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Full length article

Inflation Forecasts' Performance in Latin America[☆]

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Abstract

This paper provides a full characterization of inflation rate forecasts using the mean values from Consensus Economics for a sample of 14 Latin American countries between 1989 and 2014. It also assesses the performance of inflation rate forecasts around business cycles' turning points. Results show that inflation forecasts in the region display the standard property that as the forecast horizon shortens accuracy improves. On average, forecasters underpredict inflation, but this masks very different country experiences. We find evidence point to biasedness of inflation forecasts for year-ahead forecasts but not for current year. Tests' results point to forecast inefficiency which is also evidenced by a tendency to smooth them between revisions. Focusing on business cycle turning points, forecasters tend to slightly underpredict the inflation rate and the extent of underprediction increases during recessions. The hypothesis of forecast efficiency is overwhelmingly rejected both during recessions and recoveries.

JEL classifications: C53; E27; E37; E62; D8

Keywords: Forecast comparison; Bias; Efficiency; Information rigidity; Recession; Recovery

1. Introduction

Latin America has been known for its display of high inflation rates and even episodes of hyperinflation, particularly shortly after its political transition to democracy in the 1980s and early 1990s.[1] More recently, the important currency depreciations that affected many Latin American countries have placed renewed upward pressure on inflation, even if their impact has been milder than in the past.[2] Vigilance is in any case warranted in economies where second-round effects are potentially big, since there is quiet variability as to how well-anchored inflation expectations are in different countries. This is important since several papers typically point to the negative effects of inflation on economic growth.[3]

The severity and persistence of the fall in output during the Global Financial Crisis (GFC) led to significant declines in inflation rates around the world. Since then, inflation on average has increased and some central banks in the Latin American region currently face a trade-off. On the one hand, domestic demand is weak, with some uncertainty around output gaps, and fiscal policy space is limited or nonexistent. On the other hand, headline inflation is above target and expected to remain so in the near term.[4] Such conjuncture triggered a revival of the interest in understanding the deep causes, costs and consequences

☆ The usual disclaimer applies. All remaining errors are the author's sole responsibility.

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[1] For seminal works on inflation in Latin America refer to the studies by Baer (1967) and Cole (1987).

[2] Note that improvements in monetary frameworks over the past two decades have led to substantial and generalized declines in exchange rate pass-through to consumer prices.

[3] For instance, Fisher (1993) presented some international cross-sectional and panel data evidence to suggest that inflation outweighed the Mundell–Tobin effect. Barro (1995) making use of cross-sectional analysis, suggested that the high-inflation countries in his sample drove the negative effects of inflation on output growth. De Gregorio (1993) provided some early evidence using a panel of twelve Latin American countries during the 1950–1985 period, and suggested that inflation was indeed detrimental to economic growth.

[4] For a recent survey on the region's economic outlook see IMF (2016a).

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of inflation dynamics.[5] Understanding inflation dynamics is a very important as well as a timely and timeless issue. Forecasting it correctly, however, seems an equally important issue but it has received far less prominence. Given the well documented relationship between cyclical features of inflation and unemployment (Phillips Curve) and how structural policies can affect aggregate demand (IMF, 2016b) and improve labor market matching (Bova et al., 2016), it is important to assess how forecasters have been performing when it comes to predicting inflation. Recent studies have also documented how inflation rate (professional) forecasts are consistent with the Phillips Curve.[6] Such literature can be viewed in the broader scope of testing whether macroeconomic empirical regularities hold true when using forecasts instead of actual data.[7]

In this context, and acknowledging the relevance of business cycle behavior to inflation dynamics (Tatom, 1978; Oinonen et al., 2013), this paper aims to assess the performance of inflation forecasts in a sample of Latin American countries in both normal times but also around business cycle turning points. Recent forecasting assessment exercises around business cycles turning points for either the GDP growth or the budget balance-to-GDP-ratio for a cross-section of countries using Consensus Economics data were carried out by Loungani et al. (2013) and Jalles et al. (2015), respectively. However, a perusal of the literature finds no such analysis for the case of inflation in this particular region of the world. To this end, we rely on the private sector's predictions for the inflation rate for a sample of 14 Latin American economies between October 1989 and September 2014 brought together by Consensus Economics—which are known to be hard to beat (Batchelor and Dua, 1992).[8]

The paper proposes to address the following, more expositional, questions: (i) How do inflation forecasts behave and perform statistically? (ii) What sensitivity analysis can be made at different forecast horizons, that is, is there a marked difference between current-year and year-ahead predictions? (iii) Do forecasters, on average, under- or over-predict the inflation rate and for how long? iv) Are inflation forecasts accurate during recessions and recoveries episodes? To answer these questions, we rely on a plethora of time series methods and regression analyses.

Our results show that inflation forecasts in the region display the standard property that as the forecast horizon shortens accuracy improves. On average, forecasters underpredict inflation, but this masks very different country experiences. In fact, Paraguay and Argentina are examples of countries for which forecasts are larger than realized inflation, that is, forecasters overpredict inflation. We find evidence point to biasedness of inflation forecasts for year-ahead forecasts but not for current year. As far as efficiency is concerned, tests' results point to inefficiency which is also evidenced by a tendency to smooth forecasts. In other words, informational rigidities are present. Finally, focusing on business cycle turning points, forecasters tend to slightly underpredict the inflation rate on average, and the extent of underprediction seems to increase during recessions. The hypothesis of forecast efficiency is overwhelmingly rejected during recessions. In recovery periods, the hypothesis of efficiency in inflation forecasts is also rejected.

The remainder of the paper is organized as follows. Section 2 describes the data and presents some descriptive statistics. Section 3 outlines the empirical methodology and discusses our main findings. The last section concludes and includes some policy considerations.

