

# The Price is Right: Updating Inflation Expectations in a Randomized Price Information Experiment

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## ABSTRACT

Understanding the formation of consumer inflation expectations is considered crucial for monetary policy. Using a unique “information” experiment embedded in a survey, this paper investigates how consumers’ inflation expectations respond to new information. We elicit respondents’ expectations for future inflation before and after providing a random subset of respondents with factual information that may affect their expectations. This design creates unique panel data that allow us to identify causal effects of new information. We find that respondents, on average, update their expectations in response to (certain types of) provided information, and do so sensibly, in a manner consistent with Bayesian updating – with revisions systematically related to the strength of the information signal and uncertainty of baseline inflation expectations. Furthermore, we present evidence that baseline inflation expectations are right-skewed, and that consumers in the high-expectation right tail are relatively under-informed about objective inflation-relevant facts. As a result of information provision, however, the distribution of inflation expectations converges toward its center and cross-sectional disagreement declines. We also document heterogeneous information-processing by gender, and present suggestive evidence of respondents forecasting under asymmetric loss. Overall, our results provide support for expectation-formation models in which agents form expectations rationally, but face information constraints. We discuss implications of our results for monetary policy and for macro-economic modeling.

**JEL Codes:** C81, D80, E31.

**Key words:** inflation expectations, information, heterogeneous expectations, updating, Bayesian learning.

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# 1. Introduction

*“A fuller understanding of the public's learning rules would improve the central bank's capacity to assess its own credibility, to evaluate the implications of its policy decisions and communications strategy, and perhaps to forecast inflation.”*

(Ben Bernanke, 2007)

Many economic decisions – consumption, saving, wage bargaining, investing – are believed to be influenced by expectations about inflation. Inflation expectations have now become central to macro-economic models and monetary policy (Gali, 2008; Sims, 2009), and managing consumers' inflation expectations has become one of the main goals of policy makers.<sup>1</sup> Indeed, national surveys of public inflation expectations are now conducted in multiple countries.<sup>2</sup> However, managing inflation expectations requires not just monitoring expectations, but also understanding how these expectations are formed.

Studies based on survey data have shown substantial divergence among individuals' beliefs about future inflation (Mankiw, Reis, and Wolfers, 2003), which the recent literature attempts to explain as a result of different information sets or different expectation-formation processes: e.g., sticky information models, in which new information is slow to diffuse through the population (Mankiw and Reis, 2002), perhaps because agents only probabilistically pay attention to experts or to news (Carroll, 2003); noisy information models, in which agents form expectations based on noisy private signals (Woodford, 2001); some form of adaptive learning (Evans and Honkapohja, 2001); switching between different prediction rules (Branch, 2004); learning from lifetime inflation experiences (Malmendier and Nagel, 2010; Madeira and Zafar, 2012); or heterogeneous asymmetric costs for over- and under-estimates of inflation (Capistran and Timmermann, 2009). However, while this literature has found some aggregate data patterns consistent with these models, there nevertheless remains little direct empirical evidence on how individual consumers form their inflation expectations. This paper helps fill that gap.

We conduct an experiment in which we randomly provide a subset of survey respondents with information (which we refer to as “treatment information”) about either past-year average food price inflation (Food treatment), or the average forecast of next-year overall inflation in the Survey of Professional Forecasters (SPF treatment). Before this subset of respondents receives this information, and again after this subset receives this information, we ask *all* respondents for their expectations of future inflation. This experimental design thus creates a unique panel dataset which allows us to observe how this new information induces respondents to update their inflation expectations.

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<sup>1</sup> Bernanke, 2004, argues that “an essential prerequisite for controlling inflation is controlling inflation expectations.”

<sup>2</sup> These include the Reuters/University of Michigan Survey of Consumers, the Livingston Survey, the Conference Board's Consumer Confidence Survey and the Survey of Professional Forecasters in the US. Other central banks that survey consumers about their inflation expectations include the Bank of England, the European Central Bank, the Bank of Japan, the Reserve Bank of India, and the Sveriges Riksbank.

We also ask all respondents for their priors about the randomly-provided information (henceforth referred to as “information priors”), and test whether respondents’ ex-ante informedness can help explain (1) baseline heterogeneity of expectations for future inflation, and (2) updating of these expectations after the information is revealed. We expect respondents who are less informed about either of the information treatments ex-ante (that is, those who exhibit larger gaps on average between their information priors and the treatment information) to have more extreme baseline expectations for future inflation. For these respondents, the information treatment may contain more valuable information that causes expectations updating and may thus result in larger expectation revisions. The patterns in who updates – and how much they do so – shed light on how expectations are formed and how consumers react to (possibly) inflation-relevant, new information.

Compared to existing studies, the approach used in this paper differs in that we (1) can remain agnostic about each respondent’s information set, (2) explain the heterogeneity of expectations without imposing any particular learning rule or information-processing rule for consumers, and (3) infer the *causal* effects of different types of inflation-relevant information on individual consumers. Previous studies have mostly overlooked the panel dimension of survey expectations (see Keane and Runkle, 1990, for an exception), and instead have studied the aggregate evolution of beliefs in repeated cross-sections; this complicates the interpretation of previous work on learning in expectation updating.

Exploiting our information treatment, we find that new information in the SPF treatment, but not Food treatment, indeed causes respondents to update their inflation expectations, and to do so in a sensible manner. On average, we find that respondents: (1) revise their inflation expectations down if their information priors were over-estimates (and vice versa for under-estimates), (2) revise their expectations more when the amount by which they over- or underestimate is larger, and (3) are more receptive to the information when the uncertainty in their baseline inflation expectations is greater. Although we cannot test whether respondents are rational (Bayesian) updaters, we note that these three results are consistent with Bayesian updating.

A necessary condition for our information intervention to have an effect is, of course, that respondents are not ex-ante fully informed about the true values of the quantities about which information is revealed. That is in fact what we find: treatment respondents in the SPF treatment and Food treatment overestimate the objective information (that is, the professionals’ average forecast of year-ahead inflation for the SPF treatment, and past changes in food and beverage prices in the Food treatment) by an average of 3.61 and 7.15 percentage points, respectively. These are substantial gaps in informedness: past food and beverage price changes had not been as high as the average respondent believed since 1981, and the average SPF forecast had not been as high as believed since 1982.<sup>3</sup>

Looking beyond average effects, we find important heterogeneity in respondents’ informedness about our treatment information in general, and in respondents’ subsequent

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<sup>3</sup> This finding is generally consistent with a literature that shows individuals can be uninformed when making decisions of economic significance: low-income families are unaware of basic features of the Earned Income Tax Credit (Chetty and Saez, 2013); students have incorrect perceptions of returns to schooling (Jensen, 2010; Wiswall and Zafar, 2011); most households are unaware of their marginal price for electricity and water (Brown et al., 1975; Carter and Milon, 2005).

responsiveness to this information. Certain demographic groups – female, lower-income, and less-educated respondents, as well as those with less financial literacy – generally have larger *perception gaps* (that is, the gap between the treatment information and respondents’ information priors). It is well-documented that these same demographic groups tend to have higher expectations for future inflation than their counterparts do,<sup>4</sup> contributing to the strong right-skew of the inflation expectations distribution. Thus we offer an alternative novel explanation for the systematically high inflation expectations of these demographic groups, by identifying a relative gap in their own information sets about objective inflation measures.

We find that our information treatment leads to a significant decline in the cross-sectional disagreement of inflation expectations, and causes the distribution of inflation expectations for the overall sample as well as for each demographic group – particularly those with high baseline expectations and lower ex-ante informedness – to converge toward its center. In fact, average revised expectations are nearer to actual realized CPI inflation as a result of our intervention. This is an encouraging result: it suggests that policy-makers could partially control the high-expectation right-tail of the inflation expectations distribution through public information campaigns in the spirit of our information treatments. However, a number of respondents – even some with high perception gaps – do not revise their expectations at all. While our results shed some light on these non-revisers – they tend to have smaller perception gaps (and hence the treatments have less informational content for them), and are more likely to be male – we are not able to completely predict non-revisions based on demographics or perception gaps. Thus we must conclude that some respondents either do not find the provided information relevant for inflation expectations, or do not find the information credible. This suggests any public information campaigns to help anchor consumer inflation expectations need to be carefully designed and multi-pronged.

Our results have implications for the modeling of consumer inflation expectations. We can reject full-information rational expectations (as in Muth, 1961), because we find that the provision of readily available, public information has systematic effects on respondents’ updating. On the other hand, our results lend support to newer models of expectation formation in which individuals still form expectations rationally but do so subject to information constraints (e.g. Sims, 2003; Reis, 2006a and 2006b; Coibion and Gorodnichenko, 2012a). At a general level, the fact that respondents’ updating behavior is (1) in the direction of our experimentally-provided information signal, (2) proportional to the strength of the signal, and (3) greater when the baseline expectations are more uncertain, suggests that updating behavior is consistent with rational, Bayesian updating. More particularly, the patterns we observe in cross-sectional disagreement about inflation expectations suggest that consumers’ information constraints may be better represented by sticky-information models (as in Mankiw and Reis, 2002 or Carroll, 2003) than by noisy-information models.

We also find evidence of heterogeneous updating by gender (controlling for the information content of the signal and uncertainty of baseline expectations), indicative of heterogeneous information-processing rules by gender. This suggests that both the realism and the performance of

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<sup>4</sup>See Jonung (1981), Bryan and Venkatu (2001a, 2001b), Lombardelli and Saleheen (2003), and Bruine de Bruin et al. (2010a).

models of inflation expectations could be improved by allowing for heterogeneous use of (private and public) information.

Finally, since we gather both point-forecast and density-forecast inflation expectations from all respondents, we are able to test for whether respondents provide point forecasts under symmetric or asymmetric loss (Capistran and Timmermann, 2009). We present suggestive evidence of respondents' expectations being consistent with forecasting under asymmetric loss. As we discuss, this implies that measuring and accounting for individuals' uncertainty may be crucial when calibrating models to survey data, especially if there is reason to believe that individuals' uncertainty may be changing over time.

This paper is organized as follows. The survey design and data collection methodology are described in Section 2. Section 3 summarizes the data, and analyzes the revision of inflation expectations. Demographic heterogeneity in expectations and updating is analyzed in section 4. We discuss the implications of our results for the modeling of consumer inflation expectations in Section 5, and conclude with a discussion of the policy implications of our study and its limitations in Section 6.

## 2. Data

Our data are from an original survey that is part of an ongoing effort by the Federal Reserve Bank of New York.<sup>5</sup> The survey was conducted over the internet with RAND's American Life Panel (ALP). Our target population consists of individuals 18 or older who participated in the Reuters/University of Michigan Survey of Consumers between November 2006 and July 2010 and subsequently agreed to participate in the ALP.<sup>6</sup> Out of a total sample of 771 individuals invited to participate in the survey, 735 did so, implying a response rate of 95.3%. The survey was fielded between January 3rd, 2011 and February 9, 2011. Respondents received \$20 for each completed survey.

