Learning-through-Survey in Inflation Expectations

By GwangMin Kim and Carola Binder*

First Draft: June 4, 2018

This Draft: September 27, 2020

When surveys rely on repeat participants, this raises the possibility that survey participation may affect future responses, perhaps by prompting information acquisition between survey waves. We show that these "learning-through-survey" effects are large for household inflation expectations. Repeat survey participants generally have lower inflation expectations and uncertainty, particularly if their initial uncertainty was high. Consequently, repeat participants may be more informed, and not be representative of the broader population. This has important implications: for example, inflation expectations of new participants are more influenced by oil prices, and estimates of the elasticity of intertemporal substitution are lower for new participants.

JEL: D83, D84, E31

Inflation expectations are believed to play a central role in explaining economic outcomes. Federal Reserve Chair Jerome Powell testified to Congress in February 2019 that "Inflation expectations are the most important driver in actual inflation" (Powell, 2019). In addition, survey-based inflation expectation measures are increasingly used in macroeconomic research in various ways: for estimating the Intertemporal Elasticity of Substitution (Crump et al., 2015), studying inflation expectations of firms (Coibion, Gorodnichenko and Kumar, 2018), and estimat-

* Kim: University of Texas at Austin, 2225 Speedway BRB. 4.118, Austin, TX 78712, USA (e-mail: gmkim@utexas.edu); Binder: Haverford College, 370 Lancaster Avenue, Haverford, PA 19041-1392 (e-mail: cbinder1@haverford.edu). We are grateful to Olivier Coibion, Stefano Eusepi, and seminar participants at the University of Texas at Austin for helpful comments and suggestions.

ing expectations-augmented Phillips curve (Coibion, Gorodnichenko and Ulate, 2019).

Therefore, accurately measuring inflation expectations is crucial for monetary policymaking and economic research. For this reason, the Federal Reserve Bank of New York (FRBNY) began conducting the Survey of Consumer Expectations (SCE) monthly in 2013. Other central banks, like the European Central Bank and the Bank of Canada, are also carefully designing new household surveys. For example, the European Central Bank launched the Consumer Expectations Survey in January 2020, which is currently in the pilot phase at six countries.[1] Globally, more than dozens of countries run household inflation expectation surveys on a regular basis.[2] FRBNY SCE respondents can participate in the survey for up to twelve months in a row. A long panel dimension, as found in the SCE, is usually thought to be a desirable feature for a survey, since measuring the same person over time allows researchers to control for unobservable individual-specific characteristics. However, reliance on repeat participants—the SCE includes about 150 new participants out of 1300 in each wave—could pose problems if the act of participating in the survey affects the subsequent responses of these participants. These so-called *learning-through-survey* or *panel conditioning* effects are small in some surveys.[3]

However, we show that this is decidedly *not* the case in surveys of household inflation expectations. After being asked about their inflation expectations, individuals learn about inflation and significantly (and predictably) revise their expectations in subsequent surveys. For example, after participating twelve con-

[1]The Consumer Expectations Survey by the European Central Bank includes six countries: Belgium, France, Germany, Italy, the Netherlands, and Spain. More countries may be added if the pilot proves successful. `https://www.ecb.europa.eu/stats/ecb_surveys/consumer_exp_survey/html/index.en.html` provides further details about this new survey.

[2]See Arioli et al. (2017) and Appendix Table 1 of Coibion, Gorodnichenko and Ulate (2019) for a list of countries running inflation expectation surveys targeting households. Norway, which is not on their list, also has run an inflation expectation survey since 2002.

[3]For example, Halpern-Manners, Warren and Torche (2017) find that only about 12% of the selected core items of the General Social Survey display panel conditioning effects at a 5% significance level. They report that the responses of different survey cohorts do not appear to differ in predictable or meaningful ways in most cases.

secutive times in the SCE, respondents end up with a 2.1 percentage point lower inflation forecast and 34% lower inflation uncertainty on average than in the first interview, with most of the decline happening in the first two months of participation. Results are nearly identical for longer-run inflation expectations. These learning-through-survey effects are so large that repeat participants can no longer be considered representative of the general population.

As we will demonstrate, these results should be kept in mind by users and developers of new household surveys, as they affect empirical estimates and interpretations using the survey data in some contexts. We illustrate our findings using two application cases: the oil price collapse during "Shale Revolution" and the estimation of elasticity of intertemporal substitution by Crump et al. (2015). Household inflation expectations are known to be sensitive to gas prices in general (Coibion and Gorodnichenko, 2015*a*). However, this stylized fact tends to be significantly weaker for repeat participants of the SCE. During the periods of sharp decline in oil prices, we find that inflation expectations of new participants are more influenced by oil prices when compared to repeat survey participants. Also, by revisiting estimation of elasticity of intertemporal substitution by Crump et al. (2015), we show that the estimates of the elasticity of intertemporal substitution are lower for new participants. We suggest that users of survey microdata should check whether their estimates are robust to using subsamples of shorter-tenured and longer-tenured respondents when they use panel data.

Most of our analysis uses the SCE, a rotating panel survey that consecutively tracks respondents up to twelve times. This extensive panel component makes the SCE an ideal setting to study the panel conditioning effect. We note that Armantier et al. (2017) briefly examine panel conditioning effects in the SCE by comparing the median absolute change in the density mean of respondents' inflation expectations across different tenure groups.[4] They find that after the

[4]Throughout this paper, "tenure" refers to the total number of past survey experience of respondents, including the current survey wave. For example, a SCE respondent surveyed each month starting in January will have a tenure of 3 in March.

first month of participation, the density mean of a respondent's inflation forecast remains relatively stable. They argue that "the design of the panel, with a constant in- and outflow of respondents each month, ensures a stable survey tenure distribution, so the extent of learning and experience (and any associated impact on responses) is constant over time. As a result, month-to-month changes in median responses should capture real changes in population beliefs" (pg. 64).

We provide alternative evidence suggesting that the learning-through-survey effects are large and economically meaningful. Our approach is to use panel regressions with time and respondent fixed effects and tenure dummy variables to detect conditioning effects that may occur over multiple survey waves, without imposing parametric assumptions on how effects depend on tenure. This is a novel methodological contribution to a relatively large literature on panel conditioning.[5] The coefficients on the tenure dummies provide non-parametric estimates of how inflation expectations decline with survey tenure. Since consumers generally overestimate future inflation[6], they lower their forecasts as they receive more information.[7]

Furthermore, we characterize which individuals are most sensitive to having their beliefs change through participation in the survey. We find that respondents who report higher uncertainty about inflation at the time of their first survey tend to make larger revisions to their inflation expectations in subsequent surveys. In addition, more educated and higher-income individuals who are generally more informed about inflation prior to the survey when compared to other groups display significantly smaller learning effects throughout the survey waves.

[5]Previous studies conduct t-tests for the difference in mean responses between two cohorts of respondents who first entered the survey sample at two different dates. For example, Halpern-Manners, Warren and Torche (2017) compare responses on the 2008 General Social Survey for respondents who took the survey in 2006 and 2008 versus respondents who took the survey in 2008 and 2010. We pool information from *all* dates of the SCE rather than from a single survey date, and observe how responses change not only from a respondent's first to second round of participation, but also from her second to third round of participation and so on."

[6]Although Consumer Price Index inflation has been recently low and stable—at around 1.5% from 2013 to 2018—the inflation expectation of consumers was consistently above 2.5% during the same period.

[7]One implicit difference between our analysis and that of Armantier et al. (2017) is that we identify the average change, not the average absolute change, in inflation forecasts. This is appropriate in this context because forecasts have positive bias, so errors have non-zero mean.

The findings that the learning effect is generally stronger for respondents who are least informed about inflation prior to the survey compared to others is consistent with theories that emphasize the endogenous nature of information rigidities. For example, retirees who have economic incentive to be aware of inflation rates prior to the survey display smaller learning effects than other groups. Under the rational inattention model, economic agents have a limited cognitive ability to process information. These models allow for different types of information rigidities such as infrequent updating (Mankiw and Reis, 2002; Reis, 2006), signal-extraction problems (Sims, 2003), or model complexity restrictions (Gabaix, 2014). In all rational inattention models, economic agents optimally choose when and to which variables to pay attention because paying attention and forming expectations are costly. Therefore, if repetitive surveying about inflation makes respondents pay more attention to inflation, the effect would be larger for those respondents who largely ignored inflation before taking the survey.

The inflation rate is generally viewed as an important aggregate variable. Nevertheless, it can be optimal for households to place greater attention in tracking other variables like their own income, more so than the inflation rate. For example, Carroll et al. (2020) show that consumers tend to underreact to aggregate macroeconomic shocks because aggregate shocks comprise only a small proportion of the uncertainty that consumers face. Therefore, consumers may pay more attention to idiosyncratic variables like their own income than aggregate inflation rates in making consumption decisions. Similarly, Mackowiak and Wiederholt (2009) show that when firm-specific conditions are more important than aggregate conditions, firms pay more attention to idiosyncratic variables. Hence, firms devote few resources to collecting and processing information about inflation. Consistent with this finding, Karahan, Mihaljevich and Pilossoph (2017) find that the income expectations of consumers tend to be accurate. They show that the forecast error of the four-month-ahead expectations is only 0.5 percent, suggesting that consumers are attentive to processes affecting their income. We similarly show that the learning effect is smaller for personal earnings and household income growth expectations.

To be more precise, this does not necessarily mean that inflation expectations are not important to households and firms. Although economic agents may have imperfect and biased expectations, those beliefs significantly impact their economic decisions nonetheless. Recent literature based on natural experiments and randomized controlled experiments consistently indicate that changes in inflation expectations have a significant impact on real economic activity. D'Acunto, Hoang and Weber (2016) exploit a natural experiment case of Germany's unexpected VAT increase and show that households' increase in inflation expectations led to greater consumption expenditure. Coibion, Gorodnichenko and Ropele (2020) conducted an unique information experiment targeting firms in Italy and show that firms with higher inflation expectations raise prices on their products.

Finally, we also provide evidence of learning-through-survey effects in other contexts using the Michigan Survey of Consumers (MSC) and a survey of U.S. firms. When we combine the results from the MSC and a survey of U.S. firms, the learning-through-survey effect is not confined to a specific period or only to household surveys. We find that the learning-through-survey effect generally tends to be smaller when there is a longer period between baseline and follow-up surveys. This difference in size of learning effects is consistent with recent evidence from randomized information treatments that finds providing information about inflation to households has large contemporaneous effects on their expectations but that these effects fade very rapidly (Coibion, Gorodnichenko and Weber, 2020). These findings from the MSC and a U.S. firm survey confirm and complement the patterns of the survey effect found in the SCE dataset. At the end of the paper, we also discuss an alternative explanation for the learning-through-survey effect.

The paper is structured as follows. Section I and III begin with providing background information about the dataset. Section I estimates the learning-through-survey effect in the SCE of FRBNY and discusses related identification issues. Section II provides implications of the learning-through-survey effect for interpretation of survey data using two application cases: the oil price shock during "Shale Revolution" and estimation of elasticity of intertemporal substitution by Crump et al. (2015). Section III documents the effect in two other survey datasets. Section IV discusses an alternative explanation for the learning-through-survey effect. Section V concludes.

I. Learning Effects in the Survey of Consumer Expectations

A. Data

The Survey of Consumer Expectation (SCE) is an Internet survey spanning from 2013 to the present, undertaken by the Federal Reserve Bank of New York. The SCE is a monthly, nationally-representative household survey with a rotating panel structure. The SCE tracks a respondent up to 12 times consecutively. Each month, the SCE has a sample size of approximately 1,300, and the number of new participants is about 150. Appendix Table A6 and A7 provides summary statistics on the one-year-ahead inflation expectations of the SCE.

In addition to point-wise inflation forecasts, the NY Fed elicits the respondent's histogram or density forecasts for inflation by asking the respondent to assign probabilities that future inflation will fall into various bins, summing to 100%. Hence, for inflation uncertainty, we use the IQR (Inter-Quartile Range) estimated from each individual's probabilistic questions in SCE.[8] In section I, we mostly focus on 12-months-ahead point forecasts since point forecasts are generally more widely used for consumer expectation surveys than density forecasts based on probabilistic questions. However, in section II, we focus on density-implied mean inflation expectations and show that the learning-through-survey effect is not

[8]The FRBNY provides estimates of the mean, median, and IQR of each density forecast. These estimates are obtained by fitting parametric (beta) distributions to the density forecasts. See FRBNY SCE documentation for details.

only confined to point forecasts. Specific phrasing of questions in the surveys is available in the appendix.

