Forecasting Inflation in Latin America with Core Measures

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Abstract

We explore the ability of core inflation to predict headline CPI annual inflation for a sample of 8 developing economies in Latin America during the period January 1995-May 2017. Our in-sample and out-of-sample results are roughly consistent in providing evidence of predictability in the great majority of our countries, although, as usual, a slightly stronger evidence of predictability comes from the in-sample analysis. The bulk of the out-of-sample evidence of predictability concentrates at the short horizons of 1 and 6 months. In contrast, at longer horizons of 12 and 24 months, we only find evidence of predictability for two countries: Chile and Colombia. This is both important and challenging, given that monetary authorities in our sample of developing countries are currently implementing or given steps toward the future implementation of inflation targeting regimes, which are heavily based on long run inflation forecasts.

JEL Codes: E31, E17, E37, E52, E58, F37, O1, O2
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I. Introduction

The objective of this paper is to evaluate the ability that traditional measures of core inflation may have to forecast headline inflation. Differing from most of the existing literature, we focus on a set of 8 developing countries in Latin America. To our knowledge, a thorough study aimed at quantifying this predictability for a number of developing countries has not been written yet.

The point that we address in this paper is important because, in words of Bullard (2011a), the "core predicts headline" argument is fairly popular. In a context in which inflation is not easy to forecast (Stock and Watson, 2008) the idea that core inflation may be a useful predictor in principle is very appealing, especially for central banks that are responsible for maintaining overall price stability and need to know where inflation is heading.

There is no unique way to define a core inflation measure. In fact there are several articles comparing and analyzing the behavior of different core measures. See for instance Robalo, Duarte and Morais (2003), Clark (2001) and Rich and Steindel (2007), just to mention a few. Despite the number of different core inflation definitions, one of the most widely used is based on the Consumer Price Index (CPI) excluding "food" and "energy" components (Robalo, Duarte and Morais, 2003). In this paper we follow this tradition for our definition of core measure.

The emphasis on core inflation relies on the hope that by removing volatile components, the researcher may end up with a clearer indicator about future developments of headline inflation. According to Crone, Khettry, Mester and Novak (2013) this is the prevailing view. In fact, food and energy components have been historically highly volatile (for example, due to temporary supply disruptions), and their large price fluctuations are usually expected to correct themselves within a relatively short period of time. As Freeman (1998) explains, since inflation may be either too sensitive to exogenous variables or vulnerable to a few particular volatile components, it is common to use ''core'' or "underlying" inflation measures to capture trends in total inflation. Nevertheless, hopes are not facts, and an empirical evaluation about the information that core inflation may have to predict headline inflation is required. In fact, challenging the prevailing view, there are some interesting arguments suggesting that emphasis on core inflation might not be a good idea. First, core measures may have lower predictive ability than inflation itself because of the exclusion of items on which people spend a nontrivial portion of their income. This might be particularly relevant in developing economies, where the share of the food component of the CPI is in general higher relative to developed countries. (See Table B1 in Appendix B). In addition, food and energy prices might affect other prices in the economy and thus weaken the ability of core to predict total inflation. Second, it is frequently argued that core may be more demand than supply driven, and consequently more affected by monetary policy actions. Nevertheless, the crystal clear distinction between demand and supply shocks is at least thin. The incorporation of further processed food in the CPI baskets with more labor and non-tradable components may have ruined that distinction. Third, and following Bullard (2011b), the logic of relative prices also suggests that changes in energy consumption triggered by price changes could put pressure on all the other prices in the economy. Accordingly, if energy prices continue to increase over time, it is plausible to expect that other prices will decrease, which means that core will underestimate total inflation during that period. This implies that core inflation may not be a good predictor of future headline inflation after all. According to these arguments, headline inflation should probably have more weight on policymaking decisions than core.

Central bankers around the world have taken both sides of the debate. The European Central Bank and the Bank of England have an explicit focus on headline measures, and their policymakers pay less attention to core inflation. In contrast, the Federal Open Market Committee (FOMC) focuses on core measures (see Smith, 2012). Following the common practice of the FOMC, many central banks in developing economies seem to have taken for granted the importance of core inflation. Consequently, this variable is usually part of the discussions about the stance of monetary policy.

Differing from our paper, most articles exploring the predictive relationship between core and headline inflation, focus on either one or several developed countries. Besides, different papers use different methodologies, sample periods and definitions of trend or core inflation, which makes it hard to draw conclusions at an international level. For instance, Le Bihan and Sédillot (2000) analyze the ability of four indicators of underlying inflation to forecast inflation in France. The authors conclude that their out-of-sample results are not very compelling. A fairly similar conclusion is achieved by Freeman (1998) for the US, mentioning that measures of underlying inflation are not very useful for forecasting headline inflation. Bermingham (2007) also addresses the same topic but for the case of Ireland. Differing from the previous two papers, Bermingham does find evidence supporting the usefulness of a core measure when forecasting headline inflation. A similar result is shown by Song (2005) using Australian data. Crone et al. (2013) also analyze this topic for the US finding evidence of long term predictability from core to headline CPI, but not in the case of PCE. More efforts in these directions can be found in Cogley (2002), Khettry and Mester (2006), Giannone and Matheson (2007), Kiley (2008), Meyer and Pasaogullari (2010), Smith (2012), Stock and Watson (2015) and Faust and Wright (2013), but also with a focus mainly on one single developed country. More recently, Pincheira, Selaive and Nolazco (2016) analyze a question similar to ours, but again, with a focus on OECD economies.

Our results from the analysis of 8 developing economies indicate that core inflation does have the ability to predict headline inflation in three quarters of our countries. This share reduces to

50% when predictability is analyzed at policy relevant forecasting horizons. Similarly, this predictive ability is sizable in only 50% of the countries in our sample.

The rest of the paper is organized as follows. In section II we describe our data. We introduce the econometric setup in section III. In section IV we present our predictive evaluation strategy. Empirical results are presented in section V and section VI concludes.

II. Data

We consider the Consumer Price Index of a total of 8 Latin American countries at a monthly frequency: Chile, Colombia, Costa Rica, Dominican Republic, Guatemala, Mexico, Paraguay and Peru. We use CPI excluding food and energy as our main measure of core inflation[1]. This sample of countries is chosen in part for data availability and reliability and in part because they represent a sample of developing countries with a rich variation in income. For all our economies we include data until May 2017. The starting dates differ across countries, however. For Chile, Mexico and Peru we have data since January 1995. For Colombia, Costa Rica and Paraguay, the starting date is one year later: in January 1996. Finally, the starting date for Dominican Republic is January 2001 and for Guatemala, January 2002.

We obtain the data for Chile, Colombia, Costa Rica and Mexico from the OECD Main Economic Indicators database. For the rest of the countries we use their own central banks as source for the data. Our series are not seasonally adjusted.

