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**Working Paper**

## The price is right: Updating of inflation expectations in a randomized price information experiment

Staff Report, No. 543

**Provided in Cooperation with:**  
Federal Reserve Bank of New York

*Suggested Citation:* Armantier, Olivier; Nelson, Scott; Topa, Giorgio; van der Klaauw, Wilbert; Zafar, Basit (2012) : The price is right: Updating of inflation expectations in a randomized price information experiment, Staff Report, No. 543, Federal Reserve Bank of New York, New York, NY

This Version is available at:

<https://hdl.handle.net/10419/60937>

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Federal Reserve Bank of New York  
Staff Reports

The Price Is Right: Updating of Inflation Expectations  
in a Randomized Price Information Experiment

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Staff Report no. 543  
January 2012  
*Revised March 2012*

This paper presents preliminary findings and is being distributed to economists and other interested readers solely to stimulate discussion and elicit comments. The views expressed in this paper are those of the authors and are not necessarily reflective of views at the Federal Reserve Bank of New York or the Federal Reserve System. Any errors or omissions are the responsibility of the authors.

## **The Price Is Right: Updating of Inflation Expectations in a Randomized Price Information Experiment**

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*Federal Reserve Bank of New York Staff Reports*, no. 543

January 2012, revised March 2012

JEL classification: C81, D80, E31

### **Abstract**

Understanding the formation of consumer inflation expectations is considered crucial for managing monetary policy. This paper investigates how consumers form and update their inflation expectations using a unique “information” experiment embedded in a survey. We first elicit respondents’ expectations for future inflation either in their own consumption basket or for the economy overall. We then randomly provide a subset of respondents with inflation-relevant information: either past-year food price inflation, or a median professional forecast of next-year overall inflation. Finally, inflation expectations are re-elicited from all respondents. This design creates unique panel data that allow us to identify the effects of new information on respondents’ inflation expectations. We find that respondents revise their inflation expectations in response to information, and do so meaningfully: revisions are proportional to the strength of the information signal, and inversely proportional to the precision of prior inflation expectations. We also find systematic differences in updating across demographic groups and by question wording, underscoring how different types of information may be more or less relevant for different groups, and how the observed impact of information may depend on methods used to elicit inflation expectations.

Key words: inflation expectations, information, heterogeneous expectations, updating

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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 literature attempts to explain as a result of different expectation-formation processes: e.g., some form of bounded rationality (Sargent, 1993; Evans and Honkapohja, 2001; Mankiw and Reis, 2002), adaptive learning (Orphanides and Williams, 2006), switching between different prediction rules (Branch, 2007), time-dependent rules under which expectations are updated only at fixed intervals (Carroll, 2003), or learning from experience (Malmendier and Nagel, 2010; Madeira and Zafar, 2011). While this literature has found evidence to support some of these proposed 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 about either past-year average food price inflation, or professional economists'

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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.

median forecast of next-year overall inflation. 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.

Furthermore, following the recent literature on the importance of inflation survey question-wording (Bruine de Bruin et al., 2010a), when we elicit inflation expectations we randomly ask half of our respondents for their expectations of overall inflation (the “rate of inflation”) while asking the other half of respondents for their expectations of their own-basket inflation (the “prices of things you usually spend money on”, hereafter referred to as “prices you pay”).<sup>3</sup> We test here whether respondents process our two types of randomly-provided information differently when they update their expectations for these two types of inflation.

We also ask all respondents for their prior beliefs about the randomly-provided information, allowing us to gauge the strength of the information signal that each respondent receives. We expect respondents who are less informed about either of the information treatments to exhibit larger gaps on average between their prior beliefs and the true information. For these respondents, the information treatment may contain valuable additional information that causes expectations updating, so long as the provided information indeed plays a role in their expectation-formation process. On the other hand, for respondents who are relatively better informed about the information treatments *ex ante*, the information treatments should contain less new information, and our experiment should result in less or no updating.

Compared to existing studies, the approach used in this paper differs in that we (1) do not make assumptions about the respondent’s information set, (2) do not impose any particular learning or information-processing rule to explain the heterogeneity in expectations, and (3) observe the *causal* effects of different types of inflation-relevant information on expectation updating. Previous studies have mostly overlooked the panel dimension of survey expectations (see Keane and Runkle, 1990, for an exception). This complicates the interpretation of previous work on learning in expectation updating, since only the aggregate evolution of beliefs is analyzed, while the actual updating by individuals is not studied.

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<sup>3</sup> Thus, we have four information treatment cells (given two information treatments and two expectation-type questions), and four corresponding control treatment cells.

In our pre-treatment survey questions, we replicate some important results from the cross-sectional literature, showing that consumers can have incorrect perceptions of past changes in prices,<sup>4</sup> and that these perceptions tend to be *over*-perceptions (Bryan and Venkatu, 2001a; Duffy and Lunn, 2007). While a substantial number of our respondents have priors that are closely in line with the treatment information, the distribution of priors is highly skewed, and 37.5% of respondents have *perception gaps* – the gaps between the treatment information and their priors – of three percentage points or more. Average perceptions gaps are substantial: -56% (i.e., over-prediction by 56%) for the median forecast of professional economists, and -139% for past changes in food prices. Since our treatment is designed to influence respondents’ information sets, these perception gaps are a necessary condition for our experiment’s success.

Next, exploiting our information treatment, we find that new information does cause 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 up (down) if their perception gaps were under- (over-) estimates, (2) revise their expectations more when their perception gaps are larger, and (3) are more receptive to the information when the uncertainty in their prior beliefs is greater. These updating patterns are consistent with a Bayesian updating model. Similar to previous literature, we also see systematic differences between male and female respondents<sup>5</sup>: we find that most substantial updating behavior is driven by female respondents.

We find that both of our information treatments — past-year food price inflation and a professional forecast of next-year overall inflation — affect respondents’ expectations. This provides some empirical support for models in which consumers derive their forecasts from news reports of the forecasts of professional economists (Carroll, 2003), and models in which consumers base their inflation expectations on news releases about previous-period inflation (Garner, 1982; Hey, 1994; Lanne, Luoma, and Luoto, 2009). However, we also find that a large proportion of respondents do not revise their expectations when provided with the treatment information. On average, these respondents have smaller perception gaps than their peers – and hence less information content in the treatments – but their perception gaps are still substantial. This suggests

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<sup>4</sup> This finding is 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, 2009); 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).

<sup>5</sup> We borrow from Bryan and Venkatu (2001): “That men and women occasionally see things differently is not a remarkable observation. But that the sexes could report vastly different perspectives on the rate at which prices are rising over a long period of time is astonishing.”

that these respondents, in addition to receiving less effective information in the treatments, also either do not find the provided information to be relevant for inflation expectations or do not find the information credible.

The effect of information is heterogeneous. Our analysis reveals that information about food prices causes consumers to update expectations more for own-basket inflation rate, and less for “rate of inflation,” whereas we find that information about forecasts of *overall* inflation causes consumers to update expectations for the “rate of inflation” primarily. The greater response of own-basket inflation expectations to food price information (relative to the rate of inflation) may be a consequence of either (1) food price changes having more relevance for consumers’ own-basket inflation rate than for the overall Consumer Price Index,<sup>6</sup> or (2) consumers having biased perceptions about the share of food expenditures in their budget, or (3) consumers focusing on specific salient price changes when considering the change in “prices” rather than “inflation” (Bruine de Bruin et al., 2012).

We find substantial heterogeneity by demographics in expectation-updating. For one, we find that low-income respondents revise significantly their “prices you pay” forecast when provided with information about past food prices, while high-income respondents do not, even though both groups receive equally informative signals.<sup>7</sup> This result is consistent with food purchases occupying a larger share of lower income respondents’ (perceived) consumption baskets, suggesting some degree of sophistication in respondents’ reactions to our two information treatments. On the other hand, we find that high-education respondents update their “prices you pay” expectations in response to the median professional forecast information treatment, while low-education respondents do not. This may indicate that low-education respondents have less understanding of the overall inflation rate’s relevance to “prices [they] pay.” Both of these results underscore how different types of information may be more or less relevant for different groups.

Likewise, we find substantial gender heterogeneity: patterns in belief-updating that we observe are considerably stronger for female respondents in our sample. Since females’ average perception gap is only weakly larger than that of males, this suggests that they are more receptive to

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<sup>6</sup> The CPI is a plutocratic index, i.e., it weights individual consumers’ consumption baskets by their expenditure share (relative to total expenditure). Thus, people who consume more have larger weights in the CPI. Therefore, the simple average of food shares in individual’s consumption baskets may not be the same as the food share in the CPI. In particular, if food shares are lower for higher income individuals (McGranahan and Paulson, 2006), the food share in the CPI would be lower than the simple average of food shares in individuals’ consumption baskets).

<sup>7</sup> That is, perception gaps among high-income individuals – as revealed to respondents through the information treatment – are not significantly different from those of low-income individuals.

information. This either may be a consequence of females' less precise priors – of which we find some evidence in our data – and less overconfidence relative to men (Barber and Odean, 2001; Niederle and Vesterlund, 2007), and/or may be because they process information differently from men.

Looking at other patterns in updating heterogeneity, we find that low-income, low-education, and low financial literacy respondents are more responsive to the information treatments, relative to their counterparts. These results are important for inflation expectations survey data in general: it is well-documented that, whereas *median* consumer inflation expectation survey responses generally track official estimates of realized inflation and sometimes even outperform professional forecasters (Thomas, 1999; Ang, Bekaert & Wei, 2007), nevertheless *average* consumer inflation expectations are systematically higher than realized inflation (Bryan and Venkatu, 2001a, 2001b); previous literature indicates that this difference between mean and median responses is driven by a right-skewed distribution of inflation expectations where respondents in the right tail are more likely to be female, older, low-education, and with low financial literacy.<sup>8</sup> We replicate these results – we find that these same demographic groups tend to have higher inflation expectations than their peers (though the differences are not always significant at conventional levels) – but we also show that, on average, these same groups (1) generally have higher perception gaps about objective inflation information ex ante, (2) have marginally more uncertain prior beliefs about future inflation, and (3) are more responsive to our information treatments in their expectation updating. Thus we offer an alternative 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. This suggests a potential role for policies that incorporate public information campaigns to effectively influence the high-expectation right tail of the public's inflation expectation distribution.<sup>9</sup>

Our results also shed light on the micro-foundations of the macroeconomic effects of inflation, which has implications for macroeconomic and monetary policy at large. First, we help clarify some of the mechanisms for pass-through inflation, or the effects of non-core (e.g. food, oil) price inflation on core inflation. Pass-through inflation is of particular concern during times of sharp

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<sup>8</sup>See Jonung (1981), Bryan and Venkatu (2001a, 2001b), Lombardelli and Saleheen (2003), Blanchflower and Coille (2009), and Bruine de Bruin et al. (2010a)

<sup>9</sup> On the other hand, we find that some demographic groups, most especially males, are less responsive to the information we provide, suggesting that a public information campaign in the spirit of our “information treatments” would need a more sophisticated and multi-pronged design if it were to affect more of the population.



non-core price changes – oil shocks and food shocks – where monetary policy needs to balance the competing goals of fighting inflationary pressure and alleviating the contractionary effects of the price shock (Nakov and Pescatori, 2010). We find that information about past food price inflation has only limited pass-through to respondents’ expectations of the “*rate of inflation*”. Under the presumption that consumers understand the concept of inflation, this result is partial evidence that consumers may be sophisticated enough to distinguish between, on the one hand, shocks in volatile price components such as food and oil, and on the other hand, the overall inflation rate.

This paper is organized as follows. The survey design and data collection methodology are described in Section 2. Section 3 conducts the empirical analysis, and the main results are discussed in Section 4. We discuss the policy implications of our study and its limitations in Section 5.

