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Rationality and Instability in Professional Forecasting: Exploring the Impact of Key Variables

Abstract

We test the rationality of Brazilian inflation forecasters and analyze the relationship between rationality and macroeconomic and electoral variables with panel data and consensus. Verifying whether this relationship exists and whether it changes between panel data and consensus is our contribution. We use monthly data from the Survey of Professional Forecasters. In contrast to traditional tests, we do not reject the rationality for the consensus considering instability. The consensus forecast neutralizes the bias of individual forecasts and reduces irrationality for periods of recession, monetary policy tightening, inflation above the target and without elections.

Key words: Rationality, Forecast, Inflation

JEL codes: C53, C22, E37.

Introduction

Surveys of professional forecasters (SPFs) are used to extract information because these people have incentives to report their true predictions (Keane and Runkle, 1990). Professional forecasters seem to be more informed than consumers and their forecasts are "better" (Carroll, 2003).

Tests of forecast rationality address whether forecasts are biased or take into account the information available to the forecaster at the time of the forecast.[1] If the forecasts are not rational, it would be possible to improve their accuracy by using the available information efficiently. As these forecasts guide policymakers' and practitioners' decisions, this assessment of forecasts can generate better information to support these decisions. Traditional tests of forecast rationality such as those of Mincer and Zarnowitz (1969) and West and McCracken (1998) verify if forecast errors have a zero mean and are uncorrelated with the forecasts.

The professional macroeconomic forecasting literature on unbiasedness and rationality focuses on the United States of America (USA) and Group of Seven (G7) countries. Also, Loungani (2001) finds differences in the forecasting performance of professionals between developed and emerging economies, where emerging economies tend to have larger forecasting errors. The articles on emerging countries are more recent as Issler and Lima (2009), Gaglianone et al. (2017), Gaglianone and Issler (2021), Bentancor and Pincheira (2010), Pincheira and Álvarez (2012), Deschamps and Bianchi (2012), Capistrán and López-Moctezuma (2014), and Chen et al. (2016).

Emerging markets tend to exhibit higher and more volatile inflation. Brazil overcame hyperinflation in 1994 and most fixed income assets are still short-term. Institutions tend to put more effort into forecasting Brazilian inflation, which is a more difficult exercise than in advanced economies (Garcia et al., 2017). In addition, managing the expectations of agents about inflation is more relevant to build the reputation of the Brazilian Central Bank (BCB) in an economy with weak monetary and fiscal institutions (Fraga et al., 2003; Minella et al., 2003; Carvalho and Minella, 2012). In the sample period, Brazil lost its inflation anchor between 2011 and 2016 according to Reis (2022), and anchored inflation expectations are key for monetary policy. So we justify studying rationality and what affects agents' inflation forecasts in Brazil. We point out that the variety of changes that have occurred in Brazil over time can serve as a lesson for other countries.

We make two contributions: i) we use a different database, and ii) we investigate the relationship between the forecast errors and macroeconomic and election variables. Our database is different from most forecasting rationality studies for inflation and other variables because we use the SPF organized by Bloomberg.[2] The advantage of this database compared to that organized by Central Banks is that the analysts' and institutions' forecasts are public along with the names of those who reported the forecasts. The forecasts being public on this platform encourage the disclosure of true forecasts.[3]

Our second and main contribution is to analyze whether we are able to explain changes in the rationality and unbiasedness tests for panel data and consensus by the presence of instability through periods with different patterns of monetary policy behavior, business cycles, level of inflation in relation to the target, and election periods. We can rationalize whether periods of underprediction and overprediction are associated with macroeconomic or election variables, for example. We compare between the easing and tightening of monetary policy, between an expansion and recession in the business cycle, between inflation above or below the target, and whether there is a difference in election periods. There are few studies that seek to relate the irrationality or bias of forecasts with economic patterns, such as those of Joutz and Stekler (2000), Hanson and Whitehorn (2006), Sinclair et al. (2010), Sinclair et al. (2012), Messina et al. (2015), and Granziera et al. (2021). Most studies only consider whether the economy is in recession or expansion to explain whether forecasts are state dependent, while we seek to extend this understanding from macroeconomic and electoral variables. Also, we compare results between panel data (individuals) and time series (consensus) to understand whether there is a difference in explaining the results of the rationality and unbiasedness tests by macroeconomic and electoral variables. We find no studies that compare the results of consensus and individuals with macroeconomic and electoral variables and whether there is a difference by the aggregation of the consensus.

We use a SPF to test forecast rationality using Brazilian inflation forecast data for each month with a zero month forecast horizon - a five-day horizon on average - considering two approaches: panel data and time series. Our sample covers December 1999 to February 2019. Initially, we test the forecast rationality with panel data based on Mincer and Zarnowitz (1969), in which the individual unit is the analyst in a given institution. In the following test, we analyze the forecast rationality of the consensus, institutions, and analysts using the time series approach. Due to its robustness to instability, we also consider the fluctuation rationality test of Rossi and Sekhposyan (2016) for the consensus, institutions', and analysts' inflation forecast using the time series framework. We seek to obtain possible causes for the presence of instabilities - if they exist - that would justify the use of the fluctuation rationality test. So, we test the unbiasedness and rationality of the forecasts with time series and panel data and we seek to explain if there are changes in the test results based on election and non-election periods, the tightening and easing of monetary policy, the expansionary and recessionary cycles of economic activity, or whether inflation is above or below the target.

Considering the panel data or time series, we do not reject the null hypothesis of unbiasedness. We reject forecast rationality for the panel data or the consensus time series using the traditional tests. But we do not reject the null hypothesis of rationality for the consensus inflation forecast with the fluctuation rationality test that is robust for the presence of instabilities. This indicates that the presence of instability seems to be important and we seek to understand whether such changes over time for the rationality behavior of forecasts are related to macroeconomic or electoral variables.

Using panel data, we find that there is a bias in inflation forecasts in the easing and tightening periods of monetary policy, although there is no bias when we consider the overall sample. There is the same pattern if we compare periods with and without election or if inflation is above or below the target. We find no relationship between the behavior of rationality tests and economic or electoral patterns considered with panel data. In addition, the economic cycle does not seem to make a difference for the unbiasedness and rationality tests. When we consider the forecast consensus in the time series, we obtain unbiased forecasts regardless of whether there is a difference in monetary policy, in the business cycles, whether inflation is above or below the target, or the period is electoral or not. The lack of a relationship between forecast bias and the business cycle is in line with the finding of Hanson and Whitehorn (2006) and Messina et al. (2015) considering the results of the unbiasedness test, but different from those of Karamouzis and Lombra (1989) and Sinclair et al. (2010) for the USA. We obtain irrationality for the forecast consensus in tightening periods, in recessions, when inflation is above the target, and when there is no election. In other words, aggregation through consensus seems to neutralize the bias of forecasts obtained with the panel data, similarly to the findings of Capistrán and Timmermann (2009) and aggregation reduces irrationality for only some behavioral patterns.

As robustness, we allow the forecaster loss function to be asymmetric using the Elliott et al. (2005) approach. We do not reject rationality for any of the institutions or analysts at the 5% significance level. Our evidence is in line with that of Elliott et al. (2008) in that there is less rejection of forecast rationality when we consider the asymmetric loss function. Overpredictions of inflation are more costly than underpredictions for most institutions and the opposite is true for analysts. This result of underprediction being more costly for the analyst is similar to that found by Elliott et al. (2008) for USA inflation.

Another robustness analysis is to consider the possibility of the observed forecast being endogenous. This is because the forecasters manually adjust it based on their personal expertise and do not just report the model's forecast. We find that if the forecasters (institutions and analysts) use an econometric model, they all adjust their model forecasts considering the Franses (2021) approach. There is less evidence of forecast rationality when the observed forecast is endogenous. The median of the variance adjustments based on personal expertise for institutions is higher than for analysts. The adjustment of inflation forecasts by Brazilian professionals is greater than in the evidence of Franses (2021) for USA inflation.

This paper is organized in five sections besides this introduction. The next section presents the literature review about the forecast rationality hypothesis and whether the irrationality or bias of inflation forecasts is related to macroeconomic variables. Section 2 describes the methodology used with the panel data and time series frameworks. We report the descriptive statistics of professional forecasts in Section 3. In Section 4 we analyze the results from the test for the forecast rationality hypothesis using the panel data and time series approaches and we seek to determine whether there is bias or an irrational relationship between inflation forecasts and macroeconomic and election variables. The last section presents the conclusions.

