New Information and Updating of Market Experts' Inflation Expectations

Arnildo da Silva Correa[*] Paulo Picchetti[†]

Abstract

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, supporting Carrol's (2003) results. However, the parameter is not very high, which is consistent with sticky information and staggered updating of expectations. The precision of new information also matters: when precision increases agents put more weight on the piece of information received. These results, which are found to be robust, are consistent with Morris and Shin's (2002) model. Estimates also suggest that the magnitude of the updating depends on the distance between the sinal 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

Resumo

Esse artigo investiga como a divulgação de nova informação sobre o comportamento recente da inflação afeta as expectativas de inflação. Usando um painel com mais de 100 previsores profissionais e a divulgação de um sinal sobre a inflação para identificar os efeitos, encontra-se que nova informação faz os previsores individuais atualizarem suas expectativas imediatamente, de forma compatível com os resultados de Carrol (2003). Contudo, o parâmetro não é elevado, o que é consistente com informações rígidas e atualização infrequente de expectativas. A precisão da informação também importa: quando a precisão aumenta os agentes colocam mais peso na informação recebida. Esses resultados, que são bastante robustos, são consistentes com o modelo de Morris e Shin (2002). As estimativas também sugerem que a magnitude da atualização depende da distância entre o sinal que os agentes recebem e suas expectativas.

Palavras Chave: Nova informação, atualização, expectativas, previsores profissionais, sinal público, sinal privado

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

[*]Research Department, Banco Central do Brasil. Email: arnildo.correa@bcb.gov.br

[†]Instituto Brasileiro de Economia (IBRE-FGV). Email: paulo.picchetti@fgv.br

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, staggered updating of expectations generates strong and persistent real effects following nominal shocks (Mankiw and Reis, 2002; Sims, 2003; Maćkowiak and Wiederholt, 2009). The effects of these frictions are similar to those of price rigidity. The introduction of information frictions in macroeconomic models is also known to produce different implications for policy making (Reis, 2011; Paciello and Wiederholt, 2014) and helped to solve several empirical puzzles (see Ball et al., 2005).

There are two main approaches to rationally incorporate information frictions in macroeconomic models. In Mankiw and Reis (2002) agents update only infrequently because collecting and processing information is costly. However, if agents update, they gain full information. In Sims (2003) agents update continously but face a limited capacity of attention, which makes it impossible to process all information available. Yet, 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.

Despite the importance of expectations and differences in theoretical approaches, there is still only sparse empirical evidence about how people form their expectations. 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 is reaction 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 (CBB). 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 and since 2006 releases a daily flash estimate that mimics the IPCA, called Inflation Monitor. Every month, the Monitor covering the same reference period as the IPCA is released about eight days before the oficial IPCA. This means that the Monitor released on this date can be viewed as a 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 because we have daily data on inflations expectations.

Our paper is closely related to studies that analyze the expectations formation process empirically. Amantier et al. (2013) use an experiment embedded in a survey to invetigate 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 substatially over time and that either the 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.

The results of our estimations support the view that new information leads individual professional forecasters to update their expectations immediately, supporting Carrol's (2003) results. The parameter measuring the effect of new information is higly statistically significant. When new information indicates that inflation for the current month may be higher than the individual forecast, the agent increases their expectations; and he/she decreases expectations in the opposite case. This also provides evidence that professional forecasters consider the Monitor a valuable signal about the inflation dynamics in Brazil. However, the parameter of new information 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. In effect, the impact is nonlinear: when precision increases agents put more weight on the new information received. In summary, these results, which are subjected to several robusness checks and found to be robust, support the conclusions of Morris and Shin's (2002) model.

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 sinal 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 estimates of the coefficient of new information is almost twice as large in the state of great surprise compared to 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 and provides some prediction on how new information affects the updating of expectations. Section 3 describes the datasets used and section 4 presents the empirical 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. Our specification is similar to that in Crowe (2010), but here the toy model has three periods. In the first two periods each forecaster tries to guess the inflation rate π with the information they have. In the third period the actual inflation rate is released. In each period, agent i chooses a forecast f_i to minimize the squared error of this inflation forecast, given the actual inflation rate π:

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

Suppose that, in the first period, agents only observe their own private signal about the inflation rate and that this signal is noisy:

