Rationality of inflation expectations in an emerging economy: an artificial neural network test

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ABSTRACT

The main objective of this paper is to study the formation of inflation expectations in Brazil during the inflation targeting regime, using a connexionist model (artificial neural network model) that approaches the way agents forecast. The coordination of market expectations about the future is a crucial aspect of inflation targeting regime. Specifically, we will verify through the proposition of a formal test if the rational expectations hypothesis (standard approach of the recent macroeconomic models) is valid for the Brazilian case in the period. The results obtained from the rationality test indicate that expectations are biased and can be predicted. These findings align with the most recent literature.

Keywords: artificial neural networks, expectations, rationality, inflation target, bootstrap, inflation

JEL Classification: E31, E52, C45

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1 Introduction and Motivation

Inflation expectations play a crucial role in an inflation-targeting framework, such as the one adopted by Brazil. They are integral not only for the monetary authority but also for various market participants, including traders and portfolio managers, influencing their decision-making processes. Concerning traders and portfolio managers, inflation expectations exert influence over multiple markets. Hence, analyzing inflation expectations is imperative for effective decision-making in trading or investing, particularly regarding nominal interest rates and break-even inflation (the difference between nominal and real interest rates). For the central bank, understanding and managing inflation expectations is crucial to steering current inflation toward the target. Given that inflation expectations significantly influence present inflation, it becomes imperative for the monetary authority to ensure a thorough understanding and effective management of these expectations to maintain inflation within the desired range.

Many central banks routinely track inflation expectations. Deviations from rational expectations pose a significant concern for policymakers, as forecasting models typically rely on the assumption of rational expectations. The role of individuals' expectations regarding future inflation is paramount in driving price increments, as these expectations shape consumption and investment decisions, subsequently impacting price and wage dynamics.

Furthermore, expectational variables distinguish economic models from mathematical models used in the natural sciences. Indeed, modern economic theory recognizes that a central distinction between economics and natural sciences lies in the "forward-looking" decisions made by economic agents (Evans (2001)). Additionally, by Lucas's critique (Lucas (1976)), changes in economic policy alter the expectations of agents, thereby modifying the parameters of economic models. Understanding the process of expectation formation is, therefore, of fundamental importance in economic modeling. This poses a significant challenge for economists: comprehending how individuals interpret the world and shape the expectations that will influence relevant economic variables. This presents a substantial challenge for economists: the imperative to comprehend how individuals construe the world and formulate expectations that will exert influence upon pertinent economic variables.

Throughout the development of economic theory, various rules for expectation formation have been assumed: static (naive expectations), adaptive, and rational. The concept of rational expectations was introduced by Muth (1961) and remains the predominant assumption in macroeconomics. This concept posits that agents efficiently form their expectations based on all relevant information available, implying that agents make no systematic errors in their predictions. Despite its widespread use, this expectation formation process has faced considerable criticism as it assumes not only that agents optimally utilize all available information but also that they possess all the required information for accurate forecasting. Such assumptions are highly restrictive, implying that the agents in the model have more knowledge than the econometrician estimating these models Sargent (1993). Therefore, a more appropriate approach to model expectation formation would be to suppose that the agents in the model act, themselves, in a manner akin to an econometrician.

Following this approach, the use of artificial neural networks (ANNs) proves to be a highly suitable tool for expectation modeling. Parametric regression analysis, the most widely used tool in econometrics to examine relationships between variables and make predictions, has certain limitations. For instance, it requires assuming a probability distribution for the data and a functional form for the relationship between variables. In the process of expectation formation, assuming that agents possess this knowledge is inappropriate, as it is generally not even known to economists themselves. ANN models possess the attractive feature of recognizing highly complex (non-linear) trajectories without specifying the functional form of this relationship. They learn through examples and have the capacity for generalization, attempting to mimic the functioning of the human brain. Therefore, by modeling expectation formation using ANNs, we aim to approximate how agents genuinely form their expectations.

The main objective of this paper is to investigate expectations regarding economic variables in Brazil during the inflation targeting regime, employing a connectionist model (artificial neural networks) to approximate how agents form their predictions. Coordinating market expectations is a crucial aspect of the inflation targeting regime. Specifically, we will assess, through the proposal of a formal test, whether the hypothesis of rational expectations (the standard approach in recent macroeconomic models) is valid for the Brazilian case during the studied period.

