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New Perspectives on Forecasting Inflation in Emerging Market Economies: An Empirical Assessment*

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Abstract

We use a broad-range set of inflation models and pseudo out-of-sample forecasts to assess their predictive ability among 14 emerging market economies (EMEs) at different horizons (1 to 12 quarters ahead) with quarterly data over the period 1980Q1-2016Q4. We find, in general, that a simple arithmetic average of the current and three previous observations (the RW-AO model) consistently outperforms its standard competitors - based on the root mean squared prediction error (RMSPE) and on the accuracy in predicting the direction of change. These include conventional models based on domestic factors, existing open-economy Phillips curve-based specifications, factor-augmented models, and time-varying parameter models. Often, the RMSPE and directional accuracy gains of the RW-AO model are shown to be statistically significant. Our results are robust to forecast combinations, intercept corrections, alternative transformations of the target variable, different lag structures, and additional tests of (conditional) predictability. We argue that the RW-AO model is successful among EMEs because it is a straightforward method to downweight later data, which is a useful strategy when there are unknown structural breaks and model misspecification.

JEL codes: E31, F41, F42, F47.

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1 Introduction

Understanding what helps forecast inflation is important for any modern economy. However, systematic explorations of inflation prediction for emerging market economies (EMEs) are rather limited and generally showcase apparent discrepancies with the inflation dynamics in the U.S. and other advanced economies (Pincheira and Medel (2015), Pincheira and Gatty (2016), Mandalinci (2017)). During the last decades, EMEs have witnessed great changes in their macroeconomic dependencies—some are attributed to changes in policies (inflation-targeting), some to globalization, and some to other factors. All these changes pose a significant challenge for forecasters interested in predicting key macroeconomic variables like inflation.

The existing literature focusing on inflation forecasting for EMEs has produced few studies with only a limited cross-section and time-series dimension in some cases. Often those studies tend to cover one to three countries (Liu and Gupta (2007), Aron and Muellbauer (2012), Ögünç et al. (2013), Chen et al. (2014), Balcilar et al. (2015), Medel et al. (2016), Altug and Çakmakli (2016)), the exception being Mandalinci (2017) that covers 9 EMEs. The time coverage also tends to be limited with some of them restricted to exploring experiences during the 2000s (Pincheira and Medel (2015), Altug and Çakmakli (2016)).

This strand of the literature on inflation forecasting for EMEs mostly ignores the variant of the random walk model proposed by Atkeson and Ohanian (2001) (RW-AO, henceforth), and used by Stock and Watson (2007) and Faust and Wright (2013), among others, as an important benchmark model. Many studies use instead the naïve random walk model without good results, except for Ögünç et al. (2013) and Altug and Çakmakli (2016). However, Ögünç et al. (2013) and Altug and Çakmakli (2016) are focused on one or two countries and, in general, they do not find that the RW-AO is successful or the best model.[1] Not surprisingly, the RW-AO specification does not appear in the list of forecasting tools used by central banks around the world—many in EMEs—that use inflation targeting either (see Hammond (2012)).

Here, we show that it is difficult for a forecaster to provide value added with conventional model-based predictions beyond the simple univariate RW-AO model unless he/she incorporates subjective judgement to identify structural shifts in the data. We therefore argue that inflation among EMEs appears easier to forecast with the RW-AO model, and yet harder to interpret (in the sense that the RW-AO model does not arise from economic theory and yet its performance is quite robust in practice).

Our paper explores a broad sample of EMEs with ample cross-sectional coverage and an extensive time series encompassing a number of business cycles (going, in most cases, back to the 1980s). We study empirically the forecasting performance over a cross-section of 14 EMEs and establish that the variant of the random walk model along the lines of Atkeson and Ohanian (2001) and Faust and Wright (2013) (the RW-AO model) outperforms more complex and developed models for inflation forecasting. If we rank those models beaten by the RW-AO in terms of predictability, factor-augmented models show up at the top of the list as second-best. Based on this evidence, we argue that the RW-AO model constitutes the empirically-relevant benchmark to beat in forecasting inflation for EMEs.

This is a novel set of results that appear to challenge well-known economic-based models for inflation forecasting—even Phillips-curve-based specifications which otherwise are shown to perform well for many

[1] Ögünç et al. (2013) investigate the case of Turkey while Altug and Çakmakli (2016) explore Turkey as well as Brazil. Our country sample of EMEs does not include Brazil, but for Turkey we find the RW-AO's performance to be relatively reasonable (particularly at 4-quarter horizons). Moreover, we show that there is significant cross-country variation in the RW-AO's performance among EMEs in our sample—Turkey, in fact, does not feature as one of the countries where we uncover the stronger statistical significance in favor of the RW-AO model.

advanced economies (as seen in Duncan and Martínez-García (2015) and Kabukcuoglu and Martínez-García (2018)).

For our investigation, we focus on headline CPI inflation as our measure of inflation—as it is less subject to revisions and more timely than, for example, the GDP deflator—and run a very extensive model comparison exercise including up to 9 different specifications widely-used in the literature. We collect quarterly data on headline CPI inflation, real GDP, industrial production, and on several other indicators (bilateral exchange rates with the U.S. dollar, commodity prices) for 14 EMEs plus 18 advanced economies with consistent, reliable, and longer-coverage time series from the sources documented in Grossman et al. (2014).

The main results of our inflation forecast evaluation can be summarized as follows:

First, we establish that the RW-AO model generally outperforms a large selection of the existing inflation forecasting models. In general, the RW-AO model tends to produce a lower root mean square prediction error (RMSPE) than its competitors. The gains in smaller RMSPEs are statistically significant in a number of interesting cases, across models and countries.

Second, we also consider the performance of the forecasting models with an alternative measure of predictive success. The RW-AO model produces success ratios—assessing the ability of the forecast to correctly anticipate the direction of change in inflation—that are comparable with or higher than those of their competitors. For most countries, our findings suggest those improvements in the accuracy of the direction of change forecasted for inflation are statistically significant.

Third, we view the RW-AO specification as an important empirical benchmark for forecasting inflation across a diverse group of EMEs around the world. Among the competing models defeated by the RW-AO, factor-augmented models can be regarded as second-best options under the same metrics of predictive accuracy.

Fourth, we find that certain variables driven by foreign developments such as exchange rates and commodity prices do not seem to contribute much to predict inflation in the small open economies of our sample.

Fifth, we show that our results are mostly robust in a number of dimensions. We explore forecast combinations, intercept corrections, alternative transformations of the target variable, and different lags in the RW-AO model. Usually, the RW-AO tends to beat its competitors. A test of equal predictability across countries that takes into account cross-sectional dependence suggests that the RW-AO beats the most competitive models, particularly in the short- to medium-term.

Finally, in a comparison with subjective predictions from Consensus Forecasts™, we find that these tend to produce lower or similar RMSPEs than does the RW-AO in most of the EMEs in our sample (although the time dimension is significantly shorter than that of our baseline exercises). Potentially, this implies that the combination of subjective forecasts and inflation forecasting models can be a fruitful avenue of future research. It also suggests that professional forecasters, who are able to use their own judgment to identify structural shifts, have an advantage helping them outperform RW-AO forecasts.

In this paper we also provide a discussion of the implications of our findings for inflation modeling and forecasting. Atkeson and Ohanian (2001), among others, have argued that the empirical evidence on the validity of Phillips curve-based models is weak for forecasting U.S. inflation. Atkeson and Ohanian (2001) show that during the Great Moderation period Phillips curve-based models often underperform naïve models (in particular, the RW-AO model based on past realizations of inflation alone). The more recent literature, in turn, casts the Phillips curve and its predictions on a more positive light among advanced economies—e.g. Ball and Mazumder (2014) and Coibion and Gorodnichenko (2015) considering the role of (anchored) inflation expectations, and Duncan and Martínez-García (2015) and Kabukcuoglu and Martínez-García (2018) exploring the open-economy dimension of Phillips-curve-based models.

We take a somewhat more sanguine view of the forecasting evidence than Atkeson and Ohanian (2001), particularly as it relates to the experiences of many EMEs. We recognize the potential misspecification of conventional Phillips-curve-based specifications in a world that has become increasingly more integrated—through trade in goods, capital, labor, information, among others. We suggest however that even richer specifications incorporating the open-economy dimension may underperform among EMEs due to unmodelled parameter instability and ancillary assumptions that are violated in the data.

We note that time-variation in the parameters (in particular, on the central bank's inflation target) can partly account for the varied experiences of a number of EMEs. We also propose that monetary policy credibility and the formation of expectations can play a role as well. Allowing processes for the formation of expectations that are not fully rational and policy frameworks where the inflation target is not fully credible—as it seems plausible in the case of a number of EMEs in our dataset—may go a long way to explain the limited forecasting success among EMEs of conventional model-based specifications when compared with the simpler RW-AO model.

Finally, we argue that the success of the RW-AO in practice arises also from the difficulties of modeling all the relevant features of the economy and tracking all relevant changes and structural breaks over time. Our findings, in fact, illustrate that simpler adaptive forecasting strategies like the RW-AO model can be preferable because they are robust to many different forms of misspecification and unmodelled structural breaks (Giraitis et al. (2013)). We show that forecasting by averaging or appropriately downweighting past data as we do with the RW-AO model, without engaging in further modeling, appears to be a viable strategy for predicting inflation among EMEs. Moreover, this break-robust strategy can provide a general approach for handling trends of any nature: stochastic, linear or nonlinear deterministic trends, and structural breaks without knowledge of the nature of the trend. This strategy applies whether the series is stationary or non-stationary. For all those reasons, we view the RW-AO model as the empirically-relevant benchmark to beat in modeling inflation for forecasting among EMEs.

The rest of the paper proceeds as follows. In Section 2, we report the key forecasting models and describe our pseudo-out-of-sample forecasting strategy. In Section 3, we present and discuss the main results and robustness checks comparing our preferred model specification against a broad range of current models for inflation forecasting. Section 4 provides a discussion of the implications of our main findings and the recommendations we draw from our forecasting exercise. Section 5 concludes with some final remarks. The Appendix provides all the relevant tables and figures as well as details on the open-economy New Keynesian model that we use to frame our discussion.

2 Models and Forecast Evaluation

Our sample consists of seasonally-adjusted, average-quarterly series for 14 EMEs (Chile, China, Colombia, Hungary, Indonesia, India, Malaysia, Mexico, Nigeria, Peru, Philippines, South Africa, Thailand, and Turkey) over the 1980Q1-2016Q4 period. We also include a sample of 18 advanced economies obtained from the dataset of Grossman et al. (2014) in order to estimate static factors and use them to forecast domestic inflation in each EME. We focus on headline Consumer Price Index (CPI) as measured by the quarter-over-quarter inflation rate (π_t). For every country and quarter t in our sample we construct:

$$\pi_t \equiv 100\left[\left(\frac{CPI_t}{CPI_{t-1}}\right)^4 - 1\right]. \tag{1}$$

Table 1.A reports the data sources for the different forecasting models. Further details on the variables used in each model are included in the next subsection below. Table 1.B provides descriptive statistics for the main variable of interest, π_t, for the EMEs considered in our paper. Across time, the majority of these EMEs have experienced significant falls in both the level and volatility of inflation. However, Table 1.B suggests that there are also significant differences across countries—reflecting policy shifts (most EMEs adopted inflation-targeting during this period) and structural differences, as well as the timing and composition of shocks.

We follow Faust and Wright (2013) and evaluate directly a number of models usually suggested by the literature on inflation forecasting in advanced and developing economies. Aside from univariate specifications and frequentist techniques, we consider other elements and methods that have proved to be useful in inflation forecasting, such as factor components (Stock and Watson (2002), Ciccarelli and Mojon (2010)), standard Phillips-curve-type specifications (Stock and Watson (1999), Stock and Watson (2007)), Phillips-curve-type open-economy specifications using the real exchange rate (Kabukcuoglu and Martínez-García (2016)), commodity price indexes (Chen et al. (2014)), Bayesian VARs (Doan et al. (1984), Litterman (1986)), and time-varying coefficient models (Primiceri (2005), Mandalinci (2017)).

Random Walk (RW-AO). We consider a variant of the random walk model along the lines of Atkeson and Ohanian (2001) and Faust and Wright (2013) as our benchmark model:[2]

$$M_0: \quad \pi_{t+h} = \frac{1}{4}\sum\nolimits_{i=1}^{4} \pi_{t+1-i} + \epsilon_{t+h}$$

The set of competing models is the following:

1. **Recursive autoregression, AR(p) model (RAR)** (M_1).

   $$M_1: \quad \pi_{t+h} = \phi_0 + \Phi\left(L\right)\pi_t + \epsilon_{t+h}$$

   where $\Phi(L) = \phi_1 L + ... + \phi_p L^p$ and we set $p = 2$ in this lag polynomial.

2. **Direct forecast, AR(2) model (DAR)** (M_2).

   $$M_2: \quad \pi_{t+h} = \phi_{0,h} + \Phi\left(L,h\right)\pi_t + \epsilon_{t+h}$$

   where h denotes the forecast horizon, $\Phi(L,h) = \phi_{1,h} + \phi_{2,h} L + ... + \phi_{p,h} L^{p-1}$, and we set $p = 2$ in the lag polynomial for a given horizon h.

3. **Direct forecast, AR(4) model (DAR4)** (M_3).

   $$M_3: \quad \pi_{t+h} = \phi_{0,h} + \Phi\left(L,h\right)\pi_t + \epsilon_{t+h}$$

[2] We describe here our forecasting equations (not exactly the forecasting models), so we interpret ϵ_{t+h} as a (population) forecast error.

as before but we set $p = 4$ in the lag polynomial for a given horizon h.

4. **Factor-Augmented AR(p) model (FAR)** (M_4).

$$M_4: \quad \pi_{t+h} = \phi_{0,h} + \Phi(L,h)\,\pi_t + \Theta(L,h)\,\widehat{F}_t + \epsilon_{t+h}$$

where $\widehat{F}_t$ denotes an estimated static factor component of the inflation rates of the countries in the full sample (the static factor is computed using data for the 14 EMEs investigated here plus 18 advanced economies).

5. **Augmented Phillips Curve (APC)** (M_5).

$$M_5: \quad \pi_{t+h} = \phi_{0,h} + \Phi(L,h)\,\pi_t + A(L,h)\,y_t + B(L,h)\,e_t + C(L,h)\,p_t^c + \epsilon_{t+h}$$

where y_t, e_t, and p_t^c denote the percent change in the industrial production index, the real exchange rate, and the commodity price index, respectively.[3] The commodity price index is the simple average of the price indexes of agricultural raw materials, beverages, food, metals, and crude oil produced by the International Monetary Fund (IMF).

6. **Bivariate BVAR (BVAR2)** (M_6). Let $X_t = \left(\pi_t, \widehat{F}_t\right)'$, then the VAR model can be written as

$$M_6: \quad X_{t+h} = \Phi_{0,h} + \Phi(L,h)\,X_t + \epsilon_{t+h}$$

where $\Phi_{0,h}$ is a vector of parameters, and $\Phi(L,h)$ denotes in this case a matrix of lag polynomials that depends on h. Following Sims and Zha (1998), the VAR is estimated using Minnesota priors.[4]

7. **Multivariate BVAR (BVAR4)** (M_7). Redefining $X_t = (\pi_t, y_t, e_t, p_t^c)'$, an analogous version of the previous VAR model is estimated using Minnesota priors.

8. **Bivariate BVAR with commodity price indexes (BVAR2-COM)** (M_8). An analogous version of the VAR model above is estimated using Minnesota priors and $X_t = (\pi_t, p_t^c)'$.

9. **Time-Varying Parameter (TVP) specification** (M_9).

$$M_9: \quad \pi_{t+h} = \phi_{0h,t} + \phi_{1h,t}\pi_t + \epsilon_{t+h}$$

where $\phi_{0h,t}$ and $\phi_{1h,t}$ are random walk coefficients such that

$$\begin{aligned} \phi_{0h,t+h} &= \phi_{0h,t} + \nu_{0.t+h} \\ \phi_{1h,t+h} &= \phi_{1h,t} + \nu_{1,t+h} \end{aligned}$$

and $\nu_{0.t+h}$ and $\nu_{1.t+h}$ are uncorrelated i.i.d. shocks.

[3] Following Stock and Watson (1999), we prefer to forecast with a Phillips curve based on measures of real aggregate activity (e.g., industrial production index) to the use of unemployment rates.

[4] The hyper-parameters used in all the BVARs were $\mu_1 = 1$ ($AR(1)$ coefficient dummies), $\lambda_1 = 0.5$ (overall tightness), $\lambda_2 = 1$ (relative cross-variable weight), and $\lambda_3 = 1$ (lag decay).

We calculate pseudo out-of-sample forecasts by recursive estimation. The number of lags used in the baseline exercise for the competing models is 2.[5] The exception is the DAR4 model (M_4) that has the same lag structure as the RW-AO for comparison purposes. The forecast horizons are $h = 1$, 4, 8, and 12 quarters. The prediction error is defined as the difference between actual and predicted values. The training sample is 1980Q2-2000Q2. For $h = 1$, for instance, the first forecast is made in 2000Q3 and the last one is made in 2016Q4. The root mean squared prediction error (RMSPE) is computed for each country, model, and forecast horizon.

The Theil-U statistic (relative RMSPE), that is, the ratio of the RMSPE of our RW-AO relative to the RMSPE of each competitor model ($M_1 - M_9$) is summarized in Table 2. Values less than one imply that the RW-AO model has a lower RMSPE than does the competing model. To assess the statistical significance of the difference of the Theil's U-statistics from one, we use a simple one-sided Diebold-Mariano-West test and adjust the statistic if the models are nested according to Clark and West (2007). In addition, we use the adjustment proposed by Harvey et al. (1997) for small samples. The test statistics are constructed using heteroscedasticity and autocorrelation robust (HAC) standard errors. Values of the corresponding t-statistics larger than 1.282 indicate that the null hypothesis of equal predictive accuracy is rejected at the 10% significance level.

Additionally, we assess the directional accuracy of each competing specification including the benchmark RW-AO model—summarized in Table 3.[6] We construct success ratios as estimates of the probability with which the forecast produced by a given model correctly anticipates the direction of change in inflation at a given forecast horizon. Tossing a fair coin on a sufficiently long sample already predicts the direction of change correctly about 50% of the time. Hence, a model needs to attain a success ratio greater than 0.5 to provide an improvement in directional accuracy over pure chance. The statistical significance of the directional accuracy relative to pure chance is determined via the test of Pesaran and Timmermann (2009).

3 Empirical Results

3.1 Main Findings

The ratios of RMSPEs for our set of forecasting models are summarized in Table 2 (for each of the forecast horizons 1, 4, 8, and 12, respectively). We consider eight different 1-quarter ahead forecasts only because, as it is well known, the iterated and direct methods are equivalent when $h = 1$. Similarly, the success ratios to assess the directional accuracy of the forecasts are summarized in Table 3 (for each of the forecast horizons considered). Our main conclusions are as follows:

1. Overall, the RW-AO model mostly produces lower RMSPEs than its competitors at any forecast horizon (the average median of the relative RMSPE is generally smaller than one, see Figure 1 and Table 2).

[5] The specification of M_9 is motivated by the solution of the workhorse New Keynesian model in Martínez-García (2017) allowing for time-variation in the coefficients arising from structural change (on the inflation target, but perhaps also on the degree of openness, etc.). See the Appendix on conditions under which this solution may no longer be well-defined having to do with the credibility of monetary policy and the formation of expectations. The lag value is the same used by Faust and Wright (2013) for advanced economies and Mandalinci (2017) for EMEs. In fact, the conventional lag length used in the literature on inflation forecasting in EMEs is also 2. In addition, we analyze the sensitivity of our results to this lag structure by using an autoregressive model with 4 lags (DAR4, M_3). We find that this specification provides lower forecast accuracy measured by the RMSPE and the directional accuracy ratios (see the ranking of models provided in Table 5).

