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Forecasting Inflation in Emerging Markets: An Evaluation of Alternative Models

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JEL classification: E37, C11, E31

Keywords: Forecasting, Bayesian Analysis, Emerging Markets, Forecast Comparison

Forecasting Inflation in Emerging Markets: An Evaluation of Alternative Models

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Abstract

This paper carries out a comprehensive forecasting exercise to assess out-of-sample forecasting performance of various econometric models for inflation across three dimensions; time, emerging market countries and models. The competing forecasting models include univariate and multivariate, fixed and time varying parameter, constant and stochastic volatility, small and large dataset, with and without bayesian variable selection models. Results indicate that the forecasting performance of different models change notably both across time and countries. Similar to some of the recent findings of the literature that focus on developed countries, models that account for stochastic volatility and time-varying parameters provide more accurate forecasts for inflation than alternatives in emerging markets.

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1 Introduction

Most of the central banks around the globe have adopted inflation targeting in the last decades. Naturally, this made inflation the key economic statistic for the monetary authorities to evaluate when forming policy. However, since monetary policy is associated with significant lags, optimal policy is designed in a forward looking manner, which underlines the importance of obtaining accurate forecasts for inflation. On the other hand, during the last decades both global and national economies have gone through significant changes in the macroeconomic dynamics and dependencies. Some of these changes are commonly attributed to changes in policies (including inflation targeting), and some to globalization or other factors. For instance the great moderation brought about a significant reduction in the volatility of business cycles, and hence key indicators including inflation. In the meanwhile, emerging market countries (EMs) have witnessed even greater changes with increasing globalization, capital inflows, sounder macroeconomic policies and significantly lower level and volatility of inflation, which accompanied the rise of the BRICs. All of these changes pose significant difficulties for econometricians to forecast key indicators including inflation in various different ways. In this paper, I employ a wide range of econometric models, each of which is partially robust to the nature of changes EMs time series have gone through, and assess their forecasting performance across time, emerging market countries and models.

Although there had been various studies that conduct forecast comparisons across alternative models and time, most of these studies only focus on a particular country. For instance, D'Agostino et al. (2013) and Clark & Ravazzolo (2015) assess the macroeconomic forecasting performance of alternative models for the United States (US), Barnett et al. (2014) and Groen et al. (2009) focus on the United Kingdom (UK), Caggiano et al. (2011), Giannone et al. (2014) and Berg & Henzel (2015) on Europe. For EMs, some of the country studies include Gupta & Kabundi (2011) for South Africa; Öğünç et al. (2013) and Kaya & Yazgan (2014) for Turkey; Bailliu et al. (2003) for Mexico and Duasa et al. (2010) for Malaysia. Even though individual studies lay evidence on the forecasting performance of alternative models, it may be challenging to compare their findings about different models performance across time and countries for various reasons. For instance, Eickmeier & Ziegler (2008) conduct a meta-analysis of the literature regarding the forecasting performance of factor models. However, Stock & Watson (2011) argue about the possible difficulties in such analysis which include possible differences in methods applied, quality of implementation or benchmarks chosen. Hence, the key contribution of this paper is to implement a comprehensive forecast comparison exercise with some of the latest time series models and techniques for inflation in different EMs over time.

In total, ten econometric models have been used to forecast inflation in nine emerging market countries; Chile, India, Indonesia, Malaysia, Mexico, Philippines, South Africa, Thailand and Turkey. The motivation for the choice of forecasting models has been to include models which are partly robust to various possible causes of forecast errors. With this objective the models used include a benchmark autoregressive (AR), autoregressive moving average (ARMA), Rolling and Recursive Bayesian Vector Autoregressive (BVAR) and Factor-Augmented VAR (FAVAR)[1], Unobserved Component Stochastic Volatility (UCSV)[2], Time-Varying Parameter VAR (TVPVAR), TVP-FAVAR[3], TVPVAR with Bayesian Variable Selection (TVPVAR-BVS) and TVPFAVAR-BVS[4]. Forecast evaluation has been carried out for the period of 2001Q1 to 2014Q3. Forecasting performance is examined along three dimensions; time, models and emerging market countries.

