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Learning from potentially-biased statistics: Household inflation perceptions and expectations in Argentina

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Abstract

When forming expectations, households may be influenced by the possibility that the information they receive is biased. For instance, in the U.S. households who do not trust inflation statistics have on average 50% higher inflation expectations. In this paper, we study how individuals learn from potentially-biased statistics using data from both a natural and a survey-based experiment obtained during a period of government manipulation of inflation statistics in Argentina (2006-2015). This period is interesting because of the attention to inflation information and the availability of both official and unofficial statistics. Our evidence suggests that rather than ignoring biased statistics or naively taking them at face value, households react in a sophisticated way, as predicted by a Bayesian learning model, effectively de-biasing the official data to extract all its useful content. We also find evidence of an asymmetric reaction to inflation signals, with expectations changing more when the inflation rate rises than when it falls. These results are useful for understanding the formation of inflation expectations in less extreme contexts than Argentina, such as the United States and Europe, where experts may agree that statistics are unbiased but households do not.

JEL Classification: C93, D83, D84, E31. *Keywords:* statistics, manipulation, expectations, learning, inflation, natural experiment, survey experiment.

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1 Introduction

Household inflation expectations play a key role in models of consumption decisions and the real effects of monetary policy, yet little is known about how these expectations are formed. In recent years, a growing empirical literature provides evidence about how individuals use information to form their inflation expectations. For example, in Cavallo, Cruces and Perez-Truglia (2014) we show that individuals learn from inflation statistics and from prices of individual goods, and that they are more attentive in countries with higher inflation. In this paper, we use data from a period of manipulated official statistics in Argentina to study in more depth the degree of sophistication of this learning process, as well as the role of trust and perceived biases in the information used to form inflation expectations.

We study how people learn -in a Bayesian sense- in an environment that combines a great deal of interest in learning about inflation, with a large number of alternative inflation statistics, some of which are biased by the government. We find that consumers are sophisticated users of information. Rather than simply ignoring the official statistics or taking them at face value, households seem to effectively adjust for the perceived bias using other available information. Furthermore, the publication of biased statistics may have led to an asymmetric reaction to inflation signals (even unbiased ones), with expectations changing more when inflation rose than when it fell.

Our findings are based on both observational and experimental evidence obtained during the recent period of manipulation of inflation statistics in Argentina, from 2007 to 2015. This was an ideal setting for several reasons. First, the inflation rate fluctuated between 15% and 30%, implicating that the costs of inattention are high, so people spent a great deal of time gathering and processing information about the inflation rate.¹ Second, there is ample evidence that the official sources of inflation information, such as the official CPI, were biased (for a discussion of the evidence, see Cavallo, 2013).² Third, the lack of reliable official data promoted the creation of a large number of alternative inflation indicators during this period, thereby potentially allowing individuals to counter-react to the government manipulation by using other data.

We start with some observational data on the co-movement of inflation expectations and several alternative inflation statistics before and after the intervention of the National Statistics Institute (INDEC), when the government started reporting official statistics that were systematically below the unofficial estimates. Inflation expectations quickly diverged from official inflation levels and closely tracked those in unofficial indicators. This suggests that consumers are not naive learners who process manipulated official statistics as if they were not biased. However, this observational

¹Since they cannot write contracts in foreign currency or indexed by inflation, households needed to constantly estimate inflation to sign rent contracts, negotiate wages, and make savings and investment decisions. Indeed, inflation statistics were frequently mentioned and discussed in the front pages of newspapers and other media outlets, and opinion polls systematically indicated that inflation was perceived as one of the most important problems in the country.

²Our analysis extends the account of the main events from 2006 until December 2015, when a new government finally suspended the publication of the official CPI.

evidence presents two challenges. First, it is not conclusive because we do not observe the relevant counter-factual - i.e., the distribution of household expectations in the absence of information about biased official statistics. Second, the evidence is silent about the nature of the learning process, such as whether individuals were simply ignoring the official statistics or adjusting in some other way to them.

To address these limitations with the observational data, we provide a simple model of Bayesian learners with potentially-biased statistics, and we designed a survey experiment to test its predictions. The model shows that, far from ignoring official statistics, rational learners should react to changes in official statistics by “de-biasing” the signal based on their perceived bias, while at the same time updating their beliefs about the size of the official bias. In other words, rational consumers are expected to extract useful information contained in potentially-biased information.

We ran a large-scale survey experiment in Argentina in December 2012 to test this prediction. The experiment consisted in providing respondents with different estimates of inflation, and measuring how these pieces of information affected their subsequent inflation perceptions, inflation expectations, and their confidence in these beliefs. The large variety of inflation indicators available at the time meant that we could cross-randomize in a non-deceptive way two features of the message provided to subjects: the source of the inflation statistics (official and unofficial) and the level of the inflation rate (10%, 20%, or 30%).

Our experimental evidence rejects the hypothesis that individuals simply ignore the information coming from biased official statistics. People’s perceptions reacted significantly to all signals, including official sources of inflation. For example, relative to individuals who were told that the official inflation rate was 20%, individuals who were told that it was 10% reported lower inflation perceptions and expectations; and individuals who were told that official inflation rate was 30% reported higher inflation perceptions and expectations.

The reaction to unofficial and official statistics also confirmed the perception of the bias in the official data. Since the official statistics had been consistently 10 percentage points below the unofficial estimates, our Bayesian model would predict that individuals should react to a signal that official inflation is 10% in the same way that they would react to a signal that unofficial inflation is 20%; and they should react to an official inflation of 20% equally than to an unofficial inflation of 30%. This implies that people were not only reacting to the official information, but also effectively “de-biasing” it in a rational, sophisticated way.

The experiment also allowed us to explore a seemingly asymmetric reaction of inflation expectations to inflation signals seen in the observational data (expectations reacted more to actual inflation during periods when inflation was rising than when it was falling). Relative to individuals who were told that unofficial inflation was 20%, individuals who were told that unofficial inflation was 10% had on average lower inflation perceptions by a significant 2.31 percentage points; and individuals who were told that unofficial inflation was 30% had on average higher inflation perceptions by a significant 5.86 percentage points. This evidence suggests that individuals were nearly

twice as reactive to information about higher inflation than to information about lower inflation.³

In a related paper, Cavallo, Cruces and Perez-Truglia (2014), we show that individuals do not only form inflation expectations using information from aggregate statistics, but they also put significant weight on their perceptions about prices of individual supermarket products. This implies that the government could try to influence inflation expectations by changing the actual prices of salient products. Indeed, in an effort to curb inflation, in 2013 the Argentine government froze the prices of a relatively large and important sample of consumer products (with large weights in the CPI basket and sold by retailers with big market shares). We show that even though the inflation rate fell substantially, household inflation expectations did not fall. We ran a price-elicitation survey outside a large supermarket chain in Argentina during the time of the price controls to test whether consumers were noticing the slowdown in prices. Consistent with the observational data, we found that even though there was a substantial difference in the actual price changes between goods that were under price controls and those that were not, such difference was not perceived by consumers and it did not affect their expectations of inflation.

While the context of manipulated statistics in Argentina is an extreme case, these results are also informative about how individuals learn from inflation data in other countries. Even in developed nations, a significant share of individuals do not trust official statistics. According to data from Eurobarometer (2008), even though 69% of respondents in Europe considered that it was necessary to know about economic indicators, only 46% stated that they tended to trust official statistics such as the growth rate, the inflation rate and the unemployment rate. Among U.S. survey respondents, 27% rated their trust in official statistics 4 or lower on a 1-10 scale (Curtin, 2009). Analysts, commentators and the media routinely discuss the possibility of manipulated statistics, such as around the job creation data released right before the 2012 election in the United States.⁴ In Cavallo et al. (2014) we found that 32% of U.S. survey respondents say that they do not trust inflation statistics and have inflation expectations that are 50% higher on average. In addition to inattention, part of the reason why household do not seem to fully incorporate information from inflation statistics (Mankiw et al., 2003; Carroll, 2003) may be that individuals do not fully trust the data provided by the government.

To the best of our knowledge, our paper is the first to study how individuals learn from manipulated statistics. More generally, the study of biased statistics goes back to the seminal contribution by Morgenstern (1963) on measurement, accuracy and uncertainty in economics. Morgenstern's book discusses how both private companies and governments have strong incentives to manipulate information, including a chapter about the problems of measuring prices and price changes.⁵ More recently, some papers have used data to measure the degree of bias in official

³The absolute difference between these effects (2.31 and 5.86) is statistically significant (p-value=0.06).

⁴See Norris, Floyd. 2014. "Doubting the Economic Data? Consider the Source." The New York Times, November 6. <http://www.nytimes.com/2014/11/07/business/economy/doubting-the-economic-data-consider-the-source.html>.

⁵Morgenstern also covers the difficulties of measuring the national product, and in fact Argentina's government

statistics, including examples such as inflation in Argentina (Cavallo, 2013), the manipulation of debt indicators in Greece (Rauch et al., 2011), and alternative estimates of growth and inflation in China (Nakamura et al., 2014). Michalski and Stoltz (2013), in turn, use statistical regularities in economic indicators to suggest that countries seem to manipulate economic data systematically.

Our paper is also related to a growing literature about the formation of household economic expectations. In particular, it is widely recognized that identifying the formation of inflation expectations is important to understand the link between the nominal and real sides of the economy (Bernanke, 2007; Coibion and Gorodnichenko, 2013). A number of studies provide evidence that inflation statistics play a significant role in driving inflation expectations, including the analysis of variation in media coverage of statistics (Lamla and Lein, 2008; Badarinza and Buchmann, 2009; Drager, 2011), quasi-experimental variation in reporting official statistics (Carrillo and Emran, 2012) and information-provision experiments (Roos and Schmidt, 2012; Armantier et al., 2012a; Cavallo, Cruces and Perez-Truglia, 2014).

The paper proceeds as follows. Section 2 describes the period of manipulation of official statistics in Argentina and presents the observational evidence using the time series of inflation expectations and a set of inflation indicators (both official and private). Section 3 presents a simple model of Bayesian learning from manipulated statistics, the design of the survey experiment and its results. In Section 4 we discuss the period of price controls in 2013. The last sections concludes.

2 Manipulation of Inflation Statistics in Argentina

2.1 The Intervention of the National Statistical Institute (INDEC)

After a severe economic crisis in 2001-2002, the Argentine economy started to recover in 2003 mostly due to an unprecedented increase in commodity prices. Inflation levels were relatively low at the beginning of the recovery, but reached double digits in 2005 (12.3% per year). During 2006 the government imposed a series of price controls and organized public boycotts against some retailers. The government also started to pressure the professional staff at the National Statistics Institute (INDEC) to make methodological changes that could lower the annual inflation rate. For example, they were asked to reveal the identities of the stores where the data was being collected, introduce automatic substitutions to reduce the weight of items that had higher inflation, and use prices from price-control lists even if those goods were not available for sale at the stores where the data was collected. In February 2007, facing a second year of inflation above 10% and unwilling to scale back its expansionary policies, the government took a drastic decision to intervene INDEC and fire key high-ranking members of the staff, including Graciela Bevacqua, the statistician in charge of the team that computed the CPI. The monthly inflation rate, which in January 2006

also falsified INDEC's GDP indicator (Camacho et al., 2015), for political reasons and to avoid the payment of a GDP warrant (a bond that only paid debtors if GDP grows at a certain rate).

had been 1.1%, immediately fell to 0.4% in February and continued with a similar trend in the following months. The annual inflation rate fell below 10% and gradually started to fall. As the old employees of INDEC started to publicly disclose what had happened in previous months, the suspicions of a manipulation of the CPI steadily grew. INDEC stopped publishing some disaggregated inflation series and announced “methodological changes” that were never publicly disclosed. Figure 1 provides a time-line of the most important events from 2006 to 2015, when the manipulation of the CPI finally ended.