B. Identification of Average Learning Effects

We begin by documenting the presence of learning-through-survey effects in the FRBNY SCE dataset, using linear panel fixed effects regressions of the form:

$$y_{its} = \sum_{s=2}^{12} \beta_s \tau_s + \alpha_i + \gamma_t + \varepsilon_{it}, \tag{1}$$

where the dependent variable y_{its} is the inflation expectation or inflation uncertainty of a respondent i with survey experience (or tenure) s at time t, τ_s is an indicator variable for tenure s, α_i and γ_t are individual- and time- fixed effects to control for unobserved heterogeneity, and ε_{it} is an error term. The regression coefficients on the tenure dummies, $\{\beta_s\}_{s=2}^{12}$, measure the average learning-through-survey effects on the dependent variable. To make the regression coefficients more robust to outliers, we remove the top and bottom 5% of each dependent variable for each tenure group and period.[9]

Figure 1 shows that the estimated average learning-through-survey effect is large and statistically significant for both one-year-ahead inflation expectations and three-year-ahead inflation expectations. For example, for one-year-ahead inflation expectations, the interviewees cut their inflation expectations by approximately 1.1 percentage points immediately after the first interview. The IQR, which measures the uncertainty of expectations, also decreases by about 0.74 percentage points after the first round of the survey. In addition, both one-year-ahead inflation expectations and three-year-ahead inflation expectations display almost the same degree of learning effects. That is, households tend to revise their short-run and long-run inflation expectations in a similar manner. Given

[9] We obtain qualitatively and quantitatively similar results for different thresholds. Appendix Figure A1 reproduces the results in Figure 1 for both lower and higher thresholds.

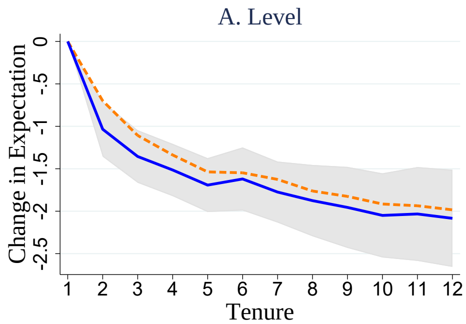

Figure 1. Average Learning-Through-Survey Effects on Inflation Expectations in the SCE

Note: The y-axis shows the change in responses of survey participants compared to their initial responses, estimated from regression (1), in percentage points. For Panel A, the dependent variable of the regression is the inflation rate point forecast, and for Panel B, the dependent variable is the interquartile range (IQR) of the density forecast for expected inflation. The solid blue (dashed orange) lines correspond to one-year (three-year) ahead inflation forecasts. The gray area shows a 95% confidence interval for the solid blue line with Driscoll-Kraay standard errors of lag one. Tenure is shown on the x-axis and corresponds to the total number of survey experiences of each respondent (including the current survey wave). We restrict samples to consist of respondents who eventually participate in the survey for twelve waves (non-attriters). We truncate the top and bottom 5% of each dependent variable for each tenure group and period. The data is from the FRBNY Survey of Consumer Expectations, taken from 2013 June to 2019 September with a monthly frequency. A full regression table is in Appendix Table A1.

this similarity, we primarily focus on one-year-ahead inflation expectations for the remainder of the paper. A full regression table for Figure 1 is provided in Table A1 of the appendix.

One identification issue is that sample selection may occur due to different panel attrition rates by individuals. For example, more educated and higher income respondents tend to stay in a survey for more waves. Therefore, differences in responses between experienced survey participants and new survey participants could reflect different demographics. In order to prevent such a panel attrition problem, we focus on "non-attrition" samples: we restrict our samples to consist of "non-attriters," or respondents who eventually participate in the survey for the maximum times, following Halpern-Manners, Warren and Torche (2017). That is, the panel attrition rate is restricted to be zero for the dataset we use, and therefore our results are not driven by panel attrition.

A potential concern to our "non-attrition" restriction is that the learning effect we identify may only exists for ready-to-learn survey respondents. For example, the learning-through-survey effects may only exist for respondents who are committed to a survey and thereby have more willingness to learn about the economy. However, quantitatively and qualitatively similar results are obtained for different sampling rules. Focusing on one-year-ahead inflation expectations, Panel A of Figure 2 reproduces our baseline results in Panel A of Figure 1 under various sampling rules. Even if we only use the data of respondents who skip a survey at least one time ("skippers"), who participate in the SCE less than six times in total ("half-participants"), or use the full samples ignoring the sampling issues ("full sample"), the estimated learning-through-survey effects are still similar to those obtained from our "non-attriters" sample. Therefore, throughout this paper, we keep "non-attriters" as our baseline sample.

Another potential identification issue is known as the Age-Period-Cohort (APC) problem, which in its original formulation refers to the problem of separating the independent effects of aging, time period, and cohort due to exact linear dependence (Hobcraft, Menken and Preston, 1985; Deaton and Paxson, 1994). In our context, survey experience dummy variables, monthly time-fixed effects, and individual-fixed effects correspond to age, period, and cohort, respectively.[10] One simple solution to this APC problem is to replace monthly time-fixed effects with quarterly ones, which we do for the remainder of the paper. Other solutions may include normalization of the parameters (Deaton and Paxson, 1994), replacing the time-fixed effects with aggregate variables (Heckman and Robb, 1985), or omitting time-fixed effects altogether. Panel B of Figure 2 reproduces our baseline results in Panel A of Figure 1 with each of these alternatives. Our results remain

[10]This correspondence is not obvious. Note that first, there is a correspondence between a cohort dummy variable and (a sum of) individual-fixed effects. To see this correspondence, imagine that respondents are "born" when they enter into a survey. Then, a sum of individual dummy variables of respondents who are "born" in period t will be identical to a cohort dummy variable for the respondents who are "born" in period t. Second, note that when there is no panel attrition, # of Survey Experiences (Age) = Current Period (Period) - Survey Entrance Period (Cohort, the date of birth) holds. That is, survey experience dummies (Age), time dummies (Period), and individual dummies (Cohort) are going to be co-linear if they are all used in same time frequency in a linear panel regression.

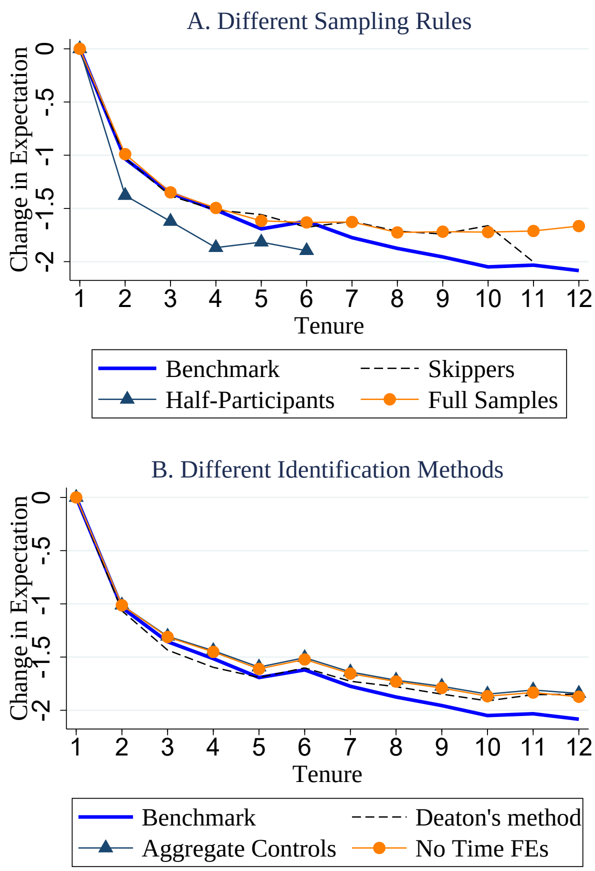

Figure 2. Baseline Results under Different Sampling Rules and Identification Methods

Note: Panel A reproduces the results of one-year-ahead inflation forecasts in Panel A of Figure 1 under different sampling rules. "Benchmark" corresponds to the results of Panel A of Figure 1 in the main text using non-attriters only. "Skippers" are respondents who skip a survey at least once. "Half-participants" participate in the SCE no more than six times. "Full samples" corresponds to the case when we do not make restrictions based on total survey participation.
Panel B reproduces the results of one-year-ahead inflation forecasts in Panel A of Figure 1 using different identification methods. "Benchmark" corresponds to the results of Panel A of Figure 1 in the main text: linear panel fixed effects regression with quarterly time fixed effects and individual fixed effects. "Deaton's method" uses normalization of monthly time fixed effects following Deaton and Paxson (1994). "Aggregate Controls" replaces time-fixed effects with macroeconomic aggregate variables: monthly CPI inflation rates, the aggregate median of MSC one-year-ahead inflation forecasts, unemployment rate, monthly growth rate of the industrial production index, and log of average WTI oil prices. "No Time FEs" corresponds to the case when neither time-fixed effects nor aggregate control variables are used.
The y-axis is measured in percentage points. Tenure in x-axis means the total number of survey experiences of each respondent (including the current survey wave). We truncate the top and bottom 5% of dependent variables for each tenure group and period.

quantitatively and qualitatively similar.[11]

[11]One possible reason for this robustness could be the fact that inflation rates have been very stable in

To summarize, these learning-through-survey effects tend to be robust. Respondents who have completed 12 consecutive surveys report very different inflation expectations compared to their first-time interviews. Relative to new participants, the most-experienced interviewees report 2.1 percentage points lower inflation expectations and 34% lower inflation uncertainty. Since the central banks often prefer median inflation expectations rather than mean inflation expectations, we also estimate the learning-through-survey effects on medians using a fixed effects panel quantile regression (Machado and Silva, 2019). The estimated median effects are very close to the mean effects from our baseline regression.

To emphasize the strength of learning-through-survey effects for inflation expectations in particular, we estimate analogous regressions for respondents' nominal personal earnings growth expectations and household income expectations. The estimated effects for personal earnings and income expectations are much smaller when compared to those for inflation expectations. The magnitude of the effects on the levels of the expectations are at most 0.66 percentage points, and the statistical significance of the effects is substantially weaker than that of inflation expectations. See Table A1 of the appendix.[12]

The larger learning-through-survey effects for inflation expectations compared to income expectations are in line with rational inattention theory, which suggests that households may selectively pay attention to economic variables. Households should be highly attentive to their own income process even prior to participating in the survey, because it is so relevant to their consumption decisions. However, especially in low-inflation environments, consumers with limited information-processing capacity may pay little attention to inflation. Thus, households may

recent years. Thereby, the effects of time-fixed effects could have been weak during our sample periods; the overall R^2 only changes from 0.5194 to 0.5179 when we drop the quarterly time-fixed effects entirely.

[12]One may point out that inflation rates could be naturally harder to forecast than respondents' own income path. That is, for example, one can argue that 0.5 percentage points of learning effects in income expectations should not be treated equally to the same magnitude in inflation expectations. Reflecting this argument that different forecasts may have different scales, we normalize the estimated learning effects by standard deviation or mean of each forecast. However, we still find that the estimated learning effects for inflation expectations are more than 50 percent larger than those for earnings and income expectations.

not have a good understanding of the nation-wide average price process before taking the survey. For example, Carroll et al. (2020) show that consumers tend to underreact to aggregate macroeconomic shocks. Consumers may neglect aggregate variables in their consumption decisions because aggregate shocks consists only a small proportion of the uncertainty that consumers face, compared to highly idiosyncratic variables like their own income.[13] Therefore, questions that ask for the respondents' beliefs about inflation are more likely to prompt additional attention to inflation, prompting participants to collect more information about inflation.

Both the frequency of forecast revisions and the size of forecast errors also decline with survey tenure. Respondents tend not to update their expectations from their previous month's forecast when they participate in the survey many times, as Appendix Table A2 shows.[14] Since consumer inflation expectations are typically biased upward, downward revision in inflation expectations with more survey experience contributes to smaller forecast errors. In the SCE, the average absolute forecast error for inflation expectations of repeat participants was approximately 2.85 percentage points lower than that of new participants. Dräger and Lamla (2017) document a similar finding. They find that the probability of updating inflation expectations increases when individuals had higher forecast errors in the past. That is, repeat participants achieve lower forecast errors and tend not to replace their current forecasts, saving cognitive effort in processing information.

C. Heterogeneity in Learning Effects

While the equation (1) estimates learning-through-survey effects for the average respondent, learning effects may be heterogeneous depending on households' ini-

[13]In section II.B of this paper, we provide more direct evidence consistent with Carroll et al. (2020); consumption expectations of new survey participants more sluggishly respond to inflation expectations, while repeat participants more promptly reflect inflation expectations to consumption expectations.