### 2.1 Survey Design

The survey consisted of two sets of questions. The first set of questions, analyzed in Armantier et al. (2013a), examines the link between self-reported beliefs and economic behavior. The second set of questions—the focus of this paper—investigates how individuals revise their inflation expectations after being exposed to new information.

For the sake of concreteness, we introduce notation here that we will use throughout the paper to refer to our survey-measured quantities of interest. As diagrammed in Figure 1, these quantities were measured in four different survey stages:

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<sup>5</sup> The general goal of this initiative is to develop better tools to measure consumers' inflation expectations, to study the link between expectations and behavior (Armanter et al., 2013a), and to better understand how the public forms and updates expectations about future inflation (Bruine de Bruin et al., 2010b).

<sup>6</sup> The Michigan survey is a monthly telephone survey with 500 respondents, consisting of a representative list assisted random-digit-dial sample of 300, and 200 respondents who were re-interviewed from the random-digit-dial sample surveyed six months earlier. Our target population is further restricted to active ALP members, defined as those who either participated in at least one ALP survey within the preceding year, or were recruited into the ALP within the past year.

## 1. **Baseline Inflation Expectations:**

In the first stage, respondents were randomly assigned to one of two questions that elicited their baseline expectations for future inflation, either for their own consumption basket (the “prices you pay,” hereafter “PP”) or for the economy overall (the “rate of inflation,” hereafter “RI”). The PP question asked the respondent for “*your expectations for the prices of things you usually spend money on going into the future,*” whereas the RI question asked for “*your expectations for the rate of inflation/deflation going into the future.*” We refer to these measured quantities as “baseline inflation expectations.”

The inflation expectation questions were asked for two different horizons: (1) a point forecast “over the next 12 months”, which corresponds to the period January 2011 and January 2012; and (2) a point forecast “over the one-year period between January 2013 and January 2014,” which, at the time of the survey, was three-year ahead one-year inflation.

In addition, we asked respondents for their density forecast over the next 12 months: here respondents assigned probabilities to possible future inflation outcomes such as “the rate of deflation will be between 0% and 2%” or “the rate of inflation will be 12% or more”. These inflation outcome intervals were mutually exclusive and collectively exhaustive, and respondents could verify that their assigned probabilities summed to 100%.

The PP question is similar to the one used in the University of Michigan’s Survey of Consumers, which produces the often-cited monthly measure of consumer inflation expectations. Prior research shows that the Michigan Survey’s question text induces mixed interpretations, with some respondents thinking about specific prices they pay and others thinking about the overall rate of inflation (Bruine de Bruin et al., 2011a). Therefore, the RI question is our preferred way of eliciting respondents’ inflation expectations, and in this paper we focus on responses to the RI question. In the analysis, we will use  $\pi_i$  to refer to individual  $i$ ’s (RI) baseline inflation expectation. For a detailed analysis of PP responses, we refer the reader to the previous working version of this paper, Armantier et al. (2013a).

## 2. **Information Priors:**

In the second stage, respondents were randomly assigned to one of two questions that measured their ex-ante informedness about (possibly) inflation-relevant information.

- a. In the “Food” treatment, respondents were asked “*Over the last twelve months, by how much do you think the average prices of food and beverages in the US have changed?*”
- b. In the “Survey of Professional Forecasters” treatment, respondents were asked “*A group of professional economists report their expectations of future inflation on a regular basis. What do you think these professional economists predicted inflation to be over the next twelve months?*”

In both cases, respondents are asked for a point estimate of year-over-year percentage change. We refer to respondents’ beliefs as their “information priors,” which we denote for

each consumer  $i$  as either  $\omega_{i,Food}$  or  $\omega_{i,SPF}$  (where ‘SPF’ is for “Survey of Professional Forecasters”).

Between stages 1 and 2, respondents participated in a battery of experimental questions related to inflation and investment (discussed in Armantier et al., 2013b), and also answered several questions about consumption behavior and sources of information about inflation/prices.

### 3. Treatment Information:

In the third stage, immediately after reporting their information priors, 75% of respondents were randomly provided with true measures—defined as those published in publicly available data series—for which their information prior was elicited in Stage 2. We refer to these quantities as “treatment information,” represented as  $\omega_{Food}^*$  and  $\omega_{SPF}^*$ . The 75% of respondents who received the objective information are referred to as the treatment group.

For the Food treatment, we used the series of average food and beverage prices for urban US consumers that is produced by the Bureau of Labor Statistics. Treated respondents saw the following information: “*According to the most recent data available from the Bureau of Labor Statistics, the average prices of food and beverages in the US **INCREASED by 1.39%** over the last twelve months.*” Thus,  $\omega_{Food}^* = 1.39$ .

For the SPF treatment, we used the average forecast of next-year Consumer Price Index (CPI) inflation from the Federal Reserve Bank of Philadelphia’s quarterly Survey of Professional Forecasters (SPF). Respondents in this treatment saw the following information: “*The Survey of Professional Forecasters (SPF) is a quarterly survey of professional economists. According to the latest data, these professional economists expect, on average, **inflation to be 1.96%** over the next twelve months. Not all of these professional economists agree about future inflation though. **However, most (90%) of them expect inflation over the next twelve months to be between 1.19% and 3.03%.***” Thus,  $\omega_{SPF}^* \equiv 1.96$ .

Also in the third stage, the remaining 25% of respondents were given no treatment information. In the analysis, we refer to these respondents as the control group. The simple act of taking a survey about inflation expectations (including receiving our questions in stage 2) may make respondents think more carefully about their responses, and may lead them to revise their expectations even if they are not provided with any new information (see Zwane et al., 2011, for a discussion of how surveying people may change their subsequent behavior). Since we are interested in revisions in expectations that are directly attributable to the information, we identify that off of *differences* between the treatment groups’ and control groups’ changes in expectations.<sup>7</sup>

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<sup>7</sup> Thus after the stage three random assignment, we have four treatment cells – RI  $\times$  Food (respondents who report RI inflation expectations and receive the Food treatment), PP  $\times$  Food, RI  $\times$  SPF, and PP  $\times$  SPF, each comprising 50%  $\times$  50%  $\times$  75% = 18.75% of the total sample – and four corresponding control groups, each comprising 50%  $\times$  50%  $\times$  25% = 6.25% of the total sample.

#### 4. **Final Inflation Expectations:**

In the final stage, inflation expectations were re-elicited from all respondents, with each respondent being asked the same inflation question they were asked in the first stage. We refer to these expectations as “final inflation expectations,” represented as  $\pi'_i$ .

## 2.2 **Survey Respondents**

Among our 735 respondents, 705 finished the survey, of whom 653 gave answers for the minimum set of questions needed for our analysis: that is, answers for information priors, as well as both baseline and final inflation expectations for at least the one-year-ahead point forecast inflation questions. We additionally exclude from our analysis 18 respondents with unusually high (greater than 50 percentage points) information priors (about Food or about the SPF forecast) or baseline inflation expectations. Thus, we are left with a total sample of 635 respondents. Since we focus on the RI question in this paper, we limit our analysis to the 325 respondents assigned the RI question. For a detailed analysis of PP responses, we refer the reader to the previous working version of this paper, Armantier et al. (2013a), where we show that our main results also hold in the PP sample, although interestingly and intuitively the more significant PP updating behavior occurs in the ‘Food’ treatment. Table 1 shows resulting sample sizes for each of the four treatment cells and corresponding control cells.

For these 325 respondents, average age is 52.5 years (standard deviation=14.0), with 42.8% being male, 86.8% non-Hispanic white, and 4.9% non-Hispanic black. The median annual family income is reported as “\$50,000 to \$59,999”, and 81.8% of respondents have an annual family income of \$30,000 or more. Respondents hail from 46 different US states, and 50.5% have a 4-year college degree. Hence our sample has higher median income and higher educational attainment, and also has more white respondents, than the US population overall.

For the analysis, we define a respondent to be high income if the annual household income is at least \$75,000; 39.2% of the sample falls in this group. We define a respondent to be “older” if the respondent is at least 55 years of age; 46.8% of the sample falls in this group.

We paid respondents a fixed compensation for completing the survey, and did not elicit respondents' inflation expectations or information priors using a financially incentivized instrument such as a scoring rule. This is because proper scoring rules may generate biases when respondents are not risk neutral (Winkler and Murphy, 1970). Moreover, incentivized belief elicitation techniques are not incentive-compatible when the respondent has a stake in the event that they are predicting (Karni and Safra, 1995), which is the case for inflation expectations. In addition, Armantier and Treich (2013) show that elicited beliefs are less biased (but noisier) in the absence of incentives.

We now move to the empirical analysis. Our analysis has two main parts. First, in the next section, we characterize whether and how our information treatments cause respondents to update their inflation expectations. In the subsequent section (section 4), we examine the cross-sectional and demographic dispersion of inflation expectations; as possible explanations for that dispersion,

we analyze demographic differences both in ex-ante informedness and in responsiveness to new information.

### 3. Impact of Information on Inflation Expectations’ Revisions

In general, we expect our information intervention to cause individuals to update their inflation expectations if i) individuals’ inflation expectations are influenced by their beliefs about the measures we use in our information treatments, i.e., food and beverage prices or professional forecasters’ forecasts, ii) respondents find the provided information to be credible, and iii) respondents are not already fully informed about the true values of these quantities.

A key ingredient in our analysis is a measure of respondents’ ex-ante informedness about the treatment information. The measure we use is the gap between the “subjective” information prior ( $\omega_i$ ) and the “true” treatment information ( $\omega^*$ ). We refer to this difference as a *perception gap*  $\Delta\omega_i$  for respondent  $i$ . We sign perception gaps such that negative perception gaps indicate overestimation (treatment information minus information prior): that is,  $\Delta\omega_{i,SPF} \equiv \omega_{SPF}^* - \omega_{i,SPF}$ , and  $\Delta\omega_{i,Food} \equiv \omega_{Food}^* - \omega_{i,Food}$ .

A second key ingredient in our analysis is a measure of respondents’ baseline uncertainty about future inflation outcomes. This is generated from respondents’ answers to the density forecast questions described in Section 2.1. Following the approach developed by Engelberg, Manski and Williams (2009), we fit a generalized beta distribution to each respondent’s stated probabilistic beliefs (see also Bruine de Bruin et al., 2011b). We then generate the variance of the respondent’s beta distribution, which we take to be a proxy for respondents’ uncertainty about future inflation outcomes.

In subsection 3.1, we preview and summarize aspects of our data relevant for characterizing updating behavior. Then in subsection 3.2, we analyze updating behavior more formally, beginning with a nonparametric analysis in 3.2.1, and then estimating a linear model of updating in 3.2.2.

#### 3.1 Data Preview and Summary

##### 3.1.1 Baseline Expectations and Perception Gaps

The two panels of Table 1 report key summary statistics for respondents assigned to the SPF treatment and Food treatment, respectively. In the first row of each panel, we see that median baseline inflation expectation for respondents in the four possible groups (control or treatment, interacted with the information type) is 3%. On the other hand, mean baseline inflation expectations for the four groups are higher, ranging between 4.8 and 6.1 percent. Indicative of successful randomization across the groups, the table shows that baseline inflation expectations are comparable for the treatment and control groups.

