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ABSTRACT

We use a series of survey experiments to examine how consumers incorporate new information about the past to form their expectations about future inflation. Our novel experimental framework allows us to disentangle learning from different sources of information, and to separate genuine from spurious learning. To assess the role of rational inattention, the experiments were conducted with 10,000 subjects in both a low-inflation context (the United States) and a high-inflation context (Argentina). To assess the role of personal consumer experience, we assembled a unique source of data consisting of information on products purchased by the subjects immediately before being surveyed, and the historical prices for those same products. We find that individuals are highly influenced by both inflation statistics and supermarket prices when forming their inflation expectations. Our results indicate that learning rates are substantially higher in the low-inflation setting, where the stakes from ignoring inflation are lower, which is consistent with rational inattention. We also find that individuals are more influenced by information that is less costly to understand (supermarket prices) relative to information that is more costly to understand (inflation statistics). The evidence also suggests that individuals form inflation expectations using their memories of the price changes of the supermarket products they purchase, even though those memories are nearly orthogonal to the actual price changes these products experienced. This is bound to induce large biases in expectations. Finally, our results highlight the importance of accounting for spurious learning in survey experiments: half of the treatment effects can be attributed to spurious rather than genuine learning in our study.

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1 Introduction

Expectations about macroeconomic variables play an essential role in economic theory and policy-making. Consumer inflation expectations, in particular, are key to understanding household consumption and investment decisions, and ultimately the impact of monetary policies. Although central banks seek to influence expectations, there is no consensus in the empirical literature on how household inflation expectations are formed or can be affected (See Bernanke, 2007; Bachmann et al., 2012; Coibion and Gorodnichenko, 2015).

Consumer surveys indicate that household inflation expectations tend to be much more heterogeneous than those of professional forecasters (Ranyard et al., 2008; Armantier et al., 2013). Two main explanations for this degree of dispersion have been given in the literature. Some authors attribute it to rational inattention, according to which individuals only partly incorporate information on topics such as inflation because acquiring that information is costly. This explanation is particularly convincing in contexts of low inflation like the United States, where the potential financial cost of ignoring inflation is negligible for most households. Other authors argue that, in forming inflation expectations, individuals use information derived from their personal experience as consumers, which can be both diverse and inaccurate (Bruine de Bruin et al., 2011; Malmendier and Nagel, 2013; Madeira and Zafar, forthcoming). These explanations are hard to distinguish empirically because they are not mutually exclusive. Individuals may choose to be rationally inattentive and, at the same time, use their personal shopping experiences as a low-cost source of information about price changes. We present evidence from a series of experiments specifically designed to disentangle the roles of rational inattention and personal consumer experience.

In a series of online and offline surveys, we randomly provided subjects with information related to past inflation using different treatment arms such as inflation statistics and tables with historical prices of specific supermarket products.[1] We combine the treatment effects on the distribution of inflation expectations induced by this the experimental variation with a Bayesian learning model to infer how much weight subjects assigned to a given piece of information relative to their prior beliefs. To assess the role of rational inattention, under which individuals only partly incorporate information that is costly to acquire, we conducted field experiments in a context of low inflation – the United States, with an average annual inflation rate of 1.8% in the five years prior to our study – and in a context of high inflation – Argentina, where the average annual inflation rate over the same time period was around 22.5%.[2] To assess the role of personal consumer experience, we assembled a unique source of data consisting of information about the purchases made by subjects immediately before being interviewed, as well as historical micro-level prices for those same products at the same store.

Our results indicate that information related to past inflation has a major impact on inflation

[1]The data was scraped off the websites of some of the largest supermarkets in the United States and Argentina as part of the Billion Prices Project at MIT.

[2]We do not use official inflation statistics for Argentina because they are widely discredited. We use instead alternative indicators compiled by the private sector, which are well known and widely cited in the media.

expectations. Indeed, this appears to be the case when we provided information on aggregate inflation statistics and when we provided data on the historical prices of a few individual supermarket produces. This evidence is consistent with the existence of *inattentive* consumers who learn from new information. The results across countries further suggest that inattention about inflation is *rational*. Rational inattention models predict that individuals in a context of higher inflation are more informed because the cost of misperceiving inflation is higher (Mankiw et al., 2003; Carroll, 2003). Consistent with this prediction, individuals in Argentina assign a weight of roughly 50% to information on recent inflation statistics, whereas individuals in the United States assign a weight of roughly 85%. The weights assigned to information about individual supermarket prices differ by similar magnitudes, which suggests that the differences between the two countries cannot be attributed to country-specific characteristics pertinent to inflation statistics (i.e., their perceived trustworthiness).

The evidence also indicates that personal consumer experience is important to the formation of inflation expectations. We found that participants incorporated more information about the price changes of a handful of individual supermarket products, such as bread and milk, than information about inflation statistics when the two types of information were provided simultaneously. In keeping with the notion of rational inattention, this discrepancy may be because it is easier for individuals to incorporate information on individual prices.[3] This is consistent with survey evidence presented by Bruine de Bruin et al. (2011), who show that, when asked about the inflation rate, most individuals report that they try to recall the prices of specific products.[4]

To deepen our understanding of the role of past shopping experiences on inflation expectations, we conducted a unique consumer-intercept survey experiment at several branches of a supermarket chain in Argentina. We recorded consumer purchases by scanning participants' supermarket purchase receipts, which we linked to data on the actual historical prices of those same products at the same store. We also asked respondents to recall historical prices for a random selection of the items that they had just purchased, which allowed us to generate exogenous variation in the salience of their own price memories. We find that the correlation between the memories of price changes and the actual price changes of the products recently bought by the subjects is very weak. Regardless, individuals have confidence in their price memories. Given the weak correlation between memories and reality, the use of price memories as inputs in the formation of inflation expectations is bound to

[3]An alternative explanation might be that respondents interpreted our survey question as addressing the prices of the specific goods they purchased rather than their country's overall inflation rate. If that were the case, individual product prices could be considered more informative. However, we find that information about product prices also has a significant impact on expectations of other variables, such as the nominal exchange rate and the nominal interest rate, which would only make sense insofar as individuals interpreted the question as referring to the average price level. Following the University of Michigan's Survey of Consumers methodology, the phrasing of our questions referred to changes in "prices in general." See the online Questionnaire Appendix for more details and variations across different surveys and languages.

[4]In our own samples, 64.4% of the subjects in the U.S. reported trying to recall the prices of specific products when answering questions about inflation expectations, twice as many as those who report trying to recall inflation statistics. Even in Argentina, where credible (non-official) inflation statistics are regularly covered in the media, 74.9% of respondents reported trying to recall prices of specific products when asked about past inflation.

induce significant errors in inflation expectations. This suggests that, beyond the question of rational inattention, some of the excessive dispersion in household inflation expectations documented in the literature is due to the use of (largely inaccurate) information derived from personal experiences (Madeira and Zafar, forthcoming).

Finally, our novel experimental design tackles one of the most common criticisms of this type of survey experiments insofar as it disentangles genuine learning from spurious learning. For instance, when an individual is told that the annual inflation rate was 2% and is then asked about her inflation expectations, she may report a figure closer to 2% for spurious reasons such as a desire to agree with the interviewer because of a desirability bias (Goffman, 1963), a fear of being deemed ignorant, or an unconscious numerical anchoring (Tversky and Kahneman, 1974). To identify spurious learning, we first used a follow-up survey conducted several months after the information was provided. Intuitively, the importance of the spurious reaction – such as unconscious anchoring or interviewer pressure – would disappear or diminish considerably after a few months, as would the salience effect of providing information that was already known by the subject. As a second strategy, we estimate the learning model using the effect of information about inflation on expectations regarding other nominal variables. Intuitively, if a piece of information causes a subject to expect a higher inflation rate, it should also affect expectations regarding the nominal interest rate (or other related nominal variables). A third strategy included a treatment arm in which – under the pretext of a cognitive test – individuals were knowingly given information about price changes of fictitious products. The results from these estimation strategies show that, while our subjects incorporated a considerable fraction of the information we provided in a meaningful way, concerns about spurious learning in survey experiments, at least in the context of inflation expectations, are still justified: only half of the responses to the information treatments can be attributed to genuine learning.

Our results suggest that it is important for macro models to incorporate informational frictions. While, from the early works of Phelps (1969) and Lucas (1972) to more recent studies by Mankiw and Reis (2002), most of the literature has focused on firms' price-setting decisions and expectations, our findings suggest that informational frictions are also worth exploring in the case of household expectations. One recent paper that takes this approach is Coibion and Gorodnichenko's (2015) work, which uses a Phillips curve that incorporates household inflation expectations to explain why deflation was not more intense during the Great Recession. Consistent with our findings, Coibion and Gorodnichenko (2015) argue that household inflation expectations rose significantly during that period because individuals based their expectations on their own experiences with variations in the prices of everyday products such as gasoline.

Our findings are also related to recent debates on the transparency and communication strategies of central banks. The ability of central banks to correct household misperceptions could help households make better financial decisions (Armentier et al., 2013).[5] While, in theory, it may not

[5] The distribution of the bias is relevant as well. If poorer and less educated consumers have a higher level of bias, correcting it may reduce those consumers' relative disadvantage.

be desirable to correct for these biases in all circumstances,[6] in practice central banks often try to use information to influence household inflation expectations. For example, at the time of writing Japan's Central Bank is struggling to increase household inflation expectations in the context of a zero-lower bound, while high-inflation countries such as Argentina and Venezuela are actively trying to reduce them by means of price controls and dubious statistical and data-dissemination practices. Our evidence suggests that, in their communications, central banks interested in affecting expectations could consider incorporating information about the price changes of individual products. Our results from Argentina suggest that it is more important that information on prices be easy to understand and relate to than for that information to address the actual purchases made by individuals.

Our paper is connected to several strands of literature. First, it is related to a group of studies that measures the role of inflation statistics in household inflation expectations, exploiting media coverage of statistics (Lamla and Lein, 2008; Badarinza and Buchmann, 2009; Drager, 2011), the publication of official statistics (Carrillo and Emran, 2012), and information-provision experiments (Roos and Schmidt, 2012; Armantier et al., 2014). Other studies have looked at the role of personal experiences in the formation of inflation expectations. There is suggestive evidence that individuals use information from their own price memories (Bates and Gabor, 1986; Bruine de Bruin et al., 2011; Coibion and Gorodnichenko, 2015) and that individuals place excessive weight on information about past inflation levels experienced in their lifetime (Malmendier and Nagel, 2013). Despite substantial research, however, the understanding of these two mechanisms – inflation statistics and personal experiences – remains fragmentary and incomplete (Ranyard et al., 2008). We contribute by providing a unified framework for measuring and comparing the contributions of these two factors to the formation of inflation expectations. Our paper also builds upon a recent group of studies that employs survey experiments to examine inflation expectations. For example, studies by Roos and Schmidt (2012) and Armantier et al. (2014) examine how individuals react to information about U.S. inflation statistics by adjusting their own self-reports about inflation. Bruine de Bruin et al. (2011) show that subjects who are asked to think about products with extreme price changes tend to report higher inflation expectations. We make a contribution to this literature by providing an original experimental design capable of identifying spurious learning, by replicating the experiments in contexts of low and high inflation, and by exploiting unique sources of data (e.g., historical prices, individual purchases) to disentangle the specific mechanisms through which expectations are formed.

The paper proceeds as follows. Section 2 describes the general experimental design. Section 3 presents evidence from a series of online experiments conducted in the United States and Argentina. Section 4 presents evidence from a field experiment conducted at a supermarket chain in Argentina. The last section offers some conclusions.

[6] Some authors argue that information disclosure is welfare-enhancing (Hellwig, 2005), while others argue the opposite (Morris and Shin, 2002).

2 Experimental Design

2.1 Structure of the Survey Experiments

In this section, we describe the experimental framework that will be used as the basis for all the empirical analysis provided in the rest of this paper. This framework builds upon a number of previous experimental studies (e.g., Bruine de Bruin et al., 2011; Roos and Schmidt, 2012; Armantier et al., 2014), but introduces innovations aimed at testing new hypothesis and addressing the concern of spurious learning. The basic structure of the survey experiments is following:

1. Eliciting subjects' inflation perceptions: i.e., the perception of the annual inflation rate over the previous twelve months. This constitutes the individual's prior belief ($\pi^0_{i,t}$ in the model in the following section).

2. Providing the subject with information related to the inflation rate over the previous twelve months, which constitutes the signal ($\pi^T_{i,t}$). In the case of the control group with no information provision, there is no signal. Some of the treatments provided information on average price changes from one or more sources, such as recent official inflation statistics or a table with the historical prices of specific products.

3. Eliciting subjects' expectations about inflation (i.e., the expected annual inflation rate over the following twelve months, $\pi_{i,t+1}$) and other nominal variables (e.g., the nominal interest rate, $i_{i,t+1}$).

In the empirical model that follows, we show how to infer how much weight individuals assign to a particular type of information (e.g., inflation statistics) from the joint distribution of the variables $\left\{\pi^0_{i,t}, \pi^T_{i,t}, \pi_{i,t+1}, i_{i,t+1}\right\}$, even if more than one signal is provided simultaneously.

2.2 Treatment Arms

After eliciting past inflation perceptions (inflation over the previous twelve months), all respondents saw the following message: "We will now ask you about future inflation." The treatments in the U.S. online experiment differed in the type of information provided, with a control group and four treatment arms randomly assigned with equal probability. Appendix E.3 provides a snapshot of the informational treatments (and the relevant questions in the survey) as seen by the respondents. Figure 1 provides some samples of the pieces of information provided to the subjects in each treatment arm in the U.S. Online experiment. After these different information provision treatments, participants were asked about their inflation expectations for the next twelve months (individuals in the control group were taken directly to this question). When eliciting inflation perceptions and expectations, we always refer to the general price level rather than to the prices of the goods purchased by the respondent.[7] We did not provide any incentives for respondents to answer accurately

[7]Specifically, for the U.S. online experiment, we asked participants the following two questions, taken directly form the University of Michigan's Survey of Consumers: "During the next 12 months, do you think that prices in

(i.e., prizes for guessing the right figures) – as shown by Armantier et al. (2012), there is a significant correlation between incentivized and non-incentivized responses on inflation expectations.

