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Arnildo da Silva Correa and Paulo Picchetti

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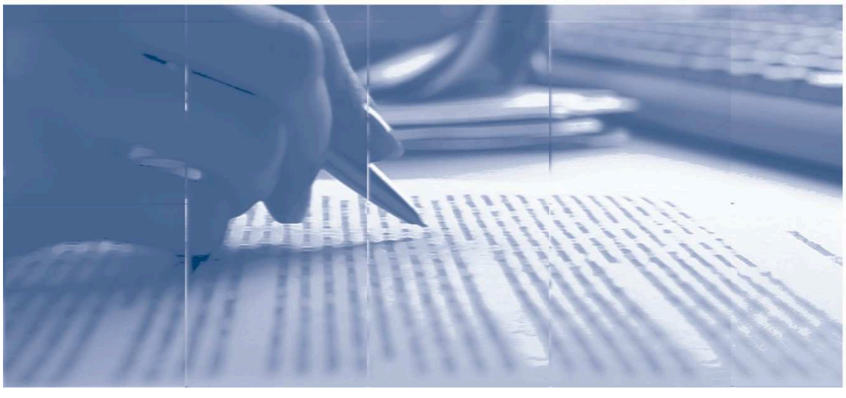

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New Information and Updating of Market Experts' Inflation Expectations

Arnildo da Silva Correa*
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Abstract

The Working Papers should not be reported as representing the views of the Banco Central do Brasil. The views expressed in the papers are those of the author(s) and do not necessarily reflect those of the Banco Central do Brasil.

This paper investigates how the disclosure of new information regarding the recent behavior of inflation affects inflation expectations. Using a panel of more than 100 professional forecasters and the release of a signal about the inflation rate to identify the effects, we find that new information leads individual forecasters to update their expectations immediately. However, the parameter is not very high, which is consistent with sticky information and staggered updating of expectations. The precision of new information matters as well: when precision increases, agents put more weight on the piece of information received, which is consistent with Morris and Shin's (2002) model. These results are found to be robust, and absent in placebo regressions. Finally, estimates suggest that the magnitude of the update depends on the distance between the signal that agents receive and their current expectations.

Keywords: New information, updating, expectations, professional forecasters, public signal, private signal

JEL Classification: D82, D84, D89, E47, E58

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1 Introduction

Expectations are a key ingredient in macro and microeconomic models, and have become central to the conduct of monetary policy. In macroeconomic models, for instance, similar to price rigidity, staggered updating of expectations generates strong and persistent real effects of nominal shocks (Mankiw and Reis 2002, Sims 2003, Maćkowiak and Wiederholt 2009). The introduction of information frictions in macroeconomic models has also been proved to produce different implications for policy making and helped to solve several empirical puzzles (see Reis 2011, Paciello and Wiederholt 2014, and Ball et al. 2005).[1]

But despite the importance of expectations, there is still only sparse empirical evidence about how people form their expectations.[2] In particular, how individual agents update their expectations when new information arises remains an open question. For instance, does it take time for agents to react when new information is released, or reaction is instantaneous? Does the precision of new information matter for the updating process? Is the updating a linear function of the magnitude of the surprise, or reaction increases, for example, when precision is higher?

This paper aims to estimate the effects of new information on the updating of expectations of market specialists. Our analysis makes use of a panel of more than 100 professional forecasters from a unique survey of expectations conducted by the Central Bank of Brazil (BCB). The distinctive feature of the BCB's survey is that data are collected every single day, allowing to identify the reaction of expectations at the moment that specific events take place.

Our study offers a direct test for the significance of the impact of new information on the updating behavior by using the release of a signal about the inflation rate. The paper focuses on inflation expectations for the current month and covers the period between January 2006 and September 2013. In Brazil, the official IPCA inflation rate is calculated by the Brazilian Institute of Geography and Statistics (IBGE), but Getulio Vargas Foundation (FGV) has developed a daily flash estimate (called Inflation Monitor) that replicates the IPCA, which is released since 2006. Every month, the Inflation Monitor covering the same reference period as the IPCA is released about eight days before the official IPCA. This means that the Monitor released on this date can be viewed as a

[1]There are basically two main approaches to rationally incorporate information frictions in macroeconomic models. In Mankiw and Reis (2002) agents update infrequently because collecting and processing information is costly. But if they update, they gain full information. In Sims (2003) agents update continuously, but face a limited capacity of attention, which makes it impossible to process all information available. However, in these two approaches there is no difference as to how different agents process information. In contrast, Carrol (2003) argues that professional forecasters and regular people respond differently to new information: professional forecasters are rational and pay close attention to all macroeconomic facts, responding immediately to news, but regular people react only slowly, absorbing the economic content of media news from period to period in a way similar to an epidemiology.

[2]One important empirical paper is Carrol (2003), which proposes and tests an alternative approach to that of rational expectations, as described in the previous footnote. Other papers in this scarse literature are mentioned later in this introduction.

signal about the IPCA inflation. We explore these events assuming as crucial identifying assumption that the window we use around the release dates is short enough to ensure that the Monitor release is the only information causing changes in expectations. This approach is possible only because we have daily individual data on inflation expectations.