2. Data issues and descriptive statistics

Since the early 1990s decade there has been a significant growth in published economic analysis stemming from banks, corporations and independent consultants around the world, and a parallel growth in "consensus forecasting" services which bring together information from these different private sources. Since 1989 Consensus Economics has published monthly forecasts for main macroeconomic variables prepared by panels of private sector forecasters. In addition to individual forecasts, the service publishes the arithmetic average of each variable, the so-called "consensus forecast" for that variable. This seems a promising alternative to official forecasts for most users of economic forecasts instead of some naive model.[9]

This paper uses the mean of the private analysts' monthly consensus forecasts of the inflation rate for the current and next year for the period from October 1989 to September 2014. Our sample is comprised of 14 Latin American countries.[10] The "event" being forecasted is annual average inflation rate. Every month a new forecast is made of the event. Hence, for each year, the sequence of forecasts is the 24 forecasts made between January of the previous year and December of the year in question. Our

[5] See the remarks of the ECB Vice-President Mr Constancio about "Understanding Inflation Dynamics and Monetary Policy in a Low Inflation Environment" (5 November 2015) — https://www.ecb.europa.eu/press/key/date/2015/html/sp151105_1.en.html.

[6] For instance, Fendel et al. (2011) provide evidence on the trust of professional forecasters in alternative expectational versions of the Phillips curve for a group of 7 advanced economies. Rülke (2012) assesses whether professional forecasters apply the Phillips curve in six Asian countries.

[7] For instance, Ball et al. (2015) test whether professional forecasters believe in the Okun's Law when making their output and unemployment predictions for a sample of 9 advanced countries. Indeed, the authors show that, consistent with Okun's Law, forecasts of real GDP growth and the change in unemployment are negatively correlated. Previously, Pierdzioch et al. (2009) provided similar evidence for the G7 countries.

[8] Even if individual private sector forecasts may be subject to various behavioral biases, many of these are likely to be eliminated by pooling forecasts from several individual forecasters. Moreover, Zarnowitz and Braun (1993) have documented that group mean ("consensus") forecasts are more accurate than virtually all individual forecasts.

[9] This is acknowledged by Artis (1996), who makes a visual comparison of IMF and Consensus Economics forecasts for real GDP and inflation, and concludes that there is "little difference between WEO and Consensus errors". In a similar vein, Loungani (2001) plots IMF and Consensus Economics real GDP forecasts and notes that "the evidence points to near-perfect collinearity between private and official (multilateral) forecasts . . ."

[10] Country list includes: Argentina, Brazil, Bolivia, Chile, Colombia, Costa Rica, Dominican Republic, Ecuador, Mexico, Panama, Paraguay, Peru, Uruguay, and Venezuela.

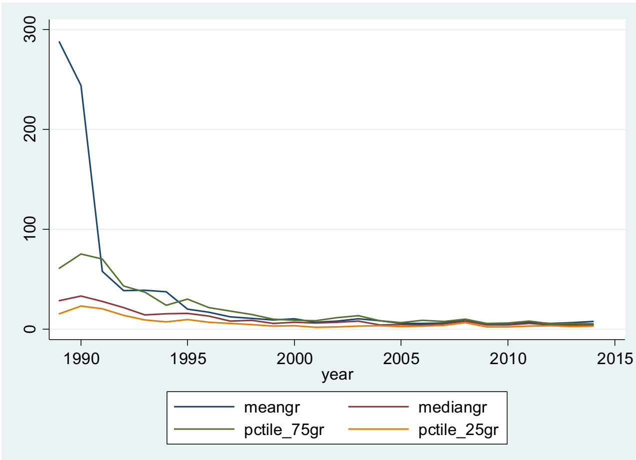

Fig. 1. Interquartile range of inflation rate, 1989–2014.
Note: Brazil is excluded from the sample. In addition to the mean inflation (blue), the median (red) and top and bottom quartiles are displayed (yellow and green, respectively).
Source: IMF IFS and authors' calculations.

dataset also includes actual data on the actual inflation rate from the International Monetary Fund's International Financial Statistics (IMF's IFS).[11] Finally, using quarterly GDP series (from IMF's IFS), recession episodes are identified based on the classical definition of a business cycle using quarterly changes in the level of real GDP (Burns and Mitchell, 1946). Countries are classified as being in a recession in a given survey month if the respective forecasted year falls in the recession year as defined following NBER's approach for dating turning points in the business cycle. Information on different financial crises comes from Laeven and Valencia's (2012) database.

We begin by plotting the interquartile range of the actual inflation rate in our sample of Latin American countries (excluding Brazil that witnessed several hyperinflation episodes during the 1990s). As shown in Fig. 1, the mean inflation for the region has slowly come down starting in the early 1990s to stabilize around much lower values (historically speaking) since the 2000s.

Fig. 2, plots the distribution of inflation forecasts at selected horizons (h = 21, 15, 9, 3) with the distribution of actual inflation rate. Both data and forecasts are pooled across the different countries composing our regional Latin American sample. The key purpose is to show that the forecasts display the reasonable property that they start to mirror the data as the forecast horizon draws to a close. As the value of h (the forecast horizon) gets smaller, the distribution of the forecasts starts to move closer to the distribution of the data.

[11] At this point a caveat should be made. Data revisions have worried economists for many years now (see Croushore, 2011 for a recent survey) and policy-makers have to base their decisions on preliminary and partially revised data, since the most recent data are usually the least reliable as it simply translates a noisy indicator for final values (Koenig et al., 2003). We are aware that data revisions pose challenges to forecasters and that forecasting studies should reflect the true forecasting performance by using real-time data instead of final data (Stark and Croushore, 2002). However, in the present case it is difficult to find reliable, consistent and comparable real-time vintages for inflation rates.

Table 1
Stylized facts on inflation forecasting performance.

Horizon	Pooled	Current year	Year ahead
Sample	All sample, N = 14		
ME	16.38	11.21	21.55
MAE	22.00	18.18	25.81
RMSE	24201.37	18779.75	29622.99
Sample	All sample, excluding Brazil, N = 13		
ME	0.396	−0.18	0.97
MAE	3.15	2.30	4.01
RMSE	45.34	28.36	62.33

Notes: This table presents some descriptive statistics for the entire sample, as well as for the sample excluding the outlier Brazil. ME, MAE and RMSE stand for the mean forecast error, the absolute forecast error and the mean square forecast error, respectively.

