

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

Roberto Duncan
Ohio University

Enrique Martínez-García
Federal Reserve Bank of Dallas

Forecasting Issues in Developing Economies
Washington, DC, April 26-27, 2017

- Inflation forecasting has resurged in advanced economies
 - global inflation
 - Ciccarelli and Mojon (2010); Duncan and Martínez-García (2015)
 - surveys of expectations
 - Faust and Wright (2013)
- A few studies for emerging market economies (EMEs)
 - Limited cross-section and time series dimension
 - Few models; exception: Mandalinci (2015)
 - Some key models are virtually ignored (e.g., RW by Atkeson and Ohanian (2001))

What we do

- A horse race with a broad-range set of specifications to forecast inflation in EMEs
- Discuss the implications of our main finding in an open-economy New Keynesian model

What we find and its importance

- The RW-AO has, in general, a superior predictive power to forecast inflation across EMEs
- If we interpret our findings as deviations from rational expectations coupled with partial credibility, we get sensible theoretical predictions about inflation dynamics.
- The RW-AO is a missing model in the literature for EMEs
- Hammond (2012) reports the list of forecasting models used by inflation targeters: the RW-AO is not one of them.

Outline

- 1 Introduction
- 2 Forecasting exercise
- 3 Models
- 4 Forecast comparison
- 5 Discussion
- 6 Final remarks

└ 2. Forecasting exercise

└ The data

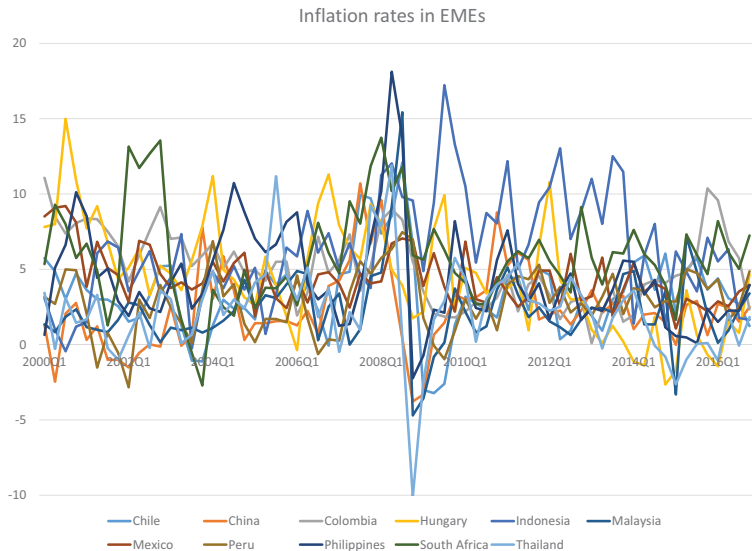
- Quarter-on-quarter headline-CPI inflation rates (π_t)

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

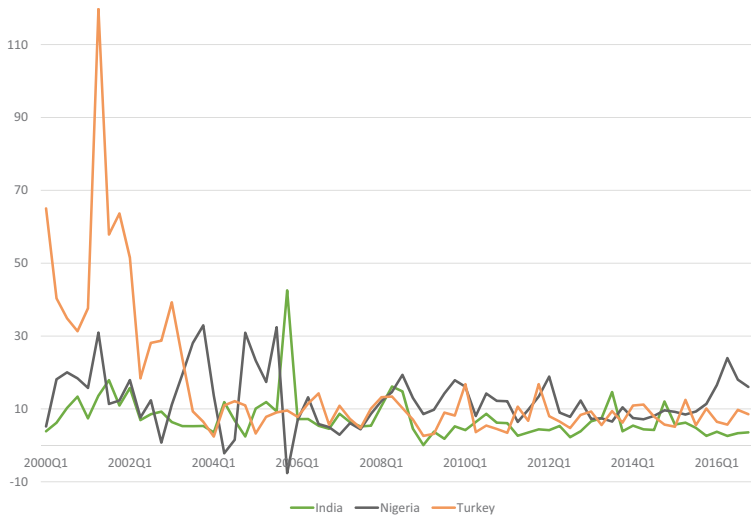
- Seasonally-adjusted, average data, 1980Q1-2016Q4.
- Sample of 14 EMEs: Chile, China, Colombia, Hungary, Indonesia, India, Malaysia, Mexico, Nigeria, Peru, Philippines, South Africa, Thailand, and Turkey.

2. Forecasting exercise

The data



Inflation rates in EMEs



└ 2. Forecasting exercise

└ The exercise

- Horse race to forecast inflation, the RW-AO vs competing models
- Pseudo out-of-sample forecasts, recursive estimation
- Forecast horizons: $h = \{1, 4, 8, 12\}$ quarters
- Training sample: 1980Q2-2000Q2

└ 3. Models

└ The null model

Random Walk (RW-AO)

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

π_{t+h} : the inflation rate

h : forecast horizon

ϵ_{t+h} : forecast error

$q = 4$

AO = Atkeson and Ohanian (2001), Faust and Wright (2013).