[6] Supplementary materials are available in the Supplemental Appendix with additional information on the results reported here in Table 2 and Table 3, detailed by country.

In a number of cases, the gains in smaller RMSPEs are statistically significant (Table 2).[7] The RW-AO also produces success ratios generally above the 0.5 threshold and, very often, statistically significant at all forecasting horizons (see Figure 2 and Table 3). The likelihood with which the RW-AO correctly anticipates the direction of change in inflation tends to be comparable with or better than that of its competitors, and in the $0.58-0.68$ range of medians (Table 3). The median success ratio of the RW-AO tends to be close to or above the maximum attained by any model for each forecasting horizon.

2. Across countries, the RW-AO model outperforms the rest of the models with statistically significant gains for Mexico, Peru, and Hungary at almost every forecast horizon (Table 4). The case of Peru is interesting because of the minuscule relative RMSPEs for most of the alternative models except the TVP. It is worth recalling that the Peruvian is the only economy in our sample that faced a hyperinflationary episode in the period under study (as illustrated in Table 1.B). Regarding the rest of countries, the statistical differences over the rest of the competing models are also notable for Colombia, Nigeria, and Philippines (especially at 4- and 8-quarter horizons). In the rest of the sample, the RW-AO's performance is relatively reasonable with the exceptions of China, Malaysia, Thailand (1-quarter horizon), and South Africa (1-, 8-, 12-quarter horizons).

3. Considering all the forecast horizons and countries, the RW-AO outperforms—or at least shows similar predictive ability to—univariate and multivariate factor-augmented models (M_4, M_6) in forecasting the inflation rate among EMEs. In terms of directional accuracy, the RW-AO seems to be better or as competitive as those models as well. In Table 5, we sort the alternative models per the number of countries in which the relative RMSPE of the RW-AO is lower than one, but considering only the statistically significant cases. Factor-augmented models show up at the top of the list which suggests they could constitute a reasonable second-best alternative. The models more frequently beaten by the RW-AO are the DAR4 (M_3), the Augmented Phillips Curve (M_5), and the BVAR4 (M_7). The RW-AO model also clearly dominates all its competitors in terms of directional accuracy (see average medians over all horizons in Table 3).

4. The time-varying parameter (TVP) specification (M_9) allows us to partly address the concern that the performance of alternative forecasting models might be influenced by structural change over the sample period. Our results generally show that the RW-AO specification tends to outperform model M_9, suggesting that such a type of parameter instability may not be the only reason explaining the success of the RW-AO model among EMEs.

5. We also learn that there are certain international macro variables that do not contribute (or at least do not contribute much) to predicting inflation among EMEs such as:[8] **(i)** the exchange rate (unlike in studies such as Kabukcuoglu and Martínez-García (2016) that find some predictive power for advanced economies), but more in line with the findings of Frankel et al. (2012) who show that EMEs have experienced a downward trending pass-through since the 1990s;[9] **(ii)** global factors (in contrast to what

[7] The RW-AO often does better at long horizons rather than at the very short one ($h = 1$).

[8] We have also considered different specifications of Phillips-curve-based models like the NOEM-BVAR proposed by Duncan and Martínez-García (2015). Our findings with this alternative specification do not overturn the main results in support of the RW-AO model among EMEs. The NOEM-BVAR results are not reported here, but are available upon request from the authors.

[9] Fluctuations in the exchange rate can affect inflation through direct and indirect channels. The direct effect arises from

Ciccarelli and Mojon (2010) and Duncan and Martínez-García (2015) find for advanced economies); and **(iii)** commodities prices (as argued by Chen et al. (2014)).

3.2 Robustness Checks and Other Exercises

We perform a number of robustness checks, whose results are available upon request, as well as forecast combinations and intercept corrections. Some conclusions from such analysis are worth mentioning here:

1. Among the Factor Augmented (M_4, M_6) and Augmented Phillips Curve (M_5) models, we also evaluate some alternatives modeling the first difference of the inflation rate without obtaining superior results. The lack of complete data on monetary aggregates for most of the EMEs prevents us from testing Phillips Curve specifications with money components on a comparable footing. The use of GDP instead of the industrial production indexes leads to similar statistics for the Augmented Phillips Curve (M_5) models. Open-economy Phillips-Curve-based specifications like the ones proposed in Duncan and Martínez-García (2015) for advanced economies do not appear to perform all that much better than the RW-AO among EMEs either.

2. We have checked the BVAR forecasts using normal-flat priors. Overall, the results are qualitatively similar or moderately better with Minnesota priors. Additionally, we use alternative vectors: $(\pi_t, \pi_t^*, y_t, y_t^*)'$, $(\pi_t, y_t, e_t)'$, and $(\pi_t, y_t^*, e_t)'$, where $*$ denotes rest-of-the-world (advanced economies) values. However, we did not obtain any noticeable improvement in predictive ability with those alternative vectors of variables.

3. The RW-AO model usually outperforms the naïve random-walk specification, with or without drift, in our sample.[10]

4. **Different RW-AO specifications.** We vary the degree of smoothing of the RW-AO model by increasing the number of observations into the moving average. Aside from our baseline RW-AO model with 4 lags used in our main results, we introduce three additional variants that include 8, 12, and 16 past values of the inflation rate. That is, the forecasting functions are

$$\pi_{t+h} = \frac{1}{q}\sum\nolimits_{i=1}^{q} \pi_{t+1-i} + \epsilon_{t+h}, \tag{2}$$

with $q = 4, 8, 12, 16$. We label them RW-AO4 (or simply RW-AO), RW-AO8, RW-AO12, and RW-AO16, respectively. We repeat the baseline exercise using the direct method and calculating the RMSPEs. Figure 3 shows the averages of the median ratios of RMSPE of each RW-AO model relative to the RMSPE of a competing forecasting model calculated over the 14 EMEs and the 9 competing models for a given forecast horizon. Again, values less than one indicate a higher predictive ability for the RW-AO compared to the alternative model. We find that the RW-AO8 minimizes the relative RMSPE, on average, and provides a suitable degree of smoothing. As Figure 3 shows, a higher number

pass-through into import prices. The indirect effect occurs because real exchange rate movements contribute to shift aggregate demand across countries.

[10] We refer to the naïve random-walk specification without drift as a special case of the general-form of the RW-AO model in (2) where only the first lag is included ($q = 1$). We introduce the case of the naïve random-walk with drift by adding a constant.

of past observations introduces noisy information in the RW-AO and raises its relative RMSPE. Put differently, the RW-AO4, the one that we use in our baseline results, can be viewed as a relatively conservative case.

5. **Time-varying parameter specifications.** The performance of forecasting models might be influenced by structural changes. The TVP specification discussed above (M_9) allows us to partly deal with this sort of instabilities. We also explore the forecasting ability of other simple specifications like a time-varying only-intercept model but this did not yield improved results. To verify the sensitivity of our results to the sample chosen, we re-estimated all the statistics starting in 1990Q2, leaving aside the 1980s, which is a decade characterized by high and volatile inflation rates across many EMEs. Even though, the same conclusions hold, we find that the predictive ability of the competing models is somewhat improved. That is, the RW-AO is still the preferred model but the alternative competing models can exploit more useful information to forecast inflation. This suggests the relative importance of structural breaks in the data generating processes.

6. **Forecast combinations.** Another possibility to deal with structural breaks is to combine forecasts. Forecast combination reduces the uncertainty inherent in choosing a specific forecasting model. There exists a number of methods to construct forecast combinations. Simple forecast averaging has proved to be successful in terms of predictive ability compared to other available methods (Clemen (1989), Stock and Watson (2004), and Clark and McCracken (2010)). In that line, we compute the average forecast over all the competing models ($M_1 - M_9$) and another over the factor-augmented models only (M_4 and M_6, which are also two of the most successful competing models). The results are shown in Table 6. The average medians over all the forecast horizons in both cases (0.91 and 0.93) just confirm our previous conclusion about the forecast ability of the RW-AO model.

7. **Intercept corrections.** A well-known strategy to cope with the perverse effects of structural breaks on forecasts is the use of intercept corrections. In its simplest form, an intercept correction consists of estimating the forecast error of certain period $t-1$ ($\pi_{t-1} - \widehat{\pi}_{t-1}$) and adding it to the forecast of period t ($\widehat{\pi}_t$). As a result, intercept corrections eliminate or reduce forecast biases in the case, for instance, that the model parameters are actually time-varying. As explained by Clements and Hendry (2001) and Elliott and Timmermann (2016), however, the gains in lower forecast biases are not free. They come at the cost of a higher forecast variance. We robustify all our competing models' predictions with intercept corrections and leave the RW-AO predictions unchanged. That is, for every alternative model m and forecast horizon h, we compute:

$$\widehat{\pi}_{m,t+h} + \left(\pi_{m,t+h-1} - \widehat{\pi}_{m,t+h-1}\right). \tag{3}$$

Table 7 and Table 8 show the summary of the relative RMSPEs and success ratios, which are comparable to our baseline results summarized in Table 2 and Table 3. At the 1-quarter horizon, intercept corrections do not produce any gain for the competing models. On the contrary, the average median of the relative RMSPEs across models is 0.85 (see last column in Table 7), much lower than the corresponding value of 0.95 obtained in the baseline results (last column in Table 2). Over longer horizons ($h = 4, 8, 12$), we observe that the gain in lower bias outweighs the cost of a larger forecast variance.

The largest improvement, from 0.75 (baseline) to 0.85 (Table 7), is observed at the 12-quarter horizon. This outcome favors the alternative models, but it does not seem to be sufficient to prefer them over the RW-AO. Table 8 shows an analogous story. The average of the median success ratio of the competing models falls at the 1-quarter horizon but improves at longer forecast horizons. The median success ratio averaged over all the horizons and the nine robustified models is 0.63 (see last column, last row in Table 8) and very close to the value produced by the RW-AO (0.65). In sum, we notice that intercept-corrected models yield some but not substantial gains in predictive ability thanks to lower forecast biases.

8. **Different transformation of the target variable.** Overall, the findings are robust to the transformation of the target variable. In addition to the exact quarter-over-quarter inflation rate annualized used in the baseline exercises (π_t; as in (1)), we construct the approximate quarter-over-quarter inflation rate annualized in logs ($\pi^{a,qoq}$), the exact year-over-year inflation rate ($\pi_t^{e,yoy}$), and the approximate year-over-year inflation rate in logs ($\pi^{a,yoy}$; as in Atkeson and Ohanian (2001)):

$$\pi_t^{a,qoq} \equiv 400\left[\ln\left(\frac{CPI_t}{CPI_{t-1}}\right)\right], \tag{4}$$

$$\pi_t^{e,yoy} \equiv 100\left[\left(\frac{CPI_t}{CPI_{t-4}}\right)-1\right], \tag{5}$$

$$\pi_t^{a,yoy} \equiv 100\left[\ln\left(\frac{CPI_t}{CPI_{t-4}}\right)\right]. \tag{6}$$

Table 9 shows the averages of the median ratios of the RMSPE of each RW-AO model relative to the RMSPE of a competing forecasting model calculated over the 14 EMEs and the 9 competing models for a given forecast horizon. On average, the use of approximate inflation rates tends to benefit the competitive models relative to the RW-AO more than the use of exact inflation rates. This difference becomes more noteworthy for year-over-year rates. Logged CPI series smooth sharp fluctuations observed in EMEs and the smoothing turns stronger for the fourth difference filter. The predictive ability of the RW-AO model relative to its competitors remains, especially at 4-, 8-, and 12-quarter horizons.

9. **Another test for differences in predictive ability.**[11] We estimate an only-intercept model for each of the 14 EMEs using SUR-GLS, where the dependent variable is the difference between the squared forecast error of an alternative model and the squared forecast error of the RW-AO model. A rolling-window estimation using a width of 75 observations generates the forecasts. Hence, this can be viewed as a type of Giacomini and White (2006) test in which we address the cross-sectional dependence by using SUR-GLS. We choose the three most competitive models according to Table 5: M_4 (FAR), M_6 (BVAR2), and M_8 (BVAR2). Table 10 reports the results and statistics. A positive (negative) intercept indicates that the RW-AO model shows higher (lower) predictive ability than does the alternative model. The null hypothesis is that all the constants are jointly equal to zero. That is, for a given forecast horizon and alternative model, we evaluate the equal predictive ability across countries. We mostly reject the null hypothesis. We conclude that the RW-AO beats those three competing models at the 4-, 8-, and 12-quarter horizons, but not at the 1-quarter horizon.

[11] We thank an anonymous reviewer for suggesting this to us.

10. **Conditional predictability.** We find similar performance of the RW-AO model in EMEs as for developed economies. We use the conditional predictability test by Giacomini and White (2006) to explore differences in predictability among EMEs relative to the U.S. (where the U.S. is viewed as representative of the advanced economies). For each country (including the U.S.) and each forecast horizon, we generate forecasts from a rolling-window estimation using a width of 75 observations and construct the difference, d_t, between the squared forecast error of an alternative model i ($e^2_{i,t}$) and the squared forecast error of the RW-AO model ($e^2_{RW-AO,t}$). We regress that indicator on its first two lags (d_{t-1}, d_{t-2}), a measure of the GDP cycle (y_t; the year-over-year growth rate of GDP), and a proxy of a high-inflationary regime (h_t; an indicator function that takes the value of 1 if the current inflation rate is higher than the median inflation rate, 5% approximately, and 0 otherwise). That is, for each economy we estimate

$$d_t = \alpha_0 + \alpha_1 d_{t-1} + \alpha_2 d_{t-2} + \alpha_3 y_t + \alpha_4 h_t + \varepsilon_t \tag{7}$$

where $d_t \equiv e^2_{i,t} - e^2_{RW-AO,t}$ for $i = \{M_4, M_6, M_8\}$. Again, we focus on three of the most competitive models (FAR, BVAR2, and BVAR2). Table 11 reports the p-values associated with the joint null hypothesis that all non-intercept coefficients are zero ($\alpha_1 = \alpha_2 = \alpha_3 = \alpha_4 = 0$) and the percentage of economies in which we reject the null hypothesis at 10% using a Wald test. We reject the null hypothesis for the U.S. and most of the EMEs. Our interpretation is that the U.S. and many EMEs in our sample are not very different in terms of this sort of conditional predictability. Past predictability, the business cycle and the high- or low-inflationary regime seem to be statistically related to the current predictability of the best competing models relative to the RW-AO.

4 Discussion

4.1 Policy Implications

There are a number of insights and policy recommendations that arise from our empirical results on inflation forecasting for EMEs:

First, since monetary policy transmission is associated with significant lags, optimal policy needs to be forward-looking which underscores the importance of obtaining accurate forecasts. The central banks among many EMEs seem to be making an important omission for inflation forecasting by setting aside the model proposed by Atkeson and Ohanian (2001). In fact, no variant of the RW-AO model is mentioned in the survey of forecasting methods for inflation-targeting central banks reported by Hammond (2012). However, as we show in the paper, the RW-AO specification has excellent predictive power, especially in the medium and long term ($h > 1$) and, therefore, we argue that it should be part of the forecasting toolbox when it comes to predicting inflation in those economies as well as for policy analysis.

Second, most of the studies that investigate how to better predict inflation in EMEs have virtually ignored the RW-AO model specification. The exceptions being Ögünç et al. (2013) and Altug and Çakmakli (2016), but they look at one or two country experiences and often do not find strong evidence in favor of the RW-AO model. Our empirical results, in turn, would lead us to recommend the RW-AO specification as an additional benchmark to those already commonly used in the literature (standard random walk, autoregressive processes, etc.). We believe this new benchmark is a harder yardstick to overcome for any proposed model of inflation forecasting for EMEs.

Third, we argue that parameter instability and model misspecification can contribute to explain the relative failure of competing economic models for the forecasting of inflation among EMEs. The challenge is to find a general framework for forecasting where the model structure and even the presence and type of structural change are all unknown and may vary both within the estimation sample and over the forecast period. In this vein, Rossi (2012) argued that widespread forecast breakdowns make it all the more pressing to develop robust forecasting models.[12] Instead of attempting to identify such breaks (which is hardly an easy task in the presence of recent and ongoing structural change), break-robust adaptive forecasting strategies have been studied by Pesaran and Pick (2009), Eklund et al. (2013), and Giraitis et al. (2013), among others, which downweight data from older periods deemed to be less relevant to predict the current dynamic behavior of the variable of interest.

Finally, we argue that understanding the dynamics of inflation requires a deeper exploration of the reasons why existing economic models appear to perform so poorly for the forecast of inflation in economies such as those of EMEs. As noted before, model misspecification, parameter instability, and even sampling error can contribute to the poor forecasting performance of most of the existing economic models. Future research along these lines can lead in our view to a better understanding of the inflation process and to the development of novel approaches to resolve this apparent empirical puzzle. We emphasize here, instead, the key idea that simpler adaptive strategies like the RW-AO model can be preferable in practice as they are robust to many different forms of misspecification and structural breaks.[13]

4.2 Structural Breaks

The key implications of our analysis on inflation forecasting among EMEs shed some light on adaptive forecasting with parameter instability and potential misspecification and can be summarized as follows:

- **Intercept corrections.** Our results with model predictions enhanced by intercept corrections suggest that structural breaks might be playing a role, although partial, in the relative failure of the competing models. When we include intercept corrections, we observe a clear gain due to the lower bias reflected especially in increased directional accuracy.

- **Forecast combination.** We observe that the predictability of inflation models changes over time. Subsampling appears to be useful in practice to deal with the possibility of unobserved structural breaks and unmodelled (time-varying) features in forecasting inflation. As mentioned in Section 3.2, when we leave aside the 1980s, a decade characterized by high and volatile inflation rates across many EMEs, we still find robust support for the RW-AO specification, but find that the predictive ability of the

[12] Interestingly, this is related to other areas of empirical forecasting such as the Meese-Rogoff puzzle on exchange rate predictability. In assessing the success of the standard random walk model to predict the exchange rate, Meese and Rogoff (1983a), Meese and Rogoff (1983b) conjectured that model misspecification, parameter instabilities, and even small sample estimation bias could potentially explain the poor forecasting performance of economic models of the exchange rate (a point discussed more recently in Bacchetta et al. (2009) and Rossi (2013)). The Meese-Rogoff literature has also postulated that near-random walk behavior may emerge naturally whenever the fundamentals are $I(1)$ and the discount factor is near one (Engel and West (2005)).

[13] More generally, appropriately downweighting the past—as the RW-AO model does—can be a robust strategy for handling trends of any nature as well as structural breaks without requiring further modeling. Giraitis et al. (2013) show that such an adaptive approach generally works well for stochastic, linear or nonlinear deterministic trends, and structural breaks without knowledge of the nature of the trend. This approach also continues to be valid whether the time series is stationary or non-stationary.

competing models is somewhat improved. An alternative to dealing with this can be achieved through forecast combination, which we explore in this paper. Our results largely confirm the finding that the RW-AO model tends to outperform many competing economic models and the forecast combination that can be obtained from them, which perform well only occasionally. Also, what our exercise with forecast combination might be suggesting is, again, that we are dealing with important parameter instabilities.