Our first treatment arm aims to capture how individuals incorporate information from official inflation statistics. The *Statistics (1.5%)* treatment arm consisted of providing a randomly selected group of participants a table with the most recent official statistics about annual inflation at the time of the survey, including the source of the information (the price changes referred to the period from August 1, 2012 to August 1, 2013 – all the questions and the information in the survey have a twelve-month reference period). Panel (c) of Figure 1 illustrates this treatment. The table included the annual inflation implied by the Bureau of Labor Statistics' Consumer Price Index, and the Personal Consumption Expenditures and Gross Domestic Product deflators as computed by the Bureau of Economic Analysis.[8] The average of the three statistics indicated an annual average inflation rate of 1.5%, which was also displayed on the table.

Our second treatment arm was designed to capture the degree to which individuals use the information related to their everyday experience when forming inflation expectations, even if that information is not as representative and precise as aggregate inflation statistics. The *Products* treatment arm presented respondents with a table containing the prices of six products at the time of the survey and one year earlier, as well as the price change (in percentage points) for each product and the average percentage change for all products presented in the table, also for the period from August 1, 2012 to August 1, 2013. The products were selected from six broad types of goods (infant formula, bread, pasta and noodle-related products, cereals, sodas, and shampoos and related products). An algorithm selected the products in the specific tables so that the average price changes would be between -2% to 7% in 1 percentage point increments for a total of ten tables. The algorithm provided tables with products with different average price changes, but it also verified that other characteristics of the tables were roughly constant, leveraging on the availability of price histories for thousands of products and on detailed information on product characteristics. For instance, every table has one product from each of the six categories of goods, and the goods within each category have similar initial prices between tables (the algorithm selects different brands within product categories, since each brand experienced different price changes). This ensured that the initial price level and the representativeness of the products remain broadly comparable across tables. The information provided was entirely truthful, and a note to the table indicated that the products were taken from a large database with information on an existing branch of a large U.S. supermarket chain.[9] There was no indication that the products in the table, or the average of price

general will go up, or go down, or stay where they are now?" with three options: "Go up," "Stay the same" and "Go down." We then asked: "By about what percent do you expect prices to change, on average, during the next 12 months?" with an open numerical answer. For the Argentina online experiment, we opted to repeat the format of the question that had been asked in previous rounds of the opinion poll: "What do you think will be the annual inflation rate for the following 12 months?" (see the Appendix for exact wording in Spanish).

[8]The table was preceded by the following text: "Before answering, please look at the table below. The table shows indicators used by different government agencies to measure the annual inflation rate - that is, how much prices have changed on average over the last 12 months, from August 1 2012 to August 1 2013."

[9]The data was scraped of the websites of some of the largest supermarkets in the United States and Argentina as

changes, were representative or that they reflected actual inflation levels.[10] Respondents in this treatment arm were randomly assigned one of the ten tables with different average price changes, which we indicate in parentheses after the *Products* treatment arm name in the rest of this paper. Panels (a) and (b) in Figure 1 illustrate the -2% and 2% cases respectively.[11]

An additional treatment arm consisted of a combination of the previous two pieces of information: i.e., the respondent was shown the table with inflation statistics and one of the tables with prices for specific products. This is the *Statistics (1.5%)+Products* treatment arm. This was designed to test whether the tables with specific prices induced learning over and above the information conveyed by the official inflation statistics. Finally, we included a fourth treatment arm to gauge the relevance of the potential anchoring effects of the information provided (Tversky and Kahneman, 1974), which we call the *Hypothetical* treatment. The respondents were asked to "eyeball" the price change of a product over a period of one year. We phrased the question in terms of the need to assess how comfortable the respondent was with questions about price changes. The table we provided contained only two prices at two points in time (January 1, 2012 and January 1, 2013), without specifying the product. The price of the hypothetical product changed from $9.99 to $10.99, a price increase of about 10% (panel (d) of Figure 1).[12] Finding a significant degree of "learning" from this information would be suggestive of a spurious effect.

2.3 Estimating Learning Rates

2.3.1 Baseline Model

In the following sections we present some reduced-form evidence on how individuals react to randomly assigned information. The main advantage of this model-free approach is its transparency. However, we need to estimate a learning model to establish the relative importance that individuals assign to the different sources of information we provided. The simple model developed here allows us to summarize the learning rate on the basis of a single parameter that can be compared across

part of the Billion Prices Project at MIT. See Cavallo (2013) for details.

[10]This treatment arm covers only changes in prices of supermarket goods, which are a subset of the price changes included in the official statistics in the previous treatment arm (the Consumer Price Index, GDP deflators, etc.). The latter take into account also durable goods, services, rent and gas, among many others expenditure items. The effect of the information provided should be stronger if we included a broader set of goods in the information about changes in prices of specific products. Moreover, Cavallo (2013) shows that, in practice, supermarket prices follow closely the evolution of the CPI.

[11]The tables were preceded by the following text: "Before answering, please look at the table below. The table shows the price of each listed product on August 1st, 2012 and on August 1st, 2013 (that is, one year later). These prices were taken from the same branch of a large supermarket chain. the six products that appear in this table were randomly selected from a database containing hundreds of products."

[12]The table was preceded by the following text: "In this survey we ask you questions about how "prices in general" evolve over time. The following question is meant to assess how comfortable you are with the way these questions are phrased. Please consider the following prices of a hypothetical product at two different moments." Immediately afterward, we asked the following question: "What is the approximate price change of this product over this period? Please do not use a calculator, pen or pencil to calculate the exact figure. We want your best guess from eye-balling these prices," with "About 1%," "About 5%," "About 10%" and "About 100%" as the possible answers. See the questionnaire appendix for more details.

experimental samples and treatment arms.

Let $\pi_{i,t}$ and $\pi_{i,t+1}$ denote perceptions about past inflation (e.g., inflation rate over the past twelve months) and inflation expectations (e.g., expected inflation rate over the next twelve months), respectively. Individuals use information about (perceived) past inflation to form their expectations about future inflation (Jonung, 1981):

$$\pi_{i,t+1} = f\left(\pi_{i,t}\right) \tag{1}$$

Significantly, this model of inflation forecasting does not make any assumptions about the agent's rationality. The fact that individuals use information about the past to estimate future inflation is suggestive of the models of adaptive learning (Sargent, 1993). However, the use of inflation perceptions to assess future inflation may also be consistent with rational expectations: e.g., some rational expectation models predict that inflation expectations follow an AR(1) process (Barr and Campbell, 1997). The evidence suggests that extrapolating on the basis of past inflation seems to be a reasonable description of the prediction strategy of the agents in the economy. For example, Atkeson and Ohanian (2001) report that, since 1984, the one-year-ahead inflation forecast of professionals in the U.S. has been no better than the "naïve" forecast of the inflation rate over the previous year. We should not expect households to come up with more accurate predictions on future inflation than those naïve estimates.

We consider a linear specification for $f()$: i.e., $\pi_{i,t+1} = \mu + \beta\pi_{i,t}$, where β is the degree of pass-through from inflation perceptions to inflation expectations. The strong linear relationship between perceptions of past inflation and expectations of future inflation has been documented in previous studies (Jonung, 1981). This same relationship is present in our data, as depicted by Figure 2, which presents the relationship between perceived past inflation and expected future inflation for our online samples in the United States (panel (a)) and Argentina (panel (b)).[13] A great deal of the variation in inflation expectations can be explained by variation in inflation perceptions: in our U.S. sample, 29% of the variation in inflation expectations is due to variation in inflation perceptions, whereas the equivalent figure for our Argentine sample is 60%. These proportions would undoubtedly be even higher if they took into account the significant measurement error in the reporting of these variables. In other words, the dispersion and bias in inflation expectations appears to be mostly a mechanical product of individuals' uncertainty about past inflation (see also Blanchflower and MacCoille, 2009). The real question, then, is not why future inflation expectations are so dispersed, but why perceptions about past inflation are so dispersed.

The experiments we carried out consist of providing information related to past inflation. Let $\pi^0_{i,t}$ denote perceptions prior to the acquisition of new information, and let $\pi^T_{i,t}$ denote the signal from the information provided in the experiment. Any learning process can be represented by the following reduced-form equation:

[13]This data is for subjects in the control group, i.e., those who were not provided any information about inflation.

$$\pi_{i,t} = g\left(\pi^0_{i,t}, \pi^T_{i,t}\right) \tag{2}$$

In our setup, we have information on these three elements $\pi^0_{i,t}, \pi^T_{i,t}, \pi_{i,t+1}$: $\pi^0_{i,t}$ is the respondent's stated past inflation perception (pre-treatment), $\pi^T_{i,t}$ is the mean inflation (or inflation-related information) provided in one of the treatments, and $\pi_{i,t+1}$ is the respondent's stated inflation expectation (post-treatment).

There are several plausible functional forms for $g()$. A simple and parsimonious alternative is to assume a Bayesian learning model with Gaussian distribution. Under this model, the prior belief is normally distributed with mean $\pi^0_{i,t}$ and standard deviation $\sigma^0_{i,t}$. This functional form is in fact consistent with the distribution observed in our survey data. The individual is presented with a signal about average inflation, $\pi^T_{i,t}$, which represents the price change for one product randomly drawn from the universe of products.[14] The population of price changes for all possible products follows a normal distribution with mean $\pi_{i,t}$ and standard deviation $\sigma^T_{i,t}$ (this functional form is also roughly consistent with the actual distribution of price changes). By construction, $\pi^{TRUE}_{i,t}$ is the actual inflation level – i.e., the average of price changes for all products. The precision of the signal is given by the inverse of $\sigma^T_{i,t}$, which is assumed to be known. Under these assumptions, the posterior belief is distributed normally with the following mean and variance:

$$\pi_{i,t} = \frac{\left(\frac{1}{\sigma^0_{i,t}}\right)^2}{\left(\frac{1}{\sigma^0_{i,t}}\right)^2 + \left(\frac{1}{\sigma^T_{i,t}}\right)^2}\pi^0_{i,t} + \frac{\left(\frac{1}{\sigma^T_{i,t}}\right)^2}{\left(\frac{1}{\sigma^0_{i,t}}\right)^2 + \left(\frac{1}{\sigma^T_{i,t}}\right)^2}\pi^T_{i,t},\ \sigma_{i,t} = \sqrt{\frac{\left(\sigma^0_{i,t}\cdot\sigma^T_{i,t}\right)^2}{\left(\sigma^0_{i,t}\right)^2+\left(\sigma^T_{i,t}\right)^2}}$$

That is, the individual updates her perception based on an average between her prior belief and the realized signal:

$$\pi_{i,t} = (1-\alpha_{i,t})\pi^0_{i,t} + \alpha_{i,t}\pi^T_{i,t} \tag{3}$$

where $\alpha_{i,t}$, the weight assigned to the new information, decreases with the accuracy of the prior belief $1/\sigma^0_{i,t}$ and increases with the accuracy of the signal $1/\sigma^T_{i,t}$. If $\sigma^0_{i,t}$ and $\sigma^T_{i,t}$ are constant across individuals, α is also constant across individuals. Replacing this expression in the forward-looking equation (1) results in the following expression:

$$\pi_{i,t+1} = \gamma_0 + \underbrace{\gamma_1}_{\beta}\pi^0_{i,t} + \underbrace{\gamma_2}_{\alpha\beta}\left(\pi^T_{i,t} - \pi^0_{i,t}\right) \tag{4}$$

Since $\pi_{i,t+1}$, $\pi^0_{i,t}$ and $\pi^T_{i,t} - \pi^0_{i,t}$ are all observed in our experimental data, we can estimate $\hat{\alpha}$ and $\hat{\beta}$ by simply running the above linear regression.[15] The parameter β represents the rate of pass-through

[14] The results would be equivalent if the price change corresponded to an average over multiple randomly-drawn products.

[15] One assumption is that the above OLS regression yields an unbiased estimate for β. Since $\pi^0_{i,t}$ is not randomized, at least in principle β could suffer from omitted variable bias, which in turn could bias the estimation of α. In

from perceptions of past inflation to future inflation expectations. The parameter α captures the weight the individual assigns to the information provided in the experiment relative to her prior belief. Intuitively, if the individual started with a prior belief of $\pi_{i,t}^0$ and the informational treatment provides a signal that inflation is $\pi_{i,t}^T$, the posterior belief can be expected to be between $\pi_{i,t}^0$ and $\pi_{i,t}^T$, and the parameter α reflects how much closer $\pi_{i,t}$ is to $\pi_{i,t}^T$ relative to $\pi_{i,t}^0$.

The following example illustrates the intuition behind our empirical model. Let us assume that, among individuals who receive no information from us, the correlation between past and future inflation is 0.5: i.e., for each 1% increase in perceived past inflation, an individual believes that future inflation will be 0.5% higher. Now assume that we take a group of individuals who believed that past inflation was 10%, and we randomly provide some of them a signal that past inflation was 20%. If – relative to the control group – individuals who received the signal believe that future inflation is going to be 1% higher, that means that the information led them to believe that past inflation was 2% higher (i.e., 1/0.5). In other words, the signal that past inflation was actually 20% increased their belief about past inflation from 10% to 12%. This indicates that, in forming her posterior belief, the individual assigned a 0.8 weight to the prior belief of 10% and a 0.2 weight to the signal of 20%: i.e., 12%=0.8×10% + 0.2×20%.

This model of Bayesian learning makes a number of additional predictions that can be directly tested with the data. It predicts that confidence in the posterior belief, $\sigma_{i,t}$, should be higher for individuals that were provided with relevant information. The model also predicts that, for a given level of confidence in the information signal ($\sigma_{i,t}^T$), the effect of providing a signal on $\sigma_{i,t}^T$ should be independent of the particular value of the signal that was drawn ($\pi_{i,t}^T$). α should be lower for individuals with lower reported confidence in their prior belief on past inflation, $\sigma_{i,T}^0$. This model also predicts that an individual's adjustment to the new information is a linear function of the distance between the new information and her prior belief. We can test whether this prediction is accurate by estimating the basic model including an additional quadratic term, $\pi_{i,t+1} = \gamma_1\pi_{i,t}^0 + \gamma_2\left(\pi_{i,t}^T - \pi_{i,t}^0\right) + \gamma_3\left(\pi_{i,t}^T - \pi_{i,t}^0\right)^2$, and testing whether $\hat{\gamma}_3 = 0$. Similarly, we can test the possibility that individuals react differently to price increases than to price decreases (Brachinger, 2008) by estimating the model $\pi_{i,t+1} = \gamma_1\pi_{i,t}^0 + \gamma_+ \cdot 1\left\{\pi_{i,t}^T > \pi_{i,t}^0\right\} \cdot \left(\pi_{i,t}^T - \pi_{i,t}^0\right) + \gamma_- \cdot 1\left\{\pi_{i,t}^T < \pi_{i,t}^0\right\}\left(\pi_{i,t}^T - \pi_{i,t}^0\right)$ and then testing whether $\hat{\gamma_-} = \hat{\gamma_+}$. All these additional robustness checks are presented in the results section and in the Appendix.[16]

2.3.2 Disentangling Genuine from Spurious Learning

A potential issue with our results is that, even if we find that the information provided has an effect on stated inflation expectations, individuals' reactions to this information may be spurious. As mentioned above, when a subject is told that the annual inflation rate was 2% and is then

unreported results (available upon request), we conducted an auxiliary experiment and found strong evidence that this is not a cause for concern.