Our paper is closely related to studies that analyze the expectations formation process empirically. For instance, Amantier et al. (2013) use an experiment embedded in a survey to investigate how consumer's inflation expectations respond to new information. Coibion (2010) and Coibion and Gorodnichenko (2012) document evidence consistent with information rigidities. Lamla and Sarferaz (2012) show that the updating of inflation expectations changes substantially over time and that both quantity and quality of the news received matter. Carvalho and Minella (2012) have also used the BCB's survey to assess a wide set of aspects characterizing market forecasts in Brazil. However, to the best of our knowledge no other paper in the literature uses specific events of disclosures of information as we do in the present paper to identify the effect on the updating behavior. Our paper also provides a direct empirical application of the Morris and Shin's (2002) model, by estimating the impact of a public signal on expectations.

The results of our estimations support the view that new information leads individual professional forecasters to update their expectations immediately. Indeed, the parameter measuring the impact of new information is highly statistically significant. When the new information suggests that inflation for the current month may be higher than the individual forecast, the agent increases their expectations. The agent decreases expectations in the opposite case. We do not have data on consumers' expectations, but these findings are in line with Carrol's (2003) results suggesting that market specialists pay close attention to all macroeconomic information and respond very fast to new information. These results also provide evidence that professional forecasters consider the Inflation Monitor a valuable signal about the inflation dynamics in Brazil.

However, the parameter of new information in our regressions is not very high (around 0.35), which is consistent with sticky information and staggered updating of expectations. The precision of new information is also found to matter a great deal—the higher the precision, the greater the size of the updating. Indeed, the impact is nonlinear: when precision increases, agents put more weight on the new information received, which is consistent with Morris and Shin's (2002) model. All these results were subjected to several robustness checks and found to be robust, and absent in placebo regressions.

We also estimate a threshold model to test more formally another nonlinear effect suggested by the data: that individual's reaction depends on the distance of the signal that agents receive from their current expectations. Estimates of the model using the size of the market surprise caused by the new information as the threshold variable support these conclusions. Point estimate of the coefficient of new information is almost twice as large in the state of great surprise than that in the state of low surprise.

The rest of the paper is organized as follows. Section 2 presents a simple signal extraction model to motivate the empirical analysis. The model provides some predictions on how new information affects the updating of expectations, which guide our econometric specifications. Section 3 describes the datasets. Section 4 outlines the empirical strategy and presents the results. Section 5 concludes.

2 Theoretical framework

We consider a simple signal extraction model, as in Morris and Shin (2002), to motivate the empirical analysis. The specification is similar to that in Crowe (2010), but here the toy model has three periods. In the first two periods, forecasters try to guess the inflation rate, π, with information they have. In the third period, the actual inflation rate is released. In each period the agent i chooses a forecast, f_i, to minimize the squared error of the inflation forecast, given the actual inflation rate, π:

$$L_i(f_i, \pi) \equiv -(f_i - \pi)^2. \tag{1}$$

We suppose that, in the first period, agents observe only their own private signal about the inflation rate. This noisy signal is given by:

$$\pi_i = \pi + \zeta_i, \tag{2}$$

where ζ_i is an i.i.d. error term with variance $\sigma^2_{\zeta_i}$ and precision $\alpha_i \equiv \frac{1}{\sigma^2_{\zeta_i}}$. We can rationalize this private signal as the whole set of information that agents collect and process privately to construct their forecasts, including the econometric models they use. In this case, the agent i's best forecast of the inflation rate is given by their own private signal:

$$f_i^* = \pi_i. \tag{3}$$

In the second period, we assume that agents observe, in addition to the private signal, a noisy public signal about the inflation rate:

$$\pi_P = \pi + \eta. \tag{4}$$

The i.i.d. error term η has variance σ^2_η and precision $\beta \equiv \frac{1}{\sigma^2_\eta}$. We also assume that:

$$\zeta_i \perp \zeta_j \perp \eta, \text{ for all periods and for all individuals } i \text{ and } j.$$

Now agents construct their forecasts optimally weighting the two signals according to their relative precisions:

$$f_i^* = \frac{\alpha_i}{\alpha_i + \beta}\pi_i + \frac{\beta}{\alpha_i + \beta}\pi_P. \tag{5}$$

The change in the agent i's inflation forecast from period one to period two (which we call *update* of the forecast produced by the new information) is given by:

$$
\begin{aligned}
u_i &= \left[\frac{\alpha_i}{\alpha_i+\beta}\pi_i + \frac{\beta}{\alpha_i+\beta}\pi_P\right] - \pi_i \\
&= \frac{\beta}{\alpha_i+\beta}\left(\pi_P - \pi_i\right) \equiv p_i s_i,
\end{aligned}
\tag{6}
$$

where $p_i \equiv \beta/\left(\alpha_i+\beta\right)$ is the relative precision of the public signal, and $s_i \equiv \pi_P - \pi_i$ is the *surprise* caused by the new information provided by the public signal.

The model thus predicts that the update of the agent i's inflation forecast depends on whether the public signal brings new valuable information about the inflation rate or not. If the new information brought by the public signal is the same as that already embedded in the private signal, there is no reason to change the forecast. In this case, the new information only reaffirms the agent's expectation. On the other hand, if the public signal differs from the private signal (i.e., $s_i \neq 0$), the forecaster recognizes that the new information provides a different story about the inflation rate, and the individual changes the forecast accordingly. Note that in our model there is no cost of collecting and processing information. If information is costly, however, agents may change expectations only if the term of surprise surpasses a certain level.[3]

The model also predicts that the update of the agent i's inflation forecast depends on another term: the relative precision of the new information provided by the public signal, $p_i = \beta/\left(\alpha_i+\beta\right)$. Thus, the effect of the new information on the size of the update is nonlinear: the higher the relative precision of the new information, the higher the weight that agents put on the piece of new information received, and, consequently, the higher the size of the update of expectations.