Our basic unit of analysis corresponds to year-on-year (y-o-y) inflation rate computed according to the following simple expression[2]:

$$\pi_t = 100 * [Ln(CPI_t) - Ln(CPI_{t-12})]$$

Similarly we define year-on-year (y-o-y) core inflation rate as follows:

$$\pi_t^{core} = 100 * [Ln(CoreCPI_t) - Ln(CoreCPI_{t-12})]$$

Where $CoreCPI_t$ is the core CPI Index. We shall refer to π_t equally as y-o-y inflation rate or annual inflation. Similarly we shall call π_t^{core} by y-o-y core inflation rate or annual core inflation rate.

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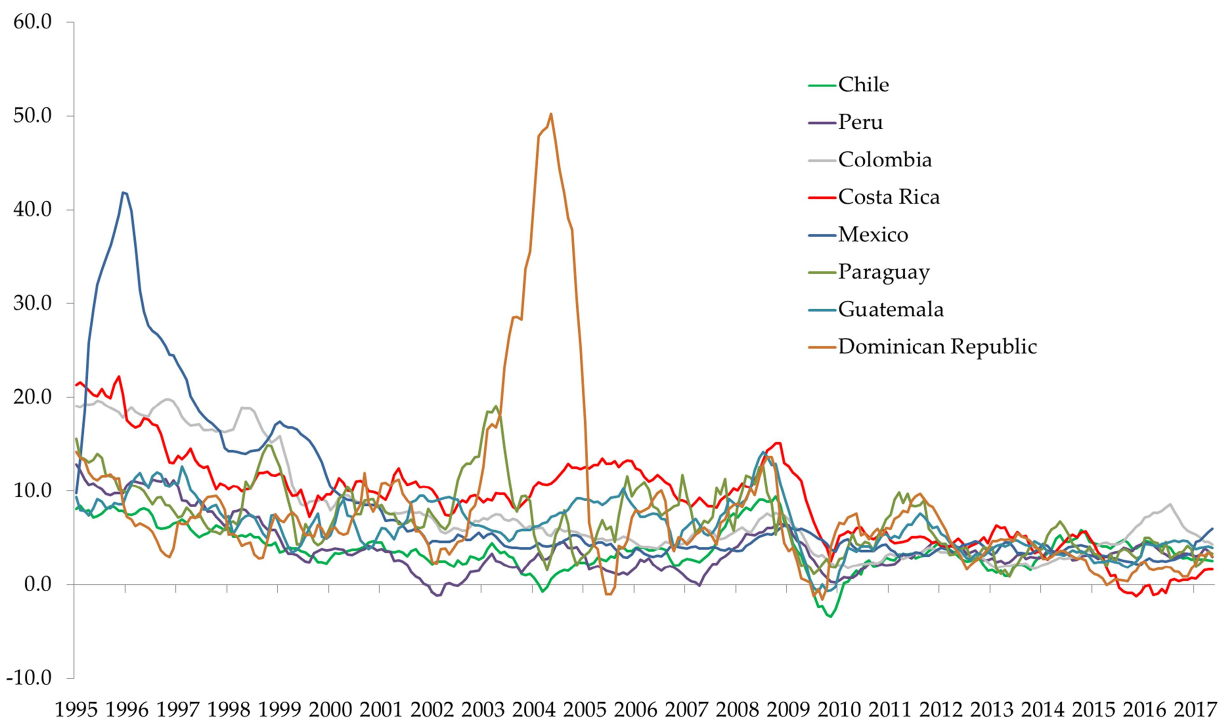
[1] In the case of Guatemala and Dominican Republic, we use the core measure available at their central banks. For Guatemala, this measure removes some highly volatile components of the CPI, such as vegetables, fruits and legumes. For Dominican Republic the core measure removes from CPI some highly volatile agricultural items, alcoholic beverages, tobacco, fuels, transportation and regulated services.

[2] Guatemala again is an exception. For Guatemala we do not have data on CPI. We do have data on annual inflation rates, for both core and headline. Therefore, instead of using the log approximation, for Guatemala we use directly data on annual inflation rates.

We depart from Stock and Watson (2002), Ciccarelli and Mojon (2010) and others, in that we focus only on forecasting year-on-year inflation rate at different horizons. We notice that in many Latin American countries the annual inflation rate is the main focus of central banks. This is also the case in many countries following inflation targeting regimes, like the UK, Sweden, Switzerland and others. Table B1 in appendix B also shows that the countries in our sample either follow inflation targeting regimes or are taking steps toward the future implementation of an inflation targeting regime. As the target in these countries is set in terms of annual inflation rates, it is natural to consider models for this variable.

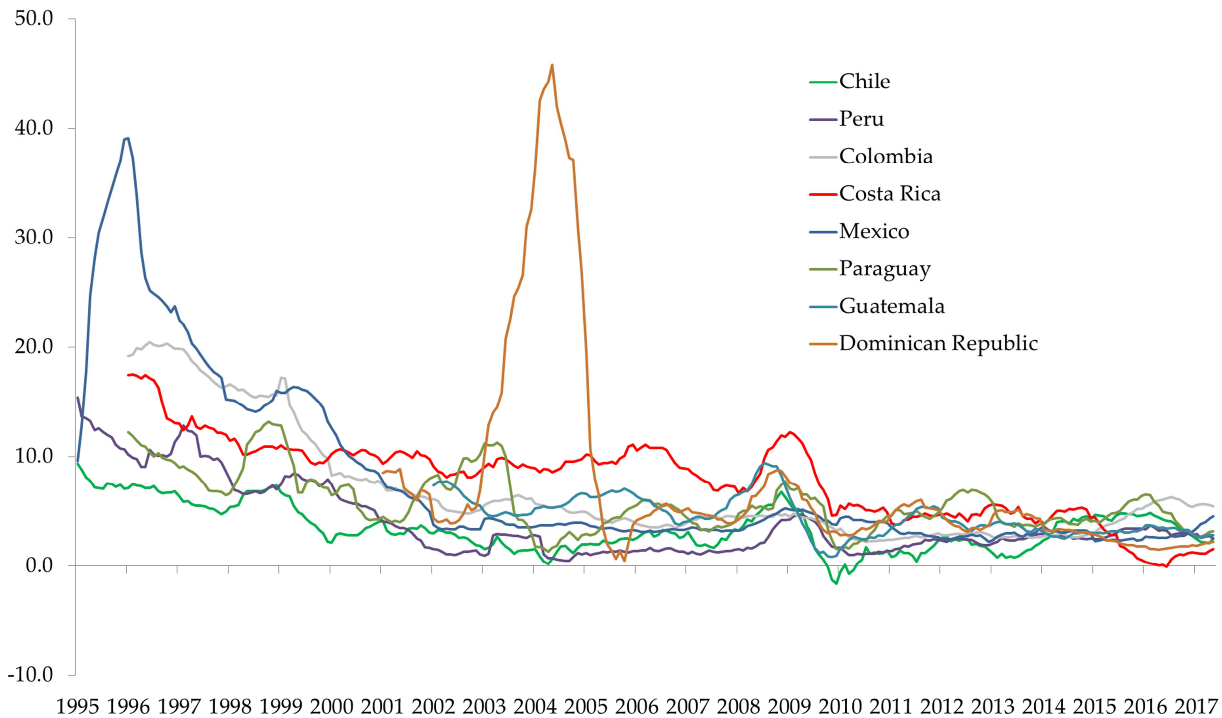
During our sample period, annual inflation rates in our countries experienced huge fluctuations. This is probably the result of changes in monetary regimes, international and domestic financial crisis, a surge and decline in commodity prices and in some cases, important natural disasters. All these issues are reflected in periods of high inflation or high inflation volatility, and in general, in an unstable time series on headline inflation, in contrast with the more stable and homogeneous inflation processes of developed countries. See Figures 1 and 2, next.