[16]Armantier et al. (2014) also provide related tests of Bayesian learning in the context of household perceptions about inflation.

asked about her inflation expectations, she may report an inflation expectation that is closer to 2% for spurious reasons: e.g., to show agreement with the interviewer due to a desirability bias (Goffman, 1963), a fear of being deemed ignorant, or unconscious numerical anchoring (Tversky and Kahneman, 1974). These spurious effects are a major concern for our experiments and for information provision experiments in general.[17] This does not mean, however, that these exercises are totally invalid. Our framework attempts to quantify how much of α responds to genuine learning and how much to spurious learning.

Our first (and preferred) strategy consists of using data on the evolution of expectations obtained through follow-up surveys. Numerical anchoring is, by definition, very short-lived, so we would not expect it to explain effects on beliefs measured months after the information was provided. Regarding interviewer pressure, it is unlikely that subjects would feel significant pressure to agree with the interviewer months after the information was provided – by that time, subjects would probably not even remember what this information was. We conducted follow-up interviews with the same subjects several months after the initial experiments, in which we did not provide any new information or reminded the subject about information provided in the past. We simply elicited their inflation expectations at the time of the follow up ($\pi_{i,t+1}^{follow-up}$). The forward-looking equation (1) thus becomes $\pi_{i,t+1}^{follow-up} = \mu + \beta\pi_{i,t}$, where β is the degree of pass-through from inflation perceptions as stated in the original survey to inflation expectations stated in the follow-up survey (which is the product between the rate at which individuals project from the past to the future, and the rate with which beliefs about past inflation persist over time). Combined with the learning equation (3), we obtain:

$$\pi_{i,t+1}^{follow-up} = \gamma_0 + \underbrace{\gamma_1}_{\beta}\pi_{i,t}^0 + \underbrace{\gamma_2}_{\alpha\beta}\left(\pi_{i,t}^T - \pi_{i,t}^0\right) \tag{5}$$

In other words, we can use the same estimation procedure with $\pi_{i,t+1}^{follow-up}$ instead of $\pi_{i,t+1}$ as the dependent variable. Since this estimation should remove spurious learning (at least to some degree), the ratio between the α coefficient based on $\pi_{i,t+1}^{follow-up}$ and the α coefficient based on $\pi_{i,t+1}$ can provide an estimate of the share of learning that is genuine rather than spurious.

The second strategy is based on individuals' perceptions and expectations regarding other economic indicators closely related to inflation. In the context of our experiments, we collected information on perceptions about the expected nominal interest rate over the next 12 months, which – just like inflation expectations – was elicited after the experimental information provision. The test is based on the following intuition: among individuals in the control group, respondents who report expecting a 1 percentage point increase in inflation also report a future interest rate that is 0.3 percentage points higher. This basically says that individuals partially understand the Fisher equation (Behrend, 1977). If, as a consequence of an informational treatment, an individual truly

[17] See Rosenthal (1966) for a discussion of the effects of factors of this sort on behavioral research, and Zizzo (2010) for a recent application to experimental economics.

believes that future inflation will be 1 percentage point higher, we should also observe that this individual expects an interest rate that is 0.3 percentage points higher. If, though, the information induced only a spurious effect on inflation expectations, it would have no impact on interest rate expectations. Let $i_{i,t+1}$ denote the expectation about the nominal annual interest rate. Formally, this test consists of replacing the forward-looking equation (1) with $i_{i,t+1} = \mu + \beta\pi_{i,t}$, where β is the degree of pass-through from inflation perceptions to interest rate expectations. Combined with the learning equation (3) we obtain:

$$i_{i,t+1} = \gamma_0 + \underbrace{\gamma_1}_{\beta} \pi^0_{i,t} + \underbrace{\gamma_2}_{\alpha\beta} \left(\pi^T_{i,t} - \pi^0_{i,t}\right) \tag{6}$$

Again, this corresponds to using $i_{i,t+1}$ instead of $\pi_{i,t+1}$ as dependent variable in our learning regression.[18] By comparing the estimated α coefficients in the two specifications, we have a second way of quantifying genuine rather and spurious learning.

3 Results from Online Experiments in the United States and Argentina

3.1 Evidence from the United States

3.1.1 Subject Pool and Descriptive Statistics

We conducted the U.S. online experiment during the month of September 2013. According to the Consumer Price Index (CPI) reported by the Bureau of Labor Statistics (BLS), the annual inflation in the United States for the five years prior to our study (2008-2012) was, on average, 1.8%. The subject pool for the U.S. online experiment was recruited from Amazon's Mechanical Turk (AMT) online marketplace. We followed several guidelines that describe the best practices for recruiting individuals for online surveys and experiments using AMT in order to ensure high quality responses (see, for instance, Crump et al., 2013). The final sample includes 3,945 individuals. The subjects in our sample are younger and more educated than the average U.S. citizen (the Online Appendix provides a description of the sample and a comparison with the U.S. population).

The main variables on which our analysis is based are perceptions of past inflation and expectations of future inflation. The mean for inflation perceptions is 5.07% with a median of 5% and a standard deviation of 4.02%, and the mean for inflation expectations is 5.08% with a median of 4% and a standard deviation of 5.8% (all values for the control group). Figure 2.a depicts the relationship between the two variables by means of a binned scatterplot. There is a strong positive association between the two, with a regression coefficient of 0.782 (p-value<0.01).

[18] Once again, an implicit assumption is that the coefficient on $\pi^0_{i,t}$ – which is identified solely with non-experimental variation – is not subject to omitted-variable bias. This assumption can also be tested with an ancillary experiment, as discussed in footnote 15.

3.1.2 Reduced-Form Effects of the Informational Treatments on the Distribution of Inflation Expectations

The basic results of our information provision U.S. online experiment are summarized in Figure 3 (see Appendix C for more detailed outputs by different treatment arms). All the panels in this Figure present the distribution of inflation expectations for two treatment arms, where one of them is always the control group (the histograms accumulate the observations below -5% and above 15% in the extreme bars).

According to the Bayesian learning model, providing a signal about inflation should shift the distribution of inflation expectations (relative to the control group) towards the value of the signal, and to produce a more concentrated distribution of expectations. For instance, our informational treatment with a table depicting products with average price changes of 2% is expected to shift the mean of inflation expectations closer to 2%, and also to compress this distribution.

Panel (a) presents the results for the *Statistics (1.5%)* treatment, which consisted of providing the respondent solely with a table of official statistics about past inflation. As expected, this signal shifts the distribution of expectations towards 1.5% and makes the distribution of expectations less dispersed. Each panel in Figure 3 also presents the results from an Epps–Singleton (ES) two-sample test using the empirical characteristic function, a version of the Kolmogorov–Smirnov test of equality of distributions valid for discrete data (Goerg and Kaiser, 2009). The comparisons indicate that in all cases the distributions of inflation expectations between all treatment groups and the control group are significantly different (all p-values below 1%). This indicates that our experimental subjects reacted substantially and incorporated into their inflation expectations the information on inflation statistics that we provided .

Panels (c) and (d) in Figure 3 present two examples from the *Products* treatments, in which we provided respondents with tables with the price changes, and the average of these changes, for a series of products.[19] Panel (c) indicates that, as expected, the signal that supermarket products increased 0-1% shifted inflation expectations towards this range, and reduced the dispersion of expectations. The distributions in panel (d) indicate that the signal that prices increased 2-3% had the same effect, although the distribution did not shift to the left as much as with the 0-1% signal. Figure 3 provides further evidence about the effects of the *Products* treatment arm. Panel (a) shows the effect of all the levels of the *Products* treatments on average inflation expectations. Each bar represents the point estimate for each of the ten sub-treatments (with average annual price changes in the tables ranging from -2 to 10% on the horizontal axis) compared to the control group. The evidence in this Figure confirms that the treatments with specific products had a systematic impact on average reported expectations. The average price changes that appear on the tables have an increasing and roughly linear impact on inflation expectations. Each percentage point increase in the average price change reported on a table as part of our treatments yielded an increase in inflation expectations of about 0.5 percentage points. These results indicate that individuals incorporate the

[19] See panels (a) and (b) in Figure 1 for two examples of the actual information provided.

prices of specific products when forming their inflation expectations if this information is available to them.

In the treatment arm *Statistics (1.5%)+Products,* experimental subjects were provided with the table of official statistics for past annual inflation averaging 1.5% and, immediately afterward, they were presented with one of the *Products* tables with the price changes of supermarket products. If individuals only cared about statistics, then the inflation expectations of subjects who already receive nationally representative, aggregate official statistics on inflation should not be affected by information on the price changes of a few arbitrarily selected products. For instance, the *Statistics (1.5%)+Products (0%)* and *Statistics (1.5%)+Products (3%)* treatments should have the same effects on expectations. However, panels (e) and (f) in Figure 3 indicate that this is not the case: individuals changed their inflation expectations on the basis of information about the price changes of specific products even when aggregate representative statistics were made readily available to them.

Finally, we also included a treatment in which respondents were provided information about price changes of about 10% for fictitious products. The results from this *Hypothetical* treatment are presented in panel (b) of Figure 3. The ES test indicates a statistically significant difference between the distribution of inflation expectations for this treatment group and for the control group. This can be attributed to an small increase in density around the 10-11% range. Since this information, even though non-factual, acted as an anchor for expectations, this evidence is suggestive of the existence of non-negligible spurious reaction to the information provided.

3.1.3 Inferring Learning Rates from the Effects of the Informational Treatments

This section presents our quantification of the effects of our experiment's informational treatments in the context of the Bayesian learning model introduced in section 2.3. The main estimates from the learning model for the U.S. online experiment are presented in Table 1. The table reports the values of α and β from equation 4.[20] As discussed above, β can be interpreted as the degree of pass-through between perceptions of past inflation and expectations of future inflation, and α as the weight placed by the respondents on the information provided in the experiment, with $(1-\alpha)$ being the weight placed on respondents' prior belief about past inflation.

The first pattern that emerges from Table 1 is that, consistent with panel (a) in Figure 2, there is a high correlation between inflation perceptions and inflation expectations, reflected in a relatively high value for β which varies from 0.757 to 0.817, all highly significant (for the control group only, the coefficient of perceptions in a regression with expectations as the dependent variable is 0.782). The second notable result from Table 1 is the high level of α for the factual informational treatments in columns (1) and (2). Results from the main regression in column (1) indicate that the weight given to the information in the *Statistics (1.5%)* treatment was 0.838, whereas the weight given to

[20] We estimated this model for the *Control* group and the *Statistics, Products* and *Hypothetical* treeatment groups (column 1), and separately for the *Control* group and the combined *Products+Statistics (1.5%)* treatment (column 2), since in that case the two pieces of information were provided simultaneously.

its equivalent in the *Products* treatment was 0.689 (the difference between the two is statistically significant at the 1% level). In the case where information about statistics and products were provided simultaneously, reported in column (2), the combined α is 0.732, which also falls in the same range.

An estimated α of about 0.7-0.85 means that, in forming their posterior beliefs about inflation expectations, individuals in our sample assigned a much greater weight to the information provided by the experiment than to their own prior belief. This is consistent with the rational inattention model (Sims, 2005; Veldkamp, 2011), which predicts that in a low-inflation country most individuals will be uninformed about inflation because the cost of misperception is low. It is costly to acquire, update and understand inflation statistics and, therefore, individuals will only pay that cost if and when they really need to.[21] For example, learning about inflation consumes attention, which is a limited resource that can be better used on financial information for which the stakes are higher, such as information on taxes and benefits, on how to best finance a large purchase, on the best alternatives for credit cards or mortgages, and so on.[22]

A second notable result from Table 1 is that both the information from the specific product tables and the information from the official statistics treatments had significant and substantial effects on reported inflation expectations in the *Statistics (1.5%)+Products* treatment, as captured by the respective α coefficients reported in column (2). When both statistics and supermarket prices were shown, the α coefficient for the supermarket prices is 0.449, even higher than the α of 0.283 for the statistics (the difference is statistically significant at the 1% level). These results suggest that, whenever the two signals disagree with each other, individuals are more willing to incorporate signals closer to their everyday experience, such as a list of price changes for specific products, than signals derived from statistics. There are several plausible explanations for this result. Individuals may distrust official statistics, or they may fail to comprehend how representative the figures in them are. Again, this may not be surprising in a country like the United States, where the stakes for misperception of the actual inflation rate are relatively low. The same result would be surprising, though, in a country with a high level of inflation where the inflation rate is a major concern for every household. We explore this hypothesis in more depth in the online experiment conducted in Argentina (section 3.2 below).

We can also test some auxiliary hypothesis that help us establish the validity and the robustness of the Bayesian learning model used to estimate the learning rates. One prediction yielded by this model is that providing relevant information will increase the accuracy of the later belief, $\sigma_{i,t}$. We can test this with our data using the respondents' confidence in their own inflation expectations,

[21] Significantly, the cost of acquiring information about inflation exceeds a simple visit to the Bureau of Labor Statistics website or other sources to check the most recent estimate of the Consumer Price Index or other measures. While that might be a simple enough task for those with some training in economics, it is not for those without that training; the cost of acquiring information about inflation includes, among other things, learning how inflation is measured and who measures it.

[22] Demery and Duck (2007) argue that individuals may optimally decide to use solely information they receive as a byproduct of their economic activity rather than complementing that information with official statistics.

which is self-reported in a question we included immediately after the elicitation of expectations. This variable was standardized to have a standard deviation of one. As expected, the confidence is significantly higher when individuals received factual information (*Products*, *Statistics (1.5%)* and *Products+Statistics* treatments), but not higher when the information was not factual *(Hypothetical)*.[23] Moreover, the learning model also predicts that all signals from the same source, regardless of its value, should be equally informative to respondents. Figure 4, panel (b), compares the impact of each treatment level for the *Products* treatment arm on the standardized confidence variable. The different signals seem to have similar effects on respondents' confidence in their stated expectations, although with a slight asymmetry. Indeed, we can reject at standard levels the equality of all ten coefficients (p-value 0.0475). This is suggestive evidence that individuals might be less prone to incorporate information about price decreases than about price increases.