Examining the results, forecasting performance of alternative models illustrate notable differences both across time and countries. On the other hand, similar to the findings of D'Agostino et al. (2013), Clark & Ravazzolo (2015), Barnett et al. (2014) for the US and the UK, models that account for time variation in the coefficients and volatilities perform relatively better than the alternatives on average across EMs and time. This implies that the forecast accuracy of aforementioned models are not only superior for inflation in developed countries, but also for EMs. Regarding the performance across time, apart from the global financial crisis (GFC) period, UCSV performed in general the best among the alternatives. Also, TVP-VAR model performed quite well across time, without any major deterioration in its performance in subsamples. In the aftermath of the GFC, factor models in general performed notably poorly. Across the countries considered, UCSV is the best performing model in Mexico and Turkey; Rolling BVAR is in Philippines; TVPVAR is in Indonesia and Rolling FAVAR is in Thailand.

Section 2 describes the dataset, forecasting exercise and forecasting models; Section 3 presents the results and Section 4 concludes.

[1] See Bernanke et al. (2005) for FAVAR.
[2] See Stock & Watson (2007) for UCSV.
[3] See for instance Primiceri (2005). Note that TVPVAR and TVPFAVAR also feature SV.
[4] See Korobilis (2013) for BVS.

2 Dataset, Forecasting Exercise and Models

2.1 Dataset

The dataset used in this paper is originally from Smith & Galesi (2011) and Dees et al. (2007).[5] The dataset is extended in this paper and covers a period from 1979Q2 to 2014Q3. For the extension, data sources include Datastream, International Monetary Fund and Organization for Economic Co-operation and Development. The analysis focuses on nine emerging countries. However, 28 developed and emerging countries are used in models with large datasets. Table 1 lists the countries used in the dataset.

Table 1: List of Countries

Focus Countries		Large Dataset			
Chile	India	Australia	Austria	Canada	China
Indonesia	Malaysia	Finland	France	Germany	Italy
Mexico	Philippines	Japan	Korea	Netherlands	N. Zealand
S. Africa	Thailand	Norway	Singapore	Spain	Sweden
Turkey		Switzerland	UK	USA	

The main variable under investigation is the quarterly percentage change in the Consumer Price Index (CPI), p. In multivariate models, quarterly percentage change in real GDP (y) and short interest rates (r) are used. In the large dataset factor models, first principle component of y and p of other countries are used. y and p series are seasonally adjusted. In large dataset models, factors are extracted from standardized y and p data.

2.2 Forecasting Exercise

For nine EMs, same forecasting exercise is performed using the same set of variables. Forecasts are cast recursively for each country, starting with 2001Q1 until 2014Q3 except for models that are estimated on a rolling basis. Rolling models are estimated with a rolling window of 40 observations. The lack of real time datasets for the countries under investigation implies that data revisions are not accounted for.

Similar to D'Agostino et al. (2013), forecast evaluation is carried out by using both point and density forecasts obtained from different models across countries. Point forecasts are compared using the ratio of Root Mean Square Error (RMSE) criteria for each model and country, relative to the RMSE for a benchmark AR(1) model forecasts. The RMSE criterion is calculated as:

$$RMSE_{h,nm} = \sqrt{\frac{1}{T-h+1}\sum_{t=h}^{T}(\widehat{p}_{nt} - p_{nt})^2}, \ \forall n = 1,..,9, \ \forall m = 1,..,10, \ \forall h = 1,4,12$$

where n denotes the emerging market country, m denotes the forecasting model, h is the forecast horizon, $\widehat{p}_{nt}$ is the forecast of inflation at time t and p_{nt} is the actual data.

In addition to the RMSEs, log scores have been calculated from forecast densities. As discussed in D'Agostino et al. (2013), log scores represent the log of the forecast density

[5] Extended by R. Marisca, A. C. Bianchi and A. Rebucci until 2013Q1, obtained from https://sites.google.com/site/gvarmodelling/data.

evaluated at the true observation of the target variable at a given time.[6] In case forecast density suggests the actual observation with complete certainty, the criteria would equal zero. Otherwise, as the accuracy of forecast density falls, log score will decrease further below zero. Unlike the RMSEs, log-scores are useful in evaluating the accuracy of the forecast density as it indicates the probability attached to the actual observations.