Now, forecasting accuracy should contain two aspects of the forecast as compared to the actual outcome (Musso and Phillips, 2002). The first one is how close both are in quantitative terms by means of a number of "standard measures", while the second one refers to the capacity of the forecast to predict the direction of change in the final outcome. Define, for each country i during year t, $e_{it} = A_{it} - F_{it}$, where e represents forecast error, F denotes the forecast, and A denotes its respective realization (in our case it corresponds to the moving average of monthly reported inflation rates). In terms of "standard measures" we use three conventional error measures to assess relative performance: the average forecast bias (ME),[12] the mean absolute error (MAE) and the root mean squared error (RMSE). While these measures have a number of limitations, the RMSE has invariably been used as standard for judging the quality of predictions.[13] The ME, MAE and RMSE statistics are reported in Table 1.[14]

The mean error is positive and much larger than one point when we pool all countries together, including Brazil. However, this masks very different country experiences and excluding Brazil gives a considerably better picture for the performance of inflation forecasts. Focusing on the bottom panel, the mean error remains positive (meaning that inflation is under-predicted) but smaller than one point (with the absolute error only slightly larger). Splitting the sample between current and year-ahead forecasts also uncovers interesting findings. In current year forecasts, there is in fact overprediction of inflation (as shown by the coefficient of −0.18). Not surprisingly, absolute errors (irrespectively of the sample under scrutiny) are always smaller for current year than for year ahead forecasts (in line with evidence presented in Fig. 1 about forecasts converging to actuals as the

[12] Defined as the average difference between the actual value and its forecasted value. For example, a positive value for bias indicates that on average over the whole run of forecasts for the inflation rate, the actual value was under-estimated, so that the forecasts were too low.

[13] The RMSE may be the most popular measure among statisticians partially because of its mathematical tractability. More recently, researchers seem to prefer the so-called Percent Better, the Mean Absolute Percentage Error and the Relative Absolute Error. For a review see Armstrong and Collopy (1992).

[14] The same table was also done splitting the sample in two time periods, from 1989 until 2002 and from 2003 until 2014. For reasons of economy of space, results are available upon request.

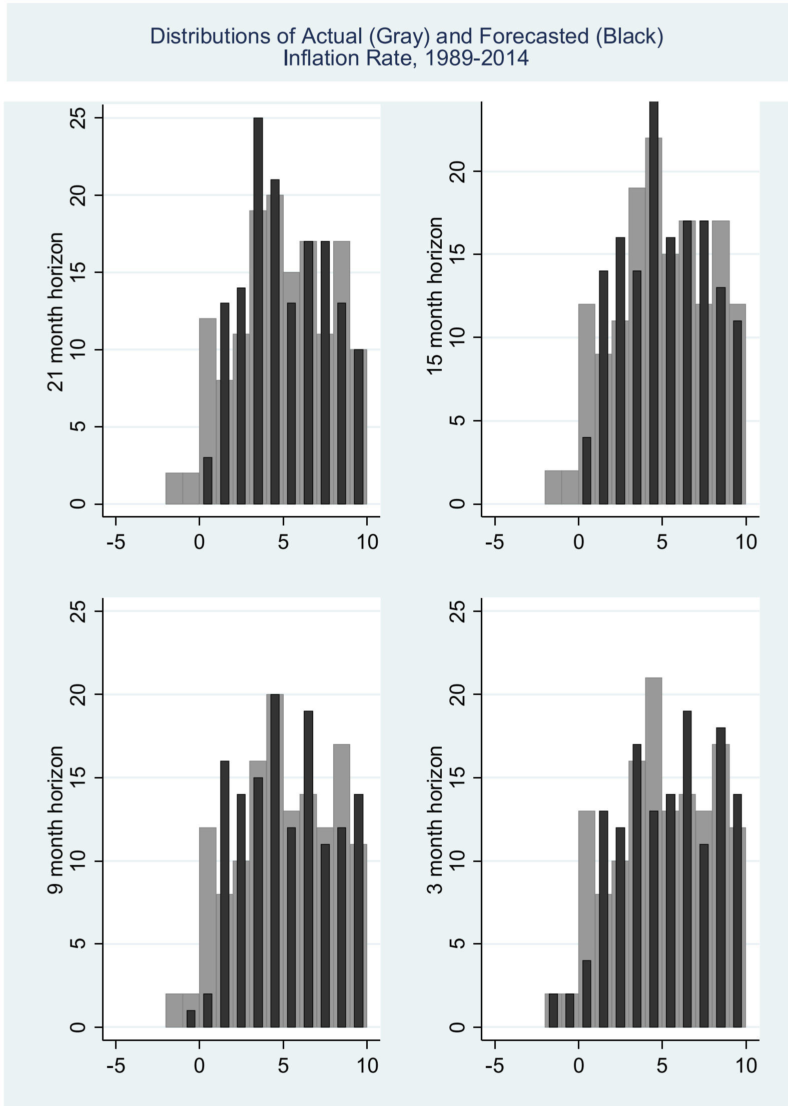

Fig. 2. Distribution of actual and forecasted inflation rate, 1989–2014.
Source: Consensus, IMF IFS and authors' calculations.

horizon draws to a close). This seems, on average, a relatively good performance for inflation forecasts in the region as results provide evidence of hardly enormous errors traditionally. In fact, the relationship between inflation and the accuracy of inflation predictions in high-inflation countries, such as those in Latin America, tends to be negative (see Maskus and Pourgerami, 1990 and references therein). The reason for the potentially negative effect of inflation on inflation uncertainty (where uncertainty is equated with lack of predictability) is that in a high-inflation environment economic agents invest more resources in generating accurate inflation forecasts and in developing instruments capable of reducing the uncertainty costs of high inflation.