Another test of the Bayesian model described in section 2.3 consist in testing for non-linearities or asymmetries in the reaction to the information provided (e.g., if individuals learn more from signals that are closer to their prior belief). Columns (1) and (2) in Table 2 present some robustness tests of the learning results for the *Statistics (1.5%)* treatment arm, and columns (3) and (4) present similar results for the *Products* treatment. The coefficients in columns (1) and (3) present a specification with a quadratic term (as discussed at the end of section 2.3). The corresponding estimates for this coefficient are virtually zero (0.007 and -0.003, respectively), and the linear terms for α and β are very similar to those presented in Table 1. This evidence also suggests that the Bayesian model fits the data very well. Columns (2) and (4) present the results yielded by a specification that allows differential learning for positive and negative differences between the signal and the prior belief, with a coefficient α of 0.632 (*Statistics*) and 0.606 (*Products*) for those with $\pi^T_{i,t} - \pi^0_{i,t} \geqslant 0$, and of 0.859 and 0.736 for those with $\pi^T_{i,t} - \pi^0_{i,t} < 0$. The difference between the two pairs of coefficients is statistically significant for the *Statistics* treatment (p-value of 0.08) but not for the *Products* treatment (p-value of 0.22). Thus, there is some weak evidence of a mild asymmetry, indicating that individuals seem more prone to revise their expectations downwards rather than upwards. A mechanical interpretation is that individuals with $\pi^T_{i,t} - \pi^0_{i,t} < 0$ are those who have high perceptions of past inflation ($\pi^0_{i,t}$), and they tend to be less informed and less confident about their own prior beliefs. Appendix C.3 presents further tests of the Bayesian learning model; the results are also strongly supportive of this simple model.

3.1.4 Disentangling Genuine from Spurious Learning

While the robustness and validation checks indicate that the data is consistent with the Bayesian learning model, a pressing concern is whether or not the learning induced by our experimental setup is spurious. As previously discussed, respondents may have reacted to the information provided by

[23] The difference in standardized confidence between the control and the *Products* treatments (pooled) is 0.226 (p-value<0.001); between the control and the *Statistics (1.5%)* treatment it is 0.324 (p-value<0.001); and between the control and the *Statistics (1.5%)+Products* it is 0.368 (p-value<0.001). The difference between the control and the *Hypothetical* treatment is a not significant and very close to zero (0.032, p-value of 0.540).

changing their reported inflation expectations, not their true inflation expectations, to acquiesce with the statements or information presented in the survey or for other reasons unrelated to genuine learning.

The results of our *Hypothetical* treatment arm yields a first test along these lines. This treatment arm was designed to gauge the relevance of potential anchoring effects pursuant to the provision of information (Tversky and Kahneman, 1974). These results are presented in column (1), Table 1. The coefficient α for the *Hypothetical* treatment is 0.232, and statistically significant at the 1% level. Though significant, this rate is economically less significant when compared to the learning rates for the other informational treatments. The effect of this treatment may be attributable to unconscious numerical anchoring. Alternatively, this evidence may reveal that some individuals are so uninformed about inflation that they are even willing to use inflation figures from a hypothetical exercise as a benchmark. In any case, the evidence suggests the presence of some degree of spurious learning.

The first methodology to weed-out the spurious learning consist of estimating the learning model using the inflation expectations in the follow-up survey. We used data on a subsample of 1,073 subjects who were re-interviewed two months after the original online experiment. This subsample was asked again about their inflation expectations, but they were not subjected to any type of new informational treatment or reminded of previous informational treatments.[24] Column (3) in Table 1 presents the results of the basic regression with inflation expectations in the original survey as the dependent variable, but only for the subsample of those who later participated in our follow-up survey (for all individuals except those in the combined *Statistics+Products* treatment group). The β and α coefficients are very similar to those presented in column (1) for the full sample (0.814 compared to 0.757 for β, and equally similar for the three α coefficients corresponding to the different treatment arms). Column (4) presents the regression for the same follow-up subsample, but in this case with inflation expectations as reported in the follow-up survey as the dependent variable. The α coefficients of 0.360 for the *Statistics* treatment and of 0.336 for the *Products* treatment are both statistically significant (at the 1% and 5% levels respectively). Although they are about half as large as those in column (3), the results still indicate that 45% to 48.2% of the effect of the information provided can be attributed to genuine, rather than spurious, learning. Notably, the α coefficient for the *Hypothetical* treatment in the follow-up results in column (4) is close to zero and statistically insignificant, in contrast to the small but positive and significant effect in column (3). This is consistent with the interpretation of short-term anchoring effects, according to which the spurious effect induced by the *Hypothetical* treatment arm should disappear over time.

The second methodology for weeding-out spurious learning consists of measuring learning rates based on the indirect effect of the information provided on the expected nominal interest rate. We report results from this exercise in Column (5) of Table 1, where the dependent variable is an individual's expectation for the nominal interest rates for the following twelve months. The

[24] Multiple tests suggest that selective attrition is not a concern (results not reported).

β coefficient indicates that for each additional percentage point in expected inflation, on average, subjects believed that the nominal interest rate would be about 0.3 percentage points higher.[25] The estimated α coefficient for both the *Statistics* and *Products* treatment are close to the corresponding coefficients estimated with the follow-up survey: 0.314 for the *Statistics* treatment (borderline insignificant at the 10% level) and 0.499 for the *Products* treatment (significant at the 1% level). Although the point estimates are different between the *Statistics* and *Products* treatments, we cannot reject the null hypothesis that they are equal at conventional levels. When these parameters are compared to those presented in column (1), they suggest that between 37.5% (0.314/0.838) and 72.5% (0.499/0.689) of the learning is genuine. The average between these two figures, 55%, is close to the corresponding share of genuine learning inferred from the follow-up survey (46.6%). That is, both of these methodologies provide very similar estimates of the degree of spurious learning. The results in column (5) for the *Hypothetical* treatment arm, on the other hand, indicate that this treatment, which provided a non-factual signal, did not have a significant effect on individuals' expected interest rates. This, again, can be interpreted as evidence that this non-factual treatment did not induce genuine learning on participants.[26]

The results for the nominal interest rate also support our findings in a more general way. Our survey questions always refer to inflation expectations in the sense of changes in the average general price level. However, it may be argued that individuals may respond instead about their own idiosyncratic experience – i.e., the price change of their own consumption basket. The results described in this paragraph show us that this cannot be the case: changes in inflation expectations affect expectations about nominal variables like the interest rate (and the exchange rate in the Argentine case discussed below), which should not be affected if the individual replied solely in terms of her own idiosyncratic experience.

3.2 Evidence from Argentina

3.2.1 Subject Pool and Descriptive Statistics

In this section, we replicate the main results yielded by the U.S. online experiment with a series of samples from Argentina. The comparison of results from similar experiments in the two countries is interesting because they were at the opposite ends of the spectrum in terms of inflation experiences at the time of our study. While in the U.S. the annual inflation rate in the five years before our study (2008-2012) was stable and, on average, 1.8%, in Argentina the average rate for the same time period was also stable but around 22.5%. As a result, the cost of ignoring inflation in Argentina was substantially higher. For example, individuals must rely on good information on inflation prospects in drawing up contracts because it is illegal to index such contracts (labor, real estate, etc.), or

[25] This is also consistent with Behrend (1977), who presents evidence that individuals have a significant amount of useful understanding of the link between inflation and other economic outcomes such as the nominal exchange rate.

[26] We present similar results for additional tests based on alternative outcome variables in the Appendix.

rely on more stable foreign currencies.[27] Opinion polls in Argentina at the time of the survey systematically indicated inflation as one of the population's primary concerns.[28] Inflation statistics were mentioned on offline and online news outlets on a regular basis, frequently making the front page of newspapers. According to the rational inattention model, then, individuals in Argentina should be more informed and, therefore, have stronger prior belief about past inflation than their U.S. counterparts.

The results of the Argentina online experiment are drawn from two different sets of respondents. The first group consists of a sample of college graduates (see Appendix D for details about the samples). This sample, which yielded a total of 691 observations, was assigned to a control group, or to the *Statistics (24%)*[29] or the *Products* treatment arms, the latter of which was divided into three sub-treatments where respondents were provided with tables showing average price changes of 19%, 24%, and 29%. The second, larger sample is based on an established public opinion research firm that carries out a quarterly online survey of adults in Argentina.[30] This sample, which yielded 3,653 responses, is also not representative of the Argentine population: while it is roughly similar in terms of age and gender composition, our sample is substantially more educated (and, therefore, richer) than the country average.[31] For this sample, we concentrated our efforts on a detailed version of the *Products* treatment.[32]

The main variables on which our analysis is based are perceptions of past inflation and expectations of future inflation. For the large (opinion poll) sample, the mean inflation perception is 27.8% with a median of 25% and a standard deviation of 13.75%; the mean inflation expectation is 28.4% with a median of 25% and a standard deviation of 15.7% (all values for the control group). Panel (b) in Figure 2 provides a binned scatterplot showing the relationship between inflation perceptions and expectations. As in the U.S. sample, there is a strong, linear, and positive association between the two, with a regression coefficient of 0.883 (p-value<0.01).

[27]See Cavallo, Cruces and Perez-Truglia (2014) for more details on the Argentine macroeconomic and institutional context at the time of our experiments.

[28]For our opinion poll (general population) sample, 40.7% of those in our control group selected inflation as one of the three main concerns for the country.

[29]The value provided in the *Statistics* treatment arm (and reported in that treatment arm) represents the average inflation estimates of private consultancies, research centers, and provincial public statistical agencies, as compiled and computed by opposition parties in the Argentine Congress since the intervention of the national statistical agency in Argentina in 2012 (Cavallo, 2013). These are the statistics that individuals used on a regular basis (for more details, see Cavallo, Cruces and Perez-Truglia, 2014).

[30]The survey has contained the same set of basic questions since 2011.

[31]See the Appendix for comparative descriptive statistics of our samples and the Argentine population.

[32]The total of 3,653 respondents were randomly assigned to a control group (N=567) or to the *Products* treatment (N=3,086); respondents in the latter group were then randomly assigned to one of 19 *Products* sub-treatments with average price changes in the tables of products provided ranging from 16% to 34% in one percentage point increments.

3.2.2 Reduced-Form Effects of the Informational Treatments on the Distribution of Inflation Expectations

Figure 5 presents the results for the online experiment in Argentina. The first two panels present the results for the sample of college graduates. Panel (a) presents the distribution of inflation expectations for the control group and for the *Statistics (24%)* treatment, and panel (b) presents the distribution of the same variable for the control group and for the *Products (24%)* treatment. As in the case of the U.S. experiment, relative to the control group, providing any signal about inflation always shifted the distribution of inflation expectations towards the value of the signal, and led to a more concentrated distribution of expectations.[33] The ES tests suggest that these differences are always statistically significant at the 1% level.

A summary of the basic results of the *Products* experiment in Argentina is presented in panels (c) and (d) of Figure 5, which, for the sake of comparison, displays the distribution of inflation expectations for a subset of the treatment groups and for the control group of the opinion poll sample. The inflation expectations of the respondents in the *Products (18%-19%)* treatments, in which average price changes were substantially lower than ongoing inflation (the annual inflation rate at the time of the survey was 24.4%), dropped substantially, with the distribution being shifted to the left of the control group's. Conversely, inflation expectations of the respondents in the *Products (31%-32%)* treatments increased substantially, with distribution to the right of the control group's. These differences are all statistically significant (p-value of 1% or lower).[34] Another summary of the effect of the *Products* treatments is presented in panel (a) of Figure 6. Each bar represents the point estimate of the effect of the *Products* treatment for each of the ten sub-treatments compared to the control group, with average annual price changes in the tables ranging from 16 to 34% on the horizontal axis (for the opinion poll sample). The evidence in that Figure suggests that the effect of the treatment in which tables with price changes for specific products were presented was roughly linear with respect to the average price change presented in each table: each one percentage point increase in the information provided on products' average price changes yielded an increase in inflation expectations of about half a percentage point, on average.

3.2.3 Inferring Learning Rates from the Effects of the Informational Treatments

Table 3 presents the estimates of the learning rates for the Argentina online experiments. Column (1) presents the results of the learning model for the *Statistics* and *Products* treatments based on the sample of college graduates. The results in the table also indicate a very high pass-through from perceptions of past inflation to expectations of future inflation of 1.138 (significant at the 1% level). The estimated α is 0.432 for *Statistics* and 0.458 for *Products*. Notably, the coefficient α in the

[33] For both treatment groups, the distribution of inflation expectations seems to have shifted to the left (the means are 2.2 and 1.5 percentage points lower, respectively, than the mean of 28.4% for the control group). Most importantly, the dispersion of inflation expectations was reduced (standard deviations of 6.5 for *Statistics (24%)* and 4.8 for *Products (24%)* versus 10.3 for the control group).

[34] See Appendix Figure D.2 for a more detailed analysis by treatment level.

estimate for the *Products* treatment in the larger opinion poll sample (column (2)), 0.494, is very close to that of the smaller college graduates sample.[35] This evidence implies that, in forming their posterior expectations about future inflation, individuals in the two samples placed a roughly equal weight on their prior belief and on the information provided in the experiment. While substantial, the weight individuals in Argentina assigned to the information about prices changes for specific products is substantially less than the value of 0.689-0.838 (*Statistics* and *Products* treatments, respectively) that what we found for our U.S. sample.

The fact that learning rates were significantly lower in Argentina is consistent with the prediction of the rational inattention model, where individuals in a context of higher inflation would tend to be more informed because the cost of inflation misperception is higher (Mankiw et al., 2003; Carroll, 2003). An alternative explanation could be that price data are generally less credible in Argentina after the manipulation of official statistics in recent years (see Cavallo 2013). Even though we used a non-official private sector statistic in our experiments, it is possible that this situation made Argentines distrust all inflation statistics, although the fact that the lower learning applies also to information about supermarket products is not consistent with this argument. Another explanation for the difference in learning rates between countries might be found in the subject pools. However, the characteristics of individuals in our samples for the two countries are quite similar in terms of sex, age, and education levels.[36] Moreover, there is low heterogeneity in learning rates by demographic characteristics (see results on heterogeneous effects in the Appendix) when compared to the difference in the α coefficient between countries, making this an implausible explanation. Finally, this difference may be due to the underlying volatility of inflation: individuals should react more to new information in more a volatile context. However, inflation levels were relatively stable in both Argentina and the United States in the five years prior to our study. While Argentina's general macroeconomic conditions can be deemed more unpredictable, this would imply a prediction of the opposite sign – i.e., that learning rates should be higher than in the U.S.

