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

Roberto Duncan†
Ohio University

Enrique Martínez-García‡
Federal Reserve Bank of Dallas and Southern Methodist University

This Draft: April 20, 2017

Abstract

This paper provides novel empirical evidence on modelling and forecasting of inflation in emerging market economies (EMEs). We use a broad-range set of specifications and pseudo out-of-sample forecasts to assess their performance at different horizons (1 to 12 quarters ahead) with quarterly data over the period 1980Q1-2016Q4. We concentrate on 14 of the EMEs with the most complete coverage and, in general, find that the RW-AO model consistently produces a lower root mean squared prediction error (RMSPE) than its standard competitors—which include most conventional forecasting models based on domestic factors, existing open-economy Phillips curve-based specifications, factor-augmented models, and time-varying parameter models. In a number of cases, the gains in smaller RMSPEs are statistically significant. These models are also accurate in predicting the direction of change for inflation in EMEs. Finally, we argue theoretically that, if we interpret our findings as deviations from rational expectations (adaptive expectations) coupled with partial credibility of the inflation target, we can still obtain model predictions that are sensible, given the reported evidence for EMEs, from an open-economy Phillips curve framework.

JEL Classification: E31, F41, F42, F47

KEY WORDS: Emerging Market Economies, Open-Economy Phillips Curves, Inflation Forecasting.

*We would like to thank Andrea Civelli, María Teresa Martínez-García, Patricia Toledo, Evan Koenig and seminar participants at Ohio University, for helpful suggestions and comments. We also acknowledge the excellent research assistance provided by Bikash Bhattarai, Valerie Grossman, Kelvinder Virdi, and Shaibu Yahaya. All remaining errors are ours alone. The views expressed in this paper are those of the authors and do not necessarily reflect the views of the Federal Reserve Bank of Dallas, or the Federal Reserve System.

†(Contacting author) Roberto Duncan, Department of Economics, Ohio University. Office: 349 Bentley Annex. Phone: +1 (740) 597-1264. E-mail: duncanr1@ohio.edu.

‡Enrique Martínez-García, Federal Reserve Bank of Dallas and adjunct at Southern Methodist University (SMU). Correspondence: 2200 N. Pearl Street, Dallas, TX 75201. Phone: +1 (214) 922-5262. Fax: +1 (214) 922-5194. E-mail: enrique.martinez-garcia@dal.frb.org. Webpage: https://sites.google.com/site/emg07uw/.

1 Introduction

Understanding the international linkages that affect domestic inflation is important for modelling as well as for forecasting. However, the evidence for emerging market economies (EMEs) is rather limited and generally showcases the apparent discrepancy with the inflation dynamics in the U.S. and other advanced economies (Mandalinci (2015), Pincheira and Medel (2015), Pincheira and Gatty (2016)).

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 (2015) that covers 9 EMEs. The time coverage can also be limited with some of them restricted to explore 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 Faust and Wright (2013) among others, as a reference model. Many use the naïve RW without good results instead. The exceptions being Ögünç et al. (2013) and Altug and Çakmakli (2016), but they are focused on one or two countries and, in general, they do not find that the RW-AO is successful or the best model. Not surprisingly, the RW-AO specification does not appear in the lists of forecasting models used by the central banks around the world—many in EMEs—that use inflation targeting either (see Hammond (2012)).

In turn, our paper develops the following key contributions on a broader 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):

1. We study empirically the forecasting performance over a cross-section of EMEs and establish that a 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 among a variety of EMEs. 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.

2. 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 seems to challenge well-known economic-based models for inflation forecasting—even Phillips-curve based specifications which otherwise are shown to perform well for many advanced economies (as seen in Duncan and Martínez-García (2015)).

3. We argue that the role of monetary policy credibility and the formation of expectations can partly account for the varied experiences of open-economy EMEs. In particular, we suggest that the limited forecasting success among EMEs of alternative model-based specifications when compared with the simpler RW-AO model does not invalidate the linkage between domestic inflation and real economic activity developments world-wide postulated by the open-economy Phillips curve.

Atkeson and Ohanian (2001), among others, have argued that the empirical evidence on the validity of (closed-economy) 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). We recognize the potential misspecification of conventional closed-economy Phillips curve-based forecasting models in a world that has become increasingly more integrated—through trade in goods, capital, labor, information, etc.

We also suggest that even more complex open-economy Phillips curve-based specifications may underperform among EMEs due to unmodelled parameter instability, ancillary assumptions that are violated in the data. 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 and predict inflation. This can accomodate to some extent the diverse experiences of EMEs and advanced economies without abandoning the idea of an open-economy New Keynesian Phillips curve altogether.

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, e.g., 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 from the sources documented in Grossman et al. (2014). We concentrate on the experiences of the 14 EMEs from the Grossman et al. (2014)'s dataset with consistent, reliable, and longer time series of data.

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

1. The RW-AO model generally outperforms the current crop of inflation forecasting models when applied to EMEs. In general, this model produces mostly a lower root mean square prediction error (RMSPE) than their competitors. The gains in smaller RMSPEs are statistically significant in a number of interesting cases, across models and countries.

2. 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 or higher than those of their competitors. For most countries, our findings suggest that those improvements in the accuracy of the direction of change forecasted for inflation are statistically significant.

3. 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.

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 main findings of the paper through the lens of the open-economy New Keynesian model and argues that a variant of this framework that accounts for deviations from full rationality and imperfect monetary policy credibility can go a long way to explain the inflation dynamics observed in many EMEs. Section 5 concludes with some final remarks. The appendix provides all the relevant tables and figures.

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 also 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 quarter-on-quarter inflation rates (π_t) as measured by the headline Consumer Price Index (CPI). For every country and quarter t in our sample we construct:

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

Table 1 reports the complete list of economies, data sources and the transformations of variables. Further details of the variables used in each model are included in the next subsection below.

We evaluate 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)), 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 (2015)).

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:[1]

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

The set of competing models is the following:

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

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

   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).**

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

   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).**

[1] These are the forecasting equations we employ (not exactly the models), so we interpret ϵ_{t+h} as a (population) forecast error.

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

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

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

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

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).**

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

where y, e and p^c denote the percent change in the industrial production index, the real exchange rate, and a commodity price index, respectively.[2] The commodity price index is the simple average of the price indexes of agricultural raw materials, beverages, food, metals and crude oil.

6. **Bivariate BVAR (BVAR2).** Let $X_t = (\pi_t,\ \widehat{F}_t)'$, 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.[3]

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

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

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

$$\phi_{0h,t+h} = \phi_{0h,t} + \nu_{0.t+h}$$

[2] 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.

[3] 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).

$$\phi_{1h,t+h} = \phi_{1h,t} + \nu_{1,t+h}$$

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

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.[4] 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 the third quarter of 2000 and the last one is made in the fourth quarter of 2016.

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 RMSPE of our RW-AO relative to the RMSPE of each competitor ($M_1 - M_9$) are reported in Table 2 and Tables $4 - 7$. Values less than one imply that the RW-AO model has a lower RMSPE than does the competitive benchmark. 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. Values of the corresponding t-statistics larger than 1.282 indicate that the null hypothesis of equal predictive accuracy is rejected at 10%.

Additionally, we assess the directional accuracy of each competing specification including the benchmark model. 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, so 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 and detailed in Tables $4 - 7$ by country (for each of the forecast horizons 1, 4, 8 and 12, respectively). In Table 4 we have eight different forecasts 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 is summarized in Table 3 and are reported in detail in Tables $8 - 11$ by country (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 mostly smaller than one, see Figure 1 and Table 2; more details in Tables $4 - 7$). In a number of cases, the gains in smaller RMSPEs are statistically significant (Table 2). The RW-AO also produces success ratios generally above the 0.5 threshold and,

[4] The same value is used by Faust and Wright (2013) for the US economy, and Mandalinci (2015) for EMEs.

very often, statistically significant at all forecasting horizons (see Figure 2 and Table 3; more details in Tables $8-11$). The likelihood with which the RW-AO correctly anticipates the direction of change in inflation tends to be comparable or better than that of its competitors, and in the $0.60-0.67$ range of medians (Table 3). The median success ratio of the RW-AO tends to be very close to or slightly above the maximum attained by any model for each forecasting horizon (Tables $8-11$).

