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Heterogeneity in Household Inflation Expectations and Monetary Policy[*]

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Abstract

We empirically characterize the heterogeneity in the conditional distribution of household inflation expectations across demographic groups using the Survey of Consumer Expectations and also investigate how monetary policy shocks affect the conditional distribution. We find that, across all the groups, the peak of the group-specific distribution of household inflation expectations aligns closely with the 2% target set by the Federal Reserve, but there is substantial heterogeneity both within and across groups, primarily on the right. However, in response to a contractionary monetary policy shock identified by high-frequency financial market responses, households overall adjust their inflation expectations significantly downwards. In addition, the magnitude of the reaction is more pronounced in the upper quantile of low income groups whose unconditional inflation expectations are less well anchored.

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1 Introduction

Household inflation expectations are closely watched by the Federal Reserve who seeks to manage them at a level close to the inflation target. Since the Federal Reserve announced the 2 percent target inflation rate in 2012, one-year ahead inflation expectations from consumer survey data have been generally stable until the post-COVID inflation.[1] For instance, the median forecast for one-year ahead inflation from the Survey of Consumer Expectations (SCE) by the Federal Reserve Bank of New York has been within the range of 2.3 percent to 3.4 percent during the period between June 2013 and December 2019. While the stability of inflation expectations is encouraging, the inflationary episode in the 1970s suggests that central banks cannot be complacent because the gradual drift in the near-term inflation expectations can signal the risk of losing the inflation anchor (Reis, 2021). Indeed, the one-year ahead inflation expectations measured by the Michigan Survey of Consumers (MSC) peaked at 10.4% in January 1980. Reis (2021) notes that this rapid rise in inflation expectations can be explained by the Federal Reserve's inability to reverse an upward drift inflation expectations that started from 1971. Hence, policymakers should pay attention to how effective monetary policy is to anchor near-term inflation expectations close to the central bank's target.

One challenge in assessing the effectiveness of monetary policy for stabilizing household inflation expectations is the substantial heterogeneity in inflation expectation across demographic or socio-economic groups of the population. As well summarized by D'Acunto et al. (2023), women tend to have higher inflation expectations than men. Also, low income and

[1] Near-term inflation expectations surged with rapid inflation beginning in 2021, but by late 2023, these expectations returned to levels close to those seen before COVID-19 as inflation declined.

less educated households tend to have higher inflation expectations than other groups. In addition, when we delve into the micro consumer survey data, we find that even households with similar demographic or socio-economic characteristics exhibit significant differences in inflation expectations. This within-group heterogeneity is greater in low income and less educated households. Understanding how monetary policy can influence the heterogeneity in household inflation expectations is important because changes in the cross-sectional distribution of inflation expectations can be informative about future shifts in inflation. For example, Reis (2021) shows that in the early 1970s, a change in right skewness in household inflation expectations in the U.S. was predictive of future inflation but he does not decompose the right tail part of household inflation expectations across different groups.

In this paper, we characterize the distribution of household inflation expectations conditional on observable demographic and socio-economic characteristics using survey data in the U.S. Our method allows us to analyze changes in the distribution of inflation expectations for different groups after controlling for group-specific heterogeneities. By taking into account potential confounding factors, we can evaluate the treatment effect of monetary policy on household inflation expectations more precisely.

To this end, we estimate a conditional quantile regression, which provides a flexible modeling of the conditional distribution of household inflation expectations. Specifically, we run the conditional quantile regression of one-year ahead inflation expectations from the survey data on demographic and socio-economic characteristics as well as some macroeconomic variables such as a monetary policy shock identified by high-frequency financial market developments from Bauer and Swanson (2023), CPI inflation, the unemployment rate, and gas price inflation. The demographic and socio-economic characteristics include income, homeownership, level of education, gender, the number of kids and adults in a household, age, region, numeracy score, and survey tenure. The conditional quantile regression is estimated using the SCE data published by the Federal Reserve Bank of New York. The monthly data cover the period from June 2013 to December 2019.[2]

In response to a contractionary monetary policy shock, we find that households adjust their inflation expectations downward. The monetary policy shock has generally bigger impacts on upper quantiles of inflation expectations than on lower quantiles except for near extreme quantiles like 5% and 95%, whose estimates are not precise.[3] That is, the upper quantiles of household inflation expectations are adjusted more than the lower quantiles. Specifically, the 25%, 50%, and 75% conditional quantile of household inflation expectations decrease by 0.548%p, 0.940%p, and 1.366%p, respectively. As policy tightening has a stronger effect in upper quantiles, the cross-sectional dispersion of the inflation expectations decreases: the estimated change in the interquartile range resulting from a one-unit monetary policy surprise is -0.818. In sum, following a contractionary monetary policy shock, the distribution of household inflation expectations shifts to the left and becomes more concentrated.

To investigate a potential heterogeneity in the response of household inflation expectations to the monetary policy shock, we run the conditional quantile regression of household inflation expectations on the monetary policy shock interacted with each of the demographic and socio-economic characteristics. Although the uncertainty surrounding the regression coefficients are somewhat larger in this alternative specification, we find similar patterns in the estimation results. In particular, a contractionary monetary policy shock is estimated to be more effective in stabilizing the upper quantile of inflation expectations in the low income group than the high income group.

As emphasized by Bauer and Swanson (2023), we reaffirm that orthogonalizing high-frequency financial market responses with respect to past macro and financial information is crucial for a well identified monetary policy shock. When we use the unorthogonalized

[2]The MSC provides a longer sample than the SCE, which dates back to late 1970s, but it does not have information on the numeracy or economic literacy of survey respondents. Since this is an important factor that determines the level of inflation expectations of a household, we chose to work with the SCE data. The cost of working with the SCE data is a shorter sample which starts only in 2013. We do a robustness check using the MSC data.

[3]Here and henceforth, unless specified otherwise, quantiles of household inflation expectations refer to quantiles of the distribution of household inflation expectations conditional on demographic and socio-economic characteristics as well as macroeconomic variables.

measure of a monetary policy shock in Bauer and Swanson (2023) that does not remove the component predictable by past macro and financial information, we do not obtain a significant and negative coefficient on the monetary policy shock measure in the quantile regression.

Regarding the distribution of household inflation expectations conditional on the demographic and socio-economic characteristics, we find that, across all the groups, the peak of the group-specific distribution of household inflation expectations aligns closely with the 2% target set by the Federal Reserve, but there is substantial heterogeneity in the left and right tails. The between-group heterogeneity primarily arises in the upper quantiles of household inflation expectations. In other words, while most households in each group hold inflation expectations close to the inflation target by the Federal Reserve, some groups have relatively more households predicting high inflation, which generates the between-group heterogeneity. The difference in the length of the right tails across groups is quite substantial, while the difference in the length of the left tails across groups is rather moderate.[4]

Income, education and gender are estimated to be important characteristics that are associated with the group-specific distribution of household inflation expectations. Households with low income or less education tend to predict higher inflation than households with high income or more education. However, the difference between groups is much bigger in upper quantiles than in lower quantiles. Compared to the households in the high income group, the households in the low income group predict higher inflation by 0.207%p at the 25% quantile but by 1.619%p at the 75% quantile. Households with at most high school diplomas predict higher inflation by 0.077%p than households with some college education or more at the 25% quantile but by 1.537%p at the 75% quantile. The same pattern is also observed when we compare female and male survey respondents. Women tend to predict higher inflation

[4]The heterogeneity we document is along the observable demographic and socio-economic household characteristics that we included in the conditional quantile regression. We note that the within-group heterogeneity across the observable characteristics can still be generated by some unobservable characteristics. We leave it for future research to explore the nature of the unobservable characteristics affecting household inflation expectations.

than men but the difference by gender is much bigger in the upper quantiles than in the lower quantiles. The female respondents predict higher inflation by 0.105%p than the male respondents at the 25% quantile but by 1.214%p at the 75% quantile. That is, some female respondents predicting relatively high inflation one year ahead are responsible for most of the difference in inflation expectations between men and women. The difference in the 25% quantile between the male and female group is not very large, although it is statistically significant.

Another important characteristic associated with the group-specific distribution of household inflation expectations is the economic literacy of the survey respondents. We find that a survey respondent with more correct answers to numeracy questions has lower inflation expectations than those with fewer correct answers. As with demographic and socio-economic characteristics, the effect of economic literacy is stronger in upper quantiles than in lower quantiles. Economic literacy is a powerful source of the heterogeneity in household inflation expectations, especially in upper quantiles. The survey respondents who answer correctly to none of the five numeracy questions predict higher inflation by 4.220%p at the 75% quantile than those with five correct answers.

We carry out several exercises to check the robustness of our main results. First, we re-do our analysis using the MSC data. We chose the SCE data as our baseline dataset to take into account the economic literacy of households. Even when the MSC data is used, we get qualitatively similar results to the baseline results despite that the economic literacy of households is not controlled for. Second, we estimate the conditional quantile regression on the sample that covers only the period when monetary policy was constrained by the zero lower bound (ZLB). This exercise is to check if unconventional monetary policy can also influence household inflation expectations. Then, we add the group-specific lagged inflation expectations to the quantile regression to allow for the dependence of household inflation expectations on prior beliefs on future inflation. Our main results are shown robust across these robustness check exercises.