As Edwards (1993) puts it, "contrarily to popular mythology, not all countries in Latin America have had long inflationary histories". Moreover, as IMF (2016a) points out, the "regional mix" in terms of economic outlooks is impressive. These two give us sufficient reasons to inspect inflation forecasting performance country-by-country. Fig. 3 shows the country-by-country mean error for both current and year-ahead forecasts. Some interesting differences can be highlighted. First, Paraguay and Argentina are examples of countries for which forecasts are larger than realized inflation, that is, forecasters overpredict inflation. On the contrary, for Mexico, Ecuador, Dominican Republic and Costa Rica the opposite applies. Countries for which the mean error is relatively smaller or close to zero is Uruguay, Colombia and Chile (for both forecast horizons).

3. Methodology and results

3.1. *An assessment of the quality of inflation forecasts*

3.1.1. *Rationality of inflation forecasts*

The key for an assessment on "rationality" or "unbiasedness" lies, firstly, in the available information at the time the forecast was elaborated (data, policy measures), and secondly in the (optimal?) use of this information. A comparison of forecast with

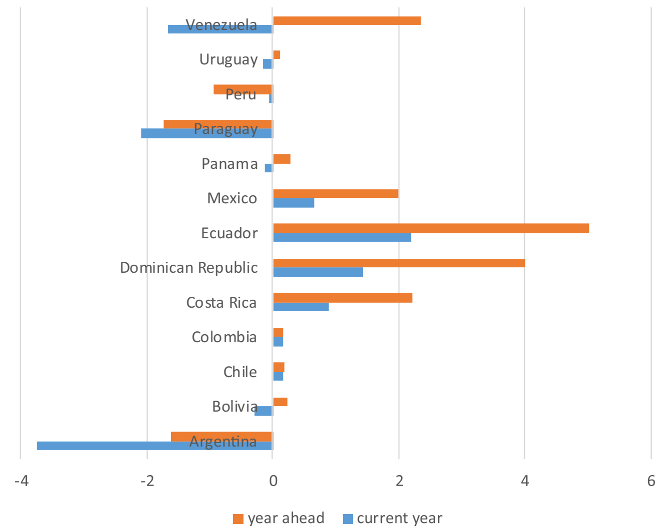

Fig. 3. Mean forecast error by horizon.
Source: Consensus, IMF IFS and authors' calculations.

benchmark standards, as we did in the previous section, determines which one has smaller errors; it does not indicate how to improve upon the observed record. Rationality tests determine whether or not the predictions are optimal with regards to a particular information set (Wallis, 1989). A forecast is unbiased if its average deviation from the outcome is zero.[15] We test for the presence of bias in inflation forecast errors by adopting a statistical approach and considering symmetric loss functions on the part of the agencies generating the forecasts. We use:

$$A_{t+h} - F_{t+h} = \alpha + \varepsilon_{t+h} \tag{1}$$

where the forecast horizon $h = 1, \ldots, 24$. A_{t+h} is the actual value of variable x in $t+h$, and F_{t+h} is the forecast for $t+h$ made at t. F_{t+h} is unbiased if we cannot reject the null hypothesis that $\alpha = 0$ (Holden and Peel, 1990). If the estimated coefficient is significantly larger or smaller than zero, the forecasts are biased toward optimism or pessimism, respectively. This last point is closely related to a behavioral economics concept: the anchoring heuristic (Tversky and Kahneman, 1974) which is increasingly considered when explaining biased forecasts. The underlying mechanism is typically described as in Harvey (2007) who states that forecasters tend to "use the last data point in the series as a mental anchor and then adjust away from that anchor to take account of the major feature(s) of the series. However, as adjustment is typically insufficient, their forecasts are biased".[16] Another prominent explanation of systematically biased forecasts points to reputational concerns of forecasters trying to strategically conceal their inability to predict future values. This results in strong incentives for herding behavior among forecasters (Ottaviani and Sørensen, 2006; Ackert et al., 2008).

Table 2 reports, for current and year-ahead, and for the pooled sample and each country individually, the t-tests for $\alpha = 0$. For the pooled sample, we can reject the null hypothesis of rational

Table 2
Rationality test.

Horizon	Pooled	Current year	Year ahead
Sample	All sample, excluding Brazil		
α	0.396***	−0.180	0.972***
	(0.111)	(0.124)	(0.182)
Country	Argentina		
α	−2.672***	−3.733***	−1.61**
	(0.644)	(1.035)	(0.761)
Country	Bolivia		
α	−0.023	−0.287*	0.241
	(0.168)	(0.151)	(0.299)
Country	Chile		
α	0.178*	0.168*	0.189
	(0.095)	(0.099)	(0.163)
Country	Colombia		
α	0.173**	0.167**	0.178
	(0.086)	(0.078)	(0.155)
Country	Costa Rica		
α	1.558***	0.884***	2.232***
	(0.167)	(0.178)	(0.272)
Country	Dominican Republic		
α	2.726***	1.435***	4.016***
	(0.640)	(0.545)	(1.150)
Country	Ecuador		
α	3.621***	2.205***	5.036***
	(0.714)	(0.663)	(1.256)
Country	Mexico		
α	1.335***	0.675***	1.996***
	(0.248)	(0.246)	(0.425)
Country	Panama		
α	0.073	−0.123	0.270
	(0.107)	(0.102)	(0.187)
Country	Paraguay		
α	−1.911***	−2.092***	−1.730***
	(0.269)	(0.336)	(0.421)
Country	Peru		
α	−0.499***	−0.062	−0.937***
	(0.145)	(0.149)	(0.245)
Country	Uruguay		
α	−0.006	−0.140	0.128
	(0.249)	(0.284)	(0.411)
Country	Venezuela		
α	0.346	−1.668***	2.360**
	(0.611)	(0.558)	(1.061)

Note: The dependent variable is Consensus forecast error. Each cell reports the results of a regression of forecast errors on a constant for the pool of all countries in our sample (that excludes Brazil) and each individual country. Heteroskedastic-consistent robust standard errors are reported in parenthesis.
* Indicates significance at 10% level.
** Indicates significance at 5% level.
*** Indicates significance at 1% level.

[15] As a rule, if forecasts are in line with the Rational Expectations Hypothesis (REH) formulated by Muth (1961), they should be unbiased. The REH states that market participants use all cost-efficient knowledge to forecast.