2. Across countries, the RW-AO always outperforms the rest of the models with statistically significant gains for Colombia, Mexico, and Peru at every forecast horizon (Table 13). The statistical differences over the rest of models are notable also for Chile and Nigeria (4-quarter horizon), and Colombia, Hungary and Turkey (4-, 8-, 12-quarter horizons). In the rest of the sample, the RW-AO's performance is relatively reasonable with the exceptions of Malaysia and Thailand (1- and 12-quarter horizons), and South Africa (1-, 4- and 8-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 in the emerging market world. In terms of directional accuracy, the RW-AO seems to be better or as competitive as such models as well. In Table 13, 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. The models more frequently beaten by the RW-AO are the DAR4 (M_3), Augmented Phillips Curve (M_5), the BVAR4 (M_7), and the BVAR with commodities (M_8; see Table 13). 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 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 parameter instability may not be the only reason explaining the success of the RW-AO model among EMEs.

3.2 Robustness Checks

We perform a number of robustness checks whose results are available upon request. Some conclusions from such analysis are nonetheless worth mentioning:

1. Among the Factor Augmented and Augmented Phillips Curve 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. The use of GDP instead of the industrial production indexes leads to similar statistics for the Augmented Phillips Curve 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 also estimate BVARs using normal-flat priors. Overall, the results are qualitatively similar or moderately better with Minnesota priors.

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

4. In addition, we estimate a RW-AO model with 6 and 8 lags. In general, the results are similar or slightly favor the specifications with such lag structures.

5. The performance of forecasting models might be influenced by structural changes. The time-varying parameter specification discussed above (M_9) allows us to partly deal with this sort of instabilities. To verify the sensitivity of our results to the sample chosen, we restimate all the statistics starting in 1990:Q2, 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 models can exploit more useful information to forecast inflation. This suggests the relative importance of time breaks in the data generating processes.

6. 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 succesful 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 14. The average medians over all the forecast horizons in both cases (0.83 and 0.89) just confirm our previous conclusion about the forecast ability of the RW-AO model.

4 Discussion

The influential work of Atkeson and Ohanian (2001) documented a break in the (closed-economy) Phillips curve during the Great Moderation period in the U.S. These authors suggested the RW-AO model as an alternative theory-agnostic forecasting benchmark and show evidence that it outperforms (closed-economy) Phillips curve-based forecasting models. The empirical relationship between domestic inflation and domestic economic activity no longer seemed to work as a tool for inflation forecasting.

Duncan and Martínez-García (2015) argued that while the closed-economy Phillips curve has limited value for forecasting inflation, it is subject to misspecification. Furthermore, open-economy Phillips curve-based models can capture domestic inflation dynamics more accurately—a result that is shown to be ubiquitous across many advanced economies. The Phillips curve appears to be alive and well—albeit in its open-economy form—or so it seemed. The main contribution of this paper is to show that, in fact, the RW-AO model appears again to be the relevant benchmark for many EMEs.

But, does the evidence on EMEs presented in this paper weaken the open-economy Phillips curve and its significance across diverse countries? We argue that the open-economy Phillips curve that emerges from the workhorse two-country New Keynesian model remains a key structural relationship that helps us understand the dynamics of inflation and, in principle, the empirical findings on EMEs documented in this paper is not necessarily inconsistent with such a relationship.

Our view is that unmodelled parameter instability in the open-economy Phillips curve as well as implicit assumptions of the New Keynesian model that can be too strict to capture the dynamics of inflation for EMEs may partly explain why simpler specifications like the RW-AO model outperforms other more complex, model-based alternatives. The reminder of this section articulates this point highlighting in particular the significance of the assumptions on full rational expectations and the credibility of the inflation target adopted by the conventional workhorse open-economy New Keynesian model.

Generalized Open-Economy Phillips Curve. Martínez-García and Wynne (2010) and Duncan and Martínez-García (2015) show that the structure of the workhorse two-country New Keynesian model can be described by a log-linearized system of three-equations for each country—an open-economy Phillips curve, an open-economy investment-savings (IS) curve, and an interest rate-based monetary policy rule. These 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.

Standard open-economy Phillips curve-based models treat inflation as determined by three factors: expected inflation, global slack (or more broadly global resource utilization) and structural shocks that exogenously shift the open-economy Phillips curve. While rational (forward-looking) expectations remain predominant in the New Keynesian literature (with only limited attention being paid to surveys of inflation forecasts due to data availability), we argue that the importance of the mechanism for the formation of expectations should not be underestimated. Well-anchored inflation expectations are thought to be a reflection of credible monetary policy. In that sense, we consider the role of imperfect credibility on the inflation target into an otherwise standard open-economy Phillips curve.

We allow for deviations from rational expectations as well—using the conventional form of adaptive expectations for illustrative purposes. We can then show that deviations from fully rational expectations together with imperfect credibility of the monetary policy indeed play an important role in bringing the implications of the open-economy New Keynesian model closer to the empirical findings found among EMEs—which, in turn, provides us with the key elements to model the diverse experience of inflation dynamics observed around the world without surrendering core features of the open-economy New Keynesian model.

Under purely rational expectations, the equilibrium of the model implies that inflation expectations must equate an inflation target (which can be a constant) set by the central bank whenever this target is perfectly credible—and this, in turn, anchors inflation expectations in the open-economy Phillips curve.[5] In equilibrium, the long-run trend inflation rate prevailing in a country, $\overline{\pi}_t$, must be equal to the country's inflation target set by their own central bank, i.e. must be equal to $\widehat{\pi}_t^T$. To see this, we can simply interpret the long-run trend inflation rate as the (stochastic) trend of the corresponding inflation process, i.e.,

$$\overline{\pi}_t = \lim_{h \to \infty} \mathbb{E}_t \left(\widehat{\pi}_{t+h} \right). \tag{1}$$

The inflation rate of each country, $\widehat{\pi}_t \equiv \widehat{p}_t - \widehat{p}_{t-1}$, fluctuates around the country's stochastic inflation target, $\widehat{\pi}_t^T$, whenever credibly set by the central bank. Since generally the literature assumes that the inflation

[5] 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 also 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 central question that we postulate in this section is that the inflation target—whether a feature of an inflation-targeting regime or not—is credible and how it pins down inflation by helping anchor inflation expectations.

target must be a constant (or perhaps a random walk), it follows that $\mathbb{E}_t\left(\widehat{\pi}^T_{t+h}\right) = \widehat{\pi}^T_t$ at any period $h > 0$ and as h goes to infinity. In that sense, (1) implies that $\overline{\pi}_t = \widehat{\pi}^T_t$—hence validating the initial conjecture that trend and target inflation must be the same in equilibrium (Woodford (2008)).

Hence, a straightforward forecasting model based on full rationality and perfect credibility suffices to efficiently predict inflation among most advanced economies—as shown in the work of Duncan and Martínez-García (2015), among others. A different story arises from the empirical evidence gathered in this paper among EMEs. A departure that introduces adaptive expectations together with partial credibility (or imperfect credibility) of the central bank's inflation target, however, can be both consistent with the open-economy Phillips curve and with the evidence suggesting that near-random walk models can be better suited to forecast inflation among many open EMEs.

The open-economy Phillips curve in Martínez-García and Wynne (2010) under perfect international risk-sharing:[6]

$$\widehat{\pi}_t \approx \beta \mathbb{E}_t\left(\widehat{\pi}_{t+1}\right) + \kappa \widehat{x}^W_t + \varepsilon_t, \tag{2}$$

$$\widehat{x}^W_t \equiv (1-\xi)\,\widehat{x}_t + \xi \widehat{x}^*_t, \tag{3}$$

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 output gaps (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 $\widehat{x}^W_t$ is the corresponding trade-weighted measure of global slack. Here trade weights are determined by the share of imported goods in the consumption basket $0 \leq \xi \leq \frac{1}{2}$.[7]

The intertemporal discount factor is $0 < \beta < 1$, while the composite coefficient $\kappa \equiv \left(\frac{(1-\alpha)(1-\beta\alpha)}{\alpha}\right)(\varphi + \gamma)$ is the slope of the open-economy Phillips curve which depends also 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 ε_t captures shocks to the open-economy Phillips curve and other transient factors.