Related Literature: This paper is related to a growing literature on exploring survey-based household inflation expectations. Weber et al. (2022) and Blinder et al. (2024) provide a comprehensive review of the literature and we will focus on papers examining the heterogeneity in inflation expectations specifically, which are most closely related to our paper.

Madeira and Zafar (2015) show a vast degree of the heterogeneity in household inflation expectation across demographic and socio-economic characteristics based on the MSC data. They find female respondents with low education level have a higher degree of heterogeneity in inflation expectations after controlling for publicly available information. Our finding of a higher within-group heterogeneity in this subgroup is consistent with their finding but we consider the treatment effect of a monetary policy shock in a quantile regression framework, which they do not consider. Armantier et al. (2021) analyze the SCE data to examine how the COVID-19 pandemic affected inflation beliefs across different households. They find a polarization in inflation beliefs at the onset of the pandemic with some households expecting high inflation and others expecting low inflation or deflation. Although highly educated (college diploma and above) and high numeracy respondents saw the pandemic largely as a deflationary demand shock, lowering their inflation expectations, the polarization in belief was rather uniform along other socio-demographic dimensions. They do not investigate the effect of monetary policy on inflation expectations as we do in this paper. Since the measure of monetary policy shock from Bauer and Swanson (2023) that we use is not available for the pandemic period, we cannot include the pandemic period in our analysis. Ahn et al. (2024) is most closely related to our paper by investigating the heterogeneous effect of monetary policy on household expectations across homeowners and renters based on both the MSC and the SCE data. They find that homeowners' inflation expectations are more responsive to monetary policy and explain their finding using a rational inattention model with two types of households-homeowners and renters. Unlike Ahn et al. (2024) we control many more demographic and socio-economic characteristics beyond homeownership and consider the distribution of inflation expectations not just the conditional mean.[5]

Our choice of relevant demographic and socio-economic characteristics are motivated by other papers. Burke and Manz (2014) emphasize the connection between economic literacy and inflation expectations. Kim and Binder (2023) find the learning-through-survey effect from the SCE data, which may contaminate the interpretation of the analysis based on the SCE data when this effect is not controlled. We include these variables on top of income, education, and gender discussed in Madeira and Zafar (2015).

Our paper is also related to D'Acunto et al. (2022), who study the effect of unconventional fiscal and monetary policies on managing household expectations using German survey data. While they find that the unexpected announcement of a value-added tax increase in Germany in 2005 to be implemented in 2007 significantly affected household inflation expectations and the willingness to purchase durable goods, they do not find a similar effect for the forward guidance on the monetary policy adopted by the ECB in 2013. In contrast, our result suggests that policy communications including forward guidance on the rate path can be effective in influencing household inflation expectations, especially at upper quantiles of the distribution. Our sample period includes the period when the federal funds rate was constrained by the effective lower bound when the policy shock reflects solely the effect of unconventional policies such as forward guidance and asset purchases.[6] Since D'Acunto et al. (2022) do not use a policy shock measure orthogonalized in the way of Bauer and Swanson (2023), their results are not directly comparable. If we use the unorthogonalized version of the monetary policy shock, our result is not much different from what they find, suggesting that the proper identification of a monetary policy shock can be important for assessing policy effectiveness

[5] We do not allow the quantile coefficient on a monetary policy shock to be different across groups unlike Ahn et al. (2024) in the baseline specification but we interact each characteristic one by one with the monetary policy shock in the alternative specification to check the robustness of our findings.

[6] The federal funds rate target was at the effective lower bound during about 30% of our sample period. Even after the federal funds rate target was lifted off the bound, our measure partially captures forward guidance but we do not separately identify the forward guidance factor during this off-the-bound period. To isolate the effect of unconventional monetary policies, we estimate the model using the MSC data for the period when federal funds rate was constrained by the effective lower bound and report the result in the online appendix.

in changing household inflation expectations.

In multiple waves of large online surveys that randomize information treatment on monetary policy, Knotek et al. (2024) find that numerical literacy is associated with the probability of hearing monetary policy news. The finding suggests that an important role of numeracy score in our study might be associated with different degrees of attention for monetary policy news or inflation. Using the survey of Canadian households, Kostyshyna and Peterson (2024) find that groups with the most unanchored inflation expectations respond more strongly to randomized information interventions on inflation. Similarly, we find that an unanticipated monetary policy tightening has a bigger impact on the upper quantiles of inflation expectations for groups more vulnerable to the unanchoring of inflation expectations.

Our paper is related to another growing literature using a quantile regression framework to estimate tail risks in macroeconomic outcomes (see Adrian et al., 2019, and López-Salido and Loria, 2024, among others). These papers use the time series of realized aggregate data and do not exploit cross-sectional distribution information, which we do by using the household survey data. Including the cross-sectional information in household survey data brings a challenge because most responses are likely to be rounded. We address this issue by using the "jittering" method in Machado and Silva (2005), which was originally developed for running quantile regression for discrete counting data. The jittering allows us to transform an integer response in the original data to a continuous real variable so that we can apply a standard quantile regression framework.

Our paper is organized as follows. Section 2 explains our empirical strategy by describing the underlying data and quantile regression framework. Section 3 reports empirical results, and Section 4 provides further discussions on the main findings. Section 5 concludes.

2 Empirical strategy

2.1 Baseline empirical model

We explore the characteristics of the conditional distribution of household inflation expectations using the conditional quantile regression. It allows for a flexible modeling of the conditional distribution of household inflation expectations beyond the conditional mean that the ordinary least squares regression provides (Koenker and Bassett, 1978).

Specifically, for $0 < \tau < 1$, the τ-th conditional quantile of household inflation expectations is described by the equation

$$Q_{y_{it}}\left(\tau | x_{it}, z_t, w_t\right) = \beta_{0,\tau} + x'_{i,t}\beta_{1,\tau} + z_t\delta_\tau + w'_t\gamma_\tau, \tag{1}$$

where $y_{i,t}$ is one-year ahead inflation expectations for household i in period t and $x_{i,t}$ includes dummy variables for income groups (low, middle, and high income groups), homeownership (owners and renters), education (at most high school diplomas and more than high school diplomas), gender (male and female), age groups (young $<$ 40 years old, middle-aged $\geq$ 40 years old and $<$ 60, and old $\geq$ 60 years old), and the region of primary residence (the West, Midwest, Northeast, and South), family sizes (the number of kids and adults in a household), survey tenure, and numeracy score.[7] We use the following group as the base group: high-income individuals, homeowners, those with education beyond high school, males, the younger generation, and those from the West. Dummy variables for this baseline group are therefore omitted. To capture the potentially non-linear effects of survey tenure and numeracy score, we include dummy variables for each value of survey tenure and numeracy score. Also, z_t is an externally-identified monetary policy shock and w_t includes macroeconomic variables such as aggregate CPI inflation, the unemployment rate gap measured by the deviation from the recent trend, and the gas price inflation rate.

[7] In the baseline dataset, the SCE, the questions on these characteristics are asked only to the first-time respondent. Hence, these variables should be time-invariant. However, the region of primary residence changes for a small set of the households so we allow $x_{i,t}$ to vary over time.

Conditional quantile regression is estimated using the R package `quantreg` (Koenker, 2022). The confidence intervals are computed using the xy-pair bootstrap, in which we resample from the $(x_{i,t}, z_t, w_t, y_{i,t})$ pairs to generate bootstrapped samples $\left(x^*_{i,t}, z^*_t, w^*_t, y^*_{i,t}\right)$ rather than resampling estimated residuals as in the standard bootstrap method. We then estimate the quantile regression coefficients $\hat{\beta}^*_{1,\tau}$, $\hat{\delta}^*_\tau$, and $\hat{\gamma}^*_\tau$ repeatedly and use the percentiles to construct confidence intervals. This is the most common resampling method in quantile regression (see Koenker, 2005).

The majority of household inflation expectations in the SCE are integers, which raises a technical problem in running the conditional quantile regression. We apply the jittering method of Machado and Silva (2005), or add random noises to integer inflation expectations observations, to address this problem. We explain the jittering method after providing the description of the data.

2.2 Alternative specification

While the baseline specification assumes that households share the common quantile regression coefficient on the monetary policy shock, they may react differently to the same monetary policy shock depending on their demographic and socio-economic characteristics. To explore how these features missing in the baseline specification influence quantile regression results, we run the quantile regression after allowing for the heterogeneous quantile response to the monetary policy shock across different demographic and socio-economic characteristics. We also estimate the conditional quantile regression allowing for differential responses across the survey tenure and the numeracy score.

To that end, we interact each characteristic individually with the monetary policy shock, one at a time, and estimate the conditional quantile regression again. Suppose that characteristic j is interacted with the monetary policy shock. Then, the equation for the heterogeneous quantile response to the monetary policy shock for characteristic j can be written as

$$Q_{y_{it}}(\tau|x_{it}, z_t, w_t) = \beta_{0,\tau} + x'_{i,t}\beta_{1,\tau} + z_t\delta_\tau + z_t x^j_{i,t}\zeta^j_\tau + w'_t\gamma_\tau, \tag{2}$$

where $x^j_{i,t}$ denotes the observation for characteristic j.