In addition to this introduction, the paper is structured as follows. Section 2 provides a concise overview of theoretical frameworks for analyzing expectations. Section 3 reviews the literature on the rationality of inflation expectations in Brazil. Section 4 proposes a test to assess this rationality and presents the empirical results. Finally, Section 5 summarizes the key findings and discusses their implications.

2 Expectations models in a nutshell

During the development of economic theory, three were the main processes assumed for expectation formation, which will be presented as follows.

i) Static Expectations (*Naive Expectations*)

In this case, it is assumed that agents form their expectations about some variable y_t considering the most recently observed value. Thus, it can be written as:

$$E_t\left(y_{t+1}\right) = y_t$$

This is the simplest process of expectation formation and was widely used in the early literature.

ii) Adaptive Expectations

Adaptive expectations originated from the works of Irving Fisher in the 1930s (Santos (2003)) and were formally introduced in the 1950s by Cagan (1956), Friedman (1957), and Nerlove (1958) (Evans (2001)). This expectation formation process played a fundamental role in macroeconomics in the 1960s and 1970s. According to this approach, agents form their expectations based on errors from past predictions:

$$E_t\left(y_{t+1}\right) = E_{t-1}\left(y_t\right) + \lambda\left(y_t - E_{t-1}\left(y_t\right)\right)$$

The equation above can also be written as:

$$E_t\left(y_{t+1}\right) = \lambda \sum_{i=0}^{\infty} \left(1-\lambda\right)^i y_{t-1-i}$$

where $0 < \lambda < 1$ is an adjustment parameter.

This equation represents a model of distributed lags with exponentially declining weights. Thus, more distant experiences have a smaller effect than more recent ones, which is in line with common sense. It should be noted that, in this case, agents are subject to making systematic errors in their predictions.

iii) Rational Expectations

Models based on adaptive expectations provided inadequate predictions in certain contexts, and significantly superior forecasting rules were readily available (Evans (2001)). Given this observation, a new approach to expectation formation was sought, giving rise to the so-called "rational expectations revolution."

The concept of rational expectations was introduced by Muth (1961)). This concept implies that economic agents form their expectations based on all available information and do so efficiently; they understand how this information affects the variable they are trying to predict. Thus, according to the hypothesis of rational expectations, agent predictions are essentially equal to the predictions of relevant economic theory. Considering rational expectations, we can write:

$$y_{t+1} = y^e_{t+1} + \eta_t$$
$$y^e_{t+1} = E_t\left(y_{t+1}|I_t\right)$$

where I_t is the set of information available at t and η_t is white noise.

The rational expectations approach is the standard hypothesis of recent economic models. According to this hypothesis, agents do not make systematic errors. This implies that economic actors incorporate all available information efficiently into their expectations, resulting in predictions that align closely with the theoretical forecasts provided by relevant economic models.

3 Rationality of expectations in Brazil: what does the literature say?

Inflation expectations are a key determinant of economic behavior and policy. Rational expectations theory posits that agents form expectations of future inflation based on all available information, including the central bank's policy framework. If agents have rational expectations, then the central bank can achieve its inflation target by simply announcing it.

According to de Mendonça, Garcia and Vicente (2021), studies of the rationality of inflation expectations and whether inflation expectations are well anchored have focused on developed economies. The literature on tests of inflation expectations rationality in Brazil is relatively limited. However, the existing studies have found mixed results. Some studies have found evidence of rational expectations, while others have found evidence of irrationality.

One study that found evidence of rational expectations was by Azevedo, Guimarães and Salles (2008). They used a vector autoregressive (VAR) model to test for rational expectations of inflation in Brazil. Their results showed that inflation expectations were well-explained by past inflation and interest rates.

Another study that found evidence of rational expectations is by Muinhos (2004). They used a rational expectations model to simulate the effects of inflation targeting in Brazil. Her results showed that inflation targeting could be effective in anchoring inflation expectations if the central bank was credible.

However, other studies have found evidence of irrationality in Brazilian inflation expectations. For example, Sachsida (2013) found that inflation expectations were biased upward in Brazil. He argued that this bias was likely due to the lack of credibility of the Brazilian central bank. More recently, de Freitas Rocha Cambara, Meurer and Lima (2022) also found that FOCUS expectations are not rational; that is, they are biased, and errors can be predicted.