Suppose that inflationary expectations are based on a weighted average of past inflation and on the central bank's inflation target (assumed to be constant, i.e., $\widehat{\pi}^T_t = \widehat{\pi}^T$). Then, the open-economy Phillips curve can be re-written as follows:

$$\widehat{\pi}_t \approx \beta\left((1-\theta)\,\widehat{\pi}_{t-1} + \theta \widehat{\pi}^T\right) + \kappa \widehat{x}^W_t + \varepsilon_t, \tag{4}$$

where θ is the corresponding weight on the inflation target and $(1-\theta)$ the weight on past inflation. The parameter $0 \leq \theta \leq 1$ can be interpreted as a measure of the credibility of the central bank's inflation target with $\theta = 1$ indicting full credibility of the target, $\theta = 0$ representing the case of no credibility, and $0 < \theta < 1$ indicating partial credibility.[8] More generally, using the fact that the average $q-$period inflation rate from

[6] The elasticity of intratemporal substitution between Home and Foreign goods is $\sigma > 0$ and the intertemporal elasticity of substitution is $\gamma > 0$. In the special case where $\sigma\gamma = 1$, perfect risk-sharing can be attained through fluctuations in international relative prices (terms of trade) only irrespective of the international asset market structure (e.g., Cole and Obstfeld (1991)). In that scenario in particular, we find that $\Theta \equiv (1-\xi)$ and this leads us to adopt a much simpler trade-weighted specification of global slack in the open-economy Phillips curve.

[7] 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.

[8] We use this special case with constant θ for illustration purposes. For details on generalizing the specifcation 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).

$t+1-q$ to t can be written as $\widehat{\pi}_t^q \approx \frac{1}{q}\sum_{j=1}^{q} \widehat{\pi}_{t+1-j}$, then we can write the open-economy Phillips curve as

$$\widehat{\pi}_t \approx \beta \left((1-\theta) \widehat{\pi}_{t-1}^q + \theta \widehat{\pi}^T \right) + \kappa \widehat{x}_t^W + \varepsilon_t, \tag{5}$$

for some $q \geq 1$. This is consistent with $\widehat{\pi}_{t-1}^q$ being the level of inflation observed at the time when the forecast is made, but permits us to consider a number of common specifications. One possibility is that the forecasts of one-period-ahead inflation at time t is given by the observed inflation rate $\widehat{\pi}_{t-1}$ (which is the case when $q=1$). The timing of the inflation rate corrects for the publication lags in the inflation data. 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. This measure alone captures well the inflation tendency and constitutes, in fact, the basis of our RW-AO model (M_0).

Basic Insights from the Generalized Open-Economy Phillips Curve. Assume now that inflationary expectations are purely backward-looking (adaptive), so that $\theta = 0$ and economic agents put no weight on the official inflation target. Hence, it follows from here that:

$$\widehat{\pi}_t \approx \beta \widehat{\pi}_{t-1}^q + \kappa \widehat{x}_t^W + \varepsilon_t \to \Delta^q \widehat{\pi}_t \approx (\beta - 1) \widehat{\pi}_{t-1}^q + \kappa \widehat{x}_t^W + \varepsilon_t, \tag{6}$$

which appears to behave like a near-unit-root autoregressive process augmented with a residual term that is partly endogenous (owing to global slack). 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 $q=1$. If $\beta \to 1$, a structural shock that produces a positive global output gap will not simply lead to higher inflation, it will lead to steadily increasing inflation. The only way to stabilize inflation in that case would be to push output back to potential. However, in order to lower above-target inflation back to target, the central bank will need 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 must 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 to this in a world economy that is deeply interconnected.

Suppose instead that inflationary expectations are firmly anchored and fully rational as assumed for the 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:

$$\widehat{\pi}_t \approx \beta \widehat{\pi}^T + \kappa \widehat{x}_t^W + \varepsilon_t \to \Delta^q \widehat{\pi}_t \approx \kappa \Delta^q \widehat{x}_t^W + \Delta^q \varepsilon_t. \tag{7}$$

Now, the implication of the model is rather different. A shock that produces a positive global output gap will increase inflation above the central bank's target, but will not unleash an inflationary spiral as before. 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, will have only a limited impact in rising 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).

Using these two polar cases, we see that the deviations in inflation given by $\Delta^q \widehat{\pi}_t$ are partly explained by the level of global slack $\widehat{x}_t^W$ whenever economic agents put no weight on the official target (if also $\beta \to 1$), but respond to the conforming deviations in global slack given by $\Delta^q \widehat{x}_t^W$ whenever the inflation target is fully credible. Not surprisingly, if the true data-generating process (DGP) is given by the former specification where agents do not believe in the inflation target (and expectations are adaptive), trying to predict inflation based on the alternative spefication which assumes full credibility and rational expectations is likely to underperform relative to a simpler empirical model that abstracts from slack altogether. That nested, simpler model which uses $\widehat{\pi}_{t-1}^q$ solely as a predictor corresponds to the empirical RW-AO specification whenever $q = 4$. Hence, we would 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 emerging economies.

Finally, consider the intermediate case in which inflationary expectations are not well-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:

$$\widehat{\pi}_t \approx \beta \left(\left(1-\theta\right) \widehat{\pi}_{t-1}^q + \theta \widehat{\pi}^T \right) + \kappa \widehat{x}_t^W + \varepsilon_t \to \Delta^q \widehat{\pi}_t \approx \beta\theta \left(\widehat{\pi}^T - \widehat{\pi}_{t-1}^q \right) + \kappa \widehat{x}_t^W + \varepsilon_t. \tag{8}$$

Hence, inflation tends to converge towards the central bank's inflation target within a specification that can be cast in the form of an error correction-type model for changes in inflation and global slack. 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, i.e. when:

$$\Delta^q \widehat{\pi}_t = 0 \to \widehat{\pi}_t = \widehat{\pi}_{t-1}^q = \widehat{\pi}^T + \frac{\kappa}{\beta\theta} \widehat{x}_t^W + \frac{1}{\beta\theta} \varepsilon_t. \tag{9}$$

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

However, a comparison with the case where inflation expectations are well-anchored is very useful as it reveals that inflation quickly becomes unanchored whenever $\theta \neq 1$ (and $\theta \to 0$) implying much larger differences between actual and target inflation for a corresponding amount of global slack than under full credibility even when policy still manages to achieve inflation stabilization. A number of recent studies have argued, in fact, that the 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)). In turn, much less work has been done for EMEs and our paper is—to the best of our knowledge—the first to explicitly propose that the credibility of the inflation target and deviations from rational expectations could help us align the predictions of the open-economy Phillips curve specification with the findings reported here for many EMEs. However, we could even estimate the credibility parameter θ associated with the inflation target in (8). 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 the policy.

We argue that deviations from full rationality are also significant factors to take under consideration. Hence, we also plan to incorporate explicitly—if available—surveys or data on the inflation target for the central bank in the estimation and forecasting. We believe, nonetheless, that our paper makes a truly novel contribution to the literature by taking some first steps empirically (and to some extent theoretically as well) to develop variants of the open-economy Phillips-curve based model of inflation determination and forecasting that can encompass experiences as different as those of the EME and advanced economies that we have investigated in this work and in our previous paper (Duncan and Martínez-García (2015)). We believe this could ultimately equip us with a more unified framework with which to explore inflation across many countries around the world.

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 (such as the RW-AO) outperforms other forecasting models of inflation and is potentially not inconsistent with inflation dynamics under an open-economy Phillips curve specification coupled with lack of credibility in the inflation target and adaptive expectations. As discussed in the previous section, under lack of credibility in the inflation target, such a simple open-economy Phillips curve can imply inflation dynamics that resembles non-stationary processes as those observed in many EMEs during the eighties and part of the ninenties. That tends to produce a behavior in the inflation rate that can possibly display permanent (or near-permanent) effects from otherwise transitory changes in either domestic or—most notably—rest of the world slack. On the other hand, 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 seen to work better for EMEs from the late nineties on. In that case, output gap shocks will only affect inflation temporarily. The inability of the forecaster to observe sudden shifts in credibility or frequent changes in the implicit target make the empirical modelling and forecasting of inflation a difficult task, particularly in the developing world.

