What Determines Household Expectations?*

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Abstract

This paper uses daily data on household expectations to examine what causes households to adjust their expectations about the future of the economy. We analyze several macro variables of policy interest and find that households respond primarily to movements in the unemployment rate. Further, these responses are non-linear and asymmetric, with households displaying higher sensitivity to larger shocks and to negative information. We also find heterogeneity across local labor markets: Households in areas with higher local unemployment are more sensitive to changes in national unemployment than those in areas with lower local unemployment. We further examine whether media plays a role in influencing household expectations, and find that news about unemployment rises sharply during a recession, consistent with the response of expectations.

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1 Introduction

Most major decisions made by households require them to predict the future state of the economy. For example, if interest rates are expected to increase in the future, then it is better to spend now and save later. Making these inter-temporal comparisons requires households to form expectations about how the economy will perform in the future. Expectations are also important in policy formulation. With interest rates hitting the zero lower bound in many advanced economies, central banks have been forced to resort to unconventional monetary policy measures such as forward guidance that work by influencing the public's expectations. More recently, the spike in inflation in the United States has led to fear of expectations becoming unanchored and causing a recession.

Although expectations affect real outcomes of households (Coibion, Georgarakos, Gorodnichenko & van Rooij (2019), Armona et al. (2018), Mueller et al. (2021), Conlon et al. (2018)), little is known about which variables are important in the formation of these expectations. Households are constantly inundated with different signals about the state of the economy, such as monetary policy announcements, government policy releases like the Bureau of Labor Statistics' (BLS) jobs report, inflation numbers, and government debt. These sources all provide different kinds of information. This paper analyzes which of these variables are important to households in their expectation formation process.

Using households' expectations about whether the economy will improve or worsen, we examine which kinds of information cause households to adjust their beliefs.[1] We focus on a small set of variables that carry the most information about the economy: inflation, output, unemployment rate, and housing. We proxy for new information on these variables by looking at the days when new data on them is publicly released. We present

[1] We use the terms 'belief' and 'expectation' interchangeably in this paper.

novel evidence by showing that household expectations about the future of the economy adjust when presented with new information about the labor market, but do not adjust in response to information about other macroeconomic variables. Further, this adjustment is non-linear, asymmetric and heterogeneous. Household expectations adjust more if the information shock is larger than if it is smaller. Households become pessimistic when faced with negative information indicating a worsening of the economy, but do not become optimistic in light of positive information indicating an improvement in the economy. Additionally, this adjustment process exhibits heterogeneity along the lines of local labor market conditions. Specifically, we find that household living in areas with higher local unemployment are more sensitive to movements in the national unemployment rate than households living in areas with lower local unemployment.

One of the key challenges with identifying which signals households use in their belief formation process has been the fact that while households receive signals quite frequently (most the statistics are released monthly, some are released weekly), we do not have measures of household beliefs at the same rate. This paper overcomes this challenge by using daily data on households' expectations from the Gallup Daily Tracking Poll from 2008 to 2017. This allows us to use a high frequency identification approach in order to determine which macroeconomic variables matter for households belief formation process. We build a narrow window around the release dates of announcements of each variable and examine whether any change in expectations occurs in that window. Since the window is small, we can argue that any effect we find must be caused by the macroeconomic announcement.

Another major challenge to identifying changes in household expectations is the lack of data on households' forecasts. In order to infer whether new information on macro statistics causes households to adjust their expectations, we first need to measure what part of the announcement was actually 'new'. In other words, we need to measure the extent to which the data were anticipated versus unanticipated. To address this, we build a model of households' expectation formation process and consider two extreme cases regarding how households form forecasts. First, we assume that households are sophisticated, i.e they incorporate all available information while forming expectations. Thus we assume that their forecast is as good as that of professional forecasters, which we take to be our benchmark. Thus in this case, the 'new' information contained in the announcement will be given by the difference between the actual value of the variable as released in the announcement and professional forecasters' prediction. On the other extreme, we assume that households are naive, i.e. they do not use any new information to form forecasts. Since they already know the previous announcement, they cannot do any worse in their prediction. So in this case households' forecast is the value of the variable released in the previous announcement. Thus the unanticipated part of the current announcement is given by the difference between the value of the macroeconomic statistic between two consecutive announcements. Looking at these two extreme cases of household forecasts helps us to provide an upper and lower bound on the true response of expectations.

Once we have a measure of unanticipated information, we analyze which statistics cause households to adjust their expectations about the future state of the economy. We arrive at two main results. First, in both the sophisticated and naive case, we find that households adjust their expectations in response to changes in labor market statistics, specifically the unemployment rate, but not other statistics (output, inflation, interest rates, housing). This result holds even after we control for movements in the stock market. Second, we find rich heterogeneity in our results along three dimensions: type, size, and area. Looking across types of shocks, we find that households become pessimistic in response to negative information suggesting a worsening of the economy, but they do not become optimistic in response to positive information indicating an improvement. Considering the size of shock, we find that household expectations change more in response to large unanticipated shocks than to small shocks. Further, households in areas with high local unemployment pay more attention to national labor market movements than households in areas with low local unemployment.

Next, we ask what role news plays in affecting expectations. It is natural to believe that households get most of their information about the going-ons in the economy via news. We analyze both the supply and demand of news, and consider how they relate to our findings on adjustment of expectations. In order to evaluate the supply of news, we restrict our attention to newspapers. We first build a measure of news coverage using articles published in the New York Times, a major US daily. We analyze whether there was a change in news coverage of a macroeconomic variable after its announcement, and find a statistically significant increase after inflation announcements. Next, we analyze the sentiment of news, because it could be that expectations might respond to the tone of newspaper articles. We use a news sentiment index of 24 national newspapers compiled by the Federal Reserve Bank of San Francisco, and analyze whether sentiment changes after announcements. Similar to coverage, we find that news sentiment changes strongly after an inflation announcement, and weakly after a GDP announcement. Put together, these results imply that newspapers are concerned with other macroeconomic statistics as well, suggesting that a lack of response of household expectations to variables other than the unemployment rate is not driven by a lack of awareness about them. Finally, we inspect the demand for news by using data from Google Trends to directly investigate which statistics households are searching for. We find that in normal times, inflation is searched more often than unemployment. However, during times of distress, searches for unemployment increase dramatically, and far exceed the searches for inflation. Thus households become concerned with unemployment in bad times, consistent with our results on adjustment of expectations.

Our paper contributes primarily to the literature that studies survey-based expectations to understand the behavior of households (Malmendier & Nagel 2015, Kuchler & Zafar 2015, Roth & Wohlfart 2019, Mian et al. 2021). Most of this literature focuses on point estimates of expectations of specific variables such as inflation (Armantier et al. 2015, Bachmann et al. 2015, Coibion et al. 2018), house prices (Armona et al. 2018), or the labor market (Potter 2020, Mueller et al. 2021). However, it is not known which expectations are the most important in the decision-making process of households. In fact, more recent papers, such as those by Kamdar (2019), Ehrmann et al. (2015), Andre et al. (2019), and Roth & Wohlfart (2019) suggest that households do not form expectations about individual variables, but rather form expectations about the aggregate economy jointly. We use a measure of household expectations about the entire economy and ask which variables are important in influencing these expectations. The closest paper to ours is that of Masolo (2022), who studies which kinds of news affects perception of business conditions. He builds a vector autoregression (VAR) model using data from the University of Michigan's Survey of Consumers, and uses a 'no contemporaneous effects' exclusion restriction to identify what affects consumers' perceptions. The key innovation of our paper is that we use daily data on expectations, in contrast to the monthly series in the Michigan survey. This allows us to build narrow windows around the dates of macroeconomic news releases, thereby permitting us to get more precise estimates of the response of expectations. The use of this data also helps us avoid the issue of time aggregation that is present in monthly or quarterly surveys of household expectations. Lastly, since different people are surveyed every day, we also avoid the problem of learning on the survey (Binder & Kim 2020) and are able to get unbiased estimates, further advancing the causal interpretation of our results.