Overall, the literature on tests of inflation expectations rationality in Brazil is mixed. Some studies have found evidence of rational expectations, while others have found evidence of irrationality. The lack of consensus in the literature suggests that further research is needed better to understand the formation of inflation expectations in Brazil.

4 Rationality tests: an artificial neural network approach

Rational expectations in the sense of Muth (1961) imply that expectations are unbiased and efficient. The unbiasedness criterion can be tested using the following simple linear regression:

$$y_{t+k} = \alpha + \beta E_t(y_{t+k}) + \varepsilon_{t+k} \tag{1}$$

The unbiasedness criterion states that the slope coefficient, β, should be equal to 1 and $\alpha = 0$ (Mincer and Zarnowitz (1969)).

The efficiency criterion implies that agents use all the information available in period t. Let x_i, $i = 1 \ldots n$, be the information available in t. The efficiency criterion can be tested using the following regression:

$$y_{t+k} = \delta_0 + \delta_1 E_t\left(y_{t+k}\right) + \gamma_1 x_1 + \ldots \gamma_n x_n + \mu_{t+k} \tag{2}$$

If expectations are efficient, then $\delta_0 = 0$, $\delta_1 = 1$, $\gamma_1 = \gamma_2 = \ldots = \gamma_n = 0$ must hold. This is because the error term cannot be used to predict the actual value of the variable if it is independent of the information variables.

In this paper, we will verify the absence of bias through equation (I). The efficiency test will be performed considering a non-linear relationship between the variables, according to the following procedure:

(i) We will train a network considering $y_{t+k} - E_t(y_{t+k})$ as the product. The significance of the inputs will be tested using the inference procedure proposed by Racine and White (2001).

(ii) The same procedure will be applied to a subsample that considers only the TOP 5 institutions[1].

It is important to highlight that, as noted by Keane and Runkle (1990), using aggregated data (such as mean or median) to test the rationality of expectations presents a challenge.

[1]The Central Bank of Brazil classifies, in each period, the top five institutions with the highest accuracy in their expectations (referred to as Top 5). Therefore, it is interesting to determine if there are differences in results when considering only these institutions in the sample. The methodology for classifying the Top 5 can be found on the Central Bank of Brazil's website: http://www.bcb.gov.br

This arises because "the mean of many individual rational forecasts, each conditional on a private information set, is not itself a rational forecast conditional on any particular information set" (Keane and Runkle (1990), p. 717). Furthermore, as underscored by Carvalho (2005), aggregating expectations results in the loss of valuable individual information. The proposed remedy for this challenge involves testing rationality using panel data. However, in the Brazilian context, implementing such a solution is not straightforward due to the unbalanced nature of the panel. The standard approach for unbalanced panels, which involves using a subsample to balance it, cannot be applied given the size of the dataset.

The next subsections present the key components of the neural network implementation. First, the ANN architecture specifications are discussed, including the determination of hidden layer size and activation functions. Then, the statistical inference procedure is presented, detailing the partial derivative tests and bootstrap methodology for hypothesis testing.

4.1 ANN architeture

For the training of an ANN, a series of decisions must be made regarding its architecture (especially the number of neurons in the hidden layer), the activation function of the neurons, and the training algorithm. This work will closely follow the procedures adopted in Racine and White (2001).

Generally, the number of neurons in the hidden layer is defined empirically. If we use too many neurons, the network may overfit the training data, leading to overfitting and, consequently, a low generalization capacity. If we use too few neurons, training can be extremely slow. Following Racine and White (2001), the network complexity will be determined using the Schwarz Information Criterion (SIC). To achieve this, we will evaluate networks with 1 to 5 hidden units and perform ten random restarts of initial weights for each configuration of input units. The configuration that yields the lowest SIC value for each network will be selected as the optimal choice, based on the number of input variables. The sigmoid (logistic) function will be used for the neurons in the hidden layer, while the "pure" linear (or identity) function will be applied to the output neuron. For network training, we will use the backpropagation algorithm with momentum and adaptive learning rate.

4.2 Valid statistical inference in ANNs: Tests based in partial derivatives

Consider the following MLP model with one hidden layer:

$$f(x,w) = w_{00} + \sum_{j-1}^{h} w_{0j}\psi\left(\tilde{x}'w_{1j}\right)$$

where: ψ = activation function of the network (logistic, in this case);

$$\tilde{x} = \left(1, x^T\right)^T$$

To test the hypothesis that some network inputs have no effect in the output is equivalent to testing the hypothesis that the partial derivatives from these inputs are zero, that is:

$$\frac{\partial f\left(x, w^*\right)}{\partial x_i} = 0 \quad i \in I_0$$

where: w^* are the optimum weights found in the network training; I_0 is the inputs set whose relevance we wish to test.