2.3 Forecasting Models

Table 2: Forecasting Models and Key Features

	Univariate	Multivariate	Large Data	SV	TVP	BVS
arma	x					
rbvar		x			x	
rfavar		x	x		x	
bvar		x				
favar		x	x			
ucsv	x			x	x	
tvpvar		x		x	x	
tvpfavar		x	x	x	x	
tvpvarbvs		x			x	x
tvpfavarbvs		x	x		x	x

In total, ten econometric models are used, each of which is partly robust to possible different features of EMs inflation data that may constitute challenges for forecasting. Following Clements & Hendry (1998, 2001, 2003) possible causes of forecast errors can be divided into various categories. For instance, one of the reasons is to mis-specify the model. In the case of inflation, univariate time series models cannot capture the dynamic interaction between different macroeconomic variables that are driven together with various structural shocks. On the other hand, findings in the forecasting literature suggest that generally more parsimonious, smaller univariate models perform better than models otherwise. Hence in this study, both univariate and multivariate models are considered. VAR Models, proposed by Sims (1980), have been widely used in forecasting and also considered in here. A drawback of VARs is that the number of parameters to estimate increases exponentially as the number of variables increase; hence finite sample estimates become less accurate, resulting in less accurate forecasts. This constitutes another category of forecast errors, mis-estimation of parameters. One way of circumventing this, as it is also considered here, is to use BVARs with shrinkage priors. However, even with these priors the number of relevant variables to include may be huge. Recent literature employed factor models to summarize the information in larger datasets and use the factors in forecasting.[7] So, similar to Bernanke et al. (2005), FAVAR models have also been considered here. Moreover, following Korobilis (2013) VAR models with BVS, which involve automatic selection of explanatory variables, are also used. Another source of forecast errors is changes in the variance of shocks over time. Therefore, models that incorporate SV have been included. Finally, to allow for changes in the parameters of models, rolling BVARs (rBVAR) and TVP models have been considered. The models and their key features are summarized in Table 2.

[6] See for instance Mitchell & Wallis (2011) and Geweke & Amisano (2010).

[7] For a survey see Stock & Watson (2006) and Stock & Watson (2011).

Models are estimated with Bayesian methods, Markov Chain Monte Carlo Gibbs Sampling. Gibbs steps are repeated 10000 times, out of which 2000 are saved.[8] Below, models are presented formally, with brief estimation steps and other particulars. Model and country subscripts are ignored for the clarity of presentation.

2.3.1 ARMA model

Starting with the Univariate models, the first model considered is the ARMA model.

$$p_t = \mu + \sum_{l=1}^{p} \beta_l p_{t-l} + \sum_{l=1}^{q} \alpha u_{t-l} + u_t, \qquad u_t \sim N(0, \sigma^2)$$

The lag orders are set to 2 and 1 for p and q. Estimation starts with setting the initial conditions and uninformative normal inverse gamma priors, then drawing consequently the MA component via Carter & Kohn (1994), the error variance, and AR coefficients.

2.3.2 UCSV Model

The second univariate model is the UCSV Model from Stock & Watson (2007).

$$\begin{aligned} p_t &= \mu_t + \sigma_{u,t}^{1/2} u_t, & \mu_t = \mu_{t-1} + \sigma_{\varepsilon,t}^{1/2} \varepsilon_t, \quad u_t \sim N(0,1), \quad \varepsilon_t \sim N(0,1) \\ \log \sigma_{u,t} &= \log \sigma_{u,t-1}^2 + v_{ut}, & \log \sigma_{\varepsilon,t} = \log \sigma_{\varepsilon,t} + v_{\varepsilon t}, \quad v_{ut} \sim N(0, \zeta_u), \quad v_{\varepsilon t} \sim N(0, \zeta_\varepsilon) \end{aligned}$$

UCSV postulates that p is the sum of a random walk (RW) and transitory component (TC), with both components featuring SV. Estimation steps involve setting the initial conditions and normal inverse gamma priors via a training sample of 10 years, then consequently drawing RW and TC components SV via the Metropolis Hastings procedure of Jacquier et al. (2002, 2004), and RW component via Carter & Kohn (1994).