We also contribute to the literature examining the effects of macroeconomic announcements. Researchers have found that announcements affect spot exchange rates (Andersen et al. 2003, Evans & Lyons 2008), commodity returns (Caporale et al. 2016), futures contracts (Balduzzi et al. 2001, Andersen et al. 2007), and market volatility (Jiang et al. 2014). A subsection of this literature has focused on the effect of monetary policy announcements on long-term interest rates (Gürkaynak et al. 2005) and household expectations (Coibion, Gorodnichenko & Weber 2019, Mertens et al. 2020). Similar to us, Mertens et al. (2020) use daily data from Gallup to analyze whether monetary policy announcements shift household expectations. Although we look at interest rates in this paper as well, our study differs from theirs in that we examine a large set of macroeconomic announcements and focus on understanding which statistics matter to households in their expectation formation process. We present novel evidence in this direction by finding that household expectations are most responsive when presented with new information about the labor market. We also extend the literature by inspecting the mechanism through which households might change their expectations. Through examining news media, we find that news coverage as well as news sentiment responds to several macroeconomic announcements, but household expectations only change in response to movements in the labor market.

2 Data

We use three main data sources for our study. Our primary data source is the Gallup Daily Tracking Poll, which provides us with daily data on household expectations. The high-frequency nature of the Gallup survey allows for a cleaner identification than other surveys of expectations such as the Michigan Survey of Consumer Sentiment or the New York Fed's Survey of Consumer Expectations, which are conducted on a monthly basis. Our second data source is Bloomberg's United States Economic Calendar, which reports the median expectations of professional forecasters prior to each macroeconomic release. These forecasts helps us in capturing a measure of the unanticipated component of releases. To obtain shocks for monetary policy, we use unexpected changes in interest rates over a 30-minute window surrounding scheduled Federal Reserve announcement à la Nakamura & Steinsson (2018). Finally, we use the Daily News Sentiment Index from the Federal Reserve Bank of San Francisco to measure changes in the sentiment of economic news.

2.1 Gallup's US Daily Tracking Poll

The US Daily Tracking Poll is a repeated cross-sectional survey conducted by Gallup, a premier polling and analytics firm. It was fielded to about 1000 individuals every day[2] from 2008 to 2017. Gallup weights the data daily to match targets from the US Census Bureau by age, sex, region, gender, education, ethnicity, race, and population density of self-reported location. Table 1 displays some summary statistics from the Gallup poll and compares them with demographics from the Current Population Survey (CPS)[3]. As can be seen, the sample matches moments from the CPS fairly well.

The main variable we are interested in is a measure of households' expectations about the future of the economy. Specifically, participants are asked the following question:

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

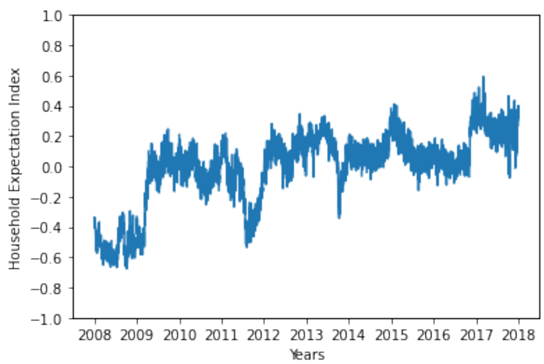
Participants can chose between three options: getting better, staying the same, or getting worse. We denote this variable as our *Expectations Index* and standardize it such that it has

[2]The survey is conducted for 350 days every year. The 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.

[3]We restrict our sample to individuals between the ages of 18 and 65, in order to focus on the working age population.

Table 1: Descriptive Statistics from the Gallup Survey and the CPS

	CPS	**Gallup**
Demographics		
Age	42.2	55
Female (%)	51	50
High school or less (%)	36	33
Some college (%)	19	24
Bachelor's Degree or more (%)	43	42
White (%)	77	79
Black (%)	13	8
Married (%)	56	55
Employed (%)	72	73
Unemployed (%)	3.6	3.7



(a) Daily Average Expectations

(b) Optimists vs Pessimists

Figure 1: Evolution of Household Expectations over Time

a mean of zero and a variance of one. Higher values of the index indicate more optimism about the future of the economy, while lower values indicate more pessimism. We use this question as a measure of household expectations about the performance of the aggregate economy in the future.

Figure 1a depicts our *Expectations Index* over time, while Figure 1b represents the evolution of the share of optimists and pessimists over time. Here, we define optimists as those participants who report that they expect the economy to be *getting better*, while we define pessimists as those participants who expect the economy to be *getting worse*. Figure 1a shows that the *Expectations Index* has risen over time as the share of optimists has increased.

Table 2: Major Events

Date	Event	O_{t+1} - O_{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

Table 2 shows the change in our Expectations Index around major events that occurred in our sample period. Column 4 reports the difference in expectations one day after the event to one day before the event. The first row reports the change in household expectations that occurred when the Lehman Brothers filed for bankruptcy. We observe that household expectations decreased by -0.22 points on average. We will use this event as a benchmark against which to compare the results in this paper.

2.1.1 Heterogeneity in Household Expectations

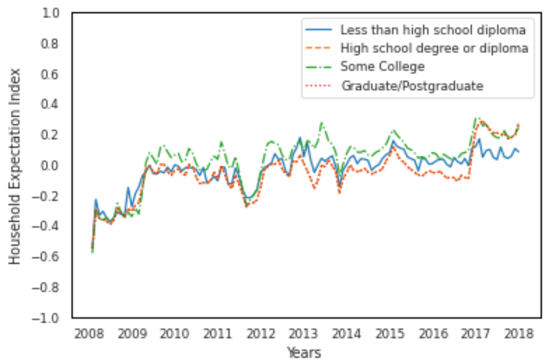
We observe substantial heterogeneity in household expectations across demographic groups. In Figure 2a, we find that college graduates were systematically the most optimistic over time. This can be linked to job status, since college graduates tend to have the highest employment rates and thus tend to be more consistently more optimistic than the unemployed (Figure 2b). Looking across age groups in Figure 2c, 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 2d), there seems to be a sharp increase among men post 2016. When we examine the data by occupation, we find that respondents in agriculture are consistently more pessimistic, while those in manufacturing and services tend to have similar expectations.

Interestingly, we find a reversal when looking at heterogeneity across political affiliation and race. As Figure 2f demonstrates, households' optimism is proportional to their party affiliation, and changes depending on who is in power (Mian et al. 2021). 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. This reversal is also present when looking at heterogeneity by race. Black households become significantly more optimistic after the 2008 Presidential election when Barack Obama is elected as the first Black president of the United States. In contrast, White households become pessimistic. After the 2016 election, which brings Donald Trump to power, the reverse occurs and Black households become more pessimistic than White households.