The perception gap – our measure of respondents’ ex-ante informedness about the treatment information – is shown in the second row in each panel of Table 1. The top panel shows that the mean perception gap for the treatment group in the SPF treatment is -3.61, that is, an average

overestimate of 3.61 percentage points for professionals' average forecast of year-ahead inflation.<sup>8</sup> Meanwhile, the mean perception gap for the treatment group in the Food treatment is an overestimate of 7.15 percentage points. The presence of large, non-zero perception gaps indicates that a necessary condition for our information intervention to have an impact – that some respondents be ex-ante uninformed about the true values of these quantities – is satisfied in our sample. As should be the case, the mean (and median) perception gaps are comparable for the treatment and control groups.

It is notable that mean and median perception gaps are larger for the Food treatment. There are several possible explanations for this. First, when respondents are asked about past changes in food and beverage prices, their responses are likely to suffer from memory bias, as respondents are likely to recall items for which perceived price changes were most extreme (Bruine de Bruin et al., 2011a). Second, frequency bias may lead respondents to report food inflation perceptions based on the frequency of purchase rather than the total dollar expenditures. Given that prices of frequently-purchased items inflate faster, this would bias their perceptions upwards (Georganas, Healy, and Li, 2013).

### 3.1.2 Revisions

The third and fourth rows in each panel of Table 1 show various statistics related to the revisions in inflation expectations. We see that (1) median revisions are zero, while average revisions are downward, (2) average absolute revisions are larger, reflecting a combination of both upward and downward revisions in our sample, and (3) average revisions are larger in the treatment groups than in the control groups. For example, in the Food treatment, the mean revision is -1.5 for the treatment group, and -0.73 for the control group.<sup>9</sup> The larger revisions for the treatment groups suggest that the treatments had a causal impact on revisions of inflation expectations. However, we see that none of the differences in revisions (between the control and treatment groups) is statistically significant, arguably because of the small sample sizes in the control groups. In the regression analysis below, we control for the size of respondents' perception gaps, which uses richer data than simply testing for average differences between groups.

As shown in the fifth row of each panel, a sizable proportion of respondents do not revise their expectations, in both the treatment and control groups. Even though the proportion of respondents who do not revise their expectations is smaller in the treatment groups (as one would expect), nevertheless many treated respondents (between 42% and 53%) do not revise their expectations.

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<sup>8</sup> Note that in the SPF treatment, respondents were also informed about the interval containing the forecasts of 90% of the professional economists: 1.19% – 3.03%. If we instead measure the SPF forecast perception gap as the minimum (signed) distance between a respondent's prior and this interval, then the median perception gap in the SPF treatment is 0. However, all regression results below are qualitatively similar when we use this alternative perception gap.

<sup>9</sup> After re-eliciting inflation expectations, we asked all respondents for a brief description of why they did or did not update. These free-response answers help us understand nonzero revisions in the control group: for example, one control-group respondent wrote, "As I was completing the questions, I began understanding more of what inflation actually meant." On the other hand, other control group respondents had responses such as, "Why would I have changed my mind in 10 minutes?"

If our information is effective in causing respondents to revise their inflation expectations, then, for the treatment groups, we should expect individuals who are ex-ante more uninformed (that is, have larger perception gaps) to be more likely to revise. That is, on average, perception gaps should be larger for respondents who revise their beliefs. No such relationship should be expected for the control groups, since the treatment information is never revealed to those respondents. The last two rows in each panel of Table 1 show that is in fact the case. The average as well as median perception gap for respondents who revise their beliefs in the treatment groups is substantially larger than for those who do not (though the differences are not always statistically significant, arguably because of the substantial heterogeneity in underlying perception gaps). For example, the average SPF treatment perception gap for respondents who revise their expectations is -4.82 percentage points versus -1.95 percentage points for those who do not (difference statistically significant at 5%). And, as we expected, there is no such relationship for the control group – in fact the average perception gap is larger for non-revisers in both treatments. This suggests that the observed revisions for the treatment group are due to the provided information. We investigate this in more detail below.

## 3.2. Updating of Inflation Expectations

### 3.2.1. Nonparametric Analysis of Updating Behavior

We start with a non-parametric analysis of observed updating behavior. If a respondent finds the treatment information relevant and credible and if she uses the treatment information sensibly to update her inflation expectations, then we expect to see an under-(over-) estimation of treatment information leading to an upward (downward) revision in inflation expectations.<sup>10</sup> For our purposes, under-estimations are signed as *positive* perception gaps. Therefore, inflation expectations' revisions should be positively related to the perception gap.

Figure 2 plots perception gaps and revisions, separately for each treatment and control group. More precisely, the figure shows the mean revision by perception gap decile,<sup>11</sup> as well as a local linear regression of mean revisions on perception gaps. Data consistent with sensible updating behavior in response to the treatment information should have the following characteristics: (1) the data points should be in either quadrants 1 or 3 (the two shaded quadrants in the figure), i.e., mean revisions should be positive for positive perception gaps, and negative for negative perception gaps; and (2) there should be a positive relationship between mean revisions and perception gaps, i.e., the spline should be upward sloping in quadrants 1 and 3. Comparing the two graphs in the first column of Figure 2 (treatment groups) with the two corresponding figures in the second column (control groups), we see two patterns. First, all of the data points are either in quadrants 1 or 3 for the treatment groups, while that is not always the case for the control groups.<sup>12</sup> Second, the spline is

<sup>10</sup> However, in the 'Food' treatment we should only expect under-(over-) estimates to lead to upward (downward) updating if respondents perceive a positive correlation between past food-price changes and future inflation outcomes.

<sup>11</sup> In cases where deciles overlap, fewer than 10 points appear on the plot. Instances of overlapping deciles are indicated by circles that are larger in size.

<sup>12</sup> We also find a greater percentage of non-zero updating respondents in the shaded quadrants for the treatment groups than for the control groups: For example, 70% of non-zero updating in the Food treatment group happens in the shaded

upward sloping and in the predicted quadrants in the SPF treatment group, while we observe a flat relationship in the control groups. These results indicate, nonparametrically, that our treatment groups had a greater prevalence (relative to the control groups) of sensible updating, and suggest that our information experiment caused respondents to revise their inflation expectations.

### 3.2.2. Parametric Analysis of Updating Behavior

We next examine updating behavior in a regression framework. We estimate the slope of a fitted line for the individual-level data underlying each of the four panels in Figure 2, regressing the revision in inflation expectations between stages one and four,  $\Delta\pi_i = \pi'_i - \pi_i$ , on the perception gap,  $\Delta\omega_i$ . Specifically, we estimate (separately for the Food and SPF treatments) the following regression:

$$\Delta\pi_i = \alpha + \beta T_{info,i} + \gamma(T_{info,i} * \Delta\omega_i) + \epsilon_i, \quad (1)$$

where  $T_{info,i}$  is an indicator that equals one if respondent  $i$  is in the treatment group, and zero otherwise. Note that  $\Delta\pi_i$  and  $\Delta\omega_i$  are, respectively, the same variables that were plotted on the y-axes and x-axes in Figure 2. In this specification,  $\alpha$  is a constant capturing average updating in the control group (inclusion of this parameter allows us to control for revisions that are attributable to the other questions asked in the survey as well as the mere act of taking the survey);  $\alpha + \beta$  is the average updating for respondents in the treatment group with a zero perception gap; and  $\gamma$ , our main coefficient of interest, shows updating behavior with respect to perception gap size for the treatment group, and provides an estimate of the causal effect of our information treatments on inflation expectations' revisions. For revisions to be consistent with meaningful expectation updating, as described above, we expect estimates of gamma to be non-negative.

We estimate equation (1) using ordinary least squares. Table 2 presents results from this baseline regression, with robust standard errors reported in parentheses. Focusing first on updating in one-year point forecasts for the Food group (column 1), we see that the estimate of  $\gamma$  is not statistically different from zero. That is, the Food perception gap appears to have no effect on revisions of inflation expectations. The imprecise estimate of  $\alpha$  indicates no significant revisions in inflation expectations in the control group. The estimate of  $\beta$  – the parameter that captures the average updating attributable to the treatment group that is not explained by the perception gap (on top of the average updating of the control group) – is negative, but also not statistically different from zero.

Turning to the SPF forecast information in column 2, we see that the estimate of  $\gamma$  is positive and significant: a 10 percentage point perception gap in the SPF treatment causes a 3.93 percentage point revision in inflation expectations (significant at 1%). This estimate implies that an increase in the SPF treatment perception gap of one standard deviation leads, on average, to a revision that is 48.9% of a standard deviation of the baseline expectations. As before, the estimate of  $\alpha$  is not statistically different from zero. We find that  $\beta$  is also not different from zero, indicating

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quadrants, as compared with 60% for the Food control, and 67.5% for the SPF treatment group, as compared with 52.4% for the SPF control.

there is no effect of the SPF treatment on inflation expectations' revisions (relative to control group responses) *other than* what is explained by the size of respondents' perception gap.

We next estimate the baseline specification, but use the revisions in the fitted mean of the one-year *density* forecasts (columns 3 and 4 of Table 2), and three-year point forecasts (columns 5 and 6) as our dependent variable. We generally find the same pattern as we had seen for the one-year point forecasts: For both one-year density forecasts and three-year point forecasts, the Food treatment has no meaningful impact on expectations revisions. On the other hand, the SPF treatment significantly affects the revision of the mean of the year-ahead density forecast. The updating coefficient (of 0.096) is about a quarter of the magnitude of the coefficient for the updating of the one-year point forecast (reported in column 2). We revisit this difference between point-forecast and density updating later, in section 5. There is a positive impact of the SPF treatment on updating at the three-year horizon; however, the estimate of 0.18 is both smaller in magnitude than its counterpart in column (2), and is not significant at conventional levels. A plausible explanation for the weaker impact on the revision for the three-year point forecast horizon is that respondents may perceive less of a pass-through of recent price changes to medium-term inflation (compared to near-term inflation).

