The Information Rigidities and Rationality of Costa Rican Inflation Expectations

Alonso Alfaro Ureña
Aarón Mora Meléndez

Abstract

Costa Rican inflation expectations cannot be characterized as rational under any existing definition of the term. They cannot be categorized as adaptive either, since in addition to historical data on inflation, other macroeconomic variables are important in explaining inflation expectations. Instead, the sticky information model is considered a more sophisticated framework to assess inflation expectations of Costa Rican agents. Results are based on the Monthly Survey of Inflation and Exchange Rate Expectations elaborated and published by the Banco Central de Costa Rica. This chapter collects evidence to assess whether the expectations from this survey are subject to information rigidities. Additionally, this chapter shows how a simulated survey, based on a sticky information model, is capable of replicating features from the observed survey.

Keywords: inflation expectations, sticky information, adaptive learning.
JEL classification: C53, D84, E31, E58.

A. Alfaro Ureña <alfaroua@bccr.fi.cr> Department of Economic Research. Economic Division, BCCR. A. Mora Meléndez, BCCR. <moramo@bccr.fi.cr>. The authors would like to thank Olivier Coibion for his guidance, advice and helpful discussion during the development of this project. Federico Herrera provided excellent research assistance. The ideas expressed in this chapter are of the authors and do not necessarily represent the view of the Banco Central de Costa Rica.

1. INTRODUCTION

Conventional economic theory highlights the crucial influence of expectations on changes in macroeconomic variables. Changes in a variable affect the expectations related to its future movement and these expectations also influence the variable's underlying path. This bilateral relation puts the problem of how agents form their expectations into the front line of macroeconomic modeling.

Most central banks acknowledge the crucial role of expectations, and argue that managing inflation expectations is paramount for attaining price stability and conducting monetary policy. The Banco Central de Costa Rica (BCCR) operates under an inflation targeting regime, in order to accomplish its goal of a low and stable inflation level. It relies heavily on the inflation expectations of Costa Rican agents aligning closely with monetary policy. It is necessary to understand how inflation expectations are formed to anchor expectations to the ones targeted by the BCCR.

Until recently the research agenda on expectation formation was eclipsed by the rational expectations (RE) hypothesis started by Muth (1961). This hypothesis revolutionized macroeconomic thinking during the seventies by incorporating the effect of expectations into most economic models. As Thomas Sargent points out[1], the RE hypothesis allowed for the disappearance of any free parameters associated with expectations, so people's beliefs became outputs of the model in question. As a result, macroeconomists widely adopted the assumption of RE to arrive at tractable equilibrium solutions.

Nevertheless, a common critique for the RE hypothesis is that it assumes that people have much more information about the economy than they really do, since it implies that agents construct expectations and make decisions by gathering and conveying all available public information. This assumption is unrealistic and empirical studies often reject the RE hypothesis. There are three popular alternatives to the re hypothesis: *1)* agents use heterogeneous mechanisms to form their expectations, as in Branch (2004) and Honkapohja and Mitra (2006); *2)* agents use different information sets, as in Angeletos and Lian (2016); and *3)* agents have different abilities to process information, see for example Woodford (2001). A good survey of alternative approaches to the specification of expectations is presented in Woodford (2013)

[1] See Evans and Honkapohja (2005).

where the author presents how macroeconomic analysis under a new Keynesian framework could be performed without relying on the RE hypothesis. Regardless, there are well developed theoretical alternatives to RE, though many features observed in expectations survey are not entirely taken into account by these alternatives. Authors like Manski (2004) have pushed for more empirical studies that deepen our knowledge of how people elicit and revise their expectations.

One approach to analyzing expectations formation has focused on the role of information rigidities and has been supported by empirical evidence, see Mankiw and Reis (2002), Woodford (2001), and Sims (2003). In particular, Mankiw et al. (2003) depart from traditional empirical approaches to expectations measurement, which have traditionally relied on measures of central tendency, such as the mean or median; instead, they study the heterogeneity of inflation expectations using statistics of dispersion. The idea is that the disagreement among agents over inflation expectations can be explained by information stickiness. They use the sticky information model developed in Mankiw and Reis (2002) to explain the mean and dispersion of the United States' inflation expectations. Under this framework, just a fraction of the agents updates their expectations with the most recent information available. This fraction is derived from the bounded rationality associated with the cost of updating expectations. Pfajfar and Santoro (2010) build on this line of work and instead of using measures of central tendency, they perform percentile analysis to study the heterogeneity, learning, and information stickiness of inflation expectations.

Alfaro and Monge (2013) also document that Costa Rican inflation expectations can neither be characterized as rational nor adaptive. If expectations were rational, the realized bias between expected and realized inflation level could not be predicted: Costa Rican data fails this test even with relaxed assumptions of rationality. On the other hand, inflation expectations cannot be categorized as adaptive neither, since in addition to historical data on inflation, other macroeconomic variables hold significant explanatory power for inflation expectations.

Alfaro and Monge (2013) note the need to evaluate more sophisticated tools to model Costa Rican inflation expectations. This chapter will evaluate the sticky information model to determine whether this need is substantial. The main source of data for this research comes from the Monthly Survey of Inflation and Exchange Rate

Expectations conducted and published by the BCCR. For this chapter, we used 135 months of survey observations from January 2006 to March 2017. We identify individual participants and place them into four separate groups based on their profession. In the survey, respondents report their 12-month expected inflation as well as expected percentage variations (to different time horizons) of the exchange rate between the Costa Rican colon and United States dollar.

The remainder of the chapter is organized as follows: Section 2 describes the Monthly Survey of Inflation and Exchange Rate Expectations, presents its main features, and analyses the disagreement and the realized bias or forecast error presented in the survey. Section 3 presents the sticky information model of Mankiw et al. (2003), gathers evidence for information rigidities in the expectations of Costa Rican agents captured in the survey as a whole and within professional groups, and simulates a sticky information model that is based on a vector autoregressive model using Costa Rican macroeconomic data. Finally, Section 4 discusses the findings of the paper, which show nonconformity of the sticky information approach for the Costa Rican data, as well as the work ahead for modeling Costa Rican inflation expectations.

2. INFLATION EXPECTATIONS SURVEY

The BCCR has conducted the Monthly Survey of Inflation and Exchange Rate Expectations since 2006. This survey gathers data on expected inflation for the next 12 months and the expected percentage variation in the exchange rate between the Costa Rican colon (CRC) and the United States dollar (USD) for the next 3, 6, 12, 24, and 36 months[2]. The questionnaire of the survey can be found in Annex A. Responses to questions on inflation and exchange rate expectations are point expectations that ask for a numerical expectation along with the main factors that were considered to form these expectations.