We could rewrite (I):

$$m^* = \sum_{i \in I_0} \int f_i\left(x, w^*\right)^2 d\mu(x)$$

where:

$$f_i\left(x, w^*\right) = \frac{\partial f\left(x, w^*\right)}{\partial x_i}$$

$\mu(x)$ = probability distribution of $\mathrm{X_t}$.

It follows that (I) will be true if, and only if $m^* = 0$. Notice, however, that w^* and $\mu(x)$ are unknown, but the weight $\hat{w}_n$ found in the network training and the empirical distribution of X are consistently estimated by w^* and $\hat{\mu}_n$, respectively (Racine and White (2001), p. 659). One feasible statistic is, therefore:

$$\hat{m}_n = \frac{1}{n}\sum_{t=1}^{n}\sum_{i \in I_0} f_i\left(X_t, \hat{w}_n\right)^2 = \int \sum_{i \in I_0} f_i\left(x, \hat{w}_n\right)^2 d\hat{\mu}_n(x).$$

For sufficiently large samples, RRacine and White (2001) (p. 660) showed that:

$$n\hat{m}_n \rightarrow N_2\left(0, C^*; M^*\right).$$

This distribution is not found in tables, but we can approximate it by using the bootstrap technique. The bootstrap statistics is given by:

$$\bar{\beta}_n^* \equiv \sum_{t=1}^{n} m\left(X_t, \hat{w}_n^*\right) - \sum_{t=1}^{n} m\left(X_t, \hat{w}_n\right) - \sum_{t=1}^{n} \nabla^T m\left(X_t, \hat{w}_n\right)\left(\hat{w}_n^* - \hat{w}_n\right)$$

where: $\hat{w}_n^*$ = optimum network weights trained with the resample of X_t and Y_t.

$$m(x, w) = \sum_{i \in I_0} f_i(x, w)^2$$

And we have that (Racine and White (2001), p. 662):

$$\bar{\beta}_n^* \xrightarrow{\mathrm{d}} N_2\left(0, C^*; M^*\right).$$

The algorithm for conducting inference according to the procedure described above is presented as follows:

i. A resample is computed with reposition (i.e., we take a new sample form the sample itself) from $\{X_{\mathrm{t}}, Y_{\mathrm{t}}\}$, and call it $\{X_{\mathrm{t}}^*, Y_{\mathrm{t}}^*\}$. We then estimate a new model with $\{X_t^*, Y_{\mathrm{t}}^*\}$. The training algorithm will be initialized from the initial values $\hat{w}_n$ found for the network trained before. With those resampled weights and the initial ones, we can therefore compute the bootstrap statistics:

$$\bar{\beta}_n^* \equiv \sum_{t=1}^{n} m\left(X_t, \hat{w}_n^*\right) - \sum_{t=1}^{n} m\left(X_t, \hat{w}_n\right) - \sum_{t=1}^{n} \nabla^T m\left(X_t, \hat{w}_n\right)\left(\hat{w}_n^* - \hat{w}_n\right)$$

ii. The procedure described in (1) is repeated 1000 times, thereby obtaining 1000 values for the bootstrap statistics. We then compute the acceptance region of the null hypothesis (c_α).

iii. The $n\hat{m}_n$ statistics will be computed. If it is bigger than c_α, then the null hypothesis of Market efficiency should be rejected.

5 Data and Results

5.1 Survey-based inflation expectations data: descriptive analysis

The data utilized in this research are from the FOCUS survey conducted by the Central Bank of Brazil. We took the monthly average of the medians of inflation expectations for two horizons: one month ahead and twelve months ahead. Additionally, we employ inflation expectations from The Top 5 ranking as a supplementary analysis to validate the information gathered from the complete set of participants. The monthly series were constructed closely following de Freitas Rocha Cambara et al. (2022). The data is detailed hereafter.

i. Monthly average of the median of one-month ahead inflation expectations (IPCA). Source: FOCUS (Central Bank of Brazil).

ii. Monthly average of the median of 12-month cumulative inflation expectations (IPCA). Source: FOCUS (Central Bank of Brazil).

iii. Monthly average of the median of inflation expectations (IPCA) for the Top 5 institutions[2]. Source: FOCUS (Central Bank of Brazil).

iv. Monthly series of IPCA - Broad Consumer Price Index. Source: IBGE.

v. Monthly series of IPCA accumulated over 12 months. Source: IBGE.