In the last two columns of Table 2, we explore the relationship between revision of inflation expectations and baseline uncertainty about future inflation. In a Bayesian framework, *ceteris paribus*, respondents who are more uncertain about future inflation should be more responsive to the treatment information. More precisely, for beliefs that are characterized by the beta distribution, the posterior (updated belief) is:

$$Posterior = \frac{\frac{1}{Variance(Prior)}}{\frac{1}{Variance(Prior)} + \frac{1}{Variance(Info)}} Prior + \frac{\frac{1}{Variance(Info)}}{\frac{1}{Variance(Prior)} + \frac{1}{Variance(Info)}} Info.$$

Then, the relative weight placed on the information is  $\left(\frac{Variance(Prior)}{Variance(Info)}\right)$ , i.e., responsiveness to information should be directly proportional to the uncertainty in the prior (that is, the baseline uncertainty about future inflation). Using the variance obtained from fitting a beta distribution to each respondent's one-year baseline density forecast, we define a dummy variable, *Uncertain*, that equals 1 if the respondent's baseline variance is above the sample median. We add three additional terms to equation (1):  $\alpha_U Uncertain_i$ ,  $\beta_U(T_{info,i} * Uncertain_i)$  and  $\gamma_U(T_{info,i} * \Delta\omega_i * Uncertain_i)$ . Similar to the coefficients  $\alpha$  and  $\beta$  in the baseline version of equation (1), the additional coefficients  $\alpha_U$  and  $\beta_U$  capture the mean updating behavior for high-uncertainty respondents in the control group, and in the treatment group with a zero perception gap (relative to low-uncertainty respondents). Meanwhile  $\gamma + \gamma_U$  shows average updating behavior with respect to the perception gap for high-uncertainty respondents. Theoretically, the sign of  $\alpha_U$  and  $\beta_U$  is unclear. However, a positive  $\gamma_U$  would be consistent with Bayesian updating.

Columns (7) and (8) of Table 2 show estimates of this specification for the Food and SPF treatments, respectively. In line with our results in the earlier columns of the table, there is no significant relationship between the perception gap and revisions in the Food treatment for either

low- or high- uncertainty respondents: estimates of both  $\gamma$  and  $\gamma_U$  in column (7) are not statistically different from zero. However, column (8) shows a significant relationship between the SPF perception gap and inflation expectations' revisions for both low- and high- uncertainty respondents. Notably, the estimate of  $\gamma_U$  is 4 times as large as that of  $\gamma$ , indicating substantially greater responsiveness to information for high-uncertainty respondents. The estimates imply that a 10 percentage point perception gap in the SPF treatment causes a 5.5 percentage point revision for high-uncertainty respondents, versus a 1.0 percentage point revision for low-uncertainty respondents. Meanwhile, the estimates of  $\alpha_U$  and  $\beta_U$ , while not estimated very precisely, indicate that high-uncertainty respondents in both the control and treatment groups exhibit larger downward average revisions relative to their counterparts. For example, we estimate that high-uncertainty respondents in the food treatment with a perception gap of zero revise their inflation expectations downward by 4.2 points (that is, relative to their low-uncertainty counterparts with a zero perception gap in the treatment group). Under the regression's linearity assumption, this suggests a sizable effect (albeit, an imprecise one) of the treatment other than what is explained by the size of treated respondents' perception gaps, for high-uncertainty respondents. Overall, the estimates in the last column of the table indicate that the updating patterns shown in the second column are primarily driven by the revisions of high-uncertainty respondents. The larger estimate of  $\gamma_U$  (than for  $\gamma$ ) is consistent with Bayesian updating.

The result that information about “future inflation” (SPF forecasts) – but not information about recent prices for food and beverages – significantly affects inflation expectations is notable. It suggests that food and beverage price information, at least as we have presented it here, has less relevance for consumers' expectations of overall inflation. On the one hand, this may be because some consumers have limited understanding of the concept of overall inflation. On the other hand, given that the share of food and beverages in the consumer price index (CPI) has been consistently around 15% in recent years, a “rational” respondent may be expected to be less responsive in their inflation expectation revisions to perception gaps in the Food treatment than the SPF treatment. Moreover, unlike SPF forecasts, the information about food prices concerns price changes over the past year, which may have more limited relevance for future food price changes.

Before we move onto the analysis of heterogeneity (in expectations and revisions), we should note that, as shown in Table 1, a substantial proportion of the respondents in the treatment groups do not revise their expectations. As shown in the table, while these respondents have, on average, smaller perception gaps (that is, the information comes as less of a surprise to them), for many their perception gaps are still quite large. For the most part, these “non-revisers” also do not revise their density forecasts. If we regress an indicator for non-revision on treatment dummies and our demographics of interest, we find that non-revision is generally difficult to predict:<sup>13</sup> while female respondents are about 15% less likely to be non-revisers (significant at the 10% level), we otherwise have no strong predictors for non-revision.<sup>14</sup> It is possible that some respondents simply

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<sup>13</sup> Here, we restrict our sample to treatment-group respondents who had perception gaps of greater than 1 percentage point, since this offers a sample of respondents we could expect to revise their expectations. Regression results are qualitatively similar if we use a cutoff of 0 percentage points, or 2 percentage points.

<sup>14</sup> We do find some evidence of differences in preferences for sources of information for the revisers and non-revisers. Our survey instrument included the question: “*When trying to come up with your answers to the question about the rate*

found the treatment information not credible or relevant, or decided not to update their beliefs for some other reason.

It should also be pointed out that the observed revisions are not driven by respondents in, say, the right-tail of the baseline expectations distribution. Figure 3 shows the distribution of baseline and final inflation expectations. We see that a non-trivial proportion of respondents in each of four baseline groups – the intervals [0,5); [5,10); [10,15); and 15+ – move to a different group, indicative of revisions originating from respondents in all parts of the baseline expectations distribution. A downward shift in the distribution is quite obvious. Looking at the respondents who report baseline expectations in, for example, the [5,10) range, we see that 41.7% of them report final expectations in the same range, but 48.3% of them report final expectations in the [0,5) range.

The analysis in this section leads to our first result:

*RESULT 1: Respondents, on average, update their expectations in response to provided information. They do so sensibly and in a direction consistent with Bayesian updating – with larger revisions for less-informed respondents and for those with greater baseline uncertainty. However, it is information about current SPF forecasts, and not about past food and beverage prices, that leads to significant updating.*

## **4. Heterogeneity in Expectations, Perception Gaps, and Updating**

In this section, we examine the cross-sectional and demographic dispersion of inflation expectations. In subsection 4.1, we study how this dispersion is related to demographic differences in ex ante informedness, as measured by perception gaps. In subsection 4.2, we turn to demographic differences in how expectations respond to new information.

### **4.1. Heterogeneity in Expectations and Perception Gaps**

#### **4.1.1 Baseline Expectations**

In section 3.1, we saw that the distribution of baseline inflation expectations has considerable variance and a right-skew: our sample overall has a mean baseline expectation of 5.57 and a median of 3.00, with a standard deviation of 6.98. Indeed, whereas *median* consumer inflation expectation survey responses generally track official estimates of realized inflation and sometimes even outperform professional forecasters (Thomas, 1999; Ang, Bekaert and Wei, 2007), *average* consumer inflation expectations are systematically higher than realized inflation (Bryan and Venkatu, 2001a, 2001b; Geroganas, Healy, and Li, 2011).

To shed light on this dispersion and heavy right tail, we next examine heterogeneity in baseline inflation expectations across several demographic groups: gender, age, financial literacy,

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*of inflation/deflation, how much did you think about the information you received from the following sources?" on a 1-7 scale. Options included TV/Radio; Newspapers; Internet; Financial advisors; Co-workers; Family, Friends; Shopping experience. Non-revisers, relative to revisers, are significantly less likely to report "Family, Friends", and significantly more likely to report "Newspapers" as sources of information for their baseline inflation expectations.*

education, and income. Various statistics for baseline expectations are presented in the top panel of Table 3 with demographics varying across columns. The table is restricted to respondents in the treatment groups, since the lower panel of the table analyzes revisions in expectations as a result of the information. Furthermore, for ease of exposition, we pool the two information treatments here, since patterns are otherwise qualitatively similar.

The first row in Panel A shows that female, lower-income (less than \$75,000), low-education (less than a 4-year college degree), and low-financial-literacy<sup>15</sup> respondents report higher baseline inflation expectations. For example, females report a mean baseline inflation expectation of 6.8 percent, versus a mean expectation of 4.4 for males (difference statistically significant at the 1% level). Notably, we do not see any significant differences by age. The second row of the table then confirms that these differences in means coincide with a greater percentage of female, lower-income, low-education, and low-literacy respondents occupying the (high-expectation) right tail of the expectations distribution: for example, 45% of female respondents report inflation expectations of 5% or more, compared to 28% of male respondents in that range (proportions different at the 1% level, using a Chi-squared test). So, a portion of the variance and skew seen in the overall distribution of expectations can be accounted for by these differences across basic demographics.<sup>16</sup>

That these demographic groups report higher inflation expectations is not a new result – this pattern has also been found in the prior literature: for example, see Jonung (1981), Bryan and Venkatu (2001a, 2001b), Lombardelli and Saleheen (2003), and Bruine de Bruin et al. (2010a). However, what is notable is that we find similar demographic patterns for informedness about current, inflation-related facts. The next two rows of the table show the average perception gaps for the two information treatments. We observe that female, low-education, low-financial literacy, and low-income respondents have average perception gaps that are larger in magnitude. These patterns indicate that the variance and right skew of inflation expectations may in part be due to a skewed distribution of perceptions about objective measures of inflation (and, hence, differences in information sets).

To further study the relationship between baseline expectations and informedness, in Figure 4 we use contour plots to show nonparametric estimates of the joint density of baseline inflation expectations and perception gaps. This joint density is markedly different between the two information treatments, so we show Food and SPF treatment groups on separate plots. Three features of these plots deserve note. First, we see that the correlation between perception gap and baseline expectations is negative and particularly strong for the SPF treatment group, illustrating the relationship between informedness and baseline expectations seen in the demographic analysis of Table 3. Second, however, this relationship is substantially weaker in the Food treatment group. This is consistent with our general pattern of null results for the Food treatment in Section 3: here, it

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<sup>15</sup> Our survey included a battery of 7 numeracy and financial literacy questions. The numeracy questions were drawn from Lipkus, Samsa, and Rimer (2001), while the questions about financial literacy were slightly adapted from Lusardi (2007). We coded a perfect score on these questions as “high financial literacy,” which included 34.3% of the sample. See Appendix for the questions.

<sup>16</sup> However, note that the expectation distribution is also right-skewed *within* each demographic group. For example, the mean baseline inflation expectation for lower-income respondents is 6.4%, while the median is 3.0%. That is, demographics cannot alone explain the skew in the expectations distribution.

is respondents' Food information *priors*, rather than the true Food information, that appear to have limited relevance for respondents' inflation expectations.

Third, by considering the marginal density along either the x-axis (baseline expectations) or y-axis (perception gaps) we again see the dispersion and skew in both quantities that motivate the present analysis. In particular, we see the prevalence of remarkably large perception gaps. Thirty-eight percent of respondents expect professional forecasts of next-year inflation to be 5% or more, while our SPF benchmark was only 1.96% and had not been as high as 5% since 1984. Respondents' overestimates are even larger when we ask about food and beverage price inflation: forty percent of respondents believe past-year food and beverage price inflation was 7% or more, while the published measure was only 1.39%, and has not risen as high as 7% since 1981.