The observation period starts on January 2006 and goes until March 2017, a total of 135 months. The individuals consulted in the survey are categorized into four different groups depending on their professional expertise: *1)* consulting, *2)* stock market analyst, *3)* academic,

[2] Consultancy of the 24- and 36-month variation in the CRC/USD exchange rate started on December 2016.

and *4)* business sector. The number of respondents to the survey and its composition have changed during the observation period; there were 27 respondents in January 2006, most of whom were stock market analysts and by March 2017, there were 61 respondents predominantly from the business sector. Figure 1 presents the composition of the sample group during the observation period.

Two features of the survey responses stand out: first, the total number of responses has increased more than twofold since the survey was first implemented, with a peak of 87 responses in June 2013[3]. Second, the composition of responses has drastically changed in the last years of the survey–the majority of responses have recently come from individuals working in the business sector–. This compositional shift has resulted from a change in the survey design from June 2012 to the present[4].

The BCCR computes the 12-month expected inflation by averaging the responses received during a particular month, expectations coming from the business sector are dominant in the expectations published, representing up to 80% of the responses since 2015. This dominance of the business sector in the average expected inflation can be observed in Figure 2 where the mean expectation is plotted for the whole sample and by group.

The average expectation has clearly declined, staying in the single digits since April 2009, and below 5% since April 2015. The behavior exhibited by the inflation expectations has been in accordance with the inflation target range of the BCCR (3%-5%) since April 2015. In January 2016, even though the inflation target range was downgraded to 2%-4%, expectations have continued to remain within the range up until the last month in our sample, March 2017.

The alignment between the expected inflation rate and the target inflation range in recent years highlights the built-up credibility of BCCR towards society. For the thirty-year period preceding 2009, Costa Rica experienced double-digit inflation rates, but the BCCR has seemingly regained credibility. Agents trust the BCCR to steer the inflation rate, which thereby anchors inflation expectations. Despite this tendency for inflation expectations to lie within the target

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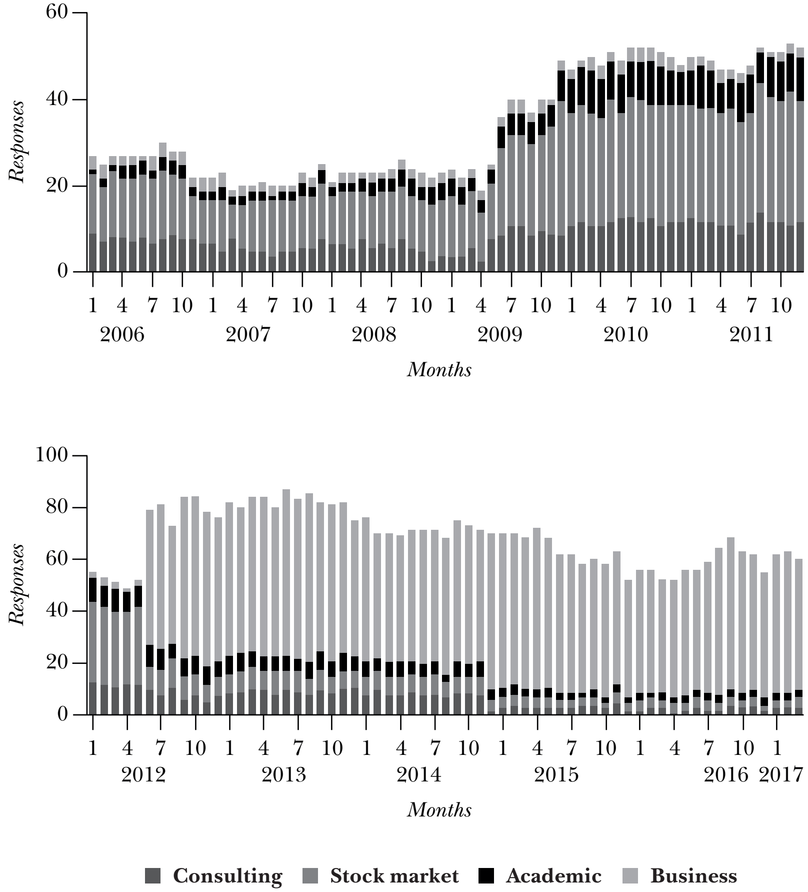
3 With 64 of them from the business sector.

4 The two samples were active for several months, but the aggregate results did not differ.

Figure 1

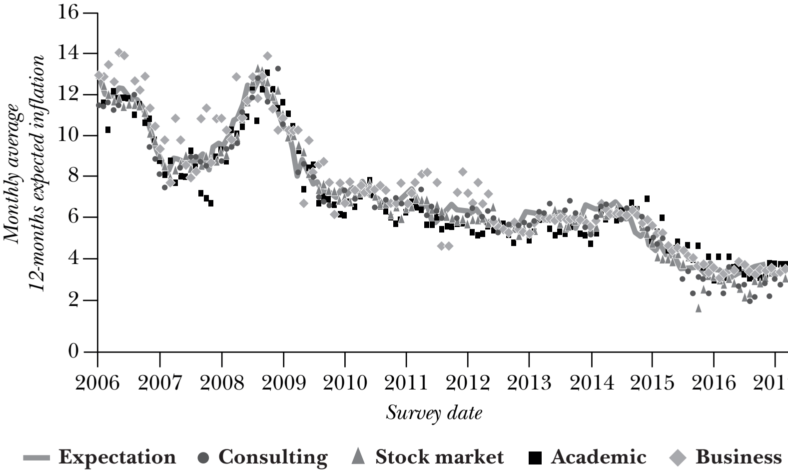
INFLATION EXPECTATIONS SURVEY: RESPONSES



Source: Own elaboration.

Figure 2

EXPECTED INFLATION MONTHLY AVERAGE



Source: Own elaboration.

range, disagreement about inflation expectations is present in the survey, not only between groups but also within groups[5].

2.1 Disagreement Among Expectations

Each individual in the survey sample has an identifier code and every month that an individual responds, the observations collected are registered with the relevant identifier (ID). This way the survey data can track respondent observations throughout the entire survey period, allowing for comparisons in the responses over time among individuals of the same group and within the full sample. In the survey there are 409 identifiers that correspond to at most 409 individuals[6] that respond the survey at some point during the observation period.

[5] Figure 9 in the Annex, shows the increase of outliers on the expectations from the business sector in recent years.

[6] Since the change in the design of the survey sample involved different nomenclature for the identifiers, the same individual can have two identifiers, one under the former sample and another one with the current sample.