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

where ζ_i is an i.i.d. error term with variance σ_ζ^2. Denote the precision of the private signal as $\alpha \equiv \frac{1}{\sigma_\zeta^2}$. We can rationalize this private signal as the whole set of information that agents collect and process privately to construct their projections, including their econometric models. In this case, the agent i's best forecast of inflation is their own private signal:

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

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

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

with the variance of the i.i.d. error term η denoted as σ_η^2 and the precision of this signal defined as $\beta \equiv \frac{1}{\sigma_\eta^2}$. We also assume that:

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

Now forecasters optimally weight the signals according to their relative precisions:

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

And the update of the agent i's inflation forecast from period one to period two, that is, the change in their forecast after receiving the new piece of information is:

$$\begin{aligned} u_i &= \left[\frac{\alpha}{\alpha+\beta}\pi_i + \frac{\beta}{\alpha+\beta}\pi_P\right] - \pi_i \\ &= \frac{\beta}{\alpha+\beta}\left(\pi_P - \pi_i\right). \end{aligned} \tag{6}$$

Therefore, agents update their expectations depending on whether the public signal brings information about the inflation rate that is different or close to individual agents' current view. If new information brought by the public signal suggests that inflation rate will be very close to agents' current forecasts, there is no reason to change their expectations. In this case, the new informational content only reaffirms their expectations, and the impact will probably be only on the cross-sectional dispersion of forecasts. But if the public signal differs much of the informational content already embedded in their expectations, forecasters recognize that new information tells a different story about the inflation rate and change their forecasts accordingly, weighting the piece of new information by its relative precision. In summary, the magnitude of the update depends on two variables: (i) how far new information released is from the individual agent's current forecast (we name this term as "surprise") and (ii) the relative precision of the new information received.

Equation (6) also suggests an interaction between the relative precision of new information and the term of surprise (the informational content brought by the public signal). Thus, the effect of new information on the size of the updating is nonlinear: the higher the relative precision of new information, the higher the weight that agents put on the piece of new information released, and, consequently, higher the size of the update of agents' expectations.

3 Data

We employ two datasets to test the predictions of the model. The first dataset is the survey conducted by the CBB among market experts. The CBB 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. 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 until 12 months ahead. Thus, we use daily information on individual inflation forecasts of a panel of market experts covering the period between January 2006 and September 2013. Inflation forecasts refer to the Broad National Consumer Price Index (IPCA), which is used for the oficial inflation target.

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 the production and publication of macroeconomics statistics and applied economics 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.[1] It should be emphasized that the official IPCA is calculated by the IBGE, not by FGV. But FGV developed a high frequency measurement of inflation that mimics the IPCA. The Inflation Monitor has the same basket and coverage as the IPCA, but it is released every day.

Figure 1 below presents schematically the disclosure of the Monitor and the IPCA information for a given month t. The IPCA measures the inflation rate for the period between the first day and the last day of the reference month, represented in Figure 1 respectively by dates j and j^*. However, the oficial result is only known some 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 oficial IPCA is represented by $j^* + m$. But every day FGV releases its moving 30-days measure of

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

inflation. Note that on day j^* the Monitor covers exactly the same reference period as the IPCA. 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. Between j^* and $j^* + m$ the Monitor inflation rate for the current month has already been released but agents do not know the oficial IPCA yet. Release dates are reported in Tables (4) and (5) in the appendix.

We explore these events (the Monitor releases) that happen every month on day j^* to identify the effects on the updating behavior, by estimating the impact of this piece of information that agents receive about the IPCA inflation rate on the market experts' inflation expectations.

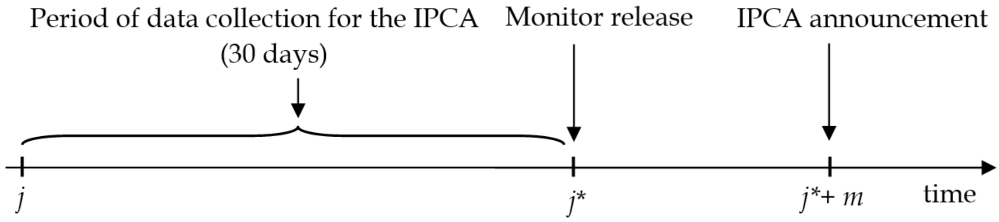

Figure 1: Data disclosure scheme

4 Empirical analysis

The model of section (2) predicts a nonlinear relation between new information and the size of the update of expectations, which depends on the relative precision of new information. Yet, precisely estimating a nonlinear relation with limited data is likely to be difficult. Thus, we first use a linearized version of equation (6), and then we explore the possibility of nonlinearities.

