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What drives inflation expectations in Brazil?[*] Public versus private information

Waldyr D. Areosa[†]

Abstract

This article applies a noisy information model with strategic interactions *à la* Morris and Shin (2002) to a panel from the Central Bank of Brazil Market Expectations System to provide evidence of how professional forecasters weight private and public information when building inflation expectations in Brazil. The main results are: (i) forecasters attach more weight to public information than private information because (ii) public information is more precise than private information. Nevertheless, (iii) forecasters overweight private information in order to (iv) differentiate themselves from each other (strategic substitutability).

Keywords: Incomplete information, public information, coordination, complementarities, externalities.

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1 Introduction

Inflation expectations have an important role in the theory and practice of monetary policy. However, little is known about the relative importance of private versus public information in the formation of these expectations, especially considering the presence of externalities, strategic complementarity or substitutability, and heterogeneous information among forecasters.[1] Morris and Shin (2002) show that the sensitivity of the equilibrium to private and public information depends not only on the relative precision of the two, but also on the private value of coordination. Considering a framework that allows for this type of strategic interaction, the present article provides evidence of how professional forecasters weight private and public information in forecasting Brazil's inflation. In particular, this paper focuses on two questions: (1) Do inflation forecasters attach more weight to public or private information? (2) Do inflation forecasters weight information differently from the efficient benchmark weights that keep forecast errors to a minimum (i.e., do they misweight information)?

The theoretical framework of this article is the strategic model of Morris and Shin (2002). This model has two relevant characteristics: (i) economic agents filter the state of economic fundamentals from private and public signals contaminated with noise and (ii) agents' optimal action depends not only on their expectation of the state of economic fundamentals, but also on their expectation of other agents' actions. In this class of models, the sensitivity of the equilibrium to private and public information depends not only on the relative precision of the two, but also on the private value of coordination. The equilibrium behavior tilts toward public or private information, depending on whether agents' actions are strategic complements or substitutes. In particular, complementarity raises the relative sensitivity to public information, while substitutability raises the relative sensitivity to private information. In either case, agents misweight information. Section 2 outlines a signal extraction model with public and private information in which agents face strategic interactions in their forecasts, to formalize the discussion.

The theoretical equilibrium forecast of the noisy information model of Section 2 is a convex combination of private and public signals about inflation. As a result, the empirical approach, described in Section 3, obtains the weight attached to public signal as the

[1] Following Bulow, Geanakoplos, and Klemperer (1985), agents' decisions are called strategic complements if they mutually reinforce one another, and they are called strategic substitutes if they mutually offset one another. For example, the production decisions of imperfectly competitive firms are strategic complements if an increase in the production of one firm increases the marginal revenues of the others, because that gives the others an incentive to produce more too. This tends to be the case if there are sufficiently strong aggregate increasing returns to scale and/or the demand curves for the firms' products have a sufficiently low own-price elasticity.

coefficient of the regression of forecast errors on public information errors alone, with the residuals representing the private information share of the forecast error. It also shows how to use the model's theoretical structure to extract the structural parameters related to the precision of public and private information and the degree of strategic interaction among forecasters. After all, the variance of the equation residuals and the weight on public information together characterize the precision of private information. Combining this precision with the precision of the observed public signal, one obtains the efficient benchmark weights. The degree of strategic interaction among forecasters arises from comparing the estimated weight attached to public information with the efficient benchmark weight.

Section 5 presents the results of the estimation of the proposed model using a sample of around 10,000 inflation forecasts from January 2004 to December 2014, presented in Section 4. The weights attached to public information are usually higher than the ones associated with private information, with values ranging from 0.50 to 0.80, depending on the horizon. The evolution is not linear, however, with higher values in both the shorter (from 0 to 3 months) and longer horizons (from 10 to 12 months). Besides this, the structural parameters regarding the precision of information show that forecasters attach more weight to public information than private information because the former is more precise than the latter. However, the parameter measuring the degree of strategic interaction shows that forecasters place larger than efficient weights on (i.e., they overweight) their private information when forecasting inflation in order to differentiate themselves from each other. Alternatively, there is strategic substitutability among inflation forecasts. The incentives behind this misweighting are beyond the scope of this article, but have been extensively debated and include forecasters trying to signal their ability or to generate trading commissions, or forecasters' overconfidence about their own ability due to attribution bias in learning.[2]

This work pertains to the recent empirical literature on rational expectations models with information frictions, Coibion and Gorodnichenko (2012) being the main reference.[3] Those authors assess both the quantitative importance and the nature of information rigidities of a large set of theoretical models with information frictions, including, among others, sticky information models *à la* Mankiw and Reis (2002), in which agents update their information sets infrequently; noisy information models as in Sims (2003) and Woodford (2002), in which agents are continuously updating their information but observe only noisy signals about the

[2]See Chen and Jiang (2006) and the references therein.

[3]Other examples are Carroll (2003), Mankiw, Reis, and Wolfers (2004), Pesaran and Weale (2006), Branch (2007), Kiley (2007), Klenow and Willis (2007), Korenok (2008), Mackowiak, Moench, and Wiederholt (2009), Capistrán and Timmermann (2009), Coibion (2010), Dupor, Kitamura, and Tsuruga (2010), Ii (2010), Andrade and Le Bihan (2013) and Lamla and Dräger (2013). For the Brazilian economy, see de Almeida Campos Cordeiro, Gaglianone, and Issler (2015).

true state; and variants of the latter in which agents face strategic complementarity in their forecasts, as Morris and Shin (2002) and Angeletos and Pavan (2007).[4] This literature, however, ignores the possibility of forecasters trying to differentiate themselves from each other. This article imposes a noisy information model that allows strategic complementarity or substitutability on a large sample of inflation forecasters in order to measure if professional inflation forecasters (i) attach more weight to public or private information and (ii) misweight information. Our work is thus more related to Chen and Jiang (2006), who provide evidence that analysts misweight information in forecasting corporate earnings.

Section 6 analyzes the robustness and sensitivity of the results along several dimensions, including robust standard error specifications, alternative public signals and exclusion of forecasters with less than a minimum number of observations and with considerable forecast errors. Section 7 presents concluding remarks.