2.3.3 BVAR Models

Starting with the multivariate models, the rBVAR, rFAVAR, BVAR and FAVAR models have the specification as below.

$$X_t = \mu + \sum_{l=1}^{p} \beta_l X_{t-l} + u_t, \qquad u_t \sim N(0, \Sigma)$$

where X includes, y, p, r in the BVAR, and also includes the first principle components extracted from y and p of other countries in the dataset in the FAVAR. Estimation starts by setting the initial conditions and normal inverse wishart minnesota priors via Banbura (2007, 2010), then consequently drawing the coefficients and variance covariance matrix.

2.3.4 TVP-VAR Models

The TVP-VAR and TVP-FAVAR models are specified as below.

$$\begin{aligned} X_t &= \mu_t + \sum_{l=1}^{p} \beta_{l,t} X_{t-l} + u_t, \quad u_t \sim N(0, A_t^{-1} \Sigma_t A_t^{-1\prime}), \\ \mu_t &= \mu_{t-1} + \zeta_t, \quad \beta_t = \beta_{t-1} + v_t, \quad a_{ij,t} = a_{ij,t-1} + e_t, \quad \log h_{i,t} = \log h_{i,t-1} + \varepsilon_{n,t}, \\ \zeta_t &\sim N(0, \sigma_\zeta^2), \quad v_t \sim N(0, \sigma_v^2), \quad e_t \sim N(0, \sigma_e^2), \quad \varepsilon_{nt} \sim N(0, \sigma_{\varepsilon n}^2), \quad n = 1, ..., N. \end{aligned}$$

[8] Estimation and evaluation codes are from the Filippeli et al. (2015) for all models except BVS model which are from Korobilis (2015).

where N is the number of variables, X include the same variables as for the cases of BVAR models, A_t^{-1} is the lower triangular contemporaneous impact matrix with the non-zero elements $a_{ij,t}$, Σ_t is the diagonal variance matrix with diagonals as $h_{i,t}$. Estimation steps involve setting the initial conditions and normal inverse wishart priors via a training sample of 40 quarters for TVP-VAR and 54 for TVP-FAVAR, then consequently drawing the TV coefficients via Carter & Kohn (1994), TV coefficient variances, contemporaneous impact matrix elements via Carter & Kohn (1994), contemporaneous impact matrix elements variances, SV via Jacquier et al. (2002, 2004), and SV variances.

2.3.5 BVS Models

Following Korobilis (2013), below are the TVP-VAR-BVS and TVP-FAVAR-BVS models.

$$X_t = \mu + \sum_{l=1}^{p} \gamma \beta_{l,t} X_{t-l} + u_t, \quad \beta_t = \beta_{t-1} + v_t, \quad u_t \sim N(0, \Sigma), \quad v_t \sim N(0, \sigma_v^2)$$

where X is the same as the VAR models. The new parameters here are the elements of γ matrix; discrete random variables with bernoulli distributions. Each element is either equal to 1 or zero, depending on whether a given variable in X is included as a relevant variable. Estimation steps involve setting the initial conditions, bernoulli and normal inverse wishart and minnesota priors, then consequently drawing the TV coefficients via Carter & Kohn (1994), TV coefficient variances, γ, and variance covariance matrix.

3 Results

Table 3 reports 1Q, 4Q and 12Q RMSE ratios of alternative models for EMs under consideration. The last row for each quarter represents the average RMSE ratios for the given model across countries for the given forecast horizon. Underlined and bold entries represent the models with the lowest RMSE ratio for a given country and horizon. Likewise, Table 4 presents the log-scores in a similar format. Entries with "." indicate that the given model for a given country attaches close to zero probability to the realized outcome of inflation. Note that greater the reported entries higher the probability attached to the actual realization of inflation, hence better the forecast.

Examining the average RMSE ratios for 1Q, UCSV model is the best performing model, followed by TVPVAR and TVPFAVAR. Interestingly, these three models are the models that feature SV in contrast to other models. With a 4Q forecast horizon, UCSV is still the best performing model, followed by TVPVAR and rBVAR. In 12Q, UCSV provides the most accurate point forecasts, followed by TVPVAR, rBVAR and TVPFAVAR. Overall, on average across time and countries, models that feature SV clearly provide the most accurate point forecasts for inflation.