The same standard multi-country, open-economy New Keynesian model that provides a rationale for forecasting models of inflation that are succesful among advanced economies, also suggests a set of assumptions that can underpin the behavior of inflation prediction for EMEs as well. Therefore, our results suggest that a more flexible—and general—approach based on the open-economy Phillips curve is possible and can plausibly be consistent with the evidence on inflation across many country experiences around the world.

But our paper also points at the importance of understanding the process that leads to the formation of expectations and the appropriate conduct of monetary policy under different credibility scenarios. Our results might also suggest that incorporating inflation expectations explicitly into our forecasting models is a promising avenue for future research which—although complicated due to data availability—we plan to explore further in future research.

Appendix

A Tables and Figures

Table 1 - Data Sources for the Different Forecasting Models

Concept	Data sources	Transformation
Headline CPI	National statistical offices and central banks; OECD; Grossman et al. (2014)	Quarter-over-quarter (%)
GDP	National statistical offices and central banks; OECD; Grossman et al. (2014)	Quarter-over-quarter (%)
Industrial production	National statistical offices and central banks; OECD; IMF; Grossman et al. (2014)	Quarter-over-quarter (%)
Nominal Exchange Rate	Central banks; Wall Street Journal; Financial Times; IMF; Grossman et al. (2014)	Quarter-over-quarter (%)
Commodity price index	IMF	Quarter-over-quarter (%)

This table reports the basic information about the data used in the forecasting exercise. The countries included in our forecasting exercises are: Chile, China, Colombia, Hungary, Indonesia, India, Malaysia, Mexico, Nigeria, Peru, Phillippines, South Africa, Thailand, and Turkey. The time series coverage spans the period between the first quarter of 1980 and the fourth quarter of 2016 across all variables and countries, with few exceptions. We use Peru's Central Bank headline CPI data for its longer coverage. For Nigeria, we use GDP data only because the industrial production series was not available for the whole period. China's headline CPI data starts in 1983:Q4.

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 nominal exchange rates times the U.S. CPI divided by the CPI of the EME.

All series are seasonally adjusted.

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

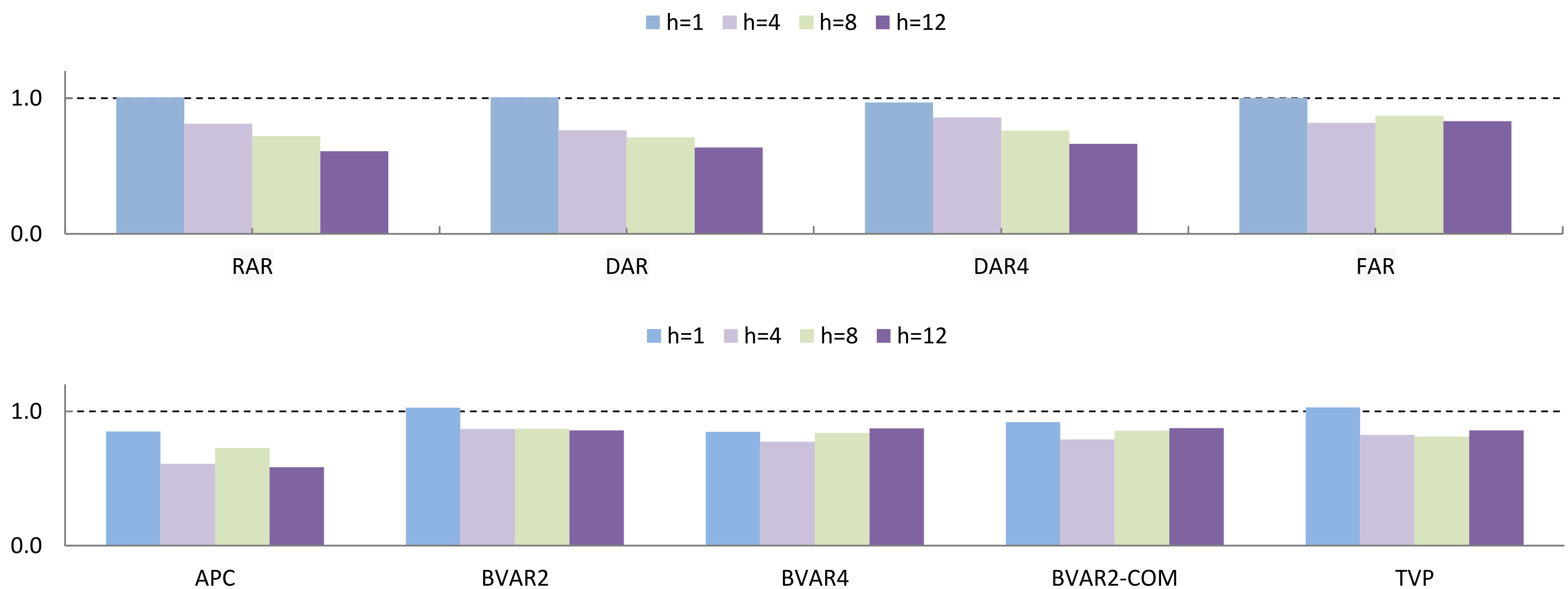

Figure 2. Directional Accuracy: Success Ratios (Medians)

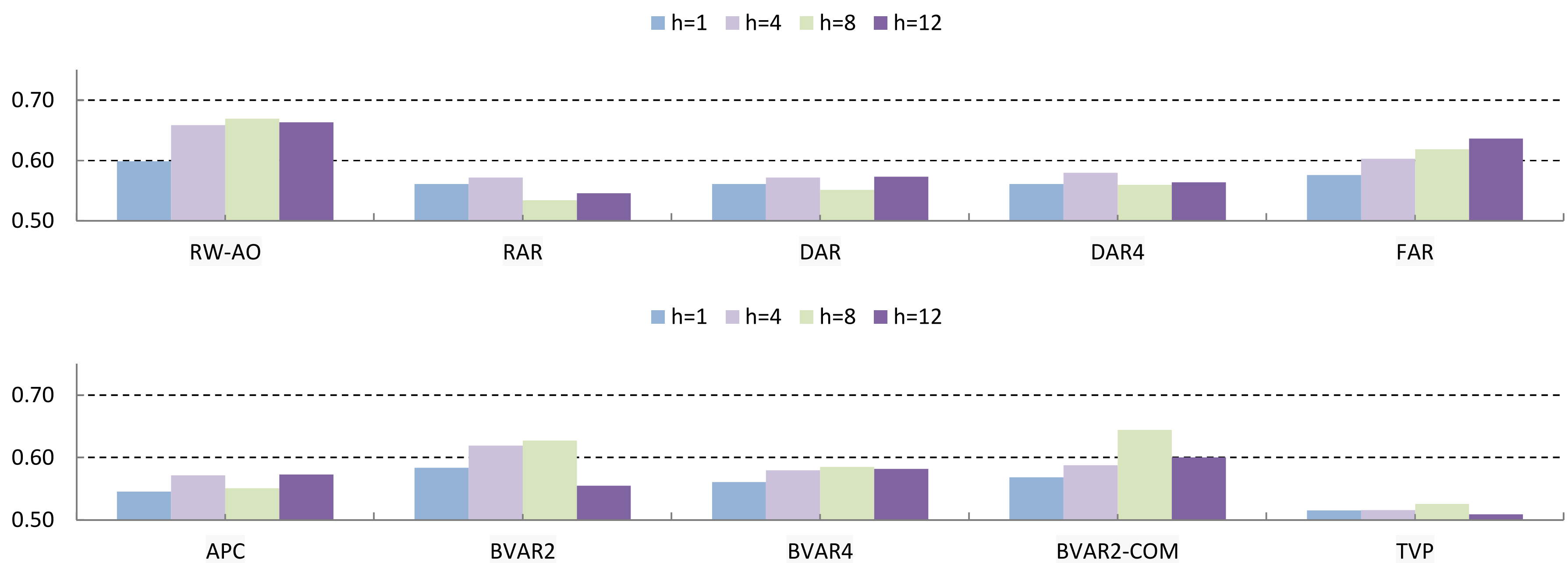

Table 2 - RMSPE of the RW-AO Model Relative to Competing Models (Summary)