2.3 Data

We now introduce the survey data and describe the demographic characteristics and the macro variables including the monetary policy shock. An issue of the rounded responses in the survey data is discussed.

2.3.1 Household inflation expectations and demographic characteristics

For household inflation expectations, we primarily use the SCE data collected by the Federal Reserve Bank of New York along with their demographic characteristics. Every month, the SCE interviews approximately 1,300 household heads via the Internet. It has a rotating panel design where respondents participate in the panel for up to twelve months, with a roughly equal number rotating in and out of the panel each month. We do not utilize this rotating panel design in the analysis and pool observations of different households. The data is available since June 2013 and we use the sample up through December 2019, right before the coronavirus pandemic. Following the literature, we winsorize the dataset by dropping observations less than or equal to the 3% quantile and greater than or equal to 97% quantile for each of the major characteristics.[8]

The selection of the demographic and socio-economic characteristics in the conditional quantile regression was motivated by the findings in the literature but restricted by the data availability. The literature has found that household inflation expectations are different across demographic and socio-economic characteristics (see, for example, Bruine de Bruin et

[8] The winsorization results in a drop of about 5% in the lower and right tails, respectively, since observations are clustered at integers.

al., 2010; ; D'Acunto et al., 2023). In particular, D'Acunto et al. (2023) use the same dataset as ours, the SCE, and document stylized cross-sectional facts of household inflation expectations by demographic characteristics including gender, age, race, income, education, and Census region. We select all these demographic characteristics but race.[9] Ahn et al. (2024) found that homeownership plays a role in the response of household inflation expectations to monetary policy. Bruine de Bruin et al. (2010) found the marital status as important for household inflation expectations. We hypothesized that the marital status affects household inflation expectations because of the difference in the family size and composition, so we included related information such as the number of adults and kids.

Recent research revealed that household inflation expectations are influenced by daily economic activities such as grocery shopping and gasoline purchase (Coibion and Gorodnichenko, 2015; D'Acunto, Malmendier, Ospina, and Weber, 2021). However, the SCE does not collect information on shopping or gasoline buying experiences. As females are more likely to do the grocery shopping for their households than males (D'Acunto, Malmendier, and Weber, 2021), gender would explain some of the influence of shopping experiences on inflation expectations. Of course, in some households, males do most of the grocery shopping, which will generate within-group heterogeneity among female households. As in the case of the shopping experience and gender, some within-group heterogeneity we estimate could arise because of the omitted variables. Therefore, we try to be careful when interpreting the empirical results.

In addition to the household characteristics described above, we also considered survey tenure and numeracy score. Burke and Manz (2014) conduct a lab experiment to find that economic literacy contributes to the success of forecasting inflation as more literate subjects are better able to make use of given data and more likely to select highly relevant information. To replicate this result in our setting, we control for the economic literacy of survey respondents by including the numeracy score in the conditional quantile regression. The

[9] We do not include race since the racial differences can be smaller once we control for income, education and economic literacy. For some discussion in terms of income, see Lee (2022).

numeracy score is the number of correct answers to numeracy questions asked by the SCE. Given the nature of the numeracy questions, we consider the numeracy score as a measure for economic literacy of survey respondents.[10]

Kim and Binder (2023) find that survey respondents lower their inflation expectations as they repeatedly participate in the survey using the SCE data and attribute their result to the learning-through-survey effect. Following them, we control for the survey tenure, which is the number of times each respondent has finished the survey including the last one he or she participates in. As in Kim and Binder (2023), we include dummy variables for each round of the survey per household to capture potential nonlinearity in the effect of the learning-through-survey.

Table 1 provides the descriptive statistics of demographic and socio-economic characteristics we consider in the empirical analysis.

2.3.2 Monetary policy shocks and macro variables

We include the monetary policy shock in the conditional quantile regression, which consists of monetary policy surprises identified by Bauer and Swanson (2023) using high-frequency financial market responses (Eurodollar futures contracts) around FOMC announcements. Their monetary policy shock addresses a concern raised for the monetary policy shock identified using high-frequency surprises previously in the literature.

In the literature, the monetary policy shock identified using high-frequency surprises was shown to be predictable with macroeconomic and financial data that pre-dates the FOMC announcement, which raised a doubt about its exogeneity. Bauer and Swanson (2023) propose to orthogonalize the monetary policy surprises in terms of information available in the past macroeconomic and financial data to make it exogenous.[11] We use the first lag of the

[10] The SCE asked five numeracy questions until April 2015 when it started to ask two more numeracy questions. We use only the first five numeracy questions for analysis to maximize the sample period. The numeracy questions by the SCE are provided in the online appendix.

[11] They also provide the monetary policy shock series that was not orthogonalized in terms of predictability, with which we do an extra analysis to check how its effect is different from the baseline effect of the orthogonalized shock.

monetary policy shock to make sure that all the survey respondents have a chance to observe a new FOMC announcement.

Lastly, we control for some macro variables. CPI inflation is the year-on-year rate of change in the CPI. The unemployment gap of a given month is the gap between the unemployment rate of the month and the twelve-month average of the unemployment rate up through the previous month. We include the second lag for CPI inflation and the unemployment rate gap to make sure that all the survey respondents have a chance to observe the announcement of new information on inflation and unemployment. Gas price inflation is the year-on-year rate of change in the gas price (US All Grades Conventional Gas Price).

2.3.3 Jittering

One issue with using the household survey data in the quantile regression is that solicited values of inflation expectations are often integers. The SCE solicits one-year ahead inflation expectations by first asking whether a respondent thinks that there will be inflation or deflation over the next 12 months and then by asking what he or she expects the rate of inflation or deflation to be over the next 12 months.[12] The survey respondent can answer any numbers, integer or non-integer, but more than 90% of the answers are an integer in our sample. This is problematic when running conditional quantile regressions as well as computing unconditional quantiles since the quantiles do not exhibit so much variation. More importantly, it violates the sufficient condition for the asymptotically valid inference of the conditional quantile regression that the conditional probability density function be continuous (Machado and Silva, 2005).

To address this issue, we *jitter* the integer data of inflation expectations, or add a random noise to the integer data, and construct a continuous variable whose conditional quantiles

[12] The SCE also asks the probability distribution of one-year ahead inflation, but we do not use that information as explanatory variables in the quantile regression in this study.

have a one-to-one relationship with the conditional quantiles of the integer data as follows:

$$\hat{y}_{i,t} = y_{i,t} + \epsilon_{i,t}, \tag{3}$$

where $\epsilon_{i,t}$ is drawn from a uniform distribution $U(-0.5, 0.5)$. Explicitly or implicitly, the respondents are likely to round their expectations to the nearest integer to answer. Therefore, the jittering process can be thought of replicating this mental process of approximation. It is also similar to the linear interpolation of the empirical distribution of inflation expectations used by the SCE to compute the median and the quantiles. Since the coefficient estimates on jittered data depend on specific realizations of the added noise, we generate multiple (500) jittered samples using equation (3) and average the estimates across them to improve the efficiency of our estimator.

We draw the random noise for jittering from a uniform distribution. However, households may vary in their levels of uncertainty about future inflation based on demographic characteristics. In particular, as found by Burke and Manz (2014), economic literacy can influence how households gather and use information, thereby affecting their uncertainty regarding future inflation. To account for this possibility and to test the robustness of our main result, we incorporate group-specific heteroskedasticity of the jittering noise based on households' numeracy scores and re-estimate the conditional quantile regression. The method to compute group-specific heteroskedasticity is described in Section 3.3.2.

3 Empirical results

This section reports the estimation results of the conditional quantile regressions and discusses the results.

3.1 Baseline specification

3.1.1 Coefficient estimates

Figures 1 and 2 present the coefficient estimates for a set of the quantiles ranging from 5% to 95%. The bands around the point estimates indicate the 90% and 95% confidence intervals. For reference, we also estimate the OLS of the same specification and report its coefficient estimates using the horizontal dashed lines. Tables 2 and 3 report the coefficient estimates and their 90% confidence intervals at the 25%, 50%, and 75% quantile together with the OLS estimates and their two-standard deviation confidence intervals.

Let us first look at the coefficient estimates on the monetary policy shock. In response to a contractionary monetary policy shock, we find that most of the households adjust their inflation expectations significantly downward. The magnitude of the effect of the monetary policy shock is however substantially different across the quantiles. Except for the left and right extreme tail (5% and 95%), the monetary policy shock has bigger impacts on upper quantiles of inflation expectations than on lower quantiles. That is, the upper quantiles of household inflation expectations are adjusted by more than the lower quantiles. For example, the 25%, 50% and 75% conditional quantile of household inflation expectations decreases by 0.548%p, 0.940%p, and 1.366%p, respectively. Since the dependent variable of the conditional quantile regression is the level of inflation expectations, not the revision in inflation expectations, the evidence does not tell us that individual households with inflation expectations at each quantile adjust their inflation expectations by the reported estimates. However, the result implies that overall the conditional distribution of household inflation expectations shifts to the left and, at the same time, the upper quantiles shrink in response to a contractionary monetary policy shock.