1 Literature Review

We intend to analyze the rationality of individual or consensus forecasts. We can divide the empirical rationality literature based on the methodology used: time series or panel data. The literature on rationality tests analyzes time series of individual or consensus forecasts or it focuses on the panel data approach with individual forecasts.

An aggregate of individual forecasts is often used as the survey series. Aggregation through the median is more common and referred to as the consensus forecast. Individual responses (from institutions or analysts) may provide too much information when one series is expected. We want to use only one series if we wish to compare the consensus with the model forecasts (e.g., Ang et al., 2007; Clements and Galvão, 2017), or to analyze the macroeconomic effect of a shock on expectations (e.g., Milani, 2012; Leduc and Sill, 2013; Clements and Galvão, 2017; Cole and Milani, 2019), or to test the predictions of aggregate expectations based on expectations theories (e.g., Carroll, 2003; Coibion and Gorodnichenko, 2012, 2015), among others. The time series approach seems more appropriate for these purposes. For other purposes such as expectations formation theories (see for example Carroll, 2003; Coibion and Gorodnichenko, 2012, 2015), we want to make predictions for aggregate expectations based on individual expectations (Clements, 2019). In this case, the panel data approach seems to be more appropriate. Keane and Runkle (1990) argue that individual data should be used to test rationality. The concern is that the use of aggregate data may lead to a false rejection of rationality and hide individual deviations from rationality. Heterogeneous irrational forecasters may appear rational in aggregate if biases cancel each other out. Crowe (2010) and Satopää (2017) find that individual forecasters with different information sets can generate a biased consensus forecast even if the individual forecasts are optimal.

Studies from the 1970s and 1980s that use expectation surveys reject the rationality of forecasts such as Su and Su (1975) and Zarnowitz (1985). But later articles (Keane and Runkle, 1990; Mankiw et al., 2003; Capistrán and Timmermann, 2009; Croushore, 2010, 2012) do not find bias for a longer full sample. For example, Capistrán and Timmermann (2009) find that individual forecasts are biased, but the forecast mean is not biased because individual biases cancel each other out.

One point to highlight is the role of instability in rationality test based on Rossi and Sekhposyan (2016). Rossi and Sekhposyan (2016) compare the USA Federal Reserve's Greenbook forecast of inflation with the private sector's forecasts from USA SPF and Blue Chip Economic Indicators (BCEI). They analyze the rationality of the forecasts using the fluctuation rationality test. First, Rossi and Sekhposyan (2016) do not reject the null hypothesis of rationality of the SPF and Greenbook forecasts for horizons from zero to five quarters ahead using the Mincer and Zarnowitz (1969) traditional rationality test.

Rossi and Sekhposyan (2016) argue that the results of studies using traditional rationality tests with the time series framework - such as those of Romer and Romer (2000), Faust and Wright (2009), and Patton and Timmermann (2012), among others - are sensitive to the sample period for inflation forecasts. The fluctuation rationality test indicates that there are periods of rejection of the null hypothesis of forecasts rationality for the three forecast series (Greenbook, SPF and BCEI) considered in the different horizons. The authors find that inflation forecasts were persistently biased downward in the 1970s and persistently biased upward in the 1980s and 1990s. The idea of the Rossi and Sekhposyan (2016) test is to estimate the forecast rationality regression in rolling windows. The fluctuation rationality test performs well when the time variation of rationality is smooth and persistent, and smaller windows improve the power of the test to detect deviations from rationality that occur repeatedly in short periods of time (Odendahl et al., 2021). We perform Rossi and Sekhposyan (2016) rationality test for its robustness to instability.

We seek to explain changes in the rationality and unbiasedness tests by the presence of instability through different patterns of monetary policy behavior, business cycles, the level of inflation in relation to the target, and election periods. Basically, we analyze whether the irrationality or bias of inflation forecasts (if any) is state-dependent and has any relationship with macroeconomic and election variables. There is regular evidence that the Fed's forecasts for inflation are underestimated when inflation is rising and overestimated when inflation is falling (Joutz and Stekler, 2000; Hanson and Whitehorn, 2006; Sinclair et al., 2010).

Karamouzis and Lombra (1989) find that the Fed's forecast error for the Gross National Product deflator is greater in periods of economic contraction in relation to those of expansion. Sinclair et al. (2010) obtain a difference for the inflation forecast of the SPF between recessionary and expansionary periods, similar to Karamouzis and Lombra (1989). On the contrary, Hanson and Whitehorn (2006) obtain evidence that the Fed's forecasting errors for inflation are associated with specific time periods and not with the state of the economy. Also Messina et al. (2015) find that the Fed's inflation forecast error is unrelated to the state of the economy. Sinclair et al. (2012) and Capistrán (2008) highlight distinct bias behavior for the Fed's forecast of inflation before and after Volcker. According to Granziera et al. (2021), the ECB tends to overpredict (underpredict) inflation when it is below (above) the target only for forecast horizons of two to four quarters. Also their evidence is of irrationality of ECB forecasts when inflation is above the target. While most studies focus on whether forecasts are state-dependent during economic expansion and recession, we examine the possibility of other macroeconomic and electoral patterns as well. We also do not find studies that analyze whether there is a difference in aggregation through consensus for the forecast to be state dependent compared to the forecasts of individuals in panel data.

For robustness, we consider the case that the loss function is asymmetric for the rationality test of forecasts following Elliott et al. (2008). If individuals weigh the costs of over and underprediction differently, they have an asymmetric loss function. So, rational forecasters generate biased forecasts according to Elliott et al. (2005). A common strategy is to examine rationality conditional on a given loss function. Elliott et al. (2005) suppose a general loss function indexed by unknown shape parameters. The authors show that the GMM over-identification test using a vector of instruments is a test of rationality that estimate one parameter that indicates whether the loss function is symmetric. Elliott et al. (2008) reject rationality for fewer forecasters by allowing for an asymmetric loss function compared to assuming a quadratic loss. But the failure to reject the null hypothesis of rationality by Elliott et al. (2008) might reflect the low power of GMM tests of over-identifying restrictions using at least 20 observations according to Clements (2014). By using the Elliott et al. (2008) approach, we seek to avoid this problem by taking at least 100 observations into account as robustness to the rationality test that allows for an asymmetric loss function.

Another analysis for the robustness of the results that we do is if forecasters do not only use the model's forecasts but adjust them according to their personal experiences. Franses (2014) find such behavior. Franses (2021) proposes a way to measure how much forecasters adjust a forecast. This forecast adjustment introduces the measurement error in the regression which leads to the presence of endogeneity. He rejects the null hypothesis of exogeneity with the Durbin-Wu-Hausman test in many cases indicating that the forecast is an endogenous regressor, meaning that the presence of forecast adjustment is common. His result is that two-stage least squares (TSLS) using the consensus forecast as an instrument leads to more evidence of an unbiased forecast when we consider the forecast as endogenous through manual adjustment. The median variance of the personal adjustments of the forecasts is 12.6% of the variance of the model forecasts for the survey respondents for USA inflation by Franses (2021).

For emerging economies, professionals tend to have larger forecasting errors compared to those in advanced countries based on Loungani (2001). Bentancor and Pincheira (2010) and Deschamps and Bianchi (2012) respectively find that inflation forecasts by professionals are biased and inefficient for Chile and China. Chen et al. (2016) show a pattern of professionals overestimating inflation forecasts for five countries (China, Hong Kong, India, Malaysia and Taiwan). According to Pincheira and Álvarez (2012), the consensus inflation forecast by SPF are unbiased and efficient for Chile. Capistrán and López-Moctezuma (2014) find that the majority of individuals have unbiased and inefficient forecasts for Mexican inflation.

Brazilian studies use data from the BCB's SPF or the Central Bank's own forecasts. Issler and Lima (2009), Gaglianone and Issler (2021), and Gaglianone et al. (2017) find that the inflation forecast of the Brazilian SPF is biased for different horizons. Additionally, Gaglianone et al. (2017) reject the null hypothesis of no bias for consumer forecasts for Brazilian inflation 12 months ahead. The next section presents the methodology of this study.

2 Methodology

Traditional tests of forecast rationality such as those of Mincer and Zarnowitz (1969) and West and McCracken (1998) verify if forecast errors have a zero mean and/or are uncorrelated with the variables available at the time the forecast is made. We use two frameworks by analysing panel data and time series.