	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 M1-M9
One-quarter ahead										
Mean	0.904	0.904	0.898	0.913	0.799	0.927	0.813	0.854	1.051	0.896
Median	1.005	1.005	0.967	1.001	0.851	1.027	0.848	0.920	1.030	0.962
#<1	7	7	8	7	11	6	9	9	5	8
#pv<.1	4	4	8	4	6	4	7	6	2	5
Four-quarter ahead										
Mean	0.706	0.722	0.764	0.745	0.659	0.799	0.724	0.732	0.832	0.743
Median	0.810	0.763	0.858	0.818	0.610	0.870	0.775	0.793	0.824	0.791
#<1	12	12	11	10	13	12	13	14	14	12
#pv<.1	9	9	11	9	9	8	10	9	10	9
Eight-quarter ahead										
Mean	0.637	0.696	0.714	0.763	0.653	0.785	0.771	0.773	0.840	0.737
Median	0.720	0.711	0.761	0.870	0.728	0.871	0.839	0.858	0.813	0.797
#<1	12	11	11	10	13	13	12	13	14	12
#pv<.1	9	10	11	8	10	9	11	10	11	10
Twelve-quarter ahead										
Mean	0.617	0.667	0.679	0.772	0.618	0.764	0.785	0.814	0.870	0.732
Median	0.608	0.636	0.664	0.830	0.586	0.859	0.874	0.876	0.860	0.755
#<1	12	11	11	10	12	14	14	14	14	12
#pv<.1	10	10	11	8	10	8	7	6	8	9
Averages (all horizons)										
Mean	0.716	0.747	0.764	0.798	0.682	0.819	0.773	0.793	0.898	0.777
Median	0.786	0.779	0.812	0.880	0.694	0.907	0.834	0.862	0.882	0.826
#<1	11	10	10	9	12	11	12	13	12	11
#pv<.1	8	8	10	7	9	7	9	8	8	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 standard 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. More detailed information by country can be found in Tables 4-7.

Table 3 - Directional Accuracy: Success Ratios (Summary)

	M_0	M_1	M_2	M_3	M_4	M_5	M_6	M_7	M_8	M_9	Average
	RW-AO	RAR	DAR	DAR4	FAR	APC	BVAR2	BVAR4	BVAR2-COM	TVP	M1-M9
One-quarter ahead											
Mean	0.615	0.549	0.549	0.563	0.575	0.530	0.573	0.540	0.541	0.519	0.549
Median	0.598	0.561	0.561	0.561	0.576	0.545	0.583	0.561	0.568	0.515	0.559
#<0.5	14	9	9	10	12	9	11	9	9	8	10
Four-quarter ahead											
Mean	0.663	0.582	0.590	0.602	0.592	0.587	0.602	0.595	0.593	0.514	0.584
Median	0.659	0.571	0.571	0.579	0.603	0.571	0.619	0.579	0.587	0.516	0.578
#<0.5	14	13	13	14	12	13	12	13	13	8	12
Eight-quarter ahead											
Mean	0.663	0.534	0.556	0.567	0.599	0.541	0.611	0.559	0.579	0.534	0.564
Median	0.669	0.534	0.551	0.559	0.619	0.551	0.627	0.585	0.644	0.525	0.577
#<0.5	14	10	9	10	9	8	12	9	8	9	9
Twelve-quarter ahead											
Mean	0.665	0.540	0.556	0.561	0.591	0.564	0.544	0.570	0.581	0.522	0.559
Median	0.664	0.545	0.573	0.564	0.636	0.573	0.555	0.582	0.600	0.509	0.571
#<0.5	14	10	10	10	10	10	12	12	12	9	11
Averages (all horizons)											
Mean	0.652	0.551	0.562	0.573	0.589	0.555	0.583	0.566	0.573	0.522	0.564
Median	0.648	0.553	0.564	0.566	0.608	0.560	0.596	0.577	0.600	0.516	0.571
#<0.5	14	11	10	11	11	10	12	11	11	9	10

Notes: Rows for means and medians report the average and median ratio of success in directional accuracy over the 14 countries. More detailed information by country can be found in Tables 8-11.

Table 4 - 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**	1.000	**0.782**	1.037	**0.838**	0.930	1.240
China	1.183	1.175	1.198	1.117	1.195	1.172	1.151	1.154
Colombia	**0.814**	**0.969**	**0.690**	**0.659**	**0.715**	**0.698**	**0.779**	1.165
Hungary	0.928	1.007	0.930	**0.784**	0.941	**0.720**	**0.796**	1.007
Indonesia	0.978	**0.966**	1.043	0.967	1.039	1.007	1.006	**0.918**
India	0.938	**0.911**	0.873	0.969	0.891	0.995	0.911	0.900
Malaysia	1.104	1.106	1.095	1.123	1.101	1.113	1.121	0.948
Mexico	**0.374**	**0.320**	**0.626**	**0.364**	**0.633**	**0.367**	**0.371**	**0.817**
Nigeria	1.055	1.039	1.003	**0.673**	1.018	**0.706**	**0.873**	0.985
Peru	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	1.047
Philippines	1.147	**0.926**	1.246	0.918	1.271	**0.858**	0.950	1.242
South Africa	1.037	1.074	1.126	0.940	1.154	1.097	1.020	1.191
Thailand	1.194	1.196	1.174	1.157	1.192	1.108	1.190	1.091
Turkey	**0.875**	**0.912**	**0.782**	0.728	**0.788**	0.696	**0.853**	1.014
Mean	0.904	0.898	0.913	0.799	0.927	0.813	0.854	1.051
Median	1.005	0.967	1.001	0.851	1.027	0.848	0.920	1.030
#<1	7	8	7	11	6	9	9	5
#pv<.1	4	8	4	6	4	7	6	2

Notes: Data are described in Table 1. Columns report the ratio of root mean squared prediction error (RMSPE) from the RW-AO model relative to the RMSPE of standard forecasting models (see section 2). 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.

Table 5 - Four-Quarter 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**	**0.730**	**0.611**	0.967	**0.803**	**0.817**	0.932
China	0.960	0.912	**0.931**	1.019	0.975	1.040	0.980	0.949	0.927
Colombia	**0.473**	**0.663**	**0.872**	**0.565**	**0.519**	**0.766**	**0.735**	**0.750**	0.907
Hungary	**0.592**	**0.751**	**0.790**	**0.784**	**0.583**	**0.827**	**0.718**	**0.724**	**0.868**
Indonesia	**0.833**	**0.847**	**0.876**	0.857	**0.766**	**0.894**	**0.868**	**0.871**	**0.787**
India	1.046	0.987	**0.972**	**0.650**	0.902	**0.822**	**0.875**	0.934	**0.815**
Malaysia	1.094	1.112	1.122	1.081	1.074	0.947	0.971	0.984	**0.750**
Mexico	**0.136**	**0.119**	**0.118**	**0.264**	**0.111**	**0.411**	**0.150**	**0.159**	**0.834**
Nigeria	**0.810**	**0.775**	**0.750**	**0.852**	**0.597**	**0.846**	**0.747**	**0.768**	**0.762**
Peru	**0.001**	**0.001**	**0.001**	**0.000**	**0.000**	**0.001**	**0.000**	**0.000**	**0.898**
Philippines	**0.811**	**0.636**	**0.592**	0.945	**0.577**	0.991	**0.699**	**0.691**	**0.809**
South Africa	0.898	0.993	1.059	1.101	0.957	1.042	1.000	0.994	**0.884**
Thailand	0.996	1.018	1.058	1.023	0.941	0.925	**0.849**	0.935	**0.732**
Turkey	**0.515**	**0.608**	**0.716**	**0.556**	**0.610**	**0.700**	0.742	**0.675**	0.742
Mean	0.706	0.722	0.764	0.745	0.659	0.799	0.724	0.732	0.832
Median	0.810	0.763	0.858	0.818	0.610	0.870	0.775	0.793	0.824
#<1	12	12	11	10	13	12	13	14	14
#pv<.1	9	9	11	9	9	8	10	9	10

Notes: Data are described in Table 1. Columns report the ratio of root mean squared prediction error (RMSPE) from the RW-AO model relative to the RMSPE of standard forecasting models (see section 2). 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.