An increase in past realized inflation correlates with heightened household inflation expectations at lower quantiles, though the effect is quantitatively small across all quantiles. An increase in the unemployment gap is associated with a downward adjustment of household inflation expectations across all quantiles, with a more pronounced impact at higher quantiles. For instance, a 1% increase in the unemployment gap is associated with a reduction of household inflation expectations by 0.379%p, 0.656%p, and 0.884%p at the 25%, 50%, and 75% quantile, respectively. It is estimated that a rise in gas price inflation over the past year is linked to an upward adjustment of household inflation expectations, aligning with the findings of Coibion and Gorodnichenko (2015), although the quantitative magnitude is smaller in our sample.[13]

Now we discuss the estimation results of the coefficients on the demographic and socio-economic factors. Income is estimated to be an important demographic characteristic that determines the group-specific distribution of household inflation expectations. Households with low income tend to predict higher inflation than households with high income across all the quantiles. However, the difference between income groups is much bigger in upper quantiles than in lower quantiles. Compared to the households in the high income group, the households in the low and middle income group predict higher inflation by 0.207%p and 0.080%p, respectively, at the 25% quantile of inflation expectations while by 1.619%p and 0.595%p, respectively, at the 75% quantile. The OLS estimate of the coefficient on the low and middle income group is 1.318 and 0.660, respectively, which would ignore these differences in the between-income group difference across the quantiles.

Education also plays an important role in determining the conditional distribution of household inflation expectations. Except for the left tail, households with less education (at most high school diplomas) are estimated to predict higher inflation than households with more education (more than high school diplomas). Again, the difference between the less educated and more educated households is bigger in the upper quantiles than in the lower quantiles. The households with less education predict higher inflation by 0.077%p, 0.491%p, and 1.537%p at the 25%, 50%, and 75% quantile, respectively, than the households with more education. The OLS estimate of the coefficient on the dummy variable for the less educated

[13] In particular, a substantial decline in the oil price during 2014-2016 period did not lower household inflation expectations significantly, weakening the correlation between gas price inflation and household inflation expectations in our sample period.

group is 0.866, which is bigger than the coefficient at the 25% and 50% quantile but smaller than the coefficient at the 75% quantile.

The same pattern of the heterogeneity in household inflation expectations also appears for gender. Females tend to predict higher inflation than males but the difference between females and males is much bigger in the upper quantiles than in the lower quantiles. The female respondents predict higher inflation by 0.105%p, 0.440%p, and 1.214%p at the 25%, 50% and 75% quantile, respectively, than the male respondents. That is, some female respondents predicting relatively high inflation one year ahead are responsible for most of the difference in inflation expectations observed between the male and female group.

Though a bit weaker than for the other demographic characteristics we discussed above, we observe the same pattern of heterogeneity for homeownership. Except for the left tail, renters are estimated to predict higher inflation than homeowners. However, the difference between the renters and homeowners is bigger in the upper quantiles than in the lower quantiles. The renters predict higher inflation by 0.028%p, 0.114%p, and 0.331%p at the 25%, 50%, and 75% quantile, respectively, than the homeowners.

Figure 2 confirms that the pattern of the heterogeneity in household inflation expectations discussed above for three major quantiles, along income, homeownership, education and gender, holds across the whole distribution.

The results regarding the other characteristics are presented in the online appendix. It is estimated that the number of kids and adults in a household and age have a similar, though a bit weaker, pattern of the heterogeneity in household inflation expectations.

Another important characteristic associated with the group-specific distribution of household inflation expectations is the economic literacy of the survey respondents. As the coefficient estimates on the numeracy score in Table 3 show, a survey respondent with a high numeracy score has lower inflation expectations than those with a low numeracy score.[14] However, the effect is not linear. Compared to the survey respondents who do not answer

[14] We present the coefficient estimates on the numeracy score and the survey tenure visually in the online appendix.

correctly to any of the numeracy questions, those respondents with one or two correct answers do not predict significantly lower inflation expectations while those respondents with three or more correct answers predict significantly lower inflation expectations. Interestingly, as with demographic and socio-economic characteristics, the effect of economic literacy is stronger in upper quantiles than in lower quantiles. The effect can be quite large. Compared to those with no correct answers, those households with five correct answers have one-year inflation expectations lower by about 4.220%p at the 75% quantile. This result can be understood based on the finding of Burke and Manz (2014) that more literate respondents are better able to make use of given data and more likely to select highly relevant information. Similarly, Knotek et al. (2024) find that respondents with higher numeracy score are likely to pay more attention to monetary policy news.

Consistent with the finding of Kim and Binder (2023), the respondents with more rounds of the survey participation tend to have lower inflation expectations. Interestingly, the learning-through-survey effect is stronger in upper quantiles than in lower quantiles. Compared to the fresh participants in the survey, Table 3 reports that the households in the second round of the survey predicts lower inflation by 0.135%p, 0.317%p, and 0.667%p at the 25%, 50%, and 75% quantile, respectively, while those in the twelfth round of the survey predicts lower inflation by 0.290%p, 0.709%p, and 1.459%p at the 25%, 50%, and 75% quantile, respectively. The marginal effect of one more round of survey participation is somewhat diminishing in the survey tenure, which is aligned with the declining learning-through-survey effects found by Kim and Binder (2023). The diminishing effect is especially visible at the 75% quantile.

3.1.2 Predicted conditional quantiles

By applying the conditional quantile regression to a fine grid of probabilities, we can approximate the conditional distribution of household inflation expectations with a high degree of precision. This approximation provides valuable insights into the structure of the conditional distribution of household inflation expectations. To highlight this, we compute the predicted conditional quantiles of inflation expectations across 24 demographic groups based on the previously estimated conditional quantile regressions.[15]

Figure 3 presents the predicted conditional quantiles in December 2019 for the groups. We find that the heterogeneity in household inflation expectations is not large in the lower quantiles but much larger in the upper quantiles. Compared to the group of the male households in the high income group and with more education and homeownership (denoted as Group 24 in the figure), the group of the female renter in the low income group and with less education (denoted as Group 1 in the figure) has higher inflation expectations across most part of the distribution. However, their difference is dramatically enlarged in the upper quantiles.

The same pattern that the between-group heterogeneity is small in lower quantiles but large in upper quantiles is also observed in the other time periods. Figure 4 presents the time series of the predicted conditional quantile of one-year ahead inflation expectations across the demographic groups for selected probabilities. As we discussed above, the heterogeneity across the groups is much larger for the 75% quantiles than for the 25% quantiles.

We also find that the high income group's median inflation expectations are strongly correlated (correlation coefficient of 0.71) with the five year inflation compensation measure from the Treasury Inflation-Protected Securities (TIPS) market data while the low income group's median inflation expectations are less so (correlation coefficient of 0.32).[16] The finding suggests that households who can hedge inflation risk through TIPS may have better

[15]The composition of the 24 demographic groups is presented in the online appendix. The predictied quantiles are calculated as

$$\hat{Q}_{y_{it}}\left(\tau|x_{it}, z_t, w_t\right) = \hat{\beta}_{0,\tau} + x'_{i,t}\hat{\beta}_{1,\tau} + z_t\hat{\delta}_\tau + w'_t\hat{\gamma}_\tau.$$

This is analogous to the prediction in the conditional mean regression

$$\hat{y}_{it} = \hat{\beta}_{0,\mathrm{OLS}} + x'_{i,t}\hat{\beta}_{1,\mathrm{OLS}} + z_t\hat{\delta}_{\mathrm{OLS}} + w'_t\hat{\gamma}_{\mathrm{OLS}},$$

where OLS indicates the OLS estimate, and indeed it is commonly used in the linear quantile prediction. For example, Adrian et al. (2019) used the same specification for the quantile prediction.

[16]The difference in the correlation between the 25% quantile of group inflation expectations is smaller because there are not much differences in inflation expectations between groups at lower quantiles.

anchored inflation expectations, though the direct evidence for this hypothesis will require the analysis of TIPS holdings by different income groups. Relatedly, Blinder et al. (2024) suggest that households who are more confident about the central bank's ability to keep inflation near the target inflation rate are less likely to respond to short-term economic news.

Since the predicted conditional quantiles in Figure 3 can be considered as the inverse function of the empirical cumulative distribution function for each group, we can use the uniform distribution inversion to generate random numbers from the conditional distribution of household inflation expectations for each group. The conditional density function can be estimated based on the generated random numbers using the kernel density estimation.

Figure 5 presents the conditional density function of household inflation expectations for different demographic and socio-economic groups. In all groups, the peak of the group-specific distribution of household inflation expectations aligns closely with the 2% target by the Federal Reserve. However, there is substantial heterogeneity in both the left and right tails. Most notably, the heterogeneity between groups mainly occurs in the upper quantiles of household inflation expectations. This implies that while many of the households of each group hold inflation expectations consistent with the Federal Reserve's inflation target, some groups have a higher number of households that predict elevated inflation, leading to the between-group heterogeneity. There is a considerable difference in the length of the right tails among the groups, whereas the difference in the left tails is relatively minor.