Table 1

DISTRIBUTION ON THE NUMBER OF RESPONSES

	Identifiers (IDs) with equal or more responses	
Responses (⩾)	*Number of IDs*	*Percentage of IDs*
1	409	100.00
10	206	50.37
20	136	33.25
30	41	10.02
40	33	8.07
50	28	6.85
60	17	4.16
70	10	2.44
80	9	2.20
90	3	0.73

Source: Own elaboration.

The number of responses from a particular identifier range from 1 to 98, with an average of 16.46 during the 135-month observation period. The observed distribution on the number of responses by ID is shown on Table 1. Decomposing this distribution into the four aforementioned professional groups, we observe that the academic and consulting groups have the highest response rates. Even though the firm group dominates the survey responses, most of the firms' identifiers have less than 48 responses.

Given the number of individuals participating in the survey, their professional expertise, and background, disagreement among the inflation expectations can be observed on the survey. Mankiw et al. (2003) are primarily concerned with this disagreement, which is typical in most expectations surveys and they posit that this heterogeneity can be explained by bounded rationality, meaning that only a fraction of the agents adjusts their expectations as new information becomes available due to the cost associated with the adjustment.

In this context, dispersion statistics like the interquartile range can be used to discriminate between different models of expectations formation by pinning down their faculty to replicate features observed on the data. Figure 3 presents the interquartile range observed every month by group, along with the realized inflation rate for the month that these expectations were registered. This is done to assess whether the dispersion tends to increase when inflation is high, as has been suggested by Ballantyne et al. (2016) and Johannsen (2014), among others.

For the stock market analyst and academic groups, the interquartile range and inflation rate attain their maximum in the last months of 2008. For these two groups, it may seem to be a positive correlation between the level of inflation and interquartile range during years near the 2008-2009 financial crisis. Nonetheless, there are periods in which the inflation rate decreases but the dispersion of the sample expectations does not follow the same trend; the clearest example is the dispersion within business sector responses since 2015 the interquartile range has moved around 2% despite the sharp decline in inflation. This suggests that for the Costa Rican case there is no clear direct relation between the dispersion in inflation expectations and the level of inflation.

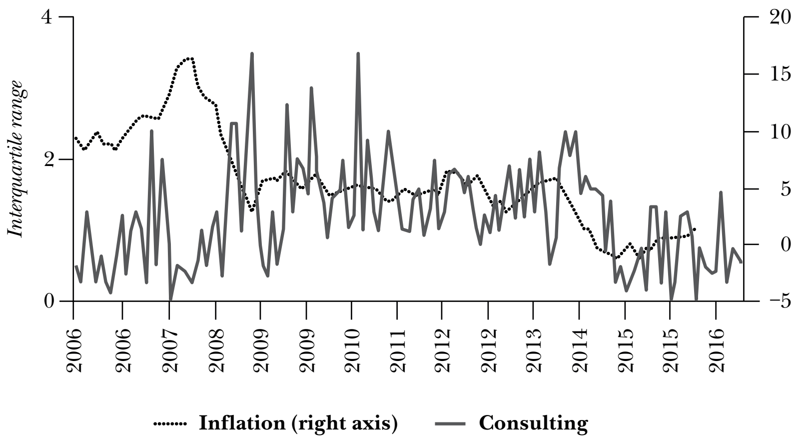
A basic regression exercise between dispersion as measured by the interquartile range and the inflation level is shown in Table 2. Regressing the interquartile range by the inflation rate does not illustrate a significant relation between the two groups: the associated coefficients are not significant when taking into account the whole survey or individual groups.

Elliott et al. (2008) and Engelberg et al. (2009) note that disagreement among inflation expectations does not necessarily indicate that agents face different degrees of uncertainty when forming their expectations. This is because the survey collects point predictions from which individual distributions or probabilistic beliefs of possible outcomes for future inflation cannot be inferred. It is possible that two forecasters who hold identical probabilistic beliefs provide different point predictions and it is also possible that two forecasters with different probabilistic beliefs provide the same point forecast. When using point forecasts, we can only interpret the phrase *disagreement among expectations* as an acknowledgment of distinct point forecasts; we cannot conclude anything about the uncertainty that forecasters face.

Figure 3

INTERQUARTILE RANGE BY GROUP

CONSULTING



ACADEMIC

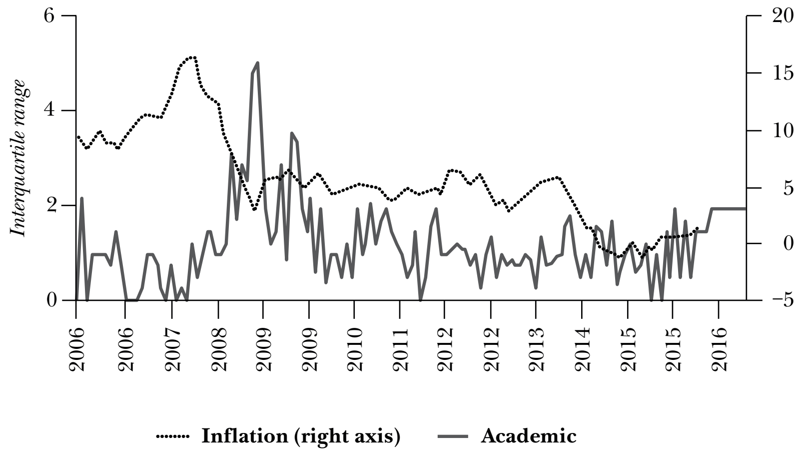
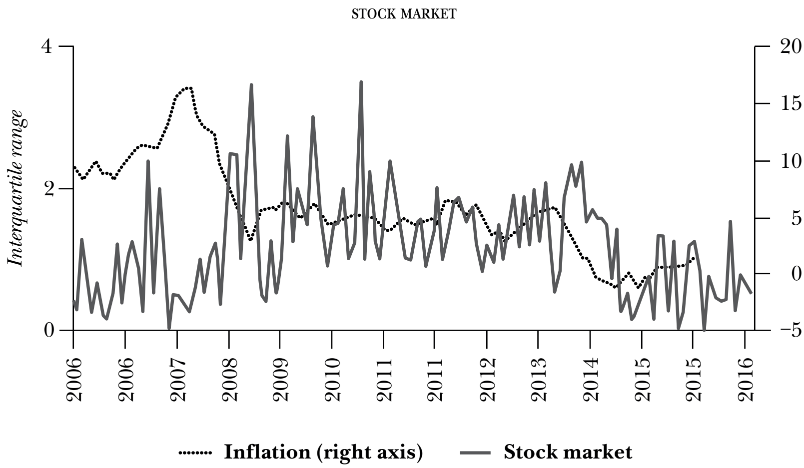
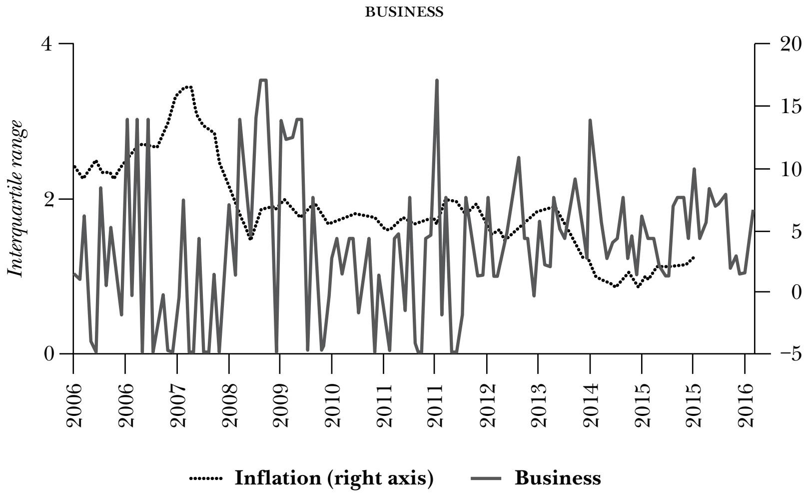