We consider

- univariate and multivariate specifications
- frequentist and Bayesian techniques
- constant and time-varying parameter models
- purely statistical and econometric specifications (exchange rates, commodity prices, global inflation via factor components)

Along the lines of: Doan *et al.* (1984), Litterman (1986), Stock and Watson (1999, 2002, 2007), Ciccarelli and Mojon (2010), Faust and Wright (2013), Primiceri (2005), among others.

└ 3. Models

└ Competing models

Recursive autoregression, AR(p) model (RAR)

$$M_1 : \pi_t = \phi_0 + \Phi(L)\pi_t + \epsilon_t$$

where $\Phi(L) = \phi_1 L + \dots + \phi_p L^p$.

Direct forecast, AR(p) model (DAR, DAR4)

$$M_2, M_3 : \pi_{t+h} = \phi_{0,h} + \Phi(L, h)\pi_t + \epsilon_{t+h}$$

where

$\Phi(L, h) = \phi_{1,h} + \phi_{2,h}L + \dots + \phi_{p,h}L^{p-1}$ (for a given h),
 $p = 2$ (M_2) and $p = 4$ (M_3).

Factor-Augmented AR(p) model (FAR)

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

where \widehat{F}_t is a static factor component of the inflation rates of the 14 EMEs plus 18 advanced economies.

Augmented Phillips Curve (APC)

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

where

y : industrial production index,

e : real exchange rate,

p^c : commodity price index (agricultural raw materials, beverages, food, metals and crude oil).

All expressed in percent changes.

Bivariate BVAR (BVAR2)

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

where

$$X_t = (\pi_t, \hat{F}_t)'$$

$\Phi_{0,h}$: vector of parameters

$\Phi(L, h)$: matrix of lag polynomials

Minnesota priors.

Multivariate BVAR (BVAR4)

$$M_7 : X_{t+h} = \Phi_{0,h} + \Phi(L, h)X_t + \epsilon_{t+h}$$

where

$$X_t = (\pi_t, y, e, p^c)'$$

Minnesota priors.

Bivariate BVAR with commodity prices (BVAR2-COM)

$$M_8 : X_{t+h} = \Phi_{0,h} + \Phi(L, h)X_t + \epsilon_{t+h}$$

where

$$X_t = (\pi_t, p^c)'$$

Minnesota priors.

└ 3. Models

└ Competing models

Time Varying Parameter specification (TVP)

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

where $\phi_{0h,t}$ and $\phi_{1h,t}$ follow

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

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

and $\nu_{0,t}$ and $\nu_{1,t}$ are i.i.d. shocks.

4. Forecast evaluation

Predictive ability: Relative RMSPE

(1) Relative RMSPE

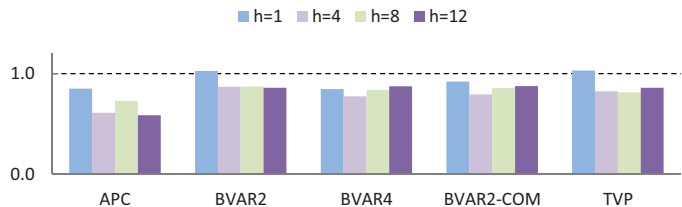
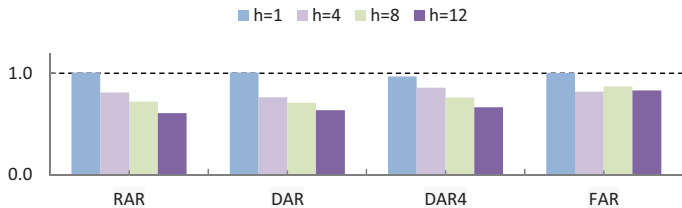
- The relative RMSPE or Theil-U statistic is

$$Theil - U_{m,c}^h = \frac{RMSPE_{RW-AO,c}^h}{RMSPE_{m,c}^h}$$

for $c = 1, 2, \dots, 14$, $m = 1, 2, \dots, 9$, $h = 1, 4, 8, 12$.

- If $Theil - U_{m,c}^h < 1$, the RW-AO has a lower RMSPE than does the competitive model m for country c at the forecast horizon h
- Statistical significance:
 - Diebold-Mariano-West test + Harvey *et al.* (1997)
 - Clark and West (2007)

Relative RMSPEs (medians)



RMSPE of the RW-AO Relative to Competing Models

	M ₄ FAR	M ₆ BVAR2	M ₇ BVAR4	M ₉ TVP	Average M1-M9
One-quarter ahead					
Median	1.001	1.027	0.848	1.030	0.962
#<1	7	6	9	5	8
#pv<.1	4	4	7	2	5
Eight-quarter ahead					
Median	0.870	0.871	0.839	0.813	0.797
#<1	10	13	12	14	12
#pv<.1	8	9	11	11	10
Averages (all horizons)					
Median	0.880	0.907	0.834	0.882	0.826
#<1	9	11	12	12	11
#pv<.1	7	7	9	8	8