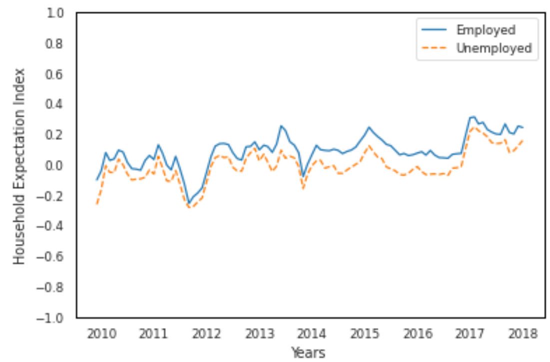
2.2 Bloomberg's US Economic Calendar

Bloomberg's US Economic Calendar reports data for all major macroeconomic announcements,[4] as well as the average ex ante median forecast of professional forecasters, called

[4]Bloomberg also reports any revisions to the actual releases. However, we only look at the initial reported data point, since that captures new information released at that time.

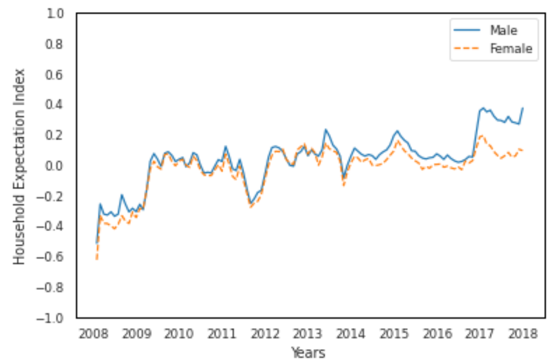


(a) Education



(b) Job Status

(c) Age



(d) Gender

(e) Race

(f) Party Affiliation

Figure 2: Heterogeneity in Household Expectations

the Consensus Forecast. Before every macroeconomic announcement, Bloomberg surveys economists and asks them what they expect to see in the upcoming announcement. For this paper, we focus on five variables of policy relevance: unemployment rate, output as measured by GDP growth (Advance), inflation as measured by the month-on-month consumer price index (CPI), initial jobless claims, and housing starts. The remaining variables are examined in the Appendix. New data for all variables come out each month, except data on jobless claims, which come out weekly. Table 11 in the Appendix reports the basic summary statistics related to these variables.

2.3 Daily News Sentiment Index

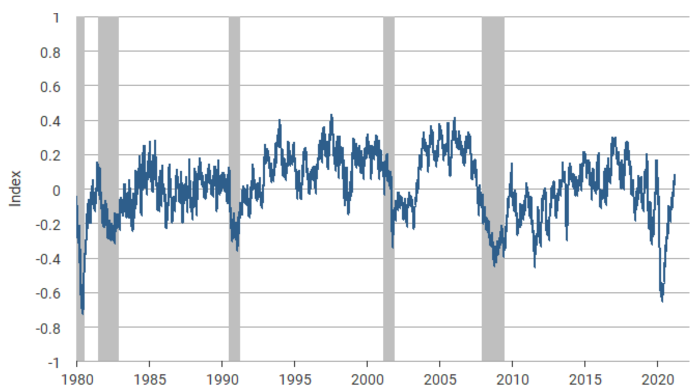


Figure 3: Daily News Sentiment Index over Time

We also use the Daily News Sentiment Index developed by the Federal Reserve Bank of San Francisco, using the methodology in Shapiro et al. (2020). This index captures the economic sentiment embedded in newspaper articles using computational text analysis. Sentiments are constructed from economic and financial news articles from 24 major US newspapers.[5] The index is standardized to have a mean of zero and a variance of one. It can be interpreted similarly to our expectations index: higher values indicate positive

[5]Further details can be found in Buckman et al. (2020).

sentiment, while lower values indicate negative sentiment. As Figure 3[6] depicts, the news sentiment index is pro-cyclical.

3 A Model of Expectation Formation

To determine which macro variables are important to households in their expectation formation process, we look at when new information on these variables is released and investigate whether expectations adjust in response to that information. To do this, we need to know how much of the information released during macroeconomic announcements is new to households; that is, we need a measure of shock to households' information set. Since the true expectation formation process is unknown, finding a shock becomes challenging. To address this problem, we develop a model of expectation formation and examine how macro announcements feature in it.

3.1 Households' Expectations Formation Process

Consider a macroeconomic announcement X_t that occurs on date t. The announcement has two components: anticipated (A_t) and unanticipated (U_t):

$$X_t = A_t + U_t$$

The anticipated component is the part of the announcement that rational agents can forecast with the information they have, while the unanticipated (U_t) component is the part of the announcement that they cannot predict given their information set. Let Y_t denote some fundamental about the economy based on which households decide what the future of the economy will be. First, consider a household that is forming expectations about the future.

[6] Source: Buckman et al. (2020)

Once the announcement is made, households' expectations can be written as:

$$Y_t = p \cdot g(X_t) + (1-p) \cdot h(\psi_t)$$

where ψ_t contains all information aside from the announcement that is available to agents for forming expectations. The parameter p indicates the weight that households give to the announcement in their belief formation process. Households' expectations before the announcement is made can be written similarly as:

$$E_{t-1}(Y_t) = E_{t-1}[p \cdot g(X_t) + (1-p) \cdot h(\psi_t)] = p \cdot E_{t-1}[g(X_t)] + (1-p) \cdot E_{t-1}[h(\psi_t)]$$

Since we have daily data on expectations, we will restrict our attention to comparing expectations right after the announcement with expectations just before.

$$Y_t - E_{t-1}[Y_t] = p \cdot [g(X_t) - E_{t-1}[g(X_t)]] + (1-p) \cdot [h(\psi_t) - E_{t-1}[h(\psi_t)]]$$

The identifying assumption is that the only new information households have between day t and $t-1$ is that provided in the announcement. This assumption implies that $\psi_t = \psi_{t-1} = \psi$. Thus, $E_{t-1}[h(\psi_t)] = E_{t-1}[h(\psi_{t-1})] = h(\psi_{t-1}) = h(\psi)$. So change in expectations simplifies to:

$$\begin{aligned} Y_t - E_{t-1}[Y_t] &= p \cdot [g(X_t) - E_{t-1}[g(X_t)]] + (1-p) \cdot [h(\psi) - h(\psi)] \\ &= p \cdot [g(X_t) - E_{t-1}[g(X_t)]] \end{aligned}$$

We assume that g is the identity function, and we get:

$$Y_t - E_{t-1}[Y_t] = p \cdot [X_t - E_{t-1}(X_t)]$$

Thus, the change in households' expectations due to the macroeconomic announcement depends on the difference between the information released in the announcement and households' forecast of it. We denote this difference by $ShockX_t$. Thus:

$$Y_t - E_{t-1}[Y_t] = p[ShockX_t] \tag{1}$$

3.2 Sophisticated versus Naive Households

Since we cannot observe households' forecasts directly, we analyze two extreme cases: sophisticated households and naive households. Considering these two extremes will help us to provide a bound on the true forecast.

Let us start with the case of sophisticated households. These households are rational and use all the information available to them to make their forecast. Thus, the sophisticated forecast if given by:

$$\mathbb{E}^S(X_t) = A_t$$

The forecast is equal to the component of the announcement that is predictable using all the information available to rational agents at time $t - 1$, which by definition is the anticipated part of the announcement. Thus, the change in expectations due to the announcements simplifies to:

$$\begin{aligned} Y_t - E_{t-1}(Y_t) &= p^S \cdot [X_t - E_{t-1}^S(X_t)] \\ &= p^S \cdot [X_t - A_t] \\ &= p^S \cdot U_t \end{aligned}$$

where p^S denotes the weight sophisticated households give to the announcement. Households' expectations in this case can only be affected by the information they were not able to predict (i.e. by the unanticipated component of the announcement). This is the standard rational expectations result.