Figure 3 (cont.)

INTERQUARTILE RANGE BY GROUP





Source: Own elaboration.

Table 2

REGRESSION: INTERQUARTILE RANGE AND INFLATION

Coefficient	*Whole survey*	*Consulting*	*Stock market*	*Academic*	*Business*
Constant	1.591[c]	1.209[c]	1.135[c]	1.254[c]	1.446[c]
	(0.090)	(0.110)	(0.090)	(0.138)	(0.134)
Inflation	−0.013	−0.007	0.003	−0.002	−0.011
	(0.012)	(0.015)	(0.012)	(0.019)	(0.018)
N	135	135	135	135	135
R^2	0.0087	0.0014	0.0006	0.0001	0.0029

Note: [a] significance level 0.1, [b] 0.05, [c] 0.01.
Source: Own elaboration.

2.2 Realized Bias

We can also perform a second descriptive analysis of the survey inflation expectations focused on how well agents forecast the inflation level. If agents can successfully predict the path of future inflation, then the realized bias, that is the difference between the (forecasted) expected inflation level for time t and the realized inflation at time t, should be close to zero.

As a result of the survey design, when 12-month expected inflation is recorded at time t, its predictive power should be compared with the realized inflation level of time $t+11$, that is eleven months later from when the observation was collected. This is because even though agents form their expectations for each annual period, they are consulted during the first month of the forecast period. This does not present an issue since agents do not know the realized inflation of the month that is consulted[7]. For instance, the expected inflation of January 2006 should be compared with the inflation rate of December 2006 to compute the realized bias of December 2006.

With this adjustment only 124 months from January 2006 to April 2016 are used to analyze realized bias rather than all 135 months

[7] The Instituto Nacional de Estadísticas y Censos (INEC) of Costa Rica publishes the inflation rate of month t until the first days of month $t+1$.

of the survey. The last eleven months do not yet have a realized inflation level to compare to, since the last observed inflation in this paper is March 2017. Panel A of Figure 4 compares the expected and realized inflation rates, while panel B. shows the average realized bias.

Our measure of realized bias has exhibited cyclical behavior, reaching its minimum at the end of 2008 and its maximum at the end of 2009. While there are months where the realized bias has been practically zero, suggesting good predictive power, it has been positive since 2005, meaning that on average, inflation expectations have been greater than realized inflation.

The average realized bias seems to have a general upward trend across the entire observation period, standing above 5% during most of 2015 and part of 2016, but decreasing since the second semester of 2016. The average realized bias does not differ substantially by group–Figure 5 shows the average realized bias for each group and also for the entire survey sample–.

As expected, the business sector has dominated recent survey results–the average bias of the business sector has largely aligned with the average of the entire survey sample–. In addition, the average bias has increased over the years for all four groups. Figure 5 suggests that the differences among groups are not significant, but this can be explained as a result of using measures of central tendency such as the average. On the other hand, valuable information can be extracted by studying disagreement among inflation expectations via statistics of dispersion. The next section explores the role of information rigidities in explaining the heterogeneity in inflation expectations.

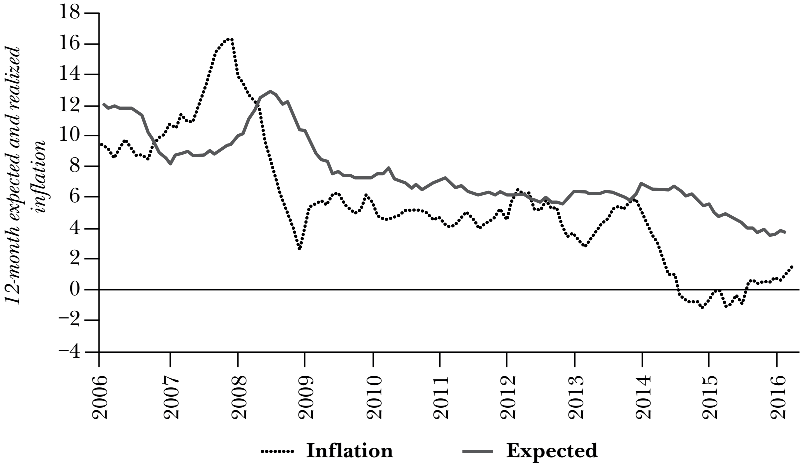
3. STICKY INFORMATION MODEL

Mankiw and Reis (2002) propose a model where information rigidities play a central role in the price and inflation dynamics. In their model, only a fraction λ of agents gather, process, and optimize their expectations with the most recent economic information available. The parameter λ, which is exogenous to the model, can be interpreted as the result of the bounded rationality associated with the cost of adjusting to new information. This model is conceived as an alternative to the new Keynesian Phillips curve since it highlights the role of information rigidities.