Table 6 - Eight-Quarter 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	**0.538**	0.891	**0.965**	0.917	**0.730**	0.915	**0.874**	**0.863**	**0.813**
China	0.833	**0.731**	**0.674**	0.960	0.905	0.938	**0.895**	0.986	**0.834**
Colombia	**0.375**	**0.690**	**0.851**	**0.668**	**0.557**	**0.903**	0.969	0.958	**0.928**
Hungary	**0.467**	**0.589**	**0.639**	**0.634**	**0.463**	**0.745**	**0.706**	**0.702**	**0.766**
Indonesia	0.839	**0.837**	**0.842**	**0.841**	**0.837**	**0.847**	**0.850**	**0.853**	**0.813**
India	0.916	0.888	**0.896**	**0.655**	**0.726**	**0.821**	**0.794**	**0.822**	**0.751**
Malaysia	1.044	1.059	1.070	1.033	1.021	**0.804**	**0.827**	0.832	**0.738**
Mexico	**0.088**	**0.083**	**0.099**	**0.164**	**0.084**	**0.368**	**0.285**	**0.248**	0.919
Nigeria	**0.769**	**0.655**	**0.679**	0.898	**0.585**	**0.884**	**0.880**	0.898	**0.811**
Peru	**0.001**	**0.000**	**0.000**	**0.000**	**0.000**	**0.001**	**0.000**	**0.000**	**0.869**
Philippines	**0.671**	**0.530**	**0.532**	1.051	**0.492**	0.901	**0.818**	**0.813**	**0.780**
South Africa	0.843	1.075	1.067	1.209	0.992	1.018	1.032	1.036	0.958
Thailand	1.033	1.051	1.008	1.025	0.937	**0.858**	**0.829**	0.903	**0.792**
Turkey	**0.499**	**0.657**	**0.679**	**0.631**	**0.818**	0.983	1.032	0.903	0.985
Mean	0.637	0.696	0.714	0.763	0.653	0.785	0.771	0.773	0.840
Median	0.720	0.711	0.761	0.870	0.728	0.871	0.839	0.858	0.813
#<1	12	11	11	10	13	13	12	13	14
#pv<.1	9	10	11	8	10	9	11	10	11

Notes: Data are described in Table 1. Columns report the ratio of root mean squared prediction error (RMSPE) from the RW-AO model relative to the RMSPE of standard forecasting models (see section 2). 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.

Table 7- Twelve-Quarter 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	**0.482**	**0.644**	**0.734**	0.960	**0.593**	0.956	0.949	0.970	0.933
China	**0.609**	**0.494**	**0.436**	**0.567**	**0.579**	**0.725**	**0.588**	0.865	**0.807**
Colombia	**0.302**	**0.610**	**0.630**	**0.619**	**0.539**	0.830	0.892	0.921	0.933
Hungary	**0.430**	**0.488**	**0.497**	**0.460**	**0.417**	**0.837**	**0.823**	**0.816**	0.916
Indonesia	0.865	**0.896**	**0.871**	**0.921**	0.899	**0.834**	**0.845**	**0.843**	**0.844**
India	0.961	0.955	**0.967**	0.841	**0.833**	0.850	0.836	0.868	0.845
Malaysia	1.094	1.106	1.075	1.101	1.100	0.868	0.883	0.884	0.835
Mexico	**0.081**	**0.111**	**0.135**	**0.190**	**0.119**	**0.233**	**0.625**	**0.654**	**0.870**
Nigeria	**0.757**	**0.654**	**0.617**	0.820	**0.618**	**0.867**	0.904	0.927	**0.850**
Peru	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.001**	**0.001**	**0.002**	**0.794**
Philippines	**0.607**	**0.580**	**0.643**	1.025	**0.500**	**0.876**	**0.865**	**0.832**	**0.784**
South Africa	0.795	1.005	1.063	1.328	0.927	0.953	0.954	0.950	0.886
Thailand	1.168	1.161	1.151	1.197	1.003	0.945	0.913	0.984	0.910
Turkey	**0.489**	**0.628**	**0.685**	**0.780**	**0.523**	0.924	0.918	0.885	0.968
Mean	0.617	0.667	0.679	0.772	0.618	0.764	0.785	0.814	0.870
Median	0.608	0.636	0.664	0.830	0.586	0.859	0.874	0.876	0.860
#<1	12	11	11	10	12	14	14	14	14
#pv<.1	10	10	11	8	10	8	7	6	8

Notes: Data are described in Table 1. Columns report the ratio of root mean squared prediction error (RMSPE) from the RW-AO model relative to the RMSPE of standard forecasting models (see section 2). 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.

Table 8 - 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 †	0.58	0.48 †	0.58	0.56	**0.56** *	0.50
China	**0.59** *	0.64 †	0.65 †	**0.70** *	0.55	**0.71** *	**0.61** *	0.59	**0.55** *
Colombia	**0.59** *	0.56 †	**0.64** *	0.53	**0.59** *	0.52	0.53	0.58	**0.55** *
Hungary	**0.56** *	0.44	0.47	0.39	0.41	0.41	0.42	0.38	0.62
Indonesia	**0.74** *	**0.58** *	**0.64** *	**0.65** *	**0.58** *	**0.65** *	**0.62** *	**0.61** *	0.39
India	**0.58** *	**0.56** *	**0.58** *	**0.56** *	**0.62** *	**0.56** *	**0.62** *	**0.58** *	0.48
Malaysia	**0.62** *	**0.65** *	**0.67** *	**0.64** *	**0.62** *	**0.64** *	0.56	**0.68** *	**0.53** *
Mexico	**0.70** *	0.47	0.47	**0.56** *	0.53	**0.56** *	0.48	0.47	**0.58** *
Nigeria	**0.68** *	**0.61** *	**0.61** *	**0.59** *	0.57	**0.59** *	0.57	0.55	0.50
Peru	**0.62** *	0.45	0.45	0.45	0.47	0.44	0.41	0.45	0.45
Philippines	0.55	**0.56** *	0.53 †	**0.64** *	0.55	**0.62** *	**0.59** *	0.58	0.52
South Africa	0.55	0.50	**0.55** *	**0.58** *	0.39	**0.59** *	0.42	0.41	0.50
Thailand	**0.64** *	**0.65** *	**0.62** *	**0.67** *	**0.67** *	**0.65** *	**0.65** *	**0.65** *	0.52
Turkey	**0.59** *	0.50 †	0.50 †	**0.52** *	0.39	0.50 †	0.50	0.50 †	**0.59** *
Mean	0.61	0.55	0.56	0.57	0.53	0.57	0.54	0.54	0.52
Median	0.60	0.56	0.56	0.58	0.55	0.58	0.56	0.57	0.52
#>0.5	14	9	10	12	9	11	9	9	8

Notes: Data are described in Table 1. 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.