A further result can be obtained by comparing the β coefficient between the follow-up and the original samples, which provides a measure of how "persistent" beliefs are over time. The β for the follow up survey is only 53.8% of the same coefficient in the original survey in the U.S. (0.438 and 0.814, Table 1) compared to about 78.2% (0.754 and 0.963, Table 3) for Argentina. This finding is also consistent with the prediction of the rational inattention model, since individuals in the U.S. are on average less informed about inflation and this implies that beliefs will be more volatile over time.

In the opinion poll sample for Argentina we replicated some of the tests of the rational model that we conducted on the U.S. online experiment data (more details and results are provided

[35]One concern with our experimental results is that they may reflect a lack of basic literacy in economics. For example, Burke and Manz (2011) show that in a laboratory experiment more economically literate individuals tend to choose more relevant information and make better use of that information. The similar results for our college graduates—all of whom had at least some basic training in economics and most of whom were professional economists or accountants—and our public opinion poll samples suggest that economic literacy does not drive our findings.

[36]See Appendix Table B1 for more details.

in Appendix D). As expected, we find that both the information on statistics and supermarket products increased the confidence in the posterior belief. Panel (b) in Figure 6 compares the impact of each treatment level on the standardized level of self-reported confidence about the answer to the question regarding inflation expectations. The results suggest that, consistent with the Bayesian model, all these different signals led to the same gain in confidence about the posterior belief. Another test, which entails the alternative specification with a quadratic term, is provided in column (3) of Table 3. The results indicate that the linear terms for α and β are very similar to those presented in column (2), while the coefficient for the quadratic term is not statistically significant (it is virtually equal to zero). Column (4) in Table 3 presents the results of an alternative specification that contemplates differential learning for upward and downward corrections of the prior beliefs. The estimated coefficient α is 0.484 for those with $\pi^T_{i,t} - \pi^0_{i,t} \geqslant 0$ and of 0.497 for those with $\pi^T_{i,t} - \pi^0_{i,t} < 0$, and their difference is not statistically significant. This evidence suggest that learning was perfectly symmetric, as predicted by the Bayesian model. This result contrasts with the evidence in the U.S. sample, where we found some weakly statistically significant evidence of a mild asymmetry.

3.2.4 Disentangling Genuine from Spurious Learning

Our first test of spurious learning is based on the effects of our treatments in the medium term. Table 3 presents the results of the learning model based on a subsample of individuals in our opinion poll sample who were re-interviewed four months after the original survey.[37] This subsample of 1,320 individuals was asked again about their perceptions of past inflation and their expectations for future inflation, but they were not subjected to any type of informational treatment or reminded about the treatment in the original survey.[38] Column (5) in Table 3 presents the results of the basic regression where inflation expectations in the original survey is the dependent variable, but the parameters are estimated with the subsample of the *Products* treatment group that later participated in the follow-up survey. The α and β coefficients are very similar to those presented in column (2) for the full sample (0.963 compared to 0.902 and 0.456 compared to 0.494, respectively). Column (6) presents the regression for the same follow-up subsample, but with inflation expectations as reported in the follow-up survey as the dependent variable. The α coefficient of 0.208 is statistically significant. While it is only half as large as the coefficient in column (5), it indicates that about 45.6% of the effect of the information provided can be attributed to genuine, rather than spurious, learning. This reinforces the findings of the U.S. online experiment, which showed a proportion of genuine learning of about 45% in the context of a similar follow-up survey.

In column (7) of Table 3, we present the second test of genuine learning, specifically the results

[37]This is longer than the period after which we carried out our follow-up interview in our U.S. online experiment. The Argentina follow-up had to be timed with the public opinion firm's quarterly survey.

[38]There was no significant difference in the probability of participating in the follow-up sample between the treatment and the control groups. As an additional robustness check, we estimated the learning regression with an attrition indicator as the dependent variable and neither α nor β was statistically significant (results not reported).

of a learning equation where individuals' expectation of the nominal interest rate is the dependent variable. Notably, the α coefficient of 0.468 is very close to the value for the inflation expectations learning equation (column (1) of the same table). This estimate suggests that the vast majority of learning is genuine rather than spurious. We carried out a similar exercise with the log of the expected nominal exchange rate of the Argentine Peso with respect to the U.S. Dollar on the free currency market. This is a key macroeconomic variable in Argentina: due to a history of high inflation, a substantial fraction of savings are held in U.S. dollars, so most individuals are aware of the market value of this exchange rate[39] and have interest in its future evolution. The α coefficient from this estimation, presented in column (8), is 0.435, that is, very close to the figure for the nominal interest rate (column (8), 0.468) and for inflation expectations (column (2), 0.494). We must note that, unlike the methodology based on follow-up surveys, this methodology suggests a lower degree of spurious learning. Given that this methodology may not remove salience effects, we prefer the estimate obtained from the follow-up survey.[40]

In sum, while there is a significant level of spurious learning, about half of it can be still be considered genuine. More importantly, once we account for spurious learning, the main results still hold: it is still true that the learning rate in Argentina is substantially lower than that in the United States.

4 The Supermarket Experiment

4.1 Remaining Hypotheses to be Tested

The tables for the *Products* treatments in the U.S. and Argentina online experiments indicate that, even when inflation statistics are readily available, individuals pay attention to prices of specific products in forming their inflation perceptions and expectations. This is suggestive evidence that individuals use their price memories to form inflation expectations. Indeed, following Bruine de Bruin et al. (2011), at the end of the surveys we asked individuals in the control group about the information they recalled when asked about inflation expectations. Nearly 63.4% of respondents in our U.S. online experiment and 74.9% of respondents in our Argentina online experiment reported to have thought about the prices of specific products when they were asked about their inflation perceptions and expectations.

[39] The perception of the exchange rate at the time of the original survey was AR$ 8.17 per U.S. Dollar in the case of the control group, a figure very close to its actual value, with a standard deviation of only 0.66.

[40] The provision of information (for instance, inflation statistics) can have two effects in the short run. The first effect is learning: those who did not know the current figures incorporate this information. A second effect is salience: even for those already aware of these figures, the provision of this information makes it more salient, which may lead individuals to assign more weight to it. In Argentina at the time of our experiment most individuals followed information about the evolution of prices very closely, and thus the salience effect may have been larger. The nature of this effect implies that it will be short-lived, and it was thus likely to have disappeared by the time of our follow-up survey. This exercise could potentially have removed both spurious learning and the salience effect (which is not truly learning) at the same.

While suggestive, these findings do not constitute conclusive evidence that individuals use price memories in forming inflation expectations. For example, subjects may have reacted to the price information insofar as they perceived it to be accurate, but they would not trust their own price memories for the same products. Furthermore, the consequences of using price memories to form inflation expectations depends on how good individuals' price history memories are. For example, if price memories were very accurate, it would be optimal for individuals to incorporate this information into their expectations, since this could correct for biases in inflation statistics arising from differences between individual consumption baskets and the average basket used to compute inflation statistics.[41] Moreover, results from our U.S. online experiment indicate that a substantial share of respondents (20.4%) do not trust inflation statistics, and, furthermore, that a majority (72.2%) do not think those statistics are very representative (both figures for individuals in the control group).

The data requirements for testing these additional hypotheses are onerous. This would require data on products purchased by subjects, the actual historical prices of those products, the individual's memories of those historical prices, and the individual's inflation perceptions and expectations. Moreover, we would need a source of exogenous variation in the price memories of subjects. We designed and conducted a unique consumer intercept survey at the main exit of several supermarkets in Buenos Aires to meet all of these requirements.

4.2 Subject Pool and Experimental Design

The consumer intercept survey was carried out in four branches of one of the largest supermarket chains in the city of Buenos Aires. The subject pool consisted of supermarket customers who, having just made a purchase, were invited to participate in a short survey for an academic study. About half of the individuals approached agreed to participate in the survey, and interviewers reported that most of those who agreed to take part showed great interest in the exercise. A total of 1,200 subjects were interviewed for about three to five minutes. Using handheld scanners, the interviewers scanned respondents' receipt from the supermarket purchase, which contained product identifiers that could be matched to our database of scrapped online data of supermarket prices for the chain where the study was conducted. After providing purchase receipts for scanning, respondents were asked twelve questions. Following our basic experimental design, we asked about perceptions of the inflation rate over the past year. We then implemented some randomly assigned informational treatments, and finally we asked about expectations for the inflation rate for the following twelve months.

The first informational treatment was aimed at generating random variation in the salience of the individual's own price memories about four specific products randomly chosen from the receipt. In the online experiments, we provided a table with specific, pre-selected product prices

[41] The evidence suggests, however, that in practice differences in inflation rates due to heterogeneous consumption patterns are small (McGranahan and Paulson, 2006).

and price changes. The first treatment in the supermarket experiment also consisted of a list of four products at random, although this time they corresponded to products that the individual had just purchased and thus were relevant for them. Additionally, instead of providing the historical prices for these four products, we asked respondents to "fill in the table" by using their own price memories. Specifically, respondents were asked to recall the current price, and the price twelve months earlier, of two specific products they had just purchased. The interviewers selected two additional products from the receipt, read each of their prices out loud, and asked the respondents what they thought the prices of these two products had been twelve months earlier. This design is consistent with models of beliefs and expectations formation – for instance, Gennaioli and Shleifer (2010) propose the idea of "local thinking, in which an agent combines data received from the external world with information retrieved from memory to evaluate a hypothesis." By chance, some of the products we made salient through this procedure corresponded to products with higher or lower actual price changes, and/or with higher or lower remembered price changes. This design allows us to test whether making salient these products had any effect on subsequent individuals' inflation expectations.[42]

The second informational treatment was identical to the one used in the online experiments, and consisted of showing the individual the actual price histories for six randomly selected products. We randomly assigned one of three tables with average price changes of 19%, 24%, and 29%.

4.3 Accuracy of Memories about Current and Past Prices

The goal of this subsection is to compare the memories about current and past prices to the actual prices. Panel (a) in Figure 7 presents a scatterplot of prices for the products the respondents had just purchased, with the prices the respondents reported paying for (without looking at the receipt) on the vertical axes and the prices they actually paid for them on the horizontal axis. The relationship between the two variables seems to be linear, with most observations clustered around the 45 degree line, indicating that individuals' memories of the prices of the products they had just purchased were fairly accurate. Panel (b) in Figure 7 presents the results of a more taxing exercise for respondents' memory: we present a scatterplot of respondents' reported recollections of the prices of the same goods one year earlier (vertical axis) and of the actual prices one year earlier (horizontal axis), obtained from our database of scrapped prices for the same supermarket chain. The main pattern that emerges indicates that individuals' recalled prices for one year earlier are systematically lower than the actual prices of those products at that time as indicated in our database.[43] Individuals seem to underestimate the past prices of the products they had purchased, and this effect remains irrespectively of whether we use the prices of products chosen by the respondents or of products

[42]Unlike in the other informational treatments in our study, subjects were not learning new information – we were only making salient some information that they already had.

[43]Bates and Gabor (1986) and Kemp (1987) also find that individuals' implicit price changes overestimate the actual price changes.

randomly selected by the interviewers.[44]

Interestingly, individuals seem greatly unaware of how bad their price memories really are. We asked respondents how confident they were about their answer to questions about prices and inflation. Only 9.81% of subjects reported to be unsure (i.e., either "unsure" or "very unsure") about their answers to the questions about prices of specific products. This high level of confidence is very similar to the level of confidence on the inflation rate over the past 12 months, about which only 9.72% responded to be "unsure" or "very unsure."

Since individuals have relatively unbiased and accurate memories of current prices but tend to underestimate past prices, they often overestimate price changes. Even though price changes are overestimated on average, there may be a correlation between remembered price changes and actual price changes. For instance, individuals might be mistakenly reporting prices for twenty months earlier rather than for twelve months earlier. Panel (c) in Figure 7 presents respondents' perceptions of aggregate inflation over the previous twelve months and the implicit average percentage price change of the products for which we requested this information. As expected, the correlation is positive and significant: i.e., individuals who believe inflation was higher also believe that, on average, prices of specific products increased more. For each percentage point increase in perceptions of past inflation, the remembered price change increases by 0.64 percentage points (p-value<1%).

Panel (d) in Figure 7, in turn, presents a comparison of the remembered price changes and the actual price changes observed in our database of supermarket prices. There is not a statistically significant correlation between the two: for each percentage point increase in the actual price change, the remembered price change increases by only 0.045 percentage points (p-value 0.40). In other words, there is a very small association between memories and reality: individuals' memories of price changes for specific products appear to be orthogonal to actual price changes.

Although individuals seem to have a poor memory about price changes for individual products, they may have a better recollection of the price of bundles of products, for instance, the price of the basket of products they had just purchased. To test this hypothesis, immediately after asking about perceived inflation, the interviewer read out loud the total amount of the purchase as reported on the receipt and asked the respondent how much they thought they would have spent twelve months earlier for exactly the same bundle of products. We compared the individual's estimate of the change in the total purchase amount and the actual total cost according to our price database. We find similar results than those with individual products (reported in the Appendix), which indicates that respondents do not seem to fare any better when asked about total purchase amounts instead of specific products.

However, individuals may follow the evolution of prices for a different set of products (e.g., a handful of "favorite" goods), and their memories for these products may be more accurate. With this caveat in mind, we show in Appendix A that even with perfectly accurate recollections, if

[44] This underestimation of past prices may be due in part to the fact that individuals may struggle with the operation of projecting percentage changes into the past. See, for example, the discussion about implicit memory in Monroe and Lee (1999).

the number of products an individual keeps track of is small, that can generate substantial excess dispersion in inflation expectations, enough to explain the observed heterogeneity in the data.

4.4 Evidence on the Use of Actual and Remembered Price Changes on the Formation of Inflation Expectations

The supermarket experiment also included an informational treatment with tables of products with three levels of average price changes. Panels (a) and (b) in Figure 8 present the distributions of inflation expectations in pairwise comparisons between the *Products* treatments. While there is no statistically significant difference between the distributions of the 19% and the 24% treatments (the ES test does not reject the null of equality of distributions – p-value of 0.24), the *Products (19%)* and *Products (29%)* treatments are statistically different: average inflation expectations are clearly higher when the subjects were shown tables with the highest average price changes. This evidence merely confirms the findings from the online experiments that individuals incorporate objective information about prices of specific products.