Figure 1: Time-line of the Manipulation of Inflation Statistics in Argentina

Feb 2006	• The Secretary of Interior Commerce, Guillermo Moreno, tries to gain access to micro data protected by statistical confidentiality laws
Oct 2006	• Moreno hires a market-research firm “Tomadato”, to produce an alternative CPI
Jan 2007	• The director of the INDEC announces that Paglieri, Moreno’s assistant, will be visiting the institution for one month to check the last estimations
	• First meeting with Paglieri and the directors of the INDEC
	• Paglieri decides to stop the publication of CPI-GBA
	• Bevacqua, the director of the Prices Department is suspended
Feb 2007	• The government officially intervenes INDEC
	• The first manipulated CPI-GBA monthly index is published
	• Bevacqua is officially fired and replaced by Paglieri
	• First mobilization of the INDEC employees takes place (repeated every month since)
	• Senators from the opposition ask a federal prosecutor to intervene
Mar 2007	• The director of INDEC, Leilo Marmora, resigns.
May 2007	• Garrido, a federal prosecutor, says serious irregularities took place at INDEC
Jul 2007	• Cynthia Pok, in charge of the "National Household Survey", is fired
	• First official strike of the INDEC employees
Sep 2007	• The INDEC modifies Mendoza province’s inflation rate before publication
	• The calculation of the CPI-Nacional is changed
Dec 2007	• Cristina Kirchner becomes the president of Argentina, succeeding her husband.
Jan 2008	• INDEC employees receive wage cuts
March 2008	• Launch of www.inflationverdadera.com ”, a website where alternative indicators using online prices are updated on a daily basis. The inflation rate is three times higher than in CPI estimates.
May 2008	• INDEC stops publishing the CPI-Nacional, an index that used price data from 7 provinces
	• INDEC announces new CPI weights. Food becomes more important in the new index.
	• Some employees of INDEC are physically assaulted by government supporters at the Finance Ministry building
Nov 2010	• The government announces an agreement with the IMF for the normalization of the statistics
Feb 2011	• Moreno asks private consultants to share the methodology of their CPI calculations. Most of them refuse.
Mar 2011	• Some private consultants are fined with 500.000 pesos for failing to comply with Moreno’s request
May 2011	• The “CPI Congreso” (an average of private consultants’ inflation rates) is born
	• A judge rejects the fines imposed on private consultants
Sep 2011	• Private consultants receive letters from the government threatening them with criminal prosecutions if they continue to publish their own inflation estimates
Feb 2012	• The IMF announces that Argentina did not improve the CPI-GBA according to the international rules
	• The Economist stops publishing Argentina’s official statistics and uses instead the index produced by PriceStats (a company working with the Billion Prices Project at MIT)
Feb 2013	• The IMF issues a “motion of censure” against Argentina for the bad quality statistics
	• Moreno is replaced by Augusto Costa as Secretary of Interior Commerce
Jan 2014	• The CPI-GBA is replaced by a new index, called CPI-Nu. It initially shows similar monthly inflation rates to unofficial estimates, but starts to diverge once again within a few months.
Apr 2014	• The government announces that the official poverty index will no longer be published
Dec 2015	• Mauricio Macri, a member of the opposition, becomes the new president of Argentina
	• Jorge Todesca became the director and Bevacqua returns as the technical director of INDEC
	• Todesca says that INDEC is like a “scorched earth” and suspends the publication of the CPI and other price indexes
Jan 2016	• Bevacqua announces that it will take 8 month for the INDEC to publish a new CPI.

Notes: Compiled by the authors from newspaper articles and other sources.

2.2 Unofficial Inflation Statistics

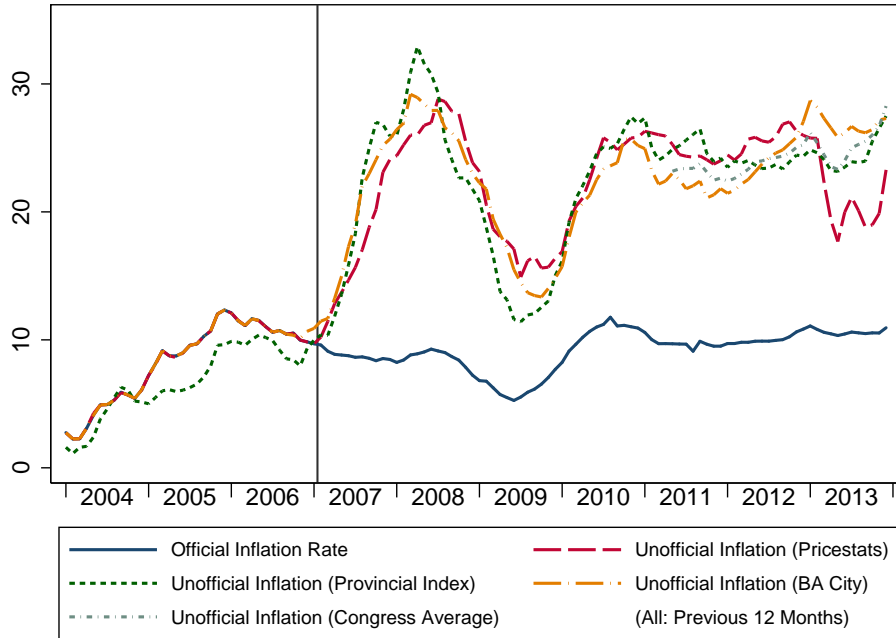
The unusual situation with INDEC led to a proliferation of alternative measures of inflation, that we refer to generally as “Unofficial” Inflation indicators. The main alternative indicator we use is computed by PriceStats, a private firm based in the US that uses online prices from large

retailers since 2007. This index is currently published by The Economist magazine every week.⁶ A second alternative indicator published since 2008 is produced by “Buenos Aires City” (BAC), a think tank lead by Graciela Bevacqua (the head of INDEC’s CPI team that was fired by the government in 2007). BAC uses prices collected from a sample of products in the City of Buenos Aires and follows the old INDEC methodology.⁷ A third unofficial indicator is the “Provincial Index”, based on the Consumer Price Indexes from nine Argentine provinces. While the official national index by INDEC was historically based on the Greater Buenos Aires (GBA) area only, provincial statistical agencies also collected regional price data and computed their own CPIs. The federal government pressured the provinces to stop publishing those indexes or to manipulate those in turn, but provinces not aligned with the federal government continued disseminating their own un-adulterated data. This index is computed by “CqP” as a geometric weighted mean of nine provincial CPIs for the post-2006 period, with weights computed to maximize the correlation between the provincial aggregate and the official (GBA-based) index during the pre-manipulation period. Finally, the “Congress Average” Index is an average of private inflation indicators that started to be widely cited in the media in 2011, after the government started to fine and prosecute economists that were publishing their own unofficial inflation estimates. Some members of Congress from the opposition, who are immune from prosecution, started compiling and publishing a monthly average of “private” estimates. There were other alternative indicators that were also publicly available. In the Appendix we provide a comprehensive list with details on their methodologies and main characteristics.

⁶PriceStats is a private company connected with the Billion Prices Project at MIT, an academic initiative created in 2008 by Alberto Cavallo (an author in this paper) and Roberto Rigobon to experiment with the use of online data in the production of price indices and other macro and international research applications. See Cavallo & Rigobon (2016) for more details on the Billion Prices Project.

⁷See Bevacqua and Salvatore (2009) for details.

Figure 2: Official Inflation and Alternative Unofficial Indicators, 2004-2013



Notes: The vertical line represents the start of the intervention of the national statistical agency (INDEC) in January 2007. “Official Inflation” is the annual inflation rate reported by INDEC. The underlying Consumer Price Index is based on a sample of prices from the Greater Buenos Aires Metropolitan Area (GBA). We present in this Figure a series of unofficial inflation rate estimates: a) “Unofficial Inflation (PricesStats)” is an indicator compiled by PriceStats LLC based on prices from online retailers (derived from the MIT’s Billion Prices Project; see Cavallo, 2013, for more details). b) “Unofficial Inflation (Provincial Index)” is based on a geometric average of nine provincial statistical agencies’ Consumer Price Indexes (source: CqP). c) “Unofficial Inflation (BA City)” is computed by Buenos Aires City from a sample of products and prices from the GBA area, following INDEC’s traditional methodology (the two series coincide until September 2006). d) “Unofficial Rate (Congress Average)”: an average of several unofficial indicators compiled by Congress representatives from opposition parties. All inflation indicators are monthly series.

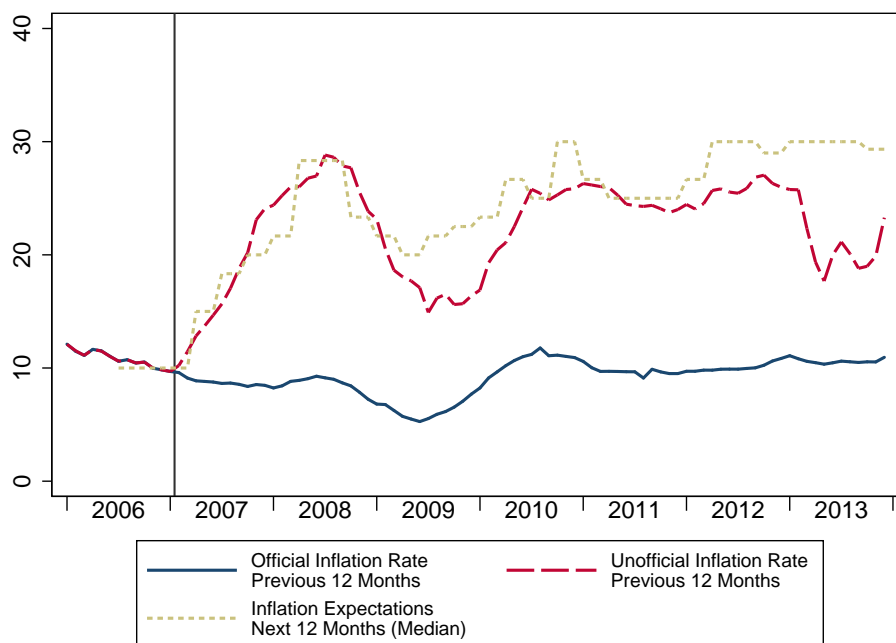
The annual inflation rate for all these unofficial indicators and the official CPI are shown in Figure 2. The vertical line shows the month of the intervention at INDEC. The official and unofficial indicators started to diverge immediately. All the unofficial indicators showed similar results, despite their differences in the sources of data and methodologies. On average, the inflation rate in the unofficial indicators was approximately 10 percentage points higher than in the official data.

2.3 Inflation Expectations and Inflation Statistics

The surge in inflation during 2006 motivated a renewed interest in the measurement of household expectations. In August 2006, the “Centro de Investigación en Finanzas” at the Torcuato Di Tella

University started to conduct a national survey of inflation expectations, published on a monthly basis.

Figure 3: Official Statistics, Unofficial Statistics and Inflation Expectations, 2006-2013



Notes: The vertical line represents the start of the intervention of the national statistical agency (INDEC) in January 2007. “Official Inflation” is the annual inflation rate reported by INDEC. The “Unofficial Inflation” indicator is computed by PriceStats (see notes in Figure 2 for more details). The mean of inflation expectations for the following 12 months are quarterly averages of the monthly series from the Encuesta de Expectativas de Inflación (carried out since August 2006 by the Centro de Investigación en Finanzas, Universidad Torcuato Di Tella). This survey collected information on the inflation expectations for the following 12 months among the general population of Argentina, based on a standard question for this type of survey (“What do you expect the annual rate of inflation will be during the next 12 months?”).

In Figure 3, we plot the official inflation rate, our main unofficial inflation indicator (PriceStats), and the mean inflation expectation from the household survey.⁸ These monthly time series allows us to study the co-evolution of the available inflation indicators and of inflation expectations for a seven year period of uninterrupted manipulation of official statistics.

Household inflation expectations closely tracked the unofficial level of inflation over time. The match is surprising in 2007 because the PriceStats index was not publicly available at the time (an early version of that index started to be published in a website called inflacionverdadera.com in March 2008). There were, however, other unofficial estimates reported in newspaper articles

⁸In Figure 3 we report quarterly averages of the mean and the median of inflation expectations to minimize the noise in the series.

during that time. In the Appendix we plot the annual inflation rates mentioned in these articles and show that they co-move with inflation expectations during 2007.

There is also some evidence of an asymmetric behavior in the response of expectations to the actual inflation rate. There are two periods, in particular, where expectations seem stickier on the way down. First, in 2009, when the country was experiencing the effects of the global financial crisis. Second, in 2013, when the unofficial inflation rate fell again due to both significant price controls and another recession. These trends suggest that manipulating inflation statistics actually made things worse from the point of view of curbing inflation expectations. One possibility is that the proliferation of unofficial indicators may have increased the uncertainty regarding which sources were reliable, particularly in 2013 when some of the unofficial indicators temporarily diverged. Another possibility is that individuals started to rely more on their own memories about price changes, which have been shown to have a substantial positive bias (see Cavallo et al., 2014). We discuss some of these options in Section 4, where we focus on the inflation slowdown of 2013.

3 Experimental Evidence with Aggregate Statistics

The patterns that emerge from the time series in the previous section support the hypothesis that households are not naive learners who believe in the official data. However, we cannot make causal inferences from this observational data, and it is unclear whether individuals are simply ignoring the official data or adjusting to it in a rational way. To address these limitations, this section develops a Bayesian learning model of inflation expectations in the presence of biased signals, and use experimental evidence to test some of its predictions.

3.1 A Model of Learning with Biased Statistics

This section provides a model of Bayesian learning in presence of potentially-biased statistics. For the sake of simplicity, we study the static case where the inflation rate is fixed at π_{actual} and an individual must learn about that rate of inflation indirectly from a series of signals. We also assume that price changes for each individual product in the economy are normally distributed, with mean π_{actual} and variance is given by σ_{actual}^2 , and that the variance is known to the individual. Relaxing these assumptions would complicate the algebra but would not change the main intuition of the model.