The linear approximation of equation (6) is:

$$u_{i,t} \simeq \gamma_0 + \gamma_1 p_{i,t} + \gamma_2 s_{i,t}, \quad \gamma_1 > 0, \quad \gamma_2 > 0, \tag{7}$$

where, for the individual i, $u_{i,t}$ is the update of expectations, $p_{i,t}$ measures the precision of the public signal relative to the private information, and $s_{i,t}$ captures the surprise, i.e., the difference between the piece of new information received and the private information.

Taking this relation to the data using the Monitor release on days 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 expectations is the Monitor release. So, the window cannot be too short, such that there is no time for the BCB survey capture the changes in expectations, or too large that others events begin to affect agents' inflation expectations. Hence, we use a two-day window around j^* in our estimations.

It must be recognized that the empirical countepart for $u_{i,t}$ may contain measurement errors and/or be contaminated by idiosyncratic time-varying shocks to forecasts' accuracy. We assume that 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, $\Delta\pi^e_{i,t} = \pi^{e\prime}_{i,t} - \pi^e_{i,t}$ represents the change in the agent i's inflation expectation for the current month in the two-day window, that is, between the day before the Monitor release $\left(\pi^e_{i,t}\right)$ and the day after the Monitor release $\left(\pi^{e\prime}_{i,t}\right)$, $s_{i,t} = M_t - \pi^e_{i,t}$ measures the surprise for forecaster i—the piece of new information, captured by the difference between the Monitor and the expectation that individual i had on the day before the Monitor release. We measure the relative precision of 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.

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 than goes on to present the baseline regression results and to outline a number of robustness exercises. Finally, it presents the results of nonlinear estimations.

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 brought by the

Monitor. The changes in expectations are calculated in the two-day window around the Monitor releases. The sample covers the whole period from January 2006 to September 2013 and includes all market specialists in our dataset. The relationship appears to be positive. Figure 2 shows a large concentration of points near zero, indicating that when new information is only slightly different from the information that individuals have, the reaction is small.[2] However, there is evidence that new information brought by the Monitor leads individuals to update their expectations, as predicted by the model.

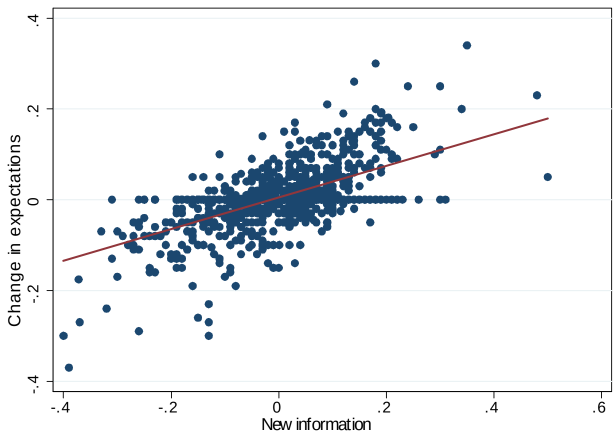

Figure 2: Scatter plot of changes in inflation expectations and new information

4.1.2 Baseline results

The results of estimating equation (8) is 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 in which the relative precision term is supressed, including only the new information term $s_{i,t}$, using OLS and Fixed Effect, respectively. Columns II and IV show estimates of the full equation.

[2] It is important to mention that points on the zero axis are not caused by individuals that did not report their new expectations after the Monitor release. Here we consider only those who have updated. But some decided not changing their expectations.

Table 1: Baseline regression results

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%.

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 new information brought by the disclosure of the Monitor affects the process of expectation formation. When the number reported by 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 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. These findings support Carrol's (2003) results 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. This result is consistent with sticky information and staggered updating of expectations. Second, there is evidence that the relative precision of the signal 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 subsection. First, the baseline estimations using the full equation were replicated for the Top 5 forecasters. In the BCB 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 our 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, probably because the small number of observations in this exercise.