[16] There are many time series forecasting experiments investigating individual prediction behavior (e.g. Reimers and Harvey, 2011).

forecasts only in year-ahead forecasts but not for current-year ones (these seem unbiased). As before, given the regional mix, country results hide a great deal of heterogeneity. More specifically, in the cases of Panama and Uruguay, inflation forecasts seem unbiased irrespectively of the forecast horizon considered. For the remainder of the countries, the null hypothesis of rational forecasts can be rejected in either one or both horizons.[17]

3.1.2. *Efficiency of Inflation forecasts*

According to Nordhaus (1987) a sequence of efficient forecasts of the same event must follow a martingale. As in Gentry (1989), we regress actual observations on a constant plus the forecast:

$$A_{t+h} = \alpha' + \beta F_{t+h} + \varepsilon_{t+h} \tag{2}$$

where the forecast horizon $h = 1, \ldots, 24$. A_{t+h} is the actual value of variable x in $t+h$, and F_{t+h} is the forecast for $t+h$ made at t. F_{t+h} is efficient if we cannot reject the null hypothesis that $\alpha' = 0$ and $\beta = 1$individually and jointly.

As Table 3 shows, in all forecast horizons, the joint hypothesis of a zero constant and a slope coefficient of unity is rejected, as indicated by the F-statistics and associated p-values.[18] This points to inefficiency of inflation forecasts. Since the data are pooled across countries and over time, there is reason to suspect that the disturbance term, ε_{t+h}, in Eq. (2) would not be random. We attempted to control for some of the possible correlations by augmenting the regression to include year fixed effects. The idea is that some years may be harder to forecast than others. Our results (not shown) still suggest inefficiency. As before, the pooled results hide heterogeneity and in Bolivia, Chile, Colombia, Dominican Republic, Mexico and Venezuela, the joint hypothesis is not rejected. This suggests that, for this group of countries, inflation forecasts may have been efficient over the period under scrutiny.

3.1.3. *From "forecast (in-)efficiency" to "informational rigidity"*

A different approach to tackle forecast efficiency was suggested by Nordhaus (1987) who defined a notion of efficiency or "information rigidity" based on forecast revisions. Nordhaus (1987) and Nordhaus and Durlauf (1984) studied "forecast smoothing", i.e., a tendency for a revision in one direction to be followed by further revisions in the same direction, in fixed-event forecasts. This is an implication of full-informational rational expectations (FIRE): successive forecasts of the same event should be uncorrelated.[19] Recent papers addressing the issue of information rigidity on macro forecasts include Isiklar et al. (2006), Loungani et al. (2013), Coibion and Gorodnichenko (2015) and Jalles et al. (2015).

We define initial revision of the forecast as the change in the forecast between October and April of the previous year, the middle revision as the change between April of the current year and October of the previous year, and the final revision as the change between October of the current year and April of the current year. Results from regressions of later revisions on earlier ones are shown in Table 4. In all, but one, regressions, there is evidence of a strong positive correlation among forecast revisions (at the 1% significance level). Overall, there is a clear tendency for "forecast smoothing", i.e., the estimated coefficient on the lagged revision points to the presence of informational rigidities. In fact, looking at the specification with both middle and initial revisions included together, it takes between 1 and 1.2 months for the information to be fully incorporated into forecasts.[20]

Alternatively, following Coibion and Gorodnichenko's (2015) approach we regress the forecast error on the forecast revision using our final, middle or initial revisions. The authors show that the coefficient on the forecast revision is zero under the null of full informational rational expectations, whereas a positive value indicates information rigidities.[21] Table 5 presents the results of this test and we observe that the coefficient estimates are all positive and statistically different from zero. The null can be rejected and this fact goes in the direction consistent with models with information rigidity. In this case, it takes between 1.2 and 1.6 months for information to be fully incorporated.[22] Overall, we can conclude that inflation rate forecasts are inefficient.

3.2. *Inflation forecasts, recessions and turning points*

The recent Global Financial Crisis has revived the interest not only in predicting recessions but also on the forecasting performance and accuracy of many macro aggregates that could help determining upward and downward movements in the business cycle (and its corresponding turning points). We now turn to the examination of the inflation rate forecast performance

[17] It is worth pointing to the possibility that many of the rejections of forecast optimality may simply be driven by the assumption of MSE loss rather than the absence of forecast rationality per se. Elliot et al. (2005) state that MSE loss, despite a generally used assumption, is often hard to justify on economic grounds and is subject to debate and criticism. In fact, asymmetric loss captures the idea that the cost of over- and underpredicting a given variable may be very different. Patton and Timmermann (2007) propose a transformation of the forecast error that possesses the same set of rationality properties under asymmetric loss and nonlinear data generating processes.

[18] We pick October and April of the current year and year-ahead as examples of the first and second half of a given forecast year. Arbitrary selection of different adjacent months (recall that we have a continuous sequence of 24 months forecast) does not qualitatively alter our results.

[19] The literature has identified three main potential explanations for "forecast smoothing" or "information rigidity" (for departure from FIRE): (i) behavioral explanations (Nordhaus, 1987); (ii) sticky-information (Mankiw and Reis, 2002) and (iii) imperfect information (Woodford, 2002).

[20] Mankiw and Reis (2002) propose a model of inattentive agents who update their information sets each period with probability $(1-\lambda)$, but acquire no new information with probability λ, so that λ can be interpreted as the degree of information rigidity and $1/(1-\lambda)$ is the average duration between information updates. In the context of sticky information models, $\lambda = \beta/(1+\beta)$, with β being the estimated rigidity coefficient.

[21] One feature of this test is that it requires the use of the actual realizations and hence requires a view on whether to use the latest data or an earlier vintage. Our tests use the latest data.

[22] Coibion and Gorodnichenko (2012) report for inflation similar speed for the updating of forecasts (1.5–2 months).

Table 3
Gentry's (1989) Test of forecast efficiency.