In summary, the magnitude of the update depends on two variables, in a nonlinear fashion: (i) the size of the surprise, and (ii) the relative precision of the new information.

3 Data

We employ two datasets to test the predictions of the model. The first dataset is the survey conducted by the BCB among market experts. The BCB collects on a daily basis market expectations of several key macroeconomic variables amongst more than 100 professional forecasters since the early years of the inflation targeting regime in Brazil, implemented in 1999. Although the survey includes a number of variables, we focus on inflation expectations. The survey compiles inflation expectations for different horizons, from the current month to 12 months ahead. From this dataset we use daily individual inflation forecasts of the Broad National Consumer Price Index (IPCA), which is used as the official inflation target by the BCB.

[3] We explore this possibility empirically in the subsection 4.2 using a threshold model.

The second dataset comes from the daily estimates of inflation calculated by the Brazilian Institute of Economics at Getulio Vargas Foundation (IBRE-FGV), which is an institution devoted to production and publication of macroeconomic statistics and applied economic research. Since January 2006, FGV calculates a daily flash estimate of the IPCA inflation for moving periods of 30 days ending on the date of computation. The whole set of daily information produced by FGV is named Inflation Monitor.[4] We emphasize that the official IPCA is calculated by the IBGE, not by FGV, but FGV developed a high frequency measurement of inflation that tries to replicate the IPCA. The Inflation Monitor has the same basket and coverage as the IPCA, but it is released every business day.

Figure 1 below presents schematically the disclosure of the Monitor and the disclosure of the IPCA for a given month t. The IPCA index measures the inflation rate for the period between the first day and the last day of the reference month, represented in Figure 1 by dates j and j^*, respectively. However, the official result is known only a few days after the end of the reference period—IBGE releases the IPCA between the 5th and the 12th day of the subsequent month. In our scheme below, the release date of the official IPCA is represented by $j^* + m$. But every day FGV releases its moving 30-days measure of inflation, and on day j^* the Monitor covers exactly the same reference period as the IPCA. Thus, between dates j^* and $j^* + m$, the Monitor inflation rate for the current month has already been released but agents do not know the official IPCA yet. This means that the release of the Monitor on day j^* is a good signal about the IPCA inflation rate that will be announced only a few days later. The IPCA and the Monitor release dates since 2006 are reported in Tables 4 and 5 in Appendix A.

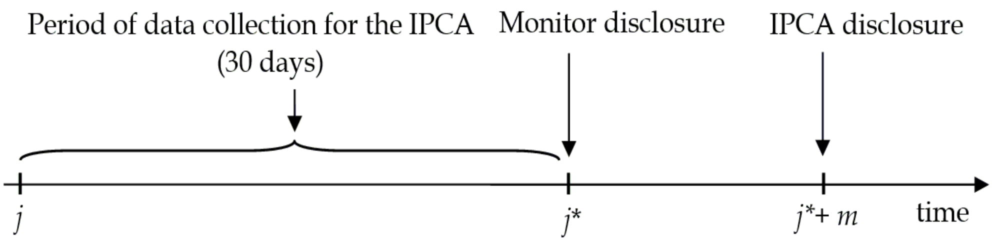

Figure 1: Scheme of information disclosure

We explore these events, which happen every month on day j^*, to identify changes in the agents's information set (produced by the Monitor) and estimating the impact of new information about the IPCA on market experts' inflation expectations. To do this, we combine daily information from the two datasets. Details about how the empirical variables are defined using the data are described in the next section, after presenting the empirical especification of the model.

Our sample is composed by a panel of 188 individual forecasters from the BCB's survey, before treatment, including economic consultancy firms, asset management firms,

[4] In fact, the Inflation Monitor produces daily information not only on the IPCA behavior, but also on the Consumer Price Index – Brazil (IPC-BR).

commercial banks, investment banks, and non-financial firms, covering the period from January 2006 to September 2013. The composition of the panel changes somehow over time as individuals enter or drop out of the survey. The original sample was treated to deal with missing data (since individuals sometimes do not provide forecasts every single day), the exclusion of forecasters with too few observations, and observations with missing data either "before" or "after" the Monitor release, which makes it impossible to calculate the update of forecasts.

4 Empirical analysis

The model developed in Section 2 to guide the empirical strategy states that the relation between the new information and the size of the update of expectations is nonlinear, and depends on the relative precision of the signal received. However, since estimating precisely a nonlinear relation with limited data is likely to be difficult, we first use a linearized version of equation (6). In Subsection 4.2 we explore nonlinear specifications.

A first-order Taylor approximation of equation (6) produces:[5]

$$u_{i,t} \simeq \gamma_0 + \gamma_1 p_{i,t} + \gamma_2 s_{i,t}, \tag{7}$$

where t is a subscript for month, $i = 1, ..., N$ represents the individual forecasters, $u_{i,t}$ is the update of expectations, $p_{i,t}$ measures the relative precision of the public signal, $s_{i,t}$ captures the surprise, and γ_0, γ_1, and γ_2 are parameters.