Figure 1: **Annual inflation rate in our sample of countries**



Source: OECD Main Economic Indicators and country specific central banks.

Figure 2: **Annual core inflation rate in our sample of countries**



Source: OECD Main Economic Indicators and country specific central banks.

Figures 1 and 2 show some noteworthy figures for Mexico at the beginning of our sample period and also for Dominican Republic around 2003. These figures are explained by the aftershocks of the "Tequila Crisis" in 1994-1995 and by the deep domestic financial crisis experienced by Dominican Republic in 2003.

At first glance, Figures 1 and 2 look extremely similar. This is in part because annual core and headline inflation rates are similar, but also because of the scale of the graphs. The differences between core and headline are maybe better illustrated in Table 1, which shows descriptive statistics of the series. We have also included 4 developed countries for comparison (Austria, US, UK and Switzerland).

Table 1 shows that traditional dispersion measures are quite different between headline and core. It also shows a huge difference between inflation in our sample of developing countries and the 4 developed countries we use for comparison. For instance, the highest entry for inflation in developed countries is 5.4 (US), whereas for our set of developing countries is 50.3 (Dominican Republic). It is also interesting to look at standard deviations. The highest standard deviation for headline inflation is 1.2 in our set of developed countries, whereas the lowest figure in our sample of developing countries is 2.3. Differences between the developed and developing world are striking.

Table 1: **Descriptive statistics**

	Annual Inflation				Annual Core Inflation			
	Mean	Maximum	Minimum	Standard Deviation	Mean	Maximum	Minimum	Standard Deviation
Chile	*3.8*	*9.4*	*-3.4*	*2.3*	*2.5*	*6.8*	*-1.6*	*1.5*
Mexico	*8.3*	*41.8*	*2.1*	*8.4*	*3.4*	*5.2*	*2.2*	*0.7*
Peru	*3.9*	*12.9*	*-1.1*	*2.9*	*2.1*	*4.7*	*0.5*	*0.9*
Colombia	*7.6*	*19.8*	*1.7*	*5.3*	*4.1*	*6.5*	*2.2*	*1.2*
Costa Rica	*8.9*	*22.3*	*-1.2*	*4.9*	*6.5*	*12.2*	*-0.1*	*3.2*
Paraguay	*7.0*	*19.1*	*0.9*	*3.7*	*4.9*	*11.3*	*1.3*	*2.1*
Guatemala	*6.3*	*14.2*	*-0.7*	*2.8*	*4.5*	*9.4*	*0.8*	*1.8*
Dominican Republic	*8.1*	*50.3*	*-1.6*	*9.1*	*7.5*	*45.8*	*0.5*	*9.7*
Austria	*1.8*	*3.8*	*-0.3*	*0.8*	*1.7*	*2.8*	*0.2*	*0.5*
United Kingdom	*2.0*	*5.0*	*-0.2*	*1.0*	*1.7*	*3.6*	*0.7*	*0.6*
United States	*2.2*	*5.4*	*-2.1*	*1.2*	*1.9*	*2.9*	*0.6*	*0.4*
Switzerland	*0.5*	*3.0*	*-1.5*	*0.9*	*0.3*	*1.6*	*-1.1*	*0.7*

Source: OECD Main Economic Indicators and country specific central banks.

After recording the highest inflation in the world in the 1980s, all countries analyzed in this paper implemented a substantial departure from past policies starting in 1990. In the 1980s the average inflation rate peaked above 200 percent a year in Latin-American (85% for the selected countries excluding Peru and 29% including Peru). In contrast, now most Latin American economies maintain low, single-digit inflation rates, closer to industrial-country levels. Price stabilization has been achieved in the region under different monetary and exchange regimes, ranging from exchange-rate-based stabilization and dollarization, to inflation targeting in combination with floating exchange rates. In fact, Latin America's recent experience strongly confirms the two-corner hypothesis regarding the choice of monetary and exchanges rate regimes. Most countries strengthen their national currencies by adopting inflation targeting combined with a float, while some economies are giving up monetary policy and national currencies by evolving toward dollarization. For a country specific description of the recent historical developments in the monetary policy of our sample of economies please see Table B1 in appendix B.

One of the striking figures we observe across developing countries is the high share of food on the CPI basket (Table B1 in appendix B). Compared to the US or the UK, where the share of food is below 10 percent, in the selected developing economies the lowest share corresponds to Mexico with 18.7 percent. The highest corresponds to Paraguay, above 30 percent. Consequently, the share of core inflation on CPI is above 80 percent in these developed economies and between 61 and 73 percent in our developing economies. This is another possible explanation behind the high fluctuations in annual inflations depicted in Figure 1.

Tables A1 and A2 in appendix A show results of standard unit root tests applied to annual headline inflation, annual core inflation and their first differences. Results are mixed for π_t and π_t^{core}. Depending on the specific test and country, the null hypothesis of a unit root may be rejected or not. On the contrary, this null hypothesis is rejected almost without exception for the variables in first differences. This argument, in addition to our visual inspection of the series, makes us to consider models in differences for our variables. In particular, the bootstrap algorithm we use to construct critical values for our out-of-sample test is based on a model for annual inflation and annual core inflation rate in first differences. Figure 3 shows that annual inflation rates in first differences do not show evident trends in the data.

Figure 3: **First difference of annual inflation rate in our sample of countries**

Source: OECD Main Economic Indicators and country specific central banks.