## 2. Data

Our data are from an original survey that is part of an ongoing effort by the Federal Reserve Bank of New York, with support from academic economists and psychologists at Carnegie Mellon University.<sup>10</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 Survey between November 2006 and July 2010 and subsequently agreed to participate in the ALP.<sup>11</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. (2011), examines the link between self-reported beliefs and economic behavior.

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<sup>10</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., 2011), and to better understand how the public forms and updates expectations about future inflation (Bruine de Bruin et al., 2010b).

<sup>11</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.

The second set of questions—the focus of this paper—investigates how individuals revise their inflation expectations after being exposed to new information.

The survey design consisted of four stages (see Figure 1):

1. **Baseline Inflation Expectations:** In the first stage, respondents were randomly assigned to one of two questions that elicit their baseline inflation expectations, either for their own consumption basket or for the economy overall. We refer to these as “baseline inflation expectations”.
2. **Treatment Beliefs:** In the second stage, respondents were randomly assigned to one of two belief elicitation questions regarding the information to be provided in the treatments. The two questions, detailed below, asked respondents for their perceptions about either average change in food and beverage prices over the last year, or about the median forecast of professional economists for one-year ahead inflation. We refer to respondents’ priors about the information as “treatment beliefs”.
3. **Information Provision Treatments:** With a probability of 75%, respondents were provided with the true values (defined as values published in two publicly available data series) of the measures for which they reported their perceptions in the second stage.
4. **Final Inflation Expectations:** In the final stage, the same inflation expectations that were initially collected in the first stage were re-elicited from all respondents, with each respondent being asked the same inflation question they were asked in the first stage.

### **2.1.1 Stage 1**

In the first stage, respondents were asked to report their inflation expectations using one of two randomly assigned questions. The two question-texts that elicit inflation expectations are:

- 1) “Prices You Pay” (PP) which asks for “*your expectations for the prices of things you usually spend money on going into the future*”;
- 2) “Rate of Inflation” (RI) which asks for “*your expectations for the rate of inflation/deflation going into the future.*”

Both questions were asked for two different horizons: (1) a point forecast “over the next 12 months”; 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 also 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 choices were mutually exclusive and collectively exhaustive, and respondents could verify that their answers summed to 100% probability. Following the approach developed by Engelberg, Manski and Williams (2009), a generalized beta distribution is fitted to each respondent’s stated probabilistic beliefs (see also Bruine de Bruin et al., 2011a). We then generate the mean and variance of the respondent’s beta distribution, which is used in the empirical analysis.

The PP question text is similar to the “prices in general” question text studied by Bruine de Bruin et al. (2011a). The “prices in general” question text is the version used in the University of Michigan’s Survey of Consumers, which produces the often-cited monthly measure of consumer inflation expectations. While the Michigan Survey’s question asks respondents “*During the next 12 months, do you think that prices in general will go up, or go down, or stay where they are now?*”, we ask respondents about “*the prices of things you usually spend money on*”. This change to the question wording was prompted by research showing 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., 2011c). The PP question is designed to be less likely to have mixed interpretations: the PP question may cue respondents to think about prices of specific purchases in their consumption basket, while the RI question may focus respondents on general price levels, or the overall cost of living (Bruine de Bruin et al., 2011b).

### **2.1.2 Stage 2**

The second stage consisted of the elicitation of one of two possible “treatment beliefs”:

1. The “Food” treatment: asked “*Over the last twelve months, by how much do you think the average prices of food and beverages in the US have changed?*”
2. The “Survey of Professional Forecasters (SPF) Forecast” Treatment: 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 forecast of year-over-year percentage change. Between stages 1 and 2, respondents participated in a battery of experimental questions related to inflation and investment (discussed in Armantier et al., 2011), and also answered several questions about consumption behavior, and sources of information about inflation/prices.

### 2.1.3 Stage 3

In the third stage, immediately after reporting their beliefs about Food or SPF Forecast inflation, 75% of respondents were randomly provided with true measures—defined as those published in publicly available data series—for which their beliefs were elicited in Stage 2. For the Food treatment, we used the series of average food and beverage prices for urban US consumers that are produced by the Bureau of Labor Statistics. 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.”*

For the SPF Forecast treatment, we used the median 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%.**”*

Our information treatments focus on either a backward-looking measure of inflation in a basket of specific goods (the food and beverages component of the CPI), or a forward-looking measure of general inflation (the overall CPI), which also includes the underlying distribution (precision) of the information. Our Food information treatment is motivated by empirical studies that show subjects’ forecasts of future prices are determined by past prices (Garner, 1982; Hey, 1994; Andersen, 2008; Lanne et al., 2009). Our SPF Forecast treatment is motivated by evidence and theory that consumers derive their forecasts from news reports of the forecasts of experts (Carroll, 2003).

Also in the third stage, 25% of respondents were given no information on the true values about the quantities for which their stage-two beliefs were elicited, and these respondents make up

our control group.<sup>12</sup> In the analysis, we refer to the 75% of respondents who receive the objective information as being in the “information” group, and refer to the remaining 25% who do not receive the true information as being in the “control” group.<sup>13</sup>

#### 2.1.4 Stage 4

Finally, all respondents were asked again for their *final* inflation expectations, using the same question-text that they received in the first stage. The reason for keeping a control group within each of the four treatment cells is that 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 information groups’ and control groups’ changes in expectations.

## 2.2 Survey Respondents

Among our 735 respondents, 705 finished the survey, of whom 667 gave answers for the minimum set of questions needed for our analysis: that is, answers for stage two beliefs (i.e. treatment beliefs), as well as at least one “Rate of Inflation” (RI) or “Prices you Pay” (PP) expectation at both stage one and stage three. We additionally exclude from our analysis 11 respondents with unusually high (greater than 50 percentage points) stage two inflation beliefs (about Food or about the SPF Forecast) or stage one inflation expectations (for PP or RI). Thus, we are left with a total sample of 656 respondents. Table 1 shows resulting sample sizes for each of the four treatment cells and corresponding control cells.

For these 656 respondents, average age is 52.7 years (standard deviation=14.0), with 43.1% being male, 87.7% non-Hispanic white, and 5.6% non-Hispanic black. The median annual family income is reported as “\$60,000 to \$74,999”, and 83.2% of respondents have an annual family income of \$30,000 or more. Respondents hail from 48 different U.S. states, and 52.3% have a 4-

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<sup>12</sup> They are primarily used for identifying the causal effect of the information provided to all other respondents.

<sup>13</sup> Thus after the stage three random assignment, we have four treatment cells – RI × Food (respondents who report RI inflation expectations and receive the Food treatment), PP × Food, RI × SPF, and PP × 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.

year college degree. Hence our sample has higher 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; 42.8% of the sample falls in this group. We define a respondent to be “older” if the respondent is at least 55 years of age; 47.6% of the sample falls in this group.

We paid respondents a fixed compensation for completing the survey, and did not elicit respondents' (inflation or treatment) beliefs 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 (2011) show that elicited beliefs are less biased (but noisier) in the absence of incentives.

### 3. Empirical Analysis

We begin our empirical analysis with summary statistics of baseline expectations, average revisions between stage one and stage three expectations for one-year point forecasts, and average absolute revisions; these are presented in Table 1.<sup>14</sup> Median baseline “prices you pay” (PP) expectations are substantially larger than baseline “rate of inflation” (RI) expectations: 5 percentage points for PP versus 3 percentage points for RI. Bruine de Bruin et al. (2012) also find that expectations tend to be higher for PP than for RI.

Median revisions are zero in all treatment and control groups, whereas the median *absolute* revision is nonzero in some cases – mostly, for respondents that were asked about the SPF Forecast – reflecting a combination of both upward and downward revisions in our sample. Meanwhile, in all four information groups and in all but one control group, mean revisions are negative, indicating average downward revisions. These downward revisions are larger in the information groups than in the control groups. For example, the mean downward revision in the RI  $\times$  SPF information group is 1.96 percentage points, compared to a mean downward revision of 0.93 percentage points in the control group. If we had very large sample sizes, and if the distribution of perception gaps were

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<sup>14</sup> Throughout this section, we first present results for respondents' point forecasts at the one-year horizon, and later extend our discussion to one-year density forecasts and three-year point forecasts. The one-year point forecast's format – that is, a single number representing inflation at a one-year horizon – most closely parallels the format of the information treatments, and is our primary outcome measure to test for meaningful updating behavior.

asymmetric around zero, then we should expect these differences to be statistically significant. However, given our small sample in the control groups, we find only one of the differences in revisions between the information and control group,  $PP \times \text{Food}$ , is statistically significant (at the 10% level). In the analysis below, we control for the size of respondents' perception gaps (since they may differ between the treatment and control groups), which uses richer data than simply testing for average differences between treatment groups.

We expect our information treatments to cause individuals to update their inflation expectations if i) individuals' inflation expectations are based in part on 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 fully informed about the true values of these quantities. As shown in the fourth row of each sub-panel, there is a sizable proportion of respondents who do revise their expectations, and a sizable proportion of respondents who do not, in both the information and control groups. And even though the proportion of respondents who do not revise their beliefs is smaller in the treatment groups (as one would expect), nevertheless many treated respondents (between 40.15% and 52.83%) do not revise their expectations. In this section, we first investigate how informed our survey respondents are about the true values of the treatments – which serves as a partial explanation of updating (and non-updating) behavior – and we then examine the other determinants of who updates their expectations, and how, in response to our information treatments.

### 3.1 Perception gap

For all respondents, we calculate the gap between the belief about information (treatment belief), and the *true* information, and refer to this difference as a perception gap. Perception gaps are calculated as true information minus treatment belief, such that negative (positive) perception gaps indicate overestimation (underestimation). The median perception gap in the Food treatment was -2.61, i.e., past food/beverage price changes were over-estimated by 2.61 percentage points, whereas in the SPF Forecast treatment it was -1.04.<sup>15</sup>

Our analysis reveals that the perception gaps are, on average, larger for respondents in our information groups who revise their inflation expectations versus those who do not. The average

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<sup>15</sup> Note that in the SPF Forecast 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 Forecast treatment is 0. All regressions results are qualitatively similar when we use this alternative perception gap.

Food treatment perception gap for respondents who revise their expectations is -7.3 percentage points versus -5.8 percentage points for those who do not (difference statistically significant at 10%), while the SPF forecast treatment perception gaps are -3.61 for revisers and -1.87 for non-revisers (significant at 5%). This suggests that the respondents who do not revise their expectations are doing so in part because the information that we provide is relatively less informative for them.

In order to understand how the perception gap varies by information treatment and demographics, Table 2 reports a series of OLS regressions in which we regress the perception gap onto individual characteristics and treatment dummies. For ease in interpreting coefficients, we set perception gaps – in this regression only – to be  $\log(\text{info}/\text{belief})$ , which preserves sign (relative to our linear distance measure) while giving the regression coefficients an elasticity interpretation: a coefficient of, e.g., 0.1 for a given demographic group indicates a 10% larger underestimate for that group.<sup>16</sup>

Column (1) of Table 2 shows results from regressing the perception gap onto treatment group dummies. The constant term in this regression shows the mean perception gap for the information group in the SPF Forecast treatment. The coefficient of -0.561 indicates that respondents in the SPF Forecast information group, on average, over-predict the forecast of professional forecasters by 56%. The average perception gap is  $-0.561 - 0.825 = -1.39$  in the Food treatment, indicating average over-prediction of 139%. Both estimates are statistically different from zero (at the 1% level), and the average Food treatment perception gap is statistically different from the average perception gap in the SPF Forecast treatment.

So, we find that our survey respondents are *on average* substantially misinformed about past changes in food/beverage prices as well as forecasts of professional forecasters, with larger perception gaps in the Food treatment. Also, we find no significant differences in perception gap between control and treatment groups; this indicates our randomization successfully produced information and control groups with comparable baseline beliefs.<sup>17</sup>

To highlight the heterogeneity in perception gap by demographics, in the remaining five columns of Table 2 we regress the perception gap on dummies for gender, older age (55 years and

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<sup>16</sup> For respondents who report a zero or negative treatment belief, we recode their treatment belief as 0.1 for the sake of calculating  $\log(\text{info}/\text{belief})$ . There are only fourteen such instances.