It must be recognized that the empirical counterpart for $u_{i,t}$ may contain measurement errors and/or be contaminated by idiosyncratic time-varying shocks to forecasts' accuracy. We assume these components are captured by a linear error term $\varepsilon_{i,t}$. We also consider that there may be individual unobserved effects, c_i. Then, our empirical specification of equation (7) is given by:

$$\Delta\pi^e_{i,t} = \gamma_0 + \gamma_1 p_{i,t} + \gamma_2 s_{i,t} + c_i + \varepsilon_{i,t}, \tag{8}$$

where t is a subscript for month, $i = 1, ..., N$ represents the individual forecasters, $\Delta\pi^e_{i,t}$ is the change in the agent i's inflation expectation in the window around day j^*, $s_{i,t}$ measures the surprise for forecaster i produced by the Monitor, and $p_{i,t}$ is the relative precision of the new information provided by the Monitor. In which follows we describe how we use the daily information from the two datasets to calculate these variables to be used in estimations.

First, taking this relation to the data using the Monitor release on day j^* of each month requires some identifying assumptions: (a) that individuals consider that piece of information a valuable signal about the IPCA and react to it; and (b) that the window around j^* is short enough to ensure that the only information affecting changes in

[5] See in Appendix A the derivation of this equation.

expectations is the Monitor release. Consequently, the window cannot be too short, so that there is no time for the BCB's survey to capture the changes in expectations, or too large that other events begin to affect agents' inflation expectations. With the objective of avoiding contamination of the estimates by other events, we decided to be severe and considered a two-day window around j^*.

Since the Monitor is a signal about the current month inflation, we focus on expectations for the current month in our empirical exercizes.[6] Thus, in estimations of equation (8), $\Delta\pi^e_{i,t} = \pi^{e\prime}_{i,t} - \pi^e_{i,t}$ is the change in the agent i's inflation expectation for the current month between the day before the Monitor release $\left(\pi^e_{i,t}\right)$ and the day after the Monitor release $\left(\pi^{e\prime}_{i,t}\right)$; the surprise for forecaster i, $s_{i,t} = M_t - \pi^e_{i,t}$, is captured by the difference between the Monitor and the expectation that the individual i had at the day before the Monitor release. We measure the relative precision of the new information using the previous month forecasting errors:

$$p_{i,t} = \sqrt{\frac{1/e^2_{M,t-1}}{\left(1/e^2_{i,t-1}\right) + \left(1/e^2_{M,t-1}\right)}},$$

where $e^2_{i,t-1} = (\pi^{e\prime}_{i,t-1} - IPCA_{t-1})^2$ and $e^2_{M,t-1} = (M_{t-1} - IPCA_{t-1})^2$ are, respectively, the squared forecasting errors of the individual i and the Monitor in the previous month. Note that $\pi^{e\prime}_{i,t-1}$ is the individual i's expectation in the previous month before receiving the Monitor information for that month.

It is worth devoting a final comment about the definition of the update of expectations considered in the empirical exercises. As already emphasized, we measure the update by changes in expectations in the identification window. Since the window is short, it is important to distinguish three cases: (i) individuals who have changed their expectations after the Monitor release, but did not have time to report them in the survey; (ii) individuals who have reported their expectations, but did not change the values; and (iii) those who have reported new values of expectations in the survey. In our estimations we considered all individuals who have informed their expectations in the survey after the monitor release, whether they have changed their expectations or not.[7]

4.1 Results

This section presents the empirical results. As a first pass, we show a simple graphical result that illustrates the relation between the surprise and the update of inflation expectations. It then goes on to present the results of the baseline regressions and to outline a number of robustness exercises. Finally, it presents the results of nonlinear estimations.

[6] The Monitor may also have impact on inflation expectations for longer horizons, via inertia mechanisms.

[7] One could argue that this may cause selection problems if those reporting their expectations in this short window behaved in such way because of specific characteristics they have (for example, the best forecasters). However, the pattern of responses in the survey suggests a random selection of individuals, as indicated by the frequency of participation.

4.1.1 Graphical results

Figure 2 plots the changes in inflation expectations for the current month $\left(\Delta\pi^e_{i,t}\right)$ against the surprise $\left(s_{i,t} = M_t - \pi^e_{i,t}\right)$, which is our measure of new information, considering all the individuals and the whole sample period. It shows a large concentration of points near zero, indicating that when the new information is only slightly different from the information that individuals already have, the reaction is small.[8] We further explore this fact in the next section. But overall the relationship appears to be positive, suggesting that new information provided by the Monitor leads individuals to update their expectations, as predicted by the model.

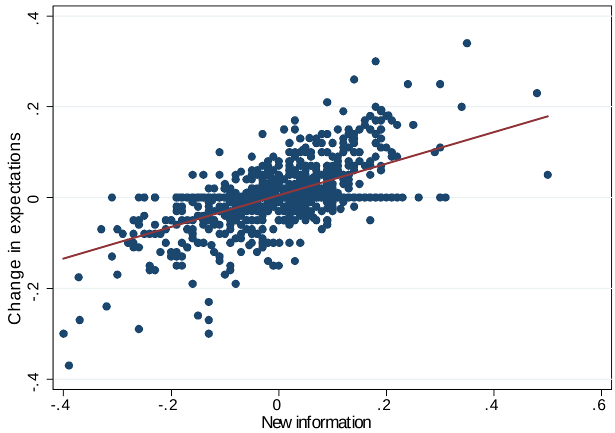

Figure 2: Scatter plot of changes in inflation expectations and new information

4.1.2 Baseline results

The estimations of equation (8) are presented in Table 1. Considering the possibility of unobserved individual effects, we carried out estimations using OLS and Fixed Effect methods. We estimate two specifications by the two methods. Columns I and III present estimates of a specification with the term of precision suppressed, including only the term of new information, $s_{i,t}$, using OLS and Fixed Effect, respectively. Columns II and IV show estimates of the full equation.