III. Econometric Setup

Our approach considers the comparison of forecasts coming from two nested models:

$$\pi_{t+h} - \pi_t = \alpha^{(h)} + \sum_{i=0}^{p_h} \gamma_i^{(h)} [\pi_{t-i} - \pi_{t-h-i}] + \varepsilon_{t+h}^{(h)} \quad \text{(Model 1)}$$

$$\pi_{t+h} - \pi_t = \alpha^{(h)} + \sum_{i=0}^{p_h} \gamma_i^{(h)} [\pi_{t-i} - \pi_{t-h-i}] + \sum_{i=0}^{q_h} \beta_i^{(h)} [\pi_{t-i}^{core} - \pi_{t-h-i}^{core}] + \varepsilon_{t+h}^{(h)} \quad \text{(Model 2)}$$

Here $\{\varepsilon_t\}$ represents a white noise process, $h \in \{1, 6, 12, 24\}$ represents the forecasting horizon, whereas p_h and q_h represent the maximum lag length of $[\pi_{t-i} - \pi_{t-h-i}]$ and $[\pi_{t-i}^{core} - \pi_{t-h-i}^{core}]$ respectively. Both p_h and q_h are selected automatically using BIC. We allow these two lag lengths to differ, but in the same range of 0 to 12. We first select $p_h = p_{h0}$ in Model 1, and use the same lag order for p_h in Model 2. Once p_h is set to p_{h0} in Model 2, we select the parameter q_h. With this strategy, we make sure that Model 1 is nested in Model 2.

Models 1 and 2 are estimated via OLS. When reporting in sample results, the t-statistics associated with each parameter in our models are constructed using HAC standard errors according to Newey and West (1987) with automatic selection of the lag length according to Newey and West (1994) when h=1, and setting the lag length to 1.5*h whenever h>1.

From Models 1 and 2 we construct forecasts for $\pi_{t+h} - \pi_t$ using the *direct* method that is traditionally used in the literature, see for instance Matheson (2006). This is in opposition to the *iterated* method of generating a multistep forecast. In this method, a single set of regression estimates is used to generate forecasts for all horizons. Despite the lack of clear superiority of one method over another, a great majority of the forecasting literature has focused on the direct method. In particular, Clark and McCracken (2005) derive the asymptotic distribution of tests of equal forecast accuracy and encompassing in nested environments, when applied to direct multistep ahead forecasts. They also show that the construction of critical values for the tests based on a simple parametric bootstrap works well. It is in light of all this literature that we focus on the direct method. We acknowledge, however, that it would be interesting to explore whether our results still stand when using the iterative rather than the direct approach. We leave this question for further research.

IV. Out-of-Sample Predictive Evaluation Strategy

Our evaluation strategy considers the comparison of two sets of forecasts coming from the nested models 1 and 2.

To describe the out-of-sample exercise, let us assume that we have a total of T+1 observations on headline inflation (π_t) for a given country. We generate a sequence of P(h) h-step-ahead forecasts estimating the models in rolling windows of fixed size R. For instance, to generate the first h-step-ahead forecasts using rolling windows, we estimate our models with the first R observations of our sample. Then, these forecasts are built with information available only at time R and are compared to observation π_{R+h}. Next, we estimate our models with the second rolling window of size R that includes observations through R+1. These h-step-ahead forecasts are compared to observation π_{R+h+1}. We iterate until the last forecasts are built using the last R available observations for estimation. These forecasts are compared to observation π_{T+1}.

Out-of-sample analyses are usually carried out using either rolling windows, recursive windows or both[3]. When recursive or expanding windows are used, the only difference with the procedure described in previous lines relies on the size of the estimation window. In the recursive scheme, this size grows with the number of available observations for estimation. Our preference for rolling over recursive windows in this application obeys to the heterogeneous pattern of the data. The use of rolling windows is usually considered more adequate to deal with potential model instabilities that seem to be very likely in our case. Anyway, as we will see next, our approach in practice means that a rolling strategy is used for Chile, Mexico, Peru, Colombia, Costa Rica and Paraguay. For Dominican Republic and Guatemala, our approach is more similar to a recursive strategy due to data limitations.

Being more specific, our first estimation window spans the period January 1995 to November 2009. This means that the size of the initial rolling window includes 179 observations for Chile, Mexico and Peru, 167 for Colombia, Costa Rica and Paraguay, 107 for Dominican Republic and 95 for Guatemala. In the case of Chile, Mexico and Peru, all the rolling windows that we use in our analysis contain the exact same number of observations: 179. For the rest of the countries, the size of their rolling windows goes through two phases: first, it mimics a recursive window by adding one observation at the time until it reaches 179 observations. From then on, they remain like usual rolling windows of fixed size. In practice this means that Colombia, Costa Rica and Paraguay experience a small increase in the first 12 rolling windows. For Guatemala and Dominican Republic, however, this means that most rolling windows experience and increment in their size, which make them fairly similar to a recursive strategy.

[3] Recursive windows are also called expanding windows in some papers.

We generate a total of P(h) forecasts, with P(h) satisfying

$$P(h)=T-h-R+2$$

In practice this means that for all our countries we build the exact same number of forecasts: 90 one-step-ahead forecasts, 85 six-step-ahead-forecasts, 79 twelve-step-ahead forecasts and 67 twenty four-step-ahead forecasts.

Forecast accuracy is measured in terms of Root Mean Squared Prediction Errors (RMSPE). Because this is a population moment, we estimate it using the following sample analog:

$$\mathrm{SRMSPE} = \sqrt{\frac{1}{P(h)} \sum_{t=R}^{T-h+1} \left(\pi_{t+h} - \hat{\pi}_{t+h|t}\right)^2}$$

where SRMSPE stands for "Sample Root Mean Squared Prediction Error" and $\hat{\pi}_{t+h|t}$ represents the forecast of π_{t+h} made with information known up until time t.

We carry out inference about predictive ability by comparing the predictive performance of forecasts coming from the models 1 and 2 defined in the previous section. We use a t-statistic commonly used to evaluate predictability in nested models. This statistic is known at least for three different "names". It is equally called ENC-t in Clark and McCracken (2005), MSPE-Adjusted in Clark and West (2006, 2007) or simply CW statistic[4].