Sample/country	Independent variables	Dependent variable: "actual" inflation rate			
		Apr. (t − 1)	Oct. (t − 1)	Apr. (t)	Oct. (t)
All	Constant	−2.242	−0.470	5.615	2.034
		(9.902)	(5.137)	(6.976)	(6.481)
	Forecast	2.095***	1.571***	1.088***	1.111***
		(0.114)	(0.038)	(0.027)	(0.026)
	F-statistic	47.85	114.70	6.18	9.38
	p-Value	0.00	0.00	0.00	0.00
Argentina	F-statistic (p-value)	0.12	0.01	0.00	0.00
Bolivia	F-statistic (p-value)	0.46	0.69	0.61	0.21
Chile	F-statistic (p-value)	0.35	0.91	0.59	0.36
Colombia	F-statistic (p-value)	0.79	0.91	0.99	0.77
Costa Rica	F-statistic (p-value)	0.01	0.09	0.12	0.68
Dominican Republic	F-statistic (p-value)	0.25	0.59	0.33	0.04
Ecuador	F-statistic (p-value)	0.02	0.03	0.00	0.09
Mexico	F-statistic (p-value)	0.29	0.19	0.12	0.17
Panama	F-statistic (p-value)	0.89	0.59	0.01	0.22
Paraguay	F-statistic (p-value)	0.00	0.00	0.00	0.00
Peru	F-statistic (p-value)	0.00	0.00	0.06	0.00
Uruguay	F-statistic (p-value)	0.18	0.34	0.52	0.83
Venezuela	F-statistic (p-value)	0.25	0.27	0.62	0.70

Notes: The regression is expressed as, where A is the actual realization and F is the forecast. The F-statistic and associated p-value are for the test of the null hypothesis that $\beta_0 = 0$ and $\beta_1 = 1$. For country-level results full set of coefficients and respective statistics are available upon request; they were omitted for reasons of parsimony. Heteroskedastic-consistent robust standard errors are reported in parenthesis.
*Indicates significance at 10% level.
**Indicates significance at 5% level.
*** Indicates significance at 1% level.

Table 4
Nordhaus' (1987) Test of forecast efficiency.

Sample	Dependent variable	Independent variables			R-squared
		Middle revision	Initial revision	Constant	
All	Final revision	0.239***		0.083	0.03
		(0.018)		(0.063)	
	Final revision		0.029***	−0.007	0.04
			(0.008)	(0.057)	
	Final revision	0.240***	0.013*	−0.026	0.04
		(0.018)	(0.007)	(0.058)	
	Middle revision		0.029		0.02
			(0.039)		

Note: The dependent variable is identified in column 2 as either Final Revision or Middle Revision. As for the independent variables included in each regression, these are identified in columns 3 and 4 together with a constant term (column 5). Heteroskedastic-consistent robust standard errors are reported in parenthesis.
**Indicates significance at 5% level.
* Indicates significance at 10% level.
*** Indicates significance at 1% level.

during recession episodes, using descriptive statistical analysis and simple regressions. It is important to look at the behavior of inflation forecasts in different phases of the business cycle due to several reasons: (1) this is when general interest (from practitioners and policy makers) in predicting this variable is highest; (2) different central banks in Latin America may have differentiated objectives (some may be concerned solely with inflation while others are wider and include output, stability and employment considerations) which tie future policy actions to alternative levels of inflation rate[23]; (3) inflation expectations can dramatically change around turning points.[24] Some basic properties of the inflation rate forecasts during recession years are summarized in Table 6.

As shown in the first row, as of April of the year preceding the recession, the consensus inflation forecasts were too opti-

[23] See Cecchetti and Ehrmann (2002) for an examination of the central bank objective functions in a large number of advanced and emerging economies.
[24] See Jalil and Rua (2015) for evidence, using narrative records, on how the Great Depression in the US in 1933 has shifted inflation expectations.

Table 5
Coibion and Gorodnichenko's (2015) Test of forecast efficiency.

Sample	Independent variables				R-squared
	Final revision	Middle revision	Initial revision	Constant	
All	0.514***			0.382***	0.09
	(0.026)			(0.111)	
		0.291***		0.082	0.07
		(0.014)		(0.112)	
			0.201***	0.402***	0.23
			(0.041)	(0.114)	
	0.624***	0.285***	0.411***	0.037	0.22
	(0.027)	(0.013)	(0.038)	(0.106)	

Notes: The dependent variable is the inflation forecast error. As for the independent variables included in each regression, these are identified in columns 2–4 together with a constant term (column 5). Heteroskedastic-consistent robust standard errors are reported in parenthesis.
*Indicates significance at 10% level.
**Indicates significance at 5% level.
*** Indicates significance at 1% level.

Table 6
Forecast performance of consensus inflation rate during recession episodes.

All countries	Apr. (t − 1)	Oct. (t − 1)	Apr. (t)	Oct. (t)
Number of episodes where forecast was too optimistic (forecast < actual) (share in total, in percentage)	10 (45)	12 (46)	9 (35)	4 (18)
Average forecast error (all recession episodes)	6.19	4.36	−2.68	−3.44

Note: Refer to the main text for details.

Table 7
Descriptive Statistics of Consensus Inflation Forecasts during Recessions and Recoveries.

Spec. All countries	Forecast errors (1) Unconditional	Absolute forecast errors (2)	Forecast errors (3) Recessions	Absolute forecast errors (4)	Forecast errors (5) Recoveries	Absolute forecast errors (6)
Mean	0.39	3.15	1.18	8.42	0.47	6.62
Standard deviation	6.72	5.94	14.14	11.41	10.79	8.76
Minimum	-65.66	0.00	-65.66	0.02	-34.08	0.02
Maximum	69.85	69.85	46.02	65.66	46.02	46.02

mistic (defined as forecast smaller than actual realization) in 10 episodes corresponding to 45% of the total number of recession episodes. By April of the year of the recession, inflation forecasts were too optimistic in only 35% of the total number of episodes. While forecasters do recognize a slowdown in the inflation rate during recessions in the year in which they occur, results seem to suggest that they cannot anticipate such downward revision in the year preceding the recession. Moreover, as shown in the final row, there is a significant upward bias in the year-ahead April forecasts that only slowly dissipates over time; we go from a mean error above 6 points in April of the year preceding the recession, to a mean error of −3 points in the year of the recession.