[14]Note that the frequency of forecast revisions is often used as a proxy for the information rigidity parameter in sticky information models. (Coibion and Gorodnichenko, 2015*a*)

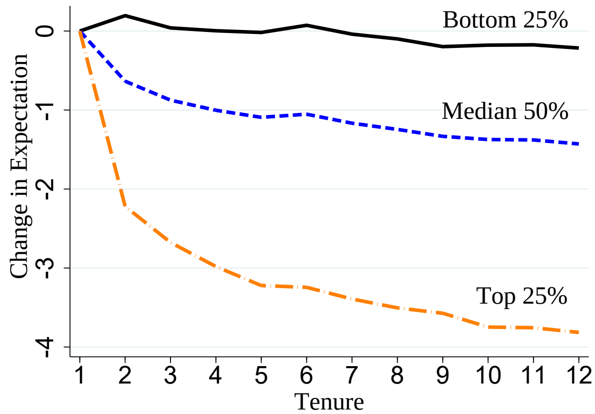

FIGURE 3. LEARNING EFFECTS ON INFLATION EXPECTATIONS BY INITIAL INFLATION UNCERTAINTY

Note: The figure plots the learning-through-survey effects by initial inflation uncertainty ($IQR_i \in \{U_H, U_M, U_L\}$), which are estimated from the equation (2). For example, the top 25% line (long dashed orange line) corresponds to the case when a respondent had a high level of inflation uncertainty in the first interview, assuming $\alpha_i = 0, \gamma_t = 0$. The y-axis shows the change in one-year-ahead inflation expectation of respondents compared to their initial responses, in percentage points. Tenure is shown on the x-axis and corresponds to the total number of survey experiences of each respondent (including the current survey wave). Sample is restricted to non-attriters. We truncate the top and bottom 5% of the dependent variable for each tenure group and period.

tial expectations and uncertainty. For example, households who enter the survey with high uncertainty may be more susceptible to learning-through-survey effects since their priors are weaker.

In the regression equation below, to allow for such heterogeneity, we extend equation (1) by including interaction terms of tenure dummies with initial inflation uncertainty of respondents from their first survey:

$$\pi^e_{its} = \sum_{s=2}^{12} \left\{ \beta_{1,s} + \beta_{2,s} IQR_i + \beta_{3,s} IQR_i^2 \right\} \tau_s + \alpha_i + \gamma_t + \varepsilon_{it}, \tag{2}$$

where π^e_{its} denotes one-year-ahead expected inflation of individual i whose tenure of survey is s at period t, and IQR_i is the interviewee's *initial* IQR reported in the first survey. We include the squared term IQR_i^2 to control for possible non-linearity. All other terms are defined as in regression (1).

In Figure 3, we plot the estimated learning-through-survey effects for values of IQR_i corresponding to the 25th, 50th, and 75th percentiles, which we denote U_L, U_M, and U_H. These values are 1.5%, 3.0%, and 6.4%, respectively. Specifically, using regression (2), assuming $\alpha_i = 0, \gamma_t = 0$, we plot

$$\{\frac{\partial \pi^e_{its}}{\partial \tau_s} \mid \; IQR_i \in \{U_H, U_M, U_L\}\}_{s=2}^{12}$$

Respondents who initially entered the survey with a high level of inflation uncertainty learn more about inflation. Figure 3 shows that respondents whose initial uncertainty over the future inflation rate was in the bottom quartile of the distribution display a marginal learning effect. However, if the respondents were initially in the top 25% of inflation uncertainty, then the effect is large: right after the first survey, inflation expectations decrease by 2.22 percentage points on average.

We find further evidence of the heterogeneity of the learning effect when including demographic variables and measures of respondents' understanding of inflation as interactions. For a categorical variable D_i describing a characteristic of respondent i, we estimate the below regression and calculate $\beta_{1,s} + \beta_{2,s} D_i$.

$$\pi^e_{its} = \sum_{s=2}^{12} \left\{ \beta_{1,s} + \beta_{2,s} D_i \right\} \tau_s + \alpha_i + \gamma_t + \varepsilon_{it} \tag{3}$$

We use three demographic variables: income level (less than \$50k, \$50k to \$100k, more than \$100k), education level (college, some college, or high school), and retiree status. In addition, in the SCE, new respondents are required to answer a set of questions measuring their numeracy and financial literacy. For example, a question designed to measure understanding of inflation asks, "Imagine that the interest rate on your savings account was 1% per year and inflation was 2% per year. After one year, how much would you be able to buy with the

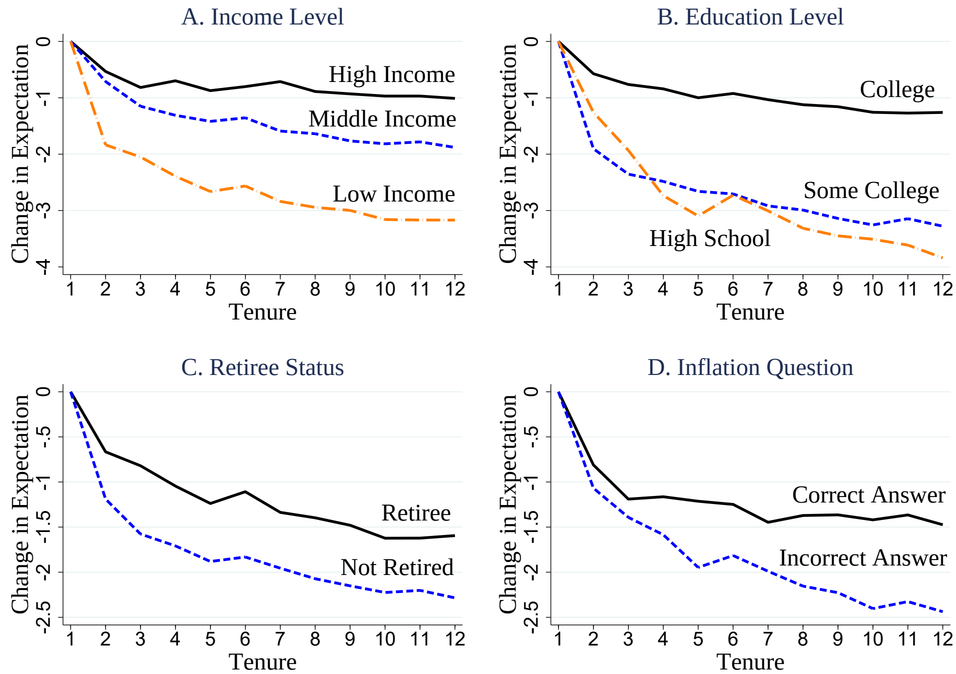

Figure 4. Learning Effects by Demographics and Understanding of Inflation

Note: Each panel plots learning-through-survey effects on one-year-ahead inflation expectation by demographic variables and inflation understanding: income level, education level, retiree status, and whether respondents gave a correct answer to a question asking about inflation. Following the equation (3), the estimates are obtained from separately running a regression using dummy variables as the interaction term. The y-axis shows the percentage point change in one-year-ahead inflation expectation of respondents compared to their initial responses. Tenure is shown on the x-axis and corresponds to the total number of survey experiences of each respondent (including the current survey wave). Sample is restricted to non-attriters. We truncate the top and bottom 5% of the dependent variable for each tenure group and period.

money in this account?" Respondents can choose "More than today," "Exactly the same," or "Less than today." We measure respondents' understanding of inflation by whether respondents gave a correct answer to this question. Only 52% answered this question correctly.[15]

[15]This does not necessarily mean households do not understand price changes at all. For a question asking about prices in a sale, 90% of respondents wrote down exactly correct numerical answers, and similarly, approximately 80% of respondents gave exactly correct numbers to the questions asking them to guess the number of lottery winners/people who are going to get a disease, when the chances of the events were given by 1% and 10% each. The answers on the inflation question shows that respondents could be inattentive to aggregate inflation rates for many possible reasons. Respondents are attentive to sale prices which are relevant to their daily consumption decisions, but may not pay attention to an aggregate price index. Similarly, Kaplan and Schulhofer-Wohl (2017) find that household-level inflation rates are vastly heterogeneous from an aggregate inflation index. We have shown that the learning-

Consistent with the previous results from Figure 3, respondents who are generally more informed about inflation prior to the survey than the other groups display significantly smaller learning effects throughout the survey waves. We also ran the same regression jointly including all indicator variables for demographics and inflation understanding, but the overall results were similar to Figure 4.

For example, Panels A and B of Figure 4 show that the estimated learning effects are substantially smaller for higher-income and more educated individuals. In addition, Panels C and D show that retirees and respondents who gave a correct answer the question measuring understanding of inflation display relatively smaller learning effects. Aguiar and Hurst (2007) find that older households invest more in shopping time and pay the lowest prices compared to other households. Therefore, retirees could be more informed about the general price increase than the other groups, thereby showing smaller learning effects.

In summary, the learning-through-survey effect robustly exists in the SCE data. On average, consumers with more past survey experience have inflation expectations that are lower in absolute terms and more accurate. They also tend to have lower uncertainty about inflation and are less likely to update their forecasts in subsequent surveys. Further, survey participants who are generally more informed about inflation prior to the survey than the others display much smaller learning effects throughout the survey waves.

II. Implications for Interpretation of Survey Data

Inflation expectation surveys conducted by the central banks are generally intended to be used for two major purposes: i) monitoring inflation expectations through an aggregate index and ii) researching consumer expectations and behavior using the underlying micro data. Using an episode of oil price collapse in 2014,

through-survey effect is generally weaker for the expectations related to respondents' own income and earnings. Another possibility consistent of this finding is that respondents could be more attentive to interest rates (a clear source of income) when compared to aggregate inflation rates of which the effects are not directly visible in general.

we show how the learning effect we found can cause a significant bias in central banks' monitoring of inflation expectations. In addition, by revisiting estimation of elasticity of intertemporal substitution by Crump et al. (2015), we show how the learning effect can influence micro estimates and provide useful insights for studies using survey micro data.

A. Oil Price Shock during the "Shale Revolution"

In order to monitor the inflation expectations of U.S. consumers, the FRBNY conducts the SCE data each month and reports the sample median of the density mean inflation expectation. However, the large learning-through-survey effects we found imply that repeat participants may no longer be representative of the general population. Their prior survey participation may have prompted them to seek information about inflation. Exploiting the episode of a sharp drop in oil prices during 2014, often called the "Shale Revolution," we show that the dynamics of inflation expectations of a population group can be significantly different than those of the repeat survey participants.

To be clear, the central banks are aware of the existence of a bias in consumer inflation expectations. For example, Armantier et al. (2017, p. 64) argue that "the design of the panel, with a constant in- and outflow of respondents each month, ensures a stable survey tenure distribution, so the extent of learning and experience (and any associated impact on responses) is constant over time. As a result, month-to-month changes in median responses should capture real changes in population beliefs." In other words, if the learning effect is constant over time, monitoring the changes (rather than levels) of aggregate statistics should be sufficient for the central banks' monitoring purpose.

However, we find that survey respondents respond differently to the same oil price shock depending on the number of their past survey experiences. It is known that household inflation expectations are sensitive to gas prices in general. Coibion and Gorodnichenko (2015*b*) find that the increase in inflation expecta-

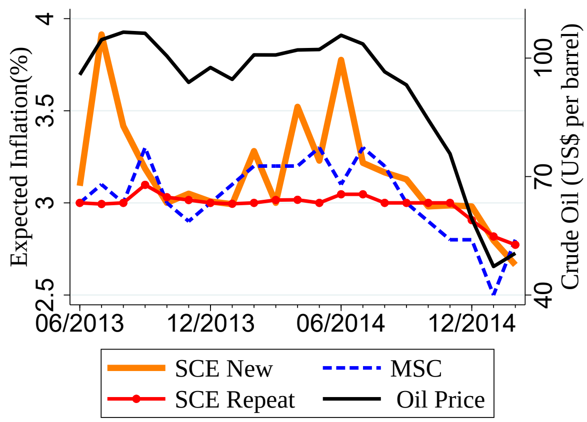

Figure 5. Inflation Expectation of New and Repeat Participants

Note: The monthly average nominal WTI crude oil price per barrel in US$ is on the right y-axis (thin solid black line; "Oil Price"). For the left y-axis, one-year-ahead median density mean inflation expectations of new survey participants of the SCE (thick solid orange line; "SCE New"), repeat survey participants of the SCE (connected red line; "SCE Repeat"), and the median inflation expectations of Michigan Survey of Consumers (dashed blue line; "MSC") are presented in percentage points. Data is from the FRBNY Survey of Consumer Expectations and Federal Reserve Economic Data, from 2013 June to 2019 September in monthly frequency.

tions of households during the Great Recession can be attributed to the rise in the oil price, since the price of gasoline is one of the most salient prices for consumers. However, this stylized fact tends to be significantly weaker for repeat participants of the FRBNY SCE.

First, in Figure 5, we can see that the once-stable crude oil prices plunged by half in only six months in 2014, from $103.59 per barrel of July 2014 to $50.58 of February 2015. One of the main causes of this plunge in oil prices was the innovation in Hydraulic Fracturing technology which exponentially boosted the oil production in the U.S. ("Shale Revolution"). In addition, during this period, from July 2014 to February 2015, the macroeconomic fundamentals of the U.S. had been stable; the seasonally-adjusted industrial production index decreased by 0.17 percent and the unemployment rate decreased by 0.7 percentage points.[16]

[16]See Baffes et al. (2015) for more discussion on the causes of the oil price plunge in 2014. As other contributing causes, the authors point to weakening global demand, a significant shift in OPEC policy, geopolitical shifts, and U.S. dollar appreciation.