The results in Table 1 provide strong evidence supporting the predictions of the theoretical model. First, the estimates of the coefficient of $s_{i,t}$ either by OLS or Fixed Effect are highly statistically significant. This means that the new information brought by the disclosure of the Monitor affects expectations. When the value of the Monitor for the current month inflation is higher than market experts' forecasts, they update their perceptions, increasing their expectations. The opposite happens when the signal suggests

[8] As already emphasized, points over the zero axis are not caused by individuals not reporting their updated expectations after the Monitor release. We consider only those who have updated, but some decided not to change their expectations.

that expectations might be too high: agents update their forecasts down. This updating process is also very rapid, since our estimations capture changes in expectations in a two-day window around the Monitor release.

Table 1: Results of baseline regressions

Dep. Variable: $\Delta\pi^e_{i,t}$	Pooled OLS		Fixed Effect	
	I	II	III	IV
Constant	0.005^{***} (0.001)	0.012^{***} (0.003)		
$p_{i,t}$		0.012^{**} (0.005)		0.012^{**} (0.005)
$s_{i,t}$	0.349^{***} (0.021)	0.355^{***} (0.094)	0.341^{***} (0.019)	0.338^{***} (0.021)
No. of observations	1167	1014	1167	1014
Adjusted R^2	0.36	0.37	0.38	0.42
RMSE	0.05	0.05	0.05	0.05

Notes: Robust standard errors in parentheses. Significance level denoted as: ***=1%;**=5%; *=10%.

We do not have data on consumers' expectations, but these findings are in line with Carrol's (2003) results suggesting that professional forecasters pay close attention to all macroeconomic facts and respond immediately to new information. However, the estimated coefficient of $s_{i,t}$ is around 0.35, which is far from 1, even considering the standard deviation. This result is consistent with sticky information and staggered updating of expectations. Second, there is evidence that the relative precision of the signal (the Monitor) matters. The coefficient of $p_{i,t}$ is positive and highly statistically significant. The higher the precision of the signal, the greater the size of the update of expectations.

4.1.3 Robustness checks

A number of robustness checks were carried out to confirm the results of the previous subsections. First, the baseline estimations of the full equation were replicated for the Top 5 forecasters. In the BCB's survey, professional forecasters are ranked according to their performance under three different forecast horizons: short, medium and long term. Every week the BCB announces the Top 5 forecasters. Since our focus is on the current month expectations, we use the short-term Top 5 forecasters in this exercise. Table 1 shows the results using OLS and Fixed Effect estimators. The results for the coefficient of $s_{i,t}$ are the same as those in the baseline estimation. The coefficient of $p_{i,t}$ is positive, but not significant.

Second, we extended the full equation to include some macroeconomic variables as controls. As our identification strategy uses a two-day window, and the disclosure of macroeconomic variables typically does not occur in such a high frequency, we do not have many macroeconomic variables available to use as controls. Table 1 reports estimates using changes in the exchange rate, $\Delta e_{i,t} = e'_{i,t} - e_{i,t}$, and swap rate, $\Delta r_{i,t} = r'_{i,t} - r_{i,t}$, in the window around j^*, as controls. The estimation is carried out using the full sample. The results are essentially unchanged compared to the baseline. Moreover, note that, since the coefficients of macroeconomic variables are not statistically significant, this exercise provides evidence in favor of our identifying assumption: that the only event causing changes in expectations in the window around j^* is the Monitor release.

Table 2: Robustness exercises results

Dep. Variable: $\Delta\pi^e_{i,t}$	Pooled OLS		Fixed Effect	
	Top 5	Macro	Top 5	Macro
Constant	-0.003 (0.009)	0.012^{***} (0.004)		
$p_{i,t}$	0.006 (0.017)	0.012^{**} (0.005)	0.020 (0.027)	0.012^{**} (0.006)
$s_{i,t}$	0.335^{***} (0.079)	0.355^{***} (0.022)	0.348^{***} (0.113)	0.338^{***} (0.021)
Exchange rate		$-3.1e-07$ (1.3e−05)		$-7.7e-06$ (1.6e−05)
Swap rate		-0.008 (0.099)		-0.023 (0.095)
No. of observations	71	1014	71	1014
Adjusted R^2	0.42	0.37	0.42	0.42
RMSE	0.04	0.05	0.04	0.05

Notes: Robust standard errors in parentheses. Significance level denoted as: ***=1%;**=5%; *=10%

.

Placebo datasets: To provide evidence that the previous results capture the impact of the new information brought by the Monitor on the update of expectations, and not the effect of any other event, we replicate the baseline estimations using two placebo datasets. Here it is important emphasizing that the Monitor on day j^* measures the inflation rate for the current month, t. This means that the Monitor is not a good signal for the inflation rate of the month $t+k$, such as, for example, the third or the ninth month ahead. Inflation expectations for these months should not be directly affected by the Monitor information. Obviously, there are indirect effects via inertia mechanisms,[9] but if the time horizon, k, is long enough, the impact of inertia should disappear. Under this assumption, we use inflation expectations of the third and the ninth month ahead as our placebo experiment.