<sup>17</sup> To obtain the average perception gap for the control group in the SPF Forecast treatment, one has to add in the coefficient on control to the constant ( $-0.0431 - 0.561 = -0.641$ ). Similarly the average perception gap for the control group in the Food treatment is  $-1.358 = -0.0431 + 0.0710 - 0.561 - 0.825$ .



older), high financial literacy,<sup>18</sup> education (college B.A. or more), high income (\$75,000 and above), and also treatment and control group dummies. Two results are statistically significant when we control for all demographics at once (column 6). First, we find that college-educated respondents have 20% and 34% smaller perception gaps (less over-prediction) on average than their less-educated peers in the SPF Forecast and Food treatments respectively (though the difference between the two treatments is not statistically significant). Second, older respondents over-predict the past change in food and beverage prices by 18% relative to their younger counterparts.<sup>19</sup> While the remaining coefficients are not statistically significant, we find that female, low financial literacy, and low income respondents are more likely to over-predict and have larger perception gaps.<sup>20</sup>

## 3.2 Inflation Expectations Revisions and Perception Gaps

If a respondent uses the treatment information sensibly to update her inflation expectations, we expect to see an under-prediction (over-prediction) of treatment information leading to an upward (downward) revision in inflation expectations. For our purposes, under-predictions are *positive* perception gaps (defined as true information minus treatment belief). 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>21</sup>, as well as a local linear regression of mean revision and perception gap decile. Data consistent with sensible updating behavior for the treatment group should have the following characteristics: (1) the data points should be in quadrants 1 or 3 (the two shaded quadrants in the figure), i.e., mean revisions should be positive (negative) for positive (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 four graphs in the right column of Figure 2 (information groups) with the four corresponding figures in the left column (control groups), we see

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<sup>18</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 31.3% of the sample. See Appendix for the questions.

<sup>19</sup> To obtain the average perception gap for older respondents in the Food Treatment, one has to add the coefficients on older and older x Food treatment (0.120 – 0.304).

<sup>20</sup> We, however, reject the null that the coefficients are jointly equal to zero (p-value of 0.097 for F-test as reported in column 6 of the table).

<sup>21</sup> In cases where deciles overlap, fewer than 10 points appear on the plot.

two patterns. First, all the data points are in quadrants 1 and 3 for the information groups (except for one duple in the PP x SPF treatment), while a substantial number of data points appear in the other quadrants for the control groups.<sup>22</sup> Second, the spline is upward sloping and in the predicted quadrants in two of the four information groups (RI x SPF; PP x Food), while we observe either a flat relationship or one that is not confined to the *predicted* quadrants in the control groups. These results indicate, nonparametrically, a greater prevalence of sensible updating in our information treatments than in our control groups, and suggest that our information experiment led to sensible revisions in inflation expectations.

### 3.2.1 Baseline Updating Model

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 eight panels in Figure 2, regressing the revision in inflation expectations between stages one and three,  $\Delta\pi$ , on the linear-distance (true information – treatment belief) perception gap (“*Gap*”). We also include a set of interacted indicator variables as regressors, allowing us to estimate an updating slope separately for each treatment cell. Specifically, we estimate (separately for the Food and SPF Forecast treatments) the following regression:

$$\begin{aligned} \Delta\pi = & \alpha_1 + \alpha_2 * I_{PP} + \beta_{RI}(T_{info} * I_{RI}) + \beta_{PP}(T_{info} * I_{PP}) + \\ & \gamma_{RI}(T_{info} * I_{RI} * Gap) + \gamma_{PP}(T_{info} * I_{PP} * Gap) + \epsilon \end{aligned} \quad (1)$$

where  $I_{PP}$  is an indicator for answering the “prices you pay” question, while  $I_{RI}$  indicates the “Rate of Inflation” question.  $T_{info}$  is an indicator that equals one if the respondent was in the information group, i.e., the true value of the treatment information was revealed to the respondent, and zero otherwise. Note that  $\Delta\pi$  and  $Gap$  are, respectively, the same variables that were plotted on the y-axis and x-axis in Figure 2. In this specification,  $\alpha_1$  is a constant capturing average updating in the RI question for respondents in the control group, and  $\alpha_2$  is a constant that similarly captures average (differences in) control-group updating for PP respondents (relative to RI respondents). Then, the

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<sup>22</sup> In the data, we also find a greater percentage of non-zero updating respondents in the shaded quadrants for the information groups than for the control groups: For example, 74.3% of non-zero updating in the PP x Food information group happens in the shaded quadrants, as compared with 53.3% for the PP x Food control, and 70.4% for the RI x SPF information group, as compared with 53.7% for the RI x SPF control.

sum  $\alpha_1 + \beta_{RI}$  shows average updating for RI question respondents in the information groups with a zero perception gap. Similarly, the sum  $\alpha_1 + \alpha_2 + \beta_{PP}$  is the average updating for PP question respondents in the treatment group with a zero perception gap. Inclusion of  $\alpha_1$  and  $\alpha_2$  in equation (1) allows us to control for the revisions that are attributable to the other questions asked in the survey (as well as the mere act of taking the survey).

The coefficients  $\gamma_{RI}$  and  $\gamma_{PP}$  are our main coefficients of interest. They show updating behavior with respect to perception gap size, in RI and PP responses respectively, i.e., they provide 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 gammas to be non-negative.

Table 3 presents results from this baseline regression. We use weighted least squares to estimate equation (1), to ensure that our estimates are robust to the inclusion of outliers.<sup>23</sup> Focusing first on updating in one-year point forecasts for the Food group (column 1), we find a significant  $\gamma$  coefficient for PP responses ( $\gamma_{PP}$ ): A perception gap of 10 percentage points in the Food treatment causes a revision of 0.35 percentage points for the PP question (significant at 5%). The estimate of  $\gamma_{PP}$  implies that a standard deviation increase in the perception gap results in a revision of 2.95 percent of a standard deviation (of the baseline expectations). Notably, we do not find a significant effect of the Food perception gap on RI responses:  $\gamma_{RI}$  is positive but not statistically different from zero.

Also, estimates of  $\alpha$  are not significantly different from zero, i.e., there are no significant revisions in inflation expectations in the control group. Moreover,  $\beta_{PP}$  is negative but not statistically different from zero, which indicates that there is no significant effect of the Food information treatment on PP responses (relative to control group responses) *other than* what is explained by the size of respondents' perception gap size.

We find an analogous result for one-year point forecast updating in the SPF Forecast group (column 2). First, the estimate of  $\gamma_{RI}$  is significant: A 10 percentage point perception gap in the SPF Forecast treatment causes a 1.25 percentage point revision in forecasts for the RI question (significant at 1%). This estimate implies that an increase in the SPF Forecast treatment perception gap of one standard deviation leads, on average, to a revision that is 11.85% of a standard deviation

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<sup>23</sup> We use weighted least squares (robust regressions) to estimate all expectation-updating regressions in this paper. Each of these regressions uses the minimum tuning constant possible for all regressions within a table. In other words, tuning constants (which determine the extent to which outliers are downweighted) are the same within tables, but not necessarily between tables. Therefore estimated coefficients may not directly comparable between tables.

of the baseline RI expectations. Second,  $\gamma_{PP}$  is positive but not significantly different from zero, i.e., the perception gap has a positive but insignificant effect on PP response. Third, both  $\beta$  coefficients in column 2 are not significantly different from zero; in particular, the insignificant  $\beta_{RI}$  coefficient indicates there is no effect of the SPF Forecast information treatment on RI responses (relative to control group responses) *other than* what is explained by the size of respondents' perception gap size.

It is notable that the Food treatment significantly affects PP responses (and not RI responses), whereas the SPF Forecast treatment affects RI (and not PP). That is to say, information about prices for “food and beverages” *only* significantly affects expectations about “the prices of things you usually spend money on”, and information about “future inflation” *only* significantly affects expectations about the “rate of inflation.” We discuss this divide in more detail in the next section.

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 3), and three-year point forecasts (columns 5 and 6) as our dependent variable. We find our  $\gamma$  coefficients have a pattern similar to what we had seen for the one-year point forecasts: For both one-year density forecasts and three-year point forecasts, the Food treatment affects significantly only the PP question, and the SPF Forecast treatment affects significantly only the RI question.

In the last two columns of Table 3, using the fitted mean of the one-year density forecasts, we explore the relationship between revision of inflation expectations and the precision of prior inflation expectations. In a Bayesian framework, *ceteris paribus*, respondents who are more uncertain about future inflation should be more responsive to the treatment information.<sup>24</sup> 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 uncertainty is above the sample median. We add two new terms to equation (1): the RI and PP *Gap* terms are interacted with the dummy, *Uncertain*. Thus  $\gamma_{RI}$ , the coefficient on  $(T_{info} * I_{RI} * Gap)$ , shows updating behavior with respect to perception gap size in RI for low-uncertainty respondents, while

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<sup>24</sup> In a Bayesian updating model, 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  $\frac{Variance(Prior)}{Variance(Info)}$ , i.e., responsiveness to information should be directly proportional to the uncertainty in the prior beliefs.

$\gamma_{RI} + \gamma_{RI-U}$  shows updating behavior with respect to the perception gap for high-uncertainty respondents. A positive  $\gamma_{PP-U}$  and  $\gamma_{RI-U}$  would be consistent with Bayesian updating. That is indeed what we find: estimates of  $\gamma_{PP}$  and  $\gamma_{PP-U}$  in column (7) suggest that the Food treatment affects PP responses, but only for high-uncertainty respondents. Similarly column (8) shows that the SPF Forecast treatment affects significantly the RI question, but only for high uncertainty respondents. These results indicate that the updating patterns shown in columns (3) and (4) are primarily driven by the revisions of high-uncertainty respondents.

### 3.2.2 Non-Linear Updating Model

Next, we test for non-linearity in the updating slopes. To do so, we estimate a separate  $\gamma$  coefficient for each tertile of perception gap size. This regression has the same constant terms as our baseline regression, but  $\gamma_{RI}$  and  $\gamma_{PP}$  are allowed to vary by the tertile of the absolute perception gap, i.e., we estimate separately  $\gamma_{RI-T1}$ ,  $\gamma_{RI-T2}$ , and  $\gamma_{RI-T3}$  (with three similar  $\gamma_{PP}$  coefficients) where T1 denotes the first (lowest) tertile, T2 denotes the second (middle) tertile, and T3 denotes the third (highest) tertile.<sup>25</sup>

Results from this tertile-wise regression are presented in Table 4. The main result to highlight is the concentration of significant updating in the *middle* tertile of respondents, with a few exceptions where we also observe significant updating for the *highest* tertile. For example, at the one-year horizon for the SPF Forecast treatment (in column 2), no  $\gamma$  coefficients from the *first* tertile of absolute perception gap are significant. Instead, significant (and positive) updating is concentrated in higher tertiles for both the RI and PP question. Likewise, for one-year point forecast updating in the Food treatment (column 1) we find a statistically significant coefficient only for the middle tertile in the PP question.

We find that the one-year *density* forecast results (columns 3 and 4) are generally consistent with the one-year point forecasts results. Density forecast updating is positive and strongly significant in either the middle or the upper tertiles in the SPF treatment for both the PP and RI questions, and for the middle tertile of the Food treatment for the PP question. Also in Table 4, we see that three-year point forecast results (columns 5 and 6) show significant updating to be concentrated in middle tertiles. We only find significant three-year point forecast updating for the PP question, for both the Food treatment and the SPF Forecast treatment.