In the same figure (Figure 5), we compare the median of density mean inflation expectation of new SCE participants, who represent an unblemished draw from the general population, with that of repeat participants whose expectations are contaminated by the learning-through-survey effect. The inflation expectation of repeat participants is essentially flat for the extended periods from June 2013 to February 2015, displaying muted response to change in oil prices. The inflation expectation of repeat participants dropped by 0.27 percentage points from July 2014 to February 2015. Only after November 2014 did repeat participants' expectations show an initial significant drop, even though the oil prices had been sharply dropped in half during the same period. By contrast, inflation expectations of new participants generally track high-frequency fluctuations in oil prices, which is consistent with what Coibion and Gorodnichenko (2015*b*) have found. In addition, the inflation expectation of the Michigan Survey of Consumers (MSC), another source of aggregate inflation expectations in the U.S, shows a similar pattern to the inflation expectations of new participants of the SCE.[17]

To be more concrete, we quantitatively evaluate the differences in responses to oil prices between new and repeat participants by using a following panel linear regression.

$$\pi^e_{its} = \sum_{s=1}^{12} \beta_s(\tau_s \times log(Oil_t)) + \alpha_i + \gamma_t + \varepsilon_{it} \tag{4}$$

where $log(Oil_t)$ is a log of the monthly average crude oil price, and τ_s is a tenure dummy variable for s number of total survey experience. π^e_{its} denotes one-year-ahead density mean inflation expectations of an individual i whose the total number of survey experience is s at period t. α_i and γ_t are individual- and

[17]MSC has a rotating panel component, but respondents are surveyed at most twice, with six months between interviews. We find that the magnitude of the learning effect of the MSC is significantly smaller than that of the SCE. We discuss why the learning effect tends to be small in the MSC relative to the SCE in a later section.

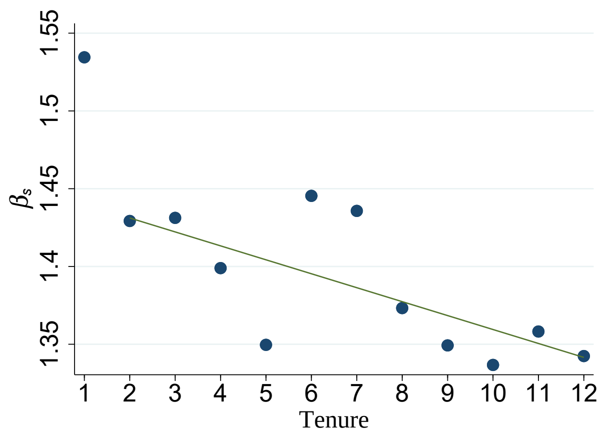

FIGURE 6. RESPONSES TO OIL PRICES BY SURVEY TENURE

Note: The regression coefficients $\{\beta_s\}_{s=1}^{12}$ obtained from our benchmark regression (4), which measures the response of density mean inflation expectation to the increase in log oil prices ($= \partial\pi^e/\partial log(oil)$), are presented in the figure by each tenure group, s. Tenure is shown on the x-axis and corresponds to the total number of survey experiences of each respondent, including the current survey wave. A linear fitted line is presented for repeat participants (tenure>1). Data is taken from the FRBNY Survey of Consumer Expectations from 2014 July to 2015 February with a monthly frequency. A full regression table is available in Appendix Table A3.

quarterly time-fixed effects. ε_{it} is an error term. The sample period is from July 2014 to February 2015, the period when oil prices plunged. We restrict samples to respondents who participate in the survey for the maximum number of times, as we did in our main result section.

Figure 6 visually shows the estimated regression coefficients $\{\beta_s\}_{s=1}^{12}$ by tenure group s. Clearly, new survey participants (Tenure = 1) display the largest regression coefficients indicating new survey participants respond most strongly to aggregate oil prices. For our benchmark regression, we find that the inflation expectations of new survey participants respond 14 percent more strongly to oil prices on average when compared to the most experienced participants. This is consistent with our previous finding from the aggregate times-series data. In Table A3 of appendix, for more robustness, various regression specifications including truncation of extreme expectations, full sample periods, and point inflation expectations are employed. Qualitative features of our results are not changed.

Rather, our benchmark regression specification tends to be conservative when compared to the results from other specifications. When we truncate 10 percent of extreme expectations, new participants respond almost twice as much as repeat participants to oil prices.

Our results are also consistent with those of Verbrugge and Binder (2016), who partitioned the MSC respondents into those with low and high inflation uncertainty, using the methodology in Binder (2017). They show that the inflation expectations of less-uncertain consumers are more stable than those of more-uncertain consumers. In particular, the expectations of less-uncertain consumers did not respond strongly to the oil price decline in 2014.

These evidences all suggest that the learning-through-survey effect we found is not constant over time. Therefore, the effect cannot be removed simply by taking a first difference. The expectations of repeat and new participants can be qualitatively different in a sense that they can respond to a same economic shock in a different manner. In such a case, repeat participants cannot be viewed as representative of the broader population who potentially lack any past survey experience. To illustrate, in our oil price shock episode, if the central banks were only given inflation expectations of repeat participants, they would mistakenly conclude that the inflation expectations of consumers do not respond to the plunging oil prices and miss the majority of timely high-frequency information from survey expectations.

B. Estimating Elasticity of Intertemporal Substitution

The survey micro data on consumer expectations has begun to be used in a variety of applications, and holds great potential for use in many more. The learning effects that we have documented may affect the estimates and interpretation of such studies. For example, Crump et al. (2015) use the SCE data to estimate the elasticity of intertemporal substitution (EIS). More precisely, they estimate the response of expected consumption growth to changes in expected inflation rates. We revisit this analysis by allowing estimates to vary by respondents' survey experience. Among regression specifications of Crump et al. (2015), we focus on a panel linear regression model with fixed effects for simplicity, which is as following:[18]

$$ExpCG^i_{t,t+12} = -\sigma ExpInf^i_{t,t+12} + \gamma ExpIG^i_{t,t+12} + \alpha_i + \beta_t + \varepsilon_{i,t} \tag{5}$$

where $ExpInf^i_{t,t+12}$ is a 12-month ahead density-implied mean inflation expectation of household i at period t, and $ExpCG^i_{t,t+12}$ is expected real consumption growth over the next 12 months by household i at period t, which is calculated as, $ExpCG^i_{t,t+12} \equiv ExpSG^i_{t,t+12} - ExpInf^i_{t,t+12}$, when $ExpSG^i_{t,t+12}$ is a point forecast for nominal spending growth of the household over the next 12 months. Similarly to the calculation of $ExpCG^i_{t,t+12}$, expected real household income growth, $ExpIG^i_{t,t+12}$, is calculated as the difference between point forecast for household nominal income growth and $ExpInf^i_{t,t+12}$. α_i and β_t are individual- and time-fixed effects.

The above regression model represents the first-order approximation of a usual consumption Euler equation. σ represents the elasticity of intertemporal substitution (EIS) which will be our main interest. The estimate for γ measures "excess sensitivity" of consumption growth to anticipated income changes. The literature studying the relationship between income and consumption commonly finds that expected/predictable income growth has a significant effect on consumption growth. Inclusion of γ in the regression model therefore reflects a possible deviation from the Euler equation and permanent income hypothesis.

First, we estimate the above regression model as-is and find that our estimates

[18]The most recent version of Crump et al. (2015) uses a panel linear regression model *without* fixed effects as their baseline since the SCE data allows many control variables. However, Crump et al. (2015) also show results based on a model with fixed effects as a robustness check. They make it clear that their main results do not change essentially with fixed effects added. See section 6.4 and table 9 of Crump et al. (2015).

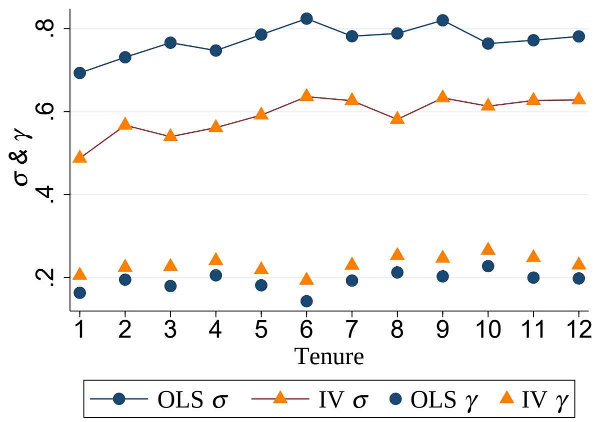

Figure 7. Estimates of EIS and Excess Sensitivity of Consumption by Survey Tenure

Note: We run a linear panel regression of Crump et al. (2015), allowing regression coefficients to vary by survey experience : $ExpCG^i_{t,t+12} = -\sum_{s=1}^{12}\tau_s\sigma_s ExpInf^i_{t,t+12} + \sum_{s=1}^{12}\tau_s\gamma_s ExpIG^i_{t,t+12} + \alpha_i + \beta_t + \varepsilon_{i,t}$. The estimated regression coefficients $\{\hat{\sigma}_s\}_{s=1}^{12}$ (EIS) and $\{\hat{\gamma}_s\}_{s=1}^{12}$ (Excess Sensitivity) are presented in the figure. For the case of IV, the point inflation expectation is used as an instrument of density-implied mean inflation expectation. All units of variables are in percentage points. The sample is restricted to non-attriters. We truncate the top and bottom 5% of all point forecasts for each tenure group and period. Data is from the FRBNY Survey of Consumer Expectations from 2013 June to 2019 September in monthly frequency. In Appendix Table A4, a full regression table is reported.

on σ and γ are indeed very similar to those of Crump et al. (2015); $\hat{\sigma}$ of Crump et al. (2015) under fixed effects is 0.713 and $\hat{\gamma}$ is 0.198 while our estimates are 0.763 and 0.189.[19] Now, we replace σ and γ with $\sum_{s=1}^{12}\sigma_s\tau_s$ and $\sum_{s=1}^{12}\gamma_s\tau_s$ and re-estimate the regression model, where τ_s is an indicator variable for tenure s. This modification allows the regression coefficients σ and γ to vary by survey experience of respondents non-parametrically.

Figure 7 shows that the estimated EIS, $\hat{\sigma}$, increases generally with survey experience. That is, more experienced survey participants tend to more actively reflect changes in inflation expectations to consumption expectations. In the

[19] Our estimates are slightly different from those of Crump et al. (2015) since we chose a different sampling rule. We use the same sampling rule throughout this paper. We truncate the top and bottom 5% of all point forecasts for each tenure group and period. We restrict samples to respondents who participate in the survey for the maximum number of times in order to minimize the effects of panel attrition. Finally, we use quarterly time-fixed effects instead of monthly time-fixed effects. While our sampling rule is different from that of Crump et al. (2015), as mentioned in the main text, our baseline estimates are very similar to their results, suggesting sampling rule did not drive our results in this section.

baseline OLS estimates, new participants tend to increase their expected consumption growth rates over the next 12 months by 0.69 percentage points when their inflation expectations decrease by one percentage point. On the contrary, the most experienced respondents increase their expected consumption growth rates by 0.78 percentage points when inflation expectations decrease by one percentage point, approximately a 13 percent larger response than that of new survey participants.

However, this does not necessarily mean all regression coefficients significantly change with survey experience. For example, in Figure 7, we show that $\hat{\gamma}$, which measures the excess sensitivity of consumption to income, stays roughly around 0.2 for all tenure groups. Also following Crump et al. (2015), we use an instrumental variable (IV) strategy that uses the point inflation expectation as an instrument of density-implied mean inflation expectation. As shown in the figure, our qualitative results are similar: $\hat{\sigma}$ moderately increases with survey experience while $\hat{\gamma}$ stays stable. A full regression table is available in Table A4 of the appendix.

Note that a major finding of Crump et al. (2015) is that their estimates of the EIS ($\hat{\sigma} \approx 0.5$ or 0.8 at most) are near the lower end of the range of micro estimates reported in existing literature. Our results indicate that even if we only focus on experienced respondents who are better informed about inflation than new participants, the EIS stays at most 0.8 which is their preferred upper bound. If we consider that the estimated EIS tends to moderately increase with survey experience, the EIS of the general population who lack any prior survey experience is likely to be even lower than the original estimates of Crump et al. (2015). Survey participation that induces learning about inflation (or equivalently, greater attention to inflation) may result in larger responsiveness to reported inflation expectations by survey respondents. In this example, it results in higher estimated EIS, $\hat{\sigma}$.