Figure 3 shows the scatter plot of changes in inflation expectations for the third and the ninth month ahead against the new information brought by the Monitor, both calculated, as before, using the two-day window. Table 3 presents the estimates of the baseline specifications using these two placebo datasets. There is no evidence of impact from the placebo new information in either case, suggesting that previous results are not due to chance or any other event.

[9] Agents know that higher inflation in the current month puts upward pressure on inflation in the coming months.

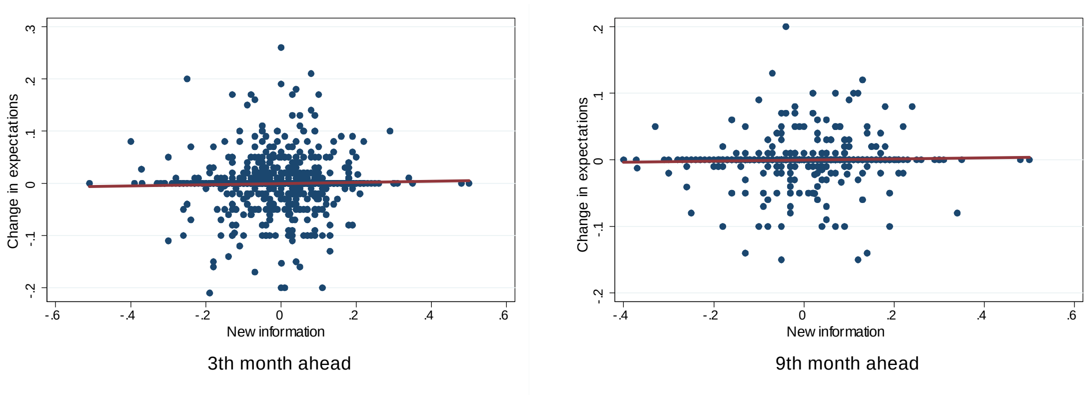

Figure 3: Scatter plot of changes in inflation expectations and new information – Placebo

Table 3: Results using placebo datasets

Dep. Variable: $\Delta\pi^e_{i,t}$	Pooled OLS		Fixed Effect	
	3th month	9th month	3th month	9th month
Constant	0.001 (0.003)	0.002 (0.002)		
$p_{i,t}$	0.001 (0.004)	0.003 (0.002)	0.001 (0.004)	0.003 (0.003)
$s_{i,t}$	0.016 (0.011)	0.009 (0.007)	0.017 (0.013)	0.008 (0.008)
No. of observations	1043	911	1043	911
Adjusted R^2	0.00	0.00	0.02	0.00
RMSE	0.04	0.02	0.04	0.02

Notes: Robust standard errors in parentheses. Significance level denoted as: ***=1%;**=5%; *=10%.

4.2 Nonlinear estimations

Here we explore the possibility of nonlinearities in the updating behavior. From the theoretical point of view, the model of Section 2 predicts that new information might have a nonlinear impact on the size of the update, which depends on the precision of the signal. In addition, from the empirical viewpoint, Figure 2 shows a mass of points concentrated around zero, indicating that there may be a different updating behavior depending on whether agents receive a signal that is very close from their current expectations, or very far. In which follows we explore these two possibilities.

To test the nonlinear effect suggested by the theoretical model, we use the baseline dataset to estimate a formulation that is closer to equation (6), by introducing the interaction term, $p_{i,t}s_{i,t}$:

$$\Delta\pi^e_{i,t} = \gamma_0 + \gamma_2 s_{i,t} + \gamma_1 p_{i,t} s_{i,t} + c_i + \varepsilon_{i,t}. \tag{9}$$

We assume that the unobserved individual components, c_i, are not correlated with the error term and use Pooled OLS method to estimate the equation. We adopt a robust variance-covariance matrix to deal with autocorrelation in the residuals. The estimates presented below in equation (10) support the nonlinear impact predicted by the theoretical model. The coefficient of the cross term $p_{i,t}s_{i,t}$ is quantitatively significant. The estimate is also statistically significant, as well as the parameter of the $s_{i,t}$ term. These results thus provide clear evidence that when precision increases, agents put more weight on the piece of information received, and, consequently, respond changing their forecasts more strongly. In summary, the higher the precision of the new information, the higher the size of the update of expectations.

$$\Delta\pi^e_{i,t} = \underset{(0.002)}{0.004^{**}} + \underset{(0.046)}{0.255^{***}}s_{i,t} + \underset{(0.068)}{0.136^{**}}p_{i,t}s_{i,t} \tag{10}$$

Method: Pooled OLS

Sample period: 2006:1 – 2013:9

Number of observations: 1014

R-squared: 0.37

Standard errors estimated using a robust variance-covariance matrix

Significance level denoted as: ***=1%; **=5%; *=10%.