Besides the above nonparametric analysis, we also estimate a series of linear regressions to study the patterns we observed in Table 3. Here we again focus on demographic differences in perception gaps. These regressions have the advantage of allowing a multivariate analysis and also facilitate a concise comparison between the two information treatments. Specifically, we estimate a series of regressions of the form:

$$\log\left(\frac{\omega^*}{\omega_i}\right) = \alpha_1 + \alpha_2 I_{Food,i} + \alpha_3 C_i + \alpha_4 (I_{Food,i} * C_i) + \epsilon_i. \quad (2)$$

Here,  $\omega^*$  and  $\omega_i$  are respectively treatment information and information priors, as defined previously in Section 2;  $I_{Food,i}$  is an indicator for whether the respondent is in the Food group (either control or treatment); and  $C_i$  is an indicator for the individual's demographic characteristic (such as a Female dummy). Our dependent variable,  $\log(\text{treatment information} / \text{information prior})$ , is a measure of the error in respondents' priors about the treatment information. It always has the same sign as our linear distance measure of perception gaps, while also giving the regression coefficients an elasticity interpretation.<sup>17</sup> Concretely,  $\alpha_1$  reflects the average of  $\log(\omega^*/\omega_i)$  in the control and treatment groups for the SPF forecast; a positive (negative) estimate would indicate underestimation (overestimation) on average for the SPF forecast in our sample. Next,  $\alpha_1 + \alpha_2$  is the average error for past food/beverage price changes;  $\alpha_3$  is the average difference in  $\log(\omega^*/\omega_i)$  for demographic characteristic  $C$  for the SPF forecast (relative to their counterparts), and likewise  $\alpha_3 + \alpha_4$  is the average difference in the error for the demographic characteristic  $C$  for food prices. So, an estimate for  $\alpha_3$  of, say, -0.1 for a given demographic group would indicate a 10% larger overestimate for that group for the SPF forecast.

Results from estimating equation (2) are shown in Appendix Table A1 for the same demographics studied in Table 3: gender, age, financial literacy, education, and income. In the first five columns, we regress the perception gap onto one demographic variable at a time, while in the last column of the table, we control for all demographics at once. In our multivariate analysis in column (6), we see that three results are statistically significant when we control for all demographics at once. First, we see that none of the demographic variables and Food treatment

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<sup>17</sup> For respondents who report a zero or negative information prior, we recode their information prior as 0.1 for the sake of calculating  $\log(\text{info}/\text{belief})$ . There are only three such instances.

interaction terms is statistically different from zero, indicating that demographic differences in perception gaps do not vary systematically across the two information treatments. Second, we find that female respondents have 35% and 9% larger perception gaps (greater over-estimation) on average than males in the SPF and Food treatments respectively.<sup>18</sup> Third, college respondents have average perception gaps that are 27% and 34% smaller than those of their less-educated peers in the SPF and Food treatments respectively. While the remaining coefficients are not statistically significant, estimates in the last column show patterns similar to those in the first five columns (and similar to the patterns in Table 3). Notably, the R-square in the last regression of Table A1 shows that demographic characteristics explain up to 27% of the variation in perception gaps.

Returning to Table 3, it is also worth noting that the same demographic groups (i.e., female, low-literacy, low-education, and lower-income respondents) not only report higher baseline inflation expectations, but also have more uncertain baseline inflation expectations. This is shown in the last row in the top panel of Table 3. For example, female respondents have a mean individual density forecast variance of 27.2, while male respondents have an average forecast variance of 10.8 (difference significant at the 10% level).<sup>19</sup>

#### 4.1.2 Revised Expectations

We next move to Panel B of Table 3, which shows various summary statistics related to final inflation expectations. The first row in Panel B shows larger average revisions in inflation expectations for the same demographic groups that we highlighted in Panel A (though the differences by demographics are not always significant). For example, females revise down their inflation expectations, on average, by 2.6 percentage points, compared to a downward revision of 0.7 percentage points for males. As a result of these different revisions, the table shows that average inflation expectations converge between gender, financial literacy, education, and income groups after the information treatment. Likewise, the disagreement among respondents, as represented by the standard deviation of the expectations distribution, falls from 7.3 percentage points to 4.6 (shown in the final row of Table 3). The revised distribution is significantly different from the baseline expectations distribution for the overall sample, as well as for female, young, low-literacy, and lower-income respondents (as indicated by the p-value of the Kolmogorov-Smirnov test for the equality of the baseline and revised distributions, reported in the last row of Table 3).<sup>20</sup>

In fact, Table 3 shows that average inflation expectations for *each* demographic group converge toward being near, or within 2 percentage points of, the actual realized CPI inflation between January 2011 and January 2012 (2.93%). Caution is warranted in using an ex-post realized outcome as a benchmark for accuracy of ex-ante expectations, since (1) inflation outcomes are uncertain and (2) respondents' point forecasts may refer to various statistics (i.e. mean, median, mode, or others) of their *subjective* probability distributions (Engelberg et al., 2009). Nevertheless,

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<sup>18</sup> To obtain the average perception gap for female respondents in the Food treatment, one has to add the coefficients on female and female x Food treatment (-0.345 + 0.258).

<sup>19</sup> Whether this is a consequence of some individuals being aware that they are relatively under-informed, or is related to innate differences in (over)confidence between demographic groups, is an intriguing question for further work.

<sup>20</sup> Furthermore, we do not find a significant change in disagreement among respondents in the control group.

we find at the baseline that 39.3% of responses are within 1 percentage point of ultimately realized CPI inflation, whereas post-treatment this percentage improves to 56.6%.

Thus we see that our information treatments reduce the variance of the expectations distribution, and in particular have a strong effect on the demographic groups that tend to populate the distribution's thick right tail. While our analysis so far has suggested that demographic differences in updating may be related to demographic differences in perception gaps, these patterns in updating could also be consistent with demographic differences in (1) baseline uncertainty about future inflation and/or (2) information-processing rules. These factors are investigated next. The analysis in this section leads to our second result:

*RESULT 2: There is substantial heterogeneity in baseline inflation expectations, with significantly higher expectations for female, low-financial literacy, low-education, and lower-income respondents. The same groups also, on average, exhibit less ex-ante informedness about the objective information, suggesting that high inflation expectations may (in part) be a result of under-informedness about objective, inflation-relevant information. Finally, as a result of information provision, the distribution of inflation expectations converges toward its center and toward actual realized CPI inflation.*

#### **4.2. Heterogeneity in Updating Rules**

In the previous section, we saw that the demographic groups that have larger perception gaps exhibit larger revisions in inflation expectations. However, we also noted that these groups have greater baseline uncertainty and may differ in their responsiveness to information (that is, updating rules). Madeira and Zafar (2012), for example, find significant differences in inflation expectation updating by gender and other demographic characteristics.<sup>21</sup> In this subsection we test for such differences and also examine the effects of different levels of uncertainty across demographic groups.

To investigate demographic differences in updating, we focus on updating at the one-year point forecast horizon. We estimate updating effects for the same demographic groups as in Table 3 – gender, age, financial literacy, education, and income. We also use an additional variable, based on the following question asked immediately after eliciting final inflation expectations (in stage 4) from the treatment group: “*To what extent is your answer [to the PP or RI question] over the next twelve months the same or different because of the information provided to you [in the Food or SPF information treatment]?*” Responses are given on a 7-point scale (with a higher number indicating a larger effect of provided information); these responses are coded such that roughly 40% of respondents are flagged as “info-affected” (the cutoff for “info-affected” is 5 or more points out of 7).

For each of the six characteristics discussed above, we modify equation (1) slightly by adding demographic interactions, and estimate the following regression:

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<sup>21</sup> In other contexts of belief-updating, Mobius, Niederle, Niehaus, and Rosenblat (2011) find significant gender differences in information processing.

$$\Delta\pi_i = \alpha_1 + \alpha_2 C_i + \beta_1 T_{info,i} + \beta_2 (T_{info,i} * C_i) + \gamma (T_{info,i} * C_i * \Delta\omega_i) + \eta (T_{info,i} * (1 - C_i) * \Delta\omega_i) + \epsilon_i, \quad (3)$$

where  $C_i$  is a binary variable that represents one of the six individual-level characteristics – gender, age, financial literacy, education, income, and “info-affected”. As in equation (1),  $T_{info,i}$  is a dummy that equals 1 if respondent  $i$  is in the treatment group, and zero otherwise. The inclusion of  $\alpha_2$  allows for the possibility that the intercept term differs by demographic group. Also similar to equation (1), the  $\beta$  terms summed with the  $\alpha$  terms capture the average revision (by demographic group) for treatment-group individuals with a zero perception gap. The parameter  $\gamma$  captures the updating behavior for individuals with the given characteristic  $C_i$ , while  $\eta$  captures updating behavior for individuals without that characteristic. As before, we estimate equation (3) separately for the Food treatment and SPF treatment.

We analyze updating one characteristic at a time. While it would be ideal to test for updating differences by all of these characteristics simultaneously – for example, gender differences in updating could partly be a result of gender differences in income, education, or financial literacy – our sample size prevents us from exploring these channels. Fortunately, the correlation between each of these demographic variables is small.<sup>22</sup>

The first two columns of Table 4 present the results for equation (3) by gender, for the two information treatments. As was the case for the full sample, there is no evidence of significant updating in the Food treatment (estimates of both  $\gamma$  and  $\eta$  are not different from zero). The second column shows that nearly all significant updating in the case of the SPF treatment that appears in Table 2 is driven by female respondents ( $\gamma = 0.404$ , while the estimate of  $\eta$  is not different from zero; the p-value reported at the bottom of the column shows that the two estimates are statistically different). Our estimate of  $\alpha_2$  is not different from zero, suggesting that males and females (in the control group) respond similarly to the act of taking a survey. Likewise, our estimate of  $\beta_2$  is not significant, suggesting that both genders have similar responses to the treatment in the case of having a zero perception gap. Overall, the second column shows that, even when we condition on perception gap size, female respondents exhibit greater responsiveness to our treatment information than male respondents. In our discussion below, we examine whether this is a result of higher baseline uncertainty for females, different information-processing, or a combination of both.

Columns (3)-(10) of the table report estimates by age, financial literacy, education, and income, again separately for the two information treatments. In contrast to our results for gender, here we find that all demographic subgroups update significantly and sensibly in the SPF treatment. (The one exception is our estimate of  $\gamma$  for high financial-literacy respondents in column (6), which is sensible and relatively large but not significant.) For example, in column (10) we estimate that high-income and low-income respondents both update significantly: in response to a one standard deviation increase in the SPF forecast perception gap, the two groups revise their expectations by 59.4% and 44.9% of a standard deviation of baseline inflation expectations, respectively. Likewise

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<sup>22</sup> The highest correlation that we observe is 0.29 between high income and college. Female and financial literacy has a correlation of -0.13; high financial literacy and college education has a correlation of 0.13; female and high income has a correlation of -0.10. All other correlations are smaller than 0.1 in magnitude.

in contrast to our results by gender, the SPF treatment reveals no significant differences in updating behavior between age, financial literacy, education, and income subgroups. For example, again considering column (10), we cannot reject the null of no difference in updating behavior by income ( $p$ -value = 0.38). Meanwhile, we see that these demographic groups' response to the Food treatment is consistent with our results for the full sample (in Table 2) – in that we find little evidence of significant updating. Furthermore, consistent with our results by gender in columns (1) and (2), we generally find no significant differences in Food-treatment updating behavior between groups. The one exception is a difference in Food-treatment updating by education in column (7), where the estimate of  $\gamma$  is marginally significant at the 10% level and positive (and statistically different from the estimate of  $\eta$ ), indicating that college-educated individuals respond to the errors in their food perception gaps when revising their inflation expectations.