Fig. 4 presents a graphical summary of the ME, MAE and RMSE descriptive statistics by forecast horizon. As we move from year-ahead towards current-year, we see a steadily decline in both the MAE and MSE (unconditional line). Moreover, we have positive values for the mean forecast errors for most of the 24-month forecast horizon meaning that forecasters underestimate the inflation rate. Looking at the recession (blue) line, we observe that it takes some time for forecasters to recognize that the economy is hitting a recession.

In Table 7, we see that forecasters tend to slightly underpredict the inflation rate on average, and the extent of underprediction seems to increase during recessions. The regression analysis confirms that as the forecast horizon increases so do the absolute forecast errors (Table 8). Moreover, the recessions' dummy is statistically different from zero and positively correlated with absolute forecast errors.

3.2.1. On the efficiency properties of inflation forecasts during recessions

We now examine forecast efficiency by conducting two types of tests. The first is due to Nordhaus (1987) who defined a notion of "information rigidity" based on forecast revisions in line with the full information rational expectations' (FIRE) premise that successive revisions should be uncorrelated. The second approach follows Gentry (1989) who regresses actual

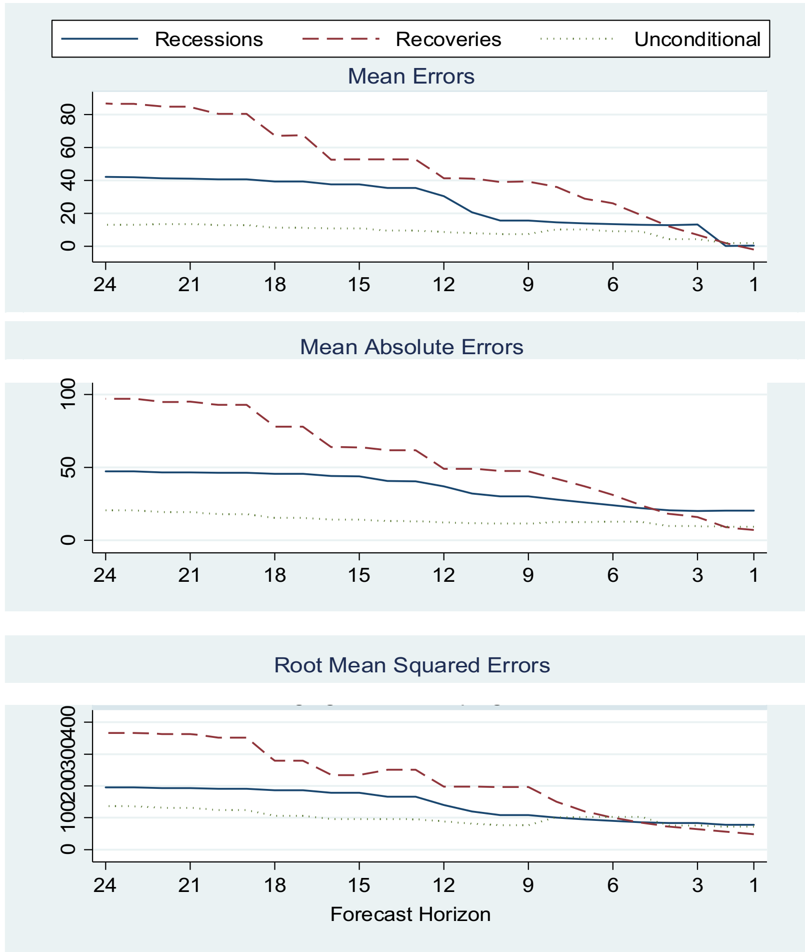

Fig. 4. Descriptive statistics inflation rate forecast errors: consensus 1989–2014.
Source: Consensus, IMF IFS and authors' calculations.

Table 8
Regression of Inflation Rate Forecast Errors on Different States of the Economy.

Sample	All sample		
Horizon	Pooled	Current year	Year ahead
Recessions	5.708***	5.212***	6.235***
	(0.344)	(0.397)	(0.574)
Recoveries	3.325***	1.874***	4.936***
	(0.312)	(0.362)	(0.518)
Horizon	0.155***	0.135***	0.107*
	(0.016)	(0.039)	(0.056)
Constant	0.305	0.671**	0.902
	(0.243)	(0.291)	(1.049)
Obs.	2878	1511	1367
R-squared	0.165	0.144	0.159

Notes: The dependent variable is absolute forecast errors. Heteroskedastic-consistent robust standard errors are reported in parenthesis.
[*] Indicates significance at 10% level.
[**] Indicates significance at 5% level.
[***] Indicates significance at 1% level.

observations on a constant plus the forecast error and jointly tests efficiency by imposing a zero intercept and unity slope coefficient.

We first run Nordhaus' (1987) regressions with the inclusion of dummies for banking crisis and for recession and recoveries episodes to ascertain differences in inflation forecasts' efficiency during these events compared to averages. The results suggest that on average forecasts are inefficient (Table 9). Looking at specification 3, during recessions, one can see that middle and initial revisions in one direction generally are followed by final revisions in the same direction (the coefficients on middle and initial revisions after recessions are statistically significant).

Finally, following Gentry's (1989) approach defined above we display the results for the joint hypothesis testing for the slope and intercept coefficients using the Wald tests in Table 10. The hypothesis of forecast efficiency is overwhelmingly rejected, including for recession episodes.

3.2.2. *On the efficiency properties of inflation forecasts during recoveries*

The above analysis documented failures in forecasting inflation during recessions. Naturally a question arises about inflation forecast performance during recoveries, another turning point of the business cycle. We explore this question briefly. In Fig. 4, looking at the recoveries' line, we observe that, mean errors of inflation forecasts during recoveries are always larger in absolute

Table 9
Nordhaus' (1987) Test of efficiency based on inflation forecast revisions and accounting for recession and recovery episodes.