Let us now examine the second case, the naive households. These households do not make use of any new information between two announcements of the same variable to update their beliefs. Since households know X_{t-1} when making their forecast about X_t, we assume that they cannot do any worse in their prediction, that is,

$$E_{t-1}^N(X_t) = X_{t-1}$$

The naive forecast is the value of the macroeconomic variable from the previous announcement. The change in expectations due to the announcement now becomes:

$$\begin{aligned} Y_t - E_{t-1}(Y_t) &= p^N \cdot [X_t - E_{t-1}^N(X_t)] \\ &= p^N \cdot [X_t - X_{t-1}] \end{aligned}$$

where p^N denotes the weight naive households give to the announcement. Hence in this case, household expectations change if the value of the macroeconomic variable changes between two announcements.

In reality, households' forecasts probably lie somewhere between these two extremes. Looking at these two cases helps us provide a bound on changes in household expectations due to new information from macroeconomic announcements.

4 Empirical Strategy

With our model of expectations formation in hand, analyzing which macroeconomic variables affect household expectations is now straightforward. Following Gürkaynak et al. (2005) and 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 so any change in expectations in the window must be due to the announcement.[7] The daily nature of the Gallup poll thus gives us the advantage of cleaner identification as compared to other surveys of expectations such as the Michigan survey or the Survey of Consumer Expectations, which are conducted monthly.

To be precise, let the announcement occur on day t. We then consider the change in household expectations in the window $[t-h, t+h]$, where h denotes days from t. Since people may take some time to update their expectations, we vary the horizon h from one to four days. Let E_t denote expectations 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 is given by:

$$Y_t - E_{t-1}(Y_t) = \alpha_h + \beta_h * ShockX_t + \epsilon_{th} \tag{2}$$

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

This follows from Equation 1. 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 up to a day to compare them. Further, 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.[8] Our results, however, remain robust to the exclusion of day t.

It is also important to talk about 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. Finally, the GDP report is released between the 27th and the last day of every month. Jobless claims are reported weekly on every Thursday.[9]

We are also not able to distinguish between multiple variables announced on the same day. For example, the jobs report contains information on not just the unemployment rate, but several other labor market indicators such as average hourly earnings and non-farm payroll. We consider unemployment rate as a proxy for the entire jobs report, and use other variables as proxies to test robustness in the Appendix.

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

[9]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. While we do not report the results in the paper, we do look at the effects of IIP announcements in a very tight window, while dropping the days that IIP and housing announcements clash. 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 number that is released on Thursday. Furthermore, ADP Research Institute also usually releases its employment reports 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. Appendix table # looks at this case and finds the results to be robust. For estimating the effect of jobless claims, we drop the first week of every month.

The shock to information coming from macroeconomic announcements will vary depending on which case we consider. In section 3.2, we showed that in the case of sophisticated households, only unanticipated changes in the announcement can influence expectations. Since households are utilizing all available information to make their forecast, we assume that their forecast is the same as that of professional forecasters, which we take to be the benchmark. This is also consistent with Carroll (2003), who shows that household expectations derive from news reports about the views of professional forecasters. We utilize data from Bloomberg's Consensus Forecast to get information on professional forecasters' expectations. Before every announcement, Bloomberg asks experts what they think will occur in the upcoming announcement. Following Gürkaynak et al. (2005), we define:

$$\text{Surprise}_t = X_t - E^F_{t-1}(X_t)$$

where X_t is the announcement that comes out on date t, and F_{t-1} is the forecast of announcement X_t made using information I_{t-1}. $Surprise_t$ thus gives a measure of the unanticipated component of every announcement. Since households have the same forecast as experts, $Surprise_t$ serves as our measure of shock to households' information set. Table 11 summarizes the surprise variable for our primary macroeconomic releases.

In the case when households are naive, households predict that the macroeconomic variable will take the same value that it had in the previous announcement. Thus households will change their expectations if the value of the variable in current announcement is different from the last announcement.

5 Results

We now move on to estimate Equation 1 for both sophisticated and naive households. We will then explore heterogeneity in response of expectations by type of shock, size of shock, and local labor market conditions. Finally, we will explore the role of news media as a transmission mechanism for these announcements.

5.1 Baseline Results

5.1.1 Sophisticated

We first consider the case of sophisticated households. We identify the effect of an announcement that comes out on day t by comparing the change in expectations before and after the announcement. The use of narrow windows allows us to give a causal interpretation to the coefficient. Since we are considering the case of sophisticated households, the shock to households' information is equal to the actual value of the variable minus the Bloomberg Consensus forecast; that is, $ShockX_t = SurpriseX_t = X_t - F_{t-1}(X_t|I_{t-1}))$. We estimate:

$$Y_t - E_{t-1}(Y_t) = \alpha_h + \beta_h * SurpriseX_t + \epsilon_{th} \tag{3}$$

where t is the day of the announcement, h indicates days from t, and E_τ indicates expectations formed on day τ. $SurpiseX_t$ denotes the unanticipated part of the announcement. We vary the horizon h to look at up to four days after the announcement in the regression tables, and up to 20 days in the impulse responses. This allows time for households to update their expectations in response to new information. However, the broader the window becomes, the murkier the estimate will be, because there is a greater chance that households could be exposed to other new information during a longer time period.

Table 3: Response of Sophisticated Households to Macroeconomic Announcements

	(1) Day 0	(2) Day 1	(3) Day 2	(4) Day 3	(5) Day 4	(6) SP500
Surprise(Unemp)	-0.0850***	-0.0769**	-0.0925***	-0.0734**	-0.0914**	-0.0793**
	(0.032)	(0.039)	(0.034)	(0.035)	(0.037)	(0.032)
Surprise(GDP)	0.0187	0.0101	-0.0158	0.000487	0.0241	0.0131
	(0.016)	(0.017)	(0.013)	(0.014)	(0.015)	(0.016)
Surprise(CPI)	0.0491	-0.00472	0.0188	-0.00688	-0.0154	0.0481
	(0.042)	(0.045)	(0.049)	(0.039)	(0.040)	(0.042)
Surprise(Housing)	-0.0785	-0.0425	-0.0246	0.0803	-0.0436	-0.0836
	(0.090)	(0.078)	(0.075)	(0.079)	(0.100)	(0.097)

This table reports estimates of β_h from Equation 3. β_h is the change in expectations, assuming households are sophisticated, due to new macroeconomic information in the window $[t-1, t+h]$, where t is the day of the announcement and $h = 0, 1, 2, 3, 4$. Sophisticated households are assumed to have full information and rational expectations, so we use forecast errors from the Bloomberg Consensus Survey as a measure of unanticipated shocks. Each of the rows report the estimates from Equation 3 for different macroeconomic announcements. Standard errors are presented in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3 presents our primary results from Equation 3. The columns denote the number of days from t (i.e., from when the announcement came out). So the dependent variable in column 1 is the change in expectations between day t and $t-1$, in column 2 is the change in expectations between day $t+1$ and $t-1$, and so on. Each row is a separate regression.[10] We find that households respond negatively to unanticipated changes in the unemployment rate, but not to other variables. This effect is persistent over time, as we show in Figure 4. Focusing on the unemployment rate, we find that household expectations decline by 0.085 on the day of the jobs report. To put this estimate in perspective, household expectations declined by 0.22 when Lehman Brothers filed for bankruptcy, which is approximately one standard deviation in $E_{t+h} - E_{t-h}$. This implies that in response to

[10] We have combined all regressions into one table for ease of viewing. Individual regressions can be found in the Appendix.

an unanticipated increase in the unemployment rate, household sentiments decline by about one third of a standard deviation on average, or by about one third of the amount they fell after the Lehman Brothers collapse on September 15, 2008. In other words, for household expectations to decline as much as they did during the Lehman Brothers crash, the unemployment rate would need to decrease by roughly 2.6%.[11]

One might be worried that macroeconomic announcements move the stock market, and households might only change their expectations in response to the stock market and not in direct response to the announcement. Column 6 examines this concern. We observe that the even after controlling for the stock market (as given by change in the SP 500 Index), we find that expectations decrease significantly in response to a surprise in the unemployment announcement.