2 Theoretical framework

This study uses the theoretical model of Morris and Shin (2002), but allowing for strategic substitutability as well as strategic complementarity, as in Angeletos and Pavan (2007). Formally, there is a continuum of inflation forecasters, indexed by the unit interval $[0, 1]$. Forecaster i chooses a forecast $f_i \in \mathbb{R}$ about inflation π. The payoff function for forecaster i is given by

$$u_i = -(1 - r)(f_i - \pi)^2 - r(f_i - \bar{f})^2, \tag{1}$$

where $\bar{f} = \int_0^1 f_i di$ is the mean forecast.

The first component of (1) is a standard quadratic loss in the distance between next-period inflation and the forecast of agent i. The second component, the "beauty contest" term, is increasing in the distance between i's forecast and the mean forecast. This second part introduces an externality: each forecaster tries to second-guess the forecasts of other forecasters. The parameter $r \in (-1, 1)$ gives the weight on this second-guessing motive and measures the private value of coordination among forecasters. If the forecasters want to stay close to their peers, r would be positive (strategic complementarity). In the opposite situation, when they want to differentiate themselves from each other (strategic substitutability), r would be negative.

Since inflation π and forecasts f_j, for all $j \neq i$, are not observed by forecaster i, the optimal forecast is given by

[4] For models considering the interaction between dispersed and sticky information, see Areosa and Areosa (2012) and Areosa, Areosa, and Carrasco (2012).

$$f_i = (1-r)\mathbb{E}_i[\pi] + r\mathbb{E}_i[\bar{f}], \tag{2}$$

where $\mathbb{E}_i[\cdot]$ is the expectation considering forecaster i's information set.

The information set of each forecaster consists of the signals $x_i = \pi + \varepsilon_{x,i}$ and $y = \pi + \varepsilon_y$, where $\varepsilon_{x,i} \sim \mathcal{NID}(0, \sigma_x^2)$ is an agent-specific private shock and $\varepsilon_y \sim \mathcal{NID}(0, \sigma_y^2)$ is a shock common to all agents. All shocks are independent of each other and from π. This article follows the conventional terminology to refer to x and y as private and public (signals) information, with σ_x^{-2} and σ_y^{-2} representing the respective precisions. The public signal y is thus the market consensus about π, which is observed by all forecasters. Given this information structure, the private posteriors are Normal with mean

$$\mathbb{E}_i[\pi_t] = (1-\delta)x_i + \delta y \tag{3}$$

and variance $\sigma^2 = \left(\sigma_x^{-2} + \sigma_y^{-2}\right)^{-1}$, where $\delta \equiv \sigma_y^{-2}/\sigma^{-2}$ is the relative precision of public information.

Because the best response of a forecaster is linear in his expectations of π and $\bar{f}$, and because his expectation of π is linear in x and y, it is natural to conjecture that a unique linear solution to (2) exists.[5] In equilibrium, the forecast of agent i is thus

$$f_i = (1-\gamma)x_i + \gamma y, \tag{4}$$

where the weight γ attached to public information is given by

$$\gamma \equiv \delta + \frac{r\delta(1-\delta)}{1-r(1-\delta)}. \tag{5}$$

If $r = 0$, the two types of information (private and public) would be given weights that are commensurate with their precision. That is, y would be given weight equal to its relative precision δ, while x_i would be given weight equal to its relative precision $1-\delta$. However, the weights in (5) deviate from this. If actions are strategic complements ($r > 0$), the best response is to put a weight on public information higher than the Bayesian one ($\gamma > \delta$), with a larger r increasing the externality. In this case, agents overweight public information. Symmetrically, the converse is true in the case of strategic substitutability ($r < 0$). The reason is that public information is a relatively better predictor of other agents' activity than private information. In equilibrium, this leads an agent to adjust upward his reliance

[5] This equilibrium can be verified at least for $r \in (-1, 1)$, following the same argument as in Morris and Shin (2002) and Angeletos and Pavan (2007).

on public information when he wishes to align his choice with other agents' choices and downward when he wishes to differentiate his choice from those of others.

3 Empirical approach

Using the model outlined in Section 2, this study proceeds in two steps. First, it estimates the weights attached to public information (γ). Second, it assumes that the weight is as in (5) in order to provide an estimate for the structural parameters: private and public information precisions (σ_x^{-2} and σ_y^{-2}) and the private value of coordination among forecasters (r).

3.1 Estimating the weight of public information

It is possible to express the forecast error of each forecaster as a function of consensus forecast error. To see this, first subtract inflation from both sides of (4) to obtain

$$f_i - \pi = \gamma(y - \pi) + (1 - \gamma)(x_i - \pi).$$

According to the equation above, the weight attached to public information can be obtained observing the coefficient estimate $\hat{\gamma}$ of the regression

$$f_i - \pi = c_i + \gamma(y - \pi) + \xi_i, \tag{6}$$

where y and π are observable, c_i is a cross-section fixed effect and $\xi_i \equiv (1-\gamma)\varepsilon_{x,i}$ is the error term of the panel equation, with mean zero and standard deviation $\sigma_\xi = (1 - \gamma)\sigma_x$.

3.2 Recovering the structural parameters

After the estimation of (6), one can use the coefficient $\hat{\gamma}$ and the resulting standard error $\hat{\sigma}_\xi$ from the equation to obtain an estimate for the standard error of the private signal x_i, by calculating

$$\hat{\sigma}_x = \frac{\hat{\sigma}_\xi}{1 - \hat{\gamma}}$$

Considering the sample variance $\hat{\sigma}_y^2$ of $y - \pi$ as a proxy for (the inverse of) public information precision, an estimative $\hat{\delta}$ for the relative precision of the signals is just

$$\hat{\delta} = \frac{\hat{\sigma}_x^2}{\hat{\sigma}_x^2 + \hat{\sigma}_y^2}.$$

Finally, one can combine $\hat{\gamma}$ and $\hat{\delta}$ into equation (5) to obtain an estimate for the strategic parameter r by calculating

$$\hat{r} = \frac{\hat{\gamma} - \hat{\delta}}{\hat{\gamma}(1 - \hat{\delta})}.$$

Given the variances $\hat{\sigma}_y^2$ and $\hat{\sigma}_\xi^2$, one can generate new sequences of public signal errors $y - \pi$ and forecast errors $f_i - \pi$ to re-estimate equation (6) and repeat the steps above to obtain the empirical joint distribution of $\{\hat{\sigma}_x^2, \hat{\sigma}_y^2, \hat{\delta}, \hat{r}\}$. This distribution is then used to test hypotheses about the structural parameters.