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<sup>25</sup> Tertiles are calculated separately for each information treatment. By defining tertiles using absolute revisions, we treat positive and negative perceptions gaps of the same size symmetrically in the regressions.

### 3.2.3 Heterogeneity in Updating

We next examine heterogeneity in updating behavior. Before studying this heterogeneity in a regression context, we document the differences in baseline expectations, baseline uncertainty, perception gaps, and revisions – by gender, education, income, financial literacy, and age. We present these summary results in Table 5. We see first that female, low-income, low-education, low-financial literacy, and older respondents report higher Stage 1 point forecasts for both RI and PP. For example, females report a mean RI (PP) point forecast of 6.8 (7.1) percent, versus a mean forecast of 4.4 (5.9) for males.<sup>26</sup> And, as shown in the distribution of (pooled) Stage 1 beliefs in Appendix Table A1, this difference in averages is driven by a greater percentage of female, low-income, low-education, and low-literacy respondents occupying the (high-expectation) right tail of the expectations distribution: for example, 54% of female respondents have expectations in the interval [5+), compared to 42% of male respondents in that range.<sup>27</sup> We also find demographic patterns in *perception* gaps (consistent with our results in Table 2). The bottom panel of Table 5 shows heterogeneity in perceptions gaps,<sup>28</sup> and we observe that female, low-education, low-financial literacy, and low-income respondents have larger perception gaps in magnitude, though the differences are not statistically significant.<sup>29</sup>

Table 5 also indicates that, especially for the RI question, the same demographic groups (i.e., female, low-education, low-literacy, and low-income respondents) not only report higher stage 1 beliefs, but they also have more uncertain inflation expectations in Stage 1. For example, female respondents for the RI question have a mean (median) individual density forecast variance of 25.1 (4.0), while male respondents have an average forecast variance of 9.7 (2.4) (differences significant at the 10% (15%) level, using pairwise t- (median) tests).

The descriptive patterns of updating in Table 5 also indicate different *revisions* in inflation expectations (though differences are not all statistically significant). For example, females revise down their RI (PP) inflation expectations, on average, by 2.6 (2.3) percentage points, compared to a

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<sup>26</sup> The lack of statistical significance in these gender differences is possibly a result of the small sample size in each of these cells.

<sup>27</sup> Systematically higher inflation expectations among these demographic groups have also been found in the literature: see Jonung (1981), Bryan and Venkatu (2001a, 2001b), Lombardelli and Saleheen (2003), and Blanchflower and Coille (2009).

<sup>28</sup> For simplification, we combine the perception gap for both treatments here. We obtain qualitatively similar patterns by demographics in perception gaps for both information treatments.

<sup>29</sup> This finding is similar to the results about forecast accuracy by demographics presented in Bryan and Venkatu (2001a), Souleles, 2004; Anderson (2008), Pfajfar and Santoro (2010), and Madeira and Zafar (2011).

downward revision of 0.7 (1.4) percentage points for males. This could be a consequence of demographic differences in (1) perception gaps, (2) precision of priors about future inflation (uncertainty), and/or (3) information-processing rules. As a result of these different revisions, the revised average beliefs converge within gender, income, education, and financial literacy groups after the information treatment.

To examine this heterogeneity in a regression context, we first test for gender differences in updating. Previous research on belief updating in the context of inflation expectations has found mixed results: Burke and Manz (2010) do not find significant differences by gender in information processing, but Madeira and Zafar (2011) find significant differences in belief updating by gender and other demographic characteristics.<sup>30</sup>

We add two new intercept terms to equation (1),  $\alpha_3 * Female$  and  $\alpha_4 * Female * I_{pp}$ , and estimate each  $\gamma$  coefficient separately for male and female respondents.<sup>31</sup> Table 6 presents the results for this baseline regression by gender. Nearly all significant updating that appears in Table 6 is driven by female respondents. In particular, we find that the effect of the SPF Forecast treatment on RI responses is driven by female respondents for one-year point and density forecasts, and the effect of the Food treatment on PP responses is driven by female respondents for one-year density forecasts and three-year point forecasts.<sup>32</sup> Moreover, the effect is quite large: a standard deviation increase in the SPF Forecast treatment perception gap leads on average to a revision of nearly 41 percent of a standard deviation of the baseline PP expectations. There is also a weak effect among females for the SPF Forecast treatment on PP responses at the 1-year point forecast horizon (column 2). These results indicate that, even when we condition on perception gap size, female respondents exhibit greater updating than male respondents. In the next section we discuss whether this is a result of higher prior uncertainty for females, different information-processing rules, or a combination of both.

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<sup>30</sup> In other contexts of belief-updating, Mobius, Niederle, Niehaus, and Rosenblat (2011) find significant gender differences in information processing, while Wiswall and Zafar (2011) do not find gender differences.

<sup>31</sup> The intercepts from the baseline specification,  $\alpha_1$  and  $\alpha_2$ , now capture average updating for male respondents in the control group, while  $\alpha_3$  and  $\alpha_4$  capture average updating differences between males and females in the control group. These four intercepts are additive: For example, average updating for females in the PP control group is given by  $\alpha_1 + \alpha_2 + \alpha_3 + \alpha_4$ , while average updating for *males* in the RI control group is given by  $\alpha_1$  only.

<sup>32</sup> Column 1 estimates of  $\gamma_{PP-F}$  (female) and  $\gamma_{PP-M}$  (male) are not significant, whereas the estimate of  $\gamma_{PP}$  in column 1 of Table 3 is marginally significant. This is probably a result of lower statistical power in Table 6 due to smaller cell sizes, and different downweighting of outliers in the two regressions (we use different tuning constants in Tables 3 and 6; see footnote 24). Meanwhile, OLS results are qualitatively similar between Tables 3 and 6, and OLS results similarly show that all significant updating in Table 6 is driven by female respondents.

We next test for heterogeneity in updating by other demographics. To simplify, we focus on updating at the one-year point forecast horizon. We estimate updating effects by some of the individual characteristics from Table 2 – income, age, education, and financial literacy. We also use an additional variable, based on the following question asked immediately after re-eliciting PP and RI expectations (in stage 3): “*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; 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 five characteristics discussed above, we estimate the following regression:

$$\begin{aligned} \Delta\pi = & \alpha_1 + \alpha_2 * I_{PP} + \alpha_3 * C + \alpha_4 * C * I_{PP} + \beta_{RI}(T_{info} * I_{RI}) + \beta_{PP}(T_{info} * I_{PP}) \\ & + \gamma_{RI}(T_{info} * I_{RI} * (1 - C) * Gap) + \gamma_{PP}(T_{info} * I_{PP} * (1 - C) * Gap) \\ & + \eta_{RI}(T_{info} * I_{RI} * C * Gap) + \eta_{PP}(T_{info} * I_{PP} * C * Gap) + \epsilon, \end{aligned} \quad (2)$$

where  $C$  is a binary variable that represents one of the five characteristics – income, age, education, financial literacy, and “info-affected”. The  $\gamma$  coefficients capture updating behavior for individuals without a given characteristic  $C$ , while the  $\eta$  coefficients capture updating behavior for individuals with “ $C$ ”. Each of these coefficients ( $\gamma$  and  $\eta$ ) takes on a RI or PP subscript, as previously, to show distinct updating behavior for the two different question-texts. All characteristics’ regression results are presented together in Table 7, with two columns for each characteristic such that we can again identify effects separately for the Food treatment and SPF Forecast treatment.

We analyze updating by characteristics 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>33</sup>

The first two columns of Table 7 present estimates of equation (2) by income (that is,  $C$  in the equation is High Income, defined as respondent’s annual income being over \$75,000). We find that Food  $\times$  PP updating is significant only among lower income individuals; this is consistent with

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<sup>33</sup> The highest correlation that we observe is 0.29 between high income and college. Females and financial literacy has a correlation of -0.19; high financial literacy and college education has a correlation of 0.13; females and income has a correlation of -0.12. All other correlations are smaller than 0.1 in magnitude: -0.06 between females and college; -0.02 between females and older; 0.09 between high financial literacy and high income; -0.04 between older and college; -0.03 between older and high income; and -0.08 between older and high financial literacy.



food and beverages receiving more weight in a basket of “things you usually spend money on” – the focus of the PP question – as income decreases (McGranahan and Paulson, 2006). Meanwhile, we find that both high and low income individuals update significantly for SPF Forecast  $\times$  RI, but for high income individuals this updating coefficient is especially large – roughly four times larger than that for low income respondents (the estimates imply that an increase of one standard deviation in the SPF Forecast treatment perception gap leads to revisions of about 61% and 12% of one standard deviation of the baseline RI expectations, for high and low income individuals respectively). In columns (3)-(6) of Table 7, we observe an interesting split by our “ability” measures – education and financial literacy – in the SPF treatment. Whereas college-educated respondents update their RI expectations more than their less educated peers in the SPF Forecast treatment, high-financial literacy respondents update *less* than their low-financial literacy peers. Particularly interesting is the updating we observe among college-educated respondents for the PP question in the SPF Forecast treatment. High-education respondents update their PP expectations significantly in the SPF treatment – the estimate corresponds to a revision that is 40 percent of one standard deviation of baseline PP expectations in response to a standard deviation increase in the SPF Forecast treatment perception gap – whereas less-educated individuals do not.

Columns (7)-(8) of the table show updating by age. We find that older respondents are the only demographic subgroup among the four we examine that exhibits significant updating in the Food treatment. Moreover, older respondents are the only group for which we observe statistically significant Food  $\times$  RI updating. Meanwhile, we find that both older and younger respondents update significantly for SPF Forecast  $\times$  RI, with the coefficient for young being nearly twice as large as that for older; these coefficients imply that, on average, revisions of 12% and 6.4% of one standard deviation of baseline RI expectations result from a one standard deviation increase in perception gaps, for younger and older respondents respectively. We also obtain a statistically significant but negative estimate for SPF Forecast  $\times$  PP updating for the young; this suggests counter-intuitive updating on their part for the PP question in response to the SPF treatment.

Estimates of the specification with the “info-affected” characteristic are shown in columns (9) and (10) of the table. If individuals in the information treatments are indeed changing their PP or RI expectations in response to the provided information, we expect to see stronger updating among respondents who report that the provided information “affected” their (re-elicited) PP or RI forecasts. That is, we expect to see the magnitudes of  $\eta_{PP}$  ( $\eta_{RI}$ ) to be greater than those of  $\gamma_{PP}$  ( $\gamma_{RI}$ ), and expect them to be statistically positive. This is indeed the case: Individuals who

report *not* being “info-affected” show no significant updating, whereas “info-affected” individuals exhibit the same updating behavior seen in our earlier baseline regressions, including a strong effect for the Food  $\times$  PP, SPF Forecast  $\times$  PP, and SPF  $\times$  RI treatment cells. Moreover, point estimates of responsiveness to information among “info-affected” respondents ( $\eta$ ) are six to ten times larger than those in the baseline regression results (Table 3, columns 1 and 2).

## 4. Discussion

In this section we discuss three main results derived from the analysis in Section 3.

*RESULT 1: Respondents are not fully informed about the objective inflation measures used in our information treatments, with significant heterogeneity by type of treatment.*

We find that average perception gaps are negative and substantial – indicating overestimation of objective measures. While a sizable proportion of respondents have treatment beliefs that are in line with the true information,<sup>34</sup> we find that many also do not: in fact, 38% 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: 40% 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.

Whereas the perception gap in food prices may be partly explained by factors such as personal experiences, these patterns suggest that respondents are not fully informed of the objective inflation measures used in our information treatments. In particular, it is hard to explain the perception gap in the SPF Forecast treatment except as a lack of knowledge on the part of respondents. Consumers’ subjective forecasts of inflation have been consistently higher than actual inflation in recent periods (Geroganas, Healy, and Li, 2011).<sup>35</sup> Our results indicate that these high forecasts may in part be due to incorrect perceptions about objective measures of realized inflation.