In Figure 4, we plot the dynamic response of household expectations over time by plotting the impulse response functions. We also plot a pre-trend of five days before the announcement and plot the impulse response for three weeks after the announcement. We report 90% confidence intervals. Sophisticated households respond the most to unanticipated changes in unemployment rate, and household expectations keep worsening for about two weeks from the time of the announcement. In contrast, for other variables, expectations do not respond on impact nor is there any dynamic impact. Unanticipated shocks from output growth, inflation, and housing starts do not change household expectations over time in any significant manner.

Our results indicate that households consider the unemployment rate to be an important indicator in their expectation formation process. The fact that households give importance

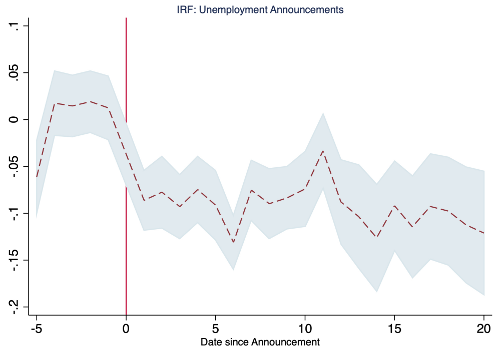
[11] The unemployment rate did not decrease by 2.6% from month to month even during the Great Recession. An increase of 2.6% in the unemployment rate would therefore be an extremely strong signal of worse future outcomes. In this context, one-third standard deviation decline in household expectations following an unanticipated increase in unemployment is quite a large effect.

to the labor market while forming expectations is not surprising since labor income is the largest component of total income for most households. Further, being unemployed has huge negative effects on households' health and well-being (Sullivan & Von Wachter 2009, Blanchflower & Oswald 2004, Lucas et al. 2004, Michaillat & Saez 2021). Carbone & Hey (2004) and Saporta-Eksten (2014) show that changes in labor markets influence households' decisions. It is therefore not surprising that the labor market influences household expectations about the economy as well. Our results are also consistent with Masolo (2022), who finds that consumers' perceptions of business conditions are mostly determined by labor market conditions.

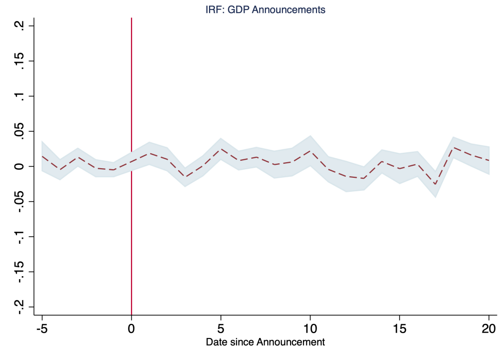
Interestingly, households do not adjust their expectations in response to unanticipated changes in any of the other variables, including output, inflation, and housing. The fact that households do not respond to unanticipated movements in inflation is consistent with Andrade et al. (2020). Furthermore, it must be noted that our sample period from 2008 to 2017 was mostly a period of low inflation, which might also contribute to the non-response of household expectations. However, it is noteworthy that output does not seem to determine expectations.

5.1.2 Naive

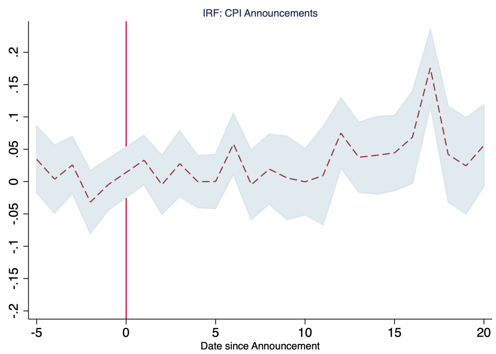
We now consider the case of naive households. In this scenario, once an announcement is made, households update their beliefs to that value, which anchors their beliefs until a new announcement is made. This, our measure of shock to households' information will be the difference between the value of the macroeconomic variable in this announcement and the value in the previous one; that is, $ShockX_t = \Delta X_t = X_t - X_{t-1}$. We follow the same high



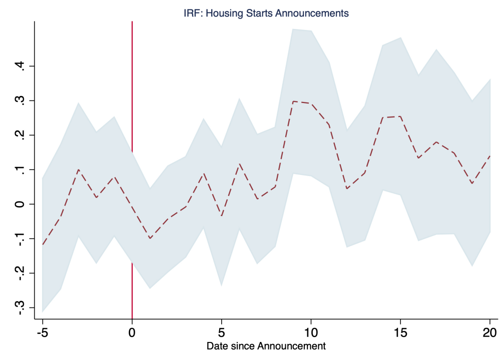
(a) Unemployment Rate



(b) Output Growth



(c) Inflation



(d) Housing Starts

Figure 4: Impulse Response Functions for Sophisticated Households

frequency–local projection approach outlined in the previous section and estimate:

$$Y_t - E_{t-1}(Y_t) = \alpha_h + \beta_h * \Delta X_t + \epsilon_{th} \tag{4}$$

where t is the day of the announcement, h indicates days from t, E_τ indicates expectations formed on day τ, and ΔX_t denotes the difference between the macroeconomic variable in this announcement and the previous one. Once again, we vary the horizon h to look at up to four days after the announcement in the regression table, and up to 20 days in the impulse responses.

Table 4: Response of Naive Households to Macroeconomic Announcements

	Day 0	Day 1	Day 2	Day 3	Day 4	SP500
Change(Unemp)	-0.0591**	-0.0538*	-0.0584**	-0.0318	-0.0631**	-0.0657**
	(0.028)	(0.030)	(0.025)	(0.029)	(0.028)	(0.028)
Change(GDP)	0.0102*	0.00445	-0.00875	-0.00195	0.0180	0.00678
	(0.005)	(0.006)	(0.013)	(0.010)	(0.012)	(0.005)
Change(CPI)	-0.000730	0.0105	0.00932	0.00715	0.0181	0.000294
	(0.017)	(0.018)	(0.019)	(0.016)	(0.016)	(0.014)
Change(Housing)	-0.142**	-0.0691	-0.00471	0.00936	0.00564	-0.129**
	(0.064)	(0.059)	(0.055)	(0.062)	(0.069)	(0.052)

This table reports estimates of β_h from Equation 4. β_h is the change in the expectations, assuming households are naive, due to new macroeconomic information in the window $[t-1, t+h]$, where t is the day of the announcement and $h = 0, 1, 2, 3, 4$. Naive households do not use any new information between two announcements to update their beliefs, so we use change in the variable between two announcements as a measure of unanticipated shocks. Each of the rows report estimates from Equation 4 for different macroeconomic announcements. Standard errors are presented in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4 reports the response of naive households' expectations to new information on macroeconomic variables. Our results are similar to the case of sophisticated households. We find that naive households respond negatively to changes in the unemployment rate, but not to changes in other variables. There is a small positive impact on the day of the announcement of output growth, but it is not persistent. A 1% change in unemployment rate decreases the future expectations of naive households by 0.06 points, which is about one fourth of a standard deviation. In other words, the unemployment rate would have to increase by 4% per month to elicit a one standard deviation decline in future expectations of naive households. Comparing it with the change in expectations during the Lehman Brothers crash, we conclude that the unemployment rate would have to increase by 3.6% to match the movement in expectations that occurred during the Lehman bankruptcy.