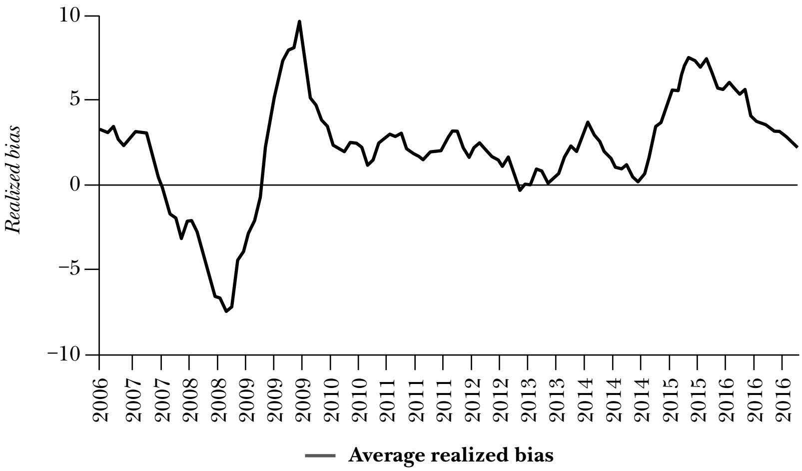
Figure 4

EXPECTED AND REALIZED INFLATION

A. EXPECTED INFLATION



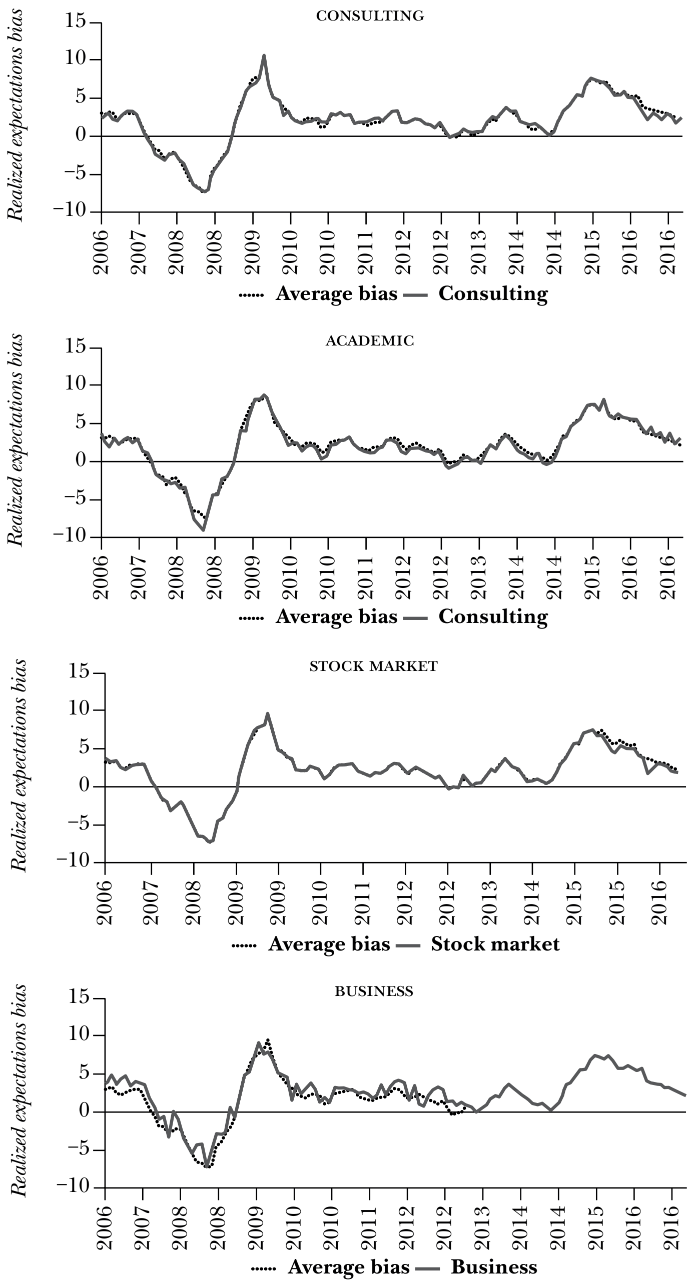
B. REALIZED AVERAGE BIAS



Source: Own elaboration.

Figure 5

AVERAGE REALIZED BIAS BY GROUP



Source: Own elaboration.

The *sticky information Phillips* curve derived in Mankiw and Reis (2002) concludes that the relevant expectations of the agents are those made in the past about current conditions. Mankiw et al. (2003) follow this idea and study the disagreement about inflation expectations by assuming there is information stickiness, meaning that only a fraction of the agents generates their expectations of future inflation using all available economic information. With this specification, we can generate cross sectional samples of simulated expectations for each period, allowing us to study the features of a simulated survey beyond measures of central tendency.

In this section, we gather evidence of information rigidities present in the Monthly Survey on Inflation and Exchange Rate Expectations at the survey and group level. Moreover, a sticky information model is simulated, assuming that the process used to generate expectations is an econometric model and the way that rational agents form their expectations is through forecasts from this model. In particular, we use a vector autoregressive model with Costa Rican macroeconomic data to generate 12-month inflation forecasts.

3.1 Evidence for Information Rigidities

Following Coibion and Gorodnichenko (2015), we can exploit the conclusion from Mankiw and Reis (2002) that states that for an economic variable x under a sticky information model, the average forecast across agents at time t for time $t+h$, $F_t x_{t+h}$, is a weighted average of the current and past rational expectation forecast such that[8]:

$$F_t x_{t+h} = (1-\lambda)\sum_{j=0}^{\infty} \lambda^j E_{t-j} x_{t+h}. \quad (1)$$

Representing rational expectations as $E_t x_{t+h} = x_{t+h} - v_{t+h,t}$, where $v_{t+h,t}$ is the rational expectation error, which is uncorrelated with information dated t or earlier, we can find a predicted relation between the ex post mean forecast error and the ex ante mean forecast revision (see Coibion and Gorodnichenko, 2015, for its derivation):

[8] In this equation the probabilities of an update are reparametrized so only $(1-\lambda)$ percent of the agents update their information sets and acquire no new information with probability λ.

2 $$x_{t+h} - F_t x_{t+h} = \frac{\lambda}{1-\lambda}\left(F_t x_{t+h} - F_{t-1} x_{t+h}\right) + v_{t+h,t}.$$

The relation in 2 can be applied to the data. Since it requires the construction of a forecast revision, we will use data on the expected exchange rate variation instead of inflation expectations; only a 12-month expected inflation is available. Under a sticky information framework relation, 2 should be satisfied for the mean of any macroeconomic variable regardless of the frequency of t and the horizon h, so gathering evidence of information rigidities using the expected exchange rate variation should be comprehensive for all expectations in the survey. Specifically, quarterly data for the expected exchange rate e variation for three and six months is used to perform the following regression based on 2:

3 $$e_{t+1} - F_t e_{t+1} = \beta\left(F_t e_{t+1} - F_{t-1} e_{t+1}\right) + \varepsilon_t.$$

Estimates for Equation 3 at the survey and the group level are shown in Table 3. These regressions can be used to assemble evidence for information rigidities present on the survey. Under a sticky information model, the β coefficient in Equation 3 should be significant, which is the case at the survey level. An advantage of the relation between the ex post forecast error and the ex ante forecast revision on Equation 3 is that it enables us to map the estimated coefficient $\hat{\beta}$ to an estimate of the information rigidity parameter λ. In our case, this gives an estimate of $\hat{\lambda} = \hat{\beta}\big/\left(1+\hat{\beta}\right) \approx 0.1797/1.1797 \approx 0.15237$, which suggests that 84.76% of the agents update their information sets at a particular period and that on average an agent updates his or her information every 1.2 months.