Second, we extended the full equation including 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. But Table 1 reports estimates using changes in the exchange rate $\left(\Delta e_{i,t} = e'_{i,t} - e_{i,t}\right)$ and changes of swap rate $\left(\Delta r_{i,t} = r'_{i,t} - r_{i,t}\right)$ in the window around j^* as controls. The results are essencially unchanged compared to the baseline. Also note that, since the macroeconomic variables are not statistically significant, this exercise provides evidence in favor of our crucial 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%

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4.1.4 Placebo datasets

To provide evidence that previous results capture the impact of 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 is essencial noting 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 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's informational content. Obviously there are indirect effects, via inflationary inertia mechanisms, since higher inflation in month t puts upward pressure on inflation in month $t+k$. But if the time horizon k is long enough, the impact of inertia disappears. Thus, in our placebo experiment we use inflation expectations of the third and the ninth month ahead.

Figure 3 shows the scatter plot of changes in inflation expectations for the third and the ninth month ahead against our measure of new information brought by the Monitor. Table 3 presents the estimates of the baseline specification 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.

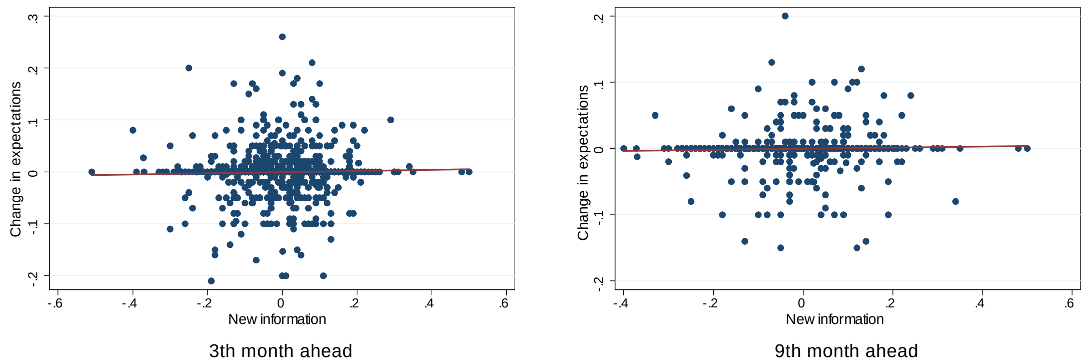

Figure 3: Scatter plot of changes in inflation expectations and new information – Placebo

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

In this subsection we explore the possibility of nonlinearities in the updating behavior of forecasters' expectations. First, from the theoretical point of view, the model of section 2 predicted that new information would have a nonlinear impact on the updating process, 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 different updating behavior depending on whether agents receive a signal that is very close or too far from their current expectations. 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 more close to equation (6), 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 the pooled OLS method to estimate the equation, adopting a robust variance-covariance matrix to deal with autocorrelation in the residuals. The estimates presented below 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 new information received, and, consequently, more strongly agents respond changing their forecasts. In summary, the higher the precision of new information, the higher the size of the update.

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

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 effect suggested by 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:

$$\Delta\pi^e_{i,t} = \left[\gamma^1_0 + \gamma^1_2 s_{i,t}\right] I\left(q_t < \tau\right) + \left[\gamma^2_0 + \gamma^2_2 s_{i,t}\right] I\left(q_t \geq \tau\right) + \varepsilon_{i,t}, \tag{10}$$

where $q_t = |s_t|$ is the threshold variable; $I(.)$ 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 as the variable determinig changes of states a function of $s_{i,t}$, which is our explanatory variable. 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 when the Monitor is released. 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 of the model are presented in equation 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 $\gamma^1_2 = 0.238$. A Wald test rejects the null that the two coefficients are equal in any of the usual confidence levels.

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

Sample period: 2006:1 – 2013:9

Number of observations: 1167

R-squared: 0.38

Standard errors estimated using a robust variance-covariance matrix

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

Wald test $\gamma^1_2 = \gamma^2_2$, 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.

Results for a panel of more than 100 professional forecasters indicate that agents update immediately their expectations 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 precision of new information is higher, 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.

A priority for further research should be exploring two aspects of our data that can shed light on the updating behavior when individuals have partial information or groups of individuals have different information sets. First, it is important noting that our identification strategy explored changes in expectations around dates in which the Monitor released covered exactly the same reference period as the IPCA. But the Monitor is a daily estimate for moving periods of 30 days. This means that in the days preceding the closing of the reference period agents already have partial information about the inflation rate to be captured by the Monitor (and by the IPCA) in that month, and probably react to that information. Since this reaction happens before our idenfitication window, it is not captured and 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 work is also needed to explore differences in the updating behavior of these two groups of forecasters.