Average log-scores for models across time and countries indicate that UCSV provide the forecasts that attach the highest probability to the true realizations of inflation. For 1Q ahead forecasts, UCSV is the best performing model for five out of nine countries. Similar to the results from the RMSEs, rBVAR and TVPVAR provide the most accurate forecasts after UCSV. Examining the log-scores for 4 and 12 quarters, UCSV is still the best forecasting model. Although on average TVPVAR and TVPFAVAR seem to perform better, rBVAR seems to be the best performing model for a larger number of countries than TVPVAR in 4 and 12 quarters. This essentially suggests heterogeneity

Table 3: RMSE Ratios

1q	arma	rbvar	rfbvar	bvar	fbvar	ucsv	tvar	tfvar	tvbvs	tfvbvs
chl	0.77	**0.67**	0.7	0.95	1.04	0.72	**0.67**	0.73	0.78	0.74
ind	0.99	1.09	1.04	1.03	1.03	0.96	1.02	**0.9**	1.02	0.98
indo	1.21	0.98	1.17	0.95	1.18	0.97	**0.89**	0.94	0.9	0.92
mal	1.02	1.26	1.28	1.01	1.1	0.91	0.99	**0.91**	1.09	1.01
mex	0.75	0.68	0.75	0.95	1.22	**0.41**	0.47	0.64	0.64	0.52
phl	1.11	**0.83**	0.93	1.06	1.37	0.98	1.05	1.06	1.13	1.13
saf	**0.91**	0.93	1.04	0.93	1.07	0.97	0.95	0.92	0.97	0.96
thai	1.02	1.05	1.09	**0.97**	1.18	1.05	1.09	1.29	1	1.1
tr	0.74	1.02	1	0.85	1.06	**0.74**	0.74	0.81	0.8	0.83
ave	0.95	0.95	1	0.97	1.14	**0.86**	0.88	0.91	0.93	0.91
4q	arma	rbvar	rfbvar	bvar	fbvar	ucsv	tvar	tfvar	tvbvs	tfvbvs
chl	0.62	**0.45**	0.47	0.84	0.83	0.54	**0.45**	0.49	0.6	0.55
ind	0.96	1.07	1.13	1.03	1.15	**0.92**	1.01	0.99	0.99	1.03
indo	1.02	0.95	1.18	0.91	1.05	1.12	**0.91**	0.96	0.95	0.94
mal	1.04	1.29	1.37	**0.99**	1.04	1.01	1	1.1	1.01	1.01
mex	0.69	0.47	0.44	0.92	0.79	**0.17**	0.25	0.35	0.56	0.41
phl	0.83	**0.6**	0.66	1.12	1.17	0.65	0.82	0.94	1.12	1.17
saf	0.92	**0.76**	0.79	0.92	0.9	0.84	0.97	0.83	0.94	0.89
thai	0.99	0.92	**0.88**	0.93	1.07	0.95	1.06	1.54	0.96	1.07
tr	0.52	0.8	0.79	0.75	0.97	**0.4**	0.6	0.57	0.69	0.63
ave	0.84	0.81	0.86	0.94	1	**0.73**	0.79	0.86	0.87	0.86
12q	arma	rbvar	rfbvar	bvar	fbvar	ucsv	tvar	tfvar	tvbvs	tfvbvs
chl	0.68	0.35	0.35	0.86	0.67	0.39	**0.35**	0.4	0.63	0.54
ind	**0.99**	1.14	1.12	1.01	1.05	1.07	1.03	1.04	1	1.03
indo	0.98	1.08	1.2	0.99	1.06	1.02	**0.86**	0.87	1.07	0.93
mal	**0.98**	1.02	1.06	0.99	0.98	1.02	1	1.03	0.99	0.99
mex	0.75	0.33	0.32	0.93	0.49	**0.1**	0.2	0.3	0.6	0.51
phl	0.84	**0.51**	0.52	0.97	0.65	0.58	0.66	0.64	1.01	0.85
saf	0.91	0.64	**0.61**	0.96	0.72	0.75	1.03	0.86	0.92	0.87
thai	0.94	0.92	**0.92**	0.93	0.96	1.06	0.97	1.09	0.96	0.96
tr	0.6	0.85	0.84	0.85	0.99	**0.38**	0.69	0.66	0.82	0.72
ave	0.85	0.76	0.77	0.94	0.84	**0.71**	0.75	0.76	0.89	0.82