4 Data

This paper employs confidential individuals' monthly inflation forecasts for the Comprehensive National Consumer Price Index (IPCA) from the Central Bank of Brazil (BCB) Market Expectations System as well as publicly available aggregate data from the same source.[6] The IPCA has been used to measure the official inflation targets since the adoption of the inflation targeting regime in 1999. The Investor Relations and Special Studies Department (Gerin) of the BCB is responsible for administering the Market Expectations System, a web interface where financial institutions, consulting firms and companies of the nonfinancial sector, previously authorized, report their expectations.

To encourage the provision of quality information, the BCB prepares the Top 5 ranking classification system of the institutions based on the accuracy of their projections. Regarding the variables subject to the Top 5 rankings, the error or deviation from the actual values of these variables is calculated based on projections valid on specific dates, which are known as reference dates. Consequently, there is a greater updating of information by the participants on these reference dates. Considering the IPCA, the reference date is the last business day preceding the date of release of the IPCA-15, a leading indicator of the IPCA for the full month.[7]

The BCB consolidates the expectations provided by the authorized forecasters every business day at 5:00 p.m., but releases only aggregate statistics once a week (next Monday). The statistics produced by the system and released by the Central Bank include the median, mean, standard deviation, coefficient of variation, maximum and minimum for all variables

[6] The collection and manipulation of data from the Central Bank of Brazil Market Expectations System is conducted exclusively by the staff of the Central Bank of Brazil.

[7] The IPCA and IPCA-15 are both consumer price indexes produced by the same institution (Brazilian Institute of Geography and Statistics - IBGE). The IPCA index measures the percentage change in consumer prices for a 30-day period, beginning the first day of each month and uses the previous month as its reference while the data collection period for the IPCA-15 ranges from approximately the 15^{th} of the previous month to the 15^{th} of the current month, using the previous 30 days as its period of reference.

Table 1: Descriptive statistics per horizon (h months ahead)

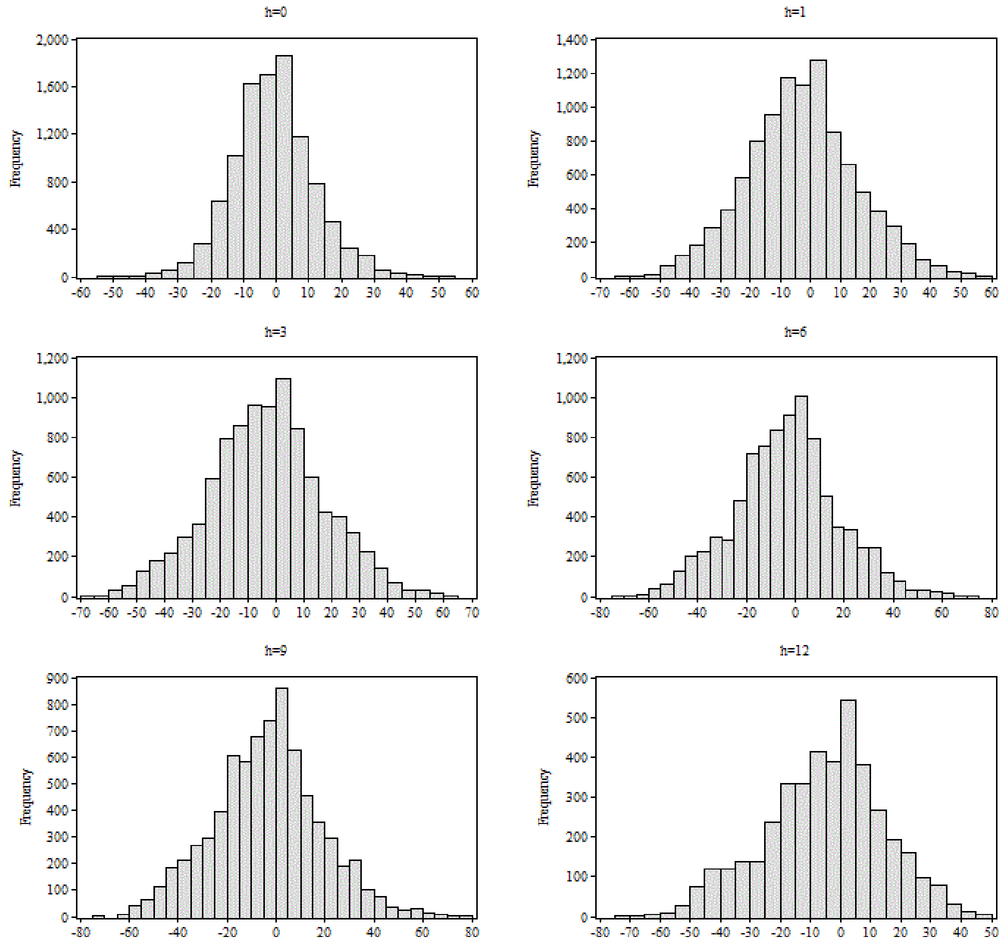
	.	Forecast errors (basis points)			Public information errors (basis points)		
h	Obs	Mean	St. dev.	Median	Mean	St. dev.	Median
0	10,580	-0.937	12.498	-1.000	4.864	14.930	4.650
1	10,382	-2.973	18.347	-3.000	10.367	19.828	9.292
2	10,170	-3.626	19.969	-4.000	14.414	23.580	12.945
3	9,944	-3.500	20.721	-4.000	16.518	26.343	13.932
4	9,694	-3.609	21.036	-4.000	18.895	28.778	15.317
5	9,413	-3.842	21.342	-4.000	20.536	30.311	16.952
6	9,056	-3.846	21.371	-3.000	20.596	31.151	17.369
7	8,720	-3.918	21.455	-4.000	20.661	31.045	17.108
8	8,364	-3.978	21.793	-4.000	21.264	31.848	16.682
9	7,980	-4.067	22.032	-4.000	20.780	31.886	15.919
10	7,562	-4.308	22.175	-4.000	15.991	29.181	12.033
11	7,062	-4.434	22.242	-4.000	11.491	27.007	8.251
12	6,045	-4.544	22.286	-5.000	9.746	26.336	7.374

Sample consists of IPCA inflation forecasts from 2004M01 to 2014M12 provided by BCB. The forecast error for horizon h measures the difference between the forecast and realized inflation h months ahead. The public information error is the difference between the public signal and the corresponding realized inflation. The public signal is the projection from a panel regression of observed inflation on the aggregate mean forecast observed by each forecaster up to the period in which the projections were made.

collected, including those of the Top 5 group for the possible horizons - up to 18 months, 6 semesters or five years ahead, as the case may be. The historical series of statistics are available since January 2000 at the Central Bank's website.