The null hypothesis under evaluation is that all the coefficients associated to core inflation in model 2 are zero:

$$H_0: \beta_0^{(h)} = \beta_1^{(h)} = \beta_2^{(h)} = \cdots = \beta_q^{(h)} = 0$$

The core statistic of the CW test is constructed as follows. Let

$$\hat{z}_{t+h} = \left(\hat{e}_{1,t+h|t}\right)^2 - \left[\left(\hat{e}_{2,t+h|t}\right)^2 - \left(\hat{\pi}_{1,t+h|t} - \hat{\pi}_{2,t+h|t}\right)^2\right]$$

where $\hat{\pi}_{1,t+h|t}$ and $\hat{\pi}_{2,t+h|t}$ denote the h-step ahead forecasts generated from the two models under consideration. Model 1 is the parsimonious or "small" model that is nested in the larger model 2. In other words, model 2 would become model 1 if some of its parameters would be set

[4] We notice that the core statistic of the CW test is the same as the core statistic of the encompassing test proposed by Harvey, Leybourne, and Newbold, (1998). This implies that the CW test is also evaluating whether a particular combination between the null and alternative model generates a forecasting strategy with the lowest RMSPE. The novelty of CW compared to Harvey, Leybourne, and Newbold (1998) relies on the interpretation of the test as a method to evaluate the difference in population MSPE between two nested models, and on the fact that CW explicitly consider the role of parameter uncertainty.

to zero. Similarly, $\hat{e}_{1,t+h|t} = \pi_{t+h} - \hat{\pi}_{1,t+h|t}$ and $\hat{e}_{2,t+h|t} = \pi_{t+h} - \hat{\pi}_{2,t+h|t}$ represent the corresponding forecast errors. With some little algebra it is straightforward to show that $\hat{z}_{t+h}$ could also be expressed as follows:

$$MSPE - Adjusted = (2/P(h)) \sum_{t=R}^{T+1-h} \hat{e}_{1,t+h|t}\left(\hat{e}_{1,t+h|t} - \hat{e}_{2,t+h|t}\right)$$

The CW statistic is built as a t-statistic using a consistent estimate of the long-run variance of

$$z_{t+h} = \left(e_{1,t+h|t}\right)^2 - \left[\left(e_{2,t+h|t}\right)^2 - \left(\pi_{1,t+h|t} - \pi_{2,t+h|t}\right)^2\right]$$

Where z_{t+h} is the population counterpart of $\hat{z}_{t+h}$.

Clark and McCracken (2001, 2005) show that the asymptotic distribution of the CW test is, in general, not standard. In these papers the correct asymptotic distribution of the CW test is derived when one-step-ahead forecasts are used (Clark and McCracken, 2001) and when longer horizon forecasts are constructed via the direct method (Clark and McCracken, 2005). In the first paper the authors show that the resulting asymptotic distribution of the CW test in general is a functional of Brownian motions depending on the number of excess parameters of the nesting model, the limit of the ratio P(h)/R and the scheme used to update the estimates of the parameters in the out-of-sample exercise. In the second paper Clark and McCracken (2005) provide a generalization of their results for multistep ahead forecasts. Unfortunately, the resulting asymptotic distribution of the CW statistic is again a functional of Brownian motions but now depending on nuisance parameters. While Clark and West (2007) show that normal critical values perform decently well when comparing one-step-ahead forecasts, the same work of Clark and McCracken (2005) shows that when comparing multi-step-ahead forecasts using the direct method, normal critical values are inadequate as they tend to produce important size distortions as the forecasting horizon increases[5]. They show, however, that a simple parametric bootstrap generates adequate critical values. Consequently, for the construction of our critical values, we basically use the same bootstrap used by Clark and McCracken (2005). We describe our bootstrap next:

First we estimate the following two equations using the full sample of data for each of our 8 countries:

$$(1) \quad \pi_{t+1} - \pi_t = \alpha + \sum_{i=0}^{p} \gamma_i [\pi_{t-i} - \pi_{t-1-i}] + \varepsilon_{t+1}$$

[5] The test becomes increasingly oversized with the forecasting horizon. This means that at longer horizons the correct critical values are bigger than standard normal ones. In contrast, the work of Clark and McCracken (2001) shows that for one-step-ahead forecasts, correct critical values are, in general, lower than standard normal ones.

$$(2)\quad \pi_{t+1}^{core} - \pi_t^{core} = \alpha^{(core)} + \sum_{i=0}^{p_{core}} \gamma_i^{(core)}[\pi_{t-i} - \pi_{t-1-i}] + \sum_{i=0}^{q_{core}} \beta_i^{(core)}[\pi_{t-i}^{core} - \pi_{t-1-i}^{core}] + \varepsilon_{t+1}^{(core)}$$

We notice that expression (1) corresponds to a version of Model 1 designed to build one-step-ahead forecasts. This is important, because the null of no predictive ability from core to headline is present here.

Expressions (1) and (2) are estimated by OLS using the full sample of data selecting the parameters p, p_{core} and q_{core} by BIC with a maximum of 12 possible lags. The residuals are therefore stored for sampling. We notice that, differing from Clark and McCracken (2005) and Kilian (1998) we do not adjust our estimates for potential small sample bias.

We generate bootstrapped time series on π_t and π_t^{core} by drawing with replacement from the previously stored sample residuals and using the autoregressive structures of the models to build our pseudo data in an iterative way. The initial observations are selected by picking one date at random and then taking the necessary number of lags from that date backwards.

We construct 5000 bootstrap replications of the pseudo time series for inflation and core inflation. The length of the pseudo series is the same as in our actual data: 269 for pseudo data on Chile, Mexico and Peru, 257 for pseudo data on Colombia, Costa Rica and Paraguay, 197 for pseudo data on Dominican Republic and 185 for pseudo data on Guatemala. Our bootstrapped series are used to carry out a full out-of-sample exercise and therefore to end up with one pseudo observation of the CW t-statistic under the null hypothesis. We sort the 5000 pseudo observations of the CW t-statistic and construct 10%, 5% and 1% critical values as the corresponding percentiles of the bootstrapped distribution of the CW statistic.

V. Empirical Results

In-sample analysis

Tables 2-3 show results of our in-sample exercises. In particular, Table 2 shows one-step-ahead in-sample estimates and diagnostic statistics of Model 2. To save space, we do not report results for the parameters $\alpha^{(1)}$and $\gamma_i^{(1)}$, i=0,…,p_1. Instead, we focus on the parameters directly associated to core inflation ($\beta_i^{(1)}$, i=0,…,q_1). In the first panel of Table 2 we show the estimates of the q_1+1 coefficients $\beta_i^{(1)}$, i=0,…,q_1. In the second panel we show diagnostic statistics. In particular we observe that the Durbin-Watson statistic is close to 2 in all our countries, which is satisfactory. Similarly, the F-test, in all cases, indicates that variables in the model are jointly statistically significant at tight significance levels.

Table 3 is more specific. It shows, for every forecasting horizon h=1,6,12 and 24, results of the Wald test for the following joint null hypothesis

$$H_0: \beta_0^{(h)} = \beta_1^{(h)} = \beta_2^{(h)} = \cdots = \beta_q^{(h)} = 0$$

Table 3 also reports the degrees of freedom of the Wald test statistic under the null hypothesis (*df*). Results in Table 3 are impressive. The null of no predictability from core to headline is rejected in 6 out of 8 countries at the 10% significance level. The exceptions being Colombia and Peru. We notice, however, that when h=12, the Wald statistic for Colombia has a p-value of 0.11. In other words, for Colombia the null hypothesis is rejected at the 12% significance level, which is "borderline significant"[6]. Similarly, we also find evidence of predictability at the 5% significance level for the same 6 countries, sometimes at different forecasting horizons. Furthermore, for Dominican Republic, Guatemala, Mexico and Paraguay we find evidence of a predictive relationship between core and headline, at the 1% significance level.

