ahead, which would you say is more likely–that in the country as a whole we'll have continuous good times during the next five years or so, or that we will have periods of widespread unemployment or depression, or what?*

MSC calculates ICE in the following manner: first computes the relative scores (the percent giving favorable replies minus the percent giving unfavorable replies, plus 100) for each of the three index questions. Each relative score is then rounded to the nearest whole number. Then, $\{ICE = \frac{X1 + X2 + X3}{4.1134} + 2.0\}$ where, the relative scores are divided by the 1966 base period total the added constant is to correct for sample design changes from the 1950s.

These three questions taken together provide a measure of household's expectations about the future of the economy, making it qualitatively similar to Gallup's Expectation Index. Changes in ICE can also be interpreted in a similar way - an increase in ICE denotes a rise in optimism, whereas a decrease denotes a fall in optimism or a rise in pessimism.

A.3.5 Level category tables

Table A16: MSC Scenarios Dependent on Level of U_t and π_t

y_t = Business Outlook	X_t = U	X_t =CPI
	1	2
Panel A: Sophisticated Households		
High U_t, High π_t	-2***	-2.8*
	(0.80)	(0.98)
Low U_t, Low π_t	-2.7***	-0.9
	(0.70)	(0.96)
High U_t, Low π_t	-1.6***	0.9
	(0.50)	(0.74)
Low U_t, High π_t	0.08	-3.6***
	(1.10)	(1.08)
Panel B: Naive Households		
High U_t, High π_t	-5.7***	-7***
	(0.43)	(0.65)
Low U_t, Low π_t	-1.2	-2.5***
	(0.78)	(0.84)
High U_t, Low π_t	-5***	1.2***
	(0.38)	(0.45)
Low U_t, High π_t	-5.4***	-2.7*
	(1.51)	(1.55)

This table shows the estimates for scenarios dependent on levels of inflation and unemployment. We define high unemployment to be greater than 5% and high inflation to be greater than 3%. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Data from Survey of Consumers, University of Michigan. Survey Research Center.

Table A17: MSC Scenarios Dependent on Level of U_t and π_t

y_t = ICE		X_t = U (1)	X_t =CPI (2)
Panel A: Sophisticated Households 1997-2019			
Baseline	Surp X_t	-0.6***	-1.2***
		(0.13)	(0.2)
Asymmetry	Surp $X_t > 0$	-10.4***	-4.7***
		(0.47)	(0.59)
	Surp $X_t < 0$	-0.5*	0.1
		(0.30)	(0.62)
Scenarios	$\Delta U > 0, \Delta\pi > 0$	-3.8***	-0.6
		(0.45)	(0.44)
	$\Delta U < 0, \Delta\pi < 0$	2.6***	-2.6***
		(0.28)	(0.40)
	$\Delta U > 0, \Delta\pi < 0$	-4.6***	-0.5
		(0.48)	(0.47)
	$\Delta U < 0, \Delta\pi > 0$	3***	-2.4***
		(0.46)	(0.4)
Panel B: Naive Households 1980-2019			
Baseline	Change X_t	-3.3***	-1.2***
		(0.09)	(0.17)
Asymmetry	Change $X_t > 0$	-5.8***	-4.4***
		(0.17)	(0.29)
	Change $X_t < 0$	-1***	2.8***
		(0.23)	(0.20)
Scenarios	$\Delta U > 0, \Delta\pi > 0$	-13***	0.02
		(0.30)	(0.26)
	$\Delta U < 0, \Delta\pi < 0$	0.9***	-2.1***
		(0.25)	(0.40)
	$\Delta U > 0, \Delta\pi < 0$	-7.1**	-2.2***
		(0.38)	(0.33)
	$\Delta U < 0, \Delta\pi > 0$	-3.6***	-3.2***
		(0.45)	(0.49)

This table shows the estimates scenarios dependent on levels of inflation and unemployment. We define high unemployment to be greater than 5% and high inflation to be greater than 3%. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Data from Survey of Consumers, University of Michigan. Survey Research Center. Surprises from Bloomberg Finance LP.

A.4 Additional Exhibits

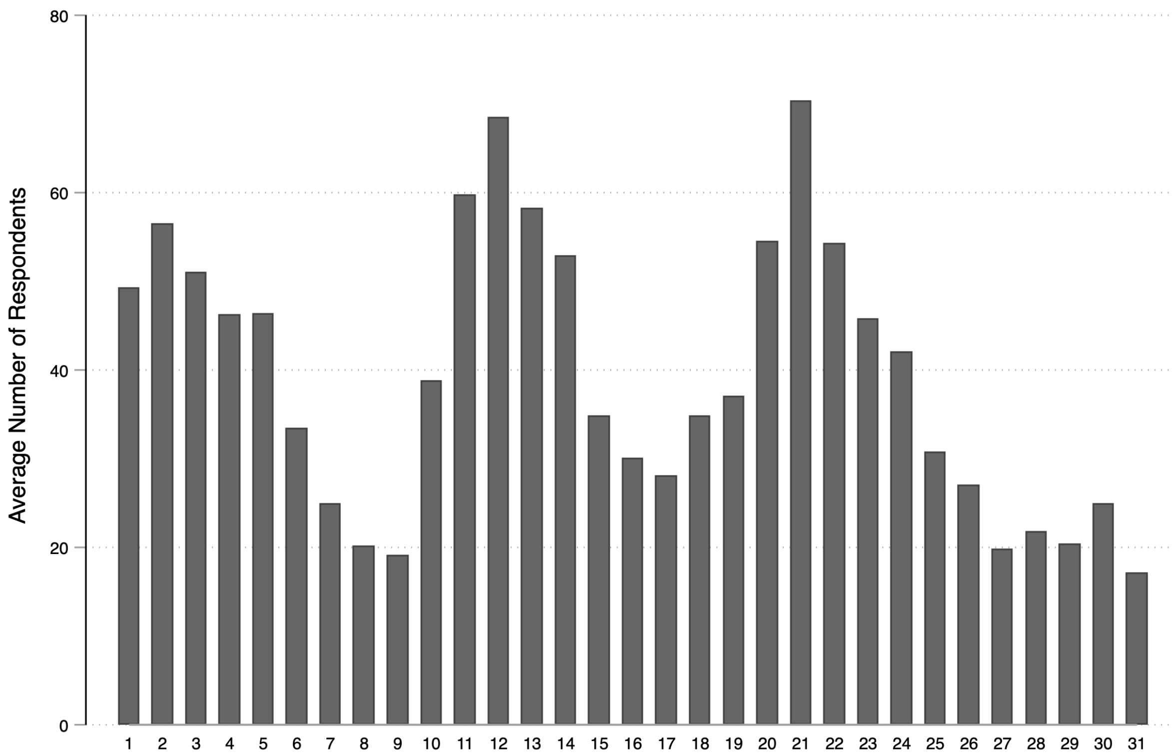


Figure 9: Number of Daily Respondents: SCE