2.1 Panel data framework

First we will detail the panel data framework we adopt. We analyze the test of unbiasedness of forecasts by estimating the restricted version

$$\pi_{t+h} - E_{i,t}(\pi_{t+h}) = \alpha + \varepsilon_{i,t} \tag{1}$$

where the null hypothesis is $\alpha = 0$, the forecast error is $e_{i,t+h} = \pi_{t+h} - E_{i,t}(\pi_{t+h})$ for individual i and h periods ahead, π_{t+h} is the realized inflation h periods ahead and $E_{i,t}(\pi_{t+h})$ is the inflation forecast h periods ahead by individual i.

We can also analyze if forecast errors are predictable or a white noise process. We test this with the following regression

$$e_{i,t+h} = \alpha + \beta_1 \pi_{t-1} + \beta_2 \Delta i_{t-1} + \varepsilon_{i,t} \tag{2}$$

where π_{t-1} is the lagged realized inflation, and Δi_{t-1} is the lagged interest rate variation. Under the null hypothesis of rationality, $\beta_1 = 0$ and $\beta_2 = 0$ and the forecast errors are unpredictable. The panel data estimator is the pooled regression as used by Keane and Runkle (1990).

2.2 Time series framework

Here we present the forecast unbiasedness and rationality test using the time series approach. We test the time series for three types of forecats error: (i) consensus, (ii) each analyst who reported at least 100 forecasts over time, and (iii) each institution that reported at least 100 forecasts over time.

Mincer and Zarnowitz (1969) propose a restricted version of the test based on the following regression

$$e_{t+h} = g_t \theta + \eta_{t+h} \tag{3}$$

where g_t is a $(l \times 1)$ vector, η_{t+h} is the error term, and $t = 1, 2, ..., P$, where P is the number of available forecasts. g_t includes a constant and the forecast itself similar to the forecast rationality test of Rossi and Sekhposyan (2016).[4] The null hypothesis is $\theta = 0$ and the intuition is that the forecast error is unpredictable at the time the forecast is made.

The Mincer and Zarnowitz (1969) test statistic MZ_P is a F test in the regression (3). This statistic is given by

$$MZ_P = P\hat{\theta}'_P \hat{V}_\theta^{-1} \hat{\theta}_P \tag{4}$$

where $\hat{V}_\theta$ is a heteroskedasticity and autocorrelation corrected (HAC) estimator of the asymptotic variance of the parameter estimates.[5] We use the Newey and West (1987) HAC estimator as the default for our estimates in the present work. This test has an asymptotic chi-squared distribution with l degrees of freedom under the null hypothesis, where l is the number of restrictions. We can test the forecast rationality with the time series approach based on Equation (3).

However, the traditional rationality test assumes stationarity and time invariant parameters, but these are invalid in the presence of instabilities in the DGP (Rossi and Sekhposyan, 2016; Rossi, 2013). Traditional tests might average out periods of under-prediction and over-prediction. This is a possible reason why traditional tests are not robust to instabilities (Clements, 2019).

Rossi and Sekhposyan (2016) propose the fluctuation rationality test for the time series approach. This test estimates the Equation (3) in rolling windows of size m and obtains $\hat{\theta}_m$ using data from $t = 1, ..., m$, then estimates $\hat{\theta}_{m+1}$ using data from $t = 2, ..., m + 1$, and so on. So we have the following Wald test

$$W_j = m\hat{\theta}_j' \hat{V}_{\theta,m}^{-1} \hat{\theta}_j \tag{5}$$

for each $j = m, .., P$. The Rossi and Sekhposyan (2016) test statistic is $\max_{j \in (m,...,P)} W_j$. The null hypothesis is $\theta_j = 0$ and the alternative hypothesis is that $\theta_j \neq 0$ for $j = m, .., P$. The null hypothesis means that the forecast errors are unpredictable given the information set available at the time the forecast is made (Rossi and Sekhposyan, 2016). We reject the null hypothesis if $\max_{j \in (m,...,P)} W_j > k_{\alpha,l}$, where $k_{\alpha,l}$ is the critical value at the $100\alpha\%$ significance level with l restrictions. The asymptotic distribution is free of nuisance parameters. Rossi and Sekhposyan (2016) tabulate the critical values for different values of l and m/P.

We have to choose the size of the the window m. The size of m leads to a trade-off between bias and efficiency: a smaller m would reduce bias in the presence of instabilities, but a bigger m would give the most efficient estimate in the absence of instabilities. Rossi and Sekhposyan (2016) recommend analyzing the sensitivity of the results to different m's values. However, El-Shagi (2019) points out that the fluctuation rationality test is oversized for small window sizes such as $m = 25$ using the asymptotic critical value of Rossi and Sekhposyan (2016). We consider a window size of 60 observations as a reference. We do a robustness exercise with smaller windows in the Supplementary Appendix and we compare between asymptotic critical values of Rossi and Sekhposyan (2016) and finite sample adjusted critical values of El-Shagi (2019).

In the two additional questions studied based on Franses (2021) and Elliott et al. (2008), we focus on the time series for two type of the forecast error: (i) each analyst, and (ii) each institution. The next point that we analyze is whether professional forecasters can also rely on their personal expertise and not only on econometric models. Consider the Mincer and Zarnowitz (1969) regression that is

$$e_{t+h} = \alpha + \beta mo_t + \eta_{t+h} \tag{6}$$

where mo_t is the model forecast.

Franses (2014) documents that many forecasts from models are manually adjusted by the professionals. The modification of the model forecast introduces a measurement error in the regression (6). This measurement error leads the observed forecast to be endogenous, as we found previously in the traditional and fluctuation rationality tests respectively according to (3) and (5) estimated by ordinary least squares (OLS).

Based on the idea that the observed forecast can have measurement errors, Franses (2021) considers the measurement error interpretable. The measurement error of a forecast is associated with the adjustment of the model forecast by the professional, which makes the measurement error interpretable.

We analyze the fit of the adjustments to the model forecasts based on the study of Franses (2021). As there are many professional forecasters, we consider the consensus forecast to be an instrumental variable in all regressions - regressions for the time series of each analyst or institution. The consensus forecast as a instrumental variable is correlated with each individual forecast and should not be correlated with the individual adjustment. So, we estimate equation (3) using TSLS.

We detail this approach below. Consider $f_t = E_t(\pi_{t+h})$ as the observed forecast. If the professional forecaster adjusts the forecast of their model, then we evaluate the observed forecast f_t and not mo_t. We can define

$$f_t = mo_t + a_t \tag{7}$$

where a_t is the adjustment.

So we can write the Mincer and Zarnowitz (1969) regression like Equation (3) as

$$e_{t+h} = \alpha + \beta f_t + \eta_{t+h} \tag{8}$$

where e_{t+h} represents the time series of the forecast error for each analyst or institution.

But this regression has an endogenous covariate due to the measurement error a_t in the case of adjustment based on personal expertise. If there is measurement error, the OLS estimates of β are smaller than the true β according to Franses (2021). So, we need an instrumental variable that is correlated with mo_t and not with a_t. We do not know the forecasts of the individual professionals based on the model so that the consensus forecast is the instrument used. We do not expect that the consensus forecast to be correlated with the adjustments made by each individual forecaster.

However, we can test for exogeneity to analyze if we should use the TSLS or OLS estimation methods. We consider the Durbin-Wu-Hausman test in which exogeneity is the null hypothesis. If we reject the null hypothesis, the difference between the TSLS and OLS estimates indicates the size of the adjustment. Consider $\hat{\beta}_{TSLS}$ as the "true" β when we reject the null hypothesis with the Durbin-Wu-Hausman test. So, following Franses (2021) we can find how much the variance of the adjustments is proportional to the variance of the model forecasts. We can calculate this ratio as

$$\frac{\sigma_a^2}{\sigma_{mo}^2} = \frac{\hat{\beta}_{TSLS} - \hat{\beta}_{OLS}}{\hat{\beta}_{OLS}} \tag{9}$$

in which $\hat{\beta}_{OLS}$ is the estimate by OLS, σ_a^2 is the variance of the adjustment, and σ_{mo}^2 is the variance of the model forecast.

Another point that we analyze is whether the forecasters' loss function is asymmetric. That is, the professionals have different costs if they over or underpredict, with an asymmetric loss function (Clements, 2019). The methodologies we previously presented assume a symmetric loss function. So, we can obtain evidence to reject forecast rationality by incorrectly considering a symmetric loss function. We use the approach of Elliott et al. (2005) that allows for a general loss function.