4. Forecast evaluation

Findings

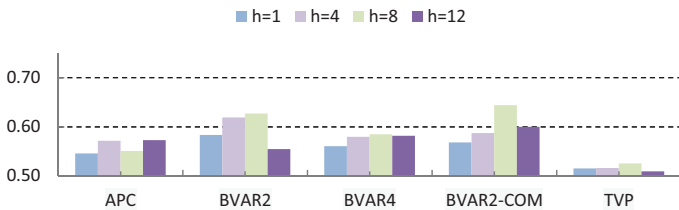
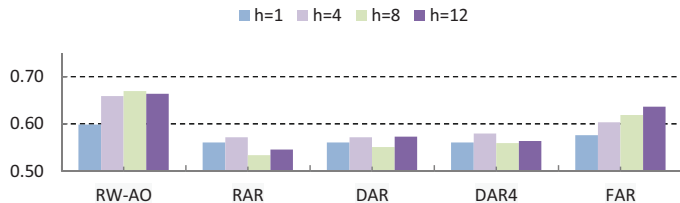
Where is the RW-AO more successful in terms of RMSPE?

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

(2) Success ratio

- An estimate of the probability that a given forecast correctly anticipates the **direction of change in inflation**
- Tossing a fair coin predicts the direction of change correctly 50% of the time
- So a model needs to attain a success ratio greater than 0.5
- Statistical significance: Pesaran and Timmermann (2009).

Success Ratios (Medians)



4. Forecast evaluation

Findings

Directional Accuracy: Success Ratios

	M_0	M_4	M_6	M_7	M_9	Average
	RW-AO	FAR	BVAR2	BVAR4	TVP	M1-M9
One-quarter ahead						
Mean	0.615	0.575	0.573	0.540	0.519	0.549
Median	0.598	0.576	0.583	0.561	0.515	0.559
#>0.5	14	12	11	9	8	10
Eight-quarter ahead						
Mean	0.663	0.599	0.611	0.559	0.534	0.564
Median	0.669	0.619	0.627	0.585	0.525	0.577
#>0.5	14	9	12	9	9	9
Averages (all horizons)						
Mean	0.652	0.589	0.583	0.566	0.522	0.564
Median	0.648	0.608	0.596	0.577	0.516	0.571
#>0.5	14	11	12	11	9	10

Robustness checks

- RW-AO($q=4$) \succ RW-AO($q=1,6$)
- RW-AO \succ specifications with $\Delta\pi_t$
- \sim with normal-flat priors in BVAR2, BVAR4
- Training sample (1990-2000)
- Forecast combination

4. Forecast evaluation

Robustness checks

Forecast Averages

	Relative RMSPE		Directional accuracy	
	M1-M9	M4 and M6	M1-M9	M4 and M6
	Average	Average	Average	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
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
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

5. Discussion

Can we reconcile our findings with the open-economy NK model?

Consider an open-economy Phillips curve:

$$\widehat{\pi}_t = \beta \mathbb{E}_t (\widehat{\pi}_{t+1}) + \kappa \widehat{x}_t^W + \varepsilon_t, \quad (1)$$

$$\widehat{x}_t^W \equiv (1 - \xi) \widehat{x}_t + \xi \widehat{x}_t^* \quad (2)$$

Assume that inflationary expectations are based on a weighted average of past inflation and on the central bank's inflation target

$$\widehat{\pi}_t = \beta \left((1 - \theta) \widehat{\pi}_{t-1}^q + \theta \widehat{\pi}^T \right) + \kappa \widehat{x}_t^W + \varepsilon_t \quad (3)$$

where $\widehat{\pi}_t^q = \frac{1}{q} \sum_{j=1}^q \widehat{\pi}_{t+1-j}$, and $0 \leq \theta \leq 1$ can be interpreted as a measure of credibility in the inflation target, $\widehat{\pi}^T$.

5. Discussion

└ Can we reconcile our findings with the open-economy NK model?

Lack of credibility ($\theta = 0$)

Assume now that inflationary expectations are purely backward-looking (adaptive). Hence,

$$\widehat{\pi}_t = \beta \widehat{\pi}_{t-1}^q + \kappa \widehat{x}_t^W + \varepsilon_t, \quad (4)$$

If $\beta \rightarrow 1$, a positive global output gap shock will not simply lead to higher inflation, it will lead to steadily increasing inflation.

5. Discussion

Can we reconcile our findings with the open-economy NK model?

Full credibility ($\theta = 1$)

Suppose instead that inflationary expectations are firmly anchored (e.g., an advanced economy). Then,

$$\widehat{\pi}_t = \beta \widehat{\pi}^T + \kappa \widehat{x}_t^W + \varepsilon_t. \quad (5)$$

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.

└ 6. Final remarks

└ Summary and final thoughts

- The RW-AO mostly produces lower RMSPEs than its competitors
- In a number of cases, these gains are statistically significant
- The RW-AO produces success ratios > 0.5 , and very often, statistically significant
- The RW-AO should be a new benchmark for inflation forecasting in EMEs
- Specifications with macroeconomic variables cannot beat it!