The individual can observe two signals based on the information about the price changes for the individual products. The first signal comes from the price changes for a randomly-drawn subset of N_u products, with an associated mean \bar{u} and variance $\frac{1}{N_u}\sigma_{actual}^2$. This signal could be an unbiased unofficial inflation index or represent the information that individuals obtain by using averages of their own memories about price changes over a set of products (Bates and Gabor, 1986; Bruine de Bruin et al., 2011; Coibion and Gorodnichenko, 2013; Cavallo et al., 2014). The second signal

is the government’s official statistics. We assume the government also takes a randomly-drawn subset of N_o products and computes its average price change, producing a signal with associated mean \bar{o} and variance $\frac{1}{N_o}\sigma_{actual}^2$. However, the government does not report \bar{o} but adds instead a bias, b_{actual} , before reporting it. In other words, the government reports $\bar{o}' = \bar{o} + b_{actual}$ instead of \bar{o} . Note that N_u and N_o determine the precision of the unofficial and official signals. To simplify notation, we will replace for $\sigma_u^2 = \frac{1}{N_u}\sigma_{actual}^2$ and $\sigma_o^2 = \frac{1}{N_o}\sigma_{actual}^2$. In practice, σ_u^2 and σ_o^2 represents not only a pure statistical error driven by sample size, but also other sources of error. For example, individuals may perceive σ_o^2 to be high because they do not understand how precise these statistics are or because they do not believe that these statistics are representative of their own consumption bundle. Similarly, σ_u^2 may take into account the individual’s imprecision in remembering historical prices. See Cavallo et al. (2014) for evidence of these two options.

The individual has two beliefs: one about the inflation rate, π , and another about the government bias, b . We denote π_0 as the belief of the inflation rate prior to obtaining new information, and π_1 as the belief of the inflation rate after doing so, while b_0 and b_1 are similarly defined. The normality assumption about the distribution of price changes determines that the conjugate distribution for beliefs about inflation and bias is bi-variate normal. For the sake of notational simplicity, we focus on the case where the prior beliefs for the inflation rate and the bias are orthogonal. In the Appendix B.3 we show that under these assumption we obtain the following equations for the posterior beliefs:

$$\pi_1 = (1 - \omega_1 - \omega_2) \pi_0 + \omega_1 \bar{u} + \omega_2 (\bar{o}' - b_0) \tag{1}$$

$$b_1 = (1 - \psi_1 - \psi_2) b_0 + \psi_1 (\bar{o}' - \pi_0) + \psi_2 (\bar{o}' - \bar{u}) \tag{2}$$

The mean posterior belief for the inflation rate, π_1 , is a weighted average between the mean prior belief, π_0 , the unofficial inflation rate, \bar{u} , and the bias-adjusted official statistics, $\bar{o}' - b_0$. The mean posterior belief for the government bias, b_1 , is a weighted average between the prior belief, b_0 , the gap between the official statistics and the prior belief about inflation, $\bar{o}' - \pi_0$, and the gap between the official statistics and the unofficial statistics, $\bar{o}' - \bar{u}$. The parameters ω_1 , ω_2 , ψ_1 , and ψ_2 are weights that depend on the precision of the signals and prior beliefs. Details for these weights are provided in the Appendix.

The most important prediction of this model is that a Bayesian learner is not expected to ignore biased statistics, but instead rationally adjust to the perceived bias. The following two scenarios are useful to understand the intuition of the model.

A first scenario explores how an individual who starts thinking that the government is not lying reacts to an official signal that is different to its prior. In particular, consider an individual that starts with $b_0 = 0$ and gets signals $\bar{u} = \pi_0$ (the unofficial signal equals the prior) and $\bar{o}' < \pi_0$ (the official signal is lower than the prior). The individual can attribute the low level of the official

statistic to a bias or believe that is driven by sampling variation. How fast would the individual learn about a bias? By making the relevant replacements in the above formula for b_1 we get that $b_1 = (\psi_1 + \psi_2)(\bar{\sigma}' - \pi_0)$. The term $\psi_1 + \psi_2$ is a set of weights that increases with the precision of both the official and unofficial signals. So, for example, if the individual perceived that there is a lot of measurement error in either of those signals, she would not change so rapidly her belief about a bias in the official data.

A second scenario explores how an individual who believes that the government is manipulating statistics reacts to the official statistics relative to the unofficial statistics. In the data, this will be studied by means of a series of information experiments during the period of manipulated statistics. Consider an individual that starts out thinking that the government biases the inflation statistics downwards: i.e., $b_0 < 0$. How does the individual react to official statistics relative to unofficial statistics? From the formula for π_1 it follows that the individual reacts to $\bar{\sigma}'$ almost the same as it reacts to \bar{u} , but with the exception that first it subtracts from $\bar{\sigma}'$ the ex-ante perceived bias: i.e., it uses $\bar{\sigma}' - \pi_0$ instead of $\bar{\sigma}'$. So if the individual believes that the bias is $b_0 = -10$, then she should react to the information $\bar{u} = 10\%$ in the same way that it reacts to $\bar{\sigma}' = 20\%$. There is, however, a small difference. If the precision of unofficial and official statistics were similar, $\frac{1}{\sigma_u^2} = \frac{1}{\sigma_o^2}$, she would still put more weight to \bar{u} than to $(\bar{\sigma}' - b_0)$. The reason is that $\omega_1 > \omega_2$ (see Appendix for details) because, when doing the correction $\bar{\sigma}' - b_0$, the individual is using b_0 , which has some uncertainty of its own.

Lastly, the existence of a bias affects the variance of posterior belief π_1 , but the level of the bias b_0 is not important. That is, the certainty of the individual about the inflation rate does not depend on the perceived magnitude of the government bias. This result depends crucially on the assumption that individuals know that the government manipulates the information by adding or subtracting a fixed number to the raw statistic (as we saw in the previous section, this might be a good approximation for the case of Argentina). In practice, individuals may be uncertain about the exact form in which the government manipulates the statistics. In that case, the existence of a bias would lead to significantly less informed agents.⁹

3.2 Experimental Design

The survey experiment in this section is related to a group of recent studies on how individuals learn about inflation and how they form their inflation expectations (e.g., Roos and Schmidt, 2012; Armantier et al., 2012a; Cavallo et al., 2014). Our survey was conducted online. We first collect

⁹For example, the government may be scaling down the true statistics by a certain factor, or they may be doing something more pervasive thus making more difficult to extract useful information from the official statistics. Individuals may use the co-evolution of official and unofficial statistics to learn which is the most accurate model for the government-induced “bias” from manipulation. Adding uncertainty about the model of the bias would add extra parameters that the individual should learn from, thereby decreasing the individual’s certainty about the inflation rate. In the extreme case, if the government reports a statistic that is purely noise (i.e., orthogonal to the raw estimate before the manipulation), then the individual will simply choose to ignore official statistics altogether.

some background information about respondents, and we then randomly assign the subjects to different groups that are provided different information related to inflation (subjects in the control group receive no information).

The informational treatments consist of information about inflation rates for the previous 12 months (levels of 10%, 20% and 30%) according to different official and unofficial sources. We cross-randomize the three inflation levels and the two sources of information in a non-deceptive way, resulting in six different treatment groups and the control group.

After providing the information, we elicit subjects' perceptions about current inflation levels (i.e. their perception about the annual inflation rate over the previous 12 months), and their inflation expectations (i.e. what they expect about inflation for the following 12 months). This allows us to measure how a particular signal about inflation affects the distribution of inflation perceptions and expectations. We also include a question about the respondents' own subjective assessment about their confidence on their answers, measured in a 1 ("Not at all sure") to 4 ("Very sure") scale. The source of information and the level of inflation were the only variation between treatment groups (those in the control group were not presented with any additional information).

We use three official sources of inflation for the treatments. The first one is INDEC's CPI, the most widely quoted and used official inflation statistic in the country. This was the main indicator targeted by the government's manipulation. At the time of our experiment, its annual inflation rate was approximately 10% (we rounded all the inflation rates to integer numbers in the experiment). Fortunately for our experiments, there were other indicators computed by INDEC's that reflected different inflation levels. One was the GDP deflator, which at the time of the experiment was 20%. The GDP deflator was lower than the real inflation rate shown by unofficial estimates, but the government could not allow it to be as low as the CPI (10%), because that would have implied an implausibly high real GDP growth rate (over 15%). The GDP deflator is not widely used as a measure of inflation, but before 2007 it closely tracked the CPI in Argentina. The divergence after 2007 is additional evidence of the manipulation in the CPI.¹⁰ We also use a third statistic compiled by INDEC and routinely used by local economists as an inflation proxy, the rate of growth of nominal wages. At the time of our survey, this indicator was around 30% per year (which the government advertised extensively to argue that real wages were increasing). The information provided to the groups of subjects randomly selected to receive information from an official source of statistics stated that, according to data from INDEC, the annual inflation rate was about X%, where X was randomly chosen to be either 10, 20 or 30 (see the Appendix C for the exact wording of these information treatments).

We also exploited the variation in the unofficial estimates seen in Figure 2, which in late 2012 ranged from 20% to 30%. A third unofficial index (not shown in Figure 2) was published by a think tank with close ties with the government and had an inflation rate of about 10% at the time of the experiment. Those people selected to receive information from unofficial sources were told

¹⁰See Cavallo (2013) for estimates of real GDP growth until 2011 using unofficial inflation statistics.

that according to private estimates the annual inflation rate was about $X\%$, where X was randomly chosen to be either 10, 20 or 30 (exact wording in the Appendix).

When eliciting inflation perceptions and expectations, we state our question using the word “inflation”, instead of referring to “prices in general” or other indirect references to inflation, as is commonly done in the United States and other developed countries.¹¹ As discussed in the previous section, Argentina’s economic history implies that the general public is well aware of inflation, which is discussed routinely in the media.¹² Similarly, our question about inflation expectations was: “What do you think will be the annual inflation rate for the following 12 months?” (see Appendix C for more details about the questionnaire and wording). Finally, we did not provide any incentives for respondents to answer accurately, such as prizes for guessing the right figures, since as shown by Armantier et al. (2012) in the context of similar studies, there is a significant correlation between incentivized and non-incentivized responses on inflation expectations.

We emphasize that we did not deceive the experimental subjects: we only conveyed information that was actually circulating in the public discussion in Argentina, and we did not claim that the information provided was true or false, nor did we endorse or disavow implicitly or explicitly any of the sources. We merely stated that according to a given source, the level of annual inflation was estimated to be $X\%$. In any case, since some of this information corresponded to manipulated statistics, and individual’s judgment about the information could vary depending on the source, we included a debriefing at the end of the questionnaire. In this debriefing statement, we disclosed that the information about inflation that we provided was randomly selected from six possible messages, with the detailed source and explanation for each of those messages. We presented the same debriefing statement to all subjects, irrespective of the treatment group to which they were assigned. Our purpose was that the subjects should leave the experiment with more and better information than what they had at the beginning of the experiment.

A small but not negligible number of individuals abandoned the questionnaire after the information treatment and the question on inflation perceptions, and before reporting their inflation expectations (105 out of 3,243, or 3.23% of the original sample). While this type of attrition occurred also in previous rounds of the opinion poll (for instance, dropout of 5.8% of the sample for the June 2012 round), in this case this might be a concern if the attrition was due to (and correlated to) the information treatments, since this could introduce biases in the experiment and complicate the interpretation of the treatment effects. For instance, government supporters who believe that inflation is low may have abandoned the experiment because they did not like to see

¹¹For instance, the University of Michigan’s Survey of Consumers elicits inflation expectations by means of the following questions: “During the next 12 months, do you think that prices in general will go up, or go down, or stay where they are now?” with three options: “Go up,” “Stay the same” and “Go down,” and then asks “By about what percent do you expect prices to change, on average, during the next 12 months?” with an open numerical answer.

¹²Moreover, the previous rounds of the online opinion poll into which we built our survey experiment used the wording in terms of inflation, as did other sources for inflation expectations, such as the Encuesta de Expectativas de Inflación from the Centro de Investigación en Finanzas, Universidad Torcuato Di Tella.

information from unofficial sources reporting high inflation levels (the opposite situation could arise with respondents opposed to the government and with high inflation perceptions). Attrition rates ranged from 2.7% to 4.1% for the different treatment groups, with 3.5% for the control group. We test for selective attrition, and we cannot accept the null of differential attrition by treatment group (p-value: 0.79). In unreported results, we tried models that correct for selective attrition among treatment groups, for example estimating bounds (Lee, 2009). However, the attrition rates were so low that the bounds are very similar to the uncorrected point estimates.

3.3 Subject Pool and Experimental Results

The sample is based on an established public opinion research firm that carries out a quarterly online survey of adults in Argentina with the same set of basic questions since 2011. The experiments were conducted on December of 2012. We slightly modified the standard format of this public opinion survey to fit our experimental design. In particular, our survey experiment was included early in the questionnaire’s flow, after which it continued with the usual set of questions about politics, politicians and public affairs. These questions are not used as outcomes in our analysis, although we use some of them for descriptive purposes and to verify the balance between treatment groups. The respondents were assigned to the control group with a probability of 22.6%, and to each of the treatment groups with a probability of 12.9%. The final sample on which the following analysis is based consists of all the respondents that completed the questions on inflation perceptions and inflation expectations, yielding a final sample of 3,138 observations.