Panel (c) in Figure 8 presents evidence on the effect of remembered prices changes on inflation expectations. It presents a comparison of the distribution of inflation expectations when, conditional on the individual's inflation perceptions, we made salient products that the individual remembered to have higher and lower price changes.[45] The results from this exercise indicate that making salient products with higher remembered price changes generates higher inflation expectations. This finding is suggestive that individuals use memories of their own experience as consumers in when forming their inflation expectations.[46] As we established above, these memories are highly inaccurate, so this may generate substantial biases in expectations. To show this more directly, Panel (d) in Figure 8 presents a comparison of the distribution of inflation expectations between groups of individuals for which we randomly made salient products whose actual price changes (rather than their price changes as remembered by the respondents) where higher. The comparison of the two distributions (and the result of the ES test) indicate that making salient products with actual higher price changes did not result in higher inflation expectations. In other words, it is the remembered price changes and not the actual price changes that mattered for the formation of our subjects' inflation expectations. This is due to the fact that the price changes that our subjects

[45]Specifically, we computed the remembered price change as the average of the price changes of the four randomly selected products that each respondent was asked to state. We then controlled for each individual's inflation perceptions by substracting the variation in the average remembered price change that can be explained by inflation perceptions. Finally, we divided those residuals in two extreme groups: the top third (i.e., high) and the bottom third (i.e. low) of the distribution.

[46]In this case, unlike the other informational treatments, we did not randomize the recalled price changes directly, but randomized instead the salience of the recalled price changes for a group of products. As a result, estimating the wight assigned to this information (the α coefficient) with our learning regression would not yield the same interpretation in terms of rate of learning as in the information provision treatments in the online experiments. Appendix E presents regression for the corresponding rate of learning, although these results should be interpreted with this caveat in mind.

remembered were nearly orthogonal to the real price changes experienced by the same products.[47]

All in all, far from correcting a representativeness bias, the use of price memories as inputs for the formation of inflation expectations tends to induce large errors in beliefs and may cause the significant dispersion observed in expectations. This evidence is consistent with the fact that, even though their price memories are actually strongly biased, subjects are largely unaware of these biases, and they report to be very confident about them.

5 Conclusions

We presented evidence from a series of survey experiments in which we randomly assigned respondents to treatments that provided different information related to inflation, such as inflation statistics or price changes for specific products. We used that exogenous variation to estimate the rate of learning from different sources of information. We find that individuals are highly influenced by both inflation statistics and supermarket prices. The evidence is consistent with rational inattention, because the learning rates are much higher in a low-inflation setting, where the stakes from ignoring inflation are lower. We find that individuals are more influenced by information that is less costly to understand (supermarket prices) relative to information that is more costly to understand (inflation statistics). The evidence also suggests that individuals, when forming inflation expectations, use their own memories about price changes of supermarket products that they buy, even though those memories are nearly orthogonal to the actual price changes and thus bound to induce biases and errors in beliefs. Finally, we also find that disentangling spurious learning is important, because only half of the responses to the information treatments can be attributed to genuine learning.

Our findings have a number of implications for macroeconomic theory and for policy-making. How households form inflation expectations is an important consideration for central banks insofar as, by anchoring expectations, the policies of monetary authorities attempt to influence decisions that households make about consumption and investment. It is, then, important to incorporate realistic informational frictions in models of households expectations and monetary policy (e.g., Coibion and Gorodnichenko, 2015). From a more practical perspective, our findings imply that central banks could have a greater influence on inflation expectations by disseminating information on individual product prices and communicating how objective, accurate and representative inflation statistics are.[48]

Our findings also contribute to the discussion on the potential usefulness of survey data on

[47]We obtain similar results if, instead of using price changes for individual products, we use the changes in the total amount of the purchase on the receipt, which we scanned in the context of the survey (see Appendix E for more details on this additional result).

[48]Along these lines, in recent years the European Central Bank and the French statistical agency have made considerable efforts to create user-friendly online tools to explain how inflation statistics are collected and processed. See http://www.ecb.europa.eu/ecb/educational/hicp/html/index.en.html and http://www.insee.fr/en/indicateurs/indic_cons/sip/sip.htm, respectively.

inflation expectations. Some researchers attribute the biases in household inflation expectations to the inherent limitations of self-reported data (Manski, 2004), which would imply that survey data on household expectations is not useful.[49] Other authors argue that the failure to incorporate public information is a natural outcome of rational inattention (Mankiw et al., 2003). But this would imply that survey data on expectations has limited value since individuals with inaccurate expectations merely reveal that they do not care about inflation. Our evidence suggests that individuals report biased beliefs on inflation partly because they use private sources of information (e.g., price memories), even when inflation statistics are readily available. This implies that some of the observed heterogeneity in reported inflation expectations reflects actual heterogeneity in deep beliefs rather than measurement error or rational inattention.[50]

[49]Of course, the limitations with subjective reports must explain at least part of the dispersion in expectations. For example, Armantier et al. (2012) show that even though individuals' inflation expectations are correlated to their actual behavior in a financially incentivized investment experiment where future inflation affects payoffs, there are substantial discrepancies correlated to numeric and financial literacy.

[50]Consistent with this interpretation, our survey data reveals that even individuals with biased inflation expectations report significant confidence about their stated expectations. For individuals in the control group in the U.S., the average levels of confidence about perceptions of past inflation of 1%, 2%, and 3% (i.e., closest to the average of official statistics, 1.5%) are 2.6 for past inflation and 2.69 for inflation expectations (on a scale of 1 to 5). The figures for confidence are 2.95 and 2.85 respectively for those whose stated perceptions of past inflation were -4% or lower or 7% or higher.

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Figure 1: Example of *Products* (various levels), *Statistics (1.5%)* and *Hypothetical (10%)* Treatments, U.S. Online Experiment

a) *Products (-2%)*

Product	Price on August 1, 2012	Price on August 1, 2013	Price change in %
Infant Formula (Enfamil Gentlease)	\$18⁶⁹	\$18⁶⁹	0.0%
Bread (Anzio & Sons Sub Rolls)	\$3⁵⁹	\$3⁵⁹	0.0%
Pasta Sauce (Barilla Marinara)	\$2⁷⁹	\$2⁸⁰	0.4%
Cereal (Cheerios Honey Nut)	\$5²⁹	\$4⁹⁹	-5.7%
Soda (Schweppes Ginger Ale)	\$1⁷⁹	\$1⁶⁷	-6.7%
Body Wash (Dial Spring Water)	\$6⁰⁹	\$6⁰⁹	0.0%
		Average change:	**-2.0%**

b) *Products (2%)*

Product	Price on August 1, 2012	Price on August 1, 2013	Price change in %
Infant Formula (Similac with Iron)	\$7²⁹	\$7⁵⁹	4.1%
Bread (Pepperidge Farm Sliders)	\$3⁰⁰	\$2⁹⁹	-0.3%
Noodles (No Yolks)	\$2⁷⁹	\$2⁷⁹	0.0%
Cereal (Natures Path Envirokidz)	\$4⁹⁹	\$5³⁹	8.0%
Soda (Dr Pepper)	\$1⁷⁹	\$1⁷⁹	0.0%
Body Wash (Dial Spring Water)	\$6⁰⁹	\$6⁰⁹	0.0%
		Average change:	**2.0%**

c) *Statistics (1.5%)*

Official Statistic	Average Annual Change in Prices
Consumer Price Index[1]	2.0%
Personal Consumption Expenditures Price Index[2]	1.1%
Gross Domestic Product Deflator[3]	1.5%
Average of the three statistics:	**1.5%**

Sources: 1 Bureau of Labor Statistics, 2 and 3: Bureau of Economic Analysis.

d) *Hypothetical (10%)*

Please consider the following prices of a hypothetical product at two different moments.

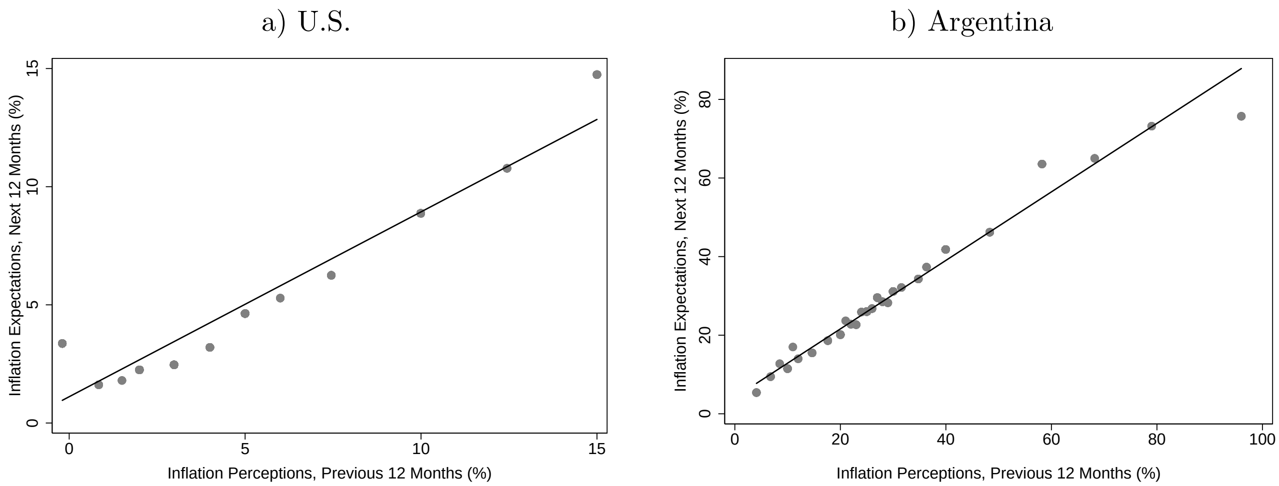
Price on January 1st 2012:	\$9.99
Price on January 1st 2013:	\$10.99

What is the approximate price change for this product over this period? Please do not use a calculator, pen, or pencil to calculate the exact figure. We want your best guess from eye-balling these prices.

- o About 1%
- o About 5%
- o About 10%
- o About 100%

Notes: The *Products* treatment arm consisted of 10 tables similar to those presented here in panels (a) and (b). The average price changes in these tables ranged from -2% to 7% in 1 percentage point increments. The prices were obtained from scrapped online supermarket prices from one of the largest supermarket chains in the United States.

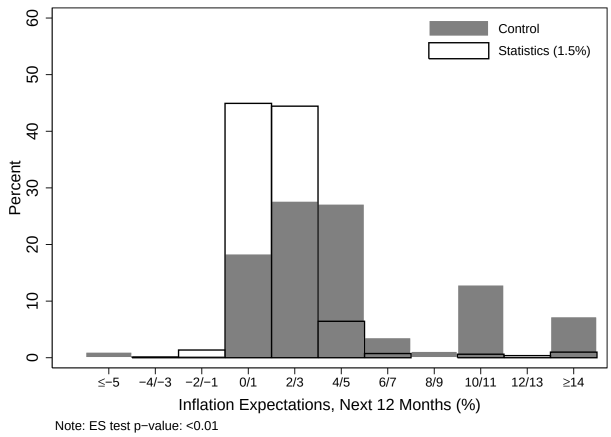
Figure 2: Past Inflation Perceptions and Future Inflation Expectations, Individuals in the *Control* group, U.S. and Argentina Online Experiments



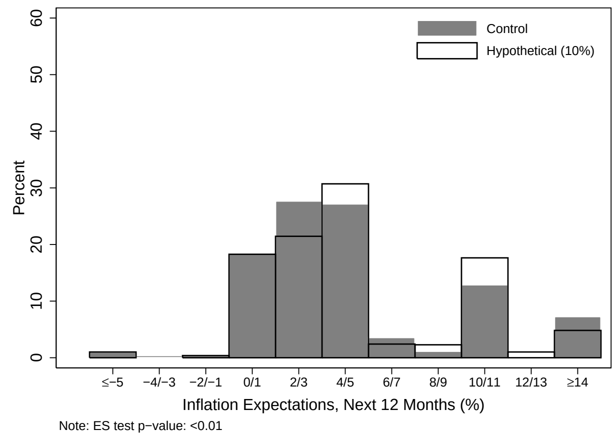
Notes: The total number of observations are 783 for the U.S. and 567 for Argentina (control group only). The darker markers represent the average inflation expectations for quantiles of inflation perceptions.