- **Time-varying specifications.** A time-varying parameter (TVP) specification (M_9, motivated by the empirical work of Mandalinci (2017)) can also partly address the concern that the performance of our alternative forecasting models might be influenced by structural change over the sample period under consideration, although our results show that the RW-AO specification still tends to outperform the TVP model. In other words, the evidence suggests that parameter instability, as modelled by the proposed TVP specification, may account only in part for the success of the RW-AO model among EMEs. A puzzling result arises here whereby the TVP model specification does not appear very successful in improving our predictive ability for inflation forecasting among EMEs. In our view, the proposed TVP specification does not fully capture the effect of structural change in forecasting across EMEs, perhaps for at least two reasons. One reason is that there are many non-linear functional forms, many forms of structural breaks (in intercepts, slopes, and variances), and that breaks can be of different magnitudes (some relevant, some not), discrete and continuous, occurring within the estimation period and within the prediction period, etc. All of this makes it challenging to model them in the estimation within the sample. Another reason is that there are different prediction methods with nonlinear models such as TVP for horizons greater than a period. We use the direct method for the TVP to be consistent with the other models, but there are also methods that use Monte Carlo simulations or bootstrapping that could be used and would give less bias than the direct method (Granger and Terasvirta (1993)). In any event, all of this implies that the forecaster should be monitoring for changes in the specification (including breaks) by country and adjusting his/her methods once change has been detected. Since detecting shifts often involves a substantial time lag and comes at a cost in terms of modeling effort, our evidence favoring the RW-AO specification suggests a simpler (less costly) alternative that is robust across many different country experiences among EMEs and sample periods. In other words, we show that forecasters can be quite successful—without attempting to identify breaks—simply using break-robust forecasting strategies like the RW-AO model.

- **Role of judgment.** We compare the RW-AO forecasts to the professional forecasts obtained from Consensus Forecasts$^{\mathrm{TM}}$ to assess the significance of subjective judgement over simple break-robust strategies like the RW-AO model. The Consensus Forecasts$^{\mathrm{TM}}$ data we use covers the period 2006Q4-2016Q4 for 12 of the 14 EMEs in our sample—predictions for Nigeria and South Africa are not available.[14] These are average predictions of a panel of professional forecasters for each country that produce

[14] Forecasts start in 2006Q4 for China, India, Indonesia, Malaysia, and Thailand; in 2007Q1 for Chile, Colombia, Hungary, Mexico, Peru, and Turkey; and in 2009Q3 for Phillipines. Our approach to calculate the implicit forecasts for the quarter-over-quarter growth rates (SAAR, %) involves: first, transforming the forecasts for the reported year-over-year exact growth rates (SA, %) into their corresponding log-approximations ($\pi_t^{a,yoy} = 100\left[\ln\left(1+\frac{\pi_t^{e,yoy}}{100}\right)\right]$); second, using the additivity of the log-approximation to the year-over-year growth rate ($\pi_t^{a,yoy} = \frac{1}{4}\left(\pi_t^{a,qoq}+\pi_{t-1}^{a,qoq}+\pi_{t-2}^{a,qoq}+\pi_{t-3}^{a,qoq}\right)$), we infer the log-approximation of the quarter-over-quarter growth rate for any forecasting horizon $h \geq 0$ ($\pi_{t+h}^{a,qoq}$) netting out the known (either directly observed date or recursively implied forecasts) log-approximation of the quarter-over-quarter growth rates over the

quarterly forecasts of year-over-year growth rates (these quarterly forecasts are regularly released at a quarterly frequency for Indonesia, Philippines, India, China, Thailand, and Malaysia and bi-annually for Mexico, Peru, Hungary, Colombia, Turkey, and Chile). These forecasts on the inflation rate in the current quarter relative to the same quarter of last year can be used together with the observed data to infer the quarter-over-quarter annualized inflation rates implicit in Consensus Forecasts^{TM} predictions. To the best of our knowledge, this is the first paper to employ the quarterly forecasts from Consensus Forecasts^{TM} among EMEs to investigate their predictive ability. Our main findings are summarized in Table 12 which shows that professional forecasts tend to be superior to RW-AO-based forecasts for the majority of EMEs. However, the RW-AO remains competitive when forecasting quarter-over-quarter growth rates (particularly at shorter horizons).[15] These findings suggest that the incorporation of subjective judgement and perhaps the use of other ancillary sources beyond what a given model would rely on in order to identify structural shifts can improve inflation forecasts relative to our preferred benchmark (outperforming the RW-AO forecasts).[16]

4.3 The Role of Central Bank's Credibility

The success of the RW-AO model arises in practice from the difficulties of incorporating all the relevant features of the economy in a forecasting model while tracking changes over time. For instance, we know that we may have more or less persistence in inflation with Phillips-curve-based models when heterogenous beliefs and imperfect credibility about the inflation target are considered. We provide a more detailed theoretical argument for this in the Appendix based on a modified version of the workhorse open-economy New Keynesian model. We see this modification of the model as providing some contextualization for the claim that the current crop of economic forecasting models—more specifically, those based on the Phillips curve—might be misspecified for the case of EMEs and subject to structural shifts like those affecting central bank's credibility.

This theoretical framework accommodates the possibility of change or instability in parameters more broadly. For instance, we could consider that it is the changes in the credibility parameter and/or the central bank's time-varying (explicit or implicit) inflation target, which generally are difficult to observe and measure but appear plausibly time-varying for EMEs, what lies behind model instability and misspecification. This, in turn, is what may explain the relatively poor performance of economic models compared to the RW-AO model.

In Section 3, we point out that the RW-AO model outperforms the rest of the competing models especially in economies such as Hungary, Mexico, and Peru at almost every forecast horizon (Table 4). In contrast,

preceding three quarters from the forecasts of the log-approximated year-over-year growth rate ($\pi^{a,qoq}_{t+h} = 4\pi^{a,yoy}_{t+h} - \pi^{a,qoq}_{t+h-1} - \pi^{a,qoq}_{t+h-2} - \pi^{a,qoq}_{t+h-3}$); finally, we recover the implicit forecasts of the exact quarter-over-quarter growth rates (SAAR, %) from the derived log-approximation ($\pi_t = 100\left[\left(\exp\left(\frac{\pi^{a,qoq}_t}{100}\right)\right)^4 - 1\right]$). We use these implicit forecasts in our evaluation exercise here.

[15] In terms of directional accuracy, we find somewhat stronger support for the RW-AO model against Consensus Forecasts^{TM}. Similarly, we also explore the predictive ability of the RW-AO model with annual inflation rates compared to that of both private forecasts from Consensus Forecasts^{TM} and institutional forecasts from the International Monetary Fund's World Economic Outlook (IMF WEO) database. Results are available from the authors upon request—a summary of those findings can be found in the Supplemental Appendix of this paper.

[16] Faust and Wright (2013) suggest that subjective forecasts are often superior to model-based forecasts for inflation among advanced economies. Related to this point, see also Mandalinci (2017) who finds institutional forecasts to be superior to model-based forecasts for many EMEs (where his institutional forecasts are from the International Monetary Fund's World Economic Outlook (IMF-WEO)).

the RW-AO predictor does not produce such an outstanding performance in countries like Malaysia, South Africa, and Thailand. We explore the reason suggested in the theory laid out in the Appendix with the aid of Figure 4. This figure plots the average of the ratios of RMSPEs of the RW-AO model relative to the competing models in the vertical axes. This average is calculated over the 9 alternative models and the 4 forecast horizons for each economy. On the horizontal axes, we measure four different proxies of lack of credibility in the monetary policy.

We plot the average relative RMSPE against: the number of years under an inflation targeting scheme (Figure 4A; based on information from Roger (2010) and Hammond (2012)), an index of central bank independence (Figure 4B; using the index proposed by Garriga (2016)[17]), the median inflation rate computed over annualized quarter-over-quarter inflation rates between 1980Q2 and 1989Q4 (Figure 4C), and the coefficient of variation of the annualized quarter-over-quarter inflation rates calculated over the 1980Q2-1989Q4 period as well (Figure 4D).

The lack of credibility in the central bank's policies during the 1980s is reflected in high inflation levels and highly volatile inflation rates. Likewise, the poor credibility in the past has probably induced central banks to adopt, sooner or later, institutional changes such as inflation-targeting schemes or statutory improvements that seek independence from central governments or other external influences. In the absence of accurate indicators, these variables relating to the adoption of an inflation-targeting and gains in central bank independence work as imperfect measures of lack of credibility. Our interpretation is that the higher the values of any of these proxies, the lower the degree of credibility in the central bank's monetary policy. Given this and the period we study here, the low credibility in the past might be what prompts the adoption of inflation targeting or greater central bank independence aimed at improving the central bank's credibility.

Figure 4 provides the sign of the correlations between these proxies for past credibility and the forecasting performance of the RW-AO model, and the corresponding p-values. Even though there are some influential observations and the sample size is small, the relationships depicted are suggestive and consistent with the implications of the theoretical model we discuss in the Appendix. The predictive ability that the RW-AO offers relative to its competitors is better in economies that experienced low credibility in the past. This is the case of Peru, Mexico, and Hungary, which ranked at the top of Table 4. These economies tend to appear with relatively high values for our proxies of lack of policy credibility. The opposite is observed for Malaysia, South Africa, and Thailand. These countries usually appear in the upper left corner of the scatter plots, indicating relatively high credibility jointly with low relative predictive ability of the RW-AO model. In sum, this piece of evidence supports the idea that the lack of credibility might be behind the relative success of the RW-AO in some countries compared to others.

Finally, we show in the Appendix that structural breaks can arise in theory from changes in the credibility of the central bank's inflation target or from shifts in the inflation target itself. The limitations to measure the policy credibility and implicit targets make the task of inflation forecasting in EMEs a challenging one. Professional forecasters (Consensus Forecasts™) tend to produce lower or similar RMSPEs than the RW-AO model suggesting that subjective judgement can improve over such break-robust forecasts by incorporating ancillary information about—among other things—any significant structural shifts (in particular in the monetary policy framework) quickly into their own predictions.

[17] Garriga (2016)'s dataset codes all relevant statutory reforms affecting central bank independence. The data indicate the occurence of central bank reforms, their direction, and also incorporate all the attributes necessary to build the well-known Cukierman et al. (1992) index for 182 countries between 1970 and 2012.

5 Concluding Remarks

Our empirical findings, based on a varied cross-section of country experiences among EMEs, show that a parsimonious forecasting model of inflation (the RW-AO model) outperforms other forecasting models of inflation. Overall, the RW-AO model mostly produces lower RMSPEs than its competitors and success ratios generally above the 0.5 threshold at any forecast horizon and, often, they are statistically significant.

We view the RW-AO specification as an important empirical benchmark for forecasting inflation across a diverse group of EMEs. Among the competing models beaten by the RW-AO, univariate and multivariate factor-augmented models can be regarded as second-best options under the same metrics of predictive accuracy. We find that certain variables driven by foreign factors such as exchange rates and commodity prices do not seem to contribute much to predict inflation in the small open economies of our sample.

The time-varying parameter specification allows us to partly address the concern that the performance of alternative forecasting models might be influenced by structural change or time-varying parameters (like the inflation target) over the sample period. Our results generally show that the RW-AO specification tends to outperform the time-varying specification as well, indicating that such a type of parameter instability may not be the only reason explaining the success of the RW-AO model among EMEs.

Finally, our findings motivate us to look for alternative ways to model inflation among EMEs. We suggest that understanding the process that leads to the formation of expectations and the appropriate conduct of monetary policy under different credibility scenarios can be important. Incorporating inflation expectations explicitly into our forecasting models is therefore a promising research avenue which—although complicated due to data availability—we aim to investigate further in the future. Even more, if we consider the favorable results from comparing the subjective predictions from Consensus Forecasts^{TM} with those from the RW-AO model.

Under lack of credibility in the inflation target, a Phillips curve can imply inflation dynamics that produce permanent (or near-permanent) effects in the inflation rate from otherwise transitory changes in output slack that resemble those observed in many EMEs during the 1980s and part of the 1990s. The gradual recovery of the confidence on the central bank's policies and its commitment with an inflation target lead to stationary processes that probably are more similar to those that work better from the late 1990s on. The inability of the forecaster to observe sudden shifts in credibility or frequent changes in the implicit target makes the empirical modeling and forecasting of inflation a difficult task, particularly among EMEs. We leave this task also for future research.

Appendix

A Phillips-Curve-Based Models: A Closer Inspection

The influential work of Atkeson and Ohanian (2001) documents a break in the performance of Phillips-curve-based forecasting models during the Great Moderation period. These authors suggest the RW-AO model as an alternative (theory-agnostic) forecasting benchmark and find evidence that it outperforms standard Phillips-curve-based specification. In this sense, the empirical Phillips curve relationship between domestic inflation and domestic economic activity no longer seems to work as a tool for inflation forecasting. More recently, Duncan and Martínez-García (2015) have argued that the closed-economy Phillips curve has limited value for forecasting inflation partly due to misspecification, as it ignores the international linkages affecting the dynamics of inflation. Furthermore, they show that open-economy Phillips curve-based models can describe domestic inflation dynamics more accurately—a finding that appears ubiquitous across many developed economies. The Phillips curve appears to be alive and well—albeit in its open-economy form.

The main empirical finding of this paper is to show that the RW-AO model appears as the more relevant benchmark for inflation forecasting for many EMEs. We argue that the RW-AO is successful because is a method to downweight past data, which is a good strategy when there are instabilities/structural breaks. We argue that the open-economy Phillips curve that emerges from the workhorse two-country New Keynesian model is still helpful to understand the dynamics of inflation and that, in principle, it also aids us to think about the potential factors explaining the empirical evidence of parameter instability on EMEs documented in this paper. We argue that unmodelled parameter instability in the open-economy Phillips curve (time-varying inflation targets) as well as some restrictive assumptions underlying the conventional specification of the New Keynesian model are challenged by the experience of many EMEs in our sample. This can partly explain why simpler, break-robust forecasting models like the RW-AO predictor outperform other more complex (model-based) alternatives.

The reminder of this Appendix articulates this point introducing explicitly a time-varying inflation target and highlighting the significance of assumptions like full rational expectations (with homogenous beliefs) and perfect credibility of the inflation target.

The Standard Open-Economy Phillips Curve. We adopt the workhorse open-economy New Keynesian model of Martínez-García and Wynne (2010), further developed in Martínez-García (2017). The model includes two countries which are symmetric, but with local-product bias in their respective consumption baskets. The share of Foreign (Home) goods in the Home (Foreign) consumption basket given by the parameter $0 \leq \xi \leq \frac{1}{2}$ determines the degree of trade openness. All goods are traded internationally. We assume for simplicity that the trade elasticity of substitution between Home and Foreign goods $\sigma > 0$ satisfies that $\sigma\gamma = 1$ where γ refers to the inverse of the intertemporal elasticity of substitution (this case implies that international financial markets become irrelevant and has been considered by Cole and Obstfeld (1991), among others).

Monetary non-neutrality arises from monopolistic competition and producer currency pricing under staggered price-setting behavior à la Calvo (1983), as is conventional in the open-economy literature. We extend the model of Martínez-García (2017) with Yun (1996)-price indexation where firms that do not re-optimize their prices in a given period increase them at the trend inflation rate of the country where they sell their variety. Furthermore, we assume that each country's central bank responds to local conditions—that is, to deviations of local inflation from target and to the country's own slack—as implied by the Taylor (1993) rule. The Home country's monetary policy rule is

$$\widehat{i}_t \approx \widehat{\pi}_t^T + \psi_\pi \left(\widehat{\pi}_t - \widehat{\pi}_t^T\right) + \psi_x \widehat{x}_t + \widehat{\vartheta}_t, \tag{8}$$

where the short-term nominal interest rate is given by $\widehat{i}_t$, inflation is $\widehat{\pi}_t \equiv \widehat{p}_t - \widehat{p}_{t-1}$, the inflation target is denoted $\widehat{\pi}_t^T$, and the output gap (actual output minus the output potential under flexible prices) is given by $\widehat{x}_t$. The policy response to inflation deviations from target is given by the parameter $\psi_\pi > 0$ while the response to slack is determined by $\psi_x > 0$.

We assume that central banks' adjust their policy rates to track changes in their country's natural rate of interest. Hence, we state—as most of the literature implicitly does—that $\widehat{\vartheta}_t \equiv \widehat{\overline{r}}_t + \widehat{m}_t$, where $\widehat{m}_t$ are zero-mean (unanticipated) innovations on the stance of Home monetary policy. The central bank's (time-varying) inflation target, $\widehat{\pi}_t^T$, is assumed to follow a random walk—that is, $\widehat{\pi}_t^T = \widehat{\pi}_{t-1}^T + \widehat{\varepsilon}_t^\pi$, where $\widehat{\varepsilon}_t^\pi$ are the corresponding zero-mean i.i.d. Home inflation target innovations. Similarly we describe the monetary policy rule of the Foreign country.[18]

Under purely rational expectations, the inflation target set by the central bank anchors inflation expectations in equilibrium whenever this target is perfectly credible. Then, the long-run trend inflation rate prevailing in each country must be equal to the country's inflation target set by their own central bank, i.e., $\overline{\pi}_t$ must be equal to $\widehat{\pi}_t^T$ (and similarly for the foreign country). To see this, we can interpret the long-run trend inflation rate as the (stochastic) trend of the corresponding inflation process, i.e.,

$$\overline{\pi}_t = \lim_{h\to\infty} \mathbb{E}_t \left(\widehat{\pi}_{t+h}\right). \tag{9}$$

The inflation rate $\widehat{\pi}_t$ fluctuates around the country's stochastic inflation target, $\widehat{\pi}_t^T$, whenever credibly set by the central bank.[19] It follows that $\mathbb{E}_t \left(\widehat{\pi}_{t+h}^T\right) = \widehat{\pi}_t^T$ at any period $h > 0$ and as h goes to infinity. In that sense, (9) implies that $\overline{\pi}_t = \widehat{\pi}_t^T$—hence validating the initial conjecture that the trend inflation and target inflation must be the same in equilibrium (also noted in Woodford (2008)). The same logic applies to equate the Foreign trend inflation and target inflation rates.

The open-economy Phillips curve for the Home country can be written for inflation in deviations from

[18] The assumption is that Home and Foreign monetary policy shocks can be described as in Martínez-García (2017), i.e.,

$$\begin{pmatrix} \widehat{m}_t \\ \widehat{m}_t^* \end{pmatrix} \approx \begin{pmatrix} \delta_m & 0 \\ 0 & \delta_m \end{pmatrix} \begin{pmatrix} \widehat{m}_{t-1} \\ \widehat{m}_{t-1}^* \end{pmatrix} + \begin{pmatrix} \widehat{\varepsilon}_t^m \\ \widehat{\varepsilon}_t^{m*} \end{pmatrix},$$
$$\begin{pmatrix} \widehat{\varepsilon}_t^m \\ \widehat{\varepsilon}_t^{m*} \end{pmatrix} \sim N\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma_m^2 & \rho_{m,m^*}\sigma_m^2 \\ \rho_{m,m^*}\sigma_m^2 & \sigma_m^2 \end{pmatrix}\right).$$

For the inflation target innovations, we simply assume that

$$\begin{pmatrix} \widehat{\varepsilon}_t^\pi \\ \widehat{\varepsilon}_t^{\pi*} \end{pmatrix} \sim N\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma_\pi^2 & 0 \\ 0 & \sigma_\pi^2 \end{pmatrix}\right).$$

[19] The inflation target is explicitly announced under an inflation-targeting regime, which is the prevailing framework for monetary policy among many of the EMEs in our sample (Hammond (2012)). However, a target for inflation can be communicated (implicitly or explicitly) to the public even without the trappings of inflation-targeting as it happens for some of the EMEs in our sample.

the inflation target directly (i.e., $\widehat{\pi}_t - \widehat{\pi}_t^T$) in the following form (Martínez-García (2017)):

$$\widehat{\pi}_t - \widehat{\pi}_t^T \approx \beta \mathbb{E}_t \left(\widehat{\pi}_{t+1} - \widehat{\pi}_{t+1}^T \right) + k \left[\widehat{x}_t^W + \widehat{v}_t \right], \tag{10}$$

where $\widehat{x}_t = \widehat{y}_t - \widehat{\overline{y}}_t$ and $\widehat{x}_t^* = \widehat{y}_t^* - \widehat{\overline{y}}_t^*$ define the Home and Foreign slack—that is, the deviations of output, $\widehat{y}_t$ and $\widehat{y}_t^*$ respectively, from output potential under flexible prices and perfect competition, $\widehat{\overline{y}}_t$ and $\widehat{\overline{y}}_t^*$ respectively—and $\widehat{x}_t^W \equiv (1-\xi)\, \widehat{x}_t + \xi \widehat{x}_t^*$ is the corresponding trade-weighted measure of global slack. Here trade weights are determined by the share of imported goods in the consumption basket $0 \leq \xi \leq \frac{1}{2}$.[20] An analogous expression can be derived for the Foreign country.