Table 1 presents some summary statistics about the demographics of the sample, along with the corresponding indicators for the general population. This sample is not representative of the Argentine general population: while it is roughly similar in terms of age and gender composition, our sample is substantially more educated (and richer) than average. Nevertheless, the qualitative results are similar if we re-weight the observations to match the distribution of characteristics at the national level (not reported).

Table 1: Descriptive Statistics. Opinion Poll Experiment Sample Characteristics Compared to Argentina’s Population

	Proportion of Women	Age (20+)	Greater Buenos Aires	College Degree	Voted C.F. Kirchner
Online Experiment Sample	57%	41.1	67.7%	60.7%	24.2%
Argentina’s Average (20 years old or older)	52.8%	44.9	36.3%	15.6%	54.1%

Notes: Source: First row (Online Experiment Sample): opinion poll carried out in December 2012 (N=3138). Second row (Argentine Average): computed from the Encuesta Anual de Hogares Urbanos, 2012 (INDEC), except for the “Voted C. F. Kirchner” variable, obtained from the 2011 presidential election results. All statistics are based on individuals aged 20 or older in the corresponding samples. “Proportion of Women” is the percentage of women in each sample. “Age” is average age in years. “Greater Buenos Aires” represents the percentage of those living in the Greater Buenos Aires Metropolitan Area. “College Degree” represents the proportion of respondents who have a college degree or completed tertiary education. “Voted C. F. Kirchner” is the percentage who reported to have voted for Cristina Fernandez de Kirchner (CFK).

Table 2 presents descriptive statistics for all the variables used in the analysis, including pre- and post-treatment variables, for the control group and for each of the treatment groups. The last column reports the p-value of a test in which the null is that the mean of each variable is equal in all seven experimental groups. As expected, these tests are not rejected for any of the pre-treatment variables, suggesting that the randomization was indeed balanced.

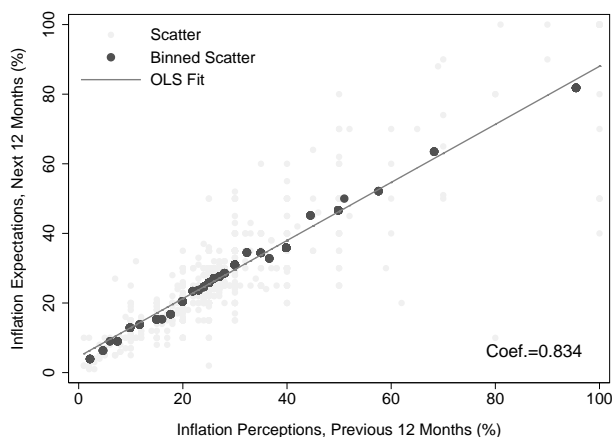
Table 2: Average pre- and post-treatment responses by treatment group

	Control	Official 10%	Official 20%	Official 30%	Unofficial 10%	Unofficial 20%	Unofficial 30%	P-value
<i>Post-Treatment</i>								
$\pi_{i,t}$	28.31 (0.591)	28.55 (0.812)	33.58 (0.809)	42.10 (0.815)	26.37 (0.805)	28.89 (0.809)	34.78 (0.816)	<0.01
Standard Deviation of $\pi_{i,t}$	15.89 (0.911)	13.94 (1.128)	16.01 (1.098)	19.43 (0.970)	14.36 (1.207)	14.55 (1.193)	18.57 (1.130)	<0.01
Confidence in $\pi_{i,t}$	3.288 (0.0256)	3.456 (0.0352)	3.350 (0.0351)	3.272 (0.0354)	3.364 (0.0349)	3.428 (0.0351)	3.435 (0.0354)	<0.01
$\pi_{i,t+1}$	28.20 (0.595)	28.22 (0.817)	33.32 (0.814)	39.24 (0.820)	26.29 (0.810)	28.62 (0.814)	33.99 (0.821)	<0.01
<i>Pre-Treatment</i>								
Proportion of Women	0.560 (0.0181)	0.539 (0.0248)	0.563 (0.0247)	0.586 (0.0249)	0.601 (0.0246)	0.545 (0.0247)	0.608 (0.0250)	0
Age	41.11 (0.390)	41.06 (0.536)	40.64 (0.534)	40.79 (0.538)	40.93 (0.532)	41.37 (0.534)	41.16 (0.539)	0.97
College Degree	0.633 (0.0178)	0.610 (0.0245)	0.650 (0.0244)	0.581 (0.0246)	0.572 (0.0243)	0.600 (0.0244)	0.578 (0.0246)	0.12
Own Economic Situation OK	0.261 (0.0155)	0.237 (0.0213)	0.228 (0.0212)	0.203 (0.0214)	0.233 (0.0211)	0.257 (0.0212)	0.211 (0.0214)	0.26
Observations	750	397	400	394	404	400	393	

Notes: Each cell represents the mean of each of the row variables for the corresponding control and treatment groups (in columns). The standard errors of these means are reported in parentheses below. The standard errors for the standard deviation of inflation perceptions ($\sigma_{\pi_{i,t}}$) are based on 2,500 replications for each of the groups. The last column reports the p-value of a balance test in which the null is that the mean of each variable is equal between all seven experimental groups (the control group and the six treatment groups). $\pi_{i,t}$ represents the respondent's inflation perceptions for the previous twelve months. "Confidence in $\pi_{i,t}$ " represents the respondent's own confidence on her response to the perceptions question on a 1 to 4 scale ("Not confident at all" to "Very confident"). The standard deviation of $\pi_{i,t}$ is the standard deviation of perceptions for each group. $\pi_{i,t+1}$ represents the respondent's inflation expectations for the following twelve months. "Proportion of Women" is the percentage of women in each sample. "Age" is the average age in years. "College Degree" represents the proportion of respondents who have a college degree or completed tertiary education. "Own Economic Situation OK" is a variable equal to one for those who responded that their economic situation was better with respect to one year earlier, and zero otherwise. Source: Online Experiment Sample (opinion poll carried out in Argentina in December 2012).

The top panel shows the post-treatment variables. We have post-treatment data on both inflation perceptions and expectations. The first row shows that the average perception of the control group, at 28.31%, is very similar to the average perception of those that received an official estimate of 10% and an unofficial signal of 20%. These were the levels of official and unofficial inflation that people likely expected to see, given that the CPI had consistently been close to 10% for several years, and the unofficial indicators were hovering 20% from 2007 to 2012. Note, however, that higher levels of official inflation and different levels of unofficial inflation significantly change the means. We discuss this impact in more detail below. The second row shows that the standard deviation of inflation perceptions tends to rise with the level of inflation in the signal, but mean confidence levels in the beliefs remain roughly the same in all informational treatments. The fourth row provides the means for inflation expectations, which closely resemble the means for inflation perceptions. Indeed, inflation perceptions are strongly correlated with expectations in our surveys, as can be seen in Figure 4.

Figure 4: Past Inflation Perceptions and Future Inflation Expectations, Binned Scatter plot

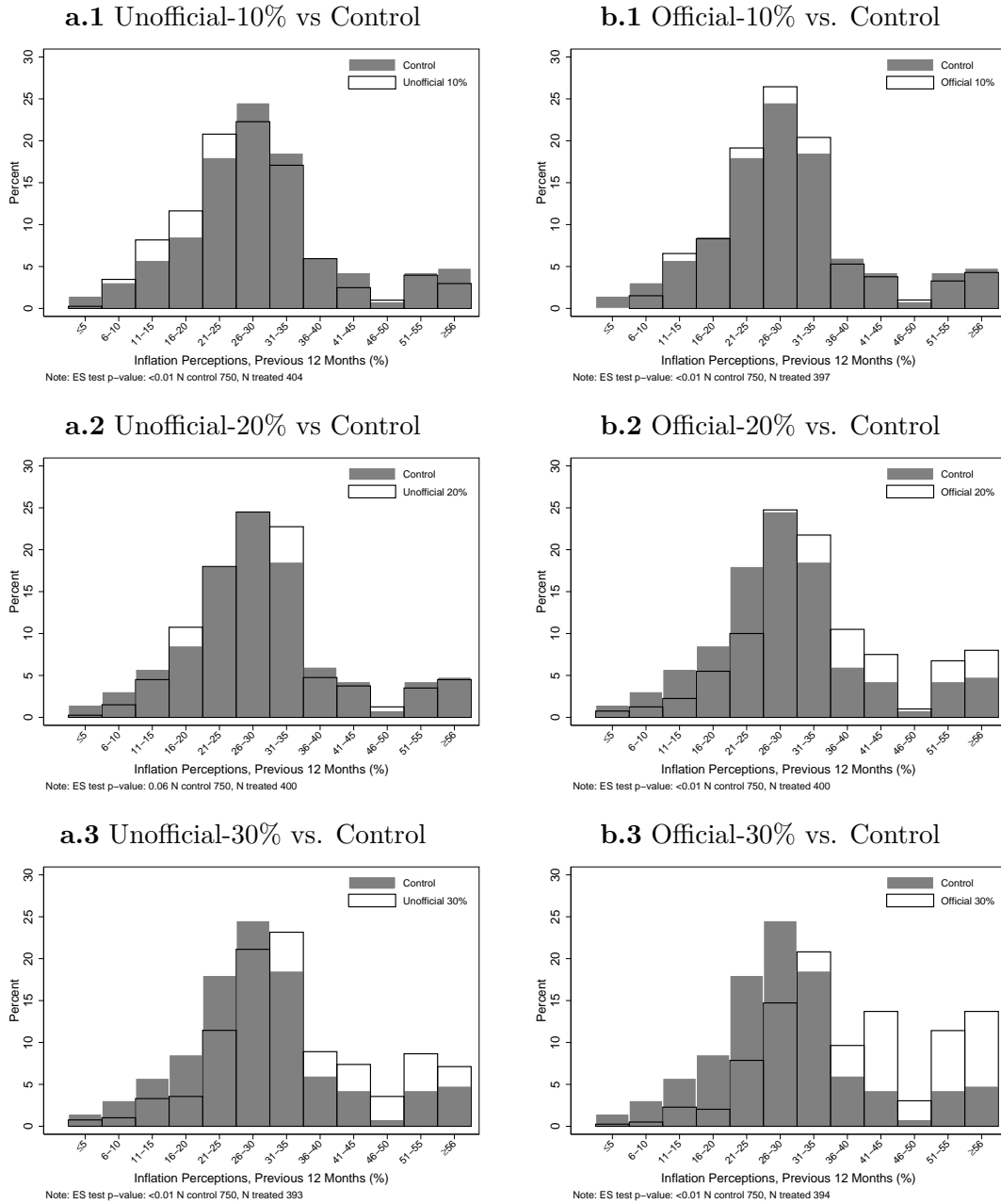


Notes: N=777. Source: Online Experiment Sample (see Section 3 below for details). This data is for subjects in the control group, i.e., those who were not provided any information about inflation.

Our benchmark results in this section are based on inflation perceptions, which are directly related to the information signals provided by the experiment (past 12 months data), but they are equivalent to those that are obtained from inflation expectations, as we argue below.

The main experimental results are presented in two complementary ways. In Figure 5 we show the distribution of inflation perceptions in the control group compared to that of each of the six informational treatments. Figure 6 summarizes the effects of the six informational treatments on the mean of various post-treatment outcomes relative to the control group.

Figure 5: Histograms Comparing Distribution of Inflation Perceptions between Control and Treatment Groups



Notes: Observations: 750 in the control group, 397 in the Official-10% group, 400 in the Official-20% group, 394 in the Official-30% group, 404 in the Unofficial-10% group, 400 in the Unofficial-20% group, and 393 in the Unofficial-30% group. Respondents in the control group were not given any information about inflation statistics. Respondents in the Official-X% groups were provided non-deceptive information about inflation estimates from official sources (either 10%, 20% or 30% in the previous year). Respondents in the Unofficial-X% groups were provided non-deceptive information about inflation estimates from unofficial sources (either 10%, 20% or 30% in the previous year). ES is the Epps-Singleton characteristic function test of equality of two distributions (Goerg and Kaiser, 2009). The histograms are censored at 5% and 56% (inclusive), but these bins represent the cumulative observations below 5% and above 56% respectively. Source: Online Experiment Sample (opinion poll carried out in Argentina in December 2012).

The first hypothesis to test is whether individuals reacted at all to the information we provided. Relative to individuals who were told that inflation according to official statistics was 20%, individuals who were told that official statistics was lower (10%) reported lower inflation perceptions, and individuals who were told that official statistics indicated higher inflation (30%) reported higher inflation perceptions. We conducted the 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). According to the ES test of equality of distribution, these two pairwise differences in distributions are statistically significant at the 1% level. These differences are substantial, and economically significant: the mean of inflation perceptions is 28.5% for the Official-10% group, 33.6% for the Official-20% group and 42.1% for the Official-30% group.