The confidential information includes only a code for each forecaster, the forecast available at the reference dates and the date on which this forecast was made. This information is relevant in order to relate each inflation forecast to the relevant inflation consensus. Regarding the consensus, an ideal measure for the public information y is the best predictor of inflation using all public information at the time of the forecast. The main analysis uses the last average aggregate forecast that was available when the forecast was made. Instead of directly using the aggregate data, however, it is important to take into account the performance of these aggregates in forecasting inflation. As a result, the final public signal measure is the projection from a regression of observed inflation on the aggregate mean forecast that was observed up to the period of the forecast. In sensitivity checks, all analyses were repeated measuring y as the average and median forecast of the Top 5 group as well as the median of the aggregate forecast.

Figure 1: Histogram of forecast errors for selected horizons (basis points)



Sample consists of IPCA inflation forecasts from 2004M01 to 2014M12 provided by BCB. The forecast error for horizon h measures the difference between the forecast and realized inflation h months ahead.

The final dataset has around 6,000 to 10,000 inflation forecasts depending on the horizon, ranging from zero (nowcasting) to 12 months, over January 2004 to December 2014. Table 1 presents the descriptive statistics for the forecast errors $f_i - \pi$ and consensus errors $y - \pi$ for each horizon $h \in \{0, 1, \ldots, 12\}$ while Figure 1 shows the histogram of forecast errors for horizons 0, 1, 3, 6, 9 and 12. For example, the mean forecast error for 6 months ahead inflation is -3,8 basis points, with 20.6 basis points reflecting the public information error. According to these figures, the projection of inflation using only the most recent aggregate forecast that was public in the period when the forecast was made tends to overestimate inflation. The average posterior individual forecast tends to correct this tendency. The final mean forecast error is small, but dispersed, as measured by the cross-section standard deviation.

5 Results

This section first uses equation (6) to present evidence related to the weight attached to public information, followed by resulting estimates for the structural parameters: private and public information precisions (σ_x^{-2}, σ_y^{-2}), and the degree of strategic interaction (r).

5.1 Estimating the weight of public information

Table 2 presents the estimate of equation (6) regarding the weight attached to public information (γ). The results for γ are significant at the 1% level for all horizons and imply that the weights attached to public information are usually higher than the ones associated with private information, with values ranging from 0.50 to 0.80, depending on the horizon. The evolution is not linear, however, with higher values in both the shorter (from 0 to 3 months) and longer horizons (from 10 to 12 months), and depends on the structural parameters of the model, considered below.

5.2 Recovering the structural parameters

Table 2 also presents implied estimates for the structural parameters related to the precisions of public and private information (σ_y^{-2} and σ_x^{-2}), with the corresponding efficient weight of public information (δ). Overall, public information is more precise than private information, which was expected given the weights of public information. However, with the exception of horizon $h = 6$, the resulting efficient weights δ are always higher than the actual weights γ, indicating that forecasters tend to overweight private information. As a result, the parameter r measuring strategic interaction is negative, reflecting that inflation forecasts are strategic substitutes. In a similar study considering the forecast of corporate earnings, Chen and Jiang (2006) also find that, on average, analysts place greater than efficient weights on their private information. One possible explanation for this quest for differentiation may be to increase the chance of being included in the ranking of the Top 5.

In order to analyze if these results are statistically significant, equation (6) was estimated 10,000 times using simulated data. Equation (6) decomposes the forecast error $f_i - \pi$ into two other errors: one associated with the public signal, $y - \pi$, and the other associated with the private signal, $x_i - \pi$. According to the theoretical framework in Section 2, these errors are independent between periods and agents. This fact is used to generate the simulations.[8]

[8] Considerations regarding alternative correlation structures are postponed to robustness analysis.

Table 2: Public information weights and implied parameters per horizon (h months ahead)

	Parameters						Eq. St.	Obs.	Adj.
	Estimated		Implied						
h	*Const.*	γ	σ_x	σ_y	δ	r	error		R^2
0	-0.040***	0.636***	0.223	0.149	0.690	-0.274	0.081	10,580	0.579
	(0.001)	(0.006)							
1	-0.114***	0.815***	0.500	0.198	0.864	-0.445	0.093	10,382	0.745
	(0.001)	(0.005)							
2	-0.137***	0.698***	0.404	0.236	0.746	-0.269	0.122	10,170	0.627
	(0.001)	(0.006)							
3	-0.135***	0.607***	0.359	0.263	0.649	-0.199	0.141	9,944	0.538
	(0.002)	(0.006)							
4	-0.137***	0.535***	0.327	0.288	0.564	-0.121	0.152	9,694	0.478
	(0.002)	(0.006)							
5	-0.144***	0.512***	0.320	0.303	0.527	-0.061	0.156	9,413	0.465
	(0.002)	(0.006)							
6	-0.142***	0.504***	0.312	0.312	0.502	0.010	0.155	9,056	0.474
	(0.002)	(0.006)							
7	-0.144***	0.507***	0.319	0.310	0.514	-0.026	0.157	8,720	0.463
	(0.002)	(0.006)							
8	-0.145***	0.496***	0.321	0.318	0.505	-0.034	0.162	8,364	0.448
	(0.002)	(0.006)							
9	-0.144***	0.495***	0.327	0.319	0.512	-0.070	0.165	7,980	0.440
	(0.002)	(0.006)							
10	-0.137***	0.585***	0.369	0.292	0.616	-0.135	0.153	7,562	0.523
	(0.002)	(0.006)							
11	-0.122***	0.677***	0.429	0.270	0.716	-0.201	0.138	7,062	0.613
	(0.002)	(0.006)							
12	-0.114***	0.708***	0.458	0.263	0.752	-0.250	0.134	6,045	0.639
	(0.002)	(0.007)							

Least-squares panel with cross-section fixed effects. Robust standard errors are in parentheses. ***, ** and * denote significance at the 1%, 5% and 10% level. Sample consists of IPCA inflation forecasts from 2004M01 to 2014M12 provided by BCB. The dependent variable is the difference between the forecast and realized inflation h months ahead. The independent variable is the difference between the public signal and the corresponding realized inflation. The public signal is the projection from a panel regression of observed inflation on the aggregate mean forecast that was observed by each forecaster up to the period of the forecast.