Table 9 - Directional Accuracy: Success Ratio of Four-Quarter-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	0.51	0.57 †	**0.63** *	0.54 †	0.59 †	0.48
China	**0.57** *	0.62 †	0.62 †	0.65 †	**0.67** *	0.60	**0.71** *	0.54	0.62 †	**0.57** *
Colombia	**0.59** *	0.54 †	**0.57** *	0.54	0.52	0.54	0.51	0.52	0.56 †	0.49
Hungary	**0.63** *	0.41 †	0.49 †	**0.56** *	0.48	0.44 †	0.48	0.44 †	0.40 †	0.56
Indonesia	**0.76** *	**0.60** *	**0.63** *	**0.67** *	**0.67** *	**0.60** *	**0.70** *	**0.67** *	**0.67** *	0.52
India	**0.60** *	**0.62** *	**0.62** *	**0.60** *	0.52 †	**0.59** *	**0.51** *	**0.57** *	**0.60** *	0.56
Malaysia	**0.71** *	**0.79** *	**0.79** *	**0.76** *	**0.76** *	**0.81** *	**0.78** *	**0.79** *	**0.79** *	0.52
Mexico	**0.71** *	0.51 †	0.51 †	0.51 †	**0.57** *	0.52 †	0.56	0.52 †	0.54 †	0.48
Nigeria	**0.70** *	**0.57** *	**0.57** *	**0.57** *	**0.63** *	**0.57** *	**0.60** *	**0.59** *	**0.59** *	0.49
Peru	**0.63** *	0.51 †	0.51 †	0.51 †	0.33	0.51	0.37	0.54	0.56	0.52
Philippines	**0.68** *	0.57 †	0.54 †	0.54 †	**0.71** *	**0.57** *	**0.70** *	**0.60** *	0.52 †	0.51
South Africa	**0.62** *	**0.67** *	**0.67** *	**0.71** *	**0.70** *	**0.68** *	**0.70** *	**0.68** *	**0.70** *	0.48
Thailand	**0.71** *	**0.63** *	**0.65** *	**0.70** *	**0.67** *	**0.65** *	**0.67** *	**0.65** *	**0.67** *	0.54
Turkey	**0.76** *	0.52 †	0.52 †	0.52 †	0.54 †	**0.56** *	0.52 †	**0.67** *	0.51 †	0.48
Mean	0.66	0.58	0.59	0.60	0.59	0.59	0.60	0.60	0.59	0.51
Median	0.66	0.57	0.57	0.58	0.60	0.57	0.62	0.58	0.59	0.52
#>0.5	14	13	13	14	12	13	12	13	13	8

Notes: Data are described in Table 1. 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.

Table 10 - Directional Accuracy: Success Ratio of Eight-Quarter-Ahead Forecasts

	M_0	M_1	M_2	M_3	M_4	M_5	M_6	M_7	M_8	M_9
	RW-AO	RAR	DAR	DAR4	FAR	APC	BVAR2	BVAR4	BVAR2-COM	TVP
Chile	**0.63** *	0.54 †	**0.69** *	**0.69** *	**0.61** *	**0.58** *	**0.71** *	**0.63** *	0.66 †	0.53
China	**0.71** *	0.56 †	0.58 †	0.58 †	**0.69** *	**0.63** *	**0.76** *	**0.63** *	**0.69** *	**0.61** *
Colombia	**0.58** *	0.47 †	0.47	0.54	0.34	0.42	0.53 †	0.47	**0.66** *	0.56
Hungary	**0.64** *	0.37 †	0.41 †	0.47	0.47	0.39 †	0.44	0.41 †	0.37 †	0.59
Indonesia	**0.69** *	**0.58** *	**0.66** *	**0.66** *	**0.68** *	**0.59** *	**0.66** *	**0.69** *	**0.69** *	0.42
India	**0.73** *	**0.53** *	**0.53** *	**0.54** *	0.44	0.46	**0.53** *	0.39	0.46	0.63
Malaysia	**0.69** *	**0.71** *	**0.73** *	**0.75** *	**0.75** *	**0.71** *	**0.73** *	**0.68** *	**0.76** *	0.47
Mexico	**0.64** *	0.32 †	0.32 †	0.32 †	0.58	0.37	0.64	0.34 †	0.36 †	0.63
Nigeria	**0.66** *	**0.58** *	**0.58** *	**0.59** *	**0.63** *	**0.63** *	**0.71** *	**0.64** *	**0.66** *	0.53
Peru	**0.69** *	0.51 †	0.51 †	0.51 †	0.49	0.53	0.51 †	0.49	0.46	0.44
Philippines	**0.68** *	0.51 †	0.49 †	0.49 †	**0.69** *	0.47	**0.58** *	**0.56** *	0.47 †	0.46
South Africa	0.54	**0.64** *	**0.63** *	**0.61** *	**0.81** *	**0.68** *	**0.61** *	**0.73** *	**0.63** *	0.49
Thailand	**0.80** *	**0.68** *	**0.73** *	**0.71** *	**0.71** *	**0.64** *	**0.68** *	**0.61** *	**0.76** *	0.53
Turkey	**0.59** *	0.47 †	0.46 †	0.46 †	0.49	0.47	0.47	0.56 †	0.46 †	0.59
Mean	0.66	0.53	0.56	0.57	0.60	0.54	0.61	0.56	0.58	0.53
Median	0.67	0.53	0.55	0.56	0.62	0.55	0.63	0.58	0.64	0.53
#>0.5	14	10	9	10	9	8	12	9	8	9

Notes: Data are described in Table 1. 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.

Table 11 - Directional Accuracy: Success Ratio of Twelve-Quarter-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** *	0.58 †	**0.55** *	**0.65** *	**0.58** *	0.51
China	**0.80** *	**0.58** *	**0.60** *	**0.58** *	**0.71** *	**0.64** *	0.51 †	0.53 †	**0.60** *	0.47
Colombia	**0.60** *	0.40 †	0.45	0.49	0.40	0.36	0.60 †	0.60 †	0.60 †	0.62
Hungary	0.51	0.35 †	0.35 †	0.38 †	0.36	0.44	0.38	0.35 †	0.35 †	0.65
Indonesia	**0.71** *	**0.53** *	**0.62** *	**0.65** *	**0.65** *	**0.55** *	0.55	**0.60** *	0.55	0.40
India	**0.60** *	**0.64** *	**0.64** *	**0.67** *	**0.58** *	**0.60** *	0.56	**0.56** *	**0.62** *	0.56
Malaysia	**0.71** *	**0.69** *	**0.69** *	**0.64** *	**0.71** *	**0.69** *	0.62	**0.60** *	**0.60** *	0.42
Mexico	**0.73** *	0.44 †	0.44 †	0.44 †	0.56	0.47	0.56 †	0.56	0.56	0.58
Nigeria	**0.69** *	**0.56** *	**0.55** *	**0.53** *	**0.62** *	**0.62** *	0.55	**0.64** *	**0.67** *	0.53
Peru	**0.80** *	0.53 †	0.53 †	0.53 †	0.40	0.56	0.53 †	0.53	0.55	0.51
Philippines	**0.80** *	**0.53** *	**0.53** *	**0.55** *	**0.69** *	**0.56** *	**0.64** *	**0.60** *	**0.64** *	0.47
South Africa	0.56	**0.62** *	**0.67** *	**0.67** *	**0.84** *	**0.67** *	0.56	**0.71** *	**0.67** *	0.51
Thailand	**0.64** *	**0.67** *	**0.67** *	**0.67** *	**0.73** *	**0.71** *	**0.64** *	0.49	**0.65** *	**0.60** *
Turkey	**0.60** *	0.47 †	0.45 †	0.45 †	0.36	0.44	0.38	0.56 †	0.49	0.47
Mean	0.66	0.54	0.56	0.56	0.59	0.56	0.54	0.57	0.58	0.52
Median	0.66	0.55	0.57	0.56	0.64	0.57	0.55	0.58	0.60	0.51
#>0.5	14	10	10	10	10	10	12	12	12	9

Notes: Data are described in Table 1. 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.