As in Kabukcuoglu and Martínez-García (2018), we abstract from the changes in the Phillips curve functional form arising when the Calvo (1983) pricing equation is log-linearized around a non-zero inflation rate (discussed elsewhere by Ascari (2004) and Sahuc (2006)). The intertemporal discount factor is $0 < \beta < 1$, while the composite coefficient $k \equiv \left(\frac{(1-\alpha)(1-\beta\alpha)}{\alpha} \right) (\varphi + \gamma)$ is the slope of the Phillips curve which depends on the Calvo price stickiness parameter $0 < \alpha < 1$, the inverse of the Frisch elasticity of labor supply $\varphi > 0$, and the intertemporal elasticity of substitution, $\gamma > 0$. The term $\widehat{v}_t$ captures other transient factors and shocks to the open-economy Phillips curve such as cost-push shocks. The structure of the workhorse two-country New Keynesian model is then completed with an open-economy investment-savings (IS) curve for each country (see, e.g., the derivation in Martínez-García (2017)).

This log-linear system characterizes the dynamics of output, inflation, and the short-term nominal interest rate around the steady state for the Home and Foreign economies. Hence, a straightforward forecasting model based on full rationality and perfect credibility for $\left(\widehat{\pi}_t - \widehat{\pi}_t^T, \widehat{y}_t, \widehat{\pi}_t^* - \widehat{\pi}_t^{T*}, \widehat{y}_t^* \right)$ can be characterized in VAR form and suffices to efficiently forecast the cyclical component of inflation, $\widehat{\pi}_t - \widehat{\pi}_t^T$, among most advanced economies—as shown in the related work of Duncan and Martínez-García (2015).

Whenever we abstract from $\widehat{v}_t$ in the specification of the open-economy Phillips curve (i.e., in equation (10)), a straightforward representation of the cyclical component of inflation arises that depends solely on monetary shocks. We retain the assumption that $(\widehat{m}_t, \widehat{m}_t^*)$ follows a random bivariate process that captures possibly-persistent and unanticipated shocks to monetary policy in both countries and, hence, whenever a solution exists and is unique, the characterization of inflation for the Home country implied by the results of Martínez-García (2017) can be expressed in the following terms,

$$\widehat{\pi}_t = \widehat{\pi}_t^T + \frac{k}{1 - \beta \delta_m} \widehat{x}_t^W, \tag{11}$$

where,

$$\widehat{\pi}_t^T = \widehat{\pi}_{t-1}^T + \widehat{\varepsilon}_t^{\pi},\ \widehat{\varepsilon}_t^{\pi} \sim N\left(0, \sigma_{\pi}^2\right), \tag{12}$$

$$\widehat{x}_t^W = \delta_m \widehat{x}_{t-1}^W + \eta_t^W,\ \eta_t^W \sim N\left(0, \sigma_W^2\right), \tag{13}$$

where σ_W^2 is a composite coefficient that depends on the parameters for the exogenous monetary shock process as well as on deep structural parameters of the model.

[20] This specification can also be recast in terms of domestic slack ($\widehat{x}_t$) and the real exchange rate gap, as explained in Martínez-García and Wynne (2010). That transformation is used for inflation forecasting by Kabukcuoglu and Martínez-García (2016), among others, and also motivates the APC (M_5) and BVAR4 (M_7) specifications of our empirical work.

If we assume (time-varying) stochastic volatility for σ_π^2 and σ_W^2, this simple representation of the solution is in line with the unobserved components model of inflation with stochastic volatility (UC-SV) proposed by Stock and Watson (2007) albeit with a more general autoregressive specification for the cyclical component (given by $\frac{k}{1-\beta\delta_m}\widehat{x}_t^W$). Whenever we assume a constant inflation target (i.e., whenever $\sigma_\pi^2 = 0$), this solution reduces to the autoregressive specification RAR (M_1) and to related specifications such as DAR and DAR4 (M_2 and M_3). The solution in (11) is also related to the more general TVP representation allowing for the coefficients to vary over time (M_9). The TVP representation is more flexible and permits a random walk (RW) for the inflation target ($\widehat{\pi}_t^T$) as well as exogenous structural shifts (partly on account of greater opennes (globalization)). In order to capture more general dynamics closer in spirit to the general solution postulated by Duncan and Martínez-García (2015), we analyze the specifications in $M_4 - M_8$ with the addition of additional economic regressors for forecasting motivated by the New Keynesian model.

Imperfect Credibility and Deviations from Rational Expectations. As shown in (10), standard open-economy Phillips curve-based models treat the cyclical component of inflation (inflation in deviations from its target) as determined by three factors: expected inflation, global slack, and structural shocks that exogenously shift the open-economy Phillips curve. We should note that even though the inflation process may be decoupled effectively into two components (a random walk inflation target plus a stationary cyclical component) as suggested by equation (11), such a model solution is hard to use to predict inflation among emerging economies. This is the case because: (a) the inflation target is difficult to observe and difficult to estimate (due to, among other reasons, the fact that inflation targets are sometimes implicit); and (b) credibility plays also a role and its changes are hard to identify and quantify.

Well-anchored inflation expectations are thought to be a reflection of credible monetary policy. In that sense, an important departure from that benchmark of credible monetary policies which underlies the inflation solution in (11) is to consider the role of imperfect credibility on the inflation target as a potential source of misspecification. While rational (forward-looking) expectations remain predominant in the New Keynesian literature (with only limited attention being paid to surveys of inflation forecasts for EMEs due to data availability), we argue that the mechanism for the formation of expectations should receive more attention. Hence, we allow for deviations from rational expectations as well—using the conventional form of adaptive expectations.

We argue that deviations from fully rational expectations together with imperfect credibility of the monetary policy play an important role in bringing the predictions of the open-economy New Keynesian model closer to the empirical findings among EMEs. Under lack of credibility in the inflation target, a Phillips-curve-based model can imply inflation dynamics that produce permanent (or near-permanent) effects in the inflation rate from otherwise transitory changes in output slack—inflation patterns that resemble those observed in many EMEs during the 1980s and part of the 1990s. The improved confidence on the central bank's policies and its commitments under explicit or implicit policy frameworks for inflation targeting lead to stationary processes that probably are more similar to those given by (11) that appear to work better from the late 1990s on.

Hence, a departure from the standard open-economy New Keynesian model that introduces adaptive expectations together with partial credibility (or imperfect credibility) of the central bank's inflation target can be both consistent with the open-economy Phillips curve and with our evidence suggesting that near-random walk models like the RW-AO can be better suited to forecast inflation among many EMEs. For tractability, let us also suppose that the central bank's inflation target is constant (i.e., $\sigma_{\pi}^2 = 0$ and $\widehat{\pi}_t^T = \widehat{\pi}^T$) and that monetary shocks are i.i.d. (i.e., non-persistent with $\delta_m = 0$). Then, the open-economy Phillips curve in (10) can be re-written as follows:

$$\widehat{\pi}_t - \widehat{\pi}^T \approx \beta \left[\left((1-\theta) \widehat{\pi}_{t-1}^q + \theta \widehat{\pi}^T \right) - \widehat{\pi}^T \right] + k \left[\widehat{x}_t^W + \widehat{v}_t \right], \tag{14}$$

where next period inflation expectations are based on a weighted average of past inflation and on the central bank's inflation target, i.e., $\mathbb{E}_t (\widehat{\pi}_{t+1}) = (1-\theta) \widehat{\pi}_{t-1}^q + \theta \widehat{\pi}^T$. The parameter $0 \leq \theta \leq 1$ in equation (14) is the corresponding weight on the inflation target and $(1-\theta)$ the weight on past inflation. We introduce adaptive expectations with the average $q-$period inflation rate from $t+1-q$ to t ($\widehat{\pi}_t^q$) which can be written as $\widehat{\pi}_t^q \approx \frac{1}{q} \sum_{j=1}^{q} \widehat{\pi}_{t+1-j}$ for some $q \geq 1$. The timing of this moving average $\widehat{\pi}_{t-1}^q$ incorporated in the inflation expectations for (14) corrects for the publication lags in the inflation data.

The parameter θ can be interpreted as a measure of the credibility of the central bank's inflation target with $\theta = 1$ indicating full credibility of the target, $\theta = 0$ representing the case of no credibility, and $0 < \theta < 1$ indicating partial credibility.[21] The parameter θ can be more also defined as the fraction of agents that do believe in the central bank's inflation target while $(1-\theta)$ is the fraction of agents that do not find monetary policy credible and rely on adaptive expectations to form their predictions about future inflation. This specification is related to a growing literature on the role of heterogenous beliefs in the New Keynesian model (Lansing (2009), Assenza et al. (2013), Di Bartolomeo et al. (2016), Gibbs (2017), and Pecora and Spelta (2017)).

The $q-$period moving average of the inflation rate given by $\widehat{\pi}_t^q \approx \frac{1}{q} \sum_{j=1}^{q} \widehat{\pi}_{t+1-j}$ permits us to consider a number of alternative specifications. One possibility is that the forecast of one-period-ahead inflation at time t is given by the observed inflation rate the prior period $\widehat{\pi}_{t-1}$ (which is the case when $q = 1$). Another conventional possibility is that adaptive expectations be based on $\widehat{\pi}_t^4$ instead, which is approximately equal to the observed rate of inflation over the previous four periods (a four-quarter moving average). This measure alone captures well the inflation tendency and constitutes, in fact, the basis of the RW-AO forecasting model (M_0).

Case 1: Perfect credibility. Let us suppose that inflation expectations are firmly anchored and fully rational as is often assumed to be the case for advanced economies. Then, theory suggests that inflationary expectations are pinned down by the central bank's target and $\theta = 1$. From here it follows that (14) implies:[22]

$$\widehat{\pi}_t \approx \widehat{\pi}^T + k \left[\widehat{x}_t^W + \widehat{v}_t \right] \rightarrow \Delta^q \widehat{\pi}_t \approx k \left[\Delta^q \widehat{x}_t^W + \Delta^q \widehat{v}_t \right], \tag{15}$$

where $\widehat{x}_t^{W,q} \approx \frac{1}{q} \sum_{j=1}^{q} \widehat{x}_{t+1-j}^W$ and $\widehat{v}_t^q \approx \frac{1}{q} \sum_{j=1}^{q} \widehat{v}_{t+1-j}$. Here, we define the inflation deviations operator as follows: $\Delta^q \widehat{\pi}_t \equiv \widehat{\pi}_t - \widehat{\pi}_{t-1}^q$, which corresponds to a conventional first-difference operator whenever $q = 1$. Similarly, we define the slack deviations operator and the cost-push shock operator as follows: $\Delta^q \widehat{x}_t^W \equiv \widehat{x}_t - \widehat{x}_{t-1}^{W,q}$ and $\Delta^q \widehat{v}_t \equiv \widehat{v}_t - \widehat{v}_{t-1}^q$, respectively.

The expression in (15) is consistent with the solution under rational expectations given in equation

[21] We use this special case with constant θ for illustration purposes. For details on generalizing the specification to allow for state-dependent changes in the perceptions of how credible monetary policy is and their linkage to inflation expectations, we refer the interested reader to Mehrotra and Yetman (2014).

[22] Here, we note that $\widehat{\pi}_t^q \approx \widehat{\pi}^T + k \left[\frac{1}{q} \sum_{j=1}^{q} \widehat{x}_{t+1-j}^W + \frac{1}{q} \sum_{j=1}^{q} \widehat{v}_{t+1-j} \right] = \widehat{\pi}^T + k \left[\widehat{x}_t^{W,q} + \widehat{v}_t^q \right]$.

(11)—albeit the rational expectations solution in (11) is derived abstracting from the cost-push shock $\widehat{v}_t$, yet allowing persistent monetary shocks and some time-variation in the inflation target ($\delta_m > 0$ and $\sigma_{\pi}^2 > 0$). This is to be expected because in the rational expectations equilibrium, inflation expectations are anchored by the inflation target (as implied by equation (11)). The implication of the open-economy Phillips curve in this case is rather standard.

A shock that produces a positive global output gap increases inflation above the central bank's target, but does not unleash an inflationary spiral as those shocks are inherently transitory. If the global output gap stabilizes—even when it is still positive and quite sizable—inflation will also stabilize. Hence, a shock that pushes output above its potential, has only a limited impact in raising inflation. In other words, a credible inflation target is a powerful anchor for actual inflation—something that appears to be corroborated in the evidence for most advanced countries presented in Duncan and Martínez-García (2015).

Case 2: No credibility with adaptive expectations. Let us assume now that inflationary expectations are purely backward-looking (adaptive expectations), so that $\theta = 0$ and economic agents put no weight on the official inflation target. Hence, it follows from here that (14) implies:

$$\widehat{\pi}_t \approx \beta \widehat{\pi}^q_{t-1} + (1-\beta)\,\widehat{\pi}^T + k\left[\widehat{x}^W_t + \widehat{v}_t\right] \rightarrow \Delta^q \widehat{\pi}_t \approx (1-\beta)\left(\widehat{\pi}^T - \widehat{\pi}^q_{t-1}\right) + k\left[\widehat{x}^W_t + \widehat{v}_t\right], \tag{16}$$

which appears to behave like a near-unit-root autoregressive process with a residual term that bundles the endogenous global slack component as well as the exogenous cost-push shock term. If the discount factor satisfies that $\beta \rightarrow 1$, a structural shock that produces a positive global output gap leads to steadily increasing inflation (i.e., $\widehat{\pi}_t > \widehat{\pi}^q_{t-1}$). The only way to stabilize inflation in that case is to push output back to potential. However, in order to lower above-target inflation back to target, the central bank needs to push output below potential (possibly causing a recession in the process). Global slack, therefore, can lead to inflationary and deflationary spirals in this context and policy must respond accordingly. In addition, we recognize that those patterns may emerge even when the local economy is operating below potential, because—owing to above-potential output in the rest of the world—it finds itself drawn into this spirals.

Not surprisingly, if the true data-generating process (DGP) is given by the specification where agents do not believe in the inflation target (and expectations are adaptive) as in equation (16), trying to predict inflation based on the alternative specification like that of equation (15) which assumes full credibility and rational expectations is likely to underperform. Hence, we argue that model misspecification in terms of monetary policy credibility and full rational expectations formation rather than the underlying open-economy Phillips curve may explain why simpler models like the RW-AO (M_0) appear to work well empirically among many EMEs.

Case 3: Partial credibility with adaptive expectations. Finally, we consider the intermediate case in which inflationary expectations are partly anchored and inflation dynamics depend on both the central bank's inflation target and past inflation. In this case, we have $0 < \theta < 1$ and that implies:

$$\widehat{\pi}_t \approx \beta\left((1-\theta)\,\widehat{\pi}^q_{t-1} + \left(\theta + \left(\frac{1-\beta}{\beta}\right)\right)\widehat{\pi}^T\right) + k\left[\widehat{x}^W_t + \widehat{v}_t\right] \rightarrow \Delta^q \widehat{\pi}_t \approx (1-\beta\,(1-\theta))\left(\widehat{\pi}^T - \widehat{\pi}^q_{t-1}\right) + k\left[\widehat{x}^W_t + \widehat{v}_t\right]. \tag{17}$$

Hence, inflation tends to converge towards the central bank's inflation target. This specification can be cast in the form of an error correction-type model for changes in inflation (even in the limit case where the discount factor satisfies that $\beta \rightarrow 1$). The inflation process also tends to increase/decrease in the direction of global slack. As a result, inflation stabilizes in the short-run whenever those forces offset each other in (17), i.e., whenever:

$$\Delta^q \widehat{\pi}_t = 0 \rightarrow \widehat{\pi}_t = \widehat{\pi}^q_{t-1} = \widehat{\pi}^T + \frac{k}{1-\beta(1-\theta)} \left[\widehat{x}^W_t + \widehat{v}_t\right]. \tag{18}$$

Even partial credibility suffices to avoid the inflationary/deflationary spirals of the case where monetary policy is not credible—i.e., whenever $\theta = 0$.

Here, a comparison with the case where inflation expectations are well-anchored ($\theta = 1$, equation (15)) is very useful as it reveals that inflation quickly becomes unanchored whenever $\theta \neq 1$. This implies much larger differences between actual and target inflation ($\Delta^q \widehat{\pi}_t$) for a corresponding amount of global slack ($\widehat{x}^W_t$) than under full credibility as $\theta \rightarrow 0$. Consistent with this logic, a number of recent studies argue that improved credibility of the central bank's inflation target helps explain the failure of inflation to keep falling despite the apparent persistence of large negative output gaps in the aftermath of the 2008-09 global recession among many advanced countries (Meier (2010), IMF WEO (2013)).

Much less work has been done exploring the role of credibility for EMEs. Our paper is—to the best of our knowledge—one of the first to explicitly propose that the credibility of the inflation target and deviations from rational expectations can help align the predictions of the open-economy Phillips curve with the findings reported for many EMEs (notably those documented in this paper). We leave for future research the estimation of the model with imperfect credibility of the inflation target and the recovery of the parameter θ associated with the credibility of monetary policy. We note again that deviations from full rationality are also important to take under consideration. Hence, we plan to incorporate explicitly—whenever available—surveys or data on the inflation target for the central bank in the future estimation and forecasting of such a model with imperfect credibility.

We believe that our paper also makes a novel contribution to the literature by taking some first steps towards developing variants of the open-economy Phillips-curve-based model that can encompass experiences as different as those of the EMEs in our sample. We believe this can ultimately equip us with a more unified framework with which to explore inflation across many countries around the world.

B Tables and Figures

Table 1.A - Data Sources for the Different Forecasting Models

Concept	Data Sources	Main Transformation
Headline CPI	National statistical offices and central banks; OECD; Grossman et al. (2014)	Quarter-over-quarter (SAAR, %)
Real GDP	National statistical offices and central banks; OECD; Grossman et al. (2014)	Quarter-over-quarter (SAAR, %)
Industrial production	National statistical offices and central banks; OECD; IMF; Grossman et al. (2014)	Quarter-over-quarter (SAAR, %)
Nominal exchange rate	Central banks; Wall Street Journal; Financial Times; IMF; Grossman et al. (2014)	Quarter-over-quarter (SAAR, %)
Commodity price index	IMF	Quarter-over-quarter (SAAR, %)
Inflation forecasts	Consensus Forecasts^{TM} : Quarterly year-over-year inflation (SA, %) forecasts	Quarterization

This table reports the main sources of the data used in our forecasting exercises. The EME countries included in our forecasting evaluation are: Chile, China, Colombia, Hungary, Indonesia, India, Malaysia, Mexico, Nigeria, Peru, Philippines, South Africa, Thailand, and Turkey. The time series coverage spans the period between 1980Q1 and 2016Q4 across all variables and countries, with few exceptions. China's headline CPI data starts in 1984Q1. For Nigeria, we use GDP data only because the industrial production series was not available for the whole period.

The commodity price index is computed as a simple average of the price indexes of agricultural raw materials, food, beverages, metals, and crude oil from the IMF. The real exchange rate used in augmented Phillips curve models is defined as the bilateral nominal exchange rate (U.S. dollars per unit of foreign currency) times the CPI of the EME divided by the U.S. CPI. We also compute static factors with an expanded country sample that includes the 14 EMEs investigated in the paper together with the following 18 advanced economies: Australia, Austria, Belgium, Canada, France, Germany, Greece, Italy, Japan, Korea, Netherlands, Portugal, Spain, Sweden, Switzerland, Taiwan, U.K., and U.S.