To explore the nonlinear effect suggested by the concentration of points around zero in Figure 2, we use a different strategy. Since the possible nonlinearity seems to come from the size of the surprise, we use a threshold model to test the existence of two states:[10]

$$\Delta\pi^e_{i,t} = \left[\gamma^1_0 + \gamma^1_2 s_{i,t}\right] I\left(q_t < \tau\right) + \left[\gamma^2_0 + \gamma^2_2 s_{i,t}\right] I\left(q_t \geq \tau\right) + \varepsilon_{i,t}, \tag{11}$$

where $q_t = |s_t|$ is the threshold variable; $I\left(.\right)$ is an indicator function that takes value zero or one, depending on whether q_t is larger or smaller than τ; and τ is the threshold value. In this type of models, the sample is divided in parts based on the value of an observed variable—if it surpasses or not the threshold value. The model is estimated in two stages. First, the threshold value is estimated using a search grid, minimizing the sum of squared residuals. In the second stage, conditional on the estimated threshold, the sample is divided and the other parameters are estimated by OLS (see Franses and Van Dijk, 2000, Caner and Hansen, 2004).

To avoid problems with having a model with an endogenous threshold variable, we do not use the individual $s_{i,t}$, which is our explanatory variable, as the variable determining changes of states. Instead, we define $q_t = |s_t| = |M_t - Med\left(\pi^e_{i,t}\right)|$, where $Med\left(\pi^e_{i,t}\right)$ is the median of expectations for the current month inflation, considering all forecasters in the BCB's survey. That is, the threshold variable captures the size of the surprise considering all forecasters, which is measured by the absolute value of the difference between the Monitor and the median of inflation expectations.

Figure 4 in Appendix A shows that the sum of squared residuals is clearly V-shaped, indicating that the threshold value ($\tau = 0.12$) is well estimated. The other parameters

[10] As already mentioned, this type of behavior may arise if information is costly.

of the model are presented in equation (12) below. They strongly support the view of a nonlinear effect of new information on the updating behavior. The coefficient of $s_{i,t}$ is highly statistically significant in both states. Point estimates suggest that the coefficient when the Monitor information produces a big surprise ($q_t \geq 0.12$) is almost the double ($\gamma_2^2 = 0.392$) than when the Monitor is close to the market consensus about the inflation rate ($q_t < 0.12$), whose value is $\gamma_2^1 = 0.238$. A Wald test rejects the null that the two coefficients are equal in any of the usual confidence levels.

$$\Delta\pi_{i,t}^{e} = [\underset{(0.001)}{0.003^{**}} + \underset{(0.023)}{0.238^{***}} s_{i,t}] I\left(q_t < 0.12\right) + [\underset{(0.004)}{0.013^{***}} + \underset{(0.027)}{0.392^{***}} s_{i,t}] I\left(q_t \geq 0.12\right)$$

Sample period: 2006:1 – 2013:9

Number of observations: 1167 (12)

R-squared: 0.38

Standard errors estimated using a robust variance-covariance matrix

Significance level denoted as: ***=1%; **=5%; *=10%.

Wald test $\gamma_2^1 = \gamma_2^2$, p-value: 0.00

5 Conclusions

Despite the importance of expectations in macro and microeconomic models, there is still sparse empirical evidence about how people form their expectations, and how they change their perception when new information arises. This paper contributes to the literature by outlining a direct empirical test for the significance of the impact of new information on the updating behavior of market experts' inflation forecasts, exploring the release of a signal about the inflation rate in Brazil.

The results for a panel of more than 100 professional forecasters indicate that agents update their expectations immediately after the release of new information, but the magnitude of the coefficient is consistent with staggered updating of expectations. There is also evidence that the precision of the signal received matters for the size of the update: the impact increases when the precision of the new information is higher. This result is consistent with Morris and Shin's (2002) model. Another documented source of nonlinearity is the own size of the surprise brought by the piece of new information released.

A priority for further research should be exploring two aspects of our data that can help to shed light on the updating behavior when (i) individuals have partial information or (ii) different groups of individuals have distinct information sets. First, it is important noting that our identification strategy explored changes in expectations around dates of the Monitor releases whose reference period is exactly the same as that of the IPCA. But the Monitor is a daily estimate for moving periods of 30 days. This means that on the days preceding the closing of the reference period of the IPCA agents already have partial information about the inflation rate captured by the Monitor, and probably react to that information. As this reaction happens before our identification window, it is not captured in our regressions and probably reduces our estimates. The effect of partial information is not explored in this paper. Second, we have assumed that all agents receive the same piece of new information. However, FGV offers a paid service in which subscribers have access to Monitor inflation rate and a full set of detailed information. Further works are needed to explore differences in the updating behavior of these two groups of forecasters.

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A Appendix

A.1 Additional econometric results

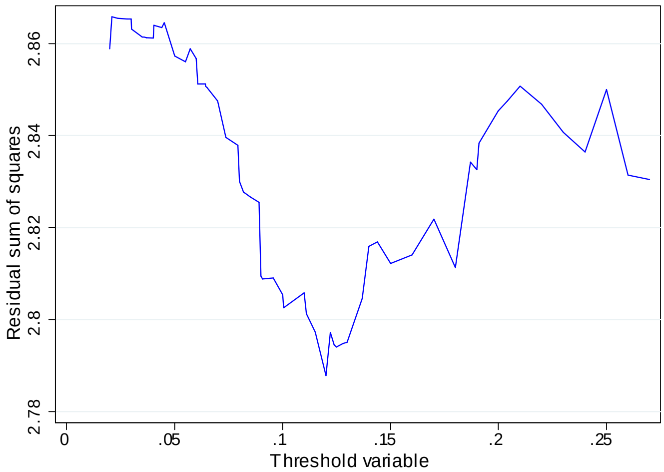

Figure 4: Sum of squared residuals of the threshold estimation

A.2 Linearization

The model predicts that the update of expectations is given by equation (6):

$$u_i = \frac{\beta}{\alpha_i + \beta} (\pi_P - \pi_i) \equiv p_i s_i,$$

A first order taylor approximation of this equation around (p_i^*, s_i^*) produces:

$$\begin{aligned} u_i &\approx p_i^* s_i^* + p_i^*(s_i - s_i^*) + s_i^*(p_i - p_i^*) \\ &= -p_i^* s_i^* + p_i^* s_i + s_i^* p_i \\ &= \gamma_0 + \gamma_1 p_{i,t} + \gamma_2 s_{i,t}, \end{aligned}$$

which is the equation (7) in the text.