We consider the moment conditions as $E\left[v_t\left(\gamma - 1_{(e_{t+1}<0)}\right)|e_{t+1}|\right] = 0$ just as Elliott et al. (2005) and Elliott et al. (2008), where v_t is a vector of instruments, $1_{.}$ is the indicator function, $\gamma \neq \frac{1}{2}$ indicates that under and overpredictions are penalized differently, and $\gamma = \frac{1}{2}$ represents the symmetric loss function. We estimate only one parameter γ using GMM and we test the null hypothesis $\gamma = 0.5$ that the loss function is symmetric. The GMM overidentification test (J-test) is a test of the null hypothesis that the forecasts are rational. This approach loses little power because we estimate only one parameter (Elliott et al., 2005). We describe the database below.

3 Data and descriptive statistics

The official Brazilian inflation data comes from the Brazilian Institute of Geography and Statistics (IBGE). The official index is the Broad National Consumer Price Index used as a reference for the inflation targeting policy of the BCB. The reference interest rate variable is the Selic rate, provided by the BCB.

In addition, we use the SPF for the official Brazilian inflation rate. We take the professional forecast for Brazilian inflation in the next month from the Bloomberg platform. We detail the database and its descriptive statistics below.

First, we consider the SPF database for each month for Brazilian inflation between December 1999 and February 2019. Our sample contemplates 7254 observations over time and for different analysts and institutions. The database contains the institutions' forecasts for the next month's inflation. The institution can additionally identify whether the forecast is linked to an analyst - or leave this blank. So the forecast is always associated with an institution but not necessarily with an analyst.

Table 1 presents the descriptive statistics of the number of analysts, forecast error, days before and number of institutions variables. We still present the standard deviation of the variables in the panel dimension in this table, but we will comment on this later. There are 221 analysts identified for their forecasts. Each analyst presented 27 inflation forecasts on average, with one releasing 171 forecasts over time and the minimum being only one forecast. However, 16% of the total number of analysts who presented forecasts did not report their names over the sample period, so that the analyst is not identified (we only have the name of the institution). So 16% of the sample of monthly inflation forecasts reveals the name of the institution, but not of the analyst. That is, there are 1205 observations with missing analyst out of the total sample of 7254 observations.

[Insert Table 1 here]

The forecast error was positive at the mean, in with the highest value being 0.62 and the lowest value being -0.93 based on Table 1. We also analyzed the number of days that the forecast is presented before the release of the inflation rate. On average, institutions present the forecast for monthly inflation five days before the release of the indicator. The forecast with the highest number of days before was presented 17 days in advance and the lowest was presented exactly on the day the index was released. Twenty-five percent of the forecasts presented are up to two days before the official inflation rate is released.

Finally, the number of institutions that presented their forecasts over time was 211 and each institution presented 34 forecasts for inflation on average. The institution with the highest number of forecasts over time had 190 forecasts. No analyst updated his/her forecast for the month's inflation, but the institutions have more than one analyst for months forecast in some cases. In addition, the institution can present forecasts for the month from each department.[6]

The variables in the panel data can vary between individuals and time. We can analyze the relative importance of panel data variations to obtain a better understanding about the database. Overall standard deviation is the common measure of the standard deviation of a sample, and is the standard deviation for all the panel data without considering the individual or time dimension. On the one hand, within standard deviation presents the variation of the variable within each individual, while it ignores all variations between individuals. On the other hand, between standard deviation presents the variation of the variable between individuals, while it ignores all variations over time of each individual (Cameron and Trivedi, 2010). Table 1 shows the standard deviation of how the forecast error and the number of days before vary between the different individuals and over time for the same individual. We have established that the individual unit is the analyst in a given institution. As shown in Table 1, the greatest variation of the forecast errors is within the individual and not between individuals. In other words, the analyst him/herself presents the greatest variation in the forecast error over time. On average, there are no analysts who have small forecasting errors over time, but periods when they make worse predictions and other periods when they make better predictions. The number of days before variable has a similar standard deviation between or within the individuals.

Figure 1 presents the number of observations per year. There is an upward trend in the number of observations per year until 2011, then there are around 500 observations per year from 2011 until 2018. Only 2019 has fewer observations because there are only forecasts until February of that year.

[Insert Figure 1 here]

Figure 2 shows the forecast error boxplot for each year (on the right).[7] The highest absolute values for the median forecast errors were in 2001, 2017 and 2018. In general, the forecast errors do not change over the years, except for the years mentioned previously. Figure 2 presents the boxplot of the variable number of days before the official inflation announcement for each year that the forecast was released (on the left). The median of the number of days before variable tends to be five days for different years. Between 1999 and 2003 there was an increase in the number of days before the forecast.[8] This may indicate a learning curve for participants of the Bloomberg platform, which begins in Brazil in 1999 - the inflation targeting regime was adopted in the same year. We present the results in the next section.

[Insert Figure 2 here]

4 Results

We now report the unbiasedness and rationality tests using the panel data and time series approaches. We also seek to analyze whether there is a difference in forecasters' forecasts due to changes in monetary policy, the business cycle, whether inflation is above or below target or the electoral period using both methodologies. The first subsection considers the panel data approach, while the second subsection addresses the time series framework.

4.1 Panel data approach

In this subsection, we analyze the unbiasedness and rationality tests with panel data. We further explore whether the unbiasedness and rationality tests results change according to monetary policy, the business cycle, whether inflation is above or below target and the election period. We break monetary policy action down into easing or tightening cycles. An easing (tightening) cycle is defined as a period when the monetary authority reduces (raises) the reference interest rate without there being any increase (decrease) in this range. We also study whether the forecast error differs when economic activity is broken down into periods of expansion and contraction or into election and non-election periods.[9]

Panel A of Table 2 presents the unbiasedness test for the inflation forecast errors for the entire sample and according to easing and tightening of the monetary policy cycles in columns 1, 2, and 3. The test result indicates that forecasting errors are unbiased with the entire sample, but this changes according to monetary policy. There is bias in the forecast errors at 5% statistical significance in the easing and tightening cycles. We find that forecasters overestimate the inflation rate in easing regimes and underestimate it during monetary policy tightening.

We report the rationality test (an F test) in columns 1, 2 and 3 in Panel B of Table 2 for the inflation forecast errors for the entire sample and for the subsamples that represent easing or tightening monetary policy cycles (an F test for each subsample). We include lagged realized inflation and lagged interest rate variation as regressors. We reject the null hypothesis of rationality at 5% statistical significance for all cases, namely the overall sample, and easing and tightening episodes. The negative coefficient for the lagged realized inflation means that when inflation increases, professionals overestimate it and when inflation falls, professionals underestimate it for the overall sample an in the tightening period. As the lagged interest rate variation coefficient is significant at 1% statistical significance for any of the samples in columns 1, 2 and 3, we can say that the forecast error is predictable based on the lagged interest rate variation.[10] The relationship is such that forecasters underestimate inflation when lagged interest rates rise, for example.

[Insert Table 2 here]

Table 3 explores the relevance of monetary policy for the inflation forecast errors. The inflation forecast errors are explained by lagged inflation, lagged interest rate variation, lagged easing and tightening dummy variables, and easing and tightening durations. Here we consider that the easing (tightening) dummy variable equals one when the Central Bank decreases (increases) the interest rate without there being any increase (decrease) in this range. We establish easing (tightening) duration as the number of consecutive periods of interest rate hikes (decreases) similarly to Dahlhaus and Sekhposyan (2018). The results suggest that the forecast errors rise when the policy rate increases. When we control for the monetary regime (column 2) and duration (column 3), the effect of policy rate changes on forecast errors remains statistically significant. In addition, we can associate an easing period with a greater forecast error and professionals underestimating inflation. Controlling for the interest rate and monetary policy (column 4), inflation is no longer related to the forecast error.

[Insert Table 3 here]

We analyzed the effect of monetary policy on the unbiasedness and rationality tests of forecasts and on the forecast error itself. The next point is to study whether realized inflation being below or above the target for the inflation rate plays a role in biasing the forecast. We obtained the target for the inflation rate each year from the BCB. We consider the inflation occuring in the last 12 months, is known by the professional at the time of the forecast to assess whether it is above or below the target. Panel A of Table 2 reports the result of the unbiasedness test for the overall sample and the subsamples for the periods of inflation above and below the target in columns 1, 4, and 5. The result indicates that professionals tend to overestimate (underestimate) inflation when realized inflation is below (above) the target at 10% significance, as shown in columns 4 and 5. The result presents a similar behavior for the ECB predictions according to Granziera et al. (2021), but the magnitude of the bias is larger when inflation is below the target which is the opposite of the result found by the same authors.