Dependent variable	Final revisions		
Sample	All sample		
Spec.	(1)	(2)	(3)
Constant	-0.373	-0.938^{***}	-0.168
	(0.814)	(0.331)	(0.288)
Dummy for recession	1.294	4.595^{***}	-1.250^{*}
	(1.979)	(0.722)	(0.682)
Dummy for recovery	-11.094^{***}	1.561^{**}	-0.939^{*}
	(1.658)	(0.652)	(0.582)
Dummy for banking crisis	5.156^{*}	3.613^{***}	3.106^{***}
	(2.725)	(1.252)	(1.152)
Middle revision	0.496^{***}		-0.564^{***}
	(0.099)		(0.035)
Middle revision after recessions	-0.611^{***}		0.682^{***}
	(0.056)		(0.023)
Middle revision recoveries	2.186^{***}		0.564^{***}
	(0.099)		(0.035)
Middle revision after banking crisis	0.652^{***}		3.732^{***}
	(0.104)		(0.589)
Initial revision		-0.081^{***}	-0.017^{**}
		(0.009)	(0.008)
Initial revision after recessions		0.419^{***}	0.188^{***}
		(0.015)	(0.015)
Initial revision recoveries		2.083^{***}	2.007^{***}
		(0.010)	(0.013)
Initial revision after banking crisis		-0.574^{***}	1.179^{***}
		(0.010)	(0.338)
Obs.	4435	4089	4089
R-squared	0.87	0.98	0.98

Notes: The dependent variable is the inflation rate final revisions. Regressions include dummy variables for recession and recovery episodes. Heteroskedastic-consistent robust standard errors are reported in parenthesis.
* Indicates significance at 10% level.
** Indicates significance at 5% level.
*** Indicates significance at 1% level.

variable compared to the unconditional but, more importantly, to mean errors during recessions. Also it takes forecasters much longer for the convergence with the unconditional line to happen.

The main finding here is that while during recoveries, inflation is more often accurately predicted than in recessions (Table 7), regression results suggest that inflation forecasts are equally as inefficient as those taking place during recessions (Tables 8 and 9). Moreover, during recoveries most forecasters revise upwards their inflation predictions (Fig. 5). Hence, there is a sense of "optimism" that the average economy's growth is picking up which drive inflation expectations towards higher levels. All in all, our results suggest "information rigidity" in forecasts also during recoveries.

4. Conclusion

This paper provides a full characterization of inflation rate forecasts using the mean values from Consensus Economics for a sample of 14 Latin American countries between 1989 and 2014. It also assesses the performance of inflation rate forecasts around business cycles' turning points. To this end, we relied on a plethora of time series methods and regression analyses.

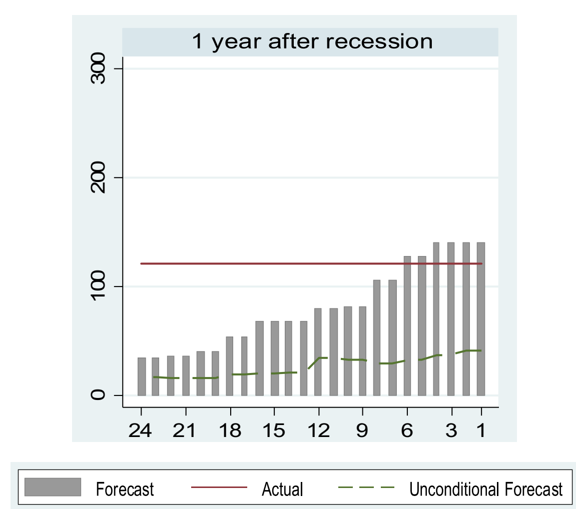

Fig. 5. Actual and forecasted inflation rate during recoveries (up to 1 year after recession ended): 1989–2014.
Source: Consensus, IMF IFS and authors' calculations.

Our results show that inflation forecasts in the region display the standard property that they start to mirror the data as the forecast horizon draws to a close. On average, the mean fore-

Table 10
Gentry's (1989) Test of forecast efficiency under recessions and recoveries.

Sample Spec.	All (1)
Constant	−0.382
	(0.257)
Dummy for recession	6.828***
	(0.633)
Dummy for recovery	0.838
	(0.572)
Dummy for banking crisis	−0.443
	(0.965)
Forecast	0.994***
	(0.018)
Forecast after recession	−0.275***
	(0.025)
Forecast after recovery	−0.016
	(0.027)
Forecast after banking crisis	0.154***
	(0.045)
Obs.	2676
R-squared	0.75
P-values for Wald tests	
Forecast after recessions	0.04
Forecast after recession	0.00
Forecast after recovery	0.00
Forecast after banking crisis	0.00

Notes: The dependent variable is actual values of inflation rate. The hypothesis for the Wald test is that the value of the respective total effect is not statistically different from zero. Heteroskedastic-consistent robust standard errors are reported in parenthesis.
* Indicates significance at 10% level.
** Indicates significance at 5% level.
*** Indicates significance at 1% level.

cast error is positive, suggesting underprediction of inflation, but this masks very different country experiences. In fact, Paraguay and Argentina are examples of countries for which forecasts are larger than realized inflation, that is, forecasters overpredict inflation. We find evidence point to biasedness of inflation forecasts for year-ahead forecasts but not for current year. As far as efficiency is concerned, tests' results point to inefficiency which is also evidenced by a tendency to smooth forecasts (forecast revisions in one direction are following by subsequent revisions in the same direction). This means that informational rigidities are present, taking on average 1.5 months for information to be fully incorporated and internalized.

Finally, focusing on business cycle turning points, while forecasters do recognize a slowdown in the inflation rate during recessions in the year in which they occur, results seem to suggest that they cannot anticipate a downward revision in inflation forecasts in the year preceding the recession. Moreover, forecasters tend to slightly underpredict the inflation rate on average, and the extent of underprediction seems to increase during recessions. The hypothesis of forecast efficiency is overwhelmingly rejected during recessions. In recoveries, there is a general sense of "optimism" that the average economy's growth is picking up which drive inflation expectations towards higher levels.

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