References

[1] Amantier, O, S. Nelson, G. Topa, W. Klaauw and B. Zafar (2012), "The Price is Right: Updating Inflation Expectations in a Randomized Price Information Experiment", Federal Reserve Bank of New York Staff Reports no. 543.

[2] Ball, L., G. Mankiw and R. Reis (2005), "Monetary Policy for Inattentive Economies", *Journal of Monetary Economics*, vol. 52(4), pp. 703–725.

[3] Caner, M. and B. Hansen (2004), "Instrumental Variable Estimation of a Threshold Model", *Econometric Theory*, vol. 20(5), pp. 813-843.

[4] Carrol, C. (2003), "Macroeconomic Expectations of Households and Professional Forecasters", Quarterly Journal of Economics, Vol. 118(1), pp. 269-298.

[5] Carvalho, F. and A. Minella (2012), "Survey Forecasts in Brazil: A Prismatic Assessment of Epidemiology, Performance, and Determinants", *Journal of International Money and Finance*, vol. 31(6), pp. 1371-1391.

[6] Cerisola, M and G. Gelos (2005), "What Drives Inflation Expectations in Brazil? An Empirical Analysis", IMF Working Paper 05/109 (Washington: International Monetary Fund).

[7] Coibion, O. (2010), "Testing the Sticky Information Phillips Curve", *The Review of Economics and Statistics*, vol. 92(1), pp. 87–101.

[8] Coibion, O. and Y. Gorodnichenko (2012), "What Can Survey Forecasts Tell Us about Information Rigidities?", *Journal of Political Economy*, vol. 120(1), pp. 116-159.

[9] Crowe, C. (2010). "Testing the Transparency Benefits of Inflation Targeting: Evidence from Private Sector Forecasts", *Journal of Monetary Economics*, vol. 57(2), pp. 226-232.

[10] Franses, P. and D. Van Dijk (2000), *Nonlinear Time Series Models in Empirical Finance*, Cambridge University Press.

[11] Guillen. D. (2008), "Ensaios sobre Expectativas de Inflação no Brasil", Master's Thesis, Puc-Rio.

[12] Lamla, M. and S. Sarferaz (2012), "Updating Inflation Expectations", KOF Working Papers No. 301, Zurich.

[13] Maćkowiak, B. and M. Wiederholt (2009), "Optimal Sticky Prices under Rational Inattention", *American Economic Review*, vol. 99 (3), 769–803.

[14] Mankiw, G. and R. Reis (2011), "Sticky Information versus Sticky Prices: A Proposal to Replace the New Keynesian Phillips Curve", *The Quarterly Journal of Economics,* vol. 117(4), pp. 1295–1328.

[15] Morris, S. and H. Shin (2002), "Social Value of Public Information", *The American Economic Review*, vol. 92(5), pp. 1521-1534.

[16] Paciello, L. and M. Wiederholt, (2014), "Exogenous Information, Endogenous Information, and Optimal Monetary Policy", *Review of Economic Studies*, vol. 81(1), pp. 356-388.

[17] Reis, R. (2011), "When Should Policymakers Make Announcements?", 2011 Meeting Papers 122, Society for Economic Dynamics.

[18] Sims, C. (2003), "Implications of Rational Inattention", *Journal of Monetary Economics*, vol. 50 (3), 665–690.

A Additional results

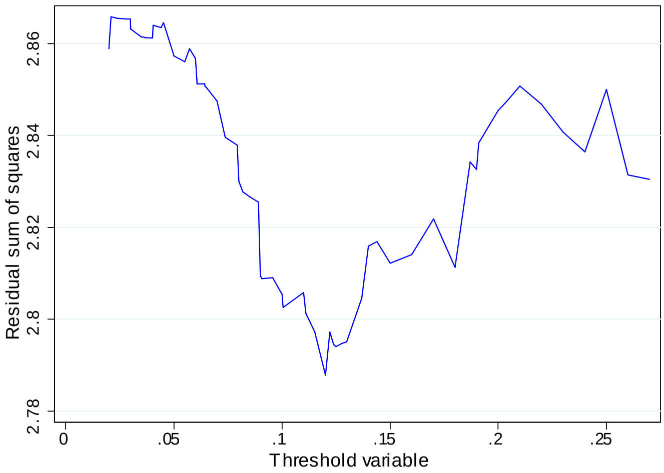

Figure 4: Sum of squared residuals of the threshold estimation

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