3.2 Alternative specification

We then investigate whether the effect of the monetary policy shock is heterogeneous across demographic and socio-economic characteristics. The baseline specification does not allow for a heterogeneous quantile response to a monetary policy shock across different groups sorted by demographic and socio-economic characteristics. We now run the quantile regression with the monetary policy shock interacted with demographic and socio-economic characteristics one at a time for a robustness check.[17]

Figure 6 shows the response of inflation expectations by different income groups. As in the baseline specification, we observe a significant and negative response of the household inflation expectation to a monetary policy shock. Interestingly, the negative response is most pronounced in the upper quantiles of the low income group. The finding suggests that a contractionary monetary policy shock is most effective in lowering inflation expectations of low income households who tend to have higher inflation expectations than others in the same income group. Overall, our analysis supports the view that a contractionary monetary policy shock either through conventional (e.g., change in the federal funds rate target) or unconventional (e.g., forward guidance) policies can lower inflation expectations of the households who are most vulnerable to the loss of inflation anchor.[18]

The point estimates suggest similar differences in terms of other demographic characteristics: renters, less educated households, and females are more sensitive to the monetary policy shock than homeowners, more educated households, and males, respectively. However, the difference across demographic groups divided by homeownership, education, and gender is not significant at 25%, 50%, and 75% quantile. We report the estimation results for these other characteristics in the online appendix.

3.3 Robustness checks

We carry out several exercises to check the robustness of our main results and report the results in this section.

[17] We interact the monetary policy shock with the characteristics one at a time because of the concern on the sample size.

[18] The response of the high income group to a monetary policy shock is relatively muted. Since the high income group's inflation expectations are well correlated with the inflation compensation from TIPS and better anchored, we conjecture that their inflation expectations may be less sensitive to any news than other groups along the observation made by Blinder et al. (2024).

3.3.1 MSC

As a robustness check, we estimate the conditional quantile regression on the MSC data with a similar specification to the baseline specification on the SCE data. To conserve the space, we describe the exact specification for the MSC data in the online appendix and also report the results on the MSC data there.

The main result is qualitatively similar to the baseline result. Especially, we find that the between-group heterogeneity is mostly driven by the difference in upper quantiles of household inflation expectations. As in the baseline result, the peak of the group-specific distribution of household inflation expectations is located closely to each other, slightly above the 2% target by the Federal Reserve.

3.3.2 Jittering

Recall that in the baseline empirical analysis, we jitter integer inflation expectations by adding a random noise from a uniform distribution over $(-0.5, 0.5)$. However, depending on their demographic characteristics, households are likely to differ in the degree of uncertainty they have about future inflation. In particular, as found by Burke and Manz (2014), economic literacy could affect how households choose and use information, and thus how uncertain they are about future inflation. Failure to account for such heterogeneity could be a source of bias in the coefficient estimates. We thus account for heterogeneity in the degree of uncertainty in jittering using the density forecast of future inflation elicited by the SCE.

We use two different methods to get the heteroskedasticity of the jittering noise based on the dispersion of the density forecast for each numeracy score group. The SCE elicits the density forecast of one-year ahead inflation from households by asking them to assign percent chances over bins of the rate of inflation over the next 12 months, and reports the interquartile range and variance of the density forecast. We use the two statistics to compute the group-specific heteroskedasticity. In the first method, we use the interquartile range. Let us denote the interquartile range of the period-t density forecast of household i with numeracy score s by

$\widehat{iqr}_{i,s,t}$. We then compute the median of $\widehat{iqr}_{i,s,t}$ across all the households with numeracy score s, which measures the dispersion of the jittering noise for this group of the households. Let us denote it by $\widehat{iqr}_{s,t}$. We draw the jittering noise from a uniform distribution $U(-\widehat{iqr}_{s,t}, \widehat{iqr}_{s,t})$ for households in group s. In the second method, we use the standard deviation of the density forecast. Let us denote the standard deviation of household i with numeracy score s by $\hat{\sigma}_{i,s,t}$, which is the square root of the variance reported by the SCE. We compute the median of $\hat{\sigma}_{i,s,t}$ across all the households with numeracy score s, which is denoted by $\hat{\sigma}_{s,t}$. Then, we draw the jittering noise from a normal distribution with mean 0 and standard deviation $\hat{\sigma}_{s,t}$ for households in group s. Since the density forecast has substantial noises, we do not use the household-level density forecast to compute household-level dispersion of the jittering noise.

In both cases, the coefficient estimates are similar to those of the baseline analysis. The results are presented in the online appendix.

3.3.3 Unconventional monetary policy

The monetary policy shock identified by Bauer and Swanson (2023) encompasses both conventional and unconventional monetary policy shocks. To investigate whether unconventional shocks influenced household inflation expectations similarly to conventional shocks, we conduct an analysis focused on the period when the Federal Funds Rate was constrained by the ZLB. To use a sufficiently large sample for estimation, we use the MSC data for the period from December 2008 through December 2015 rather than the SCE data.[19]

The coefficient estimates for the monetary policy shock in both the full and ZLB samples, as reported in the online appendix, are qualitatively similar, though smaller in magnitude for the ZLB sample. This suggests that unconventional monetary policy - such as forward guidance during the ZLB period - was also effective in influencing household inflation expectations.

[19]The SCE data was not available before June 2013. Since the MSC does not provide information on numeracy or economic literacy, the robustness exercise does not control for it. Also, it includes a dummy variable for repeat participants as survey respondents can participate in the survey at most twice in the MSC. The exact specification for this robustness exercise is described in the online appendix.

3.3.4 Lagged inflation expectations

While the baseline specification of the conditional quantile regression does not allow for the dependence on prior inflation expectations of each household, it is possible that households form expectations of future inflation based on past beliefs. To explore this possibility, we add 12-month lagged expected inflation for the demographic group to which each household belongs.[20]

Our findings reveal that the households in lower quantiles show limited dependence on their group's lagged inflation expectations, indicating low persistence in their inflation expectations. On the contrary, households in higher quantiles exhibit a stronger dependence on their group's lagged inflation expectations, suggesting a high degree of persistence in inflation expectations: those households who predict high inflation also did so 12 months back.

4 Discussion

In this section, we further discuss our main results.

Our empirical analysis suggests that monetary policy is effective in stabilizing household inflation expectations. Negative coefficient estimates on the monetary policy shock imply that, following a contractionary monetary policy shock, the distribution of household inflation expectations shifts to the left, which indicates a downward adjustment of inflation expectations by households. Moreover, since the coefficient estimates on the monetary policy shock are more pronounced in upper quantiles than in lower quantiles, the distribution's right tail is estimated to move further left than the left tail, resulting in a leftward contraction of the distribution.

To quantify the effect of the monetary policy shock on the shape of the distribution of household inflation expectations, we can compute a change in the interquartile range. The

[20]We use the same 24 grouping as above. The composition of the groups is presented in the online appendix. We do not condition on each household's own 12-month lagged inflation expectations because of the attrition of the survey sample of the SCE. To save the space, we report the estimation result in the online appendix.

conditional quantile regression equation (1) implies that the interquartile range conditional on x_{it}, z_t, and w_t is

$$\begin{aligned} IQR_{y_{it}}(x_{it}, z_t, w_t) &= Q_{y_{it}}(0.75|x_{it}, z_t, w_t) - Q_{y_{it}}(0.25|x_{it}, z_t, w_t) \\ &= (\beta_{0,0.75} - \beta_{0,0.25}) + x'_{it}(\beta_{1,0.75} - \beta_{1,0.25}) + z_t(\delta_{0.75} - \delta_{0.25}) + w'_t(\gamma_{0.75} - \gamma_{0.25}). \end{aligned}$$

It follows that the effect of a one-unit monetary policy surprise on the interquartile range, with other factors held fixed, is

$$IQR_{y_{it}}(x_{it}, z_t = 1, w_t) - IQR_{y_{it}}(x_{it}, z_t = 0, w_t) = \delta_{0.75} - \delta_{0.25}.$$

The coefficient estimates reported in Table 2 indicate that the estimated change in the interquartile range resulting from a one-unit monetary policy surprise is $-1.366 + 0.548 = -0.818$, which is negative. This result suggests that a contractionary monetary policy shock reduces the dispersion of household inflation expectations. Policy tightening has a stronger effect in upper quantiles thereby decreasing the cross-sectional dispersion of the inflation expectations. Given the linear structure of the quantile regression, a monetary easing would, conversely, lead to an increase in the dispersion.

Previous studies find that monetary policy communications or forward guidance have limited effects on household inflation expectations (see, for example, D'Acunto et al., 2022, and Coibion et al., 2023). However, some research examining inflation expectations across heterogeneous household characteristics highlights the role of monetary policy in the formation of their inflation expectations. For example, Ahn et al. (2024) find that homeowners notably reduce their inflation expectations in response to contractionary monetary policy including forward guidance on the future interest rate, while renters show less responsiveness. Kostyshyna and Petersen (2024) reveal that the groups who typically have the most unanchored inflation expectations, such as households with lower education levels, respond more strongly to randomized information interventions in terms of inflation. We complement the literature by estimating the effect of the monetary policy shock on the shape of the distribution of household inflation expectations.