Second, we must assess whether this reaction to official statistics was naive. The naive model would predict that households react to information on a given level of inflation from an official source in the same way than they would to the same figure from unofficial sources. The data strongly rejects this hypothesis: the ES test indicates that the difference between the distribution of inflation perceptions across individuals given messages Official-10% and Unofficial-10% is significant at the 1% level; the same is true when comparing distribution of perceptions for the Official-20% and Unofficial-20% groups, and for the Official-30% and Unofficial-30% groups. As in the previous results, these differences are sizable and economically significant: the mean inflation perceptions are 28.5% (Official-10%) and 26.4% (Unofficial-10%), 33.6% (Official-20%) and 28.9% (Unofficial-20%), and 42.1% (Official-30%) and 34.8 (Unofficial-30%), respectively.

We can also use these results to test our rational learning model. A plausible heuristic for the period under study is that official inflation rates were systematically 10 percentage points below those from unofficial sources. Based on this approximation, the learning model predicts that individuals should react to information conveying an official inflation level of $X\%$ in the same way as they would react to information from unofficial sources conveying a level of inflation of $(X-10)\%$. The results from our experiment are consistent with this hypothesis: we cannot reject the null hypothesis that the distribution of inflation perceptions are equal between individuals in the groups Official 10% and Unofficial 20% (ES test p-value of 0.91), and we cannot reject the null hypothesis that the distribution of inflation perceptions are equal between individuals with messages Official 20% and Unofficial 30% (ES test p-value of 0.61). The differences in the mean of inflation perceptions between the two distributions are also small and economically insignificant: only -0.34 percentage points between the Official 10% and Unofficial 20% groups, and -1.2 percentage points between the Official 20% and Unofficial 30% groups.

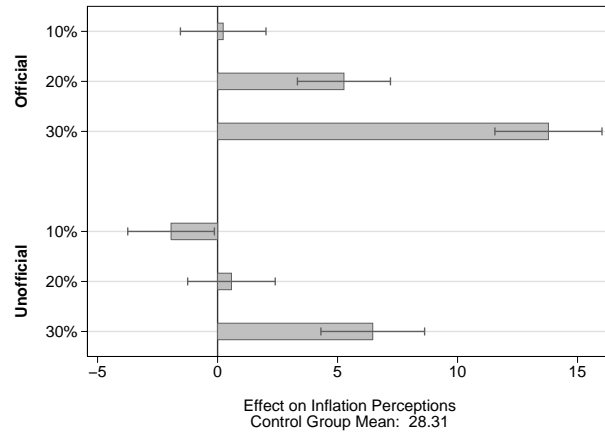
The experiment also allows us to explore further the seemingly asymmetric reaction to actual inflation suggested by the analysis of the non-experimental time series data on inflation levels and expectations discussed in the previous sections. As shown in Figure 6, individuals who received information from unofficial sources stating that inflation was 10% (Unofficial-10%) reported inflation perceptions 2.51 percentage points lower (significant at the 5% level) than those who received

information from similar sources but stating that inflation was 20% per year (Unofficial 20%). Also relative to the latter group (Unofficial 20%), those who received instead information signaling higher inflation levels (Unofficial 30%) reported inflation perceptions on average 5.89 percentage points higher (significant at the 1% level). The difference between the absolute value of these two effects is also statistically significant at conventional levels (p-value of 0.072), implying that individuals were twice as reactive to information about higher inflation than to information about lower inflation. The results are similar for those who received signals from official sources: inflation perceptions are 5 percentage points lower in the Official-10% group than in the Official-20% group, and they are 8.5 percentage points lower in the latter group compared to the Official-30% group. The difference in the absolute value of these two effects is also statistically significant (p-value of 0.082), and we cannot reject the hypothesis that the reaction to the higher signal is twice as large as the reaction to the lower signal. This asymmetry in the experimental results is consistent with the evidence in Section 2.3, where we compared the time series of inflation expectations and unofficial inflation statistics. It suggests that the policy of manipulating official statistics was counterproductive, making expectations flexible on the way up and sticky on the way down.

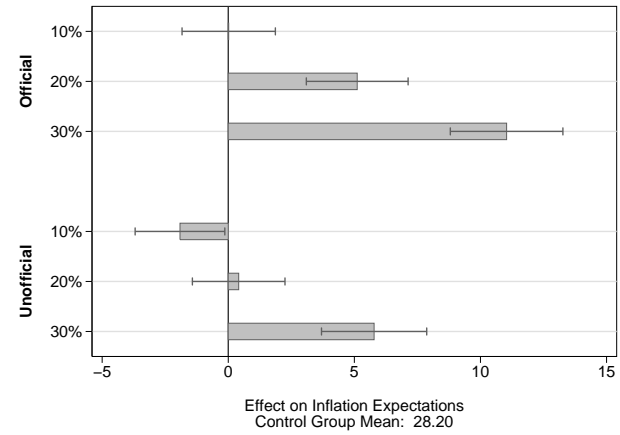
Figure 6 provides some additional insights. First, while we focused on the effects of our informational treatments on inflation perceptions, panels a) and b) indicate very similar effects on inflation expectations. This is consistent with the notion that individuals use their past inflation perceptions to form their future expectations, as discussed in Cavallo et al. (2014). Second, the results in Figure 6c indicate that several of the informational treatments substantially increased the subjects' reported confidence on their inflation perceptions. The difference between all treated and control individuals is 0.095, significant at the 1% level, indicating that the information seems to have been useful for the experimental subjects. However, the effect on confidence is almost twice as large from unofficial sources (0.151 compared to 0.086, p-value of the difference 0.066), suggesting that the information from unofficial sources was more useful than that from official sources.

Figure 6: Treatment Effects on Inflation Perceptions and Expectations

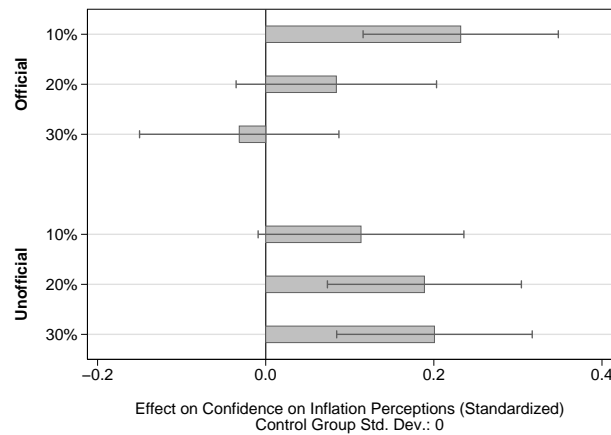
a. Mean Perceived Inflation ($\pi_{i,t}$)



b. Mean Expected Inflation ($\pi_{i,t+1}$)



c. Mean Standardized Confidence in Perceived Inflation ($\pi_{i,t}$)



Notes: Observations: 750 in the control group, 397 in the Official-10% group, 400 in the Official-20% group, 394 in the Official-30% group, 404 in the Unofficial-10% group, 400 in the Unofficial-20% group, and 393 in the Unofficial-30% group. Each bar represents the point estimate of the effect of the specific sub-treatment compared to the control group. Robust standard errors reported. $\pi_{i,t}$ represents the respondent's inflation perceptions for the previous twelve months. "Confidence in $\pi_{i,t}$ " represents the respondent's own confidence on her response to the perceptions question on a 1 to 4 scale ("Not confident at all" to "Very confident"), standardized by the control group's mean and standard deviation. $\pi_{i,t+1}$ represents the respondent's inflation expectations for the following twelve months. Source: Online Experiment Sample (opinion poll carried out in Argentina in December 2012).

4 The Price Controls of 2013

In Cavallo, Cruces and Perez-Truglia (2014) we show that individuals do not only form inflation expectations from inflation statistics, but they also put significant weight on their perceptions about prices of supermarket products. This implies that the government could try to manipulate inflation expectations by changing the actual prices of salient products.

In February 2013, the government of Argentina significantly extended its policy of price controls on retail products. These were “price agreements” with big companies and large supermarket chains temporarily applied for hundreds of products in carefully selected categories. The government targeted goods that had a significant weight in the CPI basket, and focused on brands and retailers with large market shares. To enforce the price controls, the government publicly asked its supporters to help monitor prices. The program was called “Precios Cuidados” (“Protected Prices”). It was widely advertised and discussed in the media. While there were some problems in the implementation, most of the goods included in the agreements were available for sale at the agreed prices. This is visible in the unofficial inflation series from PriceStats depicted in Figure 3, which fell from an annual inflation rate of 25.8% in January 2013 to 17.7% in May 2013. The Pricestats index draws its data mostly from large multi-channel retailers (which sell both online and offline), where the government was focusing its price control efforts.

The government apparently hoped that by controlling the prices for some key individual goods it could have a stronger effect on inflation expectations. Indeed, the Finance Minister repeatedly mentioned that the price controls were meant to “provide predictability to the economy”.¹³

Inflation levels did temporarily fall, but they had no impact on inflation expectations, which remained stable near 30%. There are several possible explanations for this. One option is that people knew the effect would be temporary, so expectations about future inflation were not impacted. This probably played an important role, but we do not have a way to test it.

Another possibility is that even though people experienced more stable prices for some goods, the information was not processed in the way the government was hoping for. To test this, we ran a consumer-intercept survey in the front door of four branches of one of the largest supermarket chains in the city of Buenos Aires, during the time of the price controls. 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 three to five minutes). Using hand-held scanners, our interviewers scanned respondents’ receipt from the supermarket purchase, which contained product identifiers that were matched to a database of scrapped online data from the same supermarket.¹⁴After scanning their receipts, respondents were asked about the prices changes they thought the products they had just purchased had experienced in the previous year.

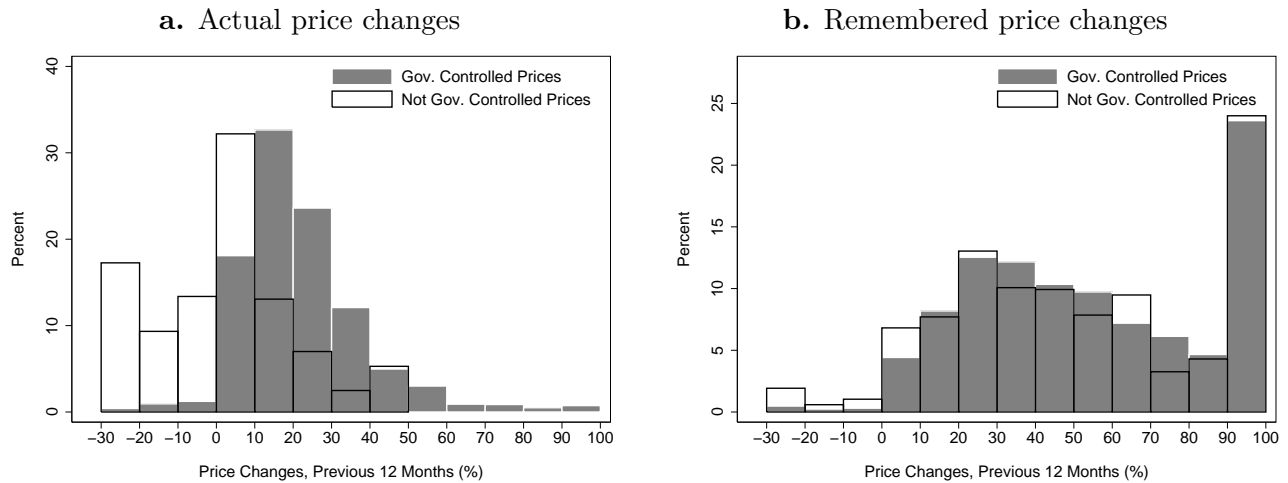
With these data we can distinguish the consumer’s perceived price changes of controlled and

¹³See for example <http://www.economia.gob.ar/wp-content/uploads/2014/04/07-04-20142.pdf>

¹⁴Prices were scrapped from the websites of the supermarket by the Billion Prices Project at MIT. See Cavallo (2013) for more details.

non controlled products, and match the respondents' perceptions with the actual price changes in the same supermarket chain. Panel a in Figure 7 depicts the distribution of actual price changes for products with controlled prices, and for those with no controls. The first results that emerges is that products with controlled prices did have a substantially lower inflation rate – average change of 1.9% compared to 21.7% for non-controlled products. However, panel b indicates that the program was not effective in changing individual perceptions of price changes: the distribution of remembered price changes (as reported by the respondents/consumers) are very similar for both types of goods. Individuals clearly overstated the level of price changes for the controlled products, even when the program was temporarily effective at moderating their price increases at the points of purchase where we conducted our survey. It should be stressed that respondents were asked about the prices of products they had just purchased, and not asked to guess aggregate price changes or random products. The comparison between panels a) and b) shows a clear upward bias in remembered price changes. Consumers not only failed to perceive a difference between controlled and non-controlled goods, they were also too pessimistic remembering prices in both cases.