Each simulation round requires two steps: (i) creating a series of simulated public errors and (ii) creating a series of simulated forecast errors. As the errors associated with the public signal are observable, it is possible to create a series of random numbers using the same distribution as the original data to meet step (i). For step (ii), the distribution of the residuals is used to create a series of random numbers. The sum of the first series, multiplied by the estimated γ, the estimated cross-section fixed effects and the second series gives the simulated forecast errors. These two simulated series are used to make a new regression. Each new estimation based on simulated data gives a new set of parameters – the constant, γ, σ_x, σ_y and r – and a new regression error, from which a new estimation of the variance of the private signal is obtained. The set of all simulations also gives the empirical joint distribution of the implied parameters – r and δ – and of the variance of the private error, σ_x^2. This empirical joint distribution allows for hypothesis testing.

Table 3 presents the mean and standard deviation of the induced parameters as well as a set of three hypothesis tests using the obtained empirical distributions. The results of all tests present p-values that are almost zero for all horizons.

The first test, $\sigma_y \geqslant \sigma_x$, rejects the null hypothesis that public information y is statistically less precise than private information x. This result explains why forecasters attach more weight to public rather than private information, as shown in Table 2.

The second test, $\gamma \geqslant \delta$, goes one step further and shows that forecasters overweight public information, meaning that actual weights γ of public information are higher than the efficient weights δ, which only take into account the relative precision of the public signal.

The third and final test, $r \geqslant 0$, is just an alternative way to test overweighting. According to the model of Section 2, the parameter $r \in (-1, 1)$ measures the strategic interaction among forecasters. If $r = 0$, forecasters do not care how their forecasts compare to those of their peers and thus the actual and efficient weights are equal ($\gamma = \delta$). One can interpret $r > 0$ as capturing strategic complementarity, when agents consider it relevant to stay close to one another, and $r < 0$ as capturing strategic substitutability, when agents are looking for differentiation. In the case $r > 0$, agents overweight public information ($\gamma > \delta$) because public signals are reference points that all agents track. If, however, $r < 0$, agents underweight public information (or overweight private information) in order to differentiate themselves from their peers. The rejection of the null hypothesis $r \geqslant 0$ is equivalent to the rejection of the null of $\gamma \geqslant \delta$.

In summary, the three tests show that forecasters attach more weight to public information because it is more precise than private information ($\sigma_x > \sigma_y$). Nevertheless, they want to differentiate themselves from one another ($r < 0$) and thus $\gamma < \delta$.

Table 3: Hypothesis tests per horizon (h months ahead)

h	Simulated parameters				Null hypothesis (p-value)		
	σ_x	σ_y	δ	r	$\sigma_x \geqslant \sigma_y$	$\gamma \geqslant \delta$	$r \geqslant 0$
0	0.231	0.149	0.705	-0.370	0.000	0.000	0.000
	(0.004)	(0.001)	(0.008)	(0.028)			
1	0.522	0.198	0.874	-0.575	0.000	0.000	0.000
	(0.014)	(0.001)	(0.006)	(0.045)			
2	0.414	0.236	0.755	-0.333	0.000	0.000	0.000
	(0.008)	(0.002)	(0.007)	(0.029)			
3	0.365	0.263	0.657	-0.241	0.000	0.000	0.000
	(0.006)	(0.002)	(0.008)	(0.026)			
4	0.336	0.288	0.576	-0.181	0.000	0.000	0.000
	(0.005)	(0.002)	(0.008)	(0.025)			
5	0.328	0.303	0.540	-0.117	0.000	0.000	0.000
	(0.004)	(0.002)	(0.008)	(0.023)			
6	0.323	0.311	0.519	-0.060	0.000	0.000	0.000
	(0.004)	(0.002)	(0.008)	(0.023)			
7	0.325	0.310	0.523	-0.066	0.000	0.000	0.000
	(0.004)	(0.002)	(0.008)	(0.023)			
8	0.330	0.319	0.517	-0.088	0.000	0.000	0.000
	(0.005)	(0.002)	(0.008)	(0.024)			
9	0.334	0.319	0.524	-0.119	0.000	0.000	0.000
	(0.005)	(0.003)	(0.008)	(0.025)			
10	0.378	0.292	0.626	-0.188	0.000	0.000	0.000
	(0.007)	(0.002)	(0.009)	(0.028)			
11	0.436	0.270	0.723	-0.241	0.000	0.000	0.000
	(0.009)	(0.002)	(0.009)	(0.033)			
12	0.467	0.263	0.758	-0.299	0.000	0.000	0.000
	(0.012)	(0.002)	(0.010)	(0.038)			

Mean and standard deviations (in parentheses) from 10,000 estimations of equation (6) using simulated data. Each simulation round requires series of simulated public errors and forecast errors. As the public errors are observable, it is possible to create a series of random numbers using the same distribution as the original data to obtain the series of public errors. For the series of forecast errors, the sum of the first series, multiplied by the estimated γ, the estimated cross-section fixed effects and the second series gives the simulated forecast errors. These two simulated series are used to make a new regression, which implies a new set of parameters. The p-values consider the problem of testing hypotheses about the mean of a Normal distribution when both the mean and the variance are unknown using the t distribution.

There is one relevant conceptual issue in the proposed measure of the public signal y that may provide an alternative interpretation to the results above. As y is constructed as the last available aggregate forecast, it is essentially from period $t-1$. Thus, one may argue that the finding that the forecasters underweight public inflation in order to differentiate themselves from each other could therefore also reflect the fact that the public signal dates from $t-1$ while the private forecasts also include information from period t. Against this view, note that the difference between the two information sets is always less than 30 days, and usually less than 15 days. As a result, it is arguable that only a minor piece of public information is being disregarded, which plays in favor of the view that forecasters underweight public information in order to differentiate themselves from each other.

6 Robustness

This section evaluates the robustness of the above results in several dimensions. First, the statistical significance of the weight of public information γ using alternative robust standard errors on the estimation of equation (6) is determined. Second, how the magnitude of the weight on public information γ and the structural parameters related to the precision of the public signal (σ_y^{-2}), the precision of the private signal (σ_x^{-2}) and the degree of strategic interaction (r) change under alternative public signals y are ascertained. Third, how the estimates of the parameters change after the exclusion of forecasters with less than a minimum number of observations is analyzed. Finally, how the results change after the exclusion of extreme forecast errors is determined.