We also find that perception gaps differ by type of inflation: When we ask respondents about food and beverage price inflation, the median perception gap is -2.61 (a 188%

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<sup>34</sup> 41% of respondents have perception gaps of 2 percentage points or less; 22% of respondents have perception gaps of 1 percentage point or less.

<sup>35</sup> Furthermore, note the average of SPF cross-sectional medians of one-year-ahead inflation forecasts since 2000 has been 1.95%; the average of Michigan Survey of Consumers cross sectional medians of one-year-ahead inflation forecasts over the same period has been 3.01%.

overprediction), whereas for SPF Forecast inflation the median perception gap is substantially smaller, -1.04 (a 53% overprediction). There are several possible explanations for larger perception gaps in the Food treatment. First, when respondents are asked about past changes in food and beverage prices, their responses are likely to suffer from recall bias and they are likely to recall items for which perceived price changes were most extreme (Bruine de Bruin et al., 2011b). 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, 2011).

*RESULT 2: Respondents, on average, update sensibly in response to information we provide to them. Furthermore, the relationship between the information treatments and inflation expectations depends on the type of inflation – own-basket or overall – about which respondents are asked.*

If respondents' inflation expectations are based in part on their perceptions of past food/beverage price changes and to expert inflation forecasts, and if respondents are not fully informed about these benchmarks *ex ante*, then our information treatments should lead them to revise their expectations. That is, in fact, what we find in Section 3 (Figure 2; Tables 3 and 4). We find that updating in the information groups does significantly differ from updating in the control groups, and that this updating is explained by the size of respondents' perception gaps (the difference between the prior beliefs and objective measure); this indicates that our observed updating is not just sensible in that it reflects the *sign* of the respondents' perception gaps, but also in that it reflects the *size* of the perception gaps as well. Moreover, we observe greater responsiveness to information for more uncertain respondents, consistent with a Bayesian updating model.<sup>36</sup> Finally, by finding consistently significant results in both information treatments, we find direct evidence that consumers can take into account forecasts of experts (as modeled in Carroll, 2003) and past price changes (Garner, 1982; Hey, 1994, Lanne et al., 2009) in their own forecasts, at least when they receive such information.<sup>37</sup>

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<sup>36</sup> Nevertheless, we are unable to investigate how respondents' revisions compare to some benchmark, such as Bayesian updating. This is because doing so requires richer, hard-to-acquire data on the underlying distributions of the information as well as detailed information on respondents' consumption bundles, such as the proportion spent on food and beverages.

<sup>37</sup> However, expectation updating may be asymmetric depending on whether the information is higher or lower than respondents' priors (Eil and Rao, 2011). We might have observed different expectation updating if food and beverage price inflation had been higher than respondents' priors, rather than lower. But in our setting, food and beverage price inflation was lower than prior beliefs for 94% of respondents.

Our second main finding is that information about food and beverage prices causes consumers to update expectations primarily for “prices you pay”, whereas information about inflation forecasts causes consumers to update expectations primarily for the “rate of inflation”. This result may be unsurprising but is important: It indicates that consumers believe the price changes in their own consumption basket to be different from the overall rate of inflation, and it indicates that consumers use different types of information to update their expectations about both. In particular, it is notable that food and beverage price information, at least as we have presented it here, has less relevance for consumers’ expectations of overall inflation. This may be because some consumers have limited understanding of overall inflation, or also may be indicative that consumers are distinguishing (either correctly or incorrectly) between different types of inflation forecasts and different types of inflation-relevant information, based on their understanding of the PP and RI question texts.

In particular, the fact that the Food and SPF Forecast treatments’ effects are primarily seen in, respectively, PP and RI responses, suggests that respondents are processing the treatment information thoughtfully, rather than unconsciously anchoring to the new information (Tversky and Kahneman, 1974). While the direction of respondents’ revisions is consistent with a naïve anchoring explanation, the differential effects by information treatment and expectation type are harder to reconcile with anchoring.

Furthermore, we find that respondents’ beliefs converge toward being near, or within 1 percentage point 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 forecasts, since (1) inflation outcomes are uncertain, such that a single year’s inflation realization may not coincide with an *objective* ex ante expectation,<sup>38</sup> and (2) respondents’ point forecasts may refer to various statistics (i.e. mean, median, mode, or others) of their *subjective* probability distributions (Engelberg, Manski and Williams, 2009), and (3) respondents’ forecasts for PP (own-basket inflation) may use a different basket of goods than the CPI. Nevertheless, we find at the baseline that 39.6% of RI responses and 35.0% of PP responses are within 1 percentage point of ultimately realized CPI inflation, whereas post-treatment these percentages improve to 55.6% and 52.8%, respectively.

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<sup>38</sup> That is, a single year’s realization is an inconsistent, albeit unbiased, estimator for the mean of the objective probability distribution.

Our results for updating of one-year inflation expectations point forecasts also extend to the updating of the one-year density forecast and the three-year point forecast. We find that updating of the mean of the year-ahead density forecast is generally consistent with one-year *point* forecast updating, but that the updating coefficients are sometimes smaller. This is consistent with density forecasts allowing individuals to respond to additional information by changing one part of the distribution without translating the entire distribution along the axis.

In contrast, we find that updating at the three-year point forecast horizon is sometimes stronger than updating for one-year point forecasts. This result is difficult to interpret. One possible explanation for the strong three-year point forecast updating would be if short-term inflation expectations are affected by recent experiences, but long-term expectations are not. That is, if respondents have recently had salient experiences with price changes, such that they hold strong priors about next-year inflation, these respondents might update less at the one-year horizon because of the strength of their priors, but might hold weaker priors at the three-year horizon, and hence update more.

We also, however, find that a substantial proportion of the respondents in the information groups do not revise their expectations. We find evidence that these respondents have, on average, smaller perception gaps (that is, the information comes as less of a surprise to them). However, their perception gaps are still quite large (especially in the Food treatment where the mean (median) perception gap is -5.80 (-3.61) percentage points as compared with -1.86 (-1.04) in the SPF Forecast treatment), suggesting that the lack of credibility or relevance of the information may be reasons for their non-response to the information.

*RESULT 3. Females, relative to males, are more responsive to our information treatments. There is heterogeneity in updating behavior, by respondents' education, age, and income, and also by a self-reported measure of how the information "affected" respondents.*

The regression results (Table 6) for updating behavior by gender are striking: Almost without exception, all significant updating behavior occurs for female respondents. Since we find only weakly different perception gaps by gender, these results suggest that males and females use different information-processing rules,<sup>39</sup> and/or females are more uncertain than men about future

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<sup>39</sup> We also find that female respondents are significantly (at the 1% level) more likely than men to answer that they "thought a lot about...the price of groceries" when initially reporting their inflation expectations, which suggests that the content of their priors is different from that of men.

inflation expectations at the baseline.<sup>40</sup> In Table 5, we find evidence of higher prior uncertainty for females for RI (rate of inflation), but no significant gender difference in prior uncertainty in PP (prices you pay). This mixed result suggests that differences both in information-processing rules and in ex ante uncertainty may be responsible for gender differences in belief updating.

Also notable is the finding that older respondents are less responsive to the SPF information treatment in updating their “rate of inflation” expectations than the young. This is consistent with models based on learning-from-experience (Malmendier and Nagel, 2009; Madeira and Zafar, 2011). These models posit that individuals are influenced by data realized during their lifetimes, and hence they imply that the young should rely to a greater extent on extrapolation of recent reports of inflation data – as we find. However, we also find a result that is harder to reconcile with learning-from-experience: younger respondents are *less* responsive to the Food treatment in their updating of PP expectations.

Next, our results by education provide insight into how different types of information affect updating for different types of inflation expectations. In the SPF information treatment, we find that both college-educated and non-college-educated respondents update their RI (rate of inflation) expectations,<sup>41</sup> but only college-educated respondents update their PP (prices you pay) expectations. This is somewhat surprising because, as shown in Table 2, college-educated respondents have smaller average perception gaps (Table 2). That is, the information content of our treatments is, on average, larger for non-college-educated respondents. This differential updating by education suggests that translating between information about inflation on the one hand, and price changes in one’s own consumption basket on the other hand, requires some sophistication. This may be because of respondents’ different familiarity with the concept of inflation, or because of differences in how respondents process new information. In either case, these differences by education have important implications for our understanding of inflation expectations in general: low-education consumers’ expectations seem to be shaped by factors *other* than information about published overall inflation indexes.<sup>42</sup>

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<sup>40</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>41</sup> The effects are, however, quite different: a standard deviation increase in the SPF Forecast treatment group leads to a revision of 32.4% (11.9%) of a standard deviation of baseline RI expectations for the college-educated (non-college-educated) respondents.

<sup>42</sup> Meanwhile, we do not find any conclusive differences in updating by financial literacy, which is somewhat at odds with Burke and Manz (2010) and Bruine de Bruin et al. (2010a), who find that financial literacy is related with the expectations formation process.

Furthermore, despite no significant differences in average perception gaps by income, we find the notable result that lower-income respondents update significantly their “prices you pay” forecast in the Food treatment, while higher-income respondents do not. This is consistent with food and beverage purchases consistently making up a larger percentage of lower-income consumers’ overall spending (McGranahan and Paulson, 2006). Equally notable is the finding that both high and low income individuals update significantly their “rate of inflation” forecast in the SPF Forecast treatment. Together, these two results indicate that both high-income and low-income respondents successfully translate between the provided information and expected changes in different consumption baskets.

Our updating results by “info-affected” help confirm our basic understanding of respondents’ expectation updating process. These results are a consistency check in support of our baseline model, in which updating is a function of the provided information. Furthermore, these results indicate that respondents are aware of the provided information’s effects on their revisions, which indicates that the updating process we observe here is a self-aware process, rather than subconscious belief updating (Hawkins, 1970). In particular, a naïve anchoring explanation for our observed updating – which is usually explained as a subconscious process – is hard to reconcile with our “info-affected” results.

## **5. 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 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 macroeconomic measures, and when provided with new 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 priors are less precise.

We also find substantial heterogeneity by respondent characteristics in how fully informed respondents are about objective inflation measures, and in their updating behavior. Female, low income, less educated, lower financial literacy, and older respondents have larger perception gaps and tend to have higher expectations of future inflation. Therefore, our findings suggest a new

explanation for these systematically high expectations previously found in the literature, whereby high expectations may be due in part to missing or inaccurate information about objective measures of actual inflation. Furthermore, we find that these same demographic groups tend to update their inflation expectations more than other respondents, even relative to their larger perception gaps.

We also document demographic heterogeneity in updating that cannot be explained by one simple model of expectations formation. Imperfect knowledge about objective measures of inflation and differential response to information are consistent with models of bounded rationality, such as sticky expectations or rational inattention (as in Barsky and Kilian, 2002; Mankiw and Reis, 2002; Carroll, 2003; Ball, Mankiw and Reis 2005). Some demographic differences in updating, such as older respondents being less responsive to the SPF Forecast information, are consistent with learning from experiences models (Malmendier and Nagel, 2010; Madeira and Zafar, 2011).

One policy implication of our results is almost immediate: Consumers respond to information about past prices as well as forecasts of experts by updating their inflation expectations, and so information campaigns might be effectively deployed to affect consumer inflation expectations. Since (1) keeping consumers' inflation expectations anchored is generally important for controlling inflation (Bernanke, 2004), and (2) consumers' inflation expectations may affect their economic decisions (Armantier et al., 2011), the large perception gaps in our sample suggest a role for public information campaigns about past and current inflation as part of prudent monetary policy. In particular, our results suggest that the (high-expectation) right tail of the distribution of public inflation expectations, consisting disproportionately of expectations from female, lower-education, lower-income, and older consumers, could be influenced and managed with effective public information campaigns, assuming we can find a way to deliver the information.