Finally, the last two columns of the table present estimates of the specification with the “info-affected” characteristic. If individuals in the information treatments are indeed changing their inflation expectations in response to the provided information, we expect to see stronger updating among respondents who report that the provided information “affected” their final expectations. That is what we see in the last column of the table, where the estimate of responsiveness to information among “info-affected” respondents ( $\eta$ ) is almost twice as large as that of their counterparts (though the estimates are not statistically different). This result is a consistency check in support of our baseline model, in which updating is a function of the provided information. It also, together with the frequent differences in response to the Food and SPF information treatments, indicates that respondents are processing the treatment information thoughtfully, rather than unconsciously anchoring to the new information (Tversky and Kahneman, 1974). A pure “anchoring” explanation would suggest that respondents would (1) report revised inflation expectations that are closer to the numbers provided to them in the information treatments – which is inconsistent with the differential effects in the Food and SPF treatments, and (2) be unaware of the treatments' effects on their responses – which is inconsistent with our “info-affected” results.

Overall, two things are of note in Table 4. One, the only marginally significant impact of the Food treatment on inflation expectations in Table 4 is observed for college-educated respondents. For other demographic groups, there is no significant pass-through of new information about food price changes onto inflation expectations.<sup>23</sup> Second, the only evidence of heterogeneous response to perception gaps in the SPF treatment is observed by gender. (It is the case that the estimates for higher-income, college-educated, and older respondents are larger than those of their counterparts, but none of those differences is statistically significant.) That is, female respondents are more responsive to information than males are, even after we control for the size of perception gaps. These results suggest that males and females use different information-processing rules, and/or that females are more uncertain than men about future inflation expectations at the baseline (of which

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<sup>23</sup> However, in a hard-to-interpret result, column (5) shows that low-literacy respondents in the treatment group exhibit a downward level shift, on average, in their revised inflation expectations that is unrelated with their perception gap (that is, the estimate of  $\beta_1$  is statistically significant and negative).

we do present evidence in Table 3).<sup>24</sup> In Appendix Table A2, we control for baseline uncertainty by augmenting equation (3) with the same terms we used in our analysis of uncertainty in Table 2,  $Uncertain_i$ ,  $(T_{info,i} * Uncertain_i)$ , and  $(T_{info,i} * \Delta\omega_i * Uncertain_i)$ , plus their interactions with gender. Even controlling for the effects of uncertainty (which are allowed to differ by gender), our conclusion that the response to the SPF treatment is driven by female respondents holds. While previous research on gender differences in inflation expectations updating has found mixed results,<sup>25</sup> our analysis suggests that gender differences in information-processing rules likely play an important role.

This leads to our third and final result:

*RESULT 3: Females are on average more responsive to our SPF information treatment relative to males (even after controlling for baseline uncertainty and perception gaps), highlighting the potential importance of allowing for heterogeneous information-processing rules.*

## 5. Discussion

In this section we discuss the implications of our results for the modeling of consumer inflation expectations. Our primary conclusion will be that our results help provide a micro-foundation for models in which agents form expectations rationally, but face information constraints (e.g. Sims, 2003; Reis, 2006a, 2006b; Mackowiak and Wiederholt, 2009). We also highlight possible enrichments to these models that, in light of our results, might parsimoniously improve both realism and performance.

### 5.1. Rational Models with Limited Information

Our Result 1 suggests that several features of respondents' updating behavior when faced with new information are consistent with rational, Bayesian updating. These features include: (1) the systematic and meaningful relationship between expectations updating and both the size and direction of perception gaps; (2) the stronger effect of new information among respondents who have greater uncertainty at baseline; and (3) the self-awareness that individuals report for whether the information treatments "affected" their expectations. Our conclusion is consistent with Coibion and Gorodnichenko's (2012a) analysis of SPF panel data, which finds that the systematic errors in SPF inflation forecasts are consistent with expectations being formed rationally – albeit subject to information constraints.<sup>26</sup> However, while these findings are consistent with Bayesian updating, they are not a wholesale confirmation of rationality or pure Bayesian updating.<sup>27</sup>

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<sup>24</sup> Our findings may also be consistent with the economics and psychology literature that finds that men are more (over)confident than women (Barber and Odean, 2001; Niederle and Vesterlund, 2007). These studies imply that, controlling for the information content of the signal, men respond less to information.

<sup>25</sup> Burke and Manz (2010) do not find significant differences by gender in information processing, but Madeira and Zafar (2011) find significant differences in expectation updating by gender and other demographic characteristics

<sup>26</sup> See also Andrade and LeBihan (2013) and Dräger and Lamla (2013), with analyses and results similar to those in Coibion and Gorodnichenko (2012a).

<sup>27</sup> Our results, however, are a clear rejection of full-information rational expectations (FIRE) for the average respondent. In a FIRE framework, all information publicly known at the time of the forecast should already be incorporated in the

Second, our Result 2 highlights the importance of information constraints in explaining both the evolution of, and the cross-sectional distribution of, inflation expectations. In the literature these constraints have variously been modeled as the result of noisy private signals (Woodford, 2001) or a limited capacity for information transmission (Sims, 2003), generally referred to as a noisy information model, or as the result of some type of “sticky” information, due to either slow information diffusion (Mankiw and Reis, 2002), or stochastic updating of information (Carroll, 2003), or a private cost of information acquisition (Reis, 2006a and 2006b).<sup>28</sup>

We view our micro-evidence as a helpful benchmark in choosing among these options for modeling information constraints. In particular, our finding that cross-sectional disagreement (variance) in expectations falls after our information treatments is more consistent with a sticky-information model than a noisy-information model. As is demonstrated in Coibion and Gorodnichenko (2012a), a noisy-information model predicts constant disagreement in inflation expectations over time under fairly general conditions;<sup>29</sup> these conditions should hold in our setting so long as our information treatments are perceived with individual-level noise (as in Woodford (2001)). On the other hand, a sticky information model predicts that disagreement can rise and fall depending on the size of inflation shocks. Indeed, so long as our information treatment sends a signal that is sufficiently similar to other recent information about inflation, a sticky-information model would predict that the new information reduces the cross-sectional variance of expectations, consistent with our findings. Especially in light of Mankiw, Reis, and Wolfers’ (2003) results that disagreement in inflation expectations co-moves with other macroeconomic aggregates, these patterns in disagreement may be important for well-performing models to replicate. Meanwhile, our observation that some individuals do not update their expectations at all, even when facing large perception gaps, also is more consistent with sticky information than noisy information. Among sticky information models, our evidence of significant updating in the SPF treatment provides some direct evidence for Carroll’s (2003) model in which consumers periodically update their expectations based on the forecasts of experts. Our experimental setup is, however, unable to identify the reasons for why expectations may be sticky. Distinguishing between possible explanations, such as stochastic updating or private cost of information acquisition, would require a longer panel of beliefs, and a richer experimental set-up that varies other dimensions such as the cost of acquiring information.

Caution is also warranted in using our results to calibrate a model of inflation expectation formation since, in our setup, respondents do not *choose* the type of information they receive. Belief-updating when individuals are directly presented with new information may differ from instances where individuals acquire the information themselves (Hertwig et al., 2004). Also, we do not wish to make assumptions about how our information treatments interact with individuals’

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forecasts, and hence our information experiment (which provides publicly available information) should have had no systematic effect on individuals’ forecasts.

<sup>28</sup> Coibion and Gorodnichenko (2012a) also show how noisy-information and sticky-information models can be unified in a useful framework of information rigidities.

<sup>29</sup> This holds for additive i.i.d. noise in private signals and for AR inflation (of any order). See also Andrade and LeBihan (2013) for a useful summary of these results.

broader, inflation-relevant information sets, which would be necessary in order to estimate a parameter such as Coibion and Gorodnichenko's (2012a) measure of information rigidity.

Our third result of gender differences in information processing is also not inconsistent with a limited-information, rational-expectations model of inflation expectation formation. Gender differences in updating behavior may indicate gender differences in gathering and evaluating new information. While a full analysis of gender-specific expectation formation is beyond the scope of this paper, our survey included some additional questions that may shed light on this point. First, we find that female respondents are significantly (at the 1% level) more likely than males to answer that they "*thought a lot about...the price of groceries*" when initially reporting their inflation expectations, which suggests that they weight types of information differently than men. We also find that female respondents are significantly (at the 1% level) more likely to "*think about the information [they] received from...family and friends*" when reporting inflation expectations than males are. On the other hand, we find no significant gender difference in preference for some other information sources, such as "*shopping experience,*" "*TV and radio,*" or "*newspapers and magazines*". This suggests that females on average gather inflation-relevant information, and weight this information, somewhat differently than males. So, whereas these demographic differences do not necessarily indicate deviations from rationality, macroeconomists should decide in their particular modelling circumstances whether (potentially large) heterogeneity in expectation formation is important to consider, and if so, allow for idiosyncratic private information in their models. This finding partially validates recent modeling work that explains heterogeneous consumer inflation expectations through heterogeneous information sets and different updating rules (Malmendier and Nagel, 2010; Madeira and Zafar, 2012).

## 5.2. Forecasting under Asymmetric Loss

Finally, our analysis points to one other important consideration in modeling inflation expectations. When calibrating models to survey data in which respondents report point predictions, researchers typically need to make assumptions about which summary statistic a respondent is reporting from her subjective probability distribution of future outcomes. Whereas it is common to assume the mean is being reported – implying that respondents generate forecasts under symmetric square loss – Capistran and Timmermann (2009) point out that an individual's reported expectation is biased away from the mean if she forecasts using an asymmetric loss function. Capistran and Timmermann argue that asymmetric loss may be important in accounting for the cross-sectional heterogeneity of inflation expectations. Also, asymmetric loss generates a mean-bias that varies in size with the uncertainty of individual expectations, and hence is likely non-constant over time.<sup>30</sup>

Since we gather both point-forecast and density-forecast expectations from all respondents, we can test if respondents provide a point forecast under symmetric square loss. To motivate our tests, we follow Elliott, Komunjer, and Timmermann (2008) and suppose that respondents' point forecasts minimize the expectation of a loss function  $L(\cdot)$ , and we transform  $L(\cdot)$ 's argument using

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<sup>30</sup> See Bruine de Bruin et al. (2011b) for evidence of substantial time-series variation in consumer uncertainty about expected inflation.

a function that reflects possible loss aversion,  $\phi(\cdot)$ . That is, we suppose point forecasts are solutions to the minimization problem,

$$\min_a \int L(\phi(a - \tilde{\pi})) dF(\tilde{\pi}) \quad (4)$$

where  $F(\cdot)$  is a subjective probability distribution over future inflation outcomes  $\tilde{\pi}$ . We consider the relatively general case where  $L(x) \equiv |x|^p$  for some  $p > 0$ , and where  $\phi(x)$  is parameterized as

$$\phi(x) \equiv \begin{cases} bx & x < 0 \\ x & x \geq 0 \end{cases} \quad (5)$$

for some  $b > 0$ . Symmetric square loss implies  $p = 2$  and  $b = 1$ .