At the group level, the estimates of Equation 3 suggest that the evidence for information rigidities is stronger among some groups compared to others. The β coefficient for Equation 3 is significant to various degrees among the groups, with the exception of the academic. For consultants and stock market analysts, the coefficient is significant at a 1% level and only at a 10% level for the businesspeople. The results imply different estimates for the rate of information acquisition λ among groups: 82.44% of the consultants, 83.61%, of the stock market analysts, 91.91% of academics, and 91.07% of the

Table 3

REGRESSION: EX POST MEAN FORECAST ON EX ANTE MEAN REVISION

	Dependent variable				
	$e_{t+h}-F_t e_{t+h}$				
	Survey	*Consulting*	*Stock market*	*Academic*	*Business*
$F_t e_{t+1}-F_{t-1} e_{t+1}$	0.1797[c]	0.213[c]	0.196[c]	0.088	0.098[a]
	(0.056)	(0.058)	(0.056)	(0.056)	(0.056)
Observations	240	240	240	240	240
R^2	0.041	0.054	0.049	0.010	0.013
Adjusted R^2	0.037	0.050	0.045	0.006	0.009
Residual standard error (df = 239)	20.290	20.940	19.937	20.367	21.007
F statistic (df = 1; 239)	10.192[c]	13.643[c]	12.409[c]	2.492	3.129[a]

Note: [a] $p < 0.1$; [b] $p < 0.05$; [c] $p < 0.01$.
Source: Own elaboration.

businesspeople update their expectations with the most recent information available every period[9]. These results, however, show a relatively low degree of information rigidity. The evidence indicates that the sticky information assumption may not be particularly well suited to account for how the inflation expectations in the Costa Rican economy are formed. Nevertheless, we will stick to this assumption to evaluate how closely a model with sticky information can simulate the data.

3.2 Simulating a Sticky Information model

In this section, we generate a simulated survey using the following algorithm proposed in Mankiw et al. (2003). In this context, an agent's rationality is pin-downed so that we can use a vector autoregressive

[9] One should keep in mind that the estimate for the academic group is not significant and for the business group is only significant at the 10% level. The coefficients are essentially unchanged if the model is estimated using a constant.

(VAR) model to generate rational forecasts[10]. The VAR model uses Costa Rican monthly data from January 1996 to March 2017 for inflation (π_t), interest rate (i_t), output gap (y_t), an inflation index of trade partners (π_t^{C}), oil prices (p_t^{oil}), and annual exchange variations (e_t). The design of the VAR model with two lags[11] is presented in 4.

$$z_t = A_1 z_{t-1} + A_2 z_{t-2} + u_t, \tag{4}$$

with

$$z_t := \begin{bmatrix} \pi_t \\ i_t \\ y_t \\ \pi_t^{C} \\ p_t^{oil} \\ e_t \end{bmatrix}.$$

As usual A_1 and A_2 are 6×6 matrices of coefficients and u_t stands for a process with a null expectation and a time invariant positive definite covariance matrix. Data used comes from different sources: *1)* monthly annual inflation (π_t) is measured using the CPI; *2)* the interest rate (i_t) is the basic passive interest rate (*tasa básica pasiva*, TBP); *3)* the output gap (y_t) is estimated following Hamilton (2017) using a series of the monthly index of economic activity (*índice mensual de actividad económica*, IMAE)[12]; *4)* the inflation index of trade partners (π_t^{C}) is an index of the inflation of countries considered to be trade partners with Costa Rica (*indicador de inflación de socios comerciales*)[13]; *5)* oil prices (p_t^{oil}) come from the monthly average of West Texas

[10] We attempted unsuccessfully to estimate the degree of information rigidity directly for inflation forecasts, using instrumental variables similarly to Coibion and Gorodnichenko (2015).

[11] Number of lags suggested by the Hannan-Quinn information criterion.

[12] We regress IMAE series at date t+24 (to include a two-year period) on the four most recent values as of date t. The residuals from this regression are set to be the cyclical component of the series.

[13] Mainly composed by the inflation of the United States, the euro zone, China and Central American countries.

Intermediate (WTI) crude prices; and *6)* the annual exchange variations (e_t) are relative annual variations on the BCCR's reference bid exchange rate between the US dollar and the Costa Rican colon by the end of the month. The TBP, IMAE, inflation index of trade partners, and reference bid exchange rate are computed and published by the Banco Central de Costa Rica.

The estimation of the VAR is done on a sample updating basis, meaning that at time t we estimate the VAR solely with information available up to time $t-1$, denoted by $I_{t-1} = \{z_{t-1}, z_{t-2}, \ldots\}$, and done for each month from January 2006 to March 2017. For example, for January 2006 Equation 4 is estimated using information on z_t from January 1996 up to December 2005, meaning that the initial sample size covers ten years; each subsequent month adds one observation to the sample size and the VAR model is reestimated with this updated sample. Using the estimates at time t, we forecast the 12-month forward inflation rate $\pi^e_{t+12|t}$ using the forecast for the next twelve months form the VAR updated up to time $t-1$:

5 $$\pi^e_{t+12|t} := \hat{\pi}_{t-1+12}.$$

The updating procedure of the parameters of the VAR is modeled as if the agents are econometricians who form their expectations about the future by incorporating new information on the sample when estimating the VAR.

With the VAR predicted values, especially for inflation $\{\hat{\pi}_t\}$, we generate cross sectional samples of expected inflation to obtain a simulated survey as follows:

1) Given that the Monthly Survey of Inflation and Exchange Rate Expectations includes data for 135 months, there will be 135 cross sectional samples, one for each t=1, ..., 135.

2) The cross-sectional sample size n is to be of 100 individuals for all periods, n=100.

3) In the first period each individual enters the simulated survey with the mean expectation observed from the survey in the first month.

4) For every $t=2, \ldots, 135$, and for each individual $i=1, \ldots, n$, a Bernoulli experiment with probability of success λ will be conducted.

   a) If the experiment is a success, individual i at time t will report his or her expected 12-month forward inflation rate $\pi^{e}_{t+12|t}$ using the 12-month forecast from the VAR model estimated with information up to time $t-1$:

6

$$\pi^{e}_{t+12|t} := \hat{\pi}_{t+11}.$$

   b) If the experiment is a failure, $\pi^{e}_{t+12|t}$ is set to the previous known expected value for individual i.