Figure 7: Actual and Remembered Price Changes for Products with Government Controlled Product Prices, Supermarket Survey



Notes: The total number of observations is 1,140. Source: consumer intercept survey carried out by the authors in June 2013 in four branches of one of the largest supermarket chains in the city of Buenos Aires. Respondents to this survey were asked about the price changes with respect to a year earlier of products they had just purchased at a supermarket (remembered price changes), and we matched those products with their current and past prices of the same products in the same stores (actual price changes; see Section 4 and Cavallo et al., 2014, for more details about the survey). Panel a presents the distribution of actual prices changes from our database of historical supermarket prices. Panel b represents the remembered price changes for the same products as reported by the respondents. The two figures present separate distributions for products with prices controlled by the government and those with no price controls at the time of the survey. See Section 4 for more details about the price controls.

While the government’s underlying objective may have been to control the prices of some key products in order to reduce inflation expectations, the evidence suggests that this strategy failed. Perhaps people understand that their memories of prices are inaccurate and choose not to use them to form expectations, or perhaps they simply believe prices are rising faster because the government is trying to convince them otherwise. In any case, just as it happens with the manipulation of the aggregate official index, good-level price controls do not seem to be an effective way to influence inflation expectations.

5 Conclusions

To understand how households learn from potentially-biased statistics, we exploit data from a natural experiment and a survey experiment based on the period of government manipulation of inflation statistics in Argentina. The evidence suggests that rather than ignoring biased statistics or taking them at face value, households react as predicted by a model of Bayesian learner, by de-biasing the official data to extract all its useful content. That is, in an environment with many alternative inflation indicators and a great deal of attention to the topic, people are sophisticated learners that can effectively process potentially-biased information. The government’s attempt to manipulate the data, either through the aggregate price index or with targeted price controls, was both ineffective and counterproductive.

These lessons are useful for understanding formation of inflation expectations in less extreme contexts than Argentina, such as the United States and Europe, where experts may believe that statistics are unbiased but households do not. For example, in Cavallo, Cruces and Perez-Truglia (2014) we surveyed people in the US and found that 32% did not trust the official inflation data. This group had inflation expectations that were significantly higher than the rest. The average inflation expectation for the group that did not trust the official statistics was 6.36 (s.e. 7.19), compared to an average of 4.22 (s.e. 4.26) in the rest of the sample (we can reject the null of equality in with a p-value of 0.001). Our current paper suggest that the difference could be driven by the way people adjust for their perceived biases in the official data. One policy implication is that governments should not only focus on providing information, but make efforts to reduce the perception of a potential bias.

More empirical evidence is needed to understand how inflation and other expectations are formed. Experimental results, in particular, can help the large theoretical literature that tries to model the formation of expectations to determine whether people use adaptive, rational, natural (Furster et al 2010), diagnostic (Bordalo et al 2015), or other types of expectations in different settings. In particular, the evidence from Argentina suggests that perceived biases in the signals are capable of creating asymmetric responses in expectations. More work is needed to understand why this happens and clarify the circumstances under which people tend to over-react and under-react to information.

References

- [1] Armantier, O., Bruine de Bruin, W., Potter, G., Topa, G., van der Klaauw, W. and Zafar, B. (2013). “Measuring Inflation Expectations,” *Annual Review of Economics*, Vol. 5, pp. 273-301.
- [2] Armantier, O., Nelson, S., Topa, G., van der Klaauw, W. and Zafar, B. (2014). “The Price Is Right: Updating of Inflation Expectations in a Randomized Price Information Experiment,” *Review of Economics and Statistics*, forthcoming.
- [3] Armantier, O., Bruine de Bruin, W., Topa, G., der Klaauw, V., Wilbert, H., and Zafar, B. (2012). “Inflation expectations and behavior: Do survey respondents act on their beliefs?” *Federal Reserve Bank of New York Staff Report No. 509*.
- [4] Atkeson, A. and Ohanian, L, (2001). “Are Phillips curves useful for forecasting inflation?,” *Quarterly Review*, Federal Reserve Bank of Minneapolis, issue Win, pages 2-11.
- [5] Badarınza, C. and Buchmann, M. (2009). “Inflation Perceptions and Expectations in the Euro Area: The Role of News,” *ECB Working Paper 1088*.
- [6] Bernanke, B. (2007). “Inflation Expectations and Inflation Forecasting”, Speech at the Monetary Economics Workshop of the NBER Summer Institute, Cambridge, Massachusetts, July 10, 2007. Available at: <http://www.federalreserve.gov/newsevents/speech/bernanke20070710a.htm>, last accessed on December 2012.
- [7] Bevacqua, G. and Salvatore, N. (2009). “Argentina. La reconstrucción de la serie de inflación minorista: El IPC City.” Buenos Aires City, Facultad de Ciencias Económicas, Universidad de Buenos Aires.
- [8] Bishop, C. (2006), “Pattern recognition and machine learning.” New York: Springer.
- [9] Blanchflower, D. and Mac Coille, C. (2009). “The formation of inflation expectations: an empirical analysis for the UK,” Paper presented at Banco do Brasil X1 Annual Inflation Targeting Seminar, Rio de Janeiro.
- [10] Branch, W. (2004). “The Theory of Rationally Heterogeneous Expectations: Evidence from Survey Data on Inflation Expectations,” *Economic Journal*, Royal Economic Society, vol. 114(497), pages 592-621, 07.
- [11] Bruine de Bruin, W., van der Klaauw, W., Downs, J., Fischhoff, B., Topa, G. and Armantier, O. (2010). “The effect of question wording on reported expectations and perceptions of inflation,” *Staff Reports 443*, Federal Reserve Bank of New York.

- [12] Bruine de Bruin, W., van der Klaauw, W., Topa, G. (2011), “Expectations of inflation: The biasing effect of thoughts about specific prices,” *Journal of Economic Psychology*, Volume 32, Issue 5, Pages 834-845.
- [13] Burke, M. and Manz, M. (2011), “Economic literacy and inflation expectations: evidence from a laboratory experiment,” *Public Policy Discussion Paper 11-8*, Federal Reserve Bank of Boston.
- [14] Camacho, M., Dal Bianco, M. and Martinez-Martin, J.. (2015) “Toward a more reliable picture of the economic activity: An application to Argentina.” *Economics Letters* 132129-132.
- [15] Carrillo, P.E., and Shahe Emran, M. (2012). “Public information and inflation expectations: Microeconometric evidence from a natural experiment,” *Review of Economics and Statistics*, Vol. 94 (4), pp. 860-877.
- [16] Carroll, C. (2003). “Macroeconomic Expectations of Households and Professional Forecasters,” *Quarterly Journal of Economics*, 118(1).
- [17] Cavallo, A.; Cruces, G. and Perez-Truglia, R. (2014), “Inflation Expectations, Learning and Supermarket Prices: Evidence from Field Experiments,” *NBER Working Paper 20576*.
- [18] Cavallo, A. (2013). “Online and Official Price Indexes: Measuring Argentina’s Inflation”, *Journal of Monetary Economics*. Volume 60, Issue 2, pp. 152-165.
- [19] Cavallo, A. and Rigobon, R. (2012). “The Distribution of the Size of Price Changes,” *NBER Working Paper 16760*.
- [20] Curtin, R. (2009), “What U.S. Consumers Know About The Economy: The Impact Of Economic Crisis On Knowledge.” Presented at the 3rd OECD World Forum On “Statistics, Knowledge And Policy,” Busan, Korea - 27-30 October 2009.
- [21] Eurobarometer (2008). “European Working Paper.s’ knowledge of economic indicators,” *Special Eurobarometer 323, Wave 67.2 – TNS Opinion & Social*, European Commission, Brussels.
- [22] Goerg, S. and Kaiser, J. (2009). “Nonparametric testing of distributions—the Epps–Singleton twosample test using the empirical characteristic function,” *Stata Journal*, Vol. 9(3), pp. 454-465.
- [23] Hellwig, C. (2005). “Heterogeneous Information and the Benefits of Public Information actually takes place on Disclosures,” *Working Paper*.
- [24] Lamla, M.J. and Lein, S.M. (2008). “The Role of Media for Consumers’ Inflation Expectation Formation.” *KOF Swiss Economic Institute, Working Paper No. 201*.

- [25] Lee, D. (2009). “Training, Wages, and Sample Selection: Estimating Sharp Bounds on Treatment Effects.” *Review of Economic Studies* 76(3).
- [26] Malmendier, U. and Nagel, S. (2013). “Learning from Inflation Experiences,” Working Paper, Berkeley
- [27] Manski, C. (2004), “Measuring expectations,” *Econometrica* 72(5), pages 1329–1376.
- [28] Michalski, T. and Stoltz, G. (2013). “Do Countries Falsify Economic Data Strategically? Some Evidence That They Might.” *Review of Economics and Statistics*, Vol. 95, No. 2, Pages 591-616.
- [29] Morgenstern, Oskar von (1963). *On the Accuracy of Economic Observations*. 2nd ed actually takes place.. Princeton, NJ: Princeton University Press.
- [30] Morris, S. and Shin, H.S. (2002). “Social Value of Public Information,” *The American Economic Review*, Vol. 92 (5), pp. 1521-1534.
- [31] Norris, F. (2014). “Doubting the Economic Data? Consider the Source.” *New York Times*, November 6, High & Low Finance Op-Ed Column.
- [32] Paredes, J., Pérez, J. and Pérez Quirós, J. (2015). “Fiscal targets. A guide to forecasters?”, CEPR Discussion Paper 10553.
- [33] Rauch, B., Götttsche, M., Brähler, G. and Engel, S. (2011). “Fact and Fiction in EU-Governmental Economic Data.” *German Economic Review*, 12: 243–255
- [34] Roos, M.W.M. and Schmidt, U. (2012). “The Importance of Time-Series Extrapolation for Macroeconomic Expectations,” *German Economic Review*, Vol. 13(2), pp. 196–210.
- [35] Fuster, Andreas, David Laibson, and Brock Mendel. 2010. "Natural Expectations and Macroeconomic Fluctuations." *Journal of Economic Perspectives*, 24(4): 67-84.
- [36] Bordalo, Pedro, Nicola Gennaioli, and Andrei Shleifer. “Diagnostic Expectations and Credit Cycles”. Working Paper. November 2015.

A Appendix

[To be completed]

A.1 Alternative Inflation Indicator in Argentina (2006-2015)

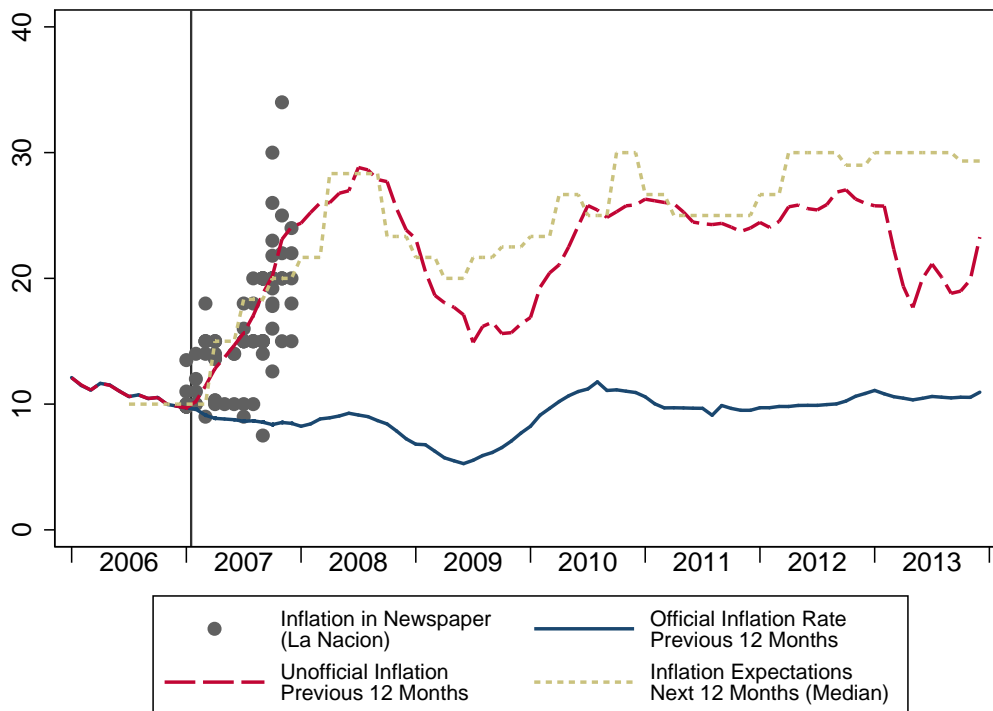
Table 3: Argentina Alternative Inflation Statistics