Figure 3: Inflation Expectations by Informational Treatments, U.S. Online Experiment

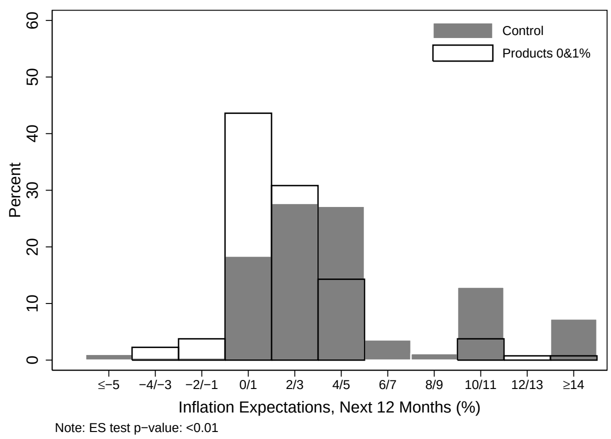
a) *Control* and *Statistics (1.5%)*



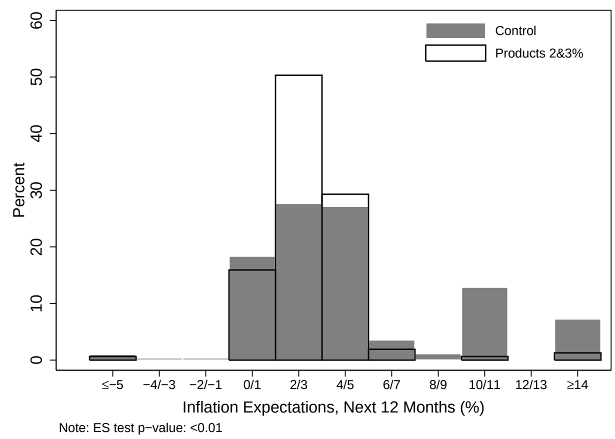
b) *Control* and *Hypothetical (10%)*



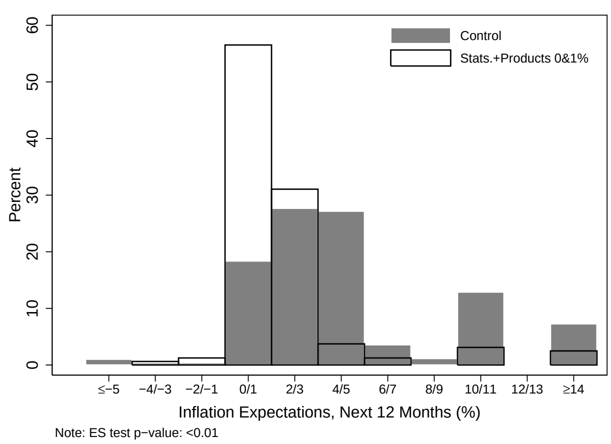
c) *Control* and *Products (0&1%)*



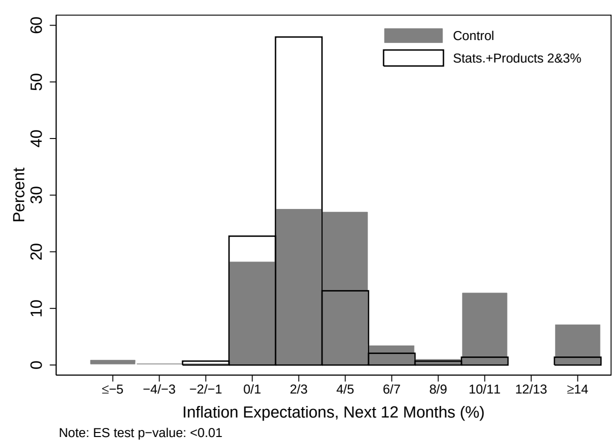
d) *Control* and *Products (2&3%)*



e) *Control* and *Statistics (1.5%)+Products (0&1%)*



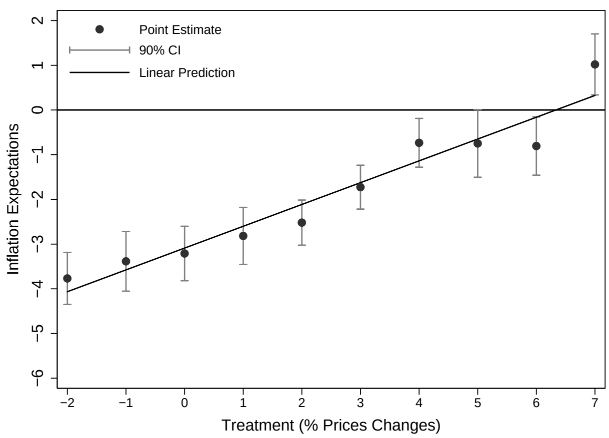
f) *Control* and *Statistics (1.5%)+Products (2&3%)*



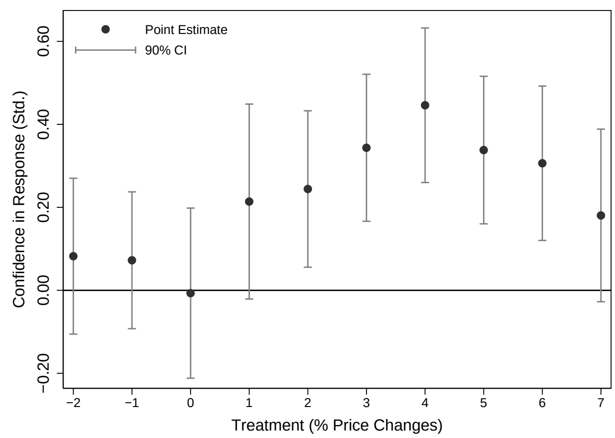
Notes: The total number of observations is 3,945, with 783 in the *Control* group, 807 in the *Statistics (1.5%)* treatment, 763 in the *Products* treatment (10 tables with average price changes from -2 to 7% in 1 percentage point increments within this treatment), 804 in the *Products+Statistics (1.5%)* combined treatment (same 10 tables as above), and 788 in the *Hypothetical* treatment. Panels (c) and (e) pool observations from the 0% and 1% average product price change tables, and panels (d) and (f) pool those from the 2% and 3% tables (see example in the previous Figure). ES is the Epps–Singleton characteristic function test of equality of two distributions. The histograms are censored at -5% and 15% (inclusive) for inflation expectations, but these bins represent the cumulative observations below -5% and above 15% respectively.

Figure 4: Treatment Effects on Inflation Expectations and Confidence about Own Expectations by Levels of *Products* Treatment, U.S. Online Experiment

a) Effect on inflation expectations



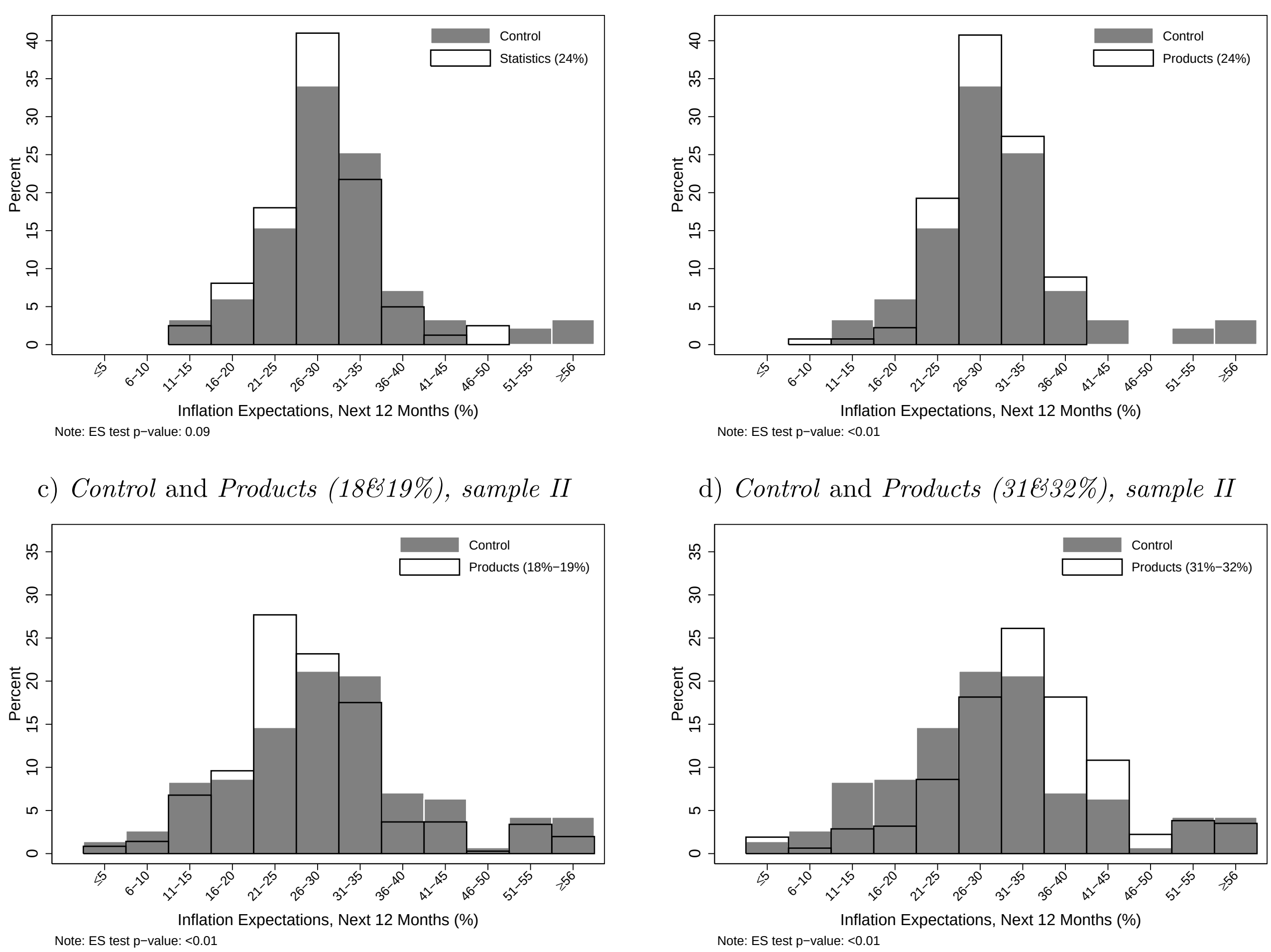
b) Effect on confidence



Notes: The total number of observations is 1,552 (783 in the control group and 763 in the 10 variations of *Products* treatment). Each bar represents the point estimate of the effect of the specific sub-treatment (average product price changes in the table presented) compared to the control group. Robust standard errors reported. The confidence variable from panel b) is based on a categorical question that was converted into a numerical scale using the Probit-OLS method (Ferrer-i-Carbonell and van Praag, 2008), and then standardized to have a standard deviation of one. For example, if a fraction q reports the lowest category (not sure at all), the highest confidence among the lowest category must be $\Phi^{-1}(q)$, where Φ is the cumulative distribution of a standard normal. Thus, the POLS method assigns the lowest category a score of $E[z|z < q]$, where z is distributed standard normal.

Figure 5: Inflation Expectations by Informational Treatments, Argentina Online Experiment

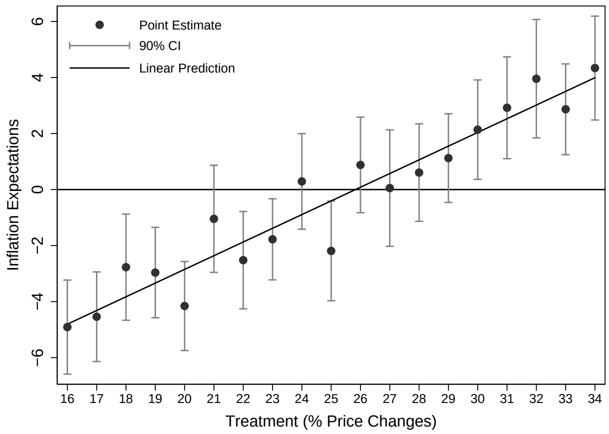
a) *Control* and *Statistics (24%), sample I* — b) *Control* and *Products (24%), sample I* — c) *Control* and *Products (18&19%), sample II* — d) *Control* and *Products (31&32%), sample II*



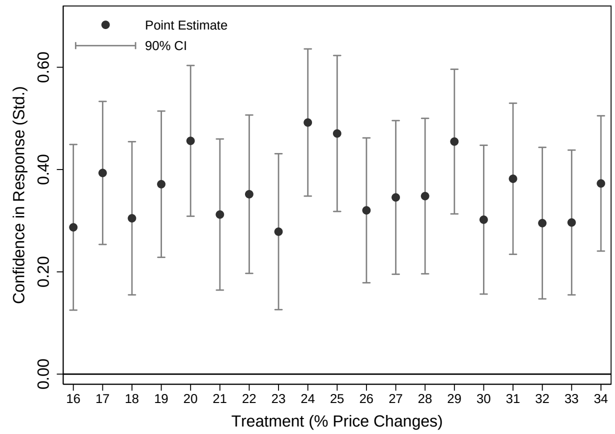
Notes: Panels (a) and (b) present results for the college graduates online experiment sample (sample I). The total number of observations is 641, with 174 in the *Control* group, 127 in the *Products (24%)* group, and 146 in the *Statistics (24%)* group. Panels (c) and (d) present results for the opinion poll online experiment sample (sample II). The total number of observations is 3,686, with 568 in the control group and 146-181 in each of the 19 treatment groups. Panel (c) pools observations from the 18% and 19% average product price change tables, and panel (d) pools those from the 31% and 32% tables. ES is the Epps–Singleton characteristic function test of equality of two distributions. The histograms are censored at 5% and 56% (inclusive), but these bins represent the cumulative observations below 5% and above 56% respectively.

Figure 6: Treatment Effects on Inflation Expectations and Confidence about Own Expectations by Levels of *Products* Treatment, Argentina Online Experiment, Opinion Poll Sample