On the other hand, the results of the rationality tests do not distinguish between inflation being above or below the target based on columns 4 and 5 of Table 2 (Panel B). We reject the null hypothesis of rationality when realized inflation is above or below the target at 5% significance. This is distinct from the result for ECB predictions not being rational only when inflation is above the target according to Granziera et al. (2021).

The next step is to investigate the role of the business cycles in a similar way. Panel A of Table 2 reports the result of the unbiasedness test for the overall sample and the subsamples for the periods of expansion and recession of the Brazilian economy in columns 1, 6, and 7. The result indicates that we cannot reject the null hypothesis of unbiasedness of forecasts for the overall sample or the break-down between business cycles. This is in line with the fnding of Hanson and Whitehorn (2006) and Messina et al. (2015) that the Fed's systematic forecasting errors for inflation are not associated with the state of the economy's business cycle. But our evidence is different from that of Karamouzis and Lombra (1989) and Sinclair et al. (2010) who found that the forecast bias changes with the state of the economy for the USA.

We then investigated whether the result of the rationality test changes between recessionary and expansionary periods. Panel B of Table 2 presents the results of rationality tests for the overall sample and the subsamples for the periods of recession and expansion in columns 1, 6, and 7. The p-value of the F test indicates that we must reject the null hypothesis of rationality for any of the samples when we control for the lagged inflation and the lagged interest rate variation in those columns. In this case, we can predict the forecast error using lagged inflation and interest rate changes.

We also considered the difference between election and non-election periods in the unbiasedness and rationality tests of forecasts. We consider an election period as starting from the moment there is political advertising and running to the second round of the election. The months of the electoral period are August, September and October in the years that there are elections. Panel A of Table 2 reports the result of the unbiasedness test for the overall sample and the subsamples for the periods of elections and no elections in the Brazilian economy, in columns 1, 8, and 9. The test result indicates that forecasting errors are unbiased for the entire sample, but this changes according to the election period. There is bias in the forecast errors at 10% statistical significance in the election periods and in periods with no election. We find that forecasters overestimate the inflation rate in election periods and underestimate it when there are no elections. In other words, the professionals do not fully incorporate information about election periods in their forecasts.

Panel B of Table 2 reports the results of rationality tests for the overall sample and the subsamples for the periods of elections and with no elections in columns 1, 8, and 9. The p-value of the F test indicates that there is no difference in rationality test result for the election periods when we control by the lagged realized inflation and the lagged interest rate variation. We reject the null hypothesis of rationality for all of the samples - overall, election and non-election periods respectively in columns 1, 8, and 9 - at 5% of statistical significance. In this case, we can predict the forecast error using lagged inflation and interest rate changes.

We find that there are distinct periods in the sample depending on monetary policy or the electoral period only for the unbiasedness test. There is no bias when considering differences according to the business cycle. When we control for lagged inflation and lagged interest rate changes, we reject rationality and there is no difference depending on monetary policy, or between electoral and non-electoral periods or business cycles. This difference in bias for the panel data based on monetary policy and the electoral period would justify a robustness test for the presence of instability, such as the fluctuation rationality test if this pattern remains for the consensus with the time series. This fluctuation rationality test is based on the time series framework. Next we present the traditional rationality test and the fluctuation rationality test of Rossi and Sekhposyan (2016).

4.2 Time series approach: the role of instability, asymmetric loss function and adjustment based on personal expertise

Here we cover the traditional Mincer and Zarnowitz (1969) test and the fluctuation rationality test of Rossi and Sekhposyan (2016) using the time series approach. In addition, we analyze whether the loss function of the forecaster is asymmetric and whether we reject the null hypothesis of rationality if it is asymmetric. As our last point, we study whether the professionals adjust the model's forecast based on their personal expertise. We consider i) the median inflation expectations (consensus), ii) the forecasts of institutions and iii) those of analysts.

First, we present the traditional Mincer and Zarnowitz (1969) test for the consensus, institutions and analysts in Table 4. We reject the null hypothesis of rationality for the consensus with the traditional test at the 5% significance level.

[Insert Table 4 here]

Next we consider the analysts and institutions. When we analyze the institutions (analysts), we consider only those institutions (analysts) that reported at least 100 forecasts over time.[11] This leaves us with 22 institutions or 12 analysts. However, there are institutions that have more than one forecast for inflation in the same month - because they have distinct estimates from different departments, but these departments do not continue to report their forecasts over time. This leaves us with a sample of 15 institutions for us to run the test. We reject the null hypothesis of forecast rationality at the 10% significance level for three of the 15 institutions - two institutions if we consider at the 5% significance level - as shown in Table 4 with the traditional test.

In addition, we analyzed the rationality test for 12 analysts, the results of which are in Table 4. We reject the null hypothesis of forecast rationality for one of the 12 analysts at the 5% significance level with the traditional test.

Next we consider the fluctuation rationality test of Rossi and Sekhposyan (2016). Table 4 presents the fluctuation rationality test for the consensus, and each of the institutions and analysts with $m = 60$ as a reference. We do not reject the null hypothesis of forecast rationality for the consensus.

Our next step is to analyze the fluctuation rationality test for each of the 15 selected institutions with $m = 60$ as a reference. Table 4 reports the maximum of the rolling windows test statistic. We reject the null hypothesis of forecast rationality for only one institution at the 5% significance level.

In short, we find that the consensus, institutions' and analysts' forecasts are rational according to the Rossi and Sekhposyan (2016) test, except for one institution at the 5% significance level. The evidence is of forecast rationality for the consensus according to the test of Rossi and Sekhposyan (2016), although the traditional test indicates the opposite. The traditional test indicates the absence of rationality for two institutions at the 5% significance level, whereas the fluctuation rationality test indicates the absence of rationality for only one institution among the 15 in the sample at the 5% significance level. Moreover, we reject the rationality hypothesis for one analyst with traditional test at the 5% significance level, while the fluctuation the rationality test does not reject the null hypothesis of rationality for any analyst at the 5% significance level. That is, the fluctuation rationality test rejects the null hypothesis less compared to the traditional test at the 5% significance level.

We consider the window size m of 60 observations using asymptotic critical values as Rossi and Sekhposyan (2016). Alternatively, we use window size of 25 and 40 observations for robustness, and we tend to reject the null hypothesis of forecast rationality more often if we do not use finite sample adjusted critical values from El-Shagi (2019). This result is reported in Supplementary Appendix.

One possible reason for not rejecting the null hypothesis of rationality of the median institutions', or analysts' forecasts may be that we have forecasts for a few days before the official inflation is released. This database presents forecasts for a maximum of 17 days before the release of official inflation, with institutions and analysts reporting their forecasts five days earlier in the median. We remember that for the forecast horizon of zero months ahead (like in our present case), Rossi and Sekhposyan (2016) reject the null hypothesis of rationality with three distinct measures with the same test to the USA inflation forecast.

Additionally, we consider the possibility that the loss function of the professionals is asymmetric. If the loss function is asymmetric, the results may lead to the rejection of the rationality of the forecasts because we consider the loss function to be symmetric. The next step is to test the rationality of the forecasts and whether the loss function is asymmetric following the procedure of Elliott et al. (2005). We use GMM estimation and three different possibilities of instruments similarly to Elliott et al. (2008). In addition to the constant, we consider the following as instruments: i) the first lag of errors, ii) the first and second lags of errors, and iii) the lag of absolute errors.

Table 5 summarizes the results for institutions and analysts allowing the loss function to be asymmetric. The first point is that we do not reject the null hypothesis of rationality for any of the institutions or analysts at the 5% significance level. This result differs from the previous analysis with the traditional or fluctuation rationality tests or with the TSLS considering the professional adjusting the forecast. Our results are similar to those of Elliott et al. (2008) in that there is less rejection of forecast rationality considering asymmetry of the loss function.

Based on Table 5, we can reject the null hypothesis of symmetry for nine institutions and five analysts at the 5% statistical significance with the first kind of instruments. This means that 60% of institutions and 42% of analysts have an asymmetric loss function. The median of $\hat{\gamma}$ is 0.45 for the institutions - or 0.41 if we consider only the institutions that reject symmetry - considering the instruments of type 1. For example, 56% of the institutions have $\hat{\gamma} < 0.5$ for those that reject asymmetry using instrument of type 1. This is robust for types 1 and 2 of the instruments in the case of institutions. This suggests that overpredictions of inflation are more costly than underpredictions for most institutions. On the other hand, the median of $\hat{\gamma}$ is higher than 0.5 if we consider only the analysts that reject symmetry for types 1 and 3 of the instruments. This suggests that underpredictions of inflation are more costly than overpredictions for most analysts. The analysts are risk-averse against "bad outcomes" such as actual inflation being higher than the expected inflation rate which is similar to Elliott et al. (2008) for USA inflation forecasts.