Active	Type of Institution	Institution	Area	Frequency	Public	Start Date	End Date	Public Start Date	Public End Date	Numer of Products	Fined by Moreno	Data Source
No	Private	Inflacion Verdadera	GBA	Daily	Yes	Nov-07	Aug-12	Nov-07	Aug-12	450		Online Prices
Yes	Private	PriceStats	National - Argentina	Daily	Yes	Oct-07	Today	Mar-11	Today	120,000		Online Prices
No	Private	Centro de Estudios Buenos Aires City	GBA	Monthly	Yes	Jul-08	Dec-09	Apr-09	Dec-09	n/r*		
Yes	Private	Elypsis	National - Argentina	Monthly	Yes	Apr-13	Today	Apr-13	Today	n/r		Online Prices + Estimation + Survey
Yes	Private	Elypsis	CABA	Monthly	Yes	Apr-13	Today	Apr-13	Today	n/r		Online Prices + Estimation + Survey
No	Private	Analytica	CABA, GBA	Monthly	Yes	Mar-07	Mar-10	Mar-07	Mar-10	n/r		Survey (by the provinces)
Yes	Private	FIEL	CABA	Monthly	No	Jan-08	Today	-	-	3,500	Yes	Survey + Online Prices + Receive information directly from retailers
n/r	Private	Ecolatina	CABA, GBA	Monthly	No	n/r	n/r	n/r	n/r	n/r	Yes	Survey
Yes	Private	Estudio Bein & Asociados	GBA	Monthly	No	Jan-08	Today	Jan-08	Jun-11	800	Yes	Survey
Yes	Private	Abeceb	GBA	Monthly	No	Jan-07	Today	-	-	400	Yes	Survey
n/r	Private	Economia y Regiones	n/r	Monthly	No	n/r	n/r	n/r	n/r	n/r	Yes	n/r
Yes	Private	Orlando J Ferreres & Asociados	n/r	Monthly	No	Jan-07	Today	-	-	n/r	Yes	Survey + Online Prices
Yes	Private	M&S Consultores	CABA, GBA	Monthly	No	Apr-02	Today	-	-	n/r	Yes	Survey + Receive information directly from retailers
n/r	Private	Finsoport	n/r	Monthly	n/r	n/r	n/r	n/r	n/r	n/r	Yes	n/r
n/r	Private	Rubinstein & Asociados	GBA	Monthly	n/r	n/r	n/r	n/r	n/r	n/r	Yes	n/r
n/r	Private	Econviews	n/r	Monthly	n/r	n/r	n/r	n/r	n/r	n/r	Yes	n/r
No	Public	Centro de Estudios para el Desarrollo Argentino (CENDA)	Jujuy, Neuquén, Entre Ríos, Chubut, Salta, La Pampa, Río Negro	Monthly	Yes	Oct-06	Dec-11	Oct-06	Dec-11			Survey (by the provinces)
Yes	Public	Direccion Provincial de Estadística y Censo - Neuquen	Neuquen Capital	Monthly	Yes	Jan-80	Today	Jan-80	Today			Survey
Yes	Public	Gobierno de la Ciudad de Buenos Aires	CABA	Monthly	Yes	Feb-03	Today	Feb-03	Today	628		Survey + Online Prices + Phone Survey
No	Public	Sistema de Informacion Socioeconomica de Posadas	Posadas	Monthly	Yes		Apr-12		Apr-12			
Yes	Public	Direccion Provincial de Estadística y Censo - San Luis	Provincia de San Luis	Monthly	Yes	Oct-05	Today	Oct-05	Today	301		Survey
No	Public	Direccion Provincial de Estadística y Censo - Chubut	Trelew - Rawson	Monthly	Yes	Jan-75	Dec-13	Jan-75	Dec-13	100		Survey
Yes	Public	Direccion Provincial de Estadística y Censo - Provincia de Tierra del Fuego	Ushuaia y Rio Grande	Monthly	Yes	Jul-13	Today	Jul-13	Today			Survey
No	Public	Direccion de Estadística de la Provincia de Tucuman		Monthly	Yes	Jan-68	Mar-08	Jan-68	Mar-08			Survey
No	Public	Direccion Provincial de Estadística y Censo - Jujuy		Monthly								
No	Public	Gobierno de la Provincia de Salta		Monthly								
No	Public	Gobierno de la Provincia de Chaco		Monthly								
No	Public	Entre Rios		Monthly								
No	Public	Gobierno de Rio Negro	Viedma	Monthly								
No	Public	La Pampa	Santa Rosa	Monthly								
No	Public	Direccion Provincial de Estadística y Censo - Catamarca		Monthly								
No	Public using private sources	Congreso Nacional		Monthly	Yes	May-11	Oct-15	May-11	Oct-15			Private Consultants' Estimations

*No response

A.2 Newspaper articles mentioning the inflation rate in 2007

Figure 8: Newspapers Articles, Official Unofficial Statistics and Inflation Expectations



Notes: The vertical line represents the start of the intervention of the national statistical agency (INDEC) in January 2007. Each gray dot in 2007 represent the annual inflation rate mentioned in an article in La Nacion Newspaper. “Official Inflation” is the annual inflation rate reported by INDEC. The “Unofficial Inflation” indicator is computed by PriceStats (please see notes to Figure 2 for more details). The mean of inflation expectations for the following 12 months are quarterly averages of the monthly series from the Encuesta de Expectativas de Inflación (carried out since August 2006 by the Centro de Investigación en Finanzas, Universidad Torcuato Di Tella). This survey collected information on the inflation expectations for the following 12 months among the general population of Argentina, based on a standard question for this type of survey (“What do you expect the annual rate of inflation will be during the next 12 months?”).

B Model

B.1 Model Details

NOTE: THIS APPENDIX SECTION NEEDS TO BE RE-WRITTEN.

Proposition 1. Let the prior belief about inflation and government bias be given by the bi-variate normal distribution with mean $\begin{bmatrix} \pi_0 \\ b_0 \end{bmatrix}$ and variance-covariance matrix $\begin{bmatrix} \sigma_{\pi,0}^2 & \sigma_{\pi b,0} \\ \sigma_{\pi b,0} & \sigma_{b,0}^2 \end{bmatrix}$. Given the signals \bar{u} and \bar{o}' , the posterior belief is distributed bi-variate normal, $\mathcal{N}(\Upsilon, \Delta)$, with:

$$\Delta = \left(\begin{bmatrix} \sigma_{\pi,0}^2 & \sigma_{\pi b,0} \\ \sigma_{\pi b,0} & \sigma_{b,0}^2 \end{bmatrix}^{-1} + \begin{bmatrix} 1 & 0 \\ 1 & 1 \end{bmatrix}^T \begin{bmatrix} \sigma_u^2 & 0 \\ 0 & \sigma_o^2 \end{bmatrix}^{-1} \begin{bmatrix} 1 & 0 \\ 1 & 1 \end{bmatrix} \right)^{-1}$$

$$\Upsilon = \Delta \left\{ \begin{bmatrix} 1 & 0 \\ 1 & 1 \end{bmatrix}^T \begin{bmatrix} \sigma_u^2 & 0 \\ 0 & \sigma_o^2 \end{bmatrix}^{-1} \begin{bmatrix} \bar{u} \\ \bar{o}' \end{bmatrix} + \begin{bmatrix} \sigma_{\pi,0}^2 & \sigma_{\pi b,0} \\ \sigma_{\pi b,0} & \sigma_{b,0}^2 \end{bmatrix}^{-1} \begin{bmatrix} \pi_0 \\ b_0 \end{bmatrix} \right\}$$

Proof: This problem is a particular case of a more general problem of Bayesian learning with multivariate normal priors and multivariate signals, which produces a posterior beliefs that is multivariate normal. This is known as Bayes' Theorem for Gaussian variables:

Theorem 1 (Bayes' Theorem for Gaussian variables). . *Given a prior belief x and a signal y with distributions in the form*

$$p(x) = \mathcal{N}(\mu, \Lambda^{-1})$$

$$p(y|x) = \mathcal{N}(Ax + b, L^{-1})$$

The posterior distribution for the signal is given

$$p(x|y) = \mathcal{N}(\Delta \{A^T L(y - b) + \Lambda \mu\}, \Delta)$$

where

$$\Delta = (\Lambda + A^T L A)^{-1}$$

Proof. See Bishop (2006), section 2.3.3, pages 90-94. □

We can simply apply Theorem 1 using the following replacements:

$$x = \begin{bmatrix} \pi \\ b \end{bmatrix}, \mu = \begin{bmatrix} \pi_0 \\ b_0 \end{bmatrix}, y = \begin{bmatrix} \bar{u} \\ \bar{o}' \end{bmatrix}, \Lambda^{-1} = \begin{bmatrix} \sigma_{\pi,0}^2 & \sigma_{\pi b,0} \\ \sigma_{\pi b,0} & \sigma_{b,0}^2 \end{bmatrix},$$

$$A = \begin{bmatrix} 1 & 0 \\ 1 & 1 \end{bmatrix}, b = 0, L^{-1} = \begin{bmatrix} \sigma_u^2 & 0 \\ 0 & \sigma_o^2 \end{bmatrix}.$$

As stated by the proposition, this results in a posterior belief distributed bi-variate normal, $\mathcal{N}(\Upsilon, \Delta)$, with:

$$\Delta = \left(\begin{bmatrix} \sigma_{\pi,0}^2 & \sigma_{\pi b,0} \\ \sigma_{\pi b,0} & \sigma_{b,0}^2 \end{bmatrix}^{-1} + \begin{bmatrix} 1 & 0 \\ 1 & 1 \end{bmatrix}^T \begin{bmatrix} \sigma_u^2 & 0 \\ 0 & \sigma_o^2 \end{bmatrix}^{-1} \begin{bmatrix} 1 & 0 \\ 1 & 1 \end{bmatrix} \right)^{-1}$$

$$\Upsilon = \Delta \left\{ \begin{bmatrix} 1 & 0 \\ 1 & 1 \end{bmatrix}^T \begin{bmatrix} \sigma_u^2 & 0 \\ 0 & \sigma_o^2 \end{bmatrix}^{-1} \begin{bmatrix} \bar{u} \\ \bar{o}' \end{bmatrix} + \begin{bmatrix} \sigma_{\pi,0}^2 & \sigma_{\pi b,0} \\ \sigma_{\pi b,0} & \sigma_{b,0}^2 \end{bmatrix}^{-1} \begin{bmatrix} \pi_0 \\ b_0 \end{bmatrix} \right\}$$

The mean posterior beliefs are an average between the average prior beliefs, $\begin{bmatrix} \pi_0 \\ b_0 \end{bmatrix}$, and the signals, $\begin{bmatrix} \bar{u} \\ \bar{o}' \end{bmatrix}$, weighted by a weighting matrix that involves a combination of their respective variance-covariance matrices. Focusing on the case where the prior beliefs for the inflation rate and the bias are orthogonal, $\sigma_{\pi b,0} = 0$, in which case the formulas simplify substantially. Focusing on this case does not mean that we believe the assumption $\sigma_{\pi b,0} = 0$ to hold.¹⁵ The intuition for the case where $\sigma_{\pi b,0} \neq 0$ would be similar, only that the formula would include several additional second-order terms that make corrections for the fact that the prior beliefs about π and b are correlated.