Our paper also differs from prior research that examines the impact of monetary policy communications on household inflation expectations (see, for example, Coibion et al., 2023 and Kostyshyna and Petersen, 2024). This body of work generally uses randomized information treatments to assess the effects of communicating policy goals and inflation information rather than actual policy actions by central banks. In contrast, our study uses policy surprises identified through high-frequency changes in asset prices following monetary policy announcements, capturing not only policy communications but also policy actions like interest rate adjustments. Thus, we assess the combined impact of standard monetary policy actions alongside public communications.

We also reaffirm the importance to remove the component in monetary policy surprises based on high-frequency financial market data predictable by pre-FOMC announcement information, to isolate exogenous variations as shown by Bauer and Swanson (2023). When the orthogonalized monetary policy shock in the baseline specification is replaced with the unorthogonalized monetary policy shock by Bauer and Swanson (2023), household inflation expectations show no significant response across quantiles.[21] This suggests that households do not significantly adjust their inflation expectations downward following an increase in the unorthogonalized monetary policy shock, as they recognize that an expansionary economic condition justifies the FOMC decision to raise the policy rate.

Recent studies, including Bachmann et al. (2015), Coibion et al. (2023), and Kostyshyna and Petersen (2024), show that households with higher inflation expectations are less likely to spend on goods than those with lower inflation expectations. Our findings on the variation in inflation expectations across household demographic characteristics may have implications for differences in consumption patterns across these same demographics. We leave further investigation to future research.

[21] We present the result in the online appendix to save the space.

Lastly, our findings suggest that after controlling for a wide range of demographic and socio-economic characteristics, including economic and financial literacy, substantial within-group and between-group heterogeneity remains. The specifics of targeted communication strategies may be crucial, since inflation expectations are unlikely to shift materially following monetary policy communications if they simply aim to fill the information gaps among demographic groups or address the lack of attention of the households.

5 Conclusion

Whether or not household inflation expectations are well anchored at the central bank's target is an important issue for monetary policy. The heterogeneity of inflation expectations across different demographic and socio-economic groups poses a challenge in assessing the degree of anchoring. We empirically characterize the heterogeneity in the conditional distribution of household inflation expectations across the demographic groups using the SCE data and also investigate how a monetary policy shock affects this conditional distribution. Our findings are somewhat encouraging for the current practice of monetary policy. We find that, across all the groups, the mode of household inflation expectations aligns closely with the 2% target by the Federal Reserve.

However, there is substantial heterogeneity in both within and across groups, primarily on the right tail. Nonetheless, in response to a contractionary monetary policy shock, households overall adjust their inflation expectations significantly downward at every quantile. This finding implies that monetary policy is effective in stabilizing inflation expectations to some degree in spite of significant heterogeneities in the level of inflation expectations among households. Further improving the degree of stability in inflation expectations would require closing the gap between different households, for which we need a deeper study on the source of the heterogeneity.

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Table 1: Descriptive Statistics of the SCE Data

(a) Income ($)	<10K	<20K	<30K	<40K	<50K	<60K	<75K	<100K	<150K	<200K	≥200K
Density (%)	2.8	6.4	8.0	8.3	9.1	9.0	12.5	14.6	15.7	7.0	6.5
Income Group	Low income					Middle income			High income		
Group density (%)	34.7					36.1			29.2		

	(b) Homeownership		(c) Gender		(d) Education	
	Homeowners	Renters	Male	Female	High school or less	Some college or more
Density (%)	73.8	26.2	52.1	47.9	11.3	88.7

	(e) Number of kids in a household					(f) Number of adults in a household				
	1	2	3	4	≥5	1	2	3	4	≥5
Density (%)	68.3	13.6	12.3	4.2	1.6	26.1	55.1	12.5	4.2	2.0
Cumulative density (%)	68.3	81.9	94.2	98.4	100.0	26.1	81.2	93.7	98.0	100.0

	(g) Age		
	Young (≤40 years old)	Mid-aged (≥40 and ≤60 years old)	Old (> 60 years old)
Density (%)	29.5	40.1	30.4

	(h) Region of primary residence			
	Midwest	Northeast	South	West
Density (%)	23.3	19.6	34.2	23.0

(i) Numeracy score	0	1	2	3	4	5
Density (%)	0.4	2.6	8.1	17.8	30.9	40.3
Cumulative density (%)	0.4	2.9	11.0	28.9	59.7	100.0

(j) Survey tenure	1	2	3	4	5	6	7	8	9	10	11	12
Survival rate (%)	100.0	91.3	87.5	84.0	78.5	73.8	70.1	65.9	61.4	55.9	48.3	36.0

Notes: All respondents are asked in their first survey about demographic characteristics such as (a) income, (b) homeownership, (c) gender, (d) education, (e) number of kids and (f) adults in their households, (g) age, and (h) region of primary residence, and asked to answer (i) numeracy questions. The descriptive statistics on characteristics from (a) income through (i) numeracy score is at the respondent level, whose total number is 12,600. The total number of observations is 86,961. Since the attrition rate of the respondents is similar across the demographic characteristics, the composition of the monthly sample is similar over time. Some respondents change the region of their primary residence, in which case each of their answers is counted separately, despite that the SCE questionnaire reports that the question on the primary residence is asked only at the first interview. There are only 127 of such cases (about 1.0% of all the respondents).

Table 2: Estimation results 1: baseline specification

Quantiles	25%	50%	75%	OLS
(Intercept)	**1.690**	**4.119**	**7.645**	**4.953**
	(1.156, 2.301)	(3.581, 5.488)	(6.419, 9.762)	(4.452, 5.454)
Monetary policy shock (L1)	**-0.548**	**-0.940**	**-1.366**	**-1.331**
	(-0.984,-0.109)	(-1.545,-0.388)	(-2.358,-0.325)	(-2.255,-0.408)
CPI inflation (L2)	**0.054**	**0.017**	**0.000**	**0.006**
	(0.027, 0.080)	(-0.016, 0.051)	(-0.054, 0.063)	(-0.047, 0.060)
Unemployment rate gap (L2)	**-0.379**	**-0.656**	**-0.884**	**-0.739**
	(-0.445,-0.312)	(-0.736,-0.568)	(-1.040,-0.739)	(-0.866,-0.612)
Gas price inflation	**0.003**	**0.005**	**0.004**	**0.005**
	(0.002, 0.005)	(0.003, 0.006)	(0.001, 0.007)	(0.002, 0.007)
Low income	**0.207**	**0.646**	**1.619**	**1.318**
	(0.172, 0.243)	(0.596, 0.700)	(1.498, 1.730)	(1.245, 1.390)
Mid income	**0.080**	**0.243**	**0.595**	**0.660**
	(0.052, 0.111)	(0.208, 0.277)	(0.526, 0.653)	(0.595, 0.725)
Renters	**0.028**	**0.114**	**0.331**	**0.352**
	(-0.009, 0.064)	(0.067, 0.163)	(0.242, 0.418)	(0.286, 0.417)
High school or less	**0.077**	**0.491**	**1.537**	**0.866**
	(0.016, 0.135)	(0.400, 0.578)	(1.324, 1.745)	(0.779, 0.953)
Female	**0.105**	**0.440**	**1.214**	**1.076**
	(0.078, 0.132)	(0.397, 0.479)	(1.139, 1.299)	(1.022, 1.130)
Number of kids	**0.023**	**0.068**	**0.121**	**0.093**
	(0.007, 0.038)	(0.050, 0.084)	(0.094, 0.147)	(0.064, 0.121)
Number of adults	**0.006**	**0.020**	**0.050**	**0.026**
	(-0.002, 0.014)	(0.011, 0.027)	(0.026, 0.078)	(0.013, 0.038)
Middle-aged	**0.269**	**0.422**	**0.629**	**0.629**
	(0.238, 0.304)	(0.379, 0.463)	(0.561, 0.705)	(0.563, 0.695)
Old	**0.512**	**0.671**	**0.882**	**0.911**
	(0.474, 0.550)	(0.624, 0.712)	(0.804, 0.967)	(0.836, 0.986)
Midwest	**-0.082**	**-0.133**	**-0.239**	**-0.239**
	(-0.117,-0.038)	(-0.182,-0.083)	(-0.322,-0.154)	(-0.314,-0.164)
Northeast	**-0.117**	**-0.243**	**-0.424**	**-0.310**
	(-0.154,-0.079)	(-0.283,-0.198)	(-0.512,-0.346)	(-0.388,-0.231)
South	**-0.028**	**0.009**	**0.076**	**0.079**
	(-0.064, 0.010)	(-0.033, 0.059)	(-0.006, 0.175)	(0.010, 0.149)

Notes: Numbers in the parentheses represent 90% confidence intervals. The dummy variables are omitted for high income, homeowners, more education, male, young, living in the West, first-time survey respondents, and no correct numeracy questions.