Why does $\hat{\sigma}$ tend to be larger for experienced survey participants, but $\hat{\gamma}$ is mostly not? Consistent with our findings throughout the paper, consumers' imperfect attention to aggregate shocks can account for this otherwise puzzling phenomenon. When it comes to spending decisions, consumers tend to focus upon their income, but may not pay careful attention to general inflation rates. Therefore, they have sluggish responses to aggregate shocks (Carroll et al., 2020). In other words, if consumers become more attentive to inflation rates because survey experience, their consumption expectations may more quickly respond to change in future inflation rates (larger $\hat{\sigma}$ with survey experience). In contrast, how households' reported consumption plans respond to expected future income may not change after taking more surveys. Prior to taking a survey, they may already understand their own future income path well and have an established rule on how to adjust their consumption plan with future income changes ($\hat{\gamma}$ stays mostly stable in survey experience).

This exercise shows how learning effects can influence micro estimates. Awareness of such learning effects is useful for interpretation of analysis using survey micro data. We suggest that it would be good practice for users of survey micro data to check whether their estimates are robust using subsamples of shorter-tenured and longer-tenured respondents.

III. Other Surveys

One potential concern is that the learning-through-survey effect might arise from a particular feature of the SCE, such as the short time period of relatively low and stable inflation in which the SCE has been conducted. In addition, inflation expectations of firms tend to resemble those of households (Coibion, Gorodnichenko and Kumar, 2018), suggesting the possibility that the learning-through-survey effects may exist for a firm survey as well as household surveys. This section uses the Michigan Survey of Consumers (MSC) and a survey of U.S. firms to provide evidence of learning-through-survey effects in other contexts.

A. Michigan Survey of Consumers

The Michigan Survey of Consumers (MSC), like the SCE, is a monthly survey of consumer expectations. However, the MSC and the SCE differ significantly in their resampling frequency. Whereas the SCE consecutively tracks respondents up to twelve times, the MSC only allows respondents to participate in a maximum of two interviews, with a six-month gap between interviews.

Since the MSC began in 1978, rather than 2013, it provides us an opportunity to check whether learning-through-survey effects only exist for recent periods when inflation rate has been low and stable.[20] In addition, because there is a six-month gap between interviews in the MSC, we can also track if learning-through-survey effects decrease with a longer period between surveys. When a follow-up survey is six months after the first survey, it may be easier for respondents to forget their past responses and take the survey as if it is their first survey.[21]

In order to estimate a time-series of learning-through-survey effects, we use a regression equation analogous to our baseline regression equation (1), but with fixed effects replaced by demographic control variables to account for the limitations of the MSC dataset. We estimate the following equation for each period t separately and obtain a sequence of survey effects, $\{\hat{\delta}_t\}_{t=1}^{T}$:

$$\pi^e_{its} = \delta_t \tau_s + \beta_t X_{it} + \varepsilon_{it} \tag{6}$$

where π^e_{its} denotes the one-year-ahead point inflation forecast of individual i at period t with tenure $s \in \{1, 2\}$, τ_s is an indicator variable for tenure s, X_{it} is a vector of control variables including sex, education, region, the number of

[20]When compared to periods of high and volatile inflation, periods when inflation is low and stable might lead households to be more inattentive to inflation. The cost of neglecting inflation in such periods is lower. Therefore, one can argue that learning-through-survey effects may only exist for the recent low and stable inflation environment.

[21]Warren and Halpern-Manners (2012) report that panel conditioning effects, which is equivalent to learning-through-survey effects in our paper, are rarely observed when baseline and follow-up surveys are separated by more than a year.

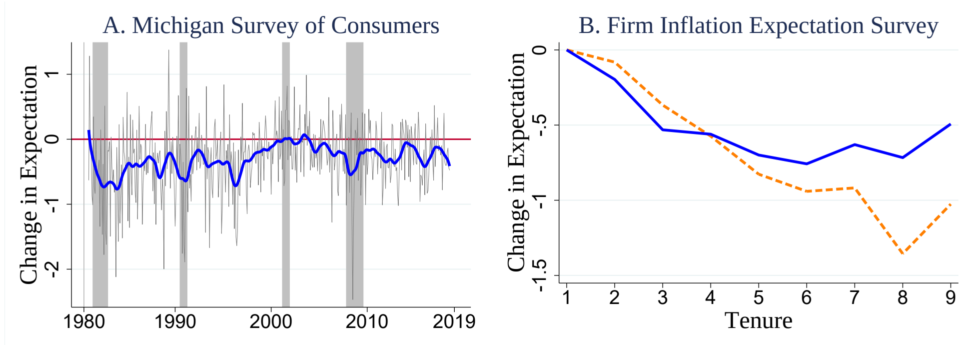

Figure 8. Learning-Through-Survey Effects on Inflation Expectations in Other Surveys

Note: Panel A shows a time-series of learning-through-survey effects, which are estimated from a regression equation (6). The thick solid blue line is a smoothed plot of $\{\hat{\delta}_t\}_{t=1}^{t=T}$, which are regression coefficients attached to the tenure dummies. Locally Weighted Scatterplot Smoothing (LOWESS) is used with for smoothing with a smoothing parameter of 0.05. If $\hat{\delta}_t$ is negative, then the second-time interviewees have lower inflation expectations than the first-time interviewees in the period t, by percentage points unit. The gray thin line shows a non-smoothed plot of $\{\hat{\delta}_t\}_{t=1}^{t=N}$. The shaded area indicates the NBER recession periods. The data is taken from the Michigan Survey of Consumers, which is gathered monthly from January 1981 to August 2018.
Panel B shows the estimated learning-through-survey effect from a U.S. firm survey, using different methods. The percentage points change in inflation expectations of survey participants compared to their initial responses is presented on the y-axis. The solid blue line corresponds to the results from Deaton's method, which normalizes quarterly dummy variables following Deaton and Paxson (1994). The dashed orange line corresponds to the results when macroeconomic aggregate variables are used to control for time effects in a linear panel fixed effects regression, including monthly CPI inflation rates, the aggregate median of MSC one-year-ahead inflation forecasts, unemployment rate, and the log of average WTI oil prices. Tenure in x-axis mans the total number of survey experiences of each respondent (including the current survey wave). We restrict samples to consist of firms who eventually participate in the survey more than three times and winsorize the top and bottom 5% of the data. The sample period is from 2018 April to 2020 April, in quarterly frequency.

kids, marital status, log of nominal household income, age, and a square term of age, and finally ε_{it} is an error term. As we did for the SCE, we apply the "non-attrition" restriction to samples; our samples consist of respondents who eventually participated in a follow-up survey.

Panel A of Figure 8 shows the resulting estimates of $\{\delta_t\}_{t=1}^{t=T}$ from the regression (6), smoothed for better visual clarity. The figure provides two major findings. The raw estimates of learning effects are very noisy because of the limitations in the MSC dataset.

First, over long periods, repeat participants have about 0.4 percentage points lower inflation expectations on average than the first-time interviewees. The lower inflation expectations for repeat participants are consistent with the results from the panel regression analysis on the SCE dataset, indicating that the effect is not only confined to the recent period of low and stable inflation. As expected, this effect is smaller than the effect found in the SCE dataset likely because the time between surveys is longer–six months instead of one. This smaller learning effect in the MSC compared to that in the SCE is consistent with recent evidence from a randomized information treatment experiment that shows providing information about inflation to households has large contemporaneous effects on their expectations but that these effects rapidly diminish over time (Coibion, Gorodnichenko and Weber, 2020).

Second,learning-through-survey effects are not constant over time and significantly vary over time. The learning-through-survey effect tends to be larger during recessions when economic uncertainty is high. Repeat survey participants have significantly lower inflation expectations than those of new participants during recessions (excepting the early 2000s recession). This suggests that households form inflation expectations in a Bayesian manner. Households put more weight on new information when they are more uncertain in their beliefs. Therefore, since repeat participants have more information than new participants because of past survey experience, the difference in responses between repeat participants and new participants could be larger during periods of high economic uncertainty.

To summarize, the results from the MSC show that during most periods, repeat participants generally report lower inflation expectations than new participants. The degree of the learning-through-survey effect changes across time and becomes larger during recessions, which suggests households put more weight on new information when they are more uncertain in their beliefs. In addition, the learning-through-survey effect tends to be smaller for the MSC than those of the SCE, likely because there is a longer period of time between baseline and follow-up surveys.

B. Inflation Expectations of Firms

While our main focus so far has been household surveys Coibion, Gorodnichenko and Kumar (2018) show that the inflation expectations of firm managers tend to resemble those of households, which suggests that learning-through-survey effects may exist in firm surveys as well. To study whether this is the case, we use a new firm expectation survey targeting businesses in the U.S.

This new firm panel survey is collected by a business intelligence company that has been collecting CEOs' and top executives' perceptions and expectations for various firm-specific economic outcomes. A question asking about one-year-ahead CPI inflation rates is added its quarterly survey in 2018. The survey covers the U.S. firms in manufacturing and services sectors. About 300 to 600 firms participate in this survey each wave and stay in the panel for about three waves on average. We use this data, which was collected from April 2018 to April 2020 at a quarterly frequency.[22]

We estimate the learning-through-survey effects of inflation expectations of U.S. firms in analogous to our baseline regression equation (1). However, because the firm inflation expectation survey is quarterly and only began in April 2018, only nine survey waves are available. Therefore, we relax our "non-attrition" restriction to save observations; we restrict our samples to consist of firms who participated in the survey more than three times. As before, we either use Deaton's normalization method or aggregate control variables to avert the APC problem[23], and winsorize the top and bottom 5% of data.

Panel B of Figure 8 shows the resulting estimates of the learning-through-survey effects from the firm survey. Inflation expectations of repeat survey participants decrease with survey experience on average, consistent with what we found in the consumer surveys. This provides additional evidence that firm executives, who

[22] Candia, Coibion and Gorodnichenko (2020) and `http://firm-expectations.org` provide more detailed information about this firm survey.

[23] We cannot use the quarterly time fixed effects method for this case since our data is quarterly.

are likely the price-setters in the economy, typically face information constraints that may influence their expectations of aggregate inflation. For example, Mackowiak and Wiederholt (2009) show that firms pay more attention to idiosyncratic variables because firm-specific conditions are generally more important in their decision-making than aggregate conditions.

Consistent with what we found from the MSC dataset, the learning-through-survey effect in the firm survey is smaller in general than the effect found in the SCE dataset, as the time between surveys is longer than that of the SCE—three months instead of one. In the firm survey, after 6 months (3 times of survey experience in total), repeat survey participants have about 0.36 to 0.53 percentage points lower inflation expectations than those of new participants. In the SCE, after 6 months (7 times of survey experience in total), repeat survey participants have about 1.6 percentage points lower inflation expectations than those of new participants. Another reason why the learning-through-survey effect in a firm survey is smaller than that of household surveys could be that the initial inflation expectations of firms are generally more accurate than those of households; after the winsorization, the average inflation expectation of firms is 2.89 percent, and its standard deviation is 1.21.

While the dataset is limited, the U.S. firm survey data we use confirms that the learning-through-survey effect is not specific to household surveys only. Also, consistent with what we found from the SCE, it shows that the degree of learning-through-survey effects may depend on time between surveys and respondents' prior level of knowledge on the subjects being asked.

IV. Discussion of an Alternative Explanation

We have shown so far that beliefs of survey respondents significantly change by participating in surveys, which we call the "learning-through-survey" effect. We have suggested that this effect arises because respondents pay more attention to inflation after being asked about inflation in one or more rounds of a survey.

However, one alternative explanation for the learning effect we found could be a "reporting error" model.[24] Under the reporting error model, survey respondents have an underlying belief distribution about inflation that is not affected by survey participation. However, respondents with lower survey tenure answer questions with extra reporting error, because they must expend cognitive effort to formalize, retrieve and report their underlying beliefs accurately.

More formally, under the reporting error model, respondent i of tenure s reports an inflation expectation $r_{its} = \pi^e_{its} + \varepsilon_{its}$ where π^e_{its} is the respondent's true underlying inflation expectation in period t and ε_{its} is a reporting error. Suppose that as a respondent gains more experience in answering survey questions, then he becomes better in expressing his beliefs more accurately. That is, the distribution of ε_{its} becomes tighter as s increases. As we and others have documented, consumer inflation expectations are upward-biased, so ε_{its} is not zero in expectation, but rather a positive figure. Suppose, for example, it has a log normal distribution, $\ln(\varepsilon_{its}) \sim N(0, \sigma^2_s)$, and σ^2_s decreases with survey experience. This simple model can generate the main effects documented in our paper: reported inflation expectation levels and uncertainty decrease with survey experience. One could further allow this reporting error to depend on demographic characteristics such as education or income in order to explain the heterogeneity in learning effects we found.

The central issue here is whether the change in responses throughout the survey waves reflects a change in belief about the economy, or indicates respondents are improving when expressing beliefs. Therefore, a key difference between our learning effect model and the reporting error model is that under the reporting error model, reported beliefs become *more* representative of true beliefs with survey experience. For example, under the reporting error model, a survey only consisting of respondents with longer tenure will be the most representative survey instead

[24]We thank an anonymous referee for providing constructive comments related to this issue. We extensively borrow from his/her "reporting error" hypothesis in this section.

of being the most biased survey, which is the exact opposite of our conclusion.