Our findings also underscore the results of Bruine de Bruin et al. (2012), who conclude that our PP question, like the similar Michigan Survey's question about "prices in general", causes respondents to focus more on price changes in their own consumption basket and hence to report expectations that are higher, more dispersed, and more correlated with gas and food price changes. The authors make the case for the RI question being a more reliable survey question, in that it is less sensitive to these transitory price changes. Here, we support that conclusion by finding direct evidence that information about food prices affects respondents' PP responses more than their RI responses.

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 share of food and beverage expenditure in each respondent's consumption bundle, we cannot evaluate whether respondents should update their inflation expectations more or less than we observe in response to the Food information treatment. Nevertheless it is unsurprising that the SPF Forecast treatment results in higher-magnitude updating than the Food treatment does. Whereas the Food treatment provides information about past price changes in only a part of a typical consumption basket, the SPF Forecast 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. Furthermore, how respondents' revisions compare to some benchmark, say, if they were Bayesian updaters, is an important question – both for policy-makers and for understanding the heterogeneity in expectations – but one that requires richer data on respondents' consumption bundles as well as on the underlying distributions of the information provided to the respondents.

It should be pointed out that, 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). The information that we provide in our study is readily available, so an important question then is why respondents do not seek out such information and pay attention to it, even though their responsiveness to such information in our study suggests they do find this information useful. 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). Finally, the long-term effects of new information on respondents' expectations are also unclear. Each of these areas requires further research.<sup>43</sup>

Also, 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

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<sup>43</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.

be *less* likely to revise their beliefs, and may even develop more polarized beliefs (Lord, Ross, and Lepper, 1979; Gentzkow and Shapiro, 2006).<sup>44</sup> Therefore, any public information campaigns to help anchor consumer inflation expectations need to be carefully designed and multi-pronged.

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<sup>44</sup> Also, evidence from Germany suggests that while intensity of the coverage of inflation in the media increases inflation expectations' accuracy, they may become more biased if the media content is not neutral (Lamla and Lein, 2010).

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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 \_\_\_\_\_

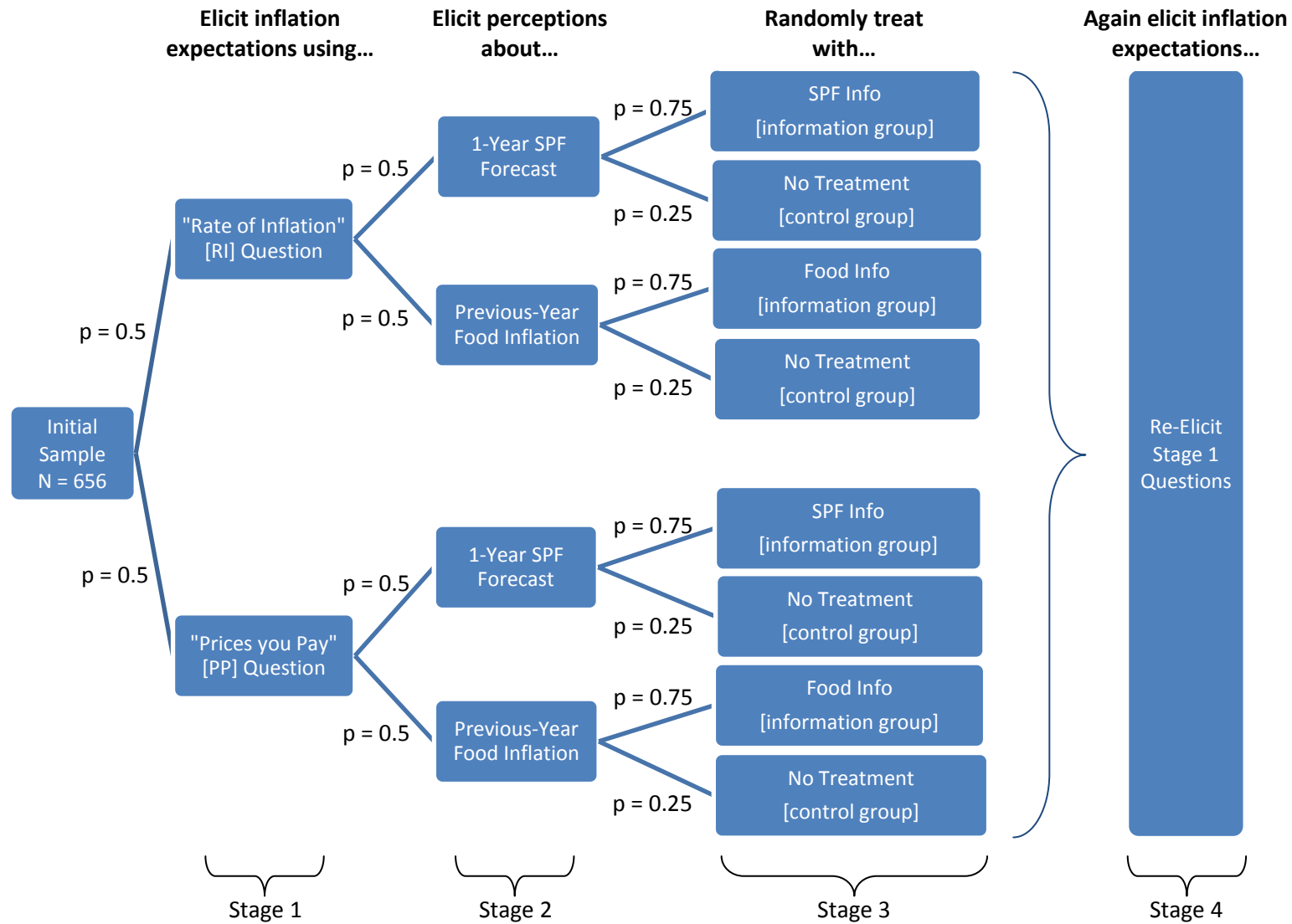
- 5) Imagine that we roll a fair, six-sided die 1,000 times. Out of 1,000 rolls, how many times do you think the die would come up as an even number?

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 Information and Control Groups**

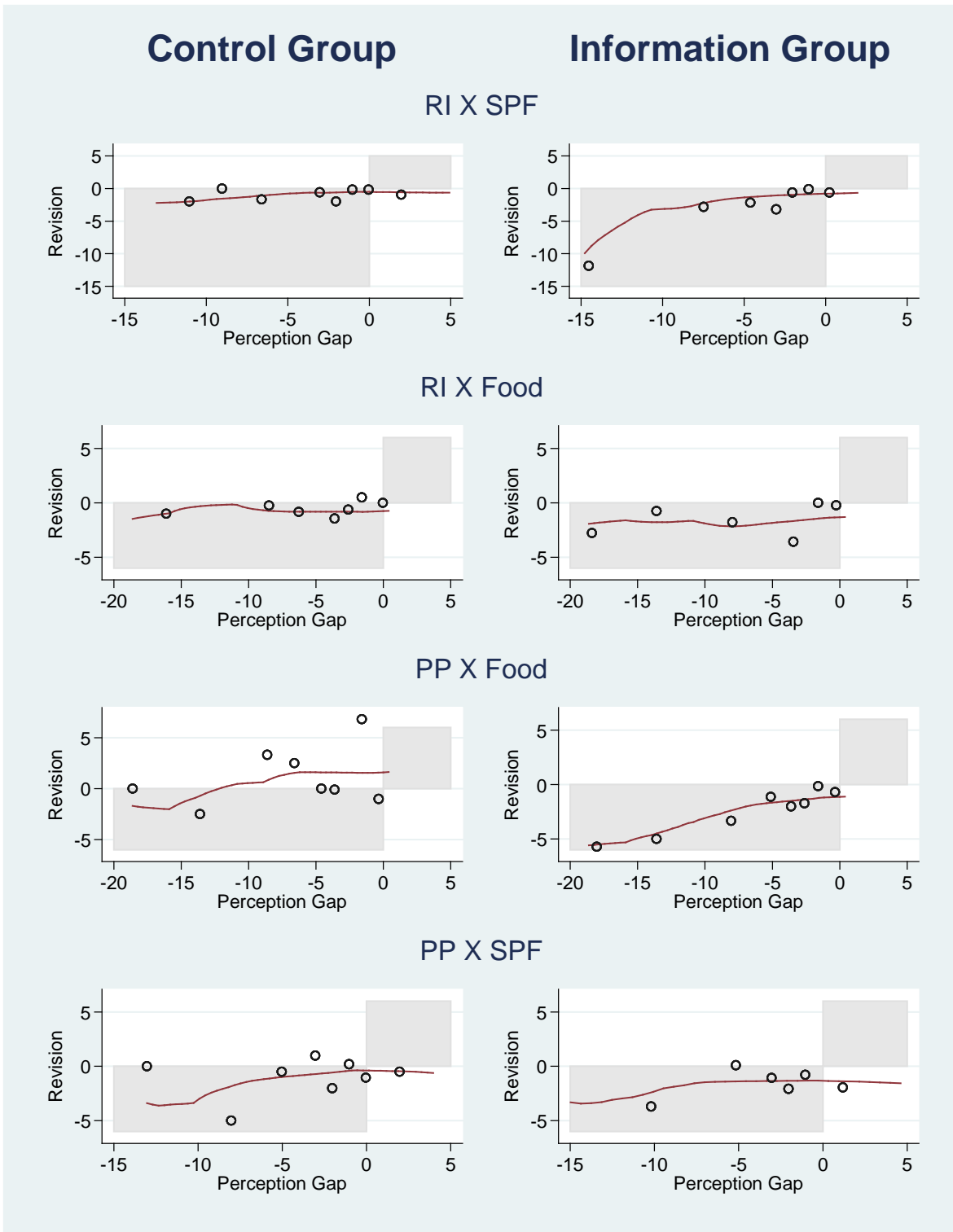




Table 1: Average Priors and Revisions by Treatment for One-Year Point Forecast

	Control Group	Information Group
<b>SPF Forecast Treatment</b>		
'Rate of Inflation' [RI]		
Stage 1 Belief	5.46 [3.00]	5.39 [3.00]
Revision (Stage 3 - Stage 1)	-0.93 [0]	-1.96 [0]
Absolute Revision	2.02 [0.38]	2.44 [1]
Frequency of Non-Revision	47.50%	42.03%
Num. Obs.	40	138
Prices you Pay [PP]		
Stage 1 Belief	8.62 [5.00]	5.85** [5.00]
Revision (Stage 3 - Stage 1)	-0.98 [0]	-1.38 [0]
Absolute Revision	2.48 [0.7]	2.55 [1]
Frequency of Non-Revision	42.86%	40.15%
Num. Obs.	35	132
<b>Food Treatment</b>		
Rate of Inflation [RI]		
Stage 1 Belief	4.77 [3.00]	6.14 [3.00]
Revision (Stage 3 - Stage 1)	-0.73 [0]	-1.5 [0]
Absolute Revision	1.15 [0]	2.58 [0]
Frequency of Non-Revision	63.41%	52.83%
Num. Obs.	41	106
Prices you Pay [PP]		
Stage 1 Belief	8.72 [5.00]	7.41 [5.00]
Revision (Stage 3 - Stage 1)	0.28 [0]	-2.46* [0*]
Absolute Revision	3.28 [0]	3.22 [1]
Frequency of Non-Revision	53.12%	46.85%
Num. Obs.	32	111

First row reports the mean [median] belief reported in the first stage. Second row reports the mean [median] revision of inflation expectations. Third row reports mean [median] of absolute revision of inflation expectations.

T-test reported for equality of mean revisions in the control and information groups, and Median-test reported for equality of medians. \*, \*\*, \*\*\* Differences statistically significant at the 10, 5, and 1 percent levels, respectively.