Under symmetric square loss, any deviation of the point forecast from the density mean should be purely noise and hence be symmetric around the density mean. We present two tests for symmetric square loss. The first test – the most natural one – compares point forecasts with density means. Under symmetric square loss, any deviations of the point forecast from the density mean should be purely noise and hence be symmetric around the density mean. For the second test, we compare revisions in point forecasts with revisions in density means. In developing our tests, we assume that respondents report their true  $F(\cdot)$  through their density forecasts.

For our first test, we find that individuals' point forecasts are on average 1.46 percentage points higher than their density means at baseline (and revised point forecasts are on average 0.51 percentage points higher than revised density means). However, we also see that an approximately equal number of respondents have point forecasts above and below their density mean both at the baseline and final stages; for example, baseline point forecasts are above baseline density forecasts for 49.8% of respondents, and are below for 47.3% of respondents.<sup>31</sup> Hence we see that a simple comparison of point forecasts with density means provides only modest evidence against the square symmetric loss hypothesis.

On the other hand, we provide stronger evidence against symmetric square loss when we compare *revisions* in point forecasts with *revisions* in density forecasts. Our approach here is to regress respondents' point-forecast revisions ( $\Delta\pi$ ) onto the revisions of the fitted means of their *density* forecasts (the "density revision"). Under symmetric square loss, we would expect the coefficient on density revision to be one. Second, we augment this regression with another regressor, the changes in respondents' density uncertainty (denoted as  $\Delta U$ , and measured as the change in the respondent's fitted density variance). We would expect the coefficient on  $\Delta U$  to be zero under symmetric square loss.

The first two columns of Table 5 present our estimates for these two specifications. In column (1), we see that the estimated coefficient on density revision is 0.811; the estimate is,

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<sup>31</sup> If we focus on larger gaps between point forecasts and density means – which may help remove some noise – we see that 27.0% of respondents have baseline point forecasts that are more than 1 percentage point above their density means, whereas only 21.0% of respondents have baseline point forecasts that are more than 1 percentage point below their density means. In contrast, Engelberg et al. (2009), in their analysis of the point forecast and density means/medians of professional forecasters, find that most point forecasts are within a narrow band around the density means/medians. However, conditional on being outside the band, they find that point predictions are much more often below the lower bounds than above the upper ones.

however, not statistically different from 1 at conventional levels.<sup>32</sup> However, when we extend this test by adding  $\Delta U$  as a regressor, we can see in column (2) that the estimated coefficient on  $\Delta U$  is statistically different from 0 at the 1% level, and a joint test of the first coefficient being equal to 1 together with the coefficient on  $\Delta U$  being equal to 0 is rejected at the 5% level. Both of these results reject symmetric square loss in updating.

The empirical facts that average point forecasts are above density means and that the coefficient on  $\Delta U$  is greater than 0 both suggest that respondents deviate from symmetric square loss in a manner consistent with the alternative  $b > 1$ . That is, respondents appear to be averse to *underestimating* inflation. For example, if  $b > 1$  then the right-tail of the subjective probability distribution receives more weight, which pushes point forecasts above density means. Likewise, because average revisions are downward in our sample, the positive coefficient on  $\Delta U$  indicates that revisions are smaller (that is, less negative) for respondents with larger increases (or smaller decreases) in uncertainty; this again is predicted by  $b > 1$ . As suggested by Elliott et al. (2008), such weights may be the result of prospect-theoretic loss aversion if individuals view higher-than-expected inflation as a “bad.” We find some evidence in favor of this interpretation by studying respondents’ answers to free-response questions that we asked on why respondents did or did not update. One respondent, for example, described his forecast as a “*safe, conservative* number” (emphasis added), and another mentioned that higher inflation outcomes are “worse” outcomes.

Of course, there are some subjective distributions  $F(\cdot)$  for which the above evidence is also consistent with the alternative  $p \neq 2$  and  $b = 1$ . For example, if  $p = 1$  and  $b = 1$  (i.e., symmetric absolute loss, such that point forecasts are the medians of respondents’ subjective distributions) and if the average  $F(\cdot)$  is left-skewed, then we should also expect that average point forecasts are above density means. While a full examination of various alternatives to square symmetric loss is beyond the scope of this paper, we can easily test the symmetric absolute loss alternative by comparing point forecasts with density medians. As was the case with the comparison with density means, individuals’ point forecasts are on average above the density medians (more specifically, 1.52 percentage points higher than density medians at baseline, and 0.54 percentage points higher than density medians after the treatment). We can also test for symmetric absolute loss in the framework of Table 5, if we use density medians as regressors in place of density means. These analyses are presented in columns (3) and (4) of the table and provide further evidence against symmetric absolute loss. We again see that the coefficient on density median is different from 1, and that the coefficient on  $\Delta U$  is greater than 0.<sup>33</sup> These results are inconsistent with the joint hypothesis that  $p = 1$  and  $b = 1$ , and again are consistent with  $b > 1$ .

Overall, we interpret the results in this section as suggestive evidence of forecasting and updating under asymmetric loss on the part of our survey respondents. This implies that measuring – and accounting for – individuals’ uncertainty may be crucial when calibrating models to survey data, especially if there is reason to believe that individuals’ uncertainty may be changing over time.

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<sup>32</sup> We note, however, that if we include PP respondents in this regression to increase statistical power, then we strongly reject that the coefficient equals 1 (p-value = 0.000).

<sup>33</sup> In column (4), a joint test of the first coefficient being equal to 1 together with the coefficient on  $\Delta U$  being equal to 0 is rejected at the 1% level.

## 6. Conclusion

A crucial aspect of monetary policy is managing inflation expectations. However, there is limited understanding of how individuals form these expectations – a primary question for economists and policy-makers. This paper, using a survey with an embedded information experiment, attempts to shed light on this question by exploring the causal determinants of inflation expectations. We find that respondents, on average, are not fully informed about past as well as future inflation-relevant measures, and when provided with (certain kinds of) inflation-relevant information, they update their inflation expectations. Moreover, the updating is meaningful in the sense that, on average, it is: (1) in the direction of the signal, (2) proportional to the strength of the signal (i.e., the revealed perception gap), and (3) greater when the baseline expectations are more uncertain. Our results are consistent with models in which agents form expectations rationally, but face information constraints.

As a result of the information treatments, the inflation expectations distribution converges towards its center, and there is a significant decline in the cross-sectional variance of the expectations distribution. An immediate implication of this result is that information campaigns might be effectively deployed as part of prudent monetary policy to affect consumer inflation expectations. In particular, our results suggest that the (high-expectation) right tail of the distribution of public inflation expectations, consisting disproportionately of expectations from female, low-financial literacy, lower-education and lower-income individuals, could be influenced and managed with public information campaigns, assuming one can find an effective way to deliver the information.

Another notable and arguably encouraging finding is that (information about) price changes in food and beverages have limited pass-through to consumers' inflation expectations. A positive interpretation of this finding is that our survey respondents understand that the Food treatment provides information about past price changes in only a part of a consumption basket, while the SPF treatment provides information in the same time frame for which we elicit respondents' expectations (next year), and provides information about price changes in a whole consumption basket. That would be an encouraging finding for policy institutions and central banks which monitor consumer inflation expectations closely, since it indicates that consumers' inflation expectations – as we measure here – are not susceptible to price changes in food and beverages, which generally tend to be volatile. On the other hand, a less favorable interpretation could be that our survey respondents either have a limited understanding of the concept of overall inflation (and hence do not understand the link between food prices and overall inflation), or do not find the objective information about the small food price increases prevalent during the study period to be credible. Additionally, it is possible that respondents would update more substantially in circumstances where they learned they had *under*-estimated food price inflation; in our setting, 94% of Food perception gaps were *overestimates*.<sup>34</sup>

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<sup>34</sup> An example of such asymmetric response to new information is given in Eil and Rao (2011).

While we have shown that respondents revise their inflation expectations sensibly in response to the provided information, we are unable to analyze whether the magnitude of their revisions is either an under- or over-reaction to the provided information. For example, without knowing the perceived effect of past food and beverage price changes on future inflation, we cannot evaluate whether respondents should update their inflation expectations more or less than we observe in response to the Food information treatment. Furthermore, in our study, respondents do not choose the type of information but are exogenously provided with a treatment. Observed heterogeneity in inflation expectations may partly arise because of demographic differences in information acquisition (Burke and Manz, 2010; Mobius et al., 2011). Moreover, belief-updating when presented with new information in a survey/experiment may be very different from instances where individuals acquire the information themselves (Hertwig et al., 2004). Likewise, the long-term effects of new information on respondents' expectations are also unclear. Finally, while we find that expectations formation in our context is consistent with a sticky-information model, we cannot identify the sources of stickiness (such as information costs or stochastic updating) in the current framework. Each of these areas requires further research.<sup>35</sup>

Finally, providing information to respondents does not necessarily guarantee more accurate expectations. Whereas we do find in our experimental setting that revised expectations converge toward the range of recent years' inflation realizations (and indeed the actual realized CPI inflation between January 2011 and January 2012), information can have different effects in other contexts: sometimes, individuals presented with new information that is inconsistent with a prior belief may be *less* likely to revise their beliefs, and may even develop more polarized beliefs (Lord, Ross, and Lepper, 1979; Gentzkow and Shapiro, 2006). Therefore, any public information campaigns to help anchor consumer inflation expectations need to be carefully designed.

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<sup>35</sup> An extension of the novel methodology presented here would be to re-survey respondents over regular intervals separated by, say, a few weeks. Changes in macroeconomic conditions may allow us to observe how inflation expectations change, especially if the surveys were randomly conducted before versus after substantial inflation-related current events, such as FOMC statements by the Federal Reserve or OPEC meetings. These surveys could occasionally incorporate experimental information treatments, generating an experimental panel of beliefs. This design would be helpful in distinguishing between short-term and long-term effects of information treatments such as the ones we use.

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## Appendix A: Financial Literacy Questions

*On the following screens, you will receive questions that ask about financial topics. For each question, you must first decide if the statement is true or false and then choose a number to show how confident you are of your answer.*

- 1) If the money on your savings account grows at an annual rate of 5%, then, regardless of inflation, you will be able to buy more with the money in this account in the future than you are able to buy today.

True  
False

- 2) If your income doubles in the next ten years and prices of all goods and services also double, then you will be able to buy fewer goods in ten years than you can buy today.