The coefficient -0.06 in the naive case is smaller in magnitude than the coefficient in the sophisticated case (-0.085). This is to be expected because in reality, households anticipate at least some part of the announcement and that dampens the change in expectations. Since these two cases provide bounds, we can conclude that the true change in expectations after the unemployment announcement is between $[-0.085, -0.06]$. Comparing it with our benchmark of the Lehman bankruptcy, the unemployment rate would need to decrease by 2.6% to 3.6% to match the change in expectations that occurred during the Lehman bankruptcy. Column 6 examines whether this effect is driven by the stock market. We can see that the even after we control for the stock market, expectations decrease significantly in response to changes in the unemployment rate.

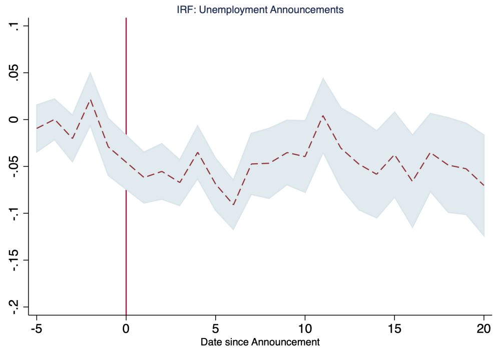
In Figure 5, we plot the dynamic response of household expectations over time by plotting the impulse response functions. Analogous to the case of sophisticated households, naive households also respond most to shocks in the unemployment rate. Here, household expectations decline for about one week from the time of the announcement versus two weeks in the sophisticated case. Once again, output growth and inflation do not respond on impact nor do they have any dynamic effects on household expectations.

5.2 Heterogeneity

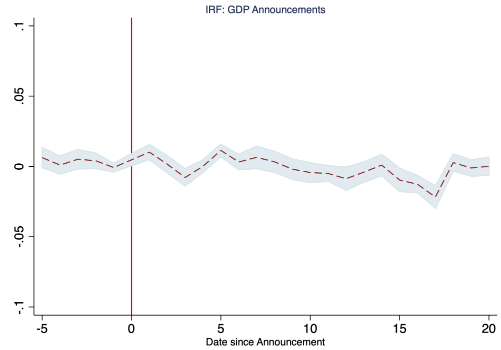
In this section, we will examine if expectations respond differently to shocks based on type of announcement, size of the shock, and local labor market conditions.

5.2.1 By Type

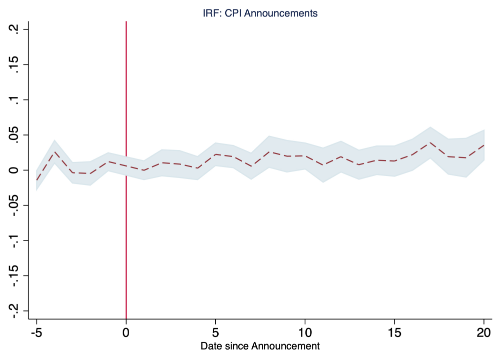
So far, we have looked at the response of household expectations to aggregate shocks. However, shocks in opposing directions could have different effects since they signify different information. Thus, it is possible that by reporting the net effect, we are miss-



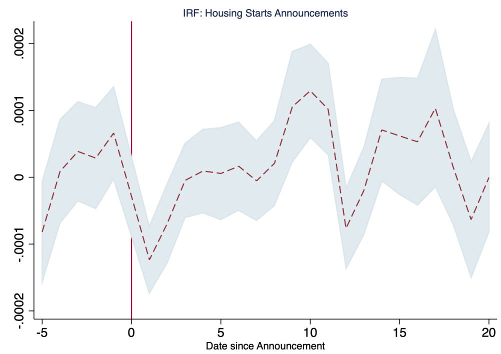
(a) Unemployment Rate



(b) Output Growth



(c) Inflation



(d) Housing Starts

Figure 5: Impulse Response Functions for Naive Households

ing out on differential movements caused by these shocks. To rectify this, we separate announcements into two categories: those with positive shocks and those with negative shocks. We estimate:

$$Y_t - E_{t-1}(Y_t) = \alpha_h + \beta_{1h} * (ShockX_t | ShockX_t > 0) + \beta_{2h} * (ShockX_t | ShockX_t < 0) + \epsilon_{th} \tag{5}$$

where t is the day of the announcement, h indicates days from t, E_τ indicates expectations formed on day τ, and $ShockX_t$ denotes the shock to households' information set. The value of $ShockX_t$ will of course be different in our two cases. In the sophisticated case,

$ShockX_t = SurpriseX_t$. A positive (negative) surprise means that the actual value of the macroeconomic variable turned out to be higher (lower) than forecasted.[12] In the naive case, $ShockX_t = \Delta X_t$. So a positive (negative) shock now means that the variable increased (decreased) in value from this announcement to the last.

Table 5: Response of Household Expectations to Positive and Negative Shocks

	Day 0	Day 1	Day 2	Day 3	Day 4
Sophisticated Households					
Surprise(Unemp) >0	-0.2535**	-0.245**	-0.253**	-0.211*	-0.253
	(0.113)	(0.093)	(0.094)	(0.105)	(0.161)
Surprise(Unemp)<0	-0.0979	-0.0584	-0.0619	-0.143*	-0.101
	(0.089)	(0.119)	(0.100)	(0.078)	(0.085)
Naive Households					
Change(Unemp)>0	-0.152**	-0.133***	-0.207***	-0.170***	-0.163**
	(0.057)	(0.047)	(0.039)	(0.059)	(0.065)
[1em] Change(Unemp)<0	0.0971	0.142	-0.0155	0.00126	0.0706
	(0.076)	(0.114)	(0.091)	(0.097)	(0.098)

This table reports the estimates of β_h from Equation 5. Here, β_h is change in the expectations of due to positive or negative shock in the BLS jobs report, in the window $[t-1, t+h]$ where t is the day of the announcement and $h = 0, 1, 2, 3, 4$. Rows 1 and 3 indicate positive and negative shocks under the assumption that households are sophisticated, while rows 2 and 4 indicate positive and negative shocks under the assumption that households are naive. Standard errors are presented in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 5 reports the results from Equation 5 for the unemployment rate. [13] We observe that household expectations decline enormously in response to positive shocks in unemployment, but they do not change significantly in response to negative unemployment shocks. Note that a positive shock to unemployment (i.e., when unemployment is higher than

[12]Note that a positive surprise might imply different things for different variables. For example, a positive surprise in unemployment indicates a worsening of the economy, whereas a positive surprise in GDP growth implies an improvement in the economy.

[13]We do not find any consistently significant effects for the other variables, which are reported in the Appendix.

anticipated, or if unemployment is higher this month compared with the previous month) indicates worsening of economic conditions. Thus, we find that households respond asymmetrically: They become pessimistic upon receiving information indicating worsening economic outcomes but do not necessarily turn optimistic upon receiving information indicating improving economic outcomes. The coefficient is also much larger (-0.25 compared with -0.085 in Table 3), which is almost the same as the change in expectations at the time of Lehman Brothers bankruptcy. There results are not surprising, especially when we consider that unemployment has been declining since the Great Recession and a higher than expected unemployment rate has been associated with a recession.