All series are seasonally adjusted. SAAR denotes seasonally-adjusted (SA), annualized rate computations of the quarter-over-quarter growth rate. Quarterization refers to the procedure whereby we derive quarter-over-quarter growth rates (SAAR, %) based on quarterly data reported in the form of year-over-year growth rates (SA, %). Our approach to calculate the implicit forecasts for the quarter-over-quarter growth rates (SAAR, %) involves three straightforward steps: first, we transform the forecasts for the reported year-over-year exact growth rates (SA, %) into their corresponding log-approximations; second, using the additivity of the log-approximation to the year-over-year growth rate, we infer the log-approximation of the quarter-over-quarter growth rate for any forecasting horizon netting out the observed or implied forecasts for the log-approximation of the quarter-over-quarter growth rate over the preceding three quarters; finally, we exponentiate the log-approximation of the quarter-over-quarter growth rates appropriately to recover the exact growth rate (SAAR, %). We use these implicit forecasts in our evaluation exercise with data covering the period 2006Q4-2016Q4 for 12 out of the 14 EMEs in our sample–predictions for Nigeria and South Africa are not available.

Table 1.B - Descriptive Statistics: Quarter-over-Quarter Inflation Rate (SAAR, %)

		Panel I. Full Sample				
Country	Region	Mean	Std. Dev.	Q_1	Q_2	Q_3
Mexico	LA	26.79	38.88	4.06	9.26	28.51
Peru	LA	2428.33	26247.78	2.90	6.42	70.21
Hungary	EE	10.52	9.73	3.62	7.70	16.43
Colombia	LA	14.47	10.07	5.14	11.74	23.33
Nigeria	AA	20.84	24.36	7.52	12.67	28.52
Indonesia	AP	9.98	14.18	4.39	6.76	11.11
Philippines	AP	8.57	11.10	3.09	6.14	10.53
Turkey	EE	41.64	36.30	10.02	35.37	65.87
Chile	LA	10.05	9.94	3.00	5.73	14.31
India	AP	7.98	4.64	5.01	7.57	10.41
China	AP	5.47	7.57	1.22	2.90	7.56
Thailand	AP	3.64	3.92	1.65	3.05	5.13
Malaysia	AP	2.96	2.86	1.34	2.73	4.19
South Africa	AA	9.25	5.69	5.20	8.08	13.09

		Panel II. 1980Q2-1990Q4					Panel III. 1991Q1-2002Q4					Panel IV. 2003Q1-2016Q4				
Country	Region	Mean	Std. Dev.	Q_1	Q_2	Q_3	Mean	Std. Dev.	Q_1	Q_2	Q_3	Mean	Std. Dev.	Q_1	Q_2	Q_3
Mexico	LA	68.41	49.29	28.48	59.36	88.52	16.12	14.16	7.81	12.71	19.87	3.97	1.40	2.93	3.86	4.83
Peru	LA	7576.85	46334.02	67.43	113.06	367.26	15.53	24.25	3.52	6.80	11.86	3.01	1.95	1.70	2.90	4.39
Hungary	EE	11.50	9.76	4.19	9.21	16.94	17.41	9.64	9.06	16.59	23.48	3.86	3.42	1.46	3.84	5.69
Colombia	LA	24.23	6.56	21.30	24.50	28.53	17.26	7.69	9.67	18.75	23.22	4.58	2.22	2.82	4.56	5.79
Nigeria	AA	23.30	30.95	6.82	11.50	38.44	28.80	27.64	8.92	17.86	41.67	12.15	7.78	7.48	10.79	16.07
Indonesia	AP	9.14	5.34	5.97	8.06	12.03	14.55	22.89	5.90	8.64	12.76	6.72	5.91	3.87	5.32	7.22
Philippines	AP	15.32	17.76	6.92	11.85	16.14	7.38	5.10	4.58	6.58	8.86	4.40	3.02	2.39	3.80	5.74
Turkey	EE	49.31	25.72	31.47	44.85	57.37	72.72	34.11	58.50	71.54	81.41	9.12	5.76	5.87	8.53	10.75
Chile	LA	10.05	9.94	3.00	5.73	14.31	7.71	5.13	3.54	5.63	10.75	3.34	2.97	1.77	3.05	4.84
India	AP	9.23	3.79	6.93	8.88	10.96	8.14	5.99	4.98	7.10	10.87	6.88	3.60	4.77	6.38	9.43
China	AP	9.78	9.73	3.62	5.99	13.27	6.18	8.85	-0.59	2.30	9.97	2.79	2.65	1.37	2.17	3.66
Thailand	AP	5.00	4.90	2.13	3.95	6.41	3.82	3.16	2.02	3.67	5.37	2.45	3.33	0.43	2.47	4.02
Malaysia	AP	3.40	3.62	1.42	3.03	4.60	3.15	1.78	1.81	2.96	4.10	2.44	2.92	1.05	2.22	3.56
South Africa	AA	14.84	5.27	12.31	13.70	17.02	8.70	4.46	5.65	8.25	11.73	5.43	2.88	3.92	5.40	6.45

Notes: LA refers to Latin America, EE is for Eastern Europe and the MENA countries (the Middle East and North Africa region), AA stands for Sub-Saharan Africa, and AP for the Asia-Pacific Region. Std. Dev. refers to the standard deviation. Q_1, Q_2, and Q_3 denote the first quartile (25%), the second quartile (50%) or median, and the third quartile (75%) of the distribution, respectively. SAAR denotes seasonally-adjusted, annualized rate computations of the quarter-over-quarter growth rate.

Table 2 - RMSPE of the RW-AO Model Relative to Competing Models (Summary)

	M_1	M_2	M_3	M_4	M_5	M_6	M_7	M_8	M_9	Average
	RAR	DAR	DAR4	FAR	APC	BVAR2	BVAR4	BVAR2-COM	TVP	M_1-M_9
One-quarter ahead										
Mean	0.898	0.898	0.892	0.912	0.810	0.929	0.824	0.846	1.055	0.896
Median	0.993	0.993	0.967	0.965	0.808	0.990	0.834	0.898	1.065	0.946
#<1	7	7	8	8	11	7	10	10	5	8
#pv<0.1	3	3	8	4	7	4	6	6	2	5
Four-quarter ahead										
Mean	0.700	0.714	0.754	0.754	0.657	0.812	0.726	0.729	0.830	0.742
Median	0.760	0.760	0.831	0.815	0.610	0.891	0.785	0.789	0.839	0.787
#<1	12	12	11	10	12	12	13	14	14	12
#pv<0.1	9	9	11	8	9	6	10	9	10	9
Eight-quarter ahead										
Mean	0.636	0.697	0.716	0.767	0.666	0.788	0.763	0.773	0.838	0.738
Median	0.662	0.702	0.766	0.919	0.717	0.885	0.828	0.861	0.812	0.795
#<1	12	11	11	10	13	13	12	13	14	12
#pv<0.1	8	8	11	6	9	9	11	9	11	9
Twelve-quarter ahead										
Mean	0.620	0.675	0.689	0.775	0.651	0.764	0.786	0.814	0.868	0.738
Median	0.563	0.637	0.658	0.826	0.600	0.854	0.879	0.880	0.860	0.751
#<1	11	10	10	9	11	14	14	14	14	12
#pv<0.1	9	9	10	6	9	7	6	5	6	7
Averages (all horizons)										
Mean	0.713	0.746	0.763	0.802	0.696	0.823	0.775	0.791	0.898	0.778
Median	0.745	0.773	0.806	0.881	0.684	0.905	0.831	0.857	0.894	0.820
#<1	11	10	10	9	12	12	12	13	12	11
#pv<0.1	7	7	10	6	9	7	8	7	7	8

Notes: Rows for means and medians report the average/median ratio of root mean squared prediction error (RMSPE) from the RW-AO model relative to the RMSPE of competing forecasting models calculated over the 14 countries. Values less than one imply that the RW-AO model has a lower RMSPE than does the competitive benchmark. The row #<1 reports the number of economies that show relative RMSPE lower than 1 for a particular model. The row #pv<0.1 reports the number of economies that show a p-value lower than 0.1 for the null of equal predictive accuracy measured by the RMSPEs of the RW-AO and the alternative model. We use the Diebold-Mariano-West statistic or the adjusted Clark-West statistic when models are nested. See Tables 1.A and 1.B for the data sources. RAR and DAR denote the AR(2) model using the iterative and direct methods to forecast, DAR4 is the AR(4) model, FAR is the Factor-Augmented AR(2) model, APC is the Augmented Phillips Curve, BVAR2 is the bivariate Bayesian VAR(2), BVAR4 is the 4-variable Bayesian VAR(2), BVAR2-COM is the bivariate Bayesian VAR(2) with commodity price indexes, and TVP is the time-varying parameter specification.

Table 3 - Directional Accuracy: Success Ratios (Summary)

	M_0 RW-AO	M_1 RAR	M_2 DAR	M_3 DAR4	M_4 FAR	M_5 APC	M_6 BVAR2	M_7 BVAR4	M_8 BVAR2-COM	M_9 TVP	Average M_1-M_9
One-quarter ahead											
Mean	0.608	0.563	0.563	0.573	0.581	0.542	0.580	0.553	0.556	0.527	0.560
Median	0.583	0.561	0.561	0.591	0.576	0.568	0.561	0.561	0.568	0.545	0.566
#>0.5	14	9	9	10	11	9	11	9	9	9	10
Four-quarter ahead											
Mean	0.673	0.582	0.590	0.599	0.587	0.593	0.599	0.586	0.582	0.517	0.582
Median	0.683	0.571	0.571	0.579	0.595	0.587	0.627	0.571	0.579	0.508	0.577
#>0.5	14	13	13	14	12	13	11	12	11	7	12
Eight-quarter ahead											
Mean	0.668	0.552	0.568	0.580	0.611	0.562	0.621	0.564	0.584	0.530	0.575
Median	0.669	0.551	0.568	0.585	0.653	0.559	0.627	0.576	0.644	0.517	0.587
#>0.5	14	10	9	10	9	8	12	10	8	9	9
Twelve-quarter ahead											
Mean	0.668	0.548	0.556	0.557	0.583	0.564	0.551	0.569	0.581	0.540	0.561
Median	0.664	0.564	0.582	0.573	0.627	0.591	0.555	0.582	0.591	0.545	0.579
#>0.5	14	10	10	10	9	10	12	11	13	10	11
Averages (all horizons)											
Mean	0.654	0.561	0.569	0.577	0.591	0.565	0.588	0.568	0.575	0.529	0.569
Median	0.650	0.562	0.570	0.582	0.613	0.576	0.592	0.573	0.596	0.529	0.577
#>0.5	14	11	10	11	10	10	12	11	10	9	10

Notes: Rows for means and medians report the average and median ratio of success in directional accuracy over the 14 countries. The row #>0.5 reports the number of economies that show a success ratio higher than 0.5 for a particular model. See Tables 1.A and 1.B for the data sources. RW-AO stands for the random walk model proposed by Atkeson and Ohanian (2001), RAR and DAR denote the AR(2) model using the iterative and direct methods to forecast, DAR4 is the AR(4) model, FAR is the Factor-Augmented AR(2) model, APC is the Augmented Phillips Curve, BVAR2 is the bivariate Bayesian VAR(2), BVAR4 is the 4-variable Bayesian VAR(2), BVAR2-COM is the bivariate Bayesian VAR(2) with commodity price indexes, and TVP is the time-varying parameter (TVP) specification.

Table 4 - Ranking of Economies per Number of Statistical Significant Cases (#U-Theils<1 with pv<0.1)							
	h=1	h=4	h=8	h=12	Average (h=1,4)	Average (h=8,12)	Average
Mexico	8	9	8	9	9	9	9
Peru	7	9	9	9	8	9	9
Hungary	4	9	9	8	7	9	8
Colombia	7	8	7	5	8	6	7
Nigeria	4	8	8	6	6	7	7
Philippines	3	7	7	8	5	8	6
Turkey	4	7	5	5	6	5	5
Chile	2	7	6	4	5	5	5
India	2	7	5	4	5	5	5
Indonesia	1	5	7	2	3	5	4
China	0	1	4	7	1	6	3
Thailand	0	3	4	1	2	3	2
Malaysia	0	1	4	1	1	3	2
South Africa	0	1	0	0	1	0	0

Notes: Rows report number of models that show a significantly lower RMSPE for the RW-AO against its competitors using a p-value of 0.1 (#U-Theils<1 with pv<0.1) for a given economy and forecast horizon (h) or average of forecast horizons. Last column reports the average over all the forecast horizons. Countries are sorted from the highest to the lowest average.

Table 5 - Ranking of Competing Models per Relative RMSPE (#U-Theils<1 with pv<0.1)						
	h=1	h=4	h=8	h=12	Average (h=8,12)	Average
FAR	4	8	6	6	6	6
BVAR2	4	6	9	7	8	7
BVAR2-COM	6	9	9	5	7	7
RAR	3	9	8	9	9	7
DAR	3	9	8	9	9	7
TVP	2	10	11	6	9	7
BVAR4	6	10	11	6	9	8
APC	7	9	9	9	9	9
DAR4	8	11	11	10	11	10

Notes: Rows report number of countries with a significantly lower RMSPE for the RW-AO against its competitors using a p-value of 0.1 (#U-Theils<1 with pv<0.1) for a given model and forecast horizon h or average of forecast horizons. Last column reports the average over all the forecast horizons. Countries are sorted from the lowest to the highest average. RAR and DAR denote the AR(2) model using the iterative and direct methods to forecast, DAR4 is the AR(4) model, FAR is the Factor-Augmented AR(2) model, APC is the Augmented Phillips Curve, BVAR2 is the bivariate Bayesian VAR(2), BVAR4 is the 4-variable Bayesian VAR(2), BVAR2-COM is the bivariate Bayesian VAR(2) with commodity price indexes, and TVP is the time-varying parameter specification.

Table 6 - Forecast Averages				
	Relative RMSPE		Directional accuracy	
	M_1-M_9 Average	M_4 and M_6 Average	M_1-M_9 Average	M_4 and M_6 Average
One-quarter ahead				
Mean	0.950	0.920	0.566	0.584
Median	1.024	0.972	0.561	0.576
#<1; #>0.5	6	7	9	11
#pv<0.1	2	4	8	8
Four-quarter ahead				
Mean	0.769	0.797	0.591	0.595
Median	0.834	0.888	0.571	0.611
#<1; #>0.5	11	11	13	12
#pv<0.1	8	7	7	8
Eight-quarter ahead				
Mean	0.785	0.818	0.568	0.619
Median	0.884	0.953	0.576	0.669
#<1; #>0.5	11	11	9	9
#pv<0.1	6	6	9	9
Twelve-quarter ahead				
Mean	0.821	0.820	0.573	0.587
Median	0.926	0.920	0.609	0.600
#<1; #>0.5	9	10	10	10
#pv<0.1	5	5	8	8
Averages (all horizons)				
Mean	0.831	0.839	0.574	0.596
Median	0.917	0.933	0.579	0.614
#<1; #>0.5	9	10	10	11
#pv<0.1	5	6	8	8

Notes: First and third columns report statistics for the forecast average of models M1 through M9 (M1-M9 Average). Second and fourth columns report the forecast average of models M4 and M6 only (M4 and M6 Average). Mean/median report those statistics for the ratio of the root mean squared prediction error (RMSPE) of the corresponding forecast average relative to the RW-AO model over the 14 countries, for a given forecast horizon. Values less than one imply that the RW-AO model has a lower RMSPE than does the forecast average. The row #<1; #>0.5 reports the number of economies that show relative RMSPE lower than 1 in the first and second columns, and the number of economies that show a success ratio higher than 0.5 in the last two columns. The row #pv<0.1 reports the number of economies that show a p-value lower than 00.1 for the null of equal predictive accuracy measured by the RMSPEs of the RW-AO and the corresponding forecast average, using the Diebold-Mariano-West statistic.

Table 7 - RMSPE of the RW-AO Model Relative to Competing Models with Intercept Corrections (Summary)

	M_1	M_2	M_3	M_4	M_5	M_6	M_7	M_8	M_9	Average
	RAR	DAR	DAR4	FAR	APC	BVAR2	BVAR4	BVAR2-COM	TVP	M_1-M_9
One-quarter ahead										
Mean	0.856	0.856	0.881	0.807	0.712	0.819	0.705	0.792	0.762	0.799
Median	0.947	0.947	0.950	0.836	0.763	0.857	0.753	0.802	0.751	0.845
#<1	9	9	8	12	14	12	14	12	14	12
#pv<0.1	6	6	8	8	11	9	11	10	12	9
Four-quarter ahead										
Mean	0.897	0.925	0.942	0.799	0.742	0.755	0.694	0.727	0.673	0.795
Median	0.983	1.013	1.020	0.885	0.779	0.822	0.765	0.783	0.675	0.858
#<1	9	6	5	8	11	14	14	14	14	11
#pv<0.1	3	2	5	4	5	6	6	5	7	5
Eight-quarter ahead										
Mean	0.993	0.965	0.966	0.817	0.707	0.700	0.674	0.700	0.698	0.802
Median	1.034	1.030	1.019	0.955	0.796	0.753	0.754	0.775	0.703	0.869
#<1	4	5	6	10	14	14	14	14	14	11
#pv<0.1	1	1	6	2	5	8	8	8	7	5
Twelve-quarter ahead										
Mean	1.007	0.982	0.944	0.740	0.700	0.696	0.692	0.702	0.721	0.798
Median	1.052	1.048	0.994	0.787	0.755	0.766	0.758	0.769	0.737	0.852
#<1	4	3	8	9	10	14	14	14	14	10
#pv<0.1	1	1	8	4	4	5	3	4	5	4
Averages (all horizons)										
Mean	0.938	0.932	0.933	0.791	0.715	0.742	0.692	0.730	0.714	0.799
Median	1.004	1.009	0.996	0.866	0.773	0.799	0.758	0.782	0.717	0.856
#<1	7	6	7	10	12	14	14	14	14	11
#pv<0.1	3	3	7	5	6	7	7	7	8	6

Notes: Forecasts of competing models include intercept corrections. Rows for means and medians report the average/median ratio of root mean squared prediction error (RMSPE) from the RW-AO model relative to the RMSPE of competing forecasting models with intercept corrections calculated over the 14 countries. Values less than one imply that the RW-AO model has a lower RMSPE than does the competitive benchmark. The row #<1 reports the number of economies that show relative RMSPE lower than 1 for a particular model. The row #pv<0.1 reports the number of economies that show a p-value lower than 00.1 for the null of equal predictive accuracy measured by the RMSPEs of the RW-AO and the alternative model. We use the Diebold-Mariano-West statistic or the adjusted Clark-West statistic when models are nested. See Tables 1.A and 1.B for the data sources. RAR and DAR denote the AR(2) model using the iterative and direct methods to forecast, DAR4 is the AR(4) model, FAR is the Factor-Augmented AR(2) model, APC is the Augmented Phillips Curve, BVAR2 is the bivariate Bayesian VAR(2), BVAR4 is the 4-variable Bayesian VAR(2), BVAR2-COM is the bivariate Bayesian VAR(2) with commodity price indexes, and TVP is the time-varying parameter specification.