B.2 Weights on equation....

$$\omega_1 = \frac{\frac{1}{\sigma_{b,0}^2} \frac{1}{\sigma_u^2} + \frac{1}{\sigma_o^2} \frac{1}{\sigma_u^2}}{\frac{1}{\sigma_{b,0}^2} \frac{1}{\sigma_{\pi,0}^2} + \frac{1}{\sigma_o^2} \frac{1}{\sigma_{\pi,0}^2} + \frac{1}{\sigma_{b,0}^2} \frac{1}{\sigma_u^2} + \frac{1}{\sigma_u^2} \frac{1}{\sigma_o^2} + \frac{1}{\sigma_o^2} \frac{1}{\sigma_{b,0}^2}}, \omega_2 = \frac{\frac{1}{\sigma_o^2} \frac{1}{\sigma_{b,0}^2}}{\frac{1}{\sigma_{b,0}^2} \frac{1}{\sigma_{\pi,0}^2} + \frac{1}{\sigma_o^2} \frac{1}{\sigma_{\pi,0}^2} + \frac{1}{\sigma_{b,0}^2} \frac{1}{\sigma_u^2} + \frac{1}{\sigma_u^2} \frac{1}{\sigma_o^2} + \frac{1}{\sigma_o^2} \frac{1}{\sigma_{b,0}^2}},$$

$$\psi_1 = \frac{\frac{1}{\sigma_{\pi,0}^2} \frac{1}{\sigma_o^2}}{\frac{1}{\sigma_{b,0}^2} \frac{1}{\sigma_{\pi,0}^2} + \frac{1}{\sigma_o^2} \frac{1}{\sigma_{\pi,0}^2} + \frac{1}{\sigma_{b,0}^2} \frac{1}{\sigma_u^2} + \frac{1}{\sigma_u^2} \frac{1}{\sigma_o^2} + \frac{1}{\sigma_o^2} \frac{1}{\sigma_{b,0}^2}} \text{ and } \psi_2 = \frac{\frac{1}{\sigma_u^2} \frac{1}{\sigma_o^2}}{\frac{1}{\sigma_{b,0}^2} \frac{1}{\sigma_{\pi,0}^2} + \frac{1}{\sigma_o^2} \frac{1}{\sigma_{\pi,0}^2} + \frac{1}{\sigma_{b,0}^2} \frac{1}{\sigma_u^2} + \frac{1}{\sigma_u^2} \frac{1}{\sigma_o^2} + \frac{1}{\sigma_o^2} \frac{1}{\sigma_{b,0}^2}}.$$

B.3 Derivation of equations 1 and 2

We can prove this proposition by replacing the orthogonality condition and finding the expected values for π_1 and b_1 . Therefore, we have:

¹⁵Indeed, even if we started out with orthogonal beliefs a rational individual would still end up with a posterior belief where $\sigma_{\pi b,0} \neq 0$.

$$\begin{aligned}
E \begin{pmatrix} \pi_1 \\ b_1 \end{pmatrix} &= \left(\begin{bmatrix} \sigma_{\pi,0}^2 & \sigma_{\pi b,0} \\ \sigma_{\pi b,0} & \sigma_{b,0}^2 \end{bmatrix}^{-1} + \begin{bmatrix} 1 & 0 \\ 1 & 1 \end{bmatrix}^T \begin{bmatrix} \sigma_u^2 & 0 \\ 0 & \sigma_o^2 \end{bmatrix}^{-1} \begin{bmatrix} 1 & 0 \\ 1 & 1 \end{bmatrix} \right)^{-1} \\
&\quad \left\{ \begin{pmatrix} 1 & 0 \\ 1 & 1 \end{pmatrix}^T \begin{pmatrix} \sigma_u^2 & 0 \\ 0 & \sigma_o^2 \end{pmatrix}^{-1} \begin{pmatrix} \bar{u} \\ \bar{o}' \end{pmatrix} + \begin{pmatrix} \sigma_{\pi,0}^2 & 0 \\ 0 & \sigma_{b,0}^2 \end{pmatrix}^{-1} \begin{pmatrix} \pi_0 \\ b_0 \end{pmatrix} \right\} \\
&= \left(\begin{bmatrix} \frac{1}{\sigma_{\pi,0}^2} & 0 \\ 0 & \frac{1}{\sigma_{b,0}^2} \end{bmatrix} + \begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} \frac{1}{\sigma_u^2} & 0 \\ 0 & \frac{1}{\sigma_o^2} \end{bmatrix} \begin{bmatrix} 1 & 0 \\ 1 & 1 \end{bmatrix} \right)^{-1} \\
&\quad \left\{ \begin{pmatrix} 1 & 1 \\ 0 & 1 \end{pmatrix} \begin{pmatrix} \frac{1}{\sigma_u^2} & 0 \\ 0 & \frac{1}{\sigma_o^2} \end{pmatrix} \begin{pmatrix} \bar{u} \\ \bar{o}' \end{pmatrix} + \begin{pmatrix} \frac{1}{\sigma_{\pi,0}^2} & 0 \\ 0 & \frac{1}{\sigma_{b,0}^2} \end{pmatrix} \begin{pmatrix} \pi_0 \\ b_0 \end{pmatrix} \right\} \\
&= \left(\begin{bmatrix} \frac{1}{\sigma_{\pi,0}^2} & 0 \\ 0 & \frac{1}{\sigma_{b,0}^2} \end{bmatrix} + \begin{bmatrix} \frac{1}{\sigma_u^2} + \frac{1}{\sigma_o^2} & \frac{1}{\sigma_o^2} \\ \frac{1}{\sigma_o^2} & \frac{1}{\sigma_o^2} \end{bmatrix} \right)^{-1} \left\{ \begin{pmatrix} \frac{\bar{u}}{\sigma_u^2} + \frac{\bar{o}'}{\sigma_o^2} \\ \frac{\bar{o}'}{\sigma_o^2} \end{pmatrix} + \begin{pmatrix} \frac{\pi_0}{\sigma_{\pi,0}^2} \\ \frac{b_0}{\sigma_{b,0}^2} \end{pmatrix} \right\} \\
&= \frac{1}{\left| \text{cov} \begin{bmatrix} \pi_1 \\ b_1 \end{bmatrix} \middle|_{\sigma_{\pi b,0}=0} \right|} \begin{pmatrix} \frac{1}{\sigma_{b,0}^2} + \frac{1}{\sigma_o^2} & -\frac{1}{\sigma_o^2} \\ -\frac{1}{\sigma_o^2} & \frac{1}{\sigma_{\pi,0}^2} + \frac{1}{\sigma_u^2} + \frac{1}{\sigma_o^2} \end{pmatrix} \begin{pmatrix} \frac{\bar{u}}{\sigma_u^2} + \frac{\bar{o}'}{\sigma_o^2} + \frac{\pi_0}{\sigma_{\pi,0}^2} \\ \frac{\bar{o}'}{\sigma_o^2} + \frac{b_0}{\sigma_{b,0}^2} \end{pmatrix}
\end{aligned}$$

Given the orthogonality condition, the determinant of the variance-covariance matrix is

$$\left| \text{cov} \begin{bmatrix} \pi_1 \\ b_1 \end{bmatrix} \middle|_{\sigma_{\pi b,0}=0} \right| = \frac{1}{\frac{1}{\sigma_{\pi,0}^2 \sigma_{b,0}^2} + \frac{1}{\sigma_{\pi,0}^2 \sigma_o^2} + \frac{1}{\sigma_u^2 \sigma_{b,0}^2} + \frac{1}{\sigma_u^2 \sigma_o^2} + \frac{1}{\sigma_o^2 \sigma_{b,0}^2}}$$

Solving this product, we obtain:

$$\begin{aligned}
E(\pi_1) &= \frac{\pi_0 \left(\frac{1}{\sigma_{\pi,0}^2 \sigma_{b,0}^2} + \frac{1}{\sigma_{\pi,0}^2 \sigma_o^2} \right) + \bar{u} \left(\frac{1}{\sigma_u^2 \sigma_{b,0}^2} + \frac{1}{\sigma_u^2 \sigma_o^2} \right) + (\bar{o}' - b_0) \frac{1}{\sigma_o^2 \sigma_{b,0}^2}}{\frac{1}{\sigma_{\pi,0}^2 \sigma_{b,0}^2} + \frac{1}{\sigma_{\pi,0}^2 \sigma_o^2} + \frac{1}{\sigma_u^2 \sigma_{b,0}^2} + \frac{1}{\sigma_u^2 \sigma_o^2} + \frac{1}{\sigma_o^2 \sigma_{b,0}^2}} \\
E(b_1) &= \frac{b_0 \left(\frac{1}{\sigma_{\pi,0}^2 \sigma_{b,0}^2} + \frac{1}{\sigma_{b,0}^2 \sigma_u^2} + \frac{1}{\sigma_{b,0}^2 \sigma_o^2} \right) + (\bar{o}' - \Pi_0) \frac{1}{\sigma_o^2 \sigma_{\pi,0}^2} + (\bar{o}' - u_0) \frac{1}{\sigma_u^2 \sigma_o^2}}{\frac{1}{\sigma_{\pi,0}^2 \sigma_{b,0}^2} + \frac{1}{\sigma_{\pi,0}^2 \sigma_o^2} + \frac{1}{\sigma_u^2 \sigma_{b,0}^2} + \frac{1}{\sigma_u^2 \sigma_o^2} + \frac{1}{\sigma_o^2 \sigma_{b,0}^2}}
\end{aligned}$$

Last, we define the following weights:

$$\omega_1 = \frac{\frac{1}{\sigma_u^2 \sigma_{b,0}^2} + \frac{1}{\sigma_u^2 \sigma_o^2}}{\frac{1}{\sigma_{\pi,0}^2 \sigma_{b,0}^2} + \frac{1}{\sigma_{\pi,0}^2 \sigma_o^2} + \frac{1}{\sigma_u^2 \sigma_{b,0}^2} + \frac{1}{\sigma_u^2 \sigma_o^2} + \frac{1}{\sigma_o^2 \sigma_{b,0}^2}}, \quad \omega_2 = \frac{\frac{1}{\sigma_o^2 \sigma_{b,0}^2}}{\frac{1}{\sigma_{\pi,0}^2 \sigma_{b,0}^2} + \frac{1}{\sigma_{\pi,0}^2 \sigma_o^2} + \frac{1}{\sigma_u^2 \sigma_{b,0}^2} + \frac{1}{\sigma_u^2 \sigma_o^2} + \frac{1}{\sigma_o^2 \sigma_{b,0}^2}}$$

$$\varphi_1 = \frac{\frac{1}{\sigma_o^2 \sigma_{\Pi,0}^2}}{\frac{1}{\sigma_{\pi,0}^2 \sigma_{b,0}^2} + \frac{1}{\sigma_{\pi,0}^2 \sigma_o^2} + \frac{1}{\sigma_u^2 \sigma_{b,0}^2} + \frac{1}{\sigma_u^2 \sigma_o^2} + \frac{1}{\sigma_o^2 \sigma_{b,0}^2}}, \quad \varphi_2 = \frac{\frac{1}{\sigma_u^2 \sigma_o^2}}{\frac{1}{\sigma_{\pi,0}^2 \sigma_{b,0}^2} + \frac{1}{\sigma_{\pi,0}^2 \sigma_o^2} + \frac{1}{\sigma_u^2 \sigma_{b,0}^2} + \frac{1}{\sigma_u^2 \sigma_o^2} + \frac{1}{\sigma_o^2 \sigma_{b,0}^2}}$$

After replacing for the weights, we obtain:

$$E(\pi_1) = \pi_0 (1 - \omega_1 - \omega_2) + \bar{u} \omega_1 + (\bar{o}' - b_0) \omega_2$$

$$E(b_1) = b_0 (1 - \varphi_1 - \varphi_2) + (\bar{o}' - \pi_0) \varphi_1 + (\bar{o}' - u_0) \varphi_2$$

C Argentina Online Experiment Questionnaire - English Translation

We include here English translations for the pre- and post-treatment questions, for all the informational treatments and for a debriefing message for all respondents included at the end of the questionnaire, which explained the use of alternative sources for the information treatments. Answer options are presented in brackets. The original questionnaire in Spanish is available upon request.

Pre-treatment questions:

- Please indicate your sex: [*Female; Male*]
- How old are you? [*0, 1, 2, ..., 99*]
- What is the highest education level you have attained? [*Primary school dropout, Completed primary school, High school dropout, Completed high school, Some tertiary education, Completed tertiary education, Some college, Completed college, Post-graduate*]
- How do you think that your personal/family economic situation is with respect to one year ago? [*Better, Worse, Same, Don't know*]
- And how do you think your personal/family economic situation will be one year from now? [*Better, Worse, Same, Don't know*]

Randomized informational treatment:

- *Control*: no message.
- *Official-10%*: “According to official indicators published by INDEC, the annual inflation rate with respect to a year ago was approximately 10%”.¹⁶
- *Official-20%*: “According to official indicators published by INDEC, the annual inflation rate with respect to a year ago was approximately 20%”.
- *Official-30%*: “According to official indicators published by INDEC, the annual inflation rate with respect to a year ago was approximately 30%”.
- *Unofficial-10%*: “According to one of the unofficial indicators published by consulting firms, analysts and research centers, the annual inflation rate with respect to a year ago was approximately 10%.”

¹⁶INDEC stands for Argentina’s “Instituto Nacional de Estadísticas y Censos.” The acronym and the institution it represents are well known in Argentina and were amply covered in media outlets at the time of the survey.

- *Unofficial-20%*: “According to one of the unofficial indicators published by consulting firms, analysts and research centers, the annual inflation rate with respect to a year ago was approximately 20%.”
- *Unofficial-30%*: “According to one of the unofficial indicators published by consulting firms, analysts and research centers, the annual inflation rate with respect to a year ago was approximately 30%.”

Post-treatment questions:

- What do you think was the annual inflation rate with respect to one year ago? Please select the value closer to your estimate from the following drop down menu. [0% or <, 1%, ... 100%; >100%]
- How certain are you about your answer to the previous question? [Very sure; Somehow sure, Not very sure; Not sure at all]
- What do you think will be the annual inflation rate with respect to one year from now? Please select the value closer to your estimate from the following drop down menu. [0% or <, 1%, ... 100%; >100%]

Debriefing:

- “At some point during the questionnaire we asked about your inflation perceptions. We provided some of the respondents an approximate estimate of the annual inflation rate with respect to one year later. The provided estimate was randomly selected among one of the following sources: INDEC’s official inflation indicator, private estimates of analysts close to the government, implicit inflation (gross domestic product deflator) from INDEC, an estimate from a private research center (Universidad del CEMA), implicit inflation (wage growth coefficient) from INDEC, or the estimate from a consulting firm (food and beverages from Inflación Verdadera).”