[Insert Table 5 here]

As our last point is to analyze the rationality of forecasts, we consider the possibility that professional forecasters do not rely only on the econometric model, but also include their adjustment according to their intuition and experience. The instrumental variable is the consensus forecast that is correlated with individual forecasts, but it should not be correlated with the individual adjustment. So, our next exercise is to use this instrumental variable following Franses (2021).

We report a summary of the regression results for the institutions and analysts in Table 6. We present the number of institutions or analysts that we reject the null hypothesis of forecast rationality based on the F test with the estimates by TSLS and OLS at the 5% significance level. The last column of this table shows the percentage difference between the estimates by TSLS and OLS like Equation (9). We reject the null hypothesis of exogeneity using the Durbin-Wu-Hausman test at the 5% significance level for all institutions and analysts. We have $\hat{\beta}_{TSLS} > \hat{\beta}_{OLS}$ for all cases and this corroborates the notion of measurement errors. I.e., if the professionals - institutions and analysts - use an econometric model, they all adjust their model forecasts.

Based on the result of the F test, we reject the null hypothesis of forecast rationality for a greater number of institutions and analysts with the estimates by TSLS compared to OLS. We obtain less evidence of rational forecasts with TSLS, which is the opposite of Franses (2021) with the forecast of professionals for USA inflation.

The median of the variance of adjustments for institutions (analysts) is 139.6% (74.8%) of the variance of the model forecasts. Institutions adjust their forecasts more than analysts. This value for the variance of the adjustments is higher for institutions and analysts forecasting Brazilian inflation than the one estimated by Franses (2021) for USA inflation.[12] In the next subsection we analyze whether the presence of instability could be related to macroeconomic or electoral changes.

[Insert Table 6 here]

4.2.1 Tests for forecast error and relationship with macroeconomics with time series approach

Now we study whether the results of the unbiasedness and rationality tests change according to monetary policy, the business cycle, whether inflation is above or below the target or electoral periods with the time series approach for the consensus. This is similar to what we did with the panel data approach.

The next step is to analyze whether there is a change in the result of the unbiasedness and rationality tests depending on the behavior of monetary policy. Panel A of Table 7 presents the unbiasedness test for the inflation forecast errors of the consensus with the entire sample and according to easing and tightening monetary policy cycles in columns 1, 2, and 3. The test result indicates that forecasting errors are unbiased for the entire sample, and easing and tightening cycles at 10% statistical significance. This result means that the consensus is unbiased in the periods of tightening and easing, while the forecast of the professionals according ti the panel data is biased in both periods. That is, the aggregation of the professionals' forecasts through the median is unbiased in the periods of easing and tightening. While the forecasts of individuals are biased, the aggregation of forecasts is unbiased. We find that the aggregation of biased forecasts leading to an unbiased forecast and this is similar to the finding of Capistrán and Timmermann (2009).

We consider the rationality test in Panel B of Table 7 for the inflation forecast errors with the entire sample and according to easing and tightening monetary policy cycles in columns 1, 2, and 3. We include lagged realized inflation and lagged interest rate variation as regressors. We do not reject the null hypothesis of rationality only for the easing episodes at 10% statistical significance. The subsample analysis suggests that the irrationality of the overall sample is mainly driven by tightening episodes. As the coefficients of the lagged interest rate variation and inflation rate are statistically significant at 10% statistical significance in columns 1 and 3, we can say that the forecast error is predictable based on the lagged interest rate variation and inflation rate. The relationship is that forecasters underestimate inflation when lagged interest rates rise, similarly to what we get with the panel data approach. We do not find this result in the literature.

[Insert Table 7 here]

Also we find that the coefficient of lagged inflation rate is negative and indicates that forecasters overestimate inflation when lagged inflation increases. This result is also a pattern for the panel data in Panel B of Table 2. Our result is the opposite of the evidence obtained for the Fed forecasts by Joutz and Stekler (2000), Hanson and Whitehorn (2006), and Sinclair et al. (2010) when inflation is rising.

The aggregation of the professionals' forecasts through the median changes the result of the rationality test when compared with those of the panel data. There is rationality only in easing periods for the consensus forecasts, unlike in the result with a panel of professionals, where there is irrationality in these periods.

Table 8 explores the relevance monetary policy for the inflation forecast errors. The inflation forecast errors are explained by lagged inflation, lagged interest rate variation, lagged easing and tightening dummy variables, and easing and tightening durations. The results suggest that the forecast errors rise when the policy rate increases, as shown in columns 1, 2 and 4 at 10% statistical significance, when we control for lagged inflation and by the monetary regime and duration. In addition, an easing period is associated with a greater forecast error for the consensus, as shown in column 4 at 10% statistical significance. This result is similar to what we obtain for the panel data.

[Insert Table 8 here]

We analyzed the effect of monetary policy on the unbiasedness and rationality tests of forecasts and on the forecast error itself. Next, we analyze whether inflation above or below the target affects the unbiasedness test for the consensus. In Panel A of Table 7, we do not reject the null hypothesis of no bias for forecasts at 5% significance if inflation is above or below target, as shown in columns 4 and 5. In the case of the rationality test, we reject the null hypothesis at 10% significance only when inflation is above the target based on columns 4 and 5 of Table 7 (Panel B). This consensus result is similar to that of Granziera et al. (2021), in which the ECB is not rational when inflation is above target. The evidence suggests that the irrationality of the overall sample is mainly driven by inflation being above target.

The next step is to investigate the role of business cycles in a similar way. In Panel A of Table 7 reports the result of the unbiasedness test for the overall sample and the subsamples for the periods of expansion and recession of the Brazilian economy in columns 1, 6, and 7. We do not reject the null hypothesis of unbiasedness of forecasts for the overall sample or the break-down into business cycles. This result with the time series approach is similar to what we obtain with panel data.

We investigated whether the result of the rationality test changes between recessionary and expansionary periods. Panel B of Table 7 presents the results of rationality tests for the overall sample and the subsamples for the periods of expansion and recession, in columns 1, 6, and 7. The p-value of the F test indicates that we reject the null hypothesis of rationality for the overall sample and in recessions respectively, as shown in columns 1 and 6 at 10% statistical significance. The behavior in periods of recession leads to the rejection of rationality in the overall sample.

Next we investigate if the election period changes the unbiasedness and rationality tests. Panel A of Table 7 reports the results of the unbiasedness test considering subsamples for the election and non-election periods in columns 1, 8, and 9. We do not reject the null hypothesis of an unbiased forecast in the forecasts for the overall sample or considering election and non-election periods.

In Panel B of Table 7, we present the rationality test considering election and non-election periods in columns 1, 8, and 9. We reject the null hypothesis of rationality for the overall sample which is based on the period without elections at 10% statistical significance. In other words, the forecast error is predictable based on the interest rate and inflation only in the period without elections.

In general, the aggregation through the median leads to greater rationality compared to the panel data results. We do not reject rationality in periods of monetary policy easing, expansion, and elections with the aggregated series, unlike for the panel of forecasters in which we reject rationality in all periods. We find that the aggregation is more rational compared to the individual series. This is similar to what Capistrán and Timmermann (2009) argue for bias, but we also find this for rationality. Our result differs from those of Crowe (2010) and Satopää (2017) - which indicate not to use the aggregation of forecasts because rational agents could become irrational through aggregation - or Keane and Runkle (1990) - in which aggregation can lead to a false rejection of rationality .

5 Conclusion

We analyzed the forecast rationality hypothesis for Brazilian inflation using the panel data and time series approaches. Forecast rationality means forecasts are unbiased and unpredictable. Our database is SPF from Bloomberg for the monthly period between 1999 and 2019. We use forecasts up to 17 days ahead for inflation.

We make two contributions. The first is to use Bloomberg's SPF database. Our study is the only one that considers the SPF organized by Bloomberg for Brazil and one of the few studies to analyze the forecast rationality hypothesis with this source. The advantage of this database is that the SPF is public, which reinforces the incentive to report their true predictions.