a) Effect on inflation expectations

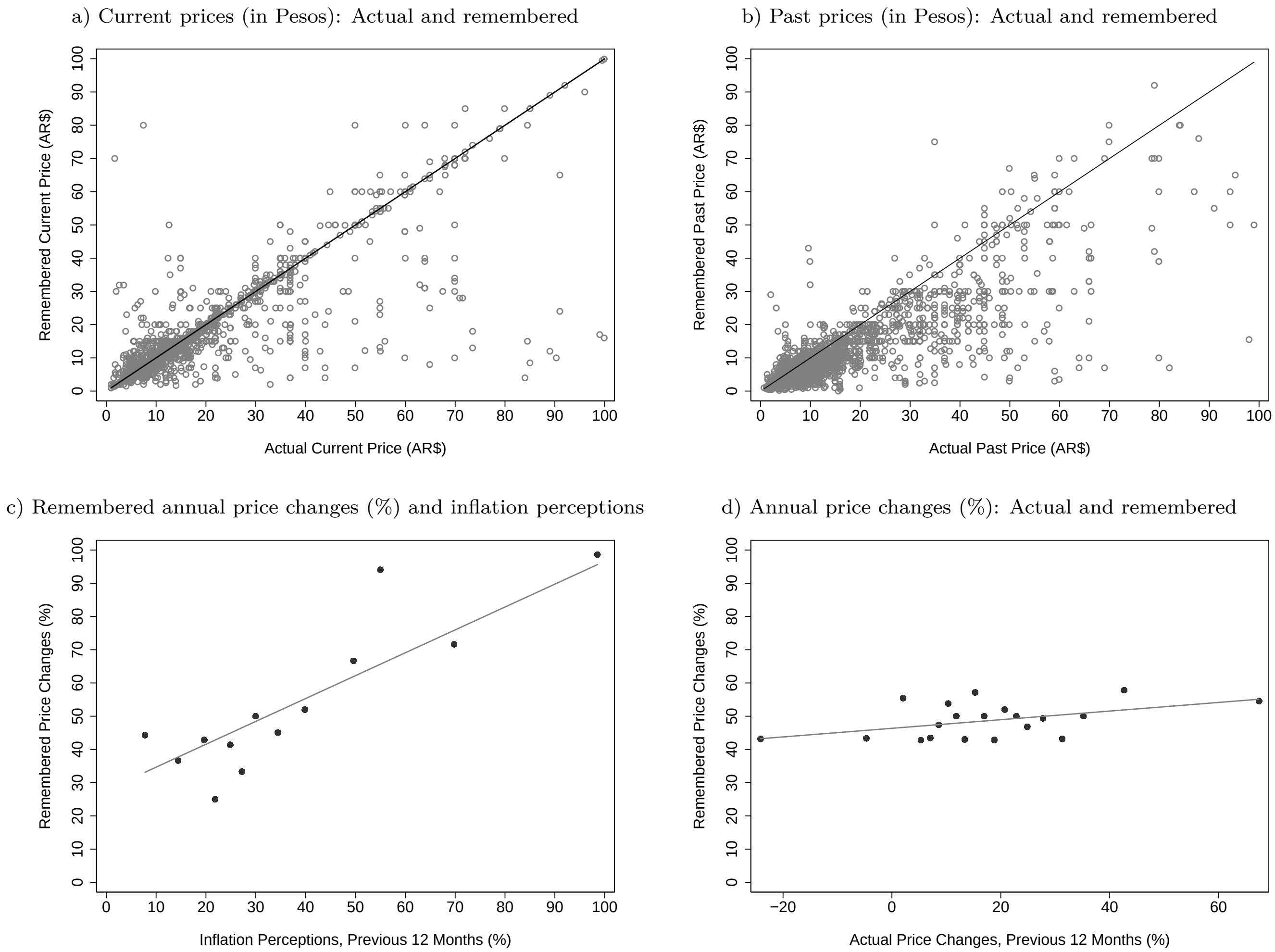


b) Effect on confidence



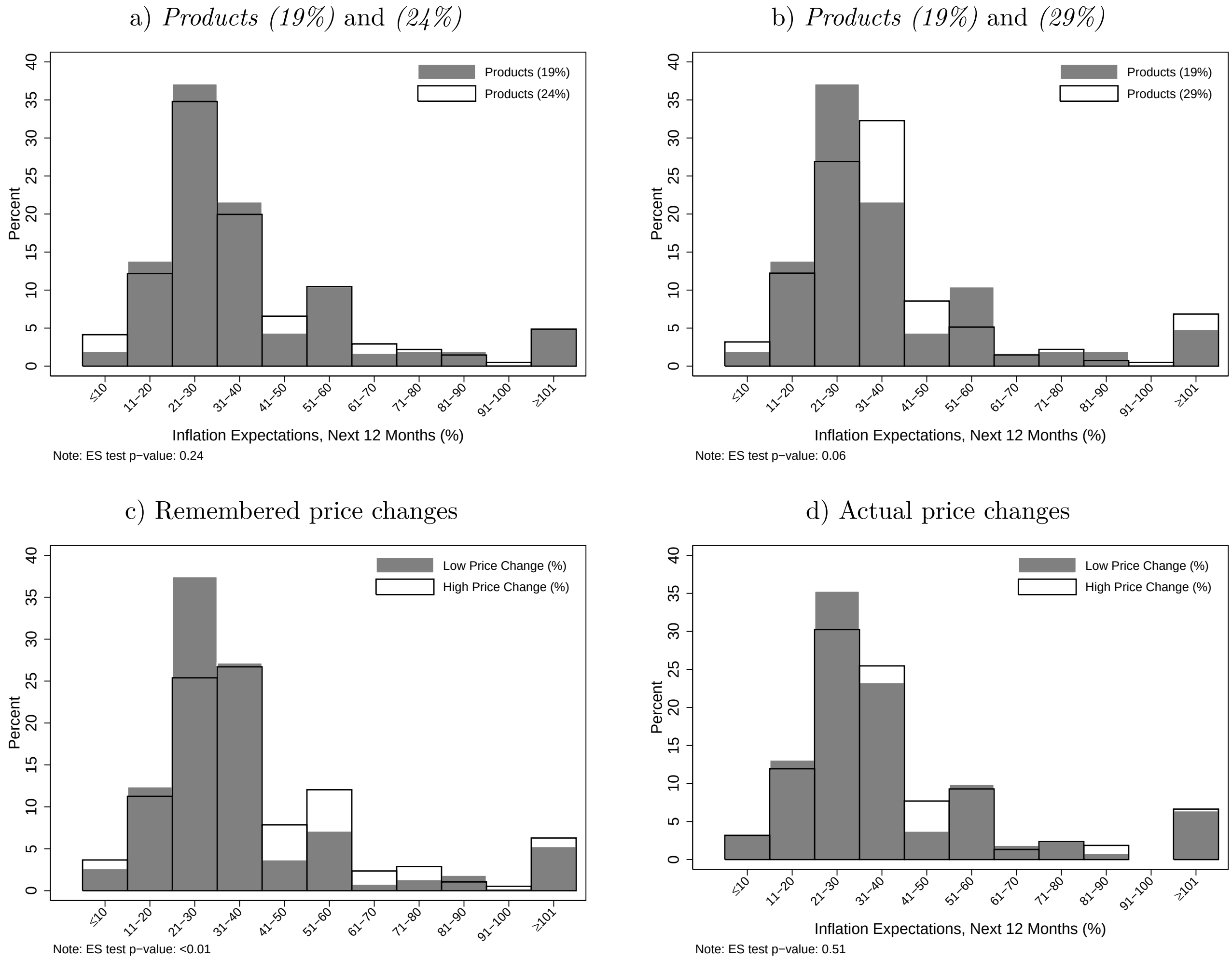
Notes: The total number of observations is 3,686, with 568 in the control group and 146-181 in each of the 19 *Products* treatment groups. Each bar represents the point estimate of the effect of the specific sub-treatment (average price changes for each product in the table presented) compared to the control group. Robust standard errors reported. The confidence variable from panel b) is based on a categorical question that was converted into a numerical scale using the Probit-OLS method (Ferrer-i-Carbonell and van Praag, 2008), and then standardized to have standard deviation of one. For example, if a fraction q reports the lowest category (not sure at all), that means that the highest confidence among the lowest category must be $\Phi^{-1}(q)$, where Φ is the cumulative distribution of a standard normal. Thus, the POLS method assigns the lowest category an score of $E[z|z < q]$, where z is distributed standard normal.

Figure 7: Remembered and Actual Past Prices, Implicit Price Changes and Inflation Expectations, Supermarket Experiment, Argentina



Notes: The total number of observations is 1,140. Panels (c) and (d) represent binned scatterplots. The annual price changes in panels (c) and (d) are implicit; they are obtained from the current and past prices in pesos (AR$) reported by the respondents.

Figure 8: Inflation Expectations by *Product* Treatment Levels and by Remembered and Actual Price Changes, Supermarket Experiment, Argentina



Notes: The total number of observations is 1,232 for panels (a) and (b) (412 in the *Products (19%)* group, 411 in the *Products (24%)* group and 409 in the *Products (29%)* group). The number of observations in panels (c) and (d) are 379 (lowest third of remembered price changes) and 381 (top third of remembered price changes). ES is the Epps–Singleton characteristic function test of equality of two distributions.

Table 1: Learning Model: Weight Given to the Information Provided in the Experiment Relative to Prior Beliefs (α), U.S. Online Experiment

	(1)	(2)	(3)	(4)	(5)
	$\pi_{\mathrm{i,t+1}}$	$\pi_{\mathrm{i,t+1}}$	$\pi_{\mathrm{i,t+1}}$	$\pi^{follow-up}_{\mathrm{i,t+1}}$	$i_{\mathrm{i,t+1}}$
β	0.757***	0.817***	0.814***	0.438***	0.291***
	(0.033)	(0.058)	(0.046)	(0.055)	(0.040)
Statistics					
α	0.838***	0.283***	0.799***	0.360***	0.314
	(0.034)	(0.063)	(0.058)	(0.138)	(0.212)
Products					
α	0.689***	0.449***	0.697***	0.336**	0.499***
	(0.036)	(0.050)	(0.045)	(0.150)	(0.135)
Hypothetical					
α	0.232***		0.215***	-0.021	0.131
	(0.027)		(0.046)	(0.092)	(0.112)
Observations	3,141	1,587	1,073	1,073	3,141
Simultaneous treatments	No	Yes	No	No	No

Notes: The α and β coefficients are obtained from the regression given by Equation 4, section 2.3. The results presented in column (2) represent the case of the *Products+Statistics (1.5%)* combined treatment, in which treated individuals received two pieces of information simultaneously. The dependent variable in columns (1) to (3) is inflation expectations (for the following 12 months) at the time of the original survey (September 2013), with the sample restricted in column (3) to a subset of respondents who were re-interviewed two months after the original survey (November 2013). The dependent variable in column (4) is inflation expectations (for the following 12 months) at the time of that follow-up interview. The dependent variable in column (5) is the expected interest rate (for the following 12 months) in the original survey. The total number of observations in columns (1) and (5) is the sum of the 783 in the *Control* group and the observations in each treatment group (807 in the *Statistics (1.5%)* treatment, 763 in the *Products* treatments, and 788 in the *Hypothetical (10%)* treatment), with the same groups with less observations in the follow-up surveys for columns (3) and (4). The total number of observations in column (2) is the sum of the 783 controls and 804 in the *Products+Statistics (1.5%)* combined treatment. The p-value of the difference between the α coefficients for *Statistics* and *Products* in column (1) is 0.0015; the p-value of the difference between the two α coefficients in column (2) (*Statistics+Products*) is 0.0038; and the p-values of the differences between the sum of the α coefficients in column (2) (*Statistics+Products*) and the α coefficients *Statistics* and *Products* in column (1) are 0.0077 and 0.8209 respectively. Robust standard errors. *significant at the 10% level, ** at the 5% level, *** at the 1% level.

Table 2: Learning Model: Weight Given to the Information Provided in the Experiment Relative to Prior Beliefs (α), Robustness Checks, *Statistics (1.5%)* and *Products* Treatments, U.S. Online Experiment

Treatment:	*Statistics*		*Products*	
	(1)	(2)	(3)	(4)
	$\pi_{\mathrm{i,t+1}}$	$\pi_{\mathrm{i,t+1}}$	$\pi_{\mathrm{i,t+1}}$	$\pi_{\mathrm{i,t+1}}$
β	0.827***	0.822***	0.778***	0.775***
	(0.057)	(0.059)	(0.051)	(0.051)
α	0.918***		0.690***	
	(0.049)		(0.042)	
α^2	0.007		-0.003	
	(0.007)		(0.005)	
α_+		0.632***		0.606***
		(0.108)		(0.078)
α_-		0.859***		0.736***
		(0.037)		(0.046)
Observations	1,590	1,590	1,546	1,546

Notes: The total number of observations in each column is the sum of the 783 in the *Control* group and the observations in each treatment group (807 in the *Statistics (1.5%)* treatment – columns (1) and (2) – and 763 in the *Products* treatments – columns (3) and (4). The α and β coefficients are obtained from the regression given by Equation 4, section 2.3. α^2 represents the squared learning weight parameter. α_+ and α_- represent the learning weight parameters differentiated for those with positive and negative differences (respectively) between the reported value of the difference between the informational signal provided and the own reported value of past inflation perception, $\left(\pi^T_{i,t} - \pi^0_{i,t}\right)$. The p-values for the differences between the α_+ and α_- parameters are 0.0754 for column (2) (*Statistics*) and 0.1985 for column (4) (*Products*). Robust standard errors. *significant at the 10% level, ** at the 5% level, *** at the 1% level.

Table 3: Learning Model: Weight Given to the Information Provided in the Experiment Relative to Prior Beliefs (α), Argentina Online Experiment

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$\pi_{\mathrm{i,t+1}}$	$\pi_{\mathrm{i,t+1}}$	$\pi_{\mathrm{i,t+1}}$	$\pi_{\mathrm{i,t+1}}$	$\pi_{\mathrm{i,t+1}}$	$\pi_{\mathrm{i,t+1}}^{follow-up}$	$i_{\mathrm{i,t+1}}$	$\log(e_{\mathrm{i,t+1}})$
β	1.138***	0.902***	0.909***	0.902***	0.963***	0.754***	0.155***	0.328***
	(0.118)	(0.042)	(0.043)	(0.042)	(0.041)	(0.086)	(0.035)	(0.088)
Statistics								
α	0.432***							
	(0.098)							
Products								
α	0.458***	0.494***	0.472***		0.456***	0.208**	0.468***	0.435**
	(0.062)	(0.027)	(0.025)		(0.037)	(0.094)	(0.133)	(0.173)
α^2			-0.001					
			(0.001)					
α_+				0.484***				
				(0.040)				
α_-				0.497***				
				(0.037)				
Observations	691	3,653	3,653	3,653	1,320	1,320	3,373	1,660
Sample	I	II	II	II	II	II	II	II

Notes: The dependent variable in columns (1) to (5) is inflation expectations (for the following 12 months) at the time of the original survey (June 2013 for sample I and March 2013 for sample II), with the sample restricted to a subset of respondents who were re-interviewed four months after the original sample II survey (August 2013). The dependent variable in column (6) is inflation expectations (for the following 12 months) at the time of the follow-up interview. The dependent variable in column (7) is the expected interest rate (for the following 12 months) in the original survey. The dependent variable in column (8) is the log of the expected nominal exchange rate of the Argentine Peso with respect to the U.S. Dollar (for the following 12 months) in the original sample II survey. Sample I is a sample of college graduates and sample II is a general population sample from the WP Public Opinion Survey (see section 3.2 for details). The total number of observations in column (1) is the sum of 182 observations in the *Control* group, 161 in the *Statistics 24%* treatment and 348 in the *Products* (*19%*, *24%* and *29%*) for the college graduates sample. The total number of observations for columns (2)-(4) is 3,653, with 568 in the control group and 146-181 in each of the 19 *Products* treatment groups for the WP Public Opinion Survey. The 1,320 observations in columns (5) and (6) represent the subsample of the WP Public Opinion Survey respondents who were re-interviewed four months after the original survey (March and August 2013 respectively). The 3,373 observations in column (7) represent the respondents of the WP Public Opinion Survey who provided a valid answer to the expected interest rate question. The 1,660 observations in column (8) represent the half of respondents of the WP Public Opinion Survey who were randomly assigned to be asked about the nominal exchange rate and provided a valid answer to this question. The α and β coefficients are obtained from the regression given by Equation 4, section 2.3. α^2 represents the squared learning weight parameter. α_+ and α_- represent the learning weight parameters differentiated for those with positive and negative differences (respectively) between the reported value of the difference between the informational signal provided and the own reported value of past inflation perception, $\left(\pi_{i,t}^T - \pi_{i,t}^0\right)$. Robust standard errors. *significant at the 10% level, ** at the 5% level, *** at the 1% level.