5) The previous steps give for each period t a series $\left\{\pi^{e}_{i,t+12|t}\right\}$ for $i=1, \ldots, n$. For each series the mean and the interquartile range (IQR) are recorded.

6) The value of λ is selected to minimize the difference between[14] the simulated mean expectation and the observed mean expectation from the survey.

Running the previous algorithm gives the results presented in Figure 6: panel A, shows the generated average expectation, the observed average from the survey, and the realized inflation level at the survey date. We found the value of λ to be 0.17, meaning that only 17% of the agents in the simulated sample adjust their expectation with the most recent information, suggesting that an agent updates his or her information set every 5.9 months on average. The simulated mean expectations fit relatively well with the observed mean expectation from the survey, especially at the beginning and the end of the sample. The correlation between these two series is 91.15%. In the three months of 2017 included in the survey the observed mean expectations were 3.60% for January, 3.78% for February and 3.86% for March; while the simulated mean values are 3.23%, 3.25% and 3.23% respectively, illustrating the simulation's ability to replicate the real survey.

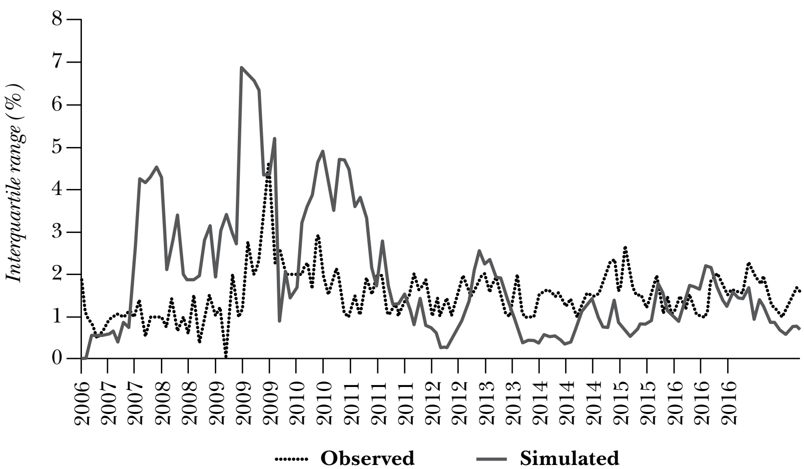
[14] We compute the mean of square differences between the simulated and observed series.

Figure 6

STICKY INFORMATION MODEL SIMULATION

A. EXPECTED INFLATION

B. REALIZED AVERAGE BIAS



Source: Own elaboration.

On the other hand, the simulated series for the interquartile range has a correlation of only 22.55% with the series from the survey. From panel B of Figure 6 we observe that simulated IQRs are close to the real IQRs only in the second half of the survey. This is due to a departure from the original algorithm in Mankiw et al. (2003) where λ is selected to maximize the correlation between the simulated series of IQRs and the survey series. Since we are interested in the mean expectation, our simulation was modified to put more emphasis on replicating the mean expectation.

The evidence of this simulated model also suggests that the sticky information assumption may not be appropriate. The value of the parameter λ required to match the dynamic of the mean forecast implies dynamics of disagreement that vary significantly from those found in the data.

4. CONCLUSIONS

This chapter builds on existing characterizations of Costa Rican inflation expectations by considering information rigidities in the expectation formation process. Our results are based on the Monthly Survey of Inflation and Exchange Rate Expectations. We analyze its panel structure to identify individual respondents and their groups of professional expertise (*consulting*, *stock market*, *academic*, and *business*). We found a set of stylized facts that describe the survey: *1)* responses are dominated by business sector respondents, implying that the mean expectations from the survey primarily reflect the mean expectation of the business sector; *2)* since April 2015 the mean expected inflation rate is within the inflation target range of the BCCR, (currently 2%-4%), suggesting that inflation expectations have been anchored by the BCCR's credibility and monetary policy; *3)* different groups have differing expectations and feature a positive interquartile range over time; *4)* there is no clear relation between the dispersion of inflation expectations and the inflation level, neither at the survey nor group level; *5)* on average agents, from the survey have positive forecast errors or realized bias, meaning that agents tend to expect greater inflation than in reality.

Because of these stylized facts, and the existing literature on Costa Rican inflation expectations, we proposed to test for information rigidities on the expectation formation process. We found some evidence suggesting that agents in the survey are subject to information stickiness and that only a fraction of agents form their expectations with the most recent information available. At the group level, we found that information rigidities are most prominent in the consulting and stock market analyst groups and less prominent in the academic and the business groups. However, the magnitude of the rigidity is not large enough to support the claim that the sticky information model is well suited to account for what we observe in the data.

Additionally, a simulated inflation expectations survey was generated using a sticky information algorithm and a vector autoregressive model to pin down the rationality of agents. This survey captured information on the inflation level, interest rates, output gap, inflation levels of trade partners, oil prices and annual exchange rate variations. The simulated survey replicated the mean expected inflation from the survey fairly well. Nevertheless, the level of stickiness required to match the data is low, and implies dynamics of disagreement that vary significantly from those found in the data.

Our findings show nonconformity of the sticky information approach for survey data along several dimensions, such as the Costa Rican data. We show that there is no correlation found between the level of inflation and the amount of disagreement among agents, the information rigidities for forecasts of exchange rates are much lower than what is needed to account for forecasts of inflation and finally, the value of needed to match dynamics of mean forecasts of inflation does not yield predictions for dynamics of disagreement that conform to those of the data.

Further work to deepen our knowledge about the expectation formation process of Costa Rican agents may consider the literature on the effects of learning on expectation formation. Moreover, we could redefine some questions in the survey to assess the probability beliefs of the respondents instead of point expectations. This would elicit information about the uncertainty agents' face when forming their expectations.