Table 4: Monitor and IPCA release dates

Month	Monitor release date	IPCA release date	Month	Monitor release date	IPCA release date	Month	Monitor release date	IPCA release date
Jan 2006	01/27/06	02/09/06	Jan 2008	01/29/08	02/13/08	Jan 2010	01/28/10	02/05/10
Feb 2006	02/24/06	03/10/06	Feb 2008	02/29/08	03/11/08	Feb 2010	02/25/10	03/05/10
Mar 2006	03/28/06	04/07/06	Mar 2008	03/28/08	04/09/08	Mar 2010	03/29/10	04/08/10
Apr 2006	04/27/06	05/10/06	Apr 2008	04/29/08	05/09/08	Apr 2010	04/28/10	05/07/10
May 2006	05/29/06	06/08/06	May 2008	05/30/08	06/11/08	May 2010	05/28/10	06/09/10
Jun 2006	06/27/06	07/07/06	Jun 2008	06/30/08	07/10/08	Jun 2010	06/28/10	07/07/10
Jul 2006	07/28/06	08/11/06	Jul 2008	07/29/08	08/08/08	Jul 2010	07/28/10	08/06/10
Aug 2006	08/28/06	09/06/06	Aug 2008	08/27/08	09/05/08	Aug 2010	08/27/10	09/09/10
Sep 2006	09/26/06	10/06/06	Sep 2008	09/29/08	08/10/08	Sep 2010	09/28/10	10/07/10
Oct 2006	10/27/06	11/10/06	Oct 2008	10/29/08	11/07/08	Oct 2010	10/28/10	11/09/10
Nov 2006	11/28/06	12/08/06	Nov 2008	11/26/08	12/05/08	Nov 2010	11/28/10	12/08/10
Dec 2006	12/28/06	01/12/07	Dec 2008	12/29/08	01/09/09	Dec 2010	12/28/10	01/07/11
Jan 2007	01/29/07	02/09/07	Jan 2009	01/28/09	02/06/09	Jan 2011	01/28/11	02/08/11
Feb 2007	02/28/07	03/09/07	Fev 2009	02/27/09	03/11/09	Feb 2011	02/24/11	03/04/11
Mar 2007	03/29/07	04/11/07	Mar 2009	03/30/09	04/08/09	Mar 2011	03/29/11	04/07/11
Apr 2007	04/27/07	05/11/07	Apr 2009	04/28/09	05/08/09	Apr 2011	04/28/11	05/06/11
May 2007	05/28/07	06/06/07	May 2009	05/29/09	06/10/09	May 2011	05/27/11	06/07/11
Jun 2007	06/27/07	07/06/07	Jun 2009	06/29/09	07/08/09	Jun 2011	06/28/11	07/07/11
Jul 2007	07/27/07	08/08/07	Jul 2009	07/28/09	08/07/09	Jul 2011	07/27/11	08/05/11
Aug 2007	08/27/07	09/06/07	Aug 2009	08/28/09	09/10/09	Aug 2011	08/26/11	09/06/11
Sep 2007	09/27/07	10/10/07	Sep 2009	09/28/08	10/08/09	Sep 2011	09/28/11	10/07/11
Oct 2007	10/26/07	11/07/07	Oct 2009	10/29/09	11/11/09	Oct 2011	10/27/11	11/11/11
Nov 2007	11/26/07	12/06/07	Nov 2009	11/27/09	12/09/09	Nov 2011	11/29/11	12/08/11
Dec 2007	12/27/07	01/11/08	Dec 2009	12/29/09	01/13/10	Dec 2011	12/28/11	01/06/12

Table 5: Monitor and IPCA release dates (Continued)

Month	Monitor release date	IPCA release date	Month	Monitor release date	IPCA release date	Month	Monitor release date	IPCA release date
Jan 2012	01/27/12	02/1012	Aug 2012	08/27/12	09/05/12	Mar 2013	03/28/13	04/10/13
Feb 2012	02/29/12	03/09/12	Sep 2012	09/27/12	10/05/12	Apr 2013	04/26/13	05/08/13
Mar 2012	03/28/12	04/05/12	Oct 2012	10/29/12	11/07/12	May 2013	05/28/13	06/07/13
Apr 2012	04/27/12	05/09/12	Nov 2012	11/28/12	12/07/12	Jun 2013	06/28/13	07/05/13
May 2012	05/28/12	06/06/12	Dec 2012	12/28/12	01/10/13	Jul 2013	07/29/13	08/07/13
Jun 2012	06/28/12	07/06/12	Jan 2013	01/29/13	02/07/13	Aug 2013	08/28/13	09/06/13
Jul 2012	07/27/12	09/08/12	Fev 2013	02/27/13	03/08/13	Sep 2013	09/30/13	10/09/13