Figures to follow display the forecast error for each horizon, along with histograms for both the error and inflation expectations. The red line represents the median of the data.

Figure 1: $\pi_t - E_{t-1}\pi_t$

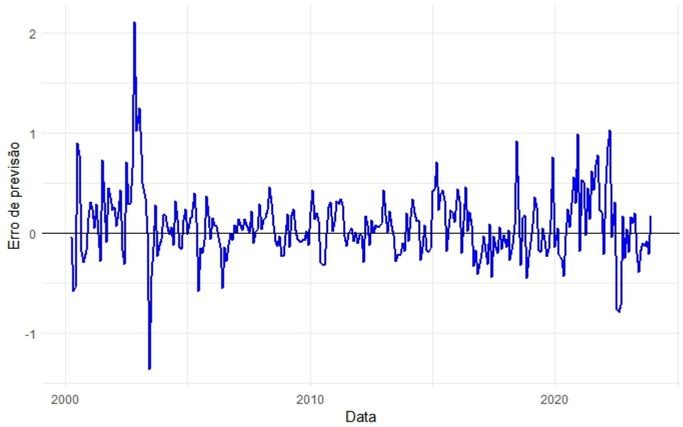
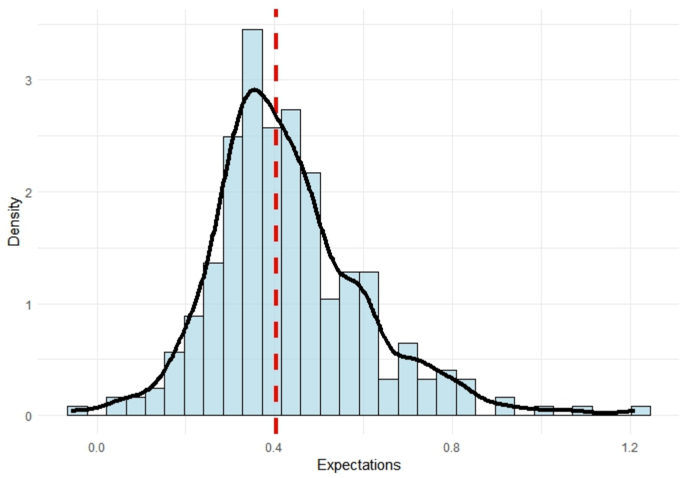


Figure 2: Histogram: $E_{t-1}\pi_t$



[2]Encouraging the enhancement of forecasting skills among survey participants and recognizing their analytical efforts, the Central Bank develops the Top 5 ranking. This classification system evaluates institutions based on the precision of their predictions across short-, medium-, and long-term horizons.