Our second and main contribution is to relate the irrationality or bias in consensus or individual forecasts with macroeconomic and election variables. We compare between the easing and tightening of monetary policy, between an expansion and recession in the business cycle, between inflation above or below the target, and whether there is a difference in election periods. Most studies focus on the relationship of forecasts with economic expansion and recession and we seek to broaden the scope of economic patterns. Also we do not find studies that assess whether the relationship of irrationality and bias - if any - of forecasts with macroeconomic and electoral variables changes by consensus aggregation compared to using individual forecasts.

We do not reject the null hypothesis of forecast unbiasedness with the panel data approach. But the forecast error is predictable by using lagged inflation and the lagged interest rate variation. If we use the time series approach, we reject the null hypothesis of rationality for the inflation consensus with the traditional test. But the result changes if we use the fluctuation rationality test, which does not reject the null hypothesis of rationality considering the presence of instability.

The fluctuation rationality test is based on the instability idea. Thus, we analyze whether there are reasons for differences in rationality or unbiasedness tests over time that would be linked with instabilities. We find that there is bias in inflation forecasts in periods of monetary policy easing and tightening, in election and non-election periods, and when inflation is above and below the target, although there is no bias when we consider the overall sample with panel data. We do not obtain any pattern between forecast bias and economic cycles similarly to Hanson and Whitehorn (2006) and Messina et al. (2015). This evidence is the opposite of that obtained by Karamouzis and Lombra (1989) and Sinclair et al. (2010). The economic cycle, monetary policy, election period, and the level of inflation compared to the target do not seem to make a difference for rationality tests with panel data. When we consider the forecast consensus with the time series approach, we obtain unbiased forecasts regardless of whether we consider different periods due to the behavior of monetary policy, elections, business cycles, or whether inflation is above or below the target. While the forecasts of individuals are biased, the aggregation of forecasts is unbiased, similar to Capistrán and Timmermann (2009).

The consensus forecast seems to neutralize the bias of individual forecasts in the panel data approach and it reduces irrationality only for periods of monetary policy tightening, recession, inflation above the target or no elections. This means that even the consensus does not fully incorporate information about the state of the economy, monetary policy regime, no election or whether inflation is above the target.

As robustness, our evidence points out that all forecasters adjust their forecasts based on their personal expertise if they use model forecasts. When we consider that professionals adjust their forecasts, there is less forecast rationality, different from the result of Franses (2021). Allowing for asymmetric loss functions, we do not reject forecast rationality for any analyst or institution at the 5% significance level, similarly to Elliott et al. (2008). Underpredictions of inflation are more costly than overpredictions for the analysts that have an asymmetric function, which is in line with the finding of Elliott et al. (2008) for USA inflation. The opposite is true for the institutions.

Figure 1 - Number of database observations per year

Figure 2 - Boxplot of the forecast error by year (on the left) and the number of days before the announcement that the forecaster presents their forecast per year (on the right)

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Notes

1. We consider the terms optimal and rational as synonyms.

2. Most studies use the SPF of the Federal Reserve Bank (Fed) of Philadelphia for the USA, that of the European Central Bank (ECB) for the Eurozone, that of the Bank of England for the United Kingdom, and those of central banks among emerging markets, as in the case of Brazil and Chile. Pincheira and Álvarez (2012), Ziembinska (2014), and Bürgi (2017) test the rationality of inflation forecasts with Bloomberg data for emerging countries.

3. The mean square error of the Bloomberg consensus is smaller than that organized by the BCB with the same number of days before the release of inflation for each month from both sources.

4. If g_t only includes a constant, this is a test of forecast unbiasedness as in equation (1). However, if $g_t = E_t(\pi_{t+h})$ - only the forecast itself -, this is a forecast efficiency test.

5. We use the Newey and West (1987) HAC estimator bandwidth chosen automatically with the Schwert (1987) criterion as used by Rossi and Sekhposyan (2016).

6. For example, the Itaú-Unibanco group presents its forecasts from three different departments in some periods.

7. We only have the 1999 forecasts for December and for only seven institutions. In this case, the median was equal to the first quartile and therefore does not appear in the boxplot for 1999.

8. The year 1999 has its own specificity as we have already previously commented for Figure 2. In 1999, all institutions reported their forecasts one day before inflation was released.

9. The Getulio Vargas Foundation created the official Brazilian committee for dating business cycles (CODACE) in 2008. This committee follows practices such as those of the dating committee of the USA National Bureau of Economic Research (NBER) according to Picchetti (2018).

10. Alternatively we consider easing (tightening) as only the periods in which there was a decrease (increase) in the interest rate as a robustness test. We present the results for the unbiasedness and rationality tests for this definition of easing and tightening episodes in Supplementary Appendix, but the result is similar to that obtained previously.

11. So we have at least 40 estimates for the fluctuation rationality test statistic with window size of 60 observations.

12. The median of the variance of adjustments for analysts is only less than that obtained by Franses (2021) with the regression including the variables in the first difference.

Table 1: Descriptive statistics of variables related to the forecast for the month

	Analysts	Forecast error	Days before	Institutions
Median	15	0	5	16
Mean	27.37	0.0008	4.82	34.38
Maximum	171	0.62	17	190
Minimum	1	-0.93	0	1
First quartile	5	-0.05	2	5
Third quartile	36.5	0.05	7	48
Number of observations	221	7254	7254	211

Standard deviation of variables in the panel dimension

	Forecast error	Days before
Overall	0.087	2.860
Between	0.043	2.118
Within	0.085	2.379

Table 2: Overall unbiasedness and rationality tests and considering subsamples based on variables for state dependence with panel data

Panel A - Unbiasedness test

		Monetary policy		Inflation target		Business cycles		Role of election	
	Overall	Easing	Tightening	Above	Below	Recession	Expansion	Election	No election
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Constant	0.0008	-0.0034**	0.0062***	0.0020*	-0.0031*	0.0015	0.0006	-0.0066***	0.0019*
	(0.81)	(-2.57)	(4.29)	(1.76)	(-1.70)	(0.71)	(0.53)	(-2.71)	(1.84)
N	7254	4067	3187	5558	1696	1755	5499	937	6317

Panel B - Rationality test

		Monetary policy		Inflation target		Business cycles		Role of election	
	Overall	Easing	Tightening	Above	Below	Recession	Expansion	Election	No election
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Lagged π	-0.015***	-0.008	-0.022***	-0.012**	-0.047***	-0.023***	-0.013**	-0.024**	-0.019***
	(-3.52)	(-1.18)	(-3.57)	(-2.33)	(-3.52)	(-3.76)	(-2.10)	(-2.21)	(-3.98)
Lagged Δi	0.024***	0.012***	0.049***	0.014***	0.083***	0.063***	0.019***	-0.008	0.028***
	(7.65)	(3.06)	(6.12)	(3.97)	(14.32)	(8.40)	(5.40)	(-1.04)	(8.39)
Constant	0.001***	0.003	0.008**	0.009***	0.029***	0.010**	0.008***	0.002	0.014***
	(4.44)	(1.10)	(1.97)	(3.04)	(7.00)	(2.17)	(3.17)	(0.54)	(5.36)
N	7254	4067	3187	5558	1696	1755	5499	937	6317
F	31.68	5.09	27.75	9.95	102.50	31.54	16.05	3.23	36.95
$P-value$	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.04	0.00

Note: *, **, *** denote statistical significance at the 10%, 5% and 1% levels respectively and the t statistics are in parentheses. We consider that the easing (tightening) dummy variable equals one when the Central Bank decreases (increases) the interest rate without there being any increase (decrease) in this range.

Table 3: Monetary Policy Implementation and Forecast Errors

	(1)	(2)	(3)	(4)
Lagged π	-0.0154***	-0.0149***	-0.0171***	-0.0178
	(-3.52)	(-3.37)	(-3.65)	(-3.77)
Lagged Δi	0.0242***	0.0377***	0.0235***	0.0375***
	(7.65)	(4.73)	(6.91)	(4.55)
Lagged Easing		0.0161***		0.0191***
		(2.94)		(3.37)
Lagged Tightening		-0.0026		-0.0006
		(-0.56)		(-0.11)
Easing duration			0.0004***	0.0004***
			(2.94)	(2.88)
Tightening duration			0.0004***	0.0005***
			(3.81)	(5.24)
Constant	0.0099***	0.0069***	0.0056**	0.0008
	(4.44)	(2.75)	(2.17)	(0.26)
N	7254	7254	7254	7254
F	31.68	19.23	24.16	19.15
$P-value$	0.00	0.00	0.00	0.00

Note: *, **, *** denote statistical significance at the 10%, 5% and 1% levels respectively and the t statistics are in parentheses. We consider that the easing (tightening) dummy variable equals one when the Central Bank decreases (increases) the interest rate without there being any increase (decrease) in this range.