We present more supporting evidence that the learning effect has changed respondents' underlying beliefs about the economy. First, reporting errors should be minimal for easy-to-answer qualitative questions. For example, an SCE question asks about respondents' outlook about their personal finances For that question, there are only five response choices: much better, somewhat better, about the same, somewhat worse, and much worse. Presumably, respondents may have only little room to "improve" their reporting errors with this simple question. Therefore, we can expect that reporting errors have little effect upon the changes in responses. We find that the fraction of respondents who choose "About the same" significantly increases with survey tenure, while that of extreme expectations ("Much Worse" or "Much Better") decreases. The most experienced participants are approximately 9.3 percentage points more likely to report that their personal finance situation will be about the same next year than new participant. This is unlikely to reflect shrinking reporting errors and may instead provide evidence of learning effects.[25]

Second, under the reporting error model, respondents' improvement in expressing their underlying economic beliefs is unconditional on economic shocks and thus should be constant over time, as a reporting error is essentially a kind of measurement error in surveys. In contrast, in our learning model, survey participation changes respondents' attentiveness to economic conditions, so tenure-based effects should depend on economic shocks. For example, if repeat participants but not new participants are attentive to inflation news and statistics, a disinflationary shock would reduce the inflation expectations of repeat participants but not of new participants. This would further increase the gap in expectations between new and repeat participants. In our "Shale Revolution" example in section II.A, we showed that the learning effect changes over time, and in particular with oil

[25]Specific phrasing of the questions in the SCE and a full table for the results are available in the appendix. See Section 3 and Table A5 of the appendix.

prices, This result is consistent with our learning model, but not with the reporting error model. To summarize, additional evidence from other survey questions and from the "Shale Revolution" example suggests that the economic expectations of repeat respondents may have indeed changed after taking the survey, not just the reporting errors.

V. Conclusion

Consumer surveys aim to provide information about the economic beliefs and expectations of average U.S. consumers. The population group therefore consists of households with potentially zero past survey experience. However, each month, new participants make up only about 12% of FRBNY SCE respondents.

We find that participating in the survey can itself affect the subsequent responses of survey participants. Because the survey asks respondents about their inflation expectations, it seems that individuals are induced to pay more attention to inflation after the first survey. They significantly and predictably revise their expectations in subsequent surveys.

The learning-through-survey effect documented here reveals the endogeneity of and mechanism behind information rigidities. The capacity to collect and process information is a scarce resource for households. Therefore, households rationally allocate their attention and cognitive efforts based on the cost and benefit of information acquisition. For example, when households are less certain in their beliefs, they can choose to collect more information or put more weight on new information since their current beliefs are less informative. Consistent with this explanation, we find that the impact of past survey experience on inflation expectations is larger for the households who are generally less informed about inflation prior to the survey than others with greater information.

Central banks running household surveys to measure inflation expectations should take note of this evidence of the learning-through-survey effect. Because of the effect, a respondent could be a different person after their first interview—in terms of their information about the economy and their expectations about the future. In such cases, the repeat participants of the panel survey may no longer represent the population group that the survey originally targeted.

This is not to say that the panel component of the survey should be removed. The panel component has the clear benefit of allowing researchers to control for unobservable individual characteristics. One possibility is that central banks could increase the size of the sample of new participants in each wave, but only invite some fraction of them to become repeat participants. This would allow researchers to conduct analysis on either a panel or on new participants, as appropriate to the situation. Alternatively, one could increase the time length between surveys to minimize learning effects. Repeat respondents would then take the survey with a fresh outlook, more like as if it were their first survey. In addition, it would be good practice for users of survey micro data to check whether their estimates are robust to using subsamples of shorter-tenured and longer-tenured respondents.

REFERENCES

Aguiar, Mark, and Erik Hurst. 2007. "Life-cycle prices and production." *American Economic Review*, 97(5): 1533–1559.

Arioli, Rodolfo, Colm Bates, Heinz Dieden, Ioana Duca, Roberta Friz, Christian Gayer, Geoff Kenny, Aidan Meyler, and Iskra Pavlova. 2017. "EU consumers' quantitative inflation perceptions and expectations: An evaluation." ECB Occasional Paper.

Armantier, Olivier, Giorgio Topa, Wilbert van der Klaauw, and Basit Zafar. 2017. "An Overview of the Survey of Consumer Expectations." *Federal Reserve Bank of New York Economic Policy Review*, 23(2): 51.

Baffes, John, M Ayhan Kose, Franziska Ohnsorge, and Marc Stocker. 2015. "The great plunge in oil prices: Causes, consequences, and policy responses." *Consequences, and Policy Responses (June 2015)*.

Binder, Carola C. 2017. "Measuring uncertainty based on rounding: New method and application to inflation expectations." *Journal of Monetary Economics*, 90: 1–12.

Candia, Bernardo, Olivier Coibion, and Yuriy Gorodnichenko. 2020. "Communication and the Beliefs of Economic Agents." National Bureau of Economic Research.

Carroll, Christopher D, Edmund Crawley, Jiri Slacalek, Kiichi Tokuoka, and Matthew N White. 2020. "Sticky expectations and consumption dynamics." *American economic journal: macroeconomics*, 12(3): 40–76.

Coibion, Olivier, and Yuriy Gorodnichenko. 2015*a*. "Information rigidity and the expectations formation process: A simple framework and new facts." *American Economic Review*, 105(8): 2644–78.

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

Coibion, Olivier, Yuriy Gorodnichenko, and Mauricio Ulate. 2019. "Is Inflation Just Around the Corner? The Phillips Curve and Global Inflationary Pressures." *AEA Papers and Proceedings*, 109: 465–69.

Coibion, Olivier, Yuriy Gorodnichenko, and Michael Weber. 2020. "Monetary policy communications and their effects on household inflation expectations." National Bureau of Economic Research.

Coibion, Olivier, Yuriy Gorodnichenko, and Saten Kumar. 2018. "How do firms form their expectations? new survey evidence." *American Economic Review*, 108(9): 2671–2713.

Coibion, Olivier, Yuriy Gorodnichenko, and Tiziano Ropele. 2020. "Inflation expectations and firm decisions: New causal evidence." *The Quarterly Journal of Economics*, 135(1): 165–219.

Crump, Richard K, Stefano Eusepi, Andrea Tambalotti, and Giorgio Topa. 2015. "Subjective intertemporal substitution." *FRB of New York Staff Report*, , (734).

Deaton, Angus S, and Christina Paxson. 1994. "Saving, growth, and aging in Taiwan." In *Studies in the Economics of Aging*. 331–362. University of Chicago Press.

Dräger, Lena, and Michael J Lamla. 2017. "Imperfect information and consumer inflation expectations: Evidence from microdata." *Oxford Bulletin of Economics and Statistics*, 79(6): 933–968.

D'Acunto, Francesco, Daniel Hoang, and Michael Weber. 2016. "The effect of unconventional fiscal policy on consumption expenditure." National Bureau of Economic Research.

Gabaix, Xavier. 2014. "A sparsity-based model of bounded rationality." *The Quarterly Journal of Economics*, 129(4): 1661–1710.

Halpern-Manners, Andrew, John Robert Warren, and Florencia Torche. 2017. "Panel Conditioning in the General Social Survey." *Sociological methods & research*, 46(1): 103–124.

Heckman, James, and Richard Robb. 1985. "Using longitudinal data to estimate age, period and cohort effects in earnings equations." In *Cohort analysis in social research*. 137–150. Springer.

Hobcraft, John, Jane Menken, and Samuel Preston. 1985. "Age, period, and cohort effects in demography: a review." In *Cohort analysis in social research*. 89–135. Springer.

Kaplan, Greg, and Sam Schulhofer-Wohl. 2017. "Inflation at the household level." *Journal of Monetary Economics*, 91: 19–38.

Karahan, Fatih, Sean Mihaljevich, and Laura Pilossoph. 2017. "Understanding Permanent and Temporary Income Shocks." *URL link retrieved on*, 3(02): 2018.

Machado, José AF, and JMC Santos Silva. 2019. "Quantiles via moments." *Journal of Econometrics*, 213(1): 145–173.

Mackowiak, Bartosz, and Mirko Wiederholt. 2009. "Optimal sticky prices under rational inattention." *American Economic Review*, 99(3): 769–803.

Mankiw, N Gregory, and Ricardo Reis. 2002. "Sticky information versus sticky prices: a proposal to replace the New Keynesian Phillips curve." *The Quarterly Journal of Economics*, 117(4): 1295–1328.

Powell, Jerome. 2019. "Hearing Before the Committee on Banking, Housing, and Urban Affairs." The Semiannual Monetary Policy Report to the Congress.

Reis, Ricardo. 2006. "Inattentive consumers." *Journal of Monetary Economics*, 53(8): 1761–1800.

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

Verbrugge, Randal J, and Carola Conces Binder. 2016. "Digging into the downward trend in consumer inflation expectations." *Economic Commentary*, , (2016-11).

Warren, John Robert, and Andrew Halpern-Manners. 2012. "Panel conditioning in longitudinal social science surveys." *Sociological Methods & Research*, 41(4): 491–534.

Online Appendix of
"Learning-through-Survey in Inflation Expectations"

September 27, 2020

1 Figures

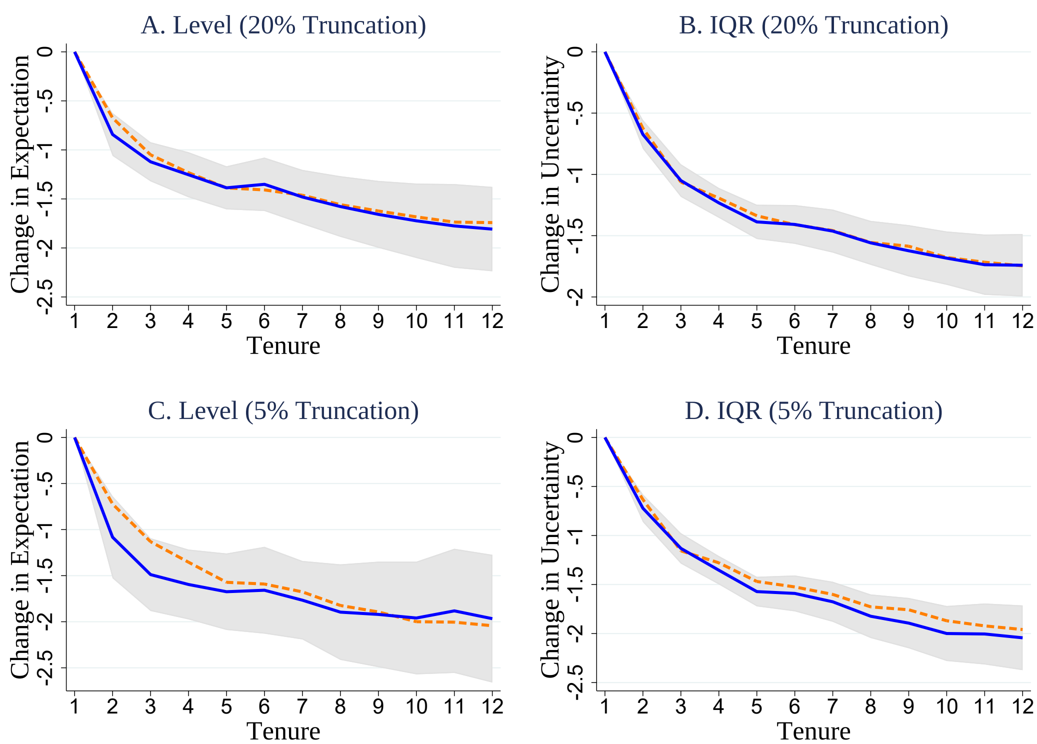

Figure A1: Average Survey Effects on Inflation Expectations in the SCE by Different Thresholds

Note: Panels A and B reproduce the results of Figure 1 for higher thresholds (trimming top and bottom 10%). Panels C and D reproduce the results of Figure 1 for lower thresholds (trimming top and bottom 2.5%). The y-axis shows the change in responses of survey participants compared to their initial responses, which is estimated from the regression (1). The y-axis is measured in percentage points. For Panel A and C, the dependent variable of the regression is the point inflation rate forecast, and for Panel B and D, the dependent variable is the IQR of consumers' inflation expectations. The solid blue (dashed orange) lines correspond to one-year (three-year) ahead inflation forecasts. The gray area shows a 95% confidence interval for the solid blue line with Driscoll-Kraay standard errors of lag one. Tenure is shown on the x-axis and corresponds to the total number of survey experiences of each respondent (including the current survey wave). The data is from the Survey of Consumer Expectation by the NY Fed, from 2013 June to 2019 September in monthly frequency.