Table 12 - Ranking per Number of Statistical Significant Cases (U-Theils; #pv<.1)

	h=1	h=4	h=8	h=12	Average (h=8,12)	Average
Mexico	8	9	8	9	9	9
Peru	7	9	9	9	9	9
Hungary	4	9	9	8	9	8
Colombia	7	8	7	5	6	7
Nigeria	4	9	7	6	7	7
Indonesia	2	8	8	7	8	6
Philippines	2	7	7	8	8	6
Turkey	5	7	5	5	5	6
Chile	3	7	6	4	5	5
India	1	5	7	2	5	4
China	1	1	4	8	6	4
Thailand	0	3	4	1	3	2
Malaysia	0	1	3	1	2	1
South Africa	0	1	0	0	0	0

Table 13 - Ranking of Competing Models per Relative RMSPE (U-Theils<1, #pv<.1)						
	h=1	h=4	h=8	h=12	Average (h=8,12)	Average
FAR	4	9	8	8	8	7
BVAR2	4	8	9	8	9	7
TVP	2	10	11	8	10	8
BVAR2-COM	6	9	10	6	8	8
RAR	4	9	9	10	10	8
DAR	4	9	10	10	10	8
APC	6	9	10	10	10	9
BVAR4	7	10	11	7	9	9
DAR4	8	11	11	11	11	10

Table 14 - Forecast Averages

	Relative RMSPE		Directional accuracy	
	M1-M9 Average	M4 and M6 Average	M1-M9 Average	M4 and M6 Average
One-quarter ahead				
Mean	0.944	0.920	0.559	0.575
Median	0.999	1.015	0.561	0.576
#<1; #>0.5	7	6	10	12
#pv<.1	3	4	8	8
Four-quarter ahead				
Mean	0.768	0.783	0.590	0.593
Median	0.834	0.859	0.571	0.595
#<1; #>0.5	11	11	12	12
#pv<.1	8	7	7	7
Eight-quarter ahead				
Mean	0.783	0.809	0.561	0.611
Median	0.883	0.915	0.576	0.661
#<1; #>0.5	12	12	9	10
#pv<.1	6	7	9	9
Twelve-quarter ahead				
Mean	0.818	0.815	0.573	0.592
Median	0.921	0.917	0.600	0.627
#<1; #>0.5	10	10	10	11
#pv<.1	6	6	7	9
Averages (all horizons)				
Mean	0.828	0.832	0.570	0.593
Median	0.909	0.927	0.577	0.615
#<1; #>0.5	10	10	10	11
#pv<.1	6	6	8	8

References

Altug, S. and C. Çakmakli (2016). Forecasting Inflation Using Survey Expectations and Target Inflation: Evidence for Brazil and Turkey. *International Journal of Forecasting 32*, 138–153.

Aron, J. and J. Muellbauer (2012). Improving Forecasting in an Emerging Economy, South Africa: Changing Trends, Long Run Restrictions and Disaggregation. *International Journal of Forecasting 28*, 456–476.

Atkeson, A. and L. E. Ohanian (2001). Are Phillips Curves Useful for Forecasting Inflation? Federal Reserve Bank of Minneapolis *Quarterly Review, 25*(1), 2–11. Winter.

Balcilar, M., R. Gupta, and K. Kotzé (2015). Forecasting Macroeconomic Data for an Emerging Market with a Nonlinear DSGE Model. *Economic Modelling 44*, 215–228.

Chen, Y.-c., S. J. Turnovsky, and E. Zivot (2014). Forecasting Inflation Using Commodity Price Aggregates. *Journal of Econometrics 183*, 117–134.

Ciccarelli, M. and B. Mojon (2010). Global inflation. *The Review of Economics and Statistics 92*(3), 524–535.

Clark, T. E. and M. W. McCracken (2010). Averaging Forecasts from VARs with Uncertain Instabilities. *Journal of Applied Econometrics 25*(1), 5–29.

Clark, T. E. and K. D. West (2007). Approximately Normal Tests for Equal Predictive Accuracy in Nested Models. *Journal of Econometrics 138*(1), 291–311.

Clemen, R. T. (1989). Combining Forecasts: A Review and Annotated Bibliography. *International Journal of Forecasting 5*(4), 559–583.

Cole, H. L. and M. Obstfeld (1991). Commodity Trade and International Risk Sharing. How Much Do Financial Markets Matter? *Journal of Monetary Economics 28*(1), 3–24.

Doan, T., R. B. Litterman, and C. A. Sims (1984). Forecasting and Conditional Projections Using Realistic Prior Distributions. *Econometric Reviews 3*(1), 1–100.

Duncan, R. and E. Martínez-García (2015). Forecasting Local Inflation with Global Inflation: When Economic Theory Meets the Facts. *Federal Reserve Bank of Dallas Globalization and Monetary Policy Institute Working Paper No. 235*.

Faust, J. and J. H. Wright (2013). *Forecasting Inflation*, Volume 2A of *Handbook of Economic Forecasting*, Chapter 1, pp. 2–56. Elsevier.

Grossman, V., A. Mack, and E. Martínez-García (2014). A New Database of Global Economic Indicators. *The Journal of Economic and Social Measurement 39*(3), 163–197.

Hammond, G. (2012). State of the Art of Inflation Targeting - 2012. *Centre for Central Banking Studies. Handbook - No. 29*.

Harvey, D., S. Leybourne, and P. Newbold (1997). Testing the Equality of Prediction Mean Squared Errors. *International Journal of Forecasting 13*(2), 281–291.

IMF WEO (2013). The Dog that Didn't Bark: Has Inflation Been Muzzled or Was it Just Sleeping? *Chapter 3. World Economic Outlook (IMF), April 2013.*

Kabukcuoglu, A. and E. Martínez-García (2016). What Helps Forecast U.S. Inflation? - Mind the Gap! *Koç University-TUSIAD Economic Research Forum Working Papers (No. 1615)*.

Litterman, R. B. (1986). Forecasting with Bayesian Vector Autoregressions: Five Years of Experience. *Journal of Business and Statistics 4*(1), 25–38.

Liu, G. D. and R. Gupta (2007). A Small-Scale DSGE Model for Forecasting the South African Economy. *South African Journal of Economics 75*(2), 179–193.

Mandalinci, Z. (2015). Forecasting Inflation in Emerging Markets: An Evaluation of Alternative Models. *CReMFi Discussion Paper 3*.

Martínez-García, E. and M. A. Wynne (2010). The Global Slack Hypothesis. Federal Reserve Bank of Dallas *Staff Papers, 10.* September.

Medel, C. A., M. Pedersen, and P. M. Pincheira (2016). The Elusive Predictive Ability of Global Inflation. *International Finance 19*(2), 120–146.

Mehrotra, A. and J. Yetman (2014). Decaying Expectations: What Inflation Forecasts Tell Us About the Anchoring of Inflation Expectations. *BIS Working Papers No. 464*.

Meier, A. (2010). Still Minding the Gap—Inflation Dynamics during Episodes of Persistent Large Output Gaps. *IMF Working Paper WP/10/189*.

Pesaran, M. H. and A. Timmermann (2009). Testing Dependence Among Serially Correlated Multicategory Variables. *Journal of the American Statistical Association 104*(485), 325–337.

Pincheira, P. M. and A. Gatty (2016). Forecasting Chilean Inflation with International Factors. *Empirical Economics 51*, 981–1010.

Pincheira, P. M. and C. A. Medel (2015). Forecasting Inflation with a Simple and Accurate Benchmark: The Case of the U.S. and a Set of Inflation Targeting Countries. *Czech Journal of Economics and Finance 65*(1), 2–29.

Primiceri, G. E. (2005). Time-varying Structural Vector Autoregressions and Monetary Policy. *The Review of Economic Studies 72*(3), 821–852.

Sims, C. A. and T. Zha (1998). Bayesian Methods for Dynamic Multivariate Models. *International Economic Review 39*(4), 949–968.

Stock, J. H. and M. W. Watson (1999). Forecasting Inflation. *Journal of Monetary Economics 44*(2), 293–335.

Stock, J. H. and M. W. Watson (2002). Macroeconomic Forecasting Using Diffusion Indexes. *Journal of Business and Economic Statistics 20*(2), 147–162.

Stock, J. H. and M. W. Watson (2004). Combination Forecasts of Output Growth in a Seven-Country Data Set. *Journal of Forecasting 23*(6), 405–430.

Woodford, M. (2008). How Important Is Money in the Conduct of Monetary Policy? *Journal of Money, Credit and Banking 40*(8), 1561–1598.

Ögünç, F., K. Akdogan, S. Baser, M. G. Chadwick, D. Ertug, T. Hülagü, S. Kösem, M. U. Özmen, and N. Tekatli (2013). Short-term Inflation Forecasting Models for Turkey and a Forecast Combination Analysis. *Economic Modelling 33*, 312–325.