rfbvar: rfavar, fbvar: favar, tvar: tvpvar, tfvar: tvpfavar, tvbvs: tvpvarbvs, tfvbvs: tvpfavarbvs

in the performance of alternative models across different countries. On the other hand, the heterogeneity does not extend significantly to other models than UCSV, rBVAR, TVPVAR and TVPFAVAR. For instance, BVS models do not appear as among the top performing models for any quarter, country, or forecast accuracy measure. Likewise, there is only a single country and a specific forecast horizon for which FAVAR appears as the top model. On a country by country basis, for Mexico and Turkey UCSV appears as the best model to forecast inflation. For Philippines rBVAR is the top performing model, whereas TVPVAR seems to be the best model for Indonesia, and rFAVAR for Thailand.

Overall, both RMSEs and log-scores strongly suggest that UCSV, rBVAR, TVPVAR and TVPFAVAR are the models that provide forecasts with highest accuracy on average across time and countries. Regarding the earlier discussion about possible causes of

Table 4: Log-Scores

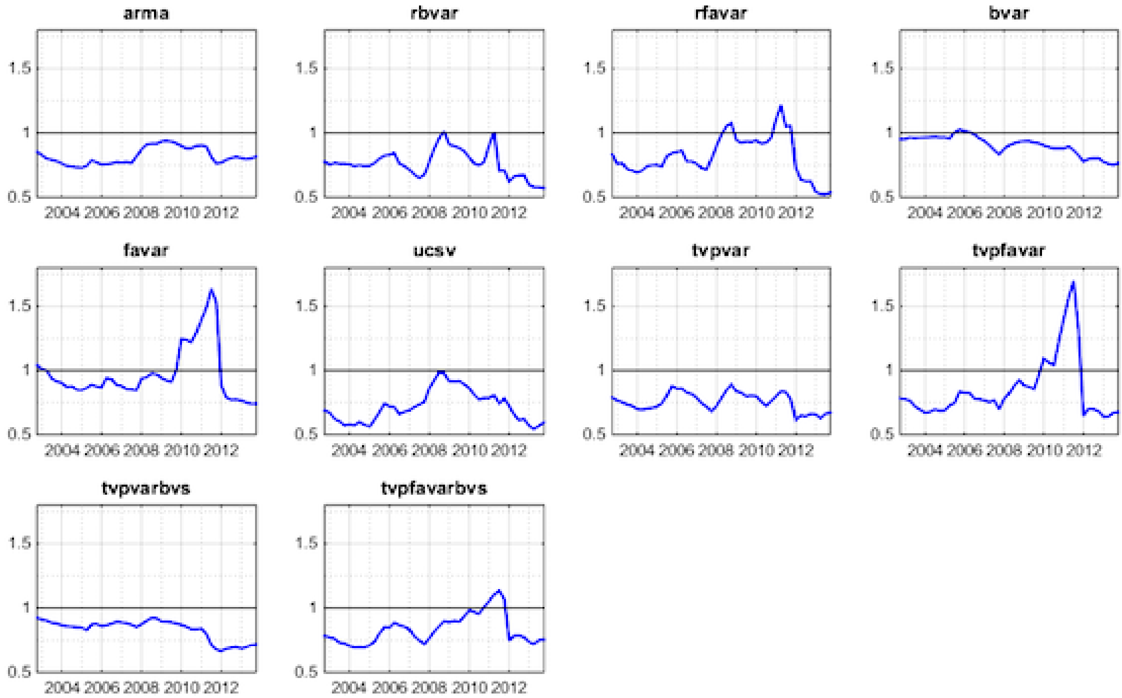
1q	arma	rbvar	rfbvar	bvar	fbvar	ucsv	tvar	tfvar	tvbvs	tfvbvs
chl	-1.71	-1.13	-0.97	-1.59	-1.58	**-0.92**	-1.3	-0.99	-13.2	-3.9
ind	-1.58	-1.89	-1.72	-1.45	-1.42	**-1.37**	-1.51	-1.53	.	.
indo	-2.48	-2.05	-2.14	-2	-2.12	**-1.83**	-3.69	-2.45	.	.
mal	-0.91	-9.54	.	-3.24	-4.71	**-0.63**	-1.29	-3.21	.	.
mex	-2.52	-1.08	-1.16	-2.4	-2.39	**-0.75**	-1.04	-0.97	-13.2	-0.9
phl	-1.83	**-1.14**	-1.18	-1.72	-1.76	-1.22	-1.33	-1.34	-4.45	-1.77
saf	-1.46	**-1.18**	-1.27	-1.2	-1.3	-1.22	-1.65	-1.41	.	-31.7
thai	-1.28	-1.31	-1.25	**-1.24**	-1.26	-1.38	-1.6	-2.07	.	-28.3
tr	-2.93	-2.55	-2.6	-2.77	-2.88	-2.46	**-2.41**	-3.14	-26.1	-8.12
ave	-1.86	-2.43	.	-1.96	-2.16	**-1.31**	-1.76	-1.9	.	.
4q	arma	rbvar	rfbvar	bvar	fbvar	ucsv	tvar	tfvar	tvbvs	tfvbvs