Figure 3: Histogram: $\pi_t - E_{t-1}\pi_t$

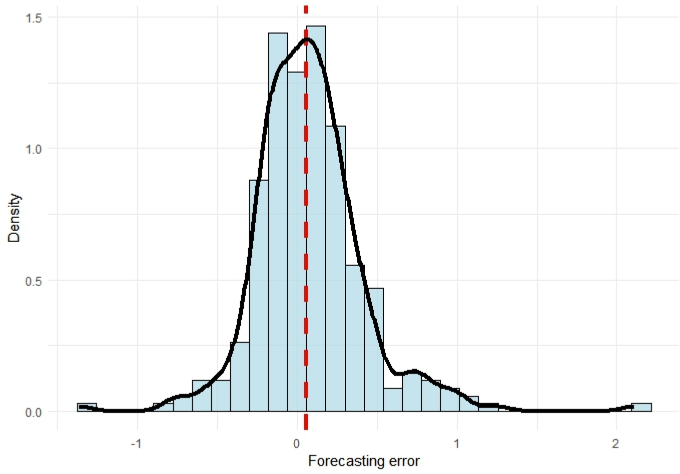


Figure 4: $\pi_t^{12m} - E_{t-12}\pi_t^{12m}$

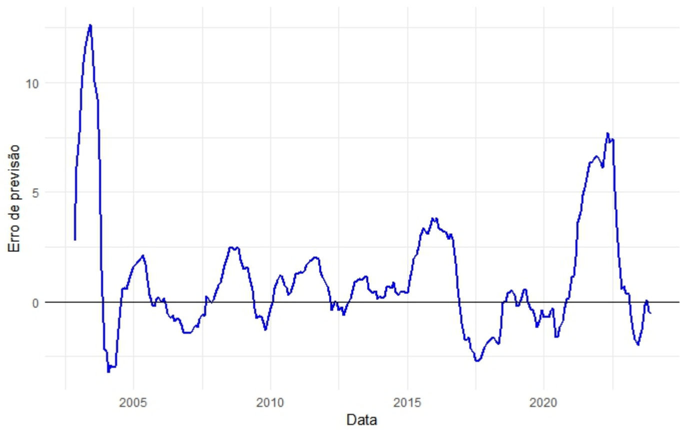


Figure 5: Histogram: $E_{t-12}\pi_t^{12m}$

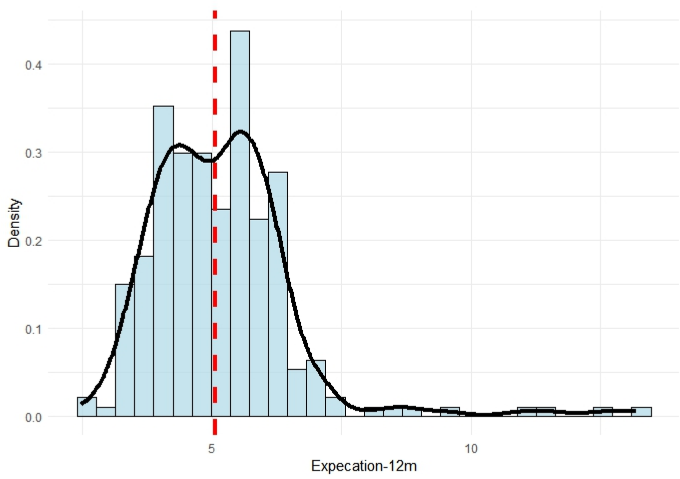


Figure 6: Histogram: $\pi_t^{12m} - E_{t-12}\pi_t^{12m}$

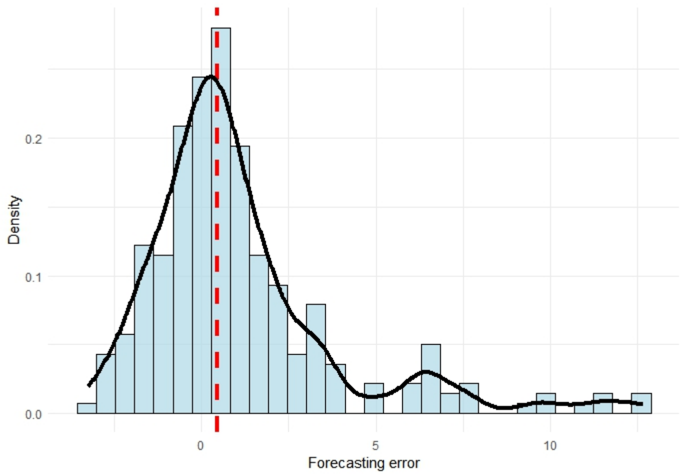


Figure 7: $\pi_t - E_{t-1}\pi_t$: Top 5

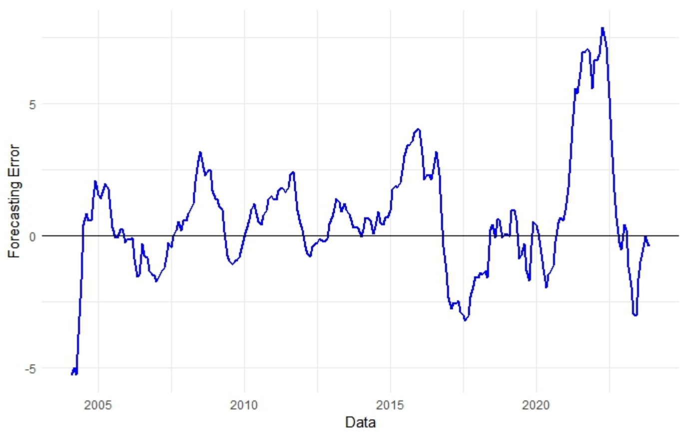


Figure 8: Histogram Top 5: $E_{t-12}\pi_t^{12m}$

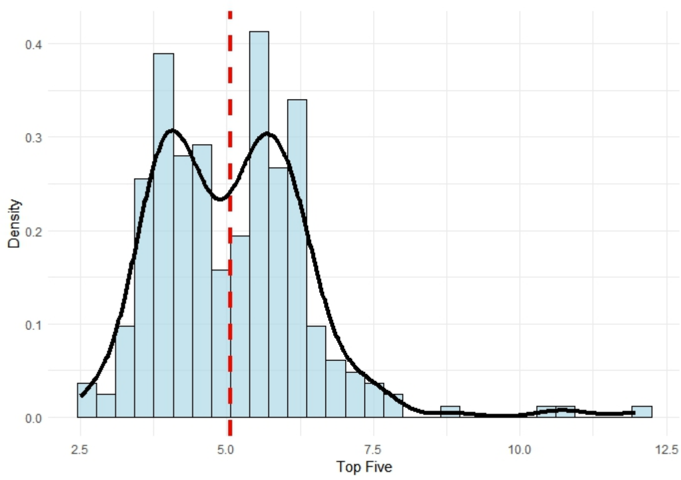
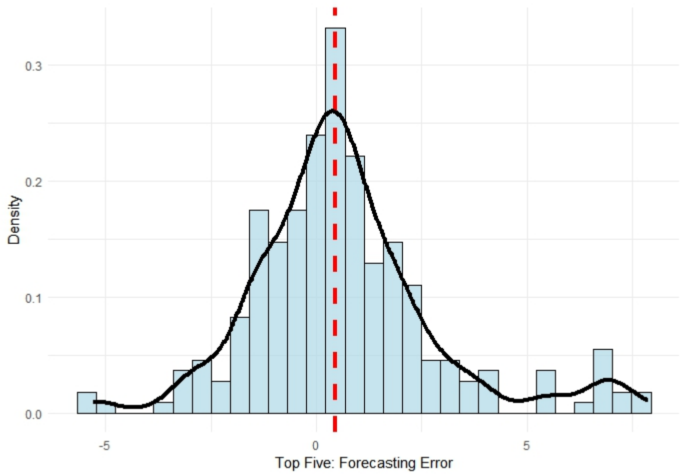


Figure 9: Histogram Top 5: $\pi_t^{12m} - E_{t-12}\pi_t^{12m}$



The table 1 displays the descriptive statistics for all the series used.

Table 1: Descriptive statistics

	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
$\pi_t - E_{t-1}\pi_t$	-1.35950	-0.13458	0.05714	0.07663	0.23550	2.10950
$E_{t-1}\pi_t$	-0.0565	0.3248	0.4045	0.4309	0.5119	1.2095
$\pi_t - E_{t-12}\pi_t^{12m}$	-3.240	-0.574	0.455	1.099	1.850	12.650
$E_{t-12}\pi_t^{12m}$	2.480	4.180	5.060	5.161	5.830	13.180
Top 5 E_t	2.509	4.053	5.057	5.092	5.876	11.976
Top 5 Error	-5.2855	-0.6099	0.4570	0.6413	1.5832	7.8740
$IPCA_t$	-0.6800	0.2600	0.4600	0.5075	0.6900	3.0200
$IPCA_{12m}$	1.880	4.345	5.815	6.259	7.178	17.240

5.2 Are Brazilian inflation expectations rational?

To assess whether inflation expectations in Brazil are rational, we conducted the tests described in the methodology section. Essentially, we conducted bias and efficiency tests. The bias test involves checking whether the forecast errors have a zero mean. On the other hand, the efficiency test assesses whether projections are inefficient, i.e., whether there was additional information readily available to the forecasters that could have been used to enhance the accuracy of the projections.

The results of the conducted regressions are presented in the tables 2 to 5. The bias tests are summarized in Table 6. Overall, our regressions indicate that the FOCUS inflation expectations for all forecast horizons are biased, including the sample considered for the TOP 5 institutions.