6.1 Alternative robust standard errors

According to the proposed information structure, forecast errors from different forecasters should only be correlated due to a common shock ε_y. To deal with alternative correlation structures, Table 4 reports the following adjusted standard errors: (i) period clustered, (ii) cross-section clustered, (iii) heteroskedasticity-robust and (iv) simultaneous period and cross-sectional clustered. Estimator (i) is robust to cross-equation (contemporaneous) correlation and heteroskedasticity, while estimator (ii) accommodates arbitrary heteroskedasticity and within cross-section serial correlation. Estimator (iii) is robust to observation specific heteroskedasticity in the disturbances, but not to correlation between residuals for different observations. Following Thompson (2011), estimator (iv), which is robust to correlation along the two dimensions, is equal to the estimator that clusters by firm, plus the estimator that clusters by time, minus the usual heteroskedasticity-robust covariance matrix.

Table 4: Alternative robust standard errors per horizon (h months ahead)

	OLS robust		Clustered by Period		Clustered by Cross-section		Clustered by Two-dimension	
h	$Const.$	γ	$Const.$	γ	$Const.$	γ	$Const.$	γ
0	0.001	0.006	0.004	0.031	0.000	0.010	0.004	0.032
1	0.001	0.005	0.004	0.024	0.001	0.008	0.004	0.025
2	0.001	0.006	0.008	0.035	0.001	0.009	0.008	0.036
3	0.002	0.006	0.010	0.036	0.002	0.010	0.010	0.037
4	0.002	0.006	0.012	0.039	0.002	0.010	0.012	0.040
5	0.002	0.006	0.013	0.035	0.002	0.010	0.013	0.036
6	0.002	0.006	0.013	0.035	0.002	0.009	0.013	0.036
7	0.002	0.006	0.014	0.037	0.002	0.010	0.014	0.038
8	0.002	0.006	0.014	0.037	0.002	0.010	0.014	0.038
9	0.002	0.006	0.014	0.036	0.002	0.011	0.014	0.037
10	0.002	0.006	0.012	0.035	0.002	0.010	0.012	0.035
11	0.002	0.006	0.010	0.032	0.001	0.010	0.010	0.032
12	0.002	0.007	0.010	0.031	0.001	0.010	0.010	0.031

Least-squares panel with cross-section fixed effects. Sample consists of IPCA inflation forecasts from 2004M01 to 2014M12 provided by BCB. The dependent variable is the difference between the forecast and realized inflation h months ahead. The independent variable is the difference between the public signal and the corresponding realized inflation. The public signal is the projection from a panel regression of observed inflation on the aggregate mean forecast that was observed by each forecaster up to the period of the forecast. All robust standard error estimators imply significance of the parameters at 1%.

According to Table 4, the estimate of γ is significant at the 1% for all the proposing methods. This result is important for the simulation exercise because, although the relevant elements for simulation, the estimated coefficients and the equation standard error are unaffected by the chosen method, the relevance of the entire exercise could be called into question if the significance of the coefficients were considerably altered.

6.2 Alternative public signals

Considering the importance of the public signal in the proposed empirical approach, Table 5 presents the estimate of γ for all horizons from 0 to 12 months for three alternative specifications other than the mean of all forecasters: (i) the aggregate median of all forecasters, (ii) the mean of the Top 5 ranking of forecasters and (iii) the median of the Top 5. The median is a natural choice because its property of being less influenced by outliers makes it the statistic most closely monitored and disclosed by the BCB Market Expectations System. The inclusion of the Top 5 could generate different results if, contrary to the model of Section 2, some forecasters usually have access to more precise information. As Table 5 shows, the difference between any two alternative measures is not quantitatively relevant.

Table 6 reports the same analyses, but now considering the impact on the values of the structural parameters for horizons 0 and 12. The degree of strategic interaction remains negative. The mean of all previous forecasts is the public signal with the lowest absolute values for both horizons ($r \approx -0.25$), while the median of all forecasters presents a higher but quantitatively similar result ($r \approx -0.35$). The most relevant change occurs when replacing the measures of all forecasters by the Top 5 equivalents ($r \approx -0.50$), with no material difference if one chooses the mean or the median.

6.3 Regular forecasters

The BCB periodically checks whether the information provided by the Market Expectations System participants is current or not, and blocks the input of those who have gone at least six months without any activity. In order to check the impact of short-lived forecasters, Table 7 reports the previous results including only forecasters with at least 30 non-valid forecasts.[9] There is no relevant impact, as a direct comparison of Tables 6 and 7 clearly shows.

6.4 Outliers

Table 8 takes the previous analyses one step further, excluding not only forecasters with less than 30 non-zero forecasts, but also forecasts which present forecast errors after the 1st up to the 99th percentile of the distribution of forecast errors in a given period. Even in this case, the main results remain almost unchanged: (i) the weight of public information is higher than its private counterpart ($\gamma > 0.5$) because (ii) public information is more precise than private information ($\sigma_y^{-2} > \sigma_x^{-2}$), but (iii) forecasters overweight private information ($\gamma < \delta$) in order to (iv) differentiate themselves from each other ($r < 0$).

[9] The choice of 30 non-valid forecasts, although arbitrary, is not uncommon. See, for example, Capistrán and Timmermann (2009).

Table 5: Results under alternative measures of public information per horizon (h months ahead) - weight of public information