Table 8 - Directional Accuracy: Success Ratios of the RW-AO and Competing Models with Intercept Corrections (Summary)

	M_0 RW-AO	M_1 RAR	M_2 DAR	M_3 DAR4	M_4 FAR	M_5 APC	M_6 BVAR2	M_7 BVAR4	M_8 BVAR2-COM	M_9 TVP	Average M_1-M_9
One-quarter ahead											
Mean	0.608	0.425	0.425	0.447	0.454	0.432	0.453	0.447	0.455	0.415	0.439
Median	0.583	0.431	0.431	0.446	0.446	0.431	0.446	0.446	0.454	0.423	0.439
#>0.5	14	1	1	3	4	1	5	3	1	1	2
Four-quarter ahead											
Mean	0.673	0.690	0.714	0.722	0.690	0.689	0.657	0.665	0.681	0.630	0.682
Median	0.683	0.702	0.726	0.742	0.694	0.710	0.661	0.653	0.669	0.645	0.689
#>0.5	14	13	13	13	13	14	12	14	14	14	13
Eight-quarter ahead											
Mean	0.668	0.720	0.722	0.729	0.703	0.685	0.643	0.637	0.649	0.621	0.679
Median	0.669	0.750	0.750	0.759	0.759	0.672	0.664	0.655	0.681	0.638	0.703
#>0.5	14	13	13	13	13	13	13	12	12	11	13
Twelve-quarter ahead											
Mean	0.668	0.737	0.735	0.728	0.681	0.677	0.659	0.661	0.660	0.663	0.689
Median	0.664	0.722	0.750	0.759	0.694	0.704	0.667	0.667	0.667	0.685	0.702
#>0.5	14	13	13	13	14	14	14	13	13	13	13
Averages (all horizons)											
Mean	0.654	0.643	0.649	0.657	0.632	0.621	0.603	0.603	0.611	0.582	0.622
Median	0.650	0.651	0.664	0.676	0.648	0.629	0.609	0.605	0.618	0.598	0.633
#>0.5	14	10	10	11	11	11	11	11	10	10	10

Notes: Forecasts of competing models (M1-M9) include intercept corrections. Rows for means and medians report the average and median ratio of success in directional accuracy over the 14 countries. The row #>0.5 reports the number of economies that show a success ratio higher than 0.5 for a particular model. See Tables 1.A and 1.B for the data sources. RW-AO stands for the random walk model proposed by Atkeson and Ohanian (2001), RAR and DAR denote the AR(2) model using the iterative and direct methods to forecast, DAR4 is the AR(4) model, FAR is the Factor-Augmented AR(2) model, APC is the Augmented Phillips Curve, BVAR2 is the bivariate Bayesian VAR(2), BVAR4 is the 4-variable Bayesian VAR(2), BVAR2-COM is the bivariate Bayesian VAR(2) with commodity price indexes, and TVP is the time-varying parameter specification.

Table 9. RMSPE of the RW-AO Model Relative to Competing Models, Different Measures of Inflation

	Exact q-o-q inflation Average M1-M9	Approximate q-o-q inflation Average M1-M9	Exact y-o-y inflation Average M1-M9	Approximate y-o-y inflation Average M1-M9
One-quarter ahead				
Mean	0.896	0.949	1.501	1.574
Median	0.946	1.002	1.580	1.636
#<1	8	7	2	2
#pv<0.1	5	4	2	2
Four-quarter ahead				
Mean	0.742	0.778	0.812	0.851
Median	0.787	0.817	0.870	0.899
#<1	12	12	10	9
#pv<0.1	9	9	6	5
Eight-quarter ahead				
Mean	0.738	0.771	0.766	0.795
Median	0.795	0.829	0.840	0.862
#<1	12	12	11	11
#pv<0.1	9	9	7	7
Twelve-quarter ahead				
Mean	0.738	0.771	0.759	0.787
Median	0.751	0.788	0.770	0.802
#<1	12	12	11	11
#pv<0.1	7	7	6	6
Averages (all horizons)				
Mean	0.778	0.817	0.959	1.002
Median	0.820	0.859	1.015	1.050
#<1	11	11	8	8
#pv<0.1	8	7	5	5

Notes: The exact quarter-over-quarter inflation (used in baseline exercises) is calculated as $100((CPI(t)/CPI(t-1))^4-1)$, the approximate quarter-on-quarter inflation is 400(log(CPI(t))-log(CPI(t-1))), the exact year-on-year inflation is (CPI(t)/CPI(t-4)-1), and the approximate year-on-year inflation is 100(log(CPI(t))-log(CPI(t-4))). Rows for means and medians report the average of the mean/median ratio of root mean squared prediction error (RMSPE) from the RW-AO model relative to the RMSPE of competing forecasting models calculated over the 14 countries and over the 9 models. Values less than one imply that the RW-AO model has, on average, a lower RMSPE than does the competitive benchmarks. The row #<1 reports the average number of cases (out of 14 EMEs) that show an average of the relative RMSPE lower than 1 over the 9 competing models. The row #pv<0.1 reports the average number of cases (out of 14 EMEs) that show a p-value lower than 0.1 for the null of equal predictive accuracy measured by the RMSPEs of the RW-AO and over the 9 competing models. We use the Diebold-Mariano-West statistic or the adjusted Clark-West statistic when models are nested.

Table 10 - Statistics for the Test of Joint Predictive Ability Across Countries			
	M_4	M_6	M_8
	FAR	BVAR2	BVAR2-COM
One-quarter ahead			
#Intercept>0	6	6	7
Median (Intercept)	-1.18	-1.33	-0.05
Chi-square statistic	48.17	50.10	80.09
P-value	0.00	0.00	0.00
Four-quarter ahead			
#Intercept>0	12	12	11
Median (Intercept)	10.84	2.89	5.21
Chi-square statistic	106.03	41.77	70.17
P-value	0.00	0.00	0.00
Eight-quarter ahead			
#Intercept>0	12	13	13
Median (Intercept)	9.19	5.03	5.06
Chi-square statistic	84.18	82.80	77.74
P-value	0.00	0.00	0.00
Twelve-quarter ahead			
#Intercept>0	10	14	14
Median (Intercept)	17.13	5.23	4.09
Chi-square statistic	177.30	105.70	61.01
P-value	0.00	0.00	0.00

Notes: We estimate an only-intercept model for each of the 14 EMEs using SUR-GLS estimation, where the regressand is the difference between the squared forecast error of the alternative model (M4, M6, and M8) and the squared forecast error of the RW-AO model. Squared forecast errors are generated from a rolling-window estimation using a width of 75 observations. The number of observations is 70 (h=1), 67 (h=4), 63 (h=8), and 59 (h=12). A positive (negative) intercept indicates that the RW-AO model shows higher(lower) predictive ability than the alternative model. #Intercept>0 is the number of countries/equations that show a positive intercept, given a forecast horizon and an alternative model. The median of all the intercepts is reported as well. The null hypothesis is that all the intercepts are jointly equal to zero (equal predictive ability across countries). The p-value and chi-square statistic are related to that null hypothesis and the statistic is compared to a critical value with 14 degrees of freedom. FAR is the Factor-Augmented AR(2) model, BVAR2 is the bivariate Bayesian VAR(2), and BVAR2-COM is the bivariate Bayesian VAR(2) with commodity price indexes.

Table 11 - Tests of Conditional Predictive Ability

	M_4 FAR	M_6 BVAR2	M_8 BVAR2-COM
One-quarter ahead			
%EMEs with P-value(Wald test)>0.1	50%	57%	86%
US P-value(Wald test)	0.04	0.01	0.00
Four-quarter ahead			
%EMEs with P-value(Wald test)>0.1	86%	71%	86%
US P-value(Wald test)	0.07	0.00	0.17
Eight-quarter ahead			
%EMEs with P-value(Wald test)>0.1	86%	71%	71%
US P-value(Wald test)	0.04	0.00	0.00
Twelve-quarter ahead			
%EMEs with P-value(Wald test)>0.1	100%	64%	71%
US P-value(Wald test)	0.04	0.00	0.00
Averages (all horizons)			
%EMEs with P-value(Wald test)>0.1	80%	66%	79%
US P-value(Wald test)	0.05	0.00	0.04

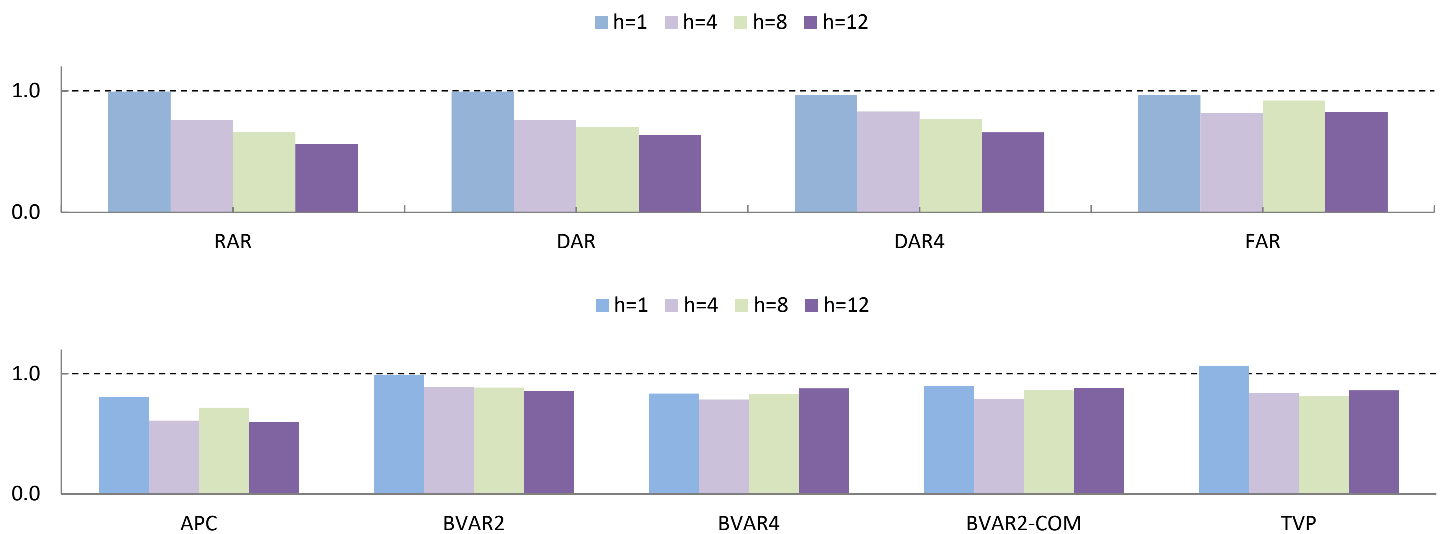
Notes: For each country including the US and each forecast horizon, we generate forecasts from a rolling-window estimation using 75 observations and construct the difference between the squared forecast error of an alternative model and the squared forecast error of the RW-AO model. We regress that indicator on its first two lags, a measure of the GDP cycle (year-on-year GDP growth rate) and a proxy of a high-inflationary regime (an indicator function that takes the value of 1 if the current inflation rate is higher than the median inflation rate, approximately 5%, and 0 otherwise). The number of observations is 68 (h=1), 65 (h=4), 61 (h=8), and 57 (h=12). We use the conditional predictability (Wald) test by Giacomini and White (2006). %EMEs with P-value(Wald test)>0.1 reports the percentage of the 14 economies in which we reject at 10% the joint null hypothesis that all non-intercept coefficients are zero. US P-value(Wald test) reports the p-value associated with an analogous joint hypothesis for the US. FAR is the Factor-Augmented AR(2) model, BVAR2 is the bivariate Bayesian VAR(2), and BVAR2-COM is the bivariate Bayesian VAR(2) with commodity price indexes.

Table 12 - RMSPE of the RW-AO Model Relative to the RMSPE of Consensus Forecasts™

	Quarter-over-quarter inflation rates			Year-over-year inflation rates		
	h=1	h=4	h=6	h=1	h=4	h=6
Chile	1.167	1.406	1.266	2.508	1.793	1.640
China	0.881	1.564	1.402	1.780	1.950	2.023
Colombia	0.713	1.353	1.161	1.801	1.317	1.355
Hungary	0.931	0.930	1.022	1.634	1.073	1.043
India	0.671	0.781	0.958	0.938	0.977	1.171
Indonesia	1.309	1.655	1.223	3.539	1.983	1.663
Malaysia	1.355	1.161	1.080	2.123	1.519	1.211
Mexico	1.139	1.043	0.918	1.938	1.484	1.465
Peru	1.018	1.509	1.323	2.369	1.737	1.693
Philippines	0.982	1.045	1.317	2.029	1.694	1.511
Thailand	1.074	1.221	0.946	1.980	1.404	1.191
Turkey	0.891	0.831	0.614	1.575	0.783	0.572
Mean	1.011	1.208	1.102	2.018	1.476	1.378
Median	1.000	1.191	1.121	1.959	1.501	1.410
#<1	6	3	4	1	2	1

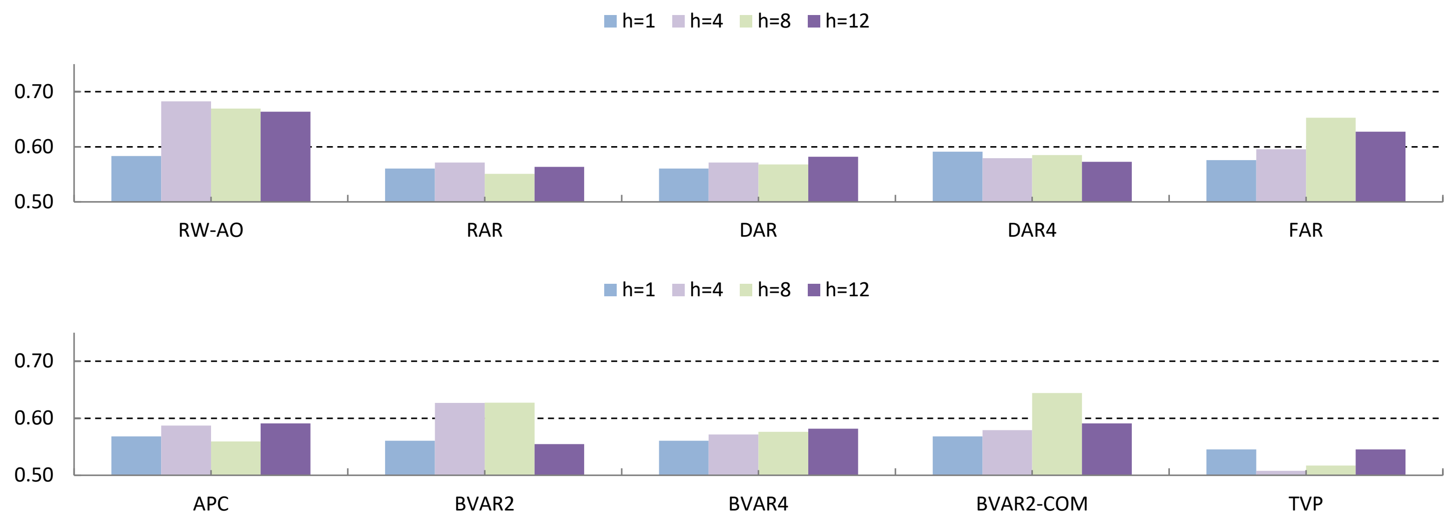
Notes: Columns report the ratio of root mean squared prediction error (RMSPE) from the RW-AO model relative to the RMSPE of Consensus Forecast (CF) predictions. Values less than one imply that the RW-AO model has a lower RMSPE than does the competitive benchmark. CF's predictions for Nigeria and South Africa were not available. Forecasts start in: 2006Q4 for China, India, Indonesia, Malaysia, and Thailand; in 2007Q1 for Chile, Colombia, Hungary, Mexico, Peru, and Turkey; and in 2009Q3 for Phillipines. The row #<1 reports the number of economies (out of 12) that show relative RMSPE lower than one for a particular forecast horizon and type of inflation rate (quarter-over-quarter or year-over-year rates).

Figure 1. RMSPE of the RW-AO Relative to Competing Models (Medians)



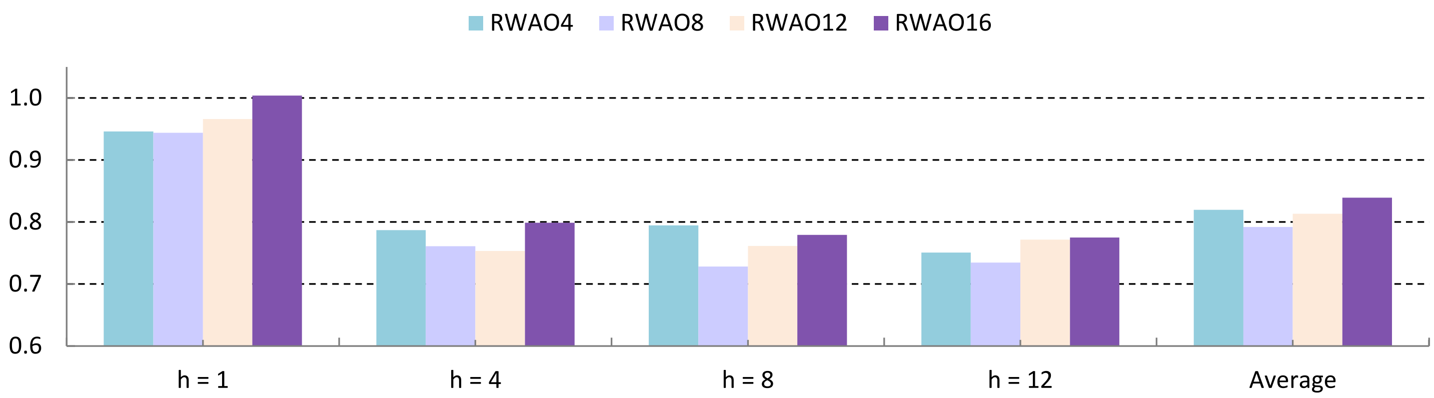
Notes: Medians of ratio of root mean squared prediction error (RMSPE) from the RW-AO model relative to the RMSPE of competing forecasting models calculated over the 14 countries for a given forecast horizon (h). Values less than one imply that the RW-AO model has a lower RMSPE than does the competitive benchmark. RAR and DAR denote the AR(2) model using the iterative and direct methods to forecast, DAR4 is the AR(4) model, FAR is the Factor-Augmented AR(2) model, APC is the Augmented Phillips Curve, BVAR2 is the bivariate Bayesian VAR(2), BVAR4 is the 4-variable Bayesian VAR(2), BVAR2-COM is the bivariate Bayesian VAR(2) with commodity price indexes, and TVP is the time-varying parameter specification.

Figure 2. Directional Accuracy: Success Ratios (Medians)



Notes: Medians of ratio of success in directional accuracy over the 14 countries for a given forecast horizon (h). RW-AO stands for the random walk model proposed by Atkeson and Ohanian (2001), RAR and DAR denote the AR(2) model using the iterative and direct methods to forecast, DAR4 is the AR(4) model, FAR is the Factor-Augmented AR(2) model, APC is the Augmented Phillips Curve, BVAR2 is the bivariate Bayesian VAR(2), BVAR4 is the 4-variable Bayesian VAR(2), BVAR2-COM is the bivariate Bayesian VAR(2) with commodity price indexes, and TVP is the time-varying parameter (TVP) specification.

Figure 3. RMSPE for Different RW-AO Models Relative to Competing Models (Average Medians)



Notes: RW-AO models with averages over the past 4, 8, 12 and 16 inflation values. Average of medians of ratio of root mean squared prediction error (RMSPE) from the RW-AO model relative to the RMSPE of competing forecasting models calculated over the 14 countries and the 9 competing models for a given forecast horizon (h). Values less than one imply that, on average, the RW-AO model has a lower RMSPE than does the competitive benchmark.