chl	-1.98	-1.44	**-1.42**	-1.97	-1.95	-1.49	-1.62	-1.46	-9.31	-3.35
ind	-1.65	-1.69	-1.64	-1.52	-1.62	**-1.41**	-1.68	-1.53	.	.
indo	-2.68	-2.29	-2.37	-2.21	-2.27	-2.23	**-1.85**	-4.91	.	-12.9
mal	-1.16	-4.62	-6.38	-1.5	-3.5	**-0.97**	-1.69	-9.75	.	.
mex	-3.02	-1.33	-1.43	-2.95	-2.91	**-1.13**	-1.42	-1.61	-4.8	-1.71
phl	-1.99	**-1.25**	-1.3	-2.09	-2.07	-1.3	-1.56	-1.65	-2.31	-2.31
saf	-1.82	**-1.45**	-1.52	-1.65	-1.6	-1.58	-3.36	-1.78	.	-30.9
thai	-1.46	-1.69	**-1.24**	-1.37	-1.49	-1.25	-1.82	-2.38	.	.
tr	-3.18	-2.86	-2.94	-3.14	-3.41	**-2.65**	-2.78	-2.71	-9.96	-5.53
ave	-2.1	-2.07	-2.25	-2.04	-2.31	**-1.56**	-1.97	-3.09	.	.
12q	arma	rbvar	rfbvar	bvar	fbvar	ucsv	tvar	tfvar	tvbvs	tfvbvs
chl	-2.23	**-1.33**	-1.44	-2.18	-2.05	-1.53	-1.72	-1.63	-2.07	-1.82
ind	-1.68	-1.87	-1.93	**-1.51**	-1.56	-1.6	-1.82	-1.61	.	.
indo	-2.73	-2.51	-2.51	-2.32	-2.36	-2.78	-1.77	**-1.66**	-2.95	-5.4
mal	-1.14	-4.91	-4.78	-1.56	-1.35	**-1.07**	-1.61	-1.17	.	.
mex	-3.33	-1.59	-1.69	-3.26	-3.14	**-1.53**	-1.72	-2.38	-2.39	-2.58
phl	-2.1	**-1.25**	-1.28	-2.13	-2.1	-1.31	-1.51	-1.74	-2.31	-1.92
saf	-1.96	**-1.36**	-1.37	-1.86	-1.55	-1.62	-2.87	-1.97	-40.1	-21.9
thai	-1.47	-1.25	**-1.24**	-1.33	-1.38	-1.46	-1.6	-1.47	.	-16.7
tr	-3.5	-3.45	-3.44	-3.57	-3.78	**-3.16**	-3.36	-3.55	-6.26	-4.63
ave	-2.24	-2.17	-2.19	-2.19	-2.14	**-1.78**	-2	-1.91	.	.

rfbvar: rfavar, fbvar: favar, tvar: tvpvar, tfvar: tvpfavar, tvbvs: tvpvarbvs, tfvbvs: tvpfavarbvs

forecast errors and the classification of models under consideration with respect to their key features, results indicate an interesting pattern. All of the aforementioned models feature changing parameters and volatilities. UCSV and TVP Models directly feature TVP and SV, and rBVAR model indirectly incorporates these features as the estimation takes place with a smaller rolling window.