	All forecasters				Top 5 forecasters			
	Mean		Median		Mean		Median	
h	*Const.*	γ	*Const.*	γ	*Const.*	γ	*Const.*	γ
0	-0.040***	0.636***	-0.048***	0.650***	-0.033***	0.668***	-0.034***	0.642***
	(0.001)	(0.006)	(0.001)	(0.006)	(0.001)	(0.007)	(0.001)	(0.007)
1	-0.114***	0.815***	-0.118***	0.795***	-0.107***	0.830***	-0.111***	0.820***
	(0.001)	(0.005)	(0.001)	(0.005)	(0.001)	(0.005)	(0.001)	(0.005)
2	-0.137***	0.698***	-0.138***	0.691***	-0.136***	0.718***	-0.137***	0.695***
	(0.001)	(0.006)	(0.001)	(0.006)	(0.001)	(0.005)	(0.001)	(0.005)
3	-0.135***	0.607***	-0.136***	0.606***	-0.137***	0.625***	-0.135***	0.609***
	(0.002)	(0.006)	(0.002)	(0.006)	(0.002)	(0.006)	(0.002)	(0.006)
4	-0.137***	0.535***	-0.138***	0.540***	-0.137***	0.557***	-0.138***	0.576***
	(0.002)	(0.006)	(0.002)	(0.006)	(0.002)	(0.006)	(0.002)	(0.006)
5	-0.144***	0.512***	-0.144***	0.513***	-0.143***	0.535***	-0.144***	0.545***
	(0.002)	(0.006)	(0.002)	(0.006)	(0.002)	(0.006)	(0.002)	(0.006)
6	-0.142***	0.504***	-0.142***	0.504***	-0.143***	0.534***	-0.143***	0.539***
	(0.002)	(0.006)	(0.002)	(0.006)	(0.002)	(0.006)	(0.002)	(0.006)
7	-0.144***	0.507***	-0.143***	0.520***	-0.145***	0.550***	-0.145***	0.561***
	(0.002)	(0.006)	(0.002)	(0.006)	(0.002)	(0.006)	(0.002)	(0.006)
8	-0.145***	0.496***	-0.145***	0.510***	-0.138***	0.557***	-0.139***	0.559***
	(0.002)	(0.006)	(0.002)	(0.006)	(0.002)	(0.006)	(0.002)	(0.006)
9	-0.144***	0.495***	-0.143***	0.502***	-0.133***	0.501***	-0.134***	0.511***
	(0.002)	(0.006)	(0.002)	(0.006)	(0.002)	(0.007)	(0.002)	(0.007)
10	-0.137***	0.585***	-0.135***	0.585***	-0.131***	0.611***	-0.130***	0.600***
	(0.002)	(0.006)	(0.002)	(0.007)	(0.002)	(0.007)	(0.002)	(0.007)
11	-0.122***	0.677***	-0.120***	0.704***	-0.104***	0.802***	-0.113***	0.786***
	(0.002)	(0.006)	(0.002)	(0.006)	(0.001)	(0.006)	(0.001)	(0.006)
12	-0.114***	0.708***	-0.113***	0.727***	-0.101***	0.800***	-0.106***	0.794***
	(0.002)	(0.007)	(0.002)	(0.007)	(0.002)	(0.006)	(0.002)	(0.006)

Least-squares panel with cross-section fixed effects. Robust standard errors are in parentheses. ***, ** and * denote significance at the 1%, 5% and 10% level. Sample: IPCA inflation forecasts from 2004M01 to 2014M12 provided by BCB. The dependent variable is the difference between forecasted and realized inflation. The independent variable is the difference between the public signal and the corresponding realized inflation. The public signal is the projection from a panel regression of inflation on the mean or median of the aggregate or top 5 forecast that was observed by each forecaster up to the period of the forecast.

7 Conclusion

Much of the existing empirical literature on rational expectations models with information frictions studies properties of the observed forecasts in order to assess both the quantitative importance and the nature of the information rigidities of these models. In particular, the studies considering the noisy models of strategic interactions, in the spirit of Morris and Shin (2002), focus on the possibility that inflation forecasts are strategic complements. This work stands apart from this literature because it allows the possibility of strategic substitutability among inflation forecasters, a common feature among other types of professional forecasters.[10]

This article applies a noisy information model with strategic interactions *à la* Morris and Shin (2002) to a panel from the Central Bank of Brazil Market Expectations System to answer two questions: (1) Do inflation forecasters attach more weight to public or private information? (2) Do inflation forecasters misweight information?

The main results, which are robust for different horizons (from 0 to 12 months ahead), several robust standard error calculations, diverse alternative public signals and the exclusion of forecasters with less than a minimum number of observations and with considerable forecast errors, are: (i) forecasters attach more weight to public information than private information because (ii) public information is more precise than private information. Nevertheless, (iii) forecasters overweight private information in order to (iv) differentiate themselves from each other (strategic substitutability).

[10] See Chen and Jiang (2006) and references therein.

Table 6: Results under alternative measures of public information - structural parameters

	Horizon 0				Horizon 12			
	All forecasters		Top 5		All forecasters		Top 5	
	Mean	Median	Mean	Median	Mean	Median	Mean	Median
Estimation								
Const.	-0.040***	-0.048***	-0.033***	-0.034***	-0.114***	-0.113***	-0.101***	-0.106***
γ	0.636***	0.650***	0.668***	0.642***	0.708***	0.727***	0.800***	0.794***
Eq. St. Error	0.081	0.079	0.080	0.083	0.134	0.131	0.116	0.117
Obs.	10,580	10,580	10,580	10,580	6,045	6,045	6,045	6,045
Adj. R2	0.579	0.596	0.586	0.561	0.639	0.653	0.729	0.722
Implied parameters								
σ_x	0.223	0.227	0.242	0.231	0.458	0.481	0.579	0.570
σ_y	0.149	0.149	0.143	0.145	0.263	0.258	0.246	0.247
δ	0.690	0.700	0.743	0.717	0.752	0.776	0.847	0.842
r	-0.274	-0.256	-0.436	-0.416	-0.250	-0.301	-0.388	-0.385
Simulated parameters								
σ_x	0.218	0.236	0.251	0.239	0.447	0.490	0.592	0.583
	(0.004)	(0.004)	(0.005)	(0.004)	(0.012)	(0.013)	(0.020)	(0.019)
σ_y	0.148	0.149	0.143	0.145	0.262	0.258	0.246	0.247
	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)	(0.002)	(0.002)	(0.002)
δ	0.686	0.716	0.757	0.731	0.745	0.782	0.852	0.848
	(0.008)	(0.007)	(0.007)	(0.007)	(0.011)	(0.010)	(0.009)	(0.009)
r	-0.272	-0.356	-0.546	-0.514	-0.254	-0.351	-0.449	-0.447
	(0.027)	(0.028)	(0.033)	(0.031)	(0.039)	(0.041)	(0.051)	(0.050)
Null hypothesis (p-value)								
$\sigma_y \geqslant \sigma_x$	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
$\gamma \geqslant \delta$	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
$r \geqslant 0$	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Least-squares panel with cross-section fixed effects. Robust standard errors are in parentheses. ***, ** and * denote significance at the 1%, 5% and 10% level. Sample consists of IPCA inflation forecasts from 2004M01 to 2014M12 provided by BCB. The dependent variable is the difference between the forecast and realized inflation h months ahead. The independent variable is the difference between the public signal and the corresponding realized inflation. The public signal is the projection from a panel regression of observed inflation on the mean or median of the aggregate or top 5 forecast that was observed by each forecaster up to the period of the forecast. Simulated parameters are the means and standard deviations (in parentheses) resulting from 10,000 simulated forecast errors and public information error series. The p-values consider the problem of testing hypotheses about the mean of a normal distribution when both the mean and the variance are unknown, using the t distribution.