Figure 4A. Average RMSPE of the RW-AO Model Relative to Competing Models and Years with Inflation Targeting Regime

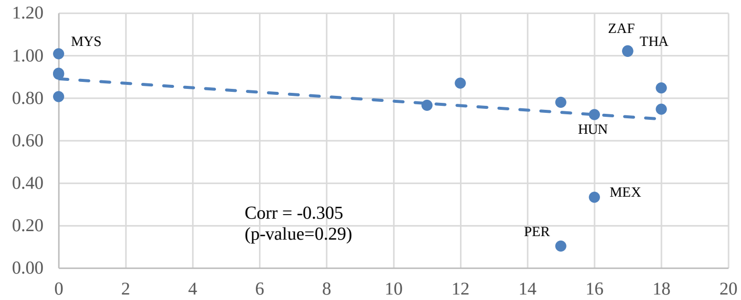


Figure 4B. Average RMSPE of the RW-AO Model Relative to Competing Models and Index of Central Bank Independence

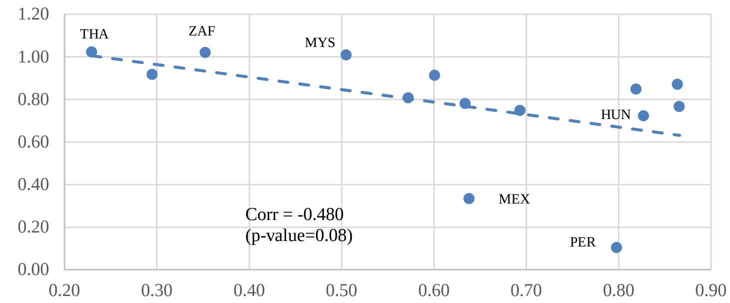


Figure 4C. Average RMSPE of the RW-AO Model Relative to Competing Models and Median Inflation Rate (1980-1990)

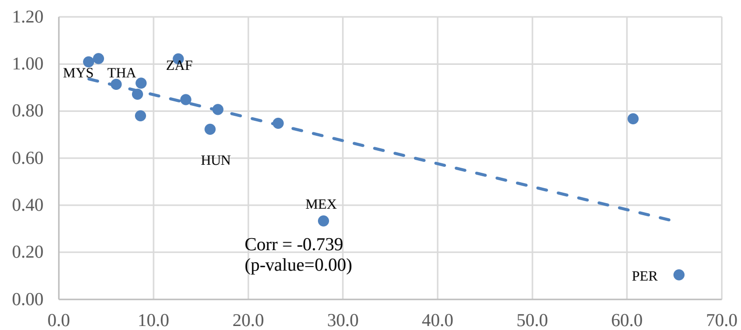
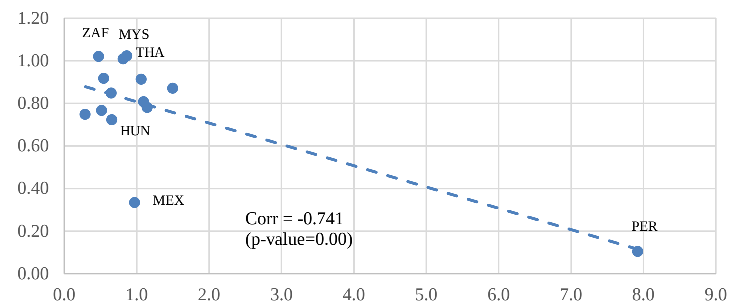


Figure 4D. Average RMSPE of the RW-AO Model Relative to Competing Models and Coefficient of Variation of Inflation Rate (1980-1990)



Notes: The average RMSPE of the RW-AO model relative to competing models is calculated over the 9 alternative models and 4 forecast horizons for each economy. Values less than one imply that, on average, the RW-AO model has a lower RMSPE than does the competitive model. The number of years under inflation targeting is calculated from 1999 to 2016 (the forecast period) using information from Hammond (2012) and Roger (2010). The index of central bank independence is an average for each country using data from Garriga (2016). The median inflation rate and the coefficient of variation are computed over the quarter-over-quarter inflation rates between 1980Q2 and 1989Q4 for each economy. Labels in graphs correspond to Hungary, Mexico, Peru (economies at the top of the ranking in Table 4) as well as Malaysia, South Africa, and Thailand (economies at the bottom of the ranking in Table 4).

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Supplementary Tables

Table S1 - One-Quarter Ahead RMSPE of the RW-AO Model Relative to Competing Models

	M_1/M_2 RAR or DAR	M_3 DAR4	M_4 FAR	M_5 APC	M_6 BVAR2	M_7 BVAR4	M_8 BVAR2-COM	M_9 TVP
Chile	1.033	**0.966**	0.914	**0.786**	0.967	0.850	0.930	1.240
China	1.178	1.220	1.187	1.161	1.186	1.222	1.146	1.153
Colombia	**0.814**	**0.969**	**0.714**	**0.702**	**0.740**	**0.774**	**0.779**	1.165
Hungary	0.928	1.007	0.935	**0.799**	0.944	**0.750**	**0.796**	1.007
India	0.953	**0.898**	1.024	0.954	1.042	0.981	0.984	**0.900**
Indonesia	0.938	**0.911**	0.874	0.992	0.892	0.979	0.911	0.900
Malaysia	1.107	1.110	1.094	1.123	1.103	1.114	1.123	0.953
Mexico	**0.374**	**0.320**	**0.621**	**0.348**	**0.631**	**0.358**	**0.371**	**0.817**
Nigeria	1.038	1.028	0.995	**0.757**	1.012	**0.818**	**0.885**	0.985
Peru	**0.001**	**0.001**	**0.000**	**0.001**	**0.000**	**0.001**	**0.001**	1.136
Philippines	1.096	**0.868**	1.305	**0.818**	1.333	**0.719**	0.852	1.195
South Africa	1.037	1.074	1.130	0.936	1.154	1.092	1.020	1.191
Thailand	1.194	1.196	1.183	1.173	1.200	1.125	1.190	1.091
Turkey	0.882	**0.920**	**0.788**	0.786	**0.796**	0.752	**0.861**	1.040
Mean	0.898	0.892	0.912	0.810	0.929	0.824	0.846	1.055
Median	0.993	0.967	0.965	0.808	0.990	0.834	0.898	1.065
#<1	7	8	8	11	7	10	10	5
#pv<0.1	3	8	4	7	4	6	6	2

Notes: Columns report the ratio of root mean squared prediction error (RMSPE) from the RW-AO model relative to the RMSPE of standard forecasting models. Values less than one imply that the RW-AO model has a lower RMSPE than does the competitive benchmark. Values in bold indicate that the null hypothesis of equal predictive accuracy is rejected at 10% level using the Diebold-Mariano-West statistic or the adjusted Clark-West statistic when models are nested. See Tables 1.A and 1.B for the data sources. RAR and DAR denote AR(2) model using the iterative and direct methods to forecast, DAR4 is the AR(4) model, FAR is the Factor-Augmented AR(2) model, APC is the Augmented Phillips Curve, BVAR2 is the bivariate Bayesian VAR(2), BVAR4 is the 4-variable Bayesian VAR(2), BVAR2-COM is the bivariate Bayesian VAR(2) with commodity price indexes, and TVP is the time-varying parameter specification.

Table S2 - Four-Quarters Ahead RMSPE of the RW-AO Model Relative to Competing Models

	M_1	M_2	M_3	M_4	M_5	M_6	M_7	M_8	M_9
	RAR	DAR	DAR4	FAR	APC	BVAR2	BVAR4	BVAR2-COM	TVP
Chile	**0.725**	**0.691**	**0.843**	**0.792**	**0.610**	0.996	**0.807**	**0.817**	0.932
China	0.945	0.933	**0.924**	1.032	1.063	1.052	1.026	0.964	0.927
Colombia	**0.473**	**0.663**	**0.872**	**0.664**	**0.535**	**0.837**	**0.763**	**0.750**	0.907
Hungary	**0.592**	**0.751**	**0.790**	**0.789**	**0.575**	**0.833**	**0.720**	**0.724**	**0.868**
India	**0.852**	**0.770**	**0.818**	0.839	**0.773**	0.948	**0.859**	**0.867**	**0.755**
Indonesia	1.046	0.987	**0.972**	**0.642**	0.839	**0.815**	**0.879**	0.934	**0.815**
Malaysia	1.096	1.117	1.126	1.083	1.075	0.947	0.971	0.984	**0.747**
Mexico	**0.136**	**0.119**	**0.118**	**0.280**	**0.113**	**0.429**	**0.153**	**0.159**	**0.834**
Nigeria	**0.756**	**0.779**	**0.737**	**0.848**	**0.605**	0.857	**0.738**	**0.760**	**0.762**
Peru	**0.001**	**0.001**	**0.001**	**0.001**	**0.000**	**0.002**	**0.000**	**0.000**	**0.866**
Philippines	**0.764**	**0.568**	**0.528**	0.887	**0.502**	0.968	**0.661**	**0.648**	**0.845**
South Africa	0.898	0.993	1.059	1.118	0.956	1.052	0.999	0.994	**0.884**
Thailand	0.996	1.018	1.058	1.024	0.935	0.925	**0.843**	0.935	**0.732**
Turkey	**0.513**	**0.608**	**0.715**	**0.559**	**0.610**	**0.702**	0.740	**0.672**	0.740
Mean	0.700	0.714	0.754	0.754	0.657	0.812	0.726	0.729	0.830
Median	0.760	0.760	0.831	0.815	0.610	0.891	0.785	0.789	0.839
#<1	12	12	11	10	12	12	13	14	14
#pv<0.1	9	9	11	8	9	6	10	9	10

Notes: Columns report the ratio of root mean squared prediction error (RMSPE) from the RW-AO model relative to the RMSPE of standard forecasting models. Values less than one imply that the RW-AO model has a lower RMSPE than does the competitive benchmark. Values in bold indicate that the null hypothesis of equal predictive accuracy is rejected at 10% level using the Diebold-Mariano-West statistic or the adjusted Clark-West statistic when models are nested. See Tables 1.A and 1.B for the data sources. RAR and DAR denote AR(2) model using the iterative and direct methods to forecast, DAR4 is the AR(4) model, FAR is the Factor-Augmented AR(2) model, APC is the Augmented Phillips Curve, BVAR2 is the bivariate Bayesian VAR(2), BVAR4 is the 4-variable Bayesian VAR(2), BVAR2-COM is the bivariate Bayesian VAR(2) with commodity price indexes, and TVP is the time-varying parameter specification.

Table S3 - Eight-Quarters Ahead RMSPE of the RW-AO Model Relative to Competing Models

	M_1	M_2	M_3	M_4	M_5	M_6	M_7	M_8	M_9
	RAR	DAR	DAR4	FAR	APC	BVAR2	BVAR4	BVAR2-COM	TVP
Chile	**0.538**	0.891	**0.965**	0.913	**0.743**	0.915	**0.872**	**0.863**	**0.813**
China	0.813	**0.714**	**0.677**	0.976	0.973	0.932	**0.874**	0.984	**0.834**
Colombia	**0.375**	**0.690**	**0.851**	**0.576**	**0.566**	**0.900**	0.966	0.958	**0.928**
Hungary	**0.467**	**0.589**	**0.639**	**0.646**	**0.475**	**0.746**	**0.704**	**0.702**	**0.766**
India	0.954	0.932	**0.919**	0.944	0.929	**0.891**	**0.903**	**0.905**	**0.797**
Indonesia	0.916	0.888	**0.896**	**0.657**	**0.690**	**0.818**	**0.794**	**0.822**	**0.751**
Malaysia	1.044	1.059	1.070	1.026	1.022	**0.807**	**0.827**	**0.832**	**0.738**
Mexico	**0.088**	**0.083**	**0.099**	**0.185**	**0.083**	**0.390**	**0.280**	**0.248**	0.919
Nigeria	**0.709**	**0.651**	**0.680**	0.926	**0.618**	**0.882**	**0.830**	**0.860**	**0.811**
Peru	**0.001**	**0.001**	**0.001**	**0.001**	**0.000**	**0.001**	**0.001**	**0.001**	**0.839**
Philippines	**0.614**	**0.473**	**0.475**	1.007	**0.450**	0.888	**0.729**	**0.793**	**0.791**
South Africa	0.843	1.075	1.067	1.216	0.994	1.016	1.033	1.036	0.958
Thailand	1.033	1.051	1.008	1.028	0.967	**0.858**	**0.826**	0.903	**0.792**
Turkey	**0.501**	**0.659**	**0.681**	**0.645**	**0.808**	0.989	1.044	0.909	0.995
Mean	0.636	0.697	0.716	0.767	0.666	0.788	0.763	0.773	0.838
Median	0.662	0.702	0.766	0.919	0.717	0.885	0.828	0.861	0.812
#<1	12	11	11	10	13	13	12	13	14
#pv<0.1	8	8	11	6	9	9	11	9	11

Notes: Columns report the ratio of root mean squared prediction error (RMSPE) from the RW-AO model relative to the RMSPE of standard forecasting models. Values less than one imply that the RW-AO model has a lower RMSPE than does the competitive benchmark. Values in bold indicate that the null hypothesis of equal predictive accuracy is rejected at 10% level using the Diebold-Mariano-West statistic or the adjusted Clark-West statistic when models are nested. See Tables 1.A and 1.B for the data sources. RAR and DAR denote AR(2) model using the iterative and direct methods to forecast, DAR4 is the AR(4) model, FAR is the Factor-Augmented AR(2) model, APC is the Augmented Phillips Curve, BVAR2 is the bivariate Bayesian VAR(2), BVAR4 is the 4-variable Bayesian VAR(2), BVAR2-COM is the bivariate Bayesian VAR(2) with commodity price indexes, and TVP is the time-varying parameter specification.

Table S4 - Twelve-Quarters Ahead RMSPE of the RW-AO Model Relative to Competing Models

	M_1 RAR	M_2 DAR	M_3 DAR4	M_4 FAR	M_5 APC	M_6 BVAR2	M_7 BVAR4	M_8 BVAR2-COM	M_9 TVP
Chile	**0.482**	**0.644**	**0.734**	0.978	**0.586**	0.959	0.950	0.970	0.933
China	**0.590**	**0.492**	**0.438**	**0.535**	0.830	**0.711**	**0.570**	0.858	**0.808**
Colombia	**0.302**	**0.610**	**0.630**	**0.560**	**0.565**	0.821	0.885	0.921	0.933
Hungary	**0.430**	**0.488**	**0.497**	**0.475**	**0.418**	**0.842**	**0.817**	**0.816**	0.916
India	1.057	1.087	1.076	1.009	1.027	**0.848**	**0.873**	**0.875**	**0.848**
Indonesia	0.961	0.955	**0.967**	0.831	**0.792**	0.847	0.837	0.868	0.845
Malaysia	1.096	1.108	1.078	1.105	1.103	0.868	0.884	0.886	0.836
Mexico	**0.081**	**0.111**	**0.135**	**0.224**	**0.118**	**0.246**	**0.632**	**0.654**	**0.870**
Nigeria	**0.695**	**0.652**	**0.622**	0.773	**0.613**	**0.860**	0.907	0.903	**0.850**
Peru	**0.001**	**0.001**	**0.001**	**0.000**	**0.000**	**0.001**	**0.001**	**0.002**	**0.757**
Philippines	**0.536**	**0.509**	**0.570**	1.006	**0.534**	**0.865**	**0.861**	**0.823**	**0.790**
South Africa	0.795	1.005	1.063	1.342	0.926	0.951	0.954	0.950	0.886
Thailand	1.168	1.161	1.151	1.198	1.061	0.944	0.910	0.984	0.910
Turkey	**0.490**	**0.629**	**0.686**	**0.820**	**0.541**	0.926	0.923	0.890	0.975
Mean	0.620	0.675	0.689	0.775	0.651	0.764	0.786	0.814	0.868
Median	0.563	0.637	0.658	0.826	0.600	0.854	0.879	0.880	0.860
#<1	11	10	10	9	11	14	14	14	14
#pv<0.1	9	9	10	6	9	7	6	5	6

Notes: Columns report the ratio of root mean squared prediction error (RMSPE) from the RW-AO model relative to the RMSPE of standard forecasting models. Values less than one imply that the RW-AO model has a lower RMSPE than does the competitive benchmark. Values in bold indicate that the null hypothesis of equal predictive accuracy is rejected at 10% level using the Diebold-Mariano-West statistic or the adjusted Clark-West statistic when models are nested. See Tables 1.A and 1.B for the data sources. RAR and DAR denote AR(2) model using the iterative and direct methods to forecast, DAR4 is the AR(4) model, FAR is the Factor-Augmented AR(2) model, APC is the Augmented Phillips Curve, BVAR2 is the bivariate Bayesian VAR(2), BVAR4 is the 4-variable Bayesian VAR(2), BVAR2-COM is the bivariate Bayesian VAR(2) with commodity price indexes, and TVP is the time-varying parameter specification.

Table S5 - Directional Accuracy: Success Ratio of One-Quarter-Ahead Forecasts

	M_0 RW-AO	M_1/M_2 RAR or DAR	M_3 DAR4	M_4 FAR	M_5 APC	M_6 BVAR2	M_7 BVAR4	M_8 BVAR2-COM	M_9 TVP
Chile	**0.61** *	0.52 †	0.52 †	0.56	0.48 †	0.56	0.55	**0.56** *	0.56
China	**0.58** *	0.65 †	**0.70** *	**0.71** *	**0.58** *	**0.67** *	**0.62** *	0.61	0.47
Colombia	**0.59** *	0.56 †	**0.64** *	0.53	0.56 †	0.53	0.56	0.58	0.44
Hungary	**0.56** *	0.44	0.47	0.39	0.39	0.42	0.44	0.38	0.50
India	**0.76** *	**0.65** *	**0.62** *	**0.71** *	**0.74** *	**0.70** *	**0.70** *	**0.70** *	**0.59** *
Indonesia	**0.58** *	**0.56** *	**0.58** *	**0.56** *	**0.61** *	**0.56** *	**0.61** *	**0.58** *	0.50
Malaysia	**0.61** *	**0.68** *	**0.70** *	**0.62** *	**0.64** *	**0.65** *	0.56	**0.68** *	**0.55** *
Mexico	**0.70** *	0.47	0.47	0.55	0.53	0.55	0.50	0.47	0.56
Nigeria	**0.68** *	**0.59** *	**0.62** *	**0.59** *	0.58	0.56	**0.59** *	0.56	0.52
Peru	**0.58** *	0.47	0.47	0.47	0.42	0.48	0.47 †	0.47	0.56
Philippines	**0.56** *	**0.65** *	0.61 †	**0.70** *	**0.64** *	**0.71** *	**0.65** *	**0.67** *	0.45
South Africa	0.55	0.50	**0.55** *	**0.61** *	0.39	**0.61** *	0.42	0.41	0.56
Thailand	**0.64** *	**0.65** *	**0.62** *	**0.65** *	**0.64** *	**0.64** *	**0.61** *	**0.65** *	0.55
Turkey	0.55	0.48 †	0.47 †	0.48	0.39	0.48 †	0.47	0.48 †	0.58
Mean	0.61	0.56	0.57	0.58	0.54	0.58	0.55	0.56	0.53
Median	0.58	0.56	0.59	0.58	0.57	0.56	0.56	0.57	0.55
#>0.5	14	9	10	11	9	11	9	9	9

Notes: Columns report the ratio of success in directional accuracy. Values in bold (*) indicate that the null hypothesis of no dependence between sign(forecast change) and sign(actual change) is rejected at 10% level using the Pesaran and Timmermann (2009) test. A "†" symbol at the right of each value indicates that the test statistic is undefined due to the presence of many forecasts in one direction. The row #>0.5 reports the number of economies that show a success ratio higher than 0.5 for a particular model. See Tables 1.A and 1.B for the data sources. RW-AO stands for the random walk model proposed by Atkeson and Ohanian (2001), RAR and DAR denote AR(2) model using the iterative and direct methods to forecast, DAR4 is the AR(4) model, FAR is the Factor-Augmented AR(2) model, APC is the Augmented Phillips Curve, BVAR2 is the bivariate Bayesian VAR(2), BVAR4 is the 4-variable Bayesian VAR(2), BVAR2-COM is the bivariate Bayesian VAR(2) with commodity price indexes, and TVP is the time-varying parameter (TVP) specification.