Table 2: **In-Sample Analysis**

Dep. Var.: d(pi)	Chile	Colombia	Costa Rica	Dominican Republic	Guatemala	Mexico	Paraguay	Peru
d(core(-1))	*-0.19***	*-0.090*	*0.15*	*0.40****	*0.43***	*0.37****	*0.44****	*0.07*
	-0.08	*(0.08)*	*(0.11)*	*(0.14)*	*(0.17)*	*(0.12)*	*(0.13)*	*(0.08)*
d(core(-2))				*-0.19*				
				(0.14)				
d(core(-3))				*0.37****				
				(0.14)				
d(core(-4))				*-0.47****				
				(0.13)				
d(core(-5))				*0.50****				
				(0.16)				
d(core(-6))				*-0.29****				
				(0.11)				
R-squared	0.43	0.34	0.30	0.46	0.30	0.60	0.41	0.34
N	256	254	244	190	183	256	244	256

[6] We use the expression "borderline significant" to denote a situation in which the null hypothesis is rejected at the x% significant level, x% being slightly greater than 10%. Colombia for h=12 and Paraguay for h=6 are the only two entries in Table 3 in this situation.

Durbin-Watson	1.99	1.98	1.90	2.04	2.02	1.92	1.79	1.83
F-statistic	13.89	42.16	7.48	22.49	37.76	27.85	12.41	9.48
P-value	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*
Schwarz criterion	1.20	0.72	1.86	3.71	1.63	1.12	3.08	1.02

Notes: * p<10%, ** p<5%, *** p<1%. HAC standard errors according to Newey & West (1987, 1994) in parentheses. The operator d() refers to the first difference of the respective variable. Estimates correspond to the "beta" parameters of Model 2 in page 9, when h=1.

Table 3 : In-Sample Wald Tests

	forecasting horizon in months			
Country	*h*=1	*h*=6	*h*=12	*h*=24
Chile	**5.31****	**3.50***	**2.87***	**4.74****
df	1	1	1	1
Colombia	1.19	8.50	**2.54†**	2.27
df	1	5	1	1
Costa Rica	1.73	**4.90****	1.95	0.60
df	1	1	1	1
Dominican Republic	**37.66*****	**9.49*****	**17.07*****	0.61
df	6	2	2	1
Guatemala	**6.40*****	**6.64****	**10.61*****	0.12
df	1	2	2	1
Mexico	**10.00*****	**33.90*****	1.52	**3.85****
df	1	7	1	1
Paraguay	**11.61*****	**4.39†**	0.08	0.18
df	1	2	1	1
Peru	0.79	0.37	0.74	0.00
df	1	1	1	1

Notes: * p<10%, ** p<5%, *** p<1%. Wald test constructed using HAC standard errors according to Newey & West (1987, 1994). The test statistic evaluates the null that all "beta" coefficients in Model 2 are zero, when h=1. The acronym *df* stands for degrees of freedom.

The evidence in favor of predictability from core to headline is slightly inclined toward the short run (1 and 6 months), horizons for which we find evidence for 6 out of 8 countries. At longer horizons of 12 and 24 months, this number of countries goes down a bit to 4 or 5 if we are generous and include the borderline case of Colombia when h=12.

All in all, our in-sample estimates provide evidence of a predictive relationship between core and headline inflation for at least 6 out of 8 countries. In-sample estimates, however, are usually criticized because they are relatively different from a real time forecasting exercise and also because they are prone to overfitting. To mitigate these shortcomings, we take the usual steps in the forecasting literature and move to an out-of-sample analysis.

Out-of-sample analysis

Table 4-5 show results of our out-of-sample exercises. Interestingly Table 4 shows evidence of predictability, at the 10% significance level, for the great majority of the countries in our sample. The exceptions are Costa Rica and Peru. Nevertheless, when h=6 the p-value of the CW-statistic for Peru is 0.1096, so, it is "borderline significant". Furthermore, we also find evidence of predictability at the 5% significance level for five countries: Chile, Colombia, Dominican Republic, Mexico and Paraguay.

Differing from our in-sample results, now the bulk of the evidence in favor of predictability from core to headline concentrates at the short horizons of 1 and 6 months (h=1,6). Leaving aside the case of Costa Rica, we find evidence of predictability at short horizons for all the countries if we allow in this group the borderline case of Peru. In contrast, at longer horizons of 12 and 24 months, we only find evidence of predictability for two countries: Chile and Colombia.

Despite this greater emphasis on short-run predictability, out-of-sample and in-sample results are roughly consistent, with slightly stronger evidence coming from the in-sample analysis. This is both reassuring and consistent with a large literature either reporting more rejections of the null of no predictability with in-sample versus out-of-sample analyses, or providing tests and possible explanations for these differences. See for instance, Clark and McCracken (2006, 2012), Inoue and Kilian (2004), Clark (2004) and Giacomini and Rossi (2009) just to mention a few[7].

The CW test focuses on predictability at the population level. It either rejects the null of equal population forecasting ability or not. In case of a rejection of the null, it would be important to gauge the gains in RMSPE stemming from the inclusion of core inflation. A lower RMSPE at the population level, however, may not be reflected at the sample level due to noisy estimates of the population parameters. Nevertheless, in our application we see that every time the CW test rejects the null, the sample RMSPE of Model 2 is smaller or equal than the sample RMSPE of model 1. Table 5 shows the ratio of RMSPE at the sample level, between models with and without the contribution of core inflation. Figures lower than 1 favor the model with core inflation. Consistent with our results at the population level, Table 5 shows that for every

[7] We are not unique in the finding of modest discrepancies between in-sample and out-of-sample results. See, for instance, Rapach and Wohar (2006).

country in our sample, with the exception of Costa Rica, there is at least one forecasting horizon with an entry lower than 1. Gains in RMSPE are more frequent at short horizons. The highest gain is achieved when h=6 for Dominican Republic, which shows an outstanding ratio of 0.68. Other than that, whenever we find gains at the sample level, they are either small or moderate in a range of 0.91 and 0.99.