Table 2: Perception Gap by Demographics and Info Treatments

Dependent Variable: $\text{Log}(\frac{\text{True Information}}{\text{Treatment Belief}})$						
	(1)	(2)	(3)	(4)	(5)	(6)
Control	-0.0431 (0.121)	-0.0337 (0.121)	-0.0258 (0.121)	-0.0116 (0.123)	0.000752 (0.122)	-0.00670 (0.123)
Control $\times$ Food Treatment	0.0710 (0.175)	0.0726 (0.174)	0.0617 (0.174)	0.0470 (0.176)	0.0476 (0.175)	0.0543 (0.176)
Female		-0.124 (0.102)	-0.121 (0.102)	-0.105 (0.105)	-0.108 (0.104)	-0.0978 (0.105)
Female $\times$ Food Treatment		-0.123 (0.149)	-0.127 (0.149)	-0.0916 (0.153)	-0.0577 (0.152)	-0.0636 (0.153)
Older <sup>a</sup>			0.0945 (0.101)	0.106 (0.102)	0.125 (0.102)	0.120 (0.102)
Older $\times$ Food Treatment			-0.268* (0.148)	-0.286* (0.150)	-0.314** (0.148)	-0.304** (0.149)
High Fin Literacy <sup>b</sup>				0.125 (0.114)	0.0951 (0.113)	0.0961 (0.114)
High Fin Literacy $\times$ Food T				0.196 (0.163)	0.177 (0.163)	0.173 (0.164)
College <sup>c</sup>					0.225** (0.101)	0.201* (0.106)
College $\times$ Food Treatment					0.131 (0.149)	0.142 (0.156)
High Income <sup>d</sup>						0.0887 (0.106)
High Income $\times$ Food T						-0.0424 (0.158)
Constant	-0.561*** (0.0569)	-0.491*** (0.0808)	-0.537*** (0.0946)	-0.588*** (0.110)	-0.707*** (0.121)	-0.734*** (0.126)
Constant $\times$ Food Treatment	-0.825*** (0.0847)	-0.761*** (0.118)	-0.625*** (0.139)	-0.700*** (0.158)	-0.764*** (0.175)	-0.755*** (0.183)
F-Test <sup>e</sup>	–	0.224	0.856	0.551	0.144	0.097
R-Squared	0.155	0.163	0.168	0.178	0.197	0.198
Number of Respondents	656	656	656	647	647	645

The table reports OLS estimates of a regression of the perception gap ( $\text{Log}(\frac{\text{True Information}}{\text{Treatment Belief}})$ ) on controls.

Standard errors in parentheses. \*, \*\*, \*\*\* Estimates statistically significant at the 10, 5, and 1 % levels, respectively.

<sup>a</sup> Older is a binary variable that equals 1 if the respondent's age is at least 55.

<sup>b</sup> High Financial literacy is a binary variable that equals 1 if the respondent answers the battery of 7 literacy questions all correctly. See Appendix for the questions.

<sup>c</sup> College is a binary variable that equals 1 if the respondent has at least a Bachelor's degree.

<sup>d</sup> High income is a binary variable that equals 1 if the respondent's income is over \$75,000 per year.

<sup>e</sup> F-test for joint significance of demographic variables (excluding the constant and control terms).

Table 3: Baseline Updating Regressions by Treatment

Dependent Variable: Stage 3 - Stage 1 Inflation Expectations	1-Year		1-Year (Density)		3-Years		1-Year (Density)	
	Food	SPF	Food	SPF	Food	SPF	Food	SPF
	Treatment	Treatment	Treatment	Treatment	Treatment	Treatment	Treatment	Treatment
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant $[\alpha_1]$	-0.155 (0.187)	-0.0984 (0.233)	-0.0667 (0.181)	-0.157 (0.222)	-0.107 (0.558)	0.287 (0.448)	-0.0676 (0.183)	-0.152 (0.231)
Constant $\times$ PP $[\alpha_2]$	0.150 (0.282)	-0.0855 (0.341)	-0.131 (0.270)	0.403 (0.334)	-1.178 (0.856)	-1.605** (0.651)	-0.130 (0.272)	0.381 (0.348)
Information Group $\times$ RI $[\beta_{RI}]$	-0.00574 (0.249)	0.0376 (0.272)	-0.246 (0.237)	-0.161 (0.261)	0.0740 (0.748)	-0.561 (0.524)	-0.275 (0.240)	-0.161 (0.272)
Information Group $\times$ PP $[\beta_{PP}]$	-0.228 (0.262)	-0.269 (0.284)	-0.214 (0.250)	-0.854*** (0.284)	1.029 (0.800)	0.251 (0.541)	-0.236 (0.252)	-0.845*** (0.297)
Gap $\times$ RI $[\gamma_{RI}]$	0.00494 (0.0164)	0.125*** (0.0178)	-0.0173 (0.0154)	0.0664*** (0.0189)	0.0384 (0.0508)	0.0578* (0.0343)	-0.0386 (0.0246)	0.0443 (0.0288)
Gap $\times$ PP $[\gamma_{PP}]$	0.0354** (0.0173)	0.0255 (0.0219)	0.0296* (0.0176)	0.0105 (0.0252)	0.441*** (0.0525)	0.0540 (0.0496)	-0.00999 (0.0273)	0.0475 (0.0533)
Gap $\times$ RI $\times$ Uncertain <sup>b</sup> $[\gamma_{RI-U}]$							0.0289 (0.0248)	0.0754** (0.0358)
Gap $\times$ PP $\times$ Uncertain $[\gamma_{PP-U}]$							0.0572** (0.0285)	-0.0437 (0.0586)
Number of Respondents	290	345	291	342	290	346	291	342

Weighted least squares estimates of a regression of the revision in inflation expectations on various controls.

Standard errors in parentheses. \*, \*\*, \*\*\* Estimates statistically significant at the 10, 5, and 1 percent levels, respectively.

RI denotes the "Rate of Inflation" question-text, while PP denotes the "Prices you Pay" question-text.

<sup>a</sup> Gap refers to the Perception Gap, defined as the (true treatment value - treatment belief).

<sup>b</sup> Uncertain is a dummy that equals 1 if the respondent's uncertainty in stage 1 inflation expectations is above the sample median.

Table 4: Updating by Tercile of Perception Gap

Dependent Variable: Stage 3 - Stage 1 Inflation Expectations	1-Year		1-Year (Density)		3-Years	
	Food	SPF	Food	SPF	Food	SPF
	Treatment	Treatment	Treatment	Treatment	Treatment	Treatment
	(1)	(2)	(3)	(4)	(5)	(6)
Constant [ $\alpha_1$ ]	0.0457 (0.0938)	-0.0574 (0.206)	0.00342 (0.147)	-0.183 (0.184)	-0.362 (0.394)	0.331 (0.367)
Constant $\times$ PP [ $\alpha_2$ ]	0.0301 (0.142)	-0.0547 (0.302)	-0.134 (0.218)	0.440 (0.277)	-0.250 (0.605)	-1.112** (0.533)
Information Group $\times$ RI [ $\beta_{RI}$ ]	-0.115 (0.153)	0.0567 (0.253)	-0.169 (0.226)	-0.0101 (0.228)	0.411 (0.644)	-0.434 (0.450)
Information Group $\times$ PP [ $\beta_{PP}$ ]	-0.110 (0.169)	-0.0989 (0.277)	-0.0285 (0.259)	-0.453* (0.258)	0.259 (0.723)	-0.391 (0.484)
<b>'RI' Question:</b>						
Gap $\times$ Tercile 1 [ $\gamma_{RI-T1}$ ]	0.00988 (0.140)	0.135 (0.218)	0.00525 (0.183)	0.123 (0.198)	0.0531 (0.594)	-0.0204 (0.386)
Gap $\times$ Tercile 2 [ $\gamma_{RI-T2}$ ]	-0.0121 (0.0407)	0.214* (0.115)	0.0250 (0.0604)	0.0591 (0.105)	0.0372 (0.172)	0.0159 (0.204)
Gap $\times$ Tercile 3 [ $\gamma_{RI-T3}$ ]	-0.00359 (0.00944)	0.110*** (0.0159)	-0.0148 (0.0139)	0.0521*** (0.0158)	0.0103 (0.0409)	0.0331 (0.0283)
<b>'PP' Question:</b>						
Gap $\times$ Tercile 1 [ $\gamma_{PP-T1}$ ]	0.0771 (0.130)	-0.104 (0.231)	0.00832 (0.195)	0.174 (0.213)	-0.322 (0.555)	-0.653 (0.408)
Gap $\times$ Tercile 2 [ $\gamma_{PP-T2}$ ]	0.0704* (0.0373)	0.267*** (0.0960)	0.135** (0.0586)	0.236*** (0.0880)	0.232 (0.159)	-0.115 (0.167)
Gap $\times$ Tercile 3 [ $\gamma_{PP-T3}$ ]	-0.00309 (0.0101)	0.0122 (0.0194)	0.0116 (0.0163)	-0.00409 (0.0211)	0.481*** (0.0429)	0.0721* (0.0409)
Number of Respondents	290	345	291	342	290	346

Weighted least squares estimates of a regression of the revision in inflation expectations on various controls.

Standard errors in parentheses. \*, \*\*, \*\*\* Estimates statistically significant at the 10, 5, and 1 percent levels, respectively.

RI denotes the "Rate of Inflation" question-text, while PP denotes the "Prices you Pay" question-text.

Gap refers to the Perception Gap, defined as the (true treatment value - treatment belief).

Table 5: Heterogeneity in Beliefs, Revisions, and Perception Gaps

	Gender		Income <sup>a</sup>		Education		Literacy <sup>b</sup>		Age <sup>c</sup>	
	Male	Female	Low	High	No Coll.	College	Low	High	Young	Older
<b>RI Question:</b>										
<u>Treatment Group</u>										
Stage 1 Belief	4.4 [3.0] (5.1)	6.8** [3.0] (8.5)	6.4 [3.0] (8.0)	4.6** [2.5] (5.9)	7.2 [4.0] (8.0)	4.5*** [2.8] (6.4)	7.00 [3.5] (8.5)	3.4*** [2.6] (2.9)	5.7 [3.0] (7.7)	5.8 [3.0] (6.7)
Stage 1 Uncertainty <sup>d</sup>	9.7 (27.8)	25.1* (48.9)	23.9 (50.3)	10.2** (21.3)	23.4 (45.3)	13.8*** (37.7)	23.7 (48.1)	9.1*** (24.3)	17.2 (38.4)	20.0 (45.5)
Stage 3 Belief	3.7 [2.0] (4.0)	4.2 [2.0] (5.1)	4.4 [2.1] (5.2)	3.4 [2.0] (3.6)	4.9 [3.0] (5.6)	3.1*** [2.0] (3.5)	4.6 [3.0] (5.5)	2.9** [2.0] (2.0)	3.6 [2.0] (3.9)	4.4 [2.5] (5.3)
Revision (Stage 3 - Stage 1)	-0.7 [0] (3.9)	-2.6*** [0] (6.7)	-2.1 [0] (6.5)	-1.3 [0] (4.2)	-2.2 [0] (6.7)	-1.4 [0] (4.6)	-2.5 [0] (6.7)	-0.5* [0] (2.5)	-2.0 [0] (6.0)	-1.5 [0] (5.3)
<u>Control Group<sup>e</sup></u>										
Revision	-0.2 [0] (0.8)	-1.2 [0] (5.1)	-1.2 [0] (5.0)	-0.4 [0] (1.7)	-1.3 [0] (5.1)	-0.2 [0] (0.9)	-0.8 [0] (4.0)	-0.9 [0] (4.1)	-1.1 [0] (4.4)	-0.5 [0] (3.5)
<b>PP Question:</b>										
<u>Treatment Group</u>										
Stage 1 Belief	5.9 [5.0] (4.8)	7.1 [5.0] (7.6)	7.0 [5.0] (7.8)	6.1 [5.0] (4.6)	7.5 [5.0] (7.9)	5.7* [4.0] (4.7)	7.0 [5.0] (7.2)	5.4 [5.0] (4.3)	5.5 [5.0] (3.8)	7.5 [5.0] (8.1)
Stage 1 Uncertainty	13.1 (21.6)	16.1 (28.9)	15.9 (24.8)	13.6 (27.1)	17.4 (27.0)	12.7 (24.8)	17.8 (29.7)	8.8 (12.9)	13.1 (22.5)	16.5 (28.9)
Stage 3 Belief	4.5 [3.0] (3.1)	4.9 [3.0] (4.6)	4.6 [3.0] (3.5)	4.8 [3.0] (4.4)	5.1 [3.0] (3.7)	4.4** [3.0] (4.1)	5.0 [3.0] (4.5)	3.8 [3.0] (2.2)	4.2 [3.0] (3.1)	5.1 [3.0] (4.6)
Revision	-1.4 [0] (3.6)	-2.3 [0] (7.4)	-2.4 [0] (6.9)	-1.3 [0] (4.6)	-2.5 [0] (7.1)	-1.3 [0] (4.8)	-2.0 [0] (7.0)	-1.6 [0] (3.4)	-1.3 [0] (3.2)	-2.4 [0] (7.7)
<u>Control Group</u>										
Revision	0.2 [0] (7.0)	-0.8 [0] (5.9)	-0.5 [0] (8.0)	-0.2 [0] (3.7)	-1.5 [0] (9.1)	0.4* [0] (2.9)	0.1 [0] (7.3)	-1.3 [0] (3.4)	-0.1 [0] (7.8)	-0.8 [0] (3.4)
<b>Perception Gap</b>										
Mean	-2.9	-4.0	-4.1	-2.7*	-4.4	-2.7***	-3.9	-2.5*	-3.5	-3.4
P25	-3.6	-4.6	-5.0	-3.6	-6.6	-3.0	-5.0	-3.6	-3.6	-4.6
Median	[-1.0]	[-1.6]	[-1.0]	[-1.0]	[-1.6]	[-1.0]	[-1.0]	[-1.0]	[-1.0]	[-1.0]
P75	0	0	0	0	0	0	0	0	0	0