Table 7: Results excluding forecasters with less than 30 observations

	Horizon 0				Horizon 12			
	All forecasters		Top 5		All forecasters		Top 5	
	Mean	Median	Mean	Median	Mean	Median	Mean	Median
Estimation								
Const.	-0.039^{***}	-0.047^{***}	-0.033^{***}	-0.034^{***}	-0.112^{***}	-0.111^{***}	-0.100^{***}	-0.104^{***}
γ	0.632^{***}	0.646^{***}	0.666^{***}	0.639^{***}	0.699^{***}	0.719^{***}	0.791^{***}	0.786^{***}
Eq. St. Error	0.080	0.079	0.079	0.082	0.134	0.131	0.116	0.117
Obs.	9,949	9,949	9,949	9,949	5,371	5,371	5,371	5,371
Adj. R2	0.577	0.595	0.586	0.559	0.635	0.650	0.726	0.719
Implied parameters								
σ_x	0.218	0.222	0.237	0.227	0.445	0.466	0.556	0.548
σ_y	0.148	0.147	0.141	0.144	0.262	0.257	0.245	0.246
δ	0.685	0.695	0.739	0.713	0.743	0.767	0.838	0.833
r	-0.267	-0.249	-0.421	-0.405	-0.242	-0.288	-0.361	-0.359
Simulated parameters								
σ_x	0.219	0.222	0.238	0.227	0.448	0.469	0.560	0.551
	(0.004)	(0.004)	(0.004)	(0.004)	(0.012)	(0.013)	(0.019)	(0.018)
σ_y	0.148	0.147	0.141	0.144	0.262	0.257	0.245	0.246
	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)	(0.002)	(0.002)	(0.002)
δ	0.686	0.696	0.739	0.714	0.745	0.769	0.839	0.834
	(0.008)	(0.008)	(0.008)	(0.008)	(0.011)	(0.010)	(0.009)	(0.009)
r	-0.273	-0.254	-0.426	-0.409	-0.255	-0.302	-0.379	-0.375
	(0.027)	(0.027)	(0.031)	(0.030)	(0.039)	(0.041)	(0.050)	(0.050)
Null hypothesis (p-value)								
$\sigma_y \geqslant \sigma_x$	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
$\gamma \geqslant \delta$	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
$r \geqslant 0$	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Least-squares panel with cross-section fixed effects. Robust standard errors are in parentheses. ***, ** and * denote significance at the 1%, 5% and 10% level. Sample consists of IPCA inflation forecasts from 2004M01 to 2014M12 provided by BCB including only forecasters with at least 30 non-zero forecasts. The dependent variable is the difference between the forecast and realized inflation h months ahead. The independent variable is the difference between the public signal and the corresponding realized inflation. The public signal is the projection from a panel regression of observed inflation on the mean or median of the aggregate or top 5 forecast that was observed by each forecaster up to the period of the forecast. Simulated parameters are the means and standard deviations (in parentheses) resulting from 10,000 simulated forecast errors and public information error series. The p-values consider the problem of testing hypotheses about the mean of a normal distribution when both the mean and the variance are unknown, using the t distribution.

Table 8: Results excluding forecasters with less than 30 observations and extreme errors

	Horizon 0				Horizon 12			
	All forecasters		Top 5		All forecasters		Top 5	
	Mean	Median	Mean	Median	Mean	Median	Mean	Median
Estimation								
Const.	-0.039***	-0.046***	-0.032***	-0.034***	-0.094***	-0.094***	-0.083***	-0.087***
γ	0.629***	0.643***	0.662***	0.636***	0.732***	0.746***	0.817***	0.808***
Eq. St. Error	0.076	0.074	0.075	0.077	0.109	0.107	0.095	0.096
Obs.	9,667	9,667	9,667	9,667	3,678	3,678	3,678	3,678
Adj. R2	0.600	0.618	0.609	0.582	0.692	0.702	0.769	0.760
Implied parameters								
σ_x	0.204	0.207	0.222	0.212	0.407	0.422	0.517	0.501
σ_y	0.147	0.146	0.141	0.143	0.230	0.227	0.215	0.216
δ	0.658	0.668	0.713	0.688	0.757	0.776	0.853	0.843
r	-0.135	-0.114	-0.267	-0.260	-0.143	-0.180	-0.300	-0.276
Simulated parameters								
σ_x	0.204	0.208	0.222	0.213	0.411	0.426	0.522	0.506
	(0.003)	(0.003)	(0.004)	(0.004)	(0.016)	(0.017)	(0.027)	(0.025)
σ_y	0.147	0.146	0.141	0.143	0.230	0.227	0.215	0.216
	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)	(0.003)	(0.003)	(0.003)
δ	0.659	0.668	0.714	0.688	0.760	0.779	0.855	0.845
	(0.008)	(0.008)	(0.008)	(0.008)	(0.015)	(0.015)	(0.013)	(0.013)
r	-0.139	-0.119	-0.271	-0.264	-0.166	-0.203	-0.323	-0.299
	(0.024)	(0.024)	(0.028)	(0.027)	(0.051)	(0.054)	(0.071)	(0.068)
Null hypothesis (p-value)								
$\sigma_y \geqslant \sigma_x$	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
$\gamma \geqslant \delta$	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
$r \geqslant 0$	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Least-squares panel with cross-section fixed effects. Robust standard errors are in parentheses. ***, ** and * denote significance at the 1%, 5% and 10% level. Sample consists of IPCA inflation forecasts from 2004M01 to 2014M12 provided by BCB including only forecasters with at least 30 non-zero forecasts and excluding extreme forecast errors. A forecast error was considered extreme if it was below the 1st percentile or above the 99th percentile of the forecast error distribution in a given period. The dependent variable is the difference between the forecast and realized inflation h months ahead. The independent variable is the difference between the public signal and the corresponding realized inflation. The public signal is the projection from a panel regression of observed inflation on the mean or median of the aggregate or top 5 forecast that was observed by each forecaster up to the period of the forecast. Simulated parameters are the means and standard deviations (in parentheses) resulting from 10,000 simulated forecast errors and public information error series. The p-values consider the problem of testing hypotheses about the mean of a normal distribution when both the mean and the variance are unknown, using the t distribution.

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