Overall, our out-of-sample results are relatively consistent but slightly stronger than those reported by Pincheira, Selaive and Nolazco (2016), who basically analyze the same question that we address here, but with a different methodology and with a focus on developed countries. They say "*Our out-of-sample results indicate that core inflation does have the ability to predict headline inflation in about two thirds of our countries. This share of countries reduces to 40% when predictability is analyzed at policy relevant forecasting horizons. Furthermore, this predictive ability is sizable only for less than 30% of the countries in our sample*" Pincheira, Selaive and Nolazco (2016, page 21). Even without considering the borderline case of Peru, we could rephrase that sentence with a slightly stronger emphasis on predictability as follows: Our out-of-sample results indicate that core inflation does have the ability to predict headline inflation in three quarters of our countries. This share reduces to 50% when predictability is analyzed at policy relevant forecasting horizons. Similarly, this predictive ability is sizable in 50% of the countries in our sample[8].

Despite our results in favor of the ability of core measures to predict headline, it is a little intriguing that most of the out-of-sample predictability is found at short horizons. This might not be very useful for the implementation of monetary policy, for instance, as the common wisdom claims that monetary policy has little impact on the very short run. In fact, most inflation targeting countries define a relatively long "monetary policy horizon" within which it is expected that central banks may have the ability to anchor expectations and keep inflation under control. One possible explanation is to blame out-of-sample tests of predictive ability for having low power at long horizons. In fact, simulations completed by Clark and McCracken (2005) and Pincheira and West (2016), show a decreasing pattern in power with the forecasting horizon, although most of their DGPs are based on stationary VARs that naturally show a decreasing pattern of population predictability when the forecasting horizon goes to infinity. This is a plausible explanation that we cannot rule out, nevertheless, it is also possible that the economic content of core inflation may not be useful in the long run for some countries.

[8] By sizable, Pincheira, Selaive and Nolazco (2016) mean a RMSPE ratio of 0.95 or lower favoring the forecasts built with core inflation.

Table 4: **Clark –West Test: Forecasting headline inflation with core measures**

Country	*forecasting horizon in months* h=1	h=6	h=12	h=24
Chile	**1.45***	**1.70***	0.44	**4.64****
Colombia	-1.18	-0.48	**2.07****	2.06
Costa Rica	-0.95	-0.46	-0.87	-0.37
Dominican Republic	**2.00****	**2.00***	-0.89	-1.00
Guatemala	**1.15***	1.27	0.95	2.12
Mexico	**2.41****	**2.02***	0.59	0.93
Paraguay	**2.80*****	-0.02	-1.39	0.09
Peru	-0.10	**1.5†**	-0.69	-0.64

Notes: * p<10%, ** p<5%, *** p<1%. CW statistic constructed using HAC standard errors. Critical values come from a parametric bootstrap. The test statistic evaluates the null that all "beta" coefficients in Model 2 are zero.

Table 5: **Ratio of Root Mean Squared Prediction Errors between models 1 and 2. Figures below 1 favors forecasts built with core measures**

Country	*forecasting horizon in months* h=1	h=6	h=12	h=24
Chile	**0.99**	**0.93**	1.00	**0.91**
Colombia	1.01	1.02	**0.98**	**0.94**
Costa Rica	1.02	1.21	1.29	1.10
Dominican Republic	**0.94**	**0.68**	1.14	1.25
Guatemala	1.00	1.00	1.04	**0.93**
Mexico	**0.96**	**0.99**	1.01	1.12
Paraguay	**0.97**	1.01	1.20	1.20
Peru	1.00	**0.98**	1.05	1.02

VI. Concluding Remarks

In this paper we use monthly CPI data for 8 developing countries from Latin America, to explore whether core inflation has some predictive power for year-on-year headline inflation. Our findings are fairly interesting, considering the fact that during our sample period (January 1995-May 2017), the countries under analysis have faced changes in monetary regimes, have endured international and domestic financial crisis, a surge and decline in commodity prices and, in some cases, important natural disasters. All these issues are reflected in periods of high inflation or high inflation volatility, and in general, in an unstable time series on headline inflation, in contrast with the more stable and homogeneous inflation processes of developed countries.

Despite the unstable features of the series, the good news are that our in-sample and out-of-sample results are roughly consistent in providing evidence of a predictive relationship between core and headline inflation in the great majority of our countries, although, as usual, a slightly stronger evidence of predictability comes from the in-sample analysis. The relatively bad news are two: First, in only 50% of our countries we find evidence of predictability at policy relevant forecasting horizons and, second, gains in forecast accuracy are sizable in only 50% of our countries.

All in all, we are impressed by our results. Let us recall that while the conventional wisdom posits that core should be a good predictor for headline inflation, there are some detractors with good arguments as those given by Bullard (2011b). Furthermore, our literature review reveals that the empirical evidence evaluating this predictive relationship is rather mixed, and mainly focused on developed countries, which are characterized by more stable inflation processes. Moreover, in the case of developing countries, we have shown that the share of core inflation in CPI is lower than in some developed economies. Similarly, the highly volatile food items have more weight in the CPI bundle of goods in lower income countries than in richer ones. These facts may be used to build arguments in opposite directions. On the one hand, core inflation may be considered less representative of headline given its lower share on the CPI. Consequently this argument may point out in the direction of lower predictive ability from core to headline. On the other hand, the greater importance of the highly volatile food component on the CPI in developing countries, suggest that by removing these items, as core does, one is removing a major source of volatility. This line of reasoning leads to suggest that core inflation may be a better tracker of overall inflation in developing countries relative to more advanced and richer economies. The presence of conflicting arguments in opposite directions requires an empirical evaluation as the one we have presented here.

Our results confirm that core is an important predictor of headline inflation for most of the countries in our sample in the short run, but also indicate that core inflation does not add much information for prediction in other countries, especially at longer horizons of one year or two. This is critical, as monetary authorities in our sample of developing countries are currently implementing or given steps toward the future implementation of inflation targeting regimes, which are heavily based on long run inflation forecasts. Here we have two avenues for future research. First, the search for potential predictors of long run inflation in developing countries must continue, and second, the behavior of traditional out-of-sample tests of predictive ability should be evaluated in their ability to detect predictability at long horizons in DGPs calibrated to match unstable features that are traditional in developing economies.

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Appendix A: Unit Roots

Table A1: Unit Root Tests for Total Inflation

	Augmented Dickey-Fuller Test				**Phillips-Perron Test**			
	Levels		*First differences*		*Levels*		*First differences*	
Levels	Without Drift	With drift	Without Drift	With drift	Without Drift	With drift	Without Drift	With drift
Chile	*-1.663*	*-2.985**	*-7.199****	*-7.208****	*-1.973**	*-3.152***	*-10.871****	*-10.867****
Colombia	*-2.775****	*-2.605**	*-4.599****	*-4.858****	*-2.376***	*-2.076*	*-8.536****	*-8.578****
Costa Rica	*-2.216***	*-1.573*	*-5.585****	*-5.843****	*-2.321***	*-2.155*	*-11.677****	*-11.581****
Dominican Republic	*-1.654**	*-2.376*	*-5.636****	*-5.626****	*-2.332***	*-2.941***	*-9.166****	*-9.184****
Guatemala	*-1.377*	*-2.483*	*-6.435****	*-6.454****	*-1.456*	*-2.864**	*-10.706****	*-10.685****
Mexico	*-2.392***	*-2.883**	*-6.161****	*-6.159****	*-1.382*	*-1.823*	*-5.339****	*-5.306****
Paraguay	*-1.485*	*-2.639**	*-6.538****	*-6.558****	*-2.097***	*-3.598****	*-12.789****	*-12.768****
Peru	*-3.151****	*-3.506****	*-5.506****	*-5.639****	*-2.643****	*-3.134***	*-11.814****	*-11.852****

* p<10%, ** p<5%, *** p<1%. The null hypothesis of both tests indicate the existence of a unit root.