5.2.2 By Size

Next, we examine whether larger shocks have different effects than smaller shocks. From the model developed in section 3, we know that the change in expectations is proportional to the size of the shock. We test whether this is also true in the data by finding the absolute value of the mean shock for every variable. Shocks that are greater in magnitude than the mean are called large shocks, while shocks that are lesser in magnitude are called small shocks.[14] We estimate:

$$\begin{aligned} Y_t - E_{t-1}(Y_t) = \alpha_h &+ \beta_{1h} * (ShockX_t | ShockX_t > median(|ShockX_t|)) \\ &+ \beta_{2h} * (ShockX_t | ShockX_t < median(|ShockX_t|)) + \epsilon_{th} \end{aligned} \tag{6}$$

where t is the day of the announcement, h indicates days from t, E_τ indicates expectations formed on day τ, and $ShockX_t$ denotes the shock to households' information set. $ShockX_t = SurpriseX_t$ in the sophisticated case, and $ShockX_t = \Delta X_t$ in the naive case.

[14] We repeat the analysis by instead splitting the sample by the median. Results stay the same, as reported in Appendix Table #.

Table 6: Response of Household Expectations to Large and Small Shocks

	Day 0	Day 1	Day 2	Day 3	Day 4
Large Shocks					
Surprise(Unemp)	-0.1859***	-0.171***	-0.0481	-0.0634	-0.136
	(0.074)	(0.061)	(0.068)	(0.083)	(0.095)
Change(Unemp)	-0.0905***	-0.147***	-0.111***	-0.0359	-0.0979*
	(0.044)	(0.034)	(0.038)	(0.050)	(0.049)
Small Shocks					
Surprise(Unemp)	-0.0979	-0.0584	-0.0619	-0.143*	-0.101
	(0.089)	(0.119)	(0.100)	(0.078)	(0.085)
Change(Unemp)	0.0971	0.142	-0.0155	0.00126	0.0706
	(0.076)	(0.114)	(0.091)	(0.097)	(0.098)

This table reports the estimates of β_h from Equation 6. Here, β_h is change in the expectations due to large or small shocks in the BLS jobs report, in the window $[t-1, t+h]$ where t is the day of the announcement and $h = 0, 1, 2, 3, 4$. Rows 1 and 3 indicate large and small shocks under the assumption that households are sophisticated, while rows 2 and 4 indicate large and small shocks under the assumption that households are naive. Standard errors are presented in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 6 reports the results from 6 for the unemployment rate. [15] We observe a similar asymmetry as in the previous section: Household expectations decline in response to large shocks in unemployment, but they do not change significantly in response to small unemployment shocks. This finding is in line with our model, since large unanticipated movements affect expectations more than smaller ones. The coefficient (-0.1859) is also larger compared with -0.085 in our baseline Table 3).

[15]We do not find any consistently significant effects for the other variables, which are reported in the Appendix.

5.2.3 By Area

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. 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. 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:

$$\begin{aligned} Y_t - E_{t-1}(Y_t) = \alpha_h &+ \beta_{1h} * (ShockU_t | LocalU_t > smean(LocalU_t)) \\ &+ \beta_{2h} * (ShockU_t | LocalU_t < mean(LocalU_t)) + \gamma_R + \epsilon_{th} \end{aligned} \tag{7}$$

where t is the day of the announcement, h indicates days from t, E_τ indicates expectations formed on day τ, $ShockX_t$ denotes the shock in information due to the announcement, and $LocalU_t$ denotes the local unemployment rate of the state. We find the mean local unemployment for all states every month, and split states according to that value. γ_R denotes region fixed effect. The standard errors are clustered by state.

Table 7 reports the results. We find that people living in areas with high local unemployment are more sensitive to changes in national unemployment than people in areas with low local unemployment. This result makes sense given the psychological costs of unemployment. Blanchflower & Oswald (2004) find that becoming unemployed is as bad as losing $60,000 of income a year. Michaillat & Saez (2021) find that psychological costs from unemployment offset the value of home production and leisure by unemployed workers.

Table 7: Response of Household Expectations by Local Labor Markets

	Day 0	Day 1	Day 2	Day 3	Day 4
High Local Unemployment					
Surprise(Unemp)	-0.1859***	-0.171***	-0.1481	-0.1634	-0.136
	(0.034)	(0.051)	(0.085)	(0.091)	(0.089)
Change(Unemp)	-0.1905***	-0.147***	-0.111***	-0.1359	-0.1979*
	(0.044)	(0.039)	(0.038)	(0.070)	(0.089)
Low Local Unemployment					
Surprise(Unemp)	-0.0925	-0.0578	-0.0645	-0.163	-0.103
	(0.055)	(0.110)	(0.093)	(0.078)	(0.083)
Change(Unemp)	0.093	0.103	-0.015	0.016	0.071
	(0.076)	(0.112)	(0.094)	(0.042)	(0.083)

This table reports the estimates of β_h from Equation 7. 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 $h = 0, 1, 2, 3, 4$. Rows 1 and 3 indicate areas with high and low local unemployment under the assumption that households are sophisticated, while rows 2 and 4 indicate areas with high and low local unemployment under the assumption that households are naive. Standard errors are presented in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

In net, it is as if unemployed workers do not engage in home production. Given these high costs, it makes sense that people living in areas with higher local unemployment would be more sensitive to movements in labor markets, at both the state and the national level.

5.3 The Role of News

Now that we know that households respond only to certain macroeconomic announcements, we attempt to understand this specifically. We posit that the mechanism through which households respond to macroeconomic information is news media. At first glance, this seems a reasonable supposition since very few households actually follow macroeconomic announcements directly and news about these announcements is the most viable source of information.

5.3.1 Supply of News

One reason for households only responding to the labor market could be that other announcements are not covered in the news. To examine this possibility, we look at the universe of articles published by the *New York Times*, one of the leading dailies in the United States. We then examine whether the number of articles concerning a macroeconomic variable increased after a new announcement of that variable was released. To be concrete, we estimate:

$$\Delta News_{t+h} = \alpha + \beta \Delta X_t + \epsilon_t$$

where X_t is the macroeconomic variable of interest, and $\Delta News_{t+h}$ is the change in number of news articles about that variable before and after the announcement. For monthly announcements, we compare the number of articles that were released up to seven days after the announcement to articles released seven days before. For UI claims announcements, which occur weekly, we compare articles released two days after the announcement versus two days before. The results are reported in table 5.3.1. We find that there is a significant increase in coverage only after announcements of inflation, not for any other variable.

It could be argued that household expectations do not change simply in response to news coverage of announcements, but instead only change according to the tone or sentiment of news after the announcement. News sentiment helps households to interpret the data released, and it could provide a signal about whether the economy is doing well or whether there is cause for concern. To measure news sentiment, we use data from an index of daily news sentiment developed by the Federal Reserve Bank of San Francisco. It is a high-frequency measure of economic sentiment based on lexical analysis of economics-related

Table 8: Variation in News Coverage Caused by Macroeconomic Announcements

	Change in Articles
Change(Unemp)	0.280
	(2.163)
Change(GDP)	0.0840
	(0.324)
Change(CPI)	-1.853**
	(0.731)
Change(Housing)	-0.0177
	(0.0195)

This table reports the estimates of β from Equation 5.3.1. Here, β is the variation in number of articles about the macroeconomic variable before and after its announcement. The window is $[t-2, t+2]$ where t is the day of the announcement for initial claims, and $[t-7, t+7]$ for all other announcements. The dependent variable is the change in the value of the macroeconomic variable between two announcements. Each of the rows report the estimates from Equation 5.3.1 for different macroeconomic announcements. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

news articles. Higher values of this index indicate a more positive sentiment, while lower values indicate a more negative sentiment.[16] We first examine the correlation between news sentiment and household expectations. As can be seen in Figure 6, the correlation is very high at 71%, suggesting that households are indeed influenced by the sentiment in the news.