2 Tables

Table A1: Average Survey Effects on Various Expectations in the SCE

	(1)	(2)	(3)	(4)	(5)	(6)
Dependents:	$\pi^e_{t,t+12}$	$\pi^e_{t+24,t+36}$	$\pi^{e,IQR}_{t,t+12}$	$\pi^{e,IQR}_{t+24,t+36}$	$EARN^e_{t,t+12}$	$INC^e_{t,t+12}$
Tenure2	-1.034	-0.899	-0.700	-0.663	-0.325	-0.312
	(0.162)	(0.138)	(0.0635)	(0.0555)	(0.125)	(0.183)
Tenure3	-1.355	-1.293	-1.108	-1.129	-0.296	-0.255
	(0.156)	(0.154)	(0.0724)	(0.0668)	(0.115)	(0.176)
Tenure4	-1.514	-1.415	-1.337	-1.256	-0.376	-0.412
	(0.155)	(0.156)	(0.0695)	(0.0642)	(0.148)	(0.186)
Tenure5	-1.692	-1.564	-1.537	-1.467	-0.487	-0.639
	(0.159)	(0.165)	(0.0714)	(0.0713)	(0.150)	(0.203)
Tenure6	-1.620	-1.661	-1.547	-1.526	-0.453	-0.662
	(0.186)	(0.187)	(0.0894)	(0.0807)	(0.174)	(0.216)
Tenure7	-1.774	-1.720	-1.625	-1.599	-0.559	-0.618
	(0.180)	(0.207)	(0.0979)	(0.0912)	(0.200)	(0.212)
Tenure8	-1.875	-1.907	-1.762	-1.725	-0.614	-0.629
	(0.211)	(0.226)	(0.103)	(0.0972)	(0.215)	(0.253)
Tenure9	-1.955	-1.967	-1.825	-1.743	-0.600	-0.729
	(0.240)	(0.253)	(0.120)	(0.106)	(0.232)	(0.275)
Tenure10	-2.049	-1.967	-1.915	-1.844	-0.608	-0.623
	(0.249)	(0.275)	(0.129)	(0.115)	(0.255)	(0.323)
Tenure11	-2.033	-2.017	-1.936	-1.886	-0.623	-0.527
	(0.277)	(0.295)	(0.146)	(0.128)	(0.256)	(0.335)
Tenure12	-2.084	-2.091	-1.984	-1.936	-0.652	-0.554
	(0.287)	(0.322)	(0.150)	(0.136)	(0.310)	(0.370)
Observations	41899	41942	41227	41271	26611	41945
F-statistics	20.34	11.04	64.08	52.87	1.452	3.998

Note: Driscoll-Kraay standard errors of lag one are in parentheses. Dependent variables of regressions are represented under the corresponding column numbers. For example, for column (1), the dependent variable, $\pi^e_{t,t+12}$, is one-year-ahead point inflation forecast. $\pi^e_{t+24,t+36}$ is three-year-ahead point inflation forecast. $\pi^{e,IQR}_{t,t+12}$ is IQR of one-year-ahead point inflation forecast which is estimated at individual-level using probabilistic forecasts of each respondent. $\pi^{e,IQR}_{t+24,t+36}$ is IQR of three-year-ahead point inflation forecast which is estimated at individual-level using probabilistic forecasts of each respondent. $EARN^e_{t,t+12}$ is one-year-ahead point personal earnings forecast. $INC^e_{t,t+12}$ is one-year-ahead point household income forecast. All units are in percentage points. We run a linear panel regression with individual and quarterly fixed effects, $y_{its} = \sum_{s=2}^{12} \beta_s \tau_s + \alpha_i + \gamma_t + \varepsilon_{it}$, where τ_s is a tenure dummy variable for s number of total survey experience. Tenure corresponds to the the total number of of survey experiences of each respondent (including the current survey wave). The estimated regression coefficients $\{\beta_s\}_2^{12}$ are presented in the table. We restrict samples to consist of respondents who eventually participate in the survey for twelve waves (non-attriters). We truncate the top and bottom 5% of each dependent variable for each tenure group and period. Data is from the FRBNY Survey of Consumer Expectations, from 2013 June to 2019 September in monthly frequency.

Table A2: Average Survey Effects on Updating of Expectations and Absolute Forecast Errors in the SCE

	(1)	(2)	(3)	(4)
Dependents:	$Update(\pi^e_{t,t+12})$	$Update(\pi^e_{t+24,t+36})$	$\lvert\pi^e_{t,t+12} - \pi_{t,t+12}\rvert$	$\lvert\pi^e_{t+24,t+36} - \pi_{t+24,t+36}\rvert$
Tenure2			-1.329	-1.169
			(0.132)	(0.138)
Tenure3	-5.366	-5.366	-1.846	-1.674
	(1.091)	(1.091)	(0.130)	(0.158)
Tenure4	-7.903	-7.903	-2.011	-1.834
	(1.279)	(1.279)	(0.143)	(0.176)
Tenure5	-10.04	-10.04	-2.243	-2.109
	(1.313)	(1.313)	(0.151)	(0.173)
Tenure6	-13.63	-13.63	-2.258	-2.238
	(1.475)	(1.475)	(0.174)	(0.196)
Tenure7	-15.08	-15.08	-2.419	-2.288
	(1.777)	(1.777)	(0.180)	(0.223)
Tenure8	-15.69	-15.69	-2.577	-2.472
	(1.837)	(1.837)	(0.202)	(0.242)
Tenure9	-17.65	-17.65	-2.652	-2.493
	(2.241)	(2.241)	(0.229)	(0.263)
Tenure10	-17.56	-17.56	-2.751	-2.635
	(2.341)	(2.341)	(0.245)	(0.280)
Tenure11	-19.16	-19.16	-2.809	-2.641
	(2.628)	(2.628)	(0.274)	(0.309)
Tenure12	-19.80	-19.80	-2.856	-2.743
	(3.172)	(3.172)	(0.288)	(0.332)
Observations	42540	42540	41556	28200
F-statistics	13.58	13.58	34.32	18.57

Note: Driscoll-Kraay standard errors of lag one are in parentheses. Dependent variables of regressions are represented under the corresponding column numbers. For example, for column (1), the dependent variable, $Update(\pi^e_{t,t+12})$, is an indicator variable for an update of one-year-ahead point inflation forecast. For example, if $\pi^e_{t,t+12} \neq \pi^e_{t-1,t+11}$ then $Update(\pi^e_{t,t+12}) = 100$ (percentage points unit) but otherwise $Update(\pi^e_{t,t+12})$ is zero. A similar rule applies to $Update(\pi^e_{t+24,t+36})$. $Update(\pi^e_{t+24,t+36})$ is an indicator variable for an update of three-year-ahead point inflation forecast. $|\pi^e_{t,t+12} - \pi_{t,t+12}|$ measures absolute forecast error of one-year-ahead point inflation forecast. $\pi_{t,t+12}$ corresponds to realized seasonally-adjusted CPI inflation rates from period t to period $t+12$ (all urban consumer items). A similar rule applies to three-year-ahead point inflation forecast. $|\pi^e_{t+24,t+36} - \pi_{t+24,t+36}|$ measures absolute forecast error of three-year-ahead point inflation forecast. All units are in percentage points. We run a linear panel regression with individual and quarterly fixed effects, $y_{its} = \sum_{s=2}^{12} \beta_s \tau_s + \alpha_i + \gamma_t + \varepsilon_{it}$, where τ_s is a tenure dummy variable for s number of total survey experience. Tenure corresponds to the the total number of of survey experiences of each respondent (including the current survey wave). The estimated regression coefficients $\{\beta_s\}_2^{12}$ are presented in the table. We restrict samples to consist of respondents who eventually participate in the survey for twelve waves (non-attriters). For column (3) and (4), We truncate the top and bottom 5% of point inflation forecasts for each tenure group and period. Data is from the FRBNY Survey of Consumer Expectations and Federal Reserve Economic Data, from 2013 June to 2019 September in monthly frequency.

Table A3: Panel Regression Estimation of Responses to Oil Prices by Survey Tenure

	(1)	(2)	(3)	(4)	(5)	(6)
Tenure1×$log(Oil)$	1.534	0.685	0.881	0.994	0.483	1.102
	(0.475)	(0.240)	(0.356)	(0.285)	(0.193)	(0.242)
Tenure2×$log(Oil)$	1.429	0.599	0.526	0.865	0.361	1.007
	(0.443)	(0.235)	(0.339)	(0.291)	(0.222)	(0.262)
Tenure3×$log(Oil)$	1.431	0.573	0.474	0.843	0.272	1.018
	(0.477)	(0.244)	(0.337)	(0.287)	(0.216)	(0.252)
Tenure4×$log(Oil)$	1.399	0.558	0.384	0.855	0.334	0.992
	(0.494)	(0.252)	(0.376)	(0.288)	(0.234)	(0.262)
Tenure5×$log(Oil)$	1.350	0.487	0.290	0.836	0.271	0.952
	(0.484)	(0.243)	(0.371)	(0.290)	(0.240)	(0.294)
Tenure6×$log(Oil)$	1.445	0.562	0.289	0.886	0.287	1.059
	(0.494)	(0.249)	(0.380)	(0.292)	(0.230)	(0.289)
Tenure7×$log(Oil)$	1.436	0.519	0.251	0.889	0.248	1.059
	(0.503)	(0.255)	(0.394)	(0.295)	(0.230)	(0.289)
Tenure8×$log(Oil)$	1.373	0.473	0.152	0.868	0.191	1.004
	(0.523)	(0.265)	(0.405)	(0.294)	(0.261)	(0.308)
Tenure9×$log(Oil)$	1.349	0.437	0.113	0.870	0.187	0.989
	(0.556)	(0.280)	(0.435)	(0.295)	(0.299)	(0.350)
Tenure10×$log(Oil)$	1.337	0.433	0.113	0.846	0.164	0.987
	(0.552)	(0.279)	(0.441)	(0.297)	(0.276)	(0.333)
Tenure11×$log(Oil)$	1.358	0.396	0.0528	0.878	0.138	1.018
	(0.578)	(0.295)	(0.456)	(0.301)	(0.277)	(0.341)
Tenure12×$log(Oil)$	1.342	0.388	0.0458	0.876	0.126	1.012
	(0.590)	(0.304)	(0.450)	(0.301)	(0.313)	(0.374)
Expectation Type	Mean	Mean	Point	Mean	Mean	Mean
10% Truncation	N	Y	Y	N	N	N
Full Survey Participation	Y	Y	Y	Y	N	Y
Individual FE	Y	Y	Y	Y	Y	Y
Quarterly Time FE	Y	Y	Y	Y	Y	N
Sample Period	14m7-15m2	14m7-15m2	14m7-15m2	13m6-19m9	14m7-15m2	14m7-15m2
Observations	5360	4799	4885	45774	9859	5360
F-statistics	27.68	61.45	107.7	8.435	324.0	76.54

Note: Driscoll-Kraay standard errors of lag one are in parentheses. Tenure corresponds to the the total number of of survey experiences of each respondent (including the current survey wave). The independent variables are interaction terms between monthly WTI crude oil price per barrel in $US and tenure dummy variables (τ_s). The dependent variable is the one-year-ahead density mean inflation expectation (in percentage points) estimated by the NY Fed, except for model (3) which uses point inflation expectations as a dependent variable with 10% truncation. For model (2) and (3), we truncate the top and bottom 5% of dependent variable for each tenure group and period. Except for model (5), we restrict samples to consist of respondents who eventually participate in the survey for twelve waves (non-attriters). Data is from the FRBNY Survey of Consumer Expectations and Federal Reserve Economic Data in monthly frequency.