True  
False

*Next we would like to ask you some questions which assess how people use numbers in everyday life. Please answer the following questions by filling in the blank. Please do not use a calculator for any of these questions.*

If the chance of getting a disease is 10%, how many people would be expected to get the disease:

- 3) Out of 100 people \_\_\_\_\_

- 4) Out of 1000 people \_\_\_\_\_

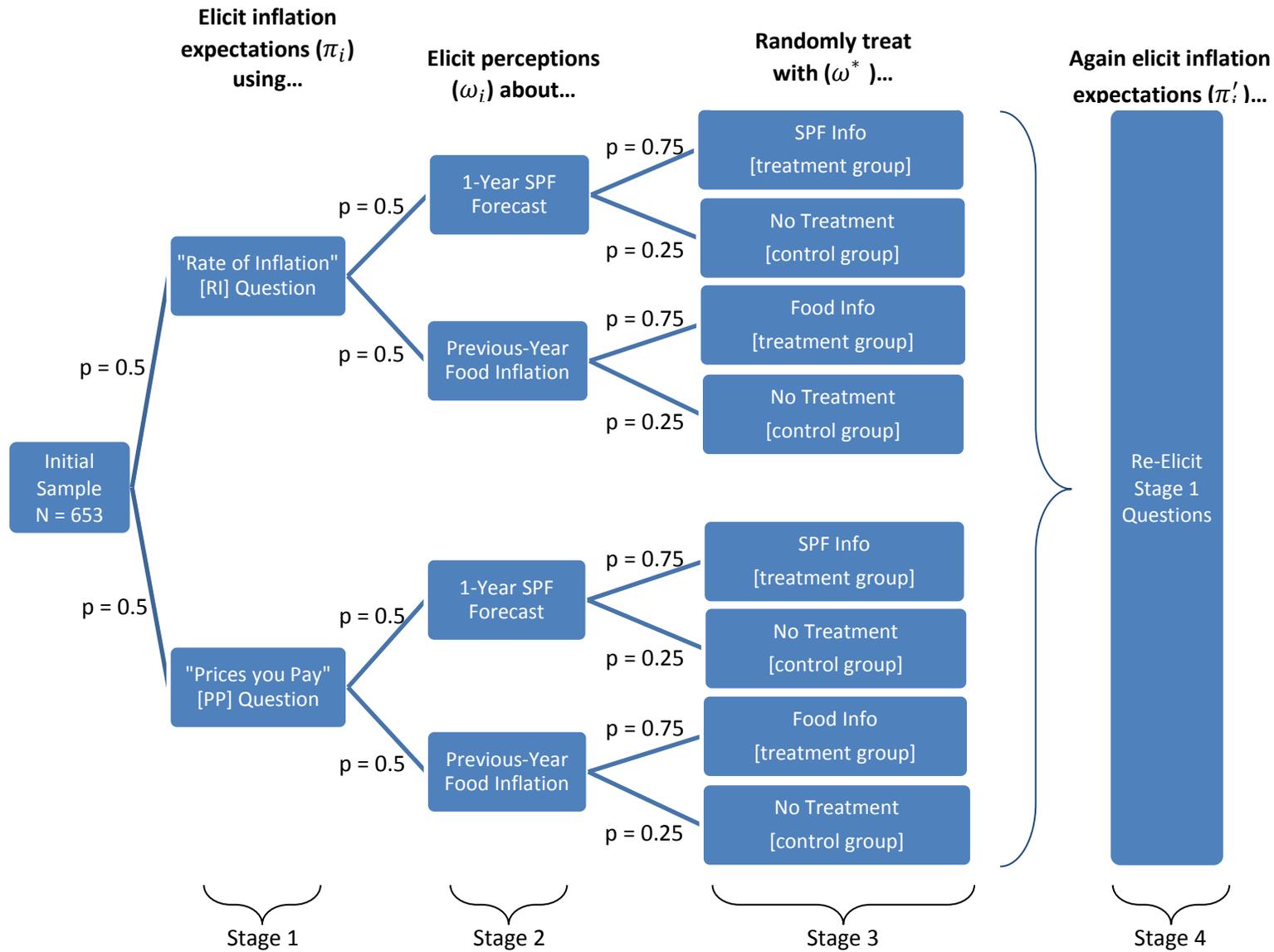
- 5) Imagine that we roll a fair, six-sided die 1,000 times. Out of 1,000 rolls, how many times do you think the die would come up as an even number?

If you have \$100 in a savings account, the interest rate is 10% per year and you never withdraw money or interest payments, how much will you have in the account after:

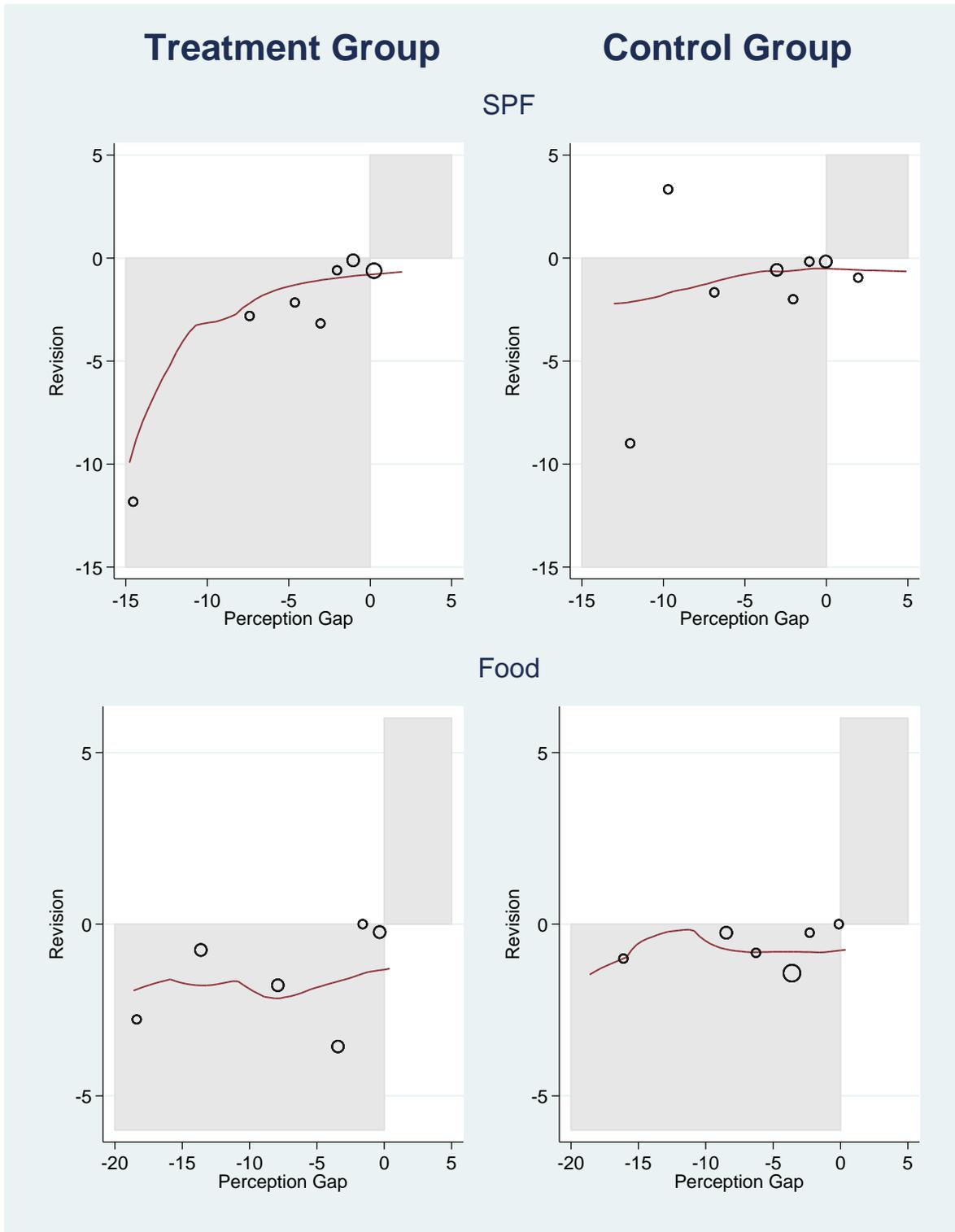
- 6) 1 year \_\_\_\_\_

- 7) 2 years \_\_\_\_\_

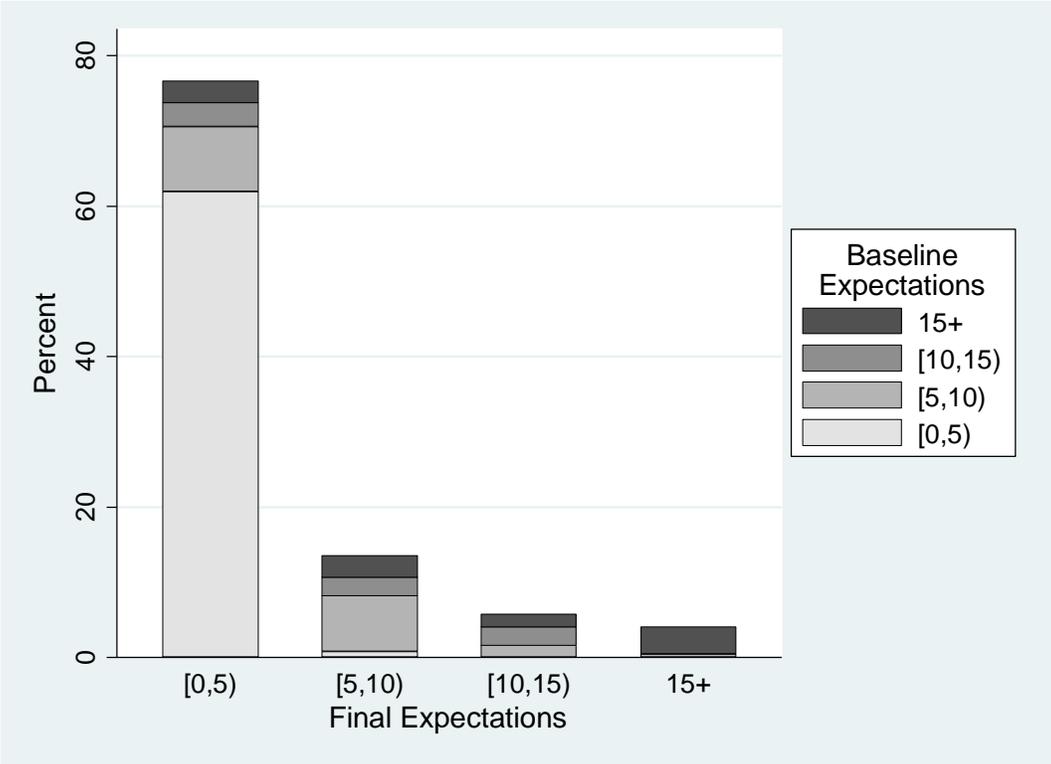
**Figure 1: Survey Design**



**Figure 2: Inflation Expectations Revisions and Perception Gaps, for Treatment and Control Groups**



**Figure 3: Distribution of Baseline and Final Inflation Expectations**



**Figure 4: Joint Density of Baseline Expectations and Perception Gaps**