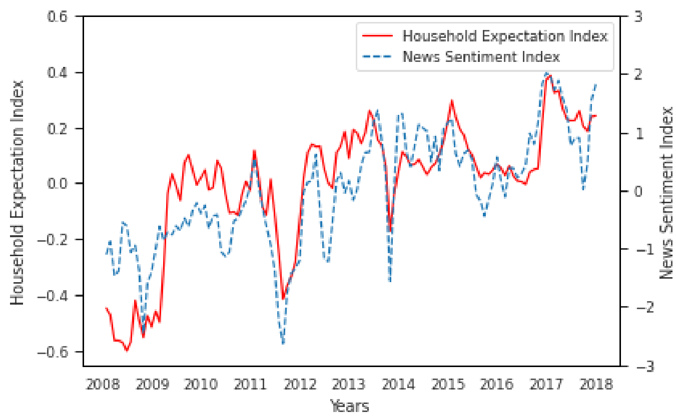


Figure 6: Correlation Between Daily News Sentiment Index and Expectations Index

To formally test whether news sentiment changes in response to macroeconomic announcements, we estimate:

$$Sentiment_{t+h} - Sentiment_{t-1} = \alpha_1 + \alpha_2 * \Delta X_t + \nu_{t+h} \tag{8}$$

where t is the day of the announcement, h indicates days from t, $Sentiment_\tau$ indicates news sentiment on day τ, and $ShockX_t$ denotes the shock in information due to the announcement. We report results in Table 9 for the naive case. [17] Once again, we observe that CPI is the main driver of news sentiment, followed by GDP announcements which weakly influence sentiment. These results suggest that the selective response of household

[16] The index is standardized to have a mean of zero and a variance of one.

[17] Results for sophisticated case are similar and are reported in the Appendix.

expectations to the labor market is not driven by solely by the supply of news.

Table 9: Variation in News Sentiment Caused by Macroeconomic Announcements

	Day 1	Day 2	Day 3	Day 4	Day 5
Change(Unemp)	-0.0270	-0.0490	-0.0701	-0.0369	0.0116
	(0.037)	(0.056)	(0.070)	(0.094)	(0.100)
Change(GDP)	0.0101	0.0168	0.0553*	0.0671**	0.0345
	(0.008)	(0.011)	(0.031)	(0.033)	(0.041)
Change(CPI)	0.0575**	0.0956***	0.129***	0.143***	0.145**
	(0.026)	(0.032)	(0.039)	(0.045)	(0.057)
Change(Housing)	-0.0554	0.00561	-0.0686	0.0349	-0.00972
	(0.112)	(0.125)	(0.146)	(0.184)	(0.194)

This table reports the estimates of α_2 from Equation 8. Here, α_2 is the variation in news sentiment that is caused by the announcement, in the window $[t-1, t+h]$ where t is the day of the announcement and $h = 0, 1, 2, 3, 4$. The dependent variable is the change in the value of the macroeconomic variable between two announcements. Each of the rows reports the estimates from Equation 8 for different macroeconomic announcements. Standard errors are presented in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

5.3.2 Demand for News

To more rigorously test the role of news, we turn our attention to looking at the demand for news. We use data from Google trends, which measure the number of searches of a particular word. We start by analyzing the number of searches for unemployment as compared to inflation. Figure 7 illustrates our results. The blue line shows searches for the phrase 'unemployment rate', while the red line shows searches for 'CPI'.[18] While searches for unemployment not only display a pro-cyclical pattern, they tend to increase after its announcement. Inflation, however, is a hotly discussed topic at all times. We can observe that before the Great Recession, inflation was searched more often than unemployment, even though inflation in the United States had been stable since the 1980s. Unemployment becomes a point of concern only during bad times, but concern about inflation seems to be acyclical.

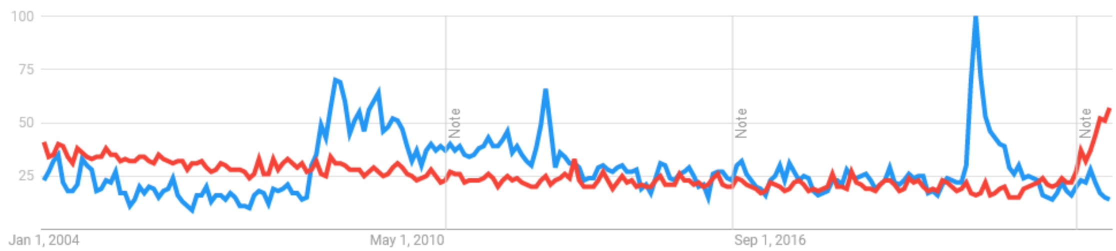


Figure 7: Google Searches for Unemployment Rate and CPI

6 Conclusion

In this paper, we have analyzed what determines household expectations. Using high-frequency identification, we test whether household expectations react to unemployment rate, initial jobless claims, GDP, CPI, and housing.

We find that households change their expectations in response to changes in labor market variables, but not in response to inflation, output, or housing. This response is not driven by the stock market. The responses are asymmetric: households become more pessimistic in response to negative information, but they do not become optimistic in reaction to positive information. Further, households only respond to large unanticipated shocks and

[18] We find a similar pattern if we instead look at searches for the word 'inflation' instead of CPI.

ignore smaller ones. Households in areas with higher local unemployment respond more to movements in national unemployment.

We also analyze the role of news in affecting household expectations. We examine articles in the *New York Times* and find that the number of articles related to inflation increases after its announcement, but find no change in coverage for other variables. We then examine news sentiment and show that household expectations are highly correlated with it. Then we formally test whether news sentiment changes in response to macroeconomic announcements. We find that CPI affects sentiment the most, followed by GDP. This suggests that the absence of a response of household expectations to other variables like inflation and GDP is not driven by lack of awareness about them. We also look directly at what things households are searching for in Google, and find that in normal times, searches for inflation exceed searches for unemployment. Unemployment becomes a concern during recessions, which is consistent with our earlier results. Thus, households may focus on the labor market the most because they understand it the best and because it is the largest part of their income.

So what are the policy implications of our results? The fact that households do not pay attention to CPI is perhaps not surprising because inflation was fairly stable in our time period. However, the fact that households do not pay attention to GDP but rather to unemployment rate suggests that perhaps the Fed could switch the output gap with the unemployment gap in the Taylor rule. Since GDP and unemployment rate are highly correlated and pro-cyclical, this should not be a problem from an implementation point of view. It would possibly help increase the response of households to monetary policy.

Finally, we suggest that our results provide a path for future research. While this paper represents a step forward in getting better estimates of household responses to macroeconomic announcements, these results could be improved with the use of panel dataset. Following the same household over time would increase confidence in the results. Further, it might be of interest to the Fed to ask for inflation or unemployment rate expectations separately. Future researchers should look at answering these question, perhaps by designing their own survey. Since we also find the results to be fairly persistent, we should also think about the implications this has for macroeconomic models.

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A Appendix

Table 10: Data on Announcements

Variable	Frequency	# Events	Mean	sd	Min	Max
Unemployment Rate	Monthly	120	6.95	1.87	4.10	10.20
GDP Growth (Advance)	Monthly	117	1.47	0.89	-0.10	4.20
CPI MoM	Monthly	120	0.13	0.35	-1.70	1.10
Housing Starts	Monthly	118	870	250	458	1323

Table 11: Bloomberg Summary Statistics

Surprise Variable	Mean	sd	Max	Min
Unemployment Rate	-.028	.157	-.5	.4
GDP Growth (Advance)	-.033	.371	-1.5	1.1
CPI (MoM)	-.010	.125	-.4	.4
Housing Starts	-6.3	63.65	-143	167