The table reports the mean belief in the first row, median belief in [...], and the standard deviation in parentheses.

Wilcoxon rank-sum test conducted for equality of means within each demographic group (male versus female, etc.). \*\*\*, \*\*, \* denotes difference is statistically significant at the 1, 5, and 10 percent levels, respectively.

<sup>a</sup> Low income respondents are those with annual income of  $\leq$  \$75,000 per year.

<sup>b</sup> Low literacy are respondents who make one or more error in the 7 financial literacy questions.

<sup>c</sup> Young respondents are those who are less than 55 yrs old.

<sup>d</sup> Uncertainty is the variance of the baseline one-year density forecast (by fitting to a beta distribution).

<sup>e</sup> Control group is the set of respondents who don't receive the information treatments.

Table 6: Gender Differences in Expectations Updating

Dependent Variable: Stage 3 - Stage 1 Inflation Expectations	1-Year		1-Year (Density)		3-Years	
	Food Treatment	SPF Treatment	Food Treatment	SPF Treatment	Food Treatment	SPF Treatment
	(1)	(2)	(3)	(4)	(5)	(6)
Constant [ $\alpha_1$ ]	0.0753 (0.111)	-0.272 (0.244)	0.0154 (0.184)	-0.111 (0.233)	-0.419 (0.555)	0.443 (0.456)
Constant $\times$ PP [ $\alpha_2$ ]	0.0797 (0.166)	0.307 (0.352)	-0.161 (0.274)	0.504 (0.339)	-0.466 (0.835)	-0.938 (0.655)
Female [ $\alpha_3$ ]	-0.0465 (0.118)	0.410* (0.216)	-0.0261 (0.192)	-0.111 (0.207)	0.269 (0.593)	-0.192 (0.404)
Female $\times$ PP [ $\alpha_4$ ]	-0.151 (0.170)	-0.617* (0.314)	0.0697 (0.278)	-0.130 (0.303)	-0.119 (0.854)	-0.299 (0.586)
Information Group $\times$ RI [ $\beta_{RI}$ ]	-0.0959 (0.119)	0.206 (0.236)	-0.208 (0.194)	-0.0820 (0.224)	0.417 (0.595)	-0.459 (0.441)
Information Group $\times$ PP [ $\beta_{PP}$ ]	-0.254** (0.126)	-0.301 (0.248)	-0.228 (0.206)	-0.676*** (0.245)	0.780 (0.639)	-0.0487 (0.458)
<b>'RI' Question:</b>						
Gap $\times$ Female [ $\gamma_{RI-F}$ ]	0.00409 (0.0111)	0.424*** (0.0161)	-0.0190 (0.0183)	0.0519*** (0.0169)	0.0885 (0.0592)	0.0321 (0.0300)
Gap $\times$ Male [ $\gamma_{RI-M}$ ]	-0.00755 (0.00980)	0.0184 (0.0597)	-0.0142 (0.0157)	0.0115 (0.0549)	0.00344 (0.0492)	-0.00454 (0.112)
<b>'PP' Question:</b>						
Gap $\times$ Female [ $\gamma_{PP-F}$ ]	-0.0140 (0.00925)	0.0341* (0.0193)	0.0671*** (0.0162)	-0.000410 (0.0224)	0.536*** (0.0465)	0.0596 (0.0433)
Gap $\times$ Male [ $\gamma_{PP-M}$ ]	-0.00479 (0.0174)	-0.0258 (0.0677)	-0.0114 (0.0290)	0.0334 (0.0652)	0.231*** (0.0877)	0.101 (0.126)
Num. of Respondents	290	345	291	342	290	346

Weighted least squares estimates of a regression on inflation expectations on various controls.

Standard errors in parentheses. \*, \*\*, \*\*\* Estimates statistically significant at the 10, 5, and 1 percent levels, respectively.

RI denotes the "Rate of Inflation" question-text, while PP denotes the "Prices you Pay" question-text.

Gap refers to the Perception Gap, defined as the (true treatment value - treatment belief).

Table 7: Heterogeneity in Updating

Dependent Variable: Stage 3 - Stage 1 Inflation Expectations (Point forecast at 1-year Horizon)	Food		SPF		Food		SPF		Food		SPF		Food		SPF	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)						
Constant $[\alpha_1]$	-0.195 (0.164)	-0.276 (0.253)	-0.0329 (0.137)	-0.17 (0.244)	0.021 (0.116)	-0.0216 (0.234)	-0.280 (0.246)	-0.176 (0.261)	-0.148 (0.184)	-0.0313 (0.186)						
Constant $\times$ PP $[\alpha_2]$	0.292 (0.243)	0.266 (0.378)	-0.0058 (0.217)	-0.0934 (0.366)	0.0336 (0.167)	0.0742 (0.358)	0.163 (0.361)	-0.332 (0.377)	0.154 (0.278)	-0.0382 (0.272)						
Characteristic("C") $\times$ RI $[\alpha_3]$	0.252 (0.196)	0.428* (0.245)	0.0383 (0.161)	0.185 (0.234)	0.0289 (0.135)	-0.184 (0.259)	0.230 (0.271)	0.200 (0.250)	-0.484 (0.327)	0.490** (0.232)						
Characteristic("C") $\times$ PP $[\alpha_4]$	-0.127 (0.194)	-0.252 (0.248)	0.146 (0.168)	0.184 (0.239)	0.118 (0.153)	-0.345 (0.302)	0.214 (0.273)	0.702*** (0.252)	-0.172 (0.308)	-0.476** (0.223)						
Information Group $\times$ RI $[\beta_{RI}]$	-0.0424 (0.194)	0.253 (0.269)	-0.0872 (0.162)	0.205 (0.263)	-0.115 (0.135)	-0.0307 (0.265)	0.0711 (0.273)	0.00357 (0.279)	0.172 (0.289)	0.0157 (0.255)						
Information Group $\times$ PP $[\beta_{PP}]$	-0.265 (0.2)	-0.314 (0.286)	-0.339** (0.172)	-0.0537 (0.275)	-0.315** (0.147)	-0.400 (0.292)	-0.153 (0.286)	-0.606** (0.296)	0.0638 (0.308)	0.0164 (0.249)						
<b>'RI' Question:</b>																
Gap $\times$ Characteristic("C") $[\eta_{RI}]$	0.0112 (0.028)	0.673*** (0.0378)	-0.00683 (0.0173)	0.401*** (0.0291)	0.00461 (0.0147)	-0.134 (0.0859)	0.0469* (0.0252)	0.0672** (0.0313)	-0.0238 (0.0239)	0.701*** (0.021)						
Gap $\times$ (1-C) $[\gamma_{RI}]$	-0.00703 (0.0137)	0.130*** (0.0198)	-0.0014 (0.0126)	0.115*** (0.0211)	-0.00878 (0.0105)	0.127*** (0.0178)	-0.0108 (0.0227)	0.129*** (0.0220)	0.0207 (0.022)	0.00749 (0.0285)						
<b>'PP' Question:</b>																
Gap $\times$ Characteristic("C") $[\eta_{PP}]$	-0.0165 (0.024)	-0.00841 (0.0571)	-0.0155 (0.0261)	0.330*** (0.0584)	-0.00739 (0.0241)	-0.0266 (0.0891)	0.105*** (0.0270)	0.0343 (0.0317)	0.315*** (0.0209)	0.295*** (0.0388)						
Gap $\times$ (1-C) $[\gamma_{PP}]$	0.0371** (0.0151)	0.0275 (0.0231)	-0.00965 (0.0126)	0.00598 (0.027)	-0.00977 (0.0109)	0.0265 (0.0215)	0.0314 (0.0246)	-0.230*** (0.0323)	0.0177 (0.0312)	-0.0013 (0.0195)						
Num. of Respondents	289	344	290	344	286	340	290	345	290	344						

Weighted least squares regression of the revision in inflation expectations on various demographic controls interacted with the perception gap.

Standard errors in parentheses. \*, \*\*, \*\*\* Estimates statistically significant at the 10, 5, and 1 percent levels, respectively.

<sup>a</sup> High income is a dummy that equals 1 if the respondent's income is over \$75,000 per year.

<sup>b</sup> College is a dummy that equals 1 if the respondent has at least a Bachelor's degree.

<sup>c</sup> High Fin literacy is a dummy that equals 1 if the respondent answers the battery of 7 literacy questions all correctly. See Appendix for the questions.

<sup>d</sup> Info Affected is a dummy that equals 1 if the respondent answered 5 or more (on a 1-7 scale) to the question : "To what extent is your answer over the next twelve months the same or different because of the information provided to you?"

Table A1: Expectation Distributions by Demographics

	Expectations Range of PP & RI Responses Pooled		
	[0,1)	[1,5)	[5+)
Male	3.18%	54.77%	42.05%
Female	2.14%	43.97%	53.89%
High Income <sup>a</sup>	2.86%	53.21%	43.93%
Low Income	2.41%	45.19%	52.41%
College <sup>c</sup>	2.33%	56.27%	41.4%
No College	2.88%	40.26%	56.87%
High Literacy <sup>b</sup>	2.46%	59.61%	37.93%
Low Literacy	2.70%	44.14%	53.15%
Young <sup>d</sup>	3.21%	46.65%	50.15%
Older	1.92%	50.80%	47.28%

The table reports the proportion of Stage 1 beliefs that fall in each interval, by row demographics. The numbers in each row sum to 100.

<sup>a</sup> High income equals 1 if the respondent's income is > \$75,000/year.

<sup>b</sup> High literacy equals 1 if the respondent answers the 7 literacy questions all correctly.

<sup>c</sup> College equals 1 if the respondent has at least a Bachelor's degree.

<sup>d</sup> Older equals 1 if the respondent's age is at least 55 years.