Table A4: Panel Regression Estimation of the EIS and Excess Sensitivity by Survey Tenure

	(1)		(2)		(3)	
	$\hat{\sigma}$	$\hat{\gamma}$	$\hat{\sigma}$	$\hat{\gamma}$	$\hat{\sigma}$	$\hat{\gamma}$
Pooled	0.763	0.189				
	(0.0161)	(0.0123)				
Tenure1			0.693	0.164	0.488	0.206
			(0.0381)	(0.0238)	(0.0704)	(0.0251)
Tenure2			0.731	0.195	0.567	0.225
			(0.0335)	(0.0260)	(0.0617)	(0.0293)
Tenure3			0.766	0.180	0.540	0.227
			(0.0327)	(0.0220)	(0.0627)	(0.0268)
Tenure4			0.747	0.206	0.562	0.241
			(0.0274)	(0.0229)	(0.0516)	(0.0260)
Tenure5			0.786	0.182	0.592	0.219
			(0.0245)	(0.0219)	(0.0483)	(0.0258)
Tenure6			0.824	0.143	0.636	0.194
			(0.0296)	(0.0316)	(0.0438)	(0.0323)
Tenure7			0.782	0.193	0.626	0.230
			(0.0269)	(0.0166)	(0.0504)	(0.0203)
Tenure8			0.789	0.213	0.581	0.253
			(0.0254)	(0.0214)	(0.0474)	(0.0258)
Tenure9			0.820	0.203	0.633	0.247
			(0.0262)	(0.0187)	(0.0431)	(0.0225)
Tenure10			0.764	0.228	0.613	0.266
			(0.0241)	(0.0261)	(0.0450)	(0.0280)
Tenure11			0.772	0.200	0.627	0.248
			(0.0264)	(0.0217)	(0.0468)	(0.0242)
Tenure12			0.781	0.198	0.628	0.230
			(0.0276)	(0.0201)	(0.0494)	(0.0248)
Regression Type	OLS		OLS		IV	
Observations	38691		38691		35701	

Note: Driscoll-Kraay standard errors of lag one are in parentheses. We run a linear panel regression of Crump et al. (2015), allowing regression coefficients to vary by survey experience of respondents: $ExpCG^i_{t,t+12} = -\sum_{s=1}^{12} \tau_s \sigma_s ExpInf^i_{t,t+12} + \sum_{s=1}^{12} \tau_s \gamma_s ExpIG^i_{t,t+12} + \alpha_i + \beta_t + \varepsilon_{i,t}$. The dependent variable is expected real consumption growth over the next twelve months of households, $ExpCG^i_{t,t+12}$. Independent variables are density-implied mean inflation rates, $ExpInf^i_{t,t+12}$, and expected real household income growth, $ExpIG^i_{t,t+12}$. α_i and β_t are individual and quarterly time fixed effects. τ_s is a dummy variable for respondents whose tenure of s. Tenure corresponds to the the total number of of survey experiences of each respondent (including the current survey wave). For the case of IV, the point inflation expectation is used as an instrument of density-implied mean inflation expectation. All units of variables are in percentage points. We truncate the top and bottom 5% of each dependent variable for each tenure group and period. We restrict samples to consist of respondents who eventually participate in the survey for twelve waves (non-attriters). Data is from the FRBNY Survey of Consumer Expectations, from 2013 June to 2019 September in monthly frequency.

Table A5: Changes in Unemployment and Personal Finance Expectations by Survey Tenure

Dependents:	(2) Same	(3) Much Worse	(4) Worse	(5) Better	(6) Much Better
Tenure2	1.607	-1.072	-1.197	1.415	-0.752
	(1.052)	(0.290)	(0.611)	(0.959)	(0.494)
Tenure3	3.075	-1.076	-0.804	0.223	-1.418
	(0.981)	(0.264)	(0.652)	(0.938)	(0.431)
Tenure4	3.673	-1.488	-1.066	0.491	-1.610
	(1.247)	(0.281)	(0.693)	(0.959)	(0.460)
Tenure5	5.029	-1.902	-1.674	0.741	-2.193
	(1.153)	(0.277)	(0.861)	(1.018)	(0.468)
Tenure6	7.306	-1.730	-1.256	-2.048	-2.272
	(1.361)	(0.301)	(0.840)	(0.973)	(0.575)
Tenure7	8.441	-1.995	-1.377	-2.725	-2.344
	(1.260)	(0.303)	(0.845)	(1.135)	(0.533)
Tenure8	8.166	-2.198	-1.407	-1.816	-2.746
	(1.631)	(0.392)	(1.030)	(1.317)	(0.595)
Tenure9	9.006	-2.260	-1.593	-2.663	-2.491
	(1.599)	(0.422)	(1.212)	(1.274)	(0.662)
Tenure10	8.796	-2.365	-2.088	-2.170	-2.172
	(1.784)	(0.486)	(1.349)	(1.543)	(0.718)
Tenure11	9.313	-2.697	-1.649	-2.173	-2.794
	(2.059)	(0.476)	(1.535)	(1.558)	(0.761)
Tenure12	9.325	-2.371	-1.674	-2.495	-2.785
	(1.950)	(0.501)	(1.530)	(1.593)	(0.779)
Observation	46606	46606	46606	46606	46606
F-statistics	6.62	5.06	0.70	3.72	6.03

Note: Driscoll-Kraay standard errors of lag one are in parentheses. For column (1) to (5), which are about responses on the personal finance outlook question, indicator variables corresponding to the column labels are used as dependents. For example, “Same” equals 100 (percentage points unit) when a respondent chose “About the same” for the question asking his/her personal finance outlook next year, otherwise it is zero. All units are in percentage points. We run a linear panel regression with individual and quarterly fixed effects, $y_{its} = \sum_{s=2}^{12} \beta_s \tau_s + \alpha_i + \gamma_t + \varepsilon_{it}$, where τ_s is a tenure dummy variable for s number of total survey experience. Tenure corresponds to the the total number of of survey experiences of each respondent (including the current survey wave). The estimated regression coefficients $\{\beta_s\}_2^{12}$ are presented in the table. We restrict samples to consist of respondents who eventually participate in the survey for twelve waves (non-attriters). Data is from the FRBNY Survey of Consumer Expectations, from 2013 June to 2019 September in monthly frequency.

Table A6: Summary Statistics of One-year-ahead Point Inflation Expectations of the SCE

Tenure	Mean	Std.	N
1	6.19	8.33	11684
2	4.98	5.79	9823
3	4.47	4.65	9155
4	4.42	4.02	8689
5	4.13	3.83	8229
6	4.05	3.74	7852
7	4.01	3.57	7469
8	3.86	3.31	6835
9	3.79	3.27	6286
10	3.76	3.30	5674
11	3.70	3.23	4840
12	3.66	3.35	3552
Total	4.41	4.89	90088

Note: Tenure refers to the total number of survey experiences including the current survey wave the respondents are taking. The one-year-ahead point inflation expectations are used. Std. denotes the standard deviation. By each tenure group and period, the top and bottom 5% of samples which showed extreme expectation level are dropped. Sample periods cover from 2013 June to September 2019. Sampling weights are unused, and the maximum tenure is not restricted in the calculation of the summary statistics. The data is from the Survey of Consumer Expectation by the NY Fed and has monthly frequency.

Table A7: Summary Statistics of One-year-ahead Density-implied Mean Inflation Expectations of the SCE

Tenure	Mean	Std.	N
1	3.63	3.18	11025
2	3.26	2.72	9490
3	3.15	2.53	8988
4	3.19	2.43	8533
5	3.19	2.42	8088
6	3.21	2.45	7720
7	3.23	2.45	7373
8	3.18	2.32	6749
9	3.16	2.33	6214
10	3.14	2.31	5595
11	3.11	2.32	4787
12	3.19	2.43	3511
Total	3.24	2.56	88073

Note: Tenure refers to the total number of survey experiences including the current survey wave the respondents are taking. The one-year-ahead density-implied mean inflation expectations are used. Std. denotes the standard deviation. By each tenure group and period, the top and bottom 5% of samples which showed extreme expectation level are dropped. Sample periods cover from 2013 June to September 2019. Sampling weights are unused, and the maximum tenure is not restricted in the calculation of the summary statistics. The data is from the Survey of Consumer Expectation by the NY Fed and has monthly frequency.

Table A8: Summary Statistics of One-year-ahead Inflation Expectations of the MSC

Tenure	Mean	Std.	N
1	4.64	4.84	150101
2	3.45	3.40	87687
Total	4.20	4.40	237788

Note: Tenure refers to the total number of survey experiences, including the current survey wave the respondents are taking. The one-year-ahead point inflation expectations are used. Std. denotes the standard deviation. By each tenure group and period, the top and bottom 5% of samples which showed extreme expectation level are dropped. Sample periods cover from 1978 January to March 2018. The repeat interview has begun from 1980 July. Sampling weights are unused, and the maximum tenure is not restricted in the calculation of the summary statistics. The data is from the Michigan Survey of Consumers by the University of Michigan and has monthly frequency.

3 Questionnaire

3.1 Questions related to Inflation in SCE

- **Q2**
  - And looking ahead, do you think you (and any family living with you) will be financially better or worse off **12 months from now** than you are these days?

    Instruction H1

    ◯ Much worse off

    ◯ Somewhat worse off

    ◯ About the same

    ◯ Somewhat better off

    ◯ Much better off

    If not response: error E1

- **Q8v2**
  - The next few questions are about inflation. **Over the next 12 months,** do you think that there will be inflation or deflation? (Note: deflation is the opposite of inflation)

    Instruction H8

    ◯ Inflation

    ◯ Deflation

- **Q8v2part2**
  - What do you expect the rate of [inflation/deflation as in Q8v2] to be **over the next 12 months**? Please give your best guess.

    Instruction H9

    Over the next 12 months, I expect the rate of [inflation/deflation] to be ______ %

- **Q9**
  - Now we would like you to think about the different things that may happen to inflation over the next 12 months. We realize that this question may take a little more effort.

    In your view, what would you say is the percent chance that, **over the next 12 months...**

    Instruction H4

    the rate of inflation will be 12% or higher: ______ percent chance

    the rate of inflation will be between 8% and 12%: ______ percent chance

    the rate of inflation will be between 4% and 8%: ______ percent chance

    the rate of inflation will be between 2% and 4%: ______ percent chance

    the rate of inflation will be between 0% and 2%: ______ percent chance

    the rate of deflation (opposite of inflation) will be between 0% and 2%: ______ percent chance

    the rate of deflation (opposite of inflation) will be between 2% and 4%: ______ percent chance

    the rate of deflation (opposite of inflation) will be between 4% and 8%: ______ percent chance

    the rate of deflation (opposite of inflation) will be between 8% and 12%: ______ percent chance

    the rate of deflation (opposite of inflation) will be 12% or higher: ______ percent chance

    TOTAL 100

    If sum not equal to 100: "Your total adds up to XX" followed by an error message

3.2 Questions related to Future Income/Earning in SCE

- **Q23v2**
  - Please think ahead to **12 months from now.** Suppose that you are working in the exact same job at the same place you currently work, and working the exact same number of hours. What do you expect to have happened to your earnings on this job, before taxes and deductions?

    Instruction H8

    Twelve months from now, I expect my earnings to have

    ◯ Increase by 0% or more

    ◯ Decrease by 0% or more

- **Q23v2part2**
  - By about what percent do you expect your earnings to have

    [increased/decreased as in Q23v2]? Please give your best guess.

    Instruction H9

    Twelve months from now, I expect my earnings to have

    [increased/decreased] by ______ %

- **Q24**
  - Suppose again that, 12 months from now, you are working in the exact same job at the same place you currently work, and working the exact same number of hours. In your view, what would you say is the percent that 12 months from now...

    Instruction H4

    Your earnings on this job, before taxes and deductions, will have...

    increase by 12% or more: ______ percent chance

    increase by 8% to 12%: ______ percent chance

    increase by 4% to 8%: ______ percent chance

    increase by 2% to 4%: ______ percent chance

    increase by 0% to 2%: ______ percent chance

    decreased by 0% to 2%: ______ percent chance

    decreased by 2% to 4%: ______ percent chance

    decreased by 4% to 8%: ______ percent chance

    decreased by 8% to 12%: ______ percent chance

    decreased by 12% or more: ______ percent chance

    TOTAL 100

    If sum not equal to 100: "Your total adds up to XX" followed by an error message

- **Q25v2**
  - Next we would like to ask you about your overall household income going forward. By household we mean everyone who usually lives in your primary residence (including yourself), excluding roommates and renters.

    Over the next 12 months, what do you expect will happened to the total income of all members of your household (including you), from all sources before taxes and deductions?

    Instruction H8

    Over the next 12months, I expect my total household income to...

◯ increase by 0% or more

◯ decrease by 0% or more

- **Q25v2part2**
  - By about what percent do you expect your total household income to [increased/decreased as in Q25v2]? Please give your best guess.

    Instruction H9

    Over the next 12 months, I expect my total household income to [increased/decreased] by ______ %

3.3 Questions related to Inflation in MSC

- **A12**
  - During the next 12 months, do you think that prices in general will go up, or go down, or stay where they are now?

    1.GO UP 2.STAY THE SAME 5.GO DOWN 8.DON'T KNOW

    (If answer 2 is chosen then go to A12a. For 1, go to A12b. For 5, go to A12c.)

- **A12a**
  - Do you mean that prices will go up at the same rate as now, or that prices in general will not go up during the next 12 months?

    2.GO UP 3.WILL NOT GO UP

- **A12b**
  - By about what percent do you expect future prices to go (up/down) on the average, during the next 12 months?

    ______ PERCENT
  - DON'T KNOW (Go to A12c if this is chosen)

- **A12c**

  (AFTER A DON'T KNOW RESPONSE IS PROVED, IF R SAYS, "I DON'T KNOW" USE THE FOLLOWING PROBE:)

  (USE PROBE BELOW IF ANSWER IS GREATER THAN 5%)
  - How many cents on the dollar do you expect prices to go (up/down) on the average, during the next 12 months?

    ______ CENTS ON DOLLAR
  - DON'T KNOW

- IF R GIVES AN ANSWER THAT IS GREATER THAN 5%, PLEASE PROBE WITH:

  "Let me make sure I have that correct. You said that you expect prices to go (up/down) during the next 12 months by (X) percent. Is that correct?"