Source: Own calculations based on data from OECD Main Economic Indicators and country specific central banks.

Table A2: Unit Root Tests for Core Inflation

	Augmented Dickey-Fuller Test				Phillips-Perron Test			
	Levels		*First differences*		*Levels*		*First differences*	
Levels	Without Drift	With drift	Without Drift	With drift	Without Drift	With drift	Without Drift	With drift
Chile	*-2.102***	*-2.723**	*-7.969****	*-8.021****	*-2.256***	*-3.099***	*-11.967****	*-11.976****
Colombia	*-3.697****	*-3.201***	*-5.933****	*-6.192****	*-3.386****	*-2.954***	*-12.223****	*-12.241****
Costa Rica	*-2.048***	*-2.234*	*-5.976****	*-6.103****	*-2.327***	*-1.994*	*-11.46****	*-11.592****
Dominican Republic	*-1.559*	*-2.197*	*-4.071****	*-4.060****	*-1.896**	*-2.316*	*-5.939****	*-5.924****
Mexico	*-2.319***	*-2.710**	*-4.537****	*-7.838****	*-1.358*	*-1.710*	*-5.268****	*-5.233****
Guatemala	*-1.671**	*-3.154***	*-5.834****	*-5.851****	*-1.454*	*-2.595**	*-5.816****	*-5.836****
Paraguay	*-1.494*	*-2.872**	*-5.370****	*-5.401****	*-1.882**	*-3.188***	*-8.401****	*-8.404****
Peru	*-3.235****	*-3.047***	*-6.729****	*-6.952****	*-3.671****	*-3.679****	*-12.962****	*-13.033****

* p<10%, ** p<5%, *** p<1%.

Source: Own calculations based on data from OECD Main Economic Indicators and country specific central banks.

Appendix B: Main Features of the Inflation Regimes in our Countries

Table B1: Features of Inflation in our Sample of Countries

	Share Core/CPI	Share Food/CPI	Current Inflation Targets	Paving the way to IT
Chile	72	19	Target 3% +/-1%.	Adopted in 1990. Exchange rate target from 1984 through 1999. On the road to stationary inflation, the Central Bank announced annual inflation targets in September of each year for the following calendar year, until 1998. In September 1999 the Bank announced one more annual target for 2000 and an indefinite target range of 2–4 percent starting in 2001
Colombia	65	28	Target 3% +/-1.0%	Adopted in 1999. In 1991 and 1992 the Constitution and the Central Bank Law granted goal and instrument independence to Central Bank. Abandonment of the exchange rate bands in 1999 (after the "sudden stop" of 1998-99). Between 1999 and 2004 the exchange rate regime could be characterized as a floating regime with sporadic and relatively small interventions in the FX market aimed at restoring the level of international reserves or curtailing excessive volatility.
Costa Rica	73	21	Target 3% +/-1.0%	Adopted in 2005. Monetary policy is moving towards inflation targeting but financial dollarization remains high. In 2005 BCCR's Board decided to migrate, in a gradual and orderly fashion, toward a monetary policy strategy focused on inflation targeting-a process which has not concluded yet. Costa Rica has moved from a crawling peg regime to an exchange-rate crawling band and then to a

				managed float since early 2015.
Dominican Republic	64	25	Target 4% +/-1%	In December 2011 the central bank formally adopted an inflation-targeting framework and set a target for inflation of 5½ percent (+/-1%) for 2012 and 4% by 2015. For most of the 1990s, the Dominican Republic experienced robust economic growth, declining unemployment rates, low inflation, and a generally manageable external position. In the second half of the decade, the Dominican Republic ranked among the world's fastest growing economies. Toward the end of 2002, a banking crisis emerged and became full blown in 2003, resulting in macroeconomic instability, which was characterized by a large rundown in government deposits, a significant fall in net international reserves, and a substantial depreciation in the value of the peso.
Guatemala	62	29	Target 4% +/-1%	Adopted formally in 2005. In 1996, the monetary policy stance was relaxed through the decrease in the level of Open Market Operations and the reduction of banking reserves, as a way to stimulate economic activity. Because the Central Bank was chasing two nominal objectives with only one instrument, there was an important loss of foreign exchange reserves. It is because of these reasons that, at the end of 1999, the Central Bank began to work in order to set only one nominal anchor, the control of inflation, as the main goal of monetary policy.
Mexico	73	19	Target 3% +/-1%	Adopted in 1999. In 1995 adopted monetary growth target as its nominal anchor, defined as a growth ceiling on net domestic credit. As in preceding years, the Bank established an annual inflation target of 42 percent for 1995, 20.5 percent for 1996, and 15 percent for 1997. This monetary policy framework was maintained in 1996 and 1997. In 1998, the monetary policy framework began a gradual transition toward an explicit full-fledged inflation targeting regime, reinforcing the role of the inflation target and raising policy transparency.
Paraguay	61	30	Target 4% +/-2%	Adopted in 2003. Financial dollarization deepened in the 1990s as consequence of a severe financial crisis that wiped out about half of the banking sector, making the U.S. dollar the preferred currency to minimize risks for both savers as well as lenders. After Peru, it has the higher ratio of credit and deposits dollarization in the region.
Peru	70	25	Target 2% +/-1%	Adopted in 2002. Dollarization in Peru started with the inflationary process of the mid-70s and peaked during the hyperinflation of 1988–90. As a result of this chronic inflation, the Peruvian currency, the sol, was replaced by the inti in mid-1985, which itself was replaced by the nuevo sol in July 1991. While inflation was high, the government forced the conversion of foreign currency deposits to local currency, resulting in capital flight and financial

				disintermediation. When the restriction on foreign currency deposits was lifted, re-dollarization was quick, and by the end-1990s, about 80 percent of deposits (and credit) were denominated in foreign currency. Since the introduction of IT, Peru has experience a gradual and sustained financial de-dollarization. Dollarization of credit has declined by nearly 25 percentage points during 2001–2016 to below 50 percent by 2016.
USA	85	7		
UK	83	9		

Source: Central Banks and Bureau of Statistics of each country