Table S6 - Directional Accuracy: Success Ratio of Four-Quarters-Ahead Forecasts

	M_0 RW-AO	M_1 RAR	M_2 DAR	M_3 DAR4	M_4 FAR	M_5 APC	M_6 BVAR2	M_7 BVAR4	M_8 BVAR2-COM	M_9 TVP
Chile	**0.59** *	0.57 †	0.56 †	0.59	0.56	0.59 †	**0.67** *	0.57 †	0.59 †	0.44
China	**0.59** *	0.62 †	0.65 †	0.65 †	**0.65** *	**0.62** *	**0.70** *	0.56	**0.63** *	0.46
Colombia	**0.59** *	0.54 †	**0.57** *	0.54	0.51	0.54 †	0.51	0.56	0.56 †	0.48
Hungary	**0.63** *	0.41 †	0.49 †	**0.56** *	0.48	0.44 †	0.48	**0.46** *	0.40 †	0.56
India	**0.78** *	**0.60** *	**0.60** *	**0.62** *	**0.68** *	**0.62** *	**0.68** *	**0.60** *	**0.60** *	**0.57** *
Indonesia	**0.60** *	**0.62** *	**0.62** *	**0.60** *	0.52 †	**0.59** *	0.49 †	**0.54** *	**0.60** *	**0.62** *
Malaysia	**0.73** *	**0.79** *	**0.79** *	**0.76** *	**0.81** *	**0.81** *	**0.78** *	**0.78** *	**0.79** *	0.49
Mexico	**0.71** *	0.51 †	0.51 †	0.51 †	0.54	0.52 †	**0.59** *	0.52 †	0.54 †	0.49
Nigeria	**0.70** *	**0.57** *	**0.57** *	**0.57** *	**0.63** *	**0.59** *	**0.62** *	**0.60** *	**0.57** *	0.52
Peru	**0.75** *	0.54 †	0.54 †	0.54 †	0.32	0.54	0.37	**0.60** *	0.49	0.48
Philippines	**0.67** *	**0.56** *	0.52 †	0.51 †	**0.63** *	0.52	**0.63** *	0.49	0.49 †	**0.60** *
South Africa	**0.62** *	**0.67** *	**0.67** *	**0.71** *	**0.67** *	**0.68** *	**0.70** *	**0.68** *	**0.70** *	0.43
Thailand	**0.71** *	**0.63** *	**0.65** *	**0.70** *	**0.67** *	**0.67** *	**0.67** *	**0.67** *	**0.67** *	0.56
Turkey	**0.76** *	0.51 †	0.51 †	0.52 †	0.56 †	**0.57** *	0.51 †	0.57	0.51 †	0.54
Mean	0.67	0.58	0.59	0.60	0.59	0.59	0.60	0.59	0.58	0.52
Median	0.68	0.57	0.57	0.58	0.60	0.59	0.63	0.57	0.58	0.51
#>0.5	14	13	13	14	12	13	11	12	11	7

Notes: Columns report the ratio of success in directional accuracy. Values in bold (*) indicate that the null hypothesis of no dependence between sign(forecast change) and sign(actual change) is rejected at 10% level using the Pesaran and Timmermann (2009) test. A "†" symbol at the right of each value indicates that the test statistic is undefined due to the presence of many forecasts in one direction. The row #>0.5 reports the number of economies that show a success ratio higher than 0.5 for a particular model. See Tables 1.A and 1.B for the data sources. RW-AO stands for the random walk model proposed by Atkeson and Ohanian (2001), RAR and DAR denote AR(2) model using the iterative and direct methods to forecast, DAR4 is the AR(4) model, FAR is the Factor-Augmented AR(2) model, APC is the Augmented Phillips Curve, BVAR2 is the bivariate Bayesian VAR(2), BVAR4 is the 4-variable Bayesian VAR(2), BVAR2-COM is the bivariate Bayesian VAR(2) with commodity price indexes, and TVP is the time-varying parameter specification.

Table S7 - Directional Accuracy: Success Ratio of Eight-Quarters-Ahead Forecasts

	M_0 RW-AO	M_1 RAR	M_2 DAR	M_3 DAR4	M_4 FAR	M_5 APC	M_6 BVAR2	M_7 BVAR4	M_8 BVAR2-COM	M_9 TVP
Chile	**0.63** *	0.54 †	**0.69** *	**0.69** *	**0.64** *	0.56 †	**0.71** *	**0.64** *	0.66 †	0.49
China	**0.69** *	0.56 †	0.56 †	0.58 †	**0.71** *	**0.71** *	**0.75** *	**0.59** *	**0.69** *	0.53
Colombia	**0.58** *	0.47 †	0.47	0.54	0.41	0.44	0.53 †	0.56	**0.66** *	0.49
Hungary	**0.64** *	0.37 †	0.41 †	0.47	0.47	0.41 †	0.44	0.39 †	0.37 †	0.61
India	**0.71** *	**0.76** *	**0.78** *	**0.78** *	**0.73** *	**0.80** *	**0.75** *	**0.81** *	**0.80** *	**0.58** *
Indonesia	**0.73** *	**0.53** *	**0.53** *	**0.54** *	0.44	0.44	**0.53** *	0.42	0.46	0.63
Malaysia	**0.68** *	**0.71** *	**0.73** *	**0.73** *	**0.75** *	**0.71** *	**0.75** *	**0.66** *	**0.73** *	0.47
Mexico	**0.64** *	0.32 †	0.32 †	0.32 †	**0.59** *	0.37	0.64	0.34 †	0.36 †	0.59
Nigeria	**0.66** *	**0.58** *	**0.58** *	**0.59** *	**0.66** *	**0.63** *	**0.66** *	**0.61** *	**0.66** *	**0.56** *
Peru	**0.71** *	0.59 †	0.59 †	0.59 †	0.46	0.56	0.59 †	0.47	0.47	0.47
Philippines	**0.75** *	**0.51** *	0.47 †	0.49 †	**0.69** *	0.47 †	**0.61** *	**0.51** *	0.46 †	0.51
South Africa	0.54	**0.64** *	**0.63** *	**0.61** *	**0.81** *	**0.68** *	**0.61** *	**0.71** *	**0.63** *	0.46
Thailand	**0.80** *	**0.68** *	**0.73** *	**0.71** *	**0.71** *	**0.61** *	**0.68** *	**0.61** *	**0.76** *	0.53
Turkey	**0.59** *	0.46 †	0.46 †	0.46 †	0.47	0.47	0.46	0.56 †	0.46 †	0.51
Mean	0.67	0.55	0.57	0.58	0.61	0.56	0.62	0.56	0.58	0.53
Median	0.67	0.55	0.57	0.58	0.65	0.56	0.63	0.58	0.64	0.52
#>0.5	14	10	9	10	9	8	12	10	8	9

Notes: Columns report the ratio of success in directional accuracy. Values in bold (*) indicate that the null hypothesis of no dependence between sign(forecast change) and sign(actual change) is rejected at 10% level using the Pesaran and Timmermann (2009) test. A "†" symbol at the right of each value indicates that the test statistic is undefined due to the presence of many forecasts in one direction. The row #>0.5 reports the number of economies that show a success ratio higher than 0.5 for a particular model. See Tables 1.A and 1.B for the data sources. RW-AO stands for the random walk model proposed by Atkeson and Ohanian (2001), RAR and DAR denote AR(2) model using the iterative and direct methods to forecast, DAR4 is the AR(4) model, FAR is the Factor-Augmented AR(2) model, APC is the Augmented Phillips Curve, BVAR2 is the bivariate Bayesian VAR(2), BVAR4 is the 4-variable Bayesian VAR(2), BVAR2-COM is the bivariate Bayesian VAR(2) with commodity price indexes, and TVP is the time-varying parameter specification.

Table S8 - Directional Accuracy: Success Ratio of Twelve-Quarters-Ahead Forecasts

	M_0 RW-AO	M_1 RAR	M_2 DAR	M_3 DAR4	M_4 FAR	M_5 APC	M_6 BVAR2	M_7 BVAR4	M_8 BVAR2-COM	M_9 TVP
Chile	0.56	0.56 †	0.60 †	0.60 †	**0.65** *	0.56 †	**0.55** *	**0.67** *	**0.58** *	**0.62** *
China	**0.80** *	**0.58** *	**0.60** *	**0.60** *	**0.73** *	**0.71** *	0.53 †	0.53 †	0.56	**0.64** *
Colombia	**0.60** *	0.40 †	0.45	0.49	0.40	0.36	0.60 †	0.60 †	0.60 †	**0.65** *
Hungary	0.51	0.35 †	0.35 †	0.38 †	0.36	0.38	0.40	0.35 †	0.35 †	0.56
India	**0.69** *	**0.73** *	**0.67** *	**0.65** *	**0.65** *	**0.69** *	**0.53** *	**0.53** *	**0.53** *	0.51
Indonesia	**0.60** *	**0.64** *	**0.64** *	**0.67** *	**0.58** *	**0.60** *	**0.60** *	0.56	**0.62** *	0.47
Malaysia	**0.71** *	**0.64** *	**0.64** *	0.58	**0.67** *	**0.64** *	**0.62** *	**0.62** *	**0.62** *	0.47
Mexico	**0.73** *	0.44 †	0.44 †	0.44 †	0.49	0.47	0.56 †	0.56	0.56	0.56
Nigeria	**0.69** *	**0.55** *	**0.55** *	**0.53** *	0.60	**0.64** *	0.53	**0.65** *	**0.69** *	0.55
Peru	**0.84** *	0.53 †	0.53 †	0.53 †	0.36	0.51	0.53 †	0.49	0.55	0.44
Philippines	**0.78** *	**0.56** *	**0.56** *	**0.56** *	**0.71** *	**0.58** *	**0.65** *	**0.64** *	**0.62** *	0.53
South Africa	0.56	**0.62** *	**0.67** *	**0.67** *	**0.82** *	**0.67** *	**0.58** *	**0.71** *	**0.67** *	0.47
Thailand	**0.64** *	**0.67** *	**0.67** *	**0.67** *	**0.73** *	**0.65** *	**0.60** *	0.45	**0.65** *	0.55
Turkey	**0.64** *	0.42 †	0.42 †	0.42 †	0.40	0.42	0.44	0.60 †	**0.53** *	0.55
Mean	0.67	0.55	0.56	0.56	0.58	0.56	0.55	0.57	0.58	0.54
Median	0.66	0.56	0.58	0.57	0.63	0.59	0.55	0.58	0.59	0.55
#>0.5	14	10	10	10	9	10	12	11	13	10

Notes: Columns report the ratio of success in directional accuracy. Values in bold (*) indicate that the null hypothesis of no dependence between sign(forecast change) and sign(actual change) is rejected at 10% level using the Pesaran and Timmermann (2009) test. A "†" symbol at the right of each value indicates that the test statistic is undefined due to the presence of many forecasts in one direction. The row #>0.5 reports the number of economies that show a success ratio higher than 0.5 for a particular model. See Tables 1.A and 1.B for the data sources. RW-AO stands for the random walk model proposed by Atkeson and Ohanian (2001), RAR and DAR denote AR(2) model using the iterative and direct methods to forecast, DAR4 is the AR(4) model, FAR is the Factor-Augmented AR(2) model, APC is the Augmented Phillips Curve, BVAR2 is the bivariate Bayesian VAR(2), BVAR4 is the 4-variable Bayesian VAR(2), BVAR2-COM is the bivariate Bayesian VAR(2) with commodity price indexes, and TVP is the time-varying parameter specification.

Table S9 - RMSPE of the RW-AO Model Relative to the RMSPE of Consensus Forecasts™

	Quarter-over-quarter inflation rates						Year-over-year inflation rates					
	h=1	h=2	h=3	h=4	h=5	h=6	h=1	h=2	h=3	h=4	h=5	h=6
Chile	1.167	1.176	1.373	1.406	1.287	1.266	2.508	2.689	2.118	1.793	1.681	1.640
China	0.881	1.147	1.610	1.564	1.211	1.402	1.780	1.918	1.891	1.950	2.016	2.023
Colombia	0.713	1.001	0.981	1.353	0.896	1.161	1.801	1.685	1.449	1.317	1.331	1.355
Hungary	0.931	1.011	0.862	0.930	0.933	1.022	1.634	1.343	1.119	1.073	1.054	1.043
India	0.671	0.821	0.875	0.781	0.775	0.958	0.938	0.953	0.930	0.977	1.072	1.171
Indonesia	1.309	1.197	1.394	1.655	1.348	1.223	3.539	3.161	2.361	1.983	1.850	1.663
Malaysia	1.355	1.190	1.123	1.161	1.061	1.080	2.123	1.934	1.674	1.519	1.344	1.211
Mexico	1.139	1.062	1.078	1.043	0.832	0.918	1.938	1.583	1.717	1.484	1.448	1.465
Peru	1.018	1.114	1.627	1.509	1.394	1.323	2.369	2.632	2.093	1.737	1.694	1.693
Philippines	0.982	1.062	1.128	1.045	1.170	1.317	2.029	2.302	1.924	1.694	1.608	1.511
Thailand	1.074	1.053	1.240	1.221	0.950	0.946	1.980	2.030	1.694	1.404	1.271	1.191
Turkey	0.891	1.078	1.054	0.831	0.678	0.614	1.575	1.594	1.193	0.783	0.585	0.572
Mean	1.011	1.076	1.195	1.208	1.045	1.102	2.018	1.985	1.680	1.476	1.413	1.378
Median	1.000	1.070	1.125	1.191	1.005	1.121	1.959	1.926	1.706	1.501	1.396	1.410
#<1	6	1	3	3	6	4	1	1	1	2	1	1

Notes: Columns report the ratio of root mean squared prediction error (RMSPE) from the RW-AO model relative to the RMSPE of Consensus Forecast (CF) predictions. Values less than one imply that the RW-AO model has a lower RMSPE than does the competitive benchmark. CF's predictions for Nigeria and South Africa were not available. Forecasts start in: 2006Q4 for China, India, Indonesia, Malaysia, and Thailand; in 2007Q1 for Chile, Colombia, Hungary, Mexico, Peru, and Turkey; and in 2009Q3 for Phillipines. The row #<1 reports the number of economies (out of 12) that show relative RMSPE lower than 1 for a particular forecast horizon and type of inflation rate (quarter-over-quarter or year-over-year rates).

Table S10 - Directional Accuracy: Success Ratio of the RW-AO Model Relative to Consensus Forecasts™

	Quarter-over-quarter inflation rates						Year-over-year inflation rates					
	h=1	h=2	h=3	h=4	h=5	h=6	h=1	h=2	h=3	h=4	h=5	h=6
Chile	1.000	1.083	0.929	0.857	0.786	0.923	0.583	0.818	0.909	0.917	1.000	1.000
China	1.160	1.115	1.074	1.040	0.926	0.929	0.773	0.760	1.053	1.000	0.952	0.818
Colombia	1.000	0.786	1.000	0.917	0.917	1.000	0.571	0.571	0.615	0.833	0.833	0.917
Hungary	0.714	1.100	0.714	0.929	1.083	1.000	0.462	0.667	0.700	0.583	0.727	0.900
India	1.160	1.115	1.074	1.040	0.926	0.929	0.773	0.760	1.053	1.000	0.952	0.818
Indonesia	1.000	0.923	0.920	0.929	1.083	1.130	0.571	0.548	0.800	1.000	1.333	1.286
Malaysia	1.000	0.966	1.000	0.929	1.080	0.963	0.500	0.588	0.759	1.000	1.037	1.071
Mexico	1.071	1.000	0.933	0.933	1.308	1.154	0.706	1.071	0.875	0.813	0.929	0.857
Peru	0.692	0.714	0.692	1.100	0.917	0.923	0.400	0.533	0.643	0.917	1.000	1.077
Philippines	0.895	0.826	1.053	0.750	0.889	0.789	0.933	0.750	0.700	0.833	1.063	1.143
Thailand	1.000	1.083	1.040	0.857	0.923	0.917	0.875	0.852	0.815	0.808	0.769	0.909
Turkey	1.000	1.083	1.000	1.071	1.154	1.143	0.917	0.846	1.083	1.364	1.273	1.444
Mean	0.974	0.983	0.952	0.946	0.999	0.983	0.672	0.730	0.834	0.922	0.989	1.020
Median	1.000	1.042	1.000	0.929	0.926	0.946	0.645	0.755	0.807	0.917	0.976	0.958
#<1	3	5	5	8	7	7	12	11	9	7	6	6

Notes: Columns report the ratio of success in directional accuracy from the RW-AO model relative to the ratio of directional accuracy of Consensus Forecast (CF) predictions. Values less than one imply that the RW-AO model has a lower success ratio than does the competitive benchmark. CF's predictions for Nigeria and South Africa were not available. Forecasts start in: 2006Q4 for China, India, Indonesia, Malaysia, and Thailand; in 2007Q1 for Chile, Colombia, Hungary, Mexico, Peru, and Turkey; and in 2009Q3 for Phillipines. The row #<1 reports the number of economies (out of 12) that show relative ratio of success lower than 1 for a particular forecast horizon and type of inflation rate (quarter-over-quarter or year-over-year rates).

Table S11 - A (Non-Exhaustive) Literature Review of Inflation Forecasting for EMEs

Study	Best forecasting model	EMEs in the sample	Data frequency	Full sample	Forecasting period	Is the RW-AO considered?	Main statistic for forecast evaluation
Altug and Cakmakli (2016)	Models with survey expectations	Brazil, Turkey	M	2001-2014	2007.1-2014.1	Yes	RMSPE
Aron and Muellbauer (2012)	Multivariate equilibrium correction models	South Africa	Q	1979-2007	2002.3-2007.4	No	RMSPE
Balcilar *et al.* (2015)	Non linear DSGE model	South Africa	Q	1960-2011	2001.1-2011.4	No	RMSPE
Chen *et al.* (2014)	Model with world commodity prices	South Africa, Chile	Q	1983-2010	2000.4-2010.3	No	RMSPE
Gupta *et al.* (2011)	Factor models	South Africa	Q	1980-2000	2001.1-2006.4	No	RMSPE
Mandalinci (2017)	UCSV and TVPVAR models	9 EMEs	Q	1979-2014	2001.1-2014.3	No	RMSPE, Log scores
Ogunc *et al.* (2013)	BVAR and combination of different forecast model	Turkey	Q	2003-2011	2009.4-2011.2	Yes	RMSPE
Pincheira and Gaty (2016)	International inflation factor augmented model	Chile	M	1995-2013	2001.9-2013.3	No	RMSPE
Pincheira and Medel (2015)	DESARIMA model	6 EMEs	M	1990-2011	1999.2-2011.12	No	RMSPE

Notes: UCSV stands for unobserved component model with stochastic volatiliy. TVP-VAR denotes the time-varying parameter VAR model. DESARIMA denotes the Driftless Extended Seasonal ARIMA model. RW-AO is the random walk model proposed by Atkeson and Ohanian (2001). M, Q and A denote monthly, quarterly, annual data frequency, respectively.

Figure S1. Quarter-over-Quarter Headline CPI Inflation Rate (SAAR, %) Across EMEs

Notes: SAAR denotes seasonally-adjusted, annualized rate computations of the quarter-over-quarter growth rate. The shaded area defines the period each country operated under a *de jure* or *de facto* inflation-targeting scheme based on information from Roger (2010) and Hammond (2012). We also include a value corresponding to the index of central bank independence (CBI) proposed by Garriga (2016) for each country whereby a higher value closer to one by this measure indicates a more independent monetary policy framework. We follow the convention on hyperinflations in the literature introduced in Phillip Cagan's 1956 book *The Monetary Dynamics of Hyperinflation* : we define an episode of hyperinflation as the period when inflation is above 50% monthly (which corresponds to approximately 250% at quarterly frequency) and cap the vertical axis of each subplot accordingly. The only country in our sample that shows a distinct episode of hyperinflation in our sample is Peru during the late 1980s and early 1990s.