Table 4: The value of the test statistic of the traditional Mincer and Zarnowitz (1969) test and the fluctuation rationality test for the consensus, institutions' and analysts' forecasts

	Traditional test		Fluctuation test (m=60)	
	Test statistic		Test statistic	
Consensus	**4.86**	**	5.71	
Institutions ID				
1	0.60		**9.79**	*
2	0.05		7.63	
3	0.10		6.93	
4	**4.98**	**	7.42	
5	1.44		5.59	
6	0.31		8.32	
7	**4.46**	**	8.83	
8	2.70		5.94	
9	0.04		5.46	
10	0.01		3.88	
11	0.04		2.47	
12	0.28		6.14	
13	1.11		3.98	
14	**3.53**	*	**36.06**	***
15	1.14		4.71	
Analysts ID				
1	2.18		**11.05**	*
2	0.14		5.46	
3	1.14		4.71	
4	0.10		6.93	
5	**4.98**	**	7.42	
6	4.97		8.83	
7	1.44		5.59	
8	0.17		2.68	
9	**3.32**	*	6.76	
10	0.60		**9.79**	*
11	0.28		4.72	
12	0.27		6.14	

Note: *, **, *** denote statistical significance at the 10%, 5% and 1% levels respectively.

Table 5: Summary of rationality and symmetry tests allowing asymmetric loss function for institutions and analysts

Instruments	1	1	2	2	3	3
	All	Only those reject symmetry at 5%	All	Only those reject symmetry at 5%	All	Only those reject symmetry at 5%
			Institutions			
Mean of $\hat{\gamma}$	0.51	0.52	0.58	0.61	0.54	0.58
Median of $\hat{\gamma}$	0.45	0.41	0.47	0.44	0.54	0.61
1^{st} quartile	0.41	0.40	0.41	0.37	0.47	0.52
3^{rd} quartile	0.57	0.63	0.58	0.62	0.59	0.66
Rejects symmetry at 10%	10		11		8	
Rejects symmetry at 5%	9		11		7	
Rejects rationality at 10%	0		0		0	
Rejects rationality at 5%	0		0		0	
Higher than 0.5 (in %)	46.67	44.44	46.67	45.45	60.00	71.43
			Analysts			
Mean of $\hat{\gamma}$	0.53	0.59	0.55	0.55	0.55	0.57
Median of $\hat{\gamma}$	0.49	0.59	0.54	0.50	0.56	0.60
1^{st} quartile	0.45	0.40	0.44	0.43	0.50	0.52
3^{rd} quartile	0.58	0.63	0.59	0.62	0.62	0.65
Rejects symmetry at 10%	6		8		9	
Rejects symmetry at 5%	5		8		8	
Rejects rationality at 10%	0		0		0	
Rejects rationality at 5%	0		0		0	
Higher than 0.5 (in %)	41.67	60.00	66.67	50.00	75.00	75.00

Note: This table reports the number of forecasters (out of a total of 15 institutions and 12 analysts) for whom the null hypothesis of rationality and symmetry could be rejected at the specific statistical significance level. The instruments are as follows: Instruments type = 1: constant plus lagged errors; Instruments type = 2: constant plus lagged errors (two lags); Instruments type = 3: constant plus absolute lagged errors.

Table 6: Summary of the number of institutions (analysts) that reject the null hypothesis of forecast rationality or exogeneity at 5% significance level and median of the variance of adjustments by institutions and analysts

	F test				Median of the
	TSLS	OLS	$\hat{\beta}_{TSLS} > \hat{\beta}_{OLS}$	Exogeneity test	variance of adjustments
Institutions	4	2	15	15	139.6%
Analysts	3	2	12	12	74.8%

Note: The column of F test (of exogeneity test) presents the number of institutions or analysts that we reject the null hypothesis of forecast rationality (of exogeneity) with the estimates at 5% significance level. The column of $\hat{\beta}_{TSLS} > \hat{\beta}_{OLS}$ reports the number of institutions (analysts) with such a pattern.

Table 7: Overall unbiasedness and rationality tests and considering subsamples based on variables for state dependence with time series

Panel A - Unbiasedness test

		Monetary policy		Inflation target		Business cycles		Role of election	
	Overall	Easing	Tightening	Above	Below	Recession	Expansion	Election	No election
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Constant	0.0020	-0.0035	0.0094	0.0033	-0.0024	0.0063	0.0007	-0.0072	0.0034
	(0.45)	(-0.61)	(1.37)	(0.61)	(-0.35)	(0.57)	(0.16)	(-0.69)	(0.72)
N	224	129	95	174	50	50	174	30	194

Panel B - Rationality test

		Monetary policy		Inflation target		Business cycles		Role of election	
	Overall	Easing	Tightening	Above	Below	Recession	Expansion	Election	No election
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Lagged π	-0.029**	-0.021	-0.045**	-0.033**	-0.030	-0.046*	-0.025	-0.004	-0.038**
	(-2.18)	(-1.07)	(-2.17)	(-2.26)	(-0.69)	(-2.01)	(-1.64)	(-0.18)	(-2.55)
Lagged Δ i	0.027*	0.001	0.068***	0.023	0.064**	0.065***	0.022	0.007	0.032*
	(1.81)	(0.08)	(2.72)	(1.42)	(2.06)	(3.15)	(1.25)	(0.29)	(1.93)
Constant	0.019**	0.006	0.020	0.023**	0.020	0.028	0.015	-0.005	0.026**
	(2.10)	(0.55)	(1.34)	(2.05)	(1.24)	(1.15)	(1.52)	(-0.37)	(2.51)
N	224	129	95	174	50	50	174	30	194
F	2.71	0.57	3.91	2.77	2.15	7.53	1.53	0.21	3.47
$P-value$	0.07	0.57	0.02	0.07	0.13	0.00	0.22	0.81	0.03

Note: *, **, *** denote statistical significance at the 10%, 5% and 1% levels respectively and the t statistics are in parentheses. We consider that the easing (tightening) dummy variable equals one when the Central Bank decreases (increases) the interest rate without there being any increase (decrease) in this range.

Table 8: Monetary Policy Implementation and Forecast Errors

	(1)	(2)	(3)	(4)
Lagged π	-0.0292**	-0.0285**	-0.0302**	-0.0312**
	(-2.18)	(-2.06)	(-2.28)	(-2.27)
Lagged Δi	0.0273*	0.0503*	0.0265	0.0517*
	(1.78)	(1.83)	(1.63)	(1.79)
Lagged easing		0.0324		0.0374*
		(1.60)		(1.73)
Lagged tightening		-0.0076		-0.0088
		(-0.39)		(-0.40)
Easing duration			0.0002	0.0001
			(0.32)	(0.15)
Tightening duration			0.0004	0.0007
			(0.84)	(1.55)
Constant	0.0188**	0.0128	0.0158	0.0087
	(2.01)	(1.26)	(1.35)	(0.62)
N	224	224	224	224
F	2.71	1.79	1.96	1.62
$P-value$	0.07	0.13	0.10	0.14

Note: *, **, *** denote statistical significance at 10%, 5% and 1% levels respectively and the t statistics are in parentheses. We consider that the easing (tightening) dummy variable equals one when the Central Bank decreases (increases) the interest rate without there being any increase (decrease) in this range.

Figure 1: Number of database observations per year

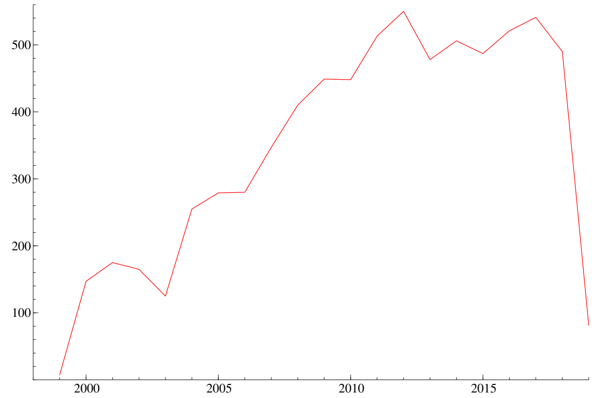

Figure 2: Boxplot of the forecast error by year (on the left) and the number of days before the announcement that the forecaster presents their forecast per year (on the right)