Table 3: Estimation results 2: baseline specification

Quantiles	**25%**	**50%**	**75%**	**OLS**
Tenure 2	**-0.135**	**-0.317**	**-0.667**	**-0.521**
	(-0.192, -0.070)	(-0.413, -0.238)	(-0.842, -0.494)	(-0.629, -0.413)
Tenure 3	**-0.141**	**-0.390**	**-0.867**	**-0.682**
	(-0.205, -0.082)	(-0.474, -0.309)	(-1.034, -0.689)	(-0.791, -0.573)
Tenure 4	**-0.163**	**-0.452**	**-1.047**	**-0.887**
	(-0.230, -0.102)	(-0.534, -0.372)	(-1.206, -0.872)	(-0.997, -0.777)
Tenure 5	**-0.178**	**-0.478**	**-1.087**	**-0.960**
	(-0.243, -0.127)	(-0.566, -0.394)	(-1.252, -0.918)	(-1.073, -0.848)
Tenure 6	**-0.207**	**-0.542**	**-1.164**	**-1.023**
	(-0.271, -0.150)	(-0.623, -0.447)	(-1.308, -1.005)	(-1.137, -0.908)
Tenure 7	**-0.231**	**-0.570**	**-1.208**	**-1.064**
	(-0.291, -0.176)	(-0.660, -0.490)	(-1.361, -1.029)	(-1.180, -0.948)
Tenure 8	**-0.227**	**-0.589**	**-1.327**	**-1.175**
	(-0.290, -0.166)	(-0.686, -0.508)	(-1.465, -1.152)	(-1.293, -1.056)
Tenure 9	**-0.244**	**-0.625**	**-1.372**	**-1.243**
	(-0.307, -0.188)	(-0.709, -0.543)	(-1.517, -1.204)	(-1.364, -1.123)
Tenure 10	**-0.266**	**-0.661**	**-1.352**	**-1.241**
	(-0.341, -0.206)	(-0.750, -0.578)	(-1.515, -1.177)	(-1.365, -1.116)
Tenure 11	**-0.260**	**-0.675**	**-1.456**	**-1.286**
	(-0.328, -0.200)	(-0.768, -0.590)	(-1.604, -1.291)	(-1.417, -1.156)
Tenure 12	**-0.290**	**-0.709**	**-1.459**	**-1.284**
	(-0.369, -0.222)	(-0.806, -0.615)	(-1.636, -1.258)	(-1.429, -1.139)
Numeracy score 1	**0.196**	**-0.473**	**-0.594**	**-0.613**
	(-0.451, 0.761)	(-1.852, 0.085)	(-2.819, 0.606)	(-1.119, -0.106)
Numeracy score 2	**0.331**	**-0.340**	**-0.574**	**-0.456**
	(-0.264, 0.861)	(-1.761, 0.179)	(-2.693, 0.614)	(-0.942, 0.030)
Numeracy score 3	**0.128**	**-1.058**	**-2.427**	**-1.280**
	(-0.476, 0.668)	(-2.450, -0.540)	(-4.622, -1.269)	(-1.760, -0.800)
Numeracy score 4	**-0.043**	**-1.588**	**-3.628**	**-1.967**
	(-0.634, 0.505)	(-2.971, -1.049)	(-5.793, -2.444)	(-2.446, -1.489)
Numeracy score 5	**-0.105**	**-1.812**	**-4.220**	**-2.461**
	(-0.695, 0.428)	(-3.181, -1.276)	(-6.353, -3.033)	(-2.940, -1.982)

Notes: Numbers in the parentheses represent 90% confidence intervals. The dummy variables are omitted for high income, homeowners, more education, male, young, living in the West, first-time survey respondents, and no correct numeracy questions.

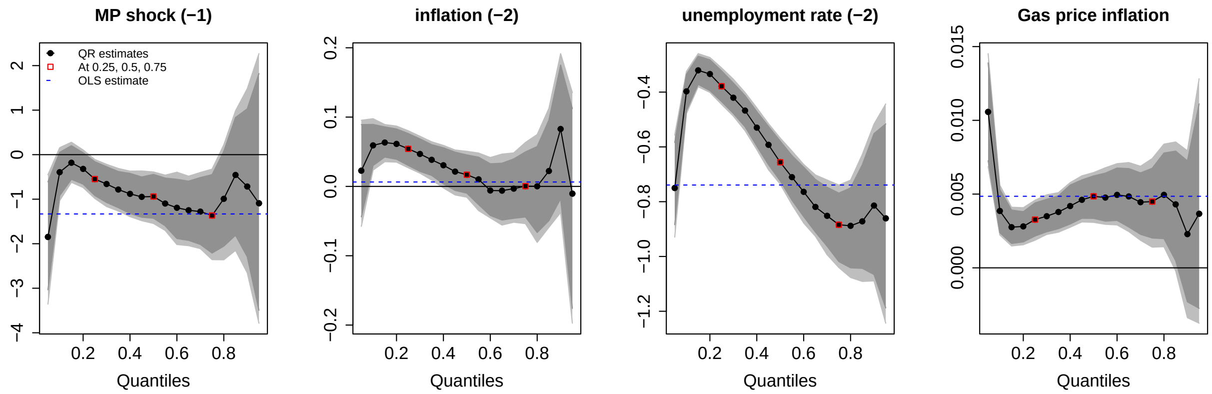

Figure 1: Coefficient estimates on macro variables across quantiles: baseline specification

Notes: The OLS estimates are the coefficient estimates of the same specification in the conditional mean regression by OLS. The bands represent the 90% and 95% confidence intervals estimated by bootstrapping.

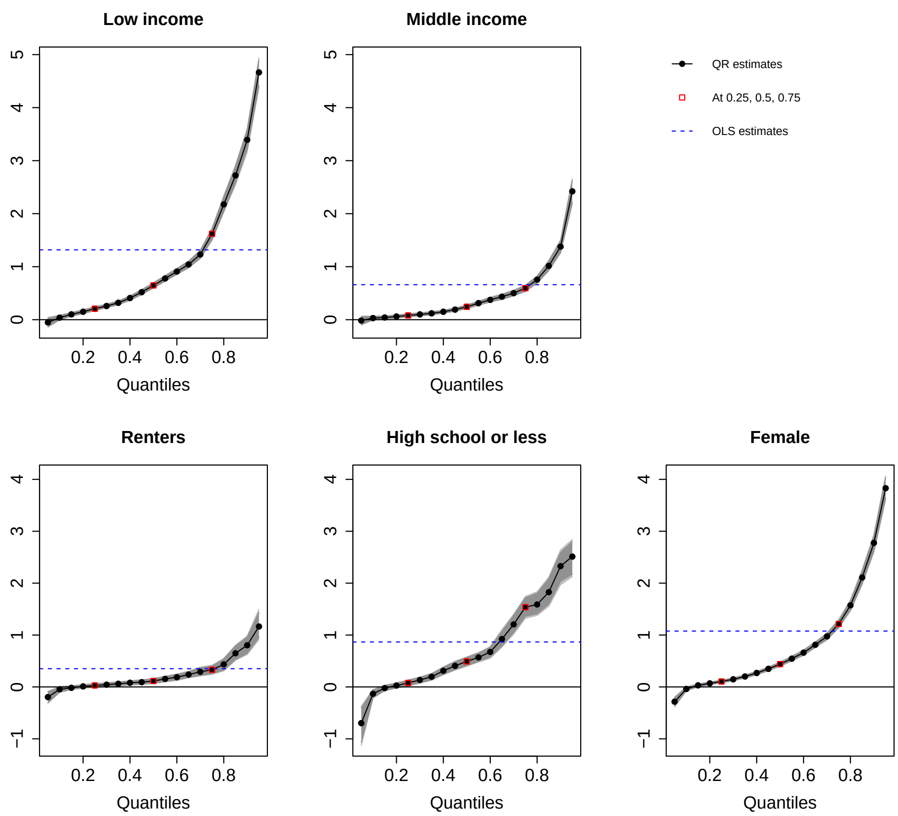

Figure 2: Coefficient estimates on demographic characteristics across quantiles: baseline specification

Notes: The base (omitted) group is a group of households with highest income quartile, more education, and homeownership and who are male and a young generation living in the West. See the notes in Figure 1 as well.