So far, forecast accuracy of models is assessed across different countries and models, average across time. In order to study whether there exist time-variation in the performance of the models under consideration, Figure 1 presents 4-quarter-horizon, 8-quarter-moving RMSE ratios for models on average across countries. Starting with the best performing model in earlier results, interestingly rolling RMSEs of UCSV around the peak of the crises are not different than the ones obtained with the benchmark AR(1)

Figure 1: Rolling RMSE Ratios



model. Likewise, the other univariate model considered, ARMA, performs worse during this period. In contrast, the TVP-VAR model performs relatively better. But, this does not apply to all other multivariate models. Another interesting observation is, accuracy of the forecasts obtained from most of the factor augmented models deteriorates with the crises, and worsens even more in the aftermath, 2010-12. Another point to note is that, TVP-VAR model performs reasonably well throughout the period considered, without any notable deterioration of its forecasting performance. This also applies to the UCSV model as it is the best performing model in general if one excludes the crisis period.

Gupta & Kabundi (2011) find that factor models in general outperform alternatives, and that BVAR also performs well for South Africa. Results here for South Africa indicate that factor augmented models do not provide a drastic improvement in forecast accuracy over the BVAR except in 12 quarters. For Turkey, results indicate that univariate models perform better than multivariate models. This is in contrast with the findings of Öğünç et al. (2013). Ferrara et al. (2015) examine the forecasting performance of non-linear models for inflation in OECD countries and find that they perform well for inflation measures, which is broadly in line with the results in here.

Comparing the findings here for EMs with the literature on developed countries, in line with the findings of D'Agostino et al. (2013) for US inflation TVPVAR performs well in forecasting inflation in EMs as well. Also, Clark & Ravazzolo (2015) find that VAR model with SV performs well in forecasting US inflation, which is again in line with the findings here for EMs. Barnett et al. (2014) find that TVPFAVAR with SV perform well in forecasting inflation in the UK. Similarly, log-scores obtained here indicate that TVPFAVAR performs the second best across the alternatives in 12 quarters on average for EMs. Interestingly, over the period of great moderation authors find UCSV and rBVAR to be the best performing models. Considering the significant changes in the dynamics of inflation in the UK over this period, it may be comparable to the period under investigation in here for EMs. In this context, their findings are in line with the findings in here since UCSV and rBVAR are some of the best performing models in forecasting inflation in EMs.

4 Conclusion

In this paper, I have assessed the forecast accuracy of various econometric models that are partly robust with respect to various sources of forecast errors for inflation in different emerging market countries. Both point and density forecast accuracy of models is investigated for alternative cases.

Results suggest, on average across time and emerging markets, models that take into account changes in the volatility of inflation provide superior forecasting performance compared to models that do not. Among these models, UCSV model performs the best, followed by TVPVAR. However, examining the forecast performance across time, UCSV performed poorly during the peak of the global financial crisis. In contrast, forecast accuracy from the TVPVAR model had been relatively stable over time. Nevertheless, excluding the crisis period, UCSV performed in general the best across time. An interesting finding is, factor models that take into account larger information about international activity have performed very poorly during 2010-12. Furthermore, BVS models never ranks the best among the other models on average across time and EMs across forecast horizons considered. Rolling window BVAR performs well in forecasting inflation across EMs on average across time. This reinforces the key observation of this paper that models that take into account change in parameters across time performs the best in forecasting inflation in EMs. Overall, findings presented here for EMs augment and reinforce the recent findings in the literature on developed countries regarding the superior forecasting performance of models that feature TVP and SV for inflation.

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