Table 2: Bias Regression:$E_{t-1}\pi_t$

	Dependent variable:
	$IPCA_t$
$E_{t-1}\pi_t$	1.254***
	(0.115)
Constant	−0.033
	(0.053)
Observations	285
R^2	0.296
Adjusted R^2	0.294
Residual Std. Error	0.337 (df = 283)
F Statistic	119.103*** (df = 1; 283)
Note:	*p<0.1; **p<0.05; ***p<0.01

Now, we will proceed to the efficiency test using the ANN described in the methodology section. The variables that we included for the test are autoregressive term, inflation target (next 12 months), inflation rate (IPCA 12 months), Selic short-term interest rate, nominal exchange rate (R$/US$) and Embi + Br. It's important to highlight that each training session for the ANNs requires over a day to complete. Here, we offer a condensed overview of the achieved outcomes. The ANN used here consists of a three-layer (single hidden layer), feed-forward neural network.

Table 3: Bias Regression: $E_{t-12}\pi_t^{12m}$

	Dependent variable:
	$IPCA^{12m}$
$E_{t-12}\pi_t^{12m}$	0.681^{***}
	(0.125)
Constant	2.747^{***}
	(0.667)
Observations	254
R^2	0.106
Adjusted R^2	0.102
Residual Std. Error	2.769 (df = 252)
F Statistic	29.784^{***} (df = 1; 252)
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 4: Bias Regression: Top 5

	Dependent variable:
	$IPCA^{12months}$
$E_{t-12}\pi_t^{12m}$	0.391^{***}
	(0.103)
Constant	3.763^{***}
	(0.546)
Observations	239
R^2	0.057
Adjusted R^2	0.053
Residual Std. Error	2.087 (df = 237)
F Statistic	14.426^{***} (df = 1; 237)
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 7 reveals that there is information available in the data that can aid in forecasting errors. Consequently, we conclude that inflation expectations are not efficient. These results are in line with the most recent literature. de Freitas Rocha Cambara et al. (2022), for example, find that the expectations are biased and can be predicted, deviating from the rationality hypothesis.

Table 5: Bias Regression: Top 5 - without intercept

	Dependent variable:
	$IPCA^{12m}$
$E_{t-12}\pi_t^{12m}$	1.080***
	(0.028)
Observations	239
R^2	0.863
Adjusted R^2	0.862
Residual Std. Error	2.282 (df = 238)
F Statistic	1,500.106*** (df = 1; 238)
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 6: Bias test: $H_0 : \alpha = 0$ and $\beta = 1$

	Top Five	$E_{t-12}\pi_t$	$E_{t-1}\pi_t$
Statistic	57.51	46.72	19.38
P-value	0.00	0.00	0.00

Table 7: Efficiency test: ANN

	Top Five	$E_{t-12}\pi_t^{12m} - \pi_t^{12m}$	$E_{t-1}\pi_t - \pi_t$
Joint test (all variables)	105.86	107.51	102.37
P-value	0.00	0.00	0.00
Neurons (hidden layer)	3	3	4
Note:	Number of bootstrap replications: 1000		

6 Conclusions

The core element of the inflation targeting regime lies in coordinating agents' expectations. When the monetary authority possesses credibility, inflation targets function as a stabilizing force in shaping these expectations. Consequently, understanding the factors that influence such expectations becomes critically essential for effectively steering monetary policy.

This research contributed to the literature on inflation expectations in Brazil by examining the validity of the rationality hypothesis for expectations over the one-month and twelve-month horizons and for the sample of the TOP 5 institutions. The methodology employed in this research, utilizing ANN models (three-layer - single hidden layer -feed-forward neural network.), is also an innovation. The results obtained from the rationality test indicate that expectations are biased. These findings align with the most recent literature.

Despite the valuable insights gained from this research, it is essential to acknowledge its limitations and potential avenues for future research. The tests and results presented here were conducted for the entire sample. It is well-known that there were significant changes during the period considered, and a time-varying approach would be more robust. Therefore, one suggestion for future work is to use subsamples or a time-varying approach, which will require considerable effort given the nature of the method employed here. Additionally, a possibility is to compare the results obtained here with the inference procedure proposed by Horel and Giesecke (2020) and also with the Bayesian approach proposed by Liu, Li, Wang and He (2024). Another fruitful research topic is to investigate whether the results change considering a state-dependent approach.

In conclusion, while this study contributes significantly to understanding inflation expectations in Brazil, acknowledging its limitations and proposing avenues for future research is vital to advance our understanding of this research topic. We hope that future research addresses these limitations as we continue to work on several of them.

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