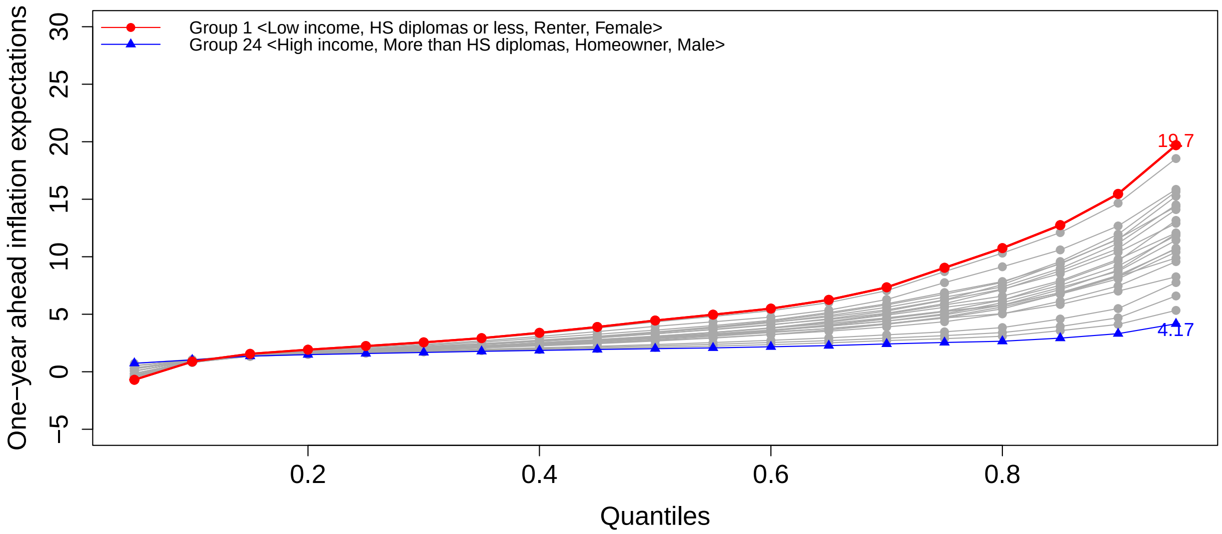

Figure 3: Predicted conditional quantiles of household inflation expectations across demographic groups: December 2019

Notes: There are 24 groups in total: 3 income groups, 2 education groups, 2 homeownership groups, 2 gender groups. See Table A1 in the online appendix for the composition of groups. For the other variables in the conditional quantile regression in (1), when computing the predicted conditional quantiles, it is assumed that the survey tenure, the numeracy score, the number of kids and adults are equal to the respective medians for each group, the age group is the young generation, and the region of primary residence is the West.

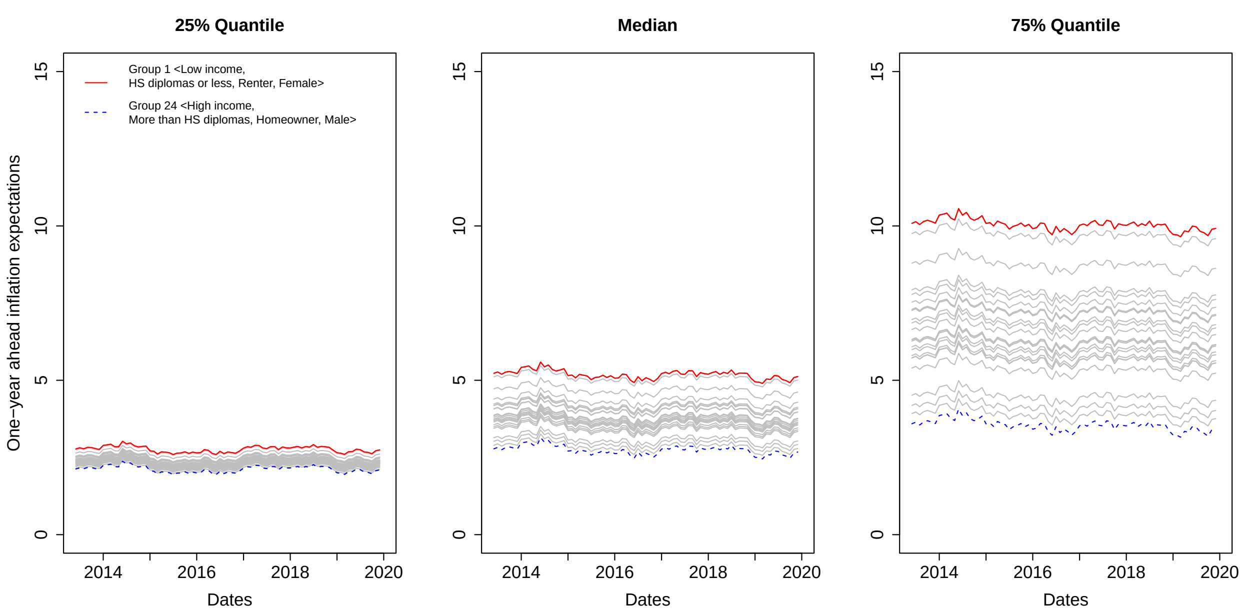

Figure 4: Predicted conditional quantiles of household inflation expectations over time: 25%, 50%, and 75% quantiles

Notes: With the orthogonalized monetary policy shock. See the notes in Figure 3 as well.

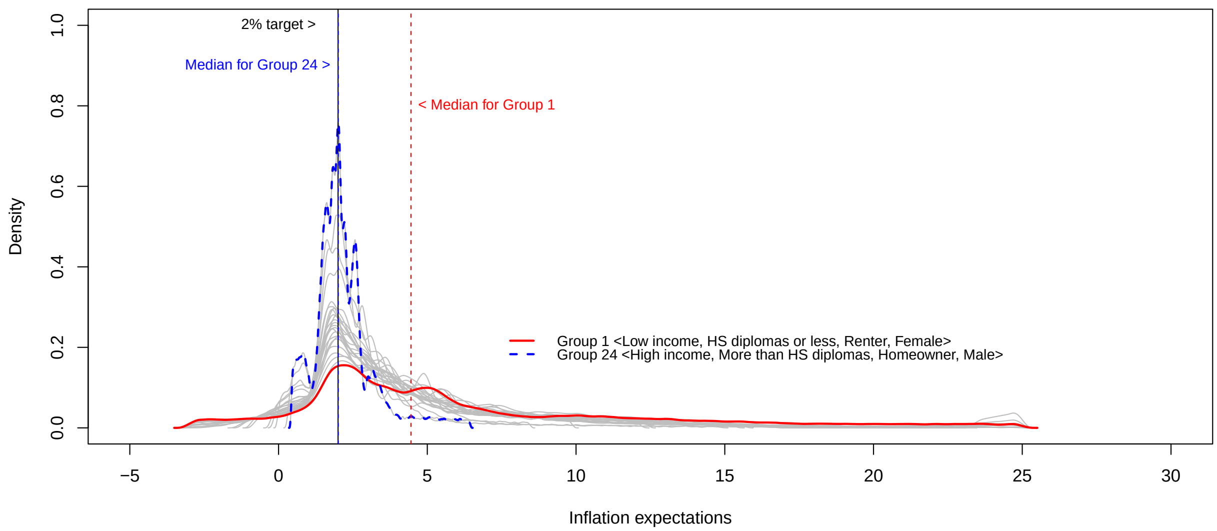

Figure 5: Predicted conditional density function of household inflation expectations across demographic groups: December 2019

Notes: With the orthogonalized monetary policy shock. See the notes in Figure 3 as well. See the online appendix on the method of computing the predicted conditional distribution.

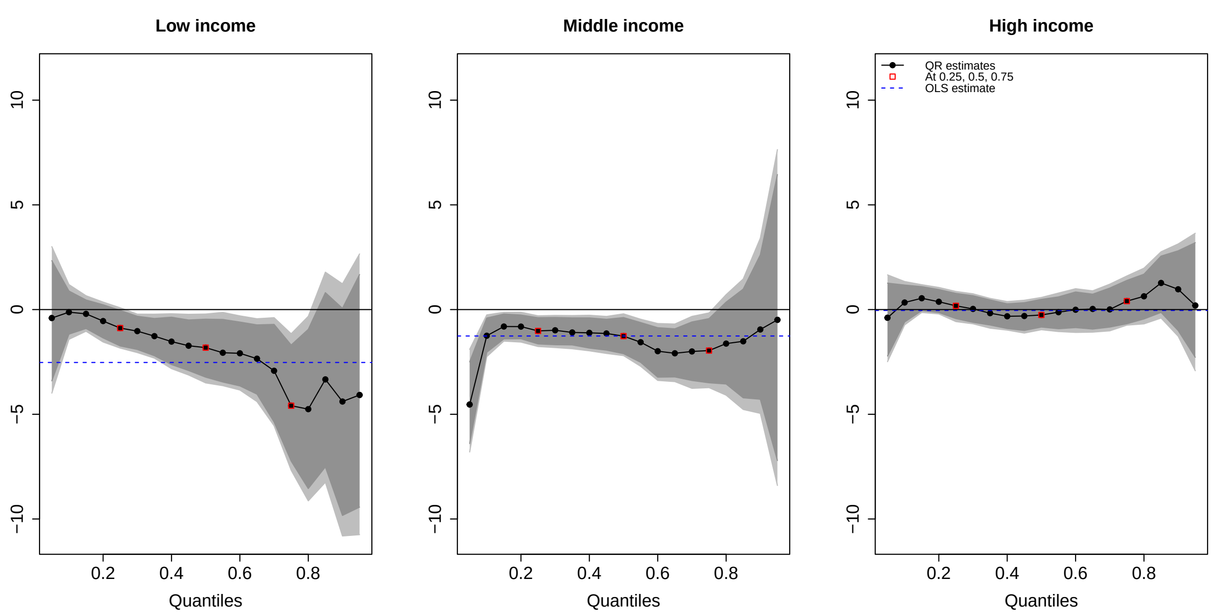

Figure 6: Response of different income groups to a contractionary monetary policy shock

Notes: The panels report the response of inflation expectations by different income groups. The OLS estimates in the blue dash lines are the coefficient estimates of the same specification in the conditional mean regression by OLS. The bands represent the 90% and 95% confidence intervals estimated by bootstrapping.