ANNEX

Annex A. Monthly Inflation and Exchange Rates Expectations Survey

Banco Central de Costa Rica, Economic Division
Monthly Survey on Inflation and Exchange Rate Expectations
July 2017
We appreciate your responses between July 10 and July 24

Respondent code:____________

1. What is your expected inflation rate, measure by the consumer price index, for the period between July 1, 2017 and June 30, 2018 (12 months)?
Answer:___________________(%)

2. Mention, in order of importance, the variables you take into consideration to form your expected inflation for the 12-month period:
*i)*____
*ii)*____
*iii)*____
*vi)*____
*v)*____

3. The reference bid rate calculated by the Banco Central de Costa Rica for June 30, 2017 was of 567.09 colones for US dollar. What is you your expected level for the reference bid exchange rate on the following dates?
3.1 On September 30, 2017 (3 months):____________________
3.2 On December 31, 2017 (6 months):____________________
3.3 On June 30, 2018 (12 months):________________________
3.4 On June 30, 2019 (24 months):________________________
3.5 On June 30, 2020 (36 months):________________________

4. Please detail the elements considered to form your exchange rate expectations in the short and long run:
Short run (3, 6 and 12 months):

i) ____

ii) ____

iii) ____

Long run (24 and 36 months)

i) ____

ii) ____

iii) ____

5. How do you consider that the general economic conditions for private production activities will evolve in the next six months in contrast with the past six months? (Please check one box)

Will improve	[]
Will be the same	[]
Will deteriorate	[]

Explain why: ______________________________________

6. How do you label the current conditions for firms to invest in the country? (Please check one box)

Good conditions	[]
Bad conditions	[]
Not sure	[]

Contact: BCCREncuestaMensua@bccr.fi.cr
Telephone: (506) 2243-3312. Fax: (506) 2243-4559
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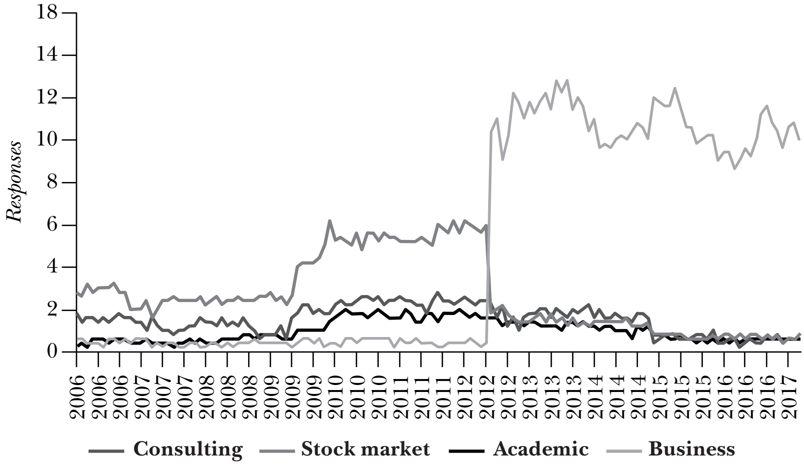
Annex B. Expected Inflation, Responses and Dispersion by Group

Figure 7

INFLATION EXPECTATIONS SURVEY, RESPONSES BY GROUP



Source: Own elaboration.

Figure 8

DISPERSION OF EXPECTED INFLATION BY GROUP

CONSULTING

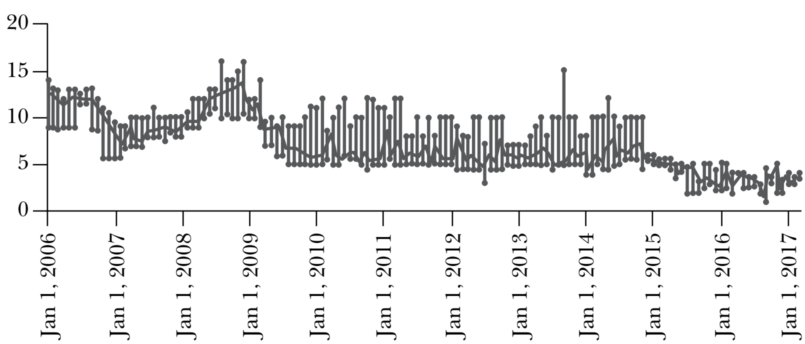
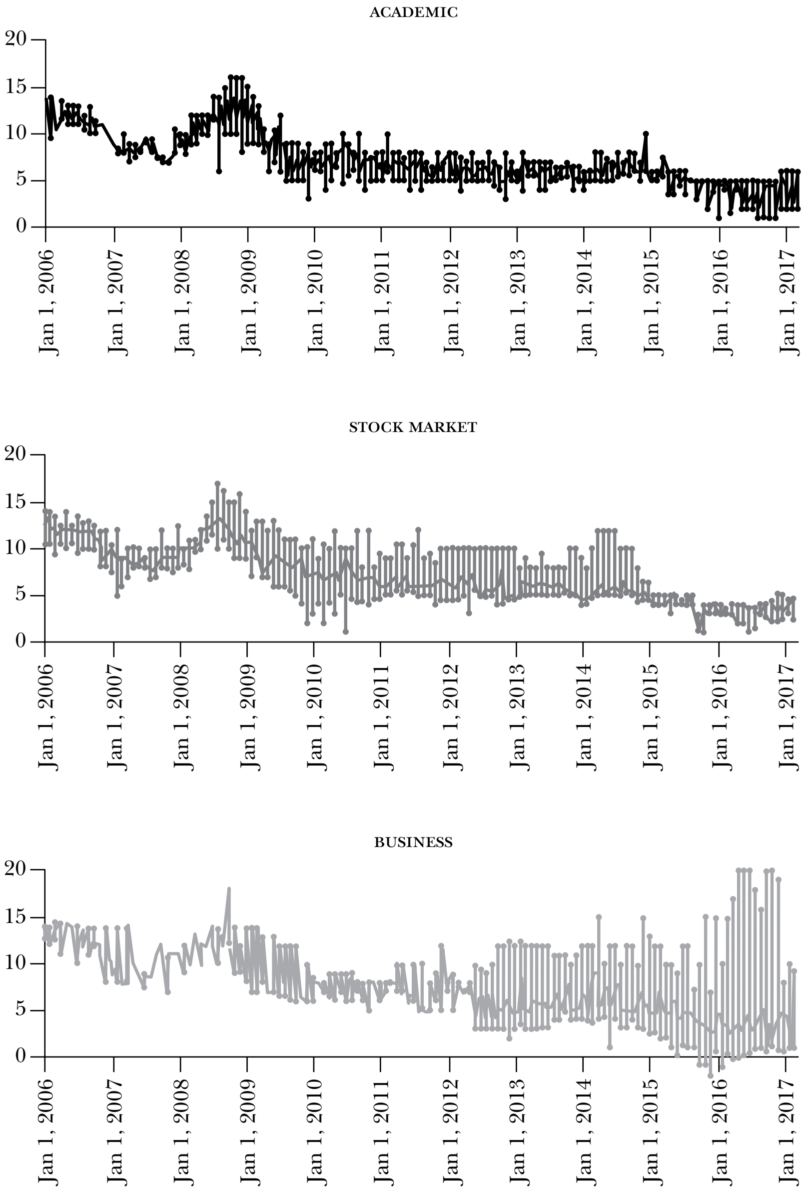


Figure 8 (cont.)

DISPERSION OF EXPECTED INFLATION BY GROUP



Source: Own elaboration.

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