Beating a Random Walk: "Hard Times" for Forecasting Inflation in Post-Oil Boom Years?

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ABSTRACT

In this study, we investigate forecasting performance of various univariate and multivariate models in predicting inflation for different horizons. We design our forecast experiment for the post-oil boom years of 2010-2014 and compare forecasting ability of the different models with that of naïve ones. We find that for all forecast horizons simple naïve models have equal forecasting ability with relatively sophisticated models which allow for richer economic dynamics. To check whether forecasting ability of naïve models has not been inferior to relatively sophisticated ones in boom and pre-boom years as well, we repeat our forecast experiment and estimate the models for the period 2003-2006 and keep the years 2006-2010 for undertaking pseudo out-of-sample exercise. Our experiment reveals that surprising forecasting performance of naïve models in post-oil boom years is a new phenomenon and in fact, the employed models have exhibited significant forecasting advantage over naïve ones in boom and pre-boom years. We find that despite declining volatility in inflation over the post-oil boom years, it has become considerably difficult for our models to beat naïve ones due to recently unpredictable behavior of inflation.

JEL classification: C11, C13, C32, C53
Keywords: Inflation; Forecasting; Time Series methods; Bayesian methods

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"Now, what I want is, Facts. .... nothing else will ever be of any service to them. .... Stick to the Facts, sir!"

Charles Dickens, "Hard Times"

I. Introduction

Forecasting is an integral part of a central bank decision making process and provides important inputs for proactive policy formulation. Stronger advocacy for adoption of inflation targeting for central banks and its general approval by public empowered increasing number of central banks with more independence and consequently, with a greater leeway to pursue an independent monetary policy. But one of the necessary conditions for a successful monetary policy is the ability of an authority to predict probable economic development scenarios in near future. Because there is a secular time lag between policy decisions and their expected effects on economy, or in other words, in the transmission effects of monetary policy instruments, every central bank is interested in developing forecasting tools to predict economic developments in advance and thus, allocate considerable resources to that end.

In this paper, we study the ability of popular forecasting tools employed by a typical central bank for forecasting inflation for different horizons. In particular, we investigate whether available forecasting methods do indeed allow the Central Bank of Azerbaijan to predict inflation in advance and timely undertake necessary actions, if required. Because price stability is a prior mandate of the monetary authority by law, reading future price dynamics from available information is a compelling task of the Central Bank. Forecasting inflation accurately helps to control future inflation within the target range and anchor inflation expectations of the public, thus to enhance the credibility of the monetary authority.

In fact, inflation forecasting can be considered a comparative advantage of a central bank as it maintains information advantage about the state of the economy over the public. Asymmetric information between a central bank and the public can have important policy implications for the effectiveness of monetary policy. Romer and Romer (2000) show that Fed has considerable information advantage beyond what is known to the public and thus, its forecasts are more accurate than commercial forecasters. However, Edge and Gürkaynak (2010) find that this forecasting advantage has declined considerably since the onset of the Great Moderation. In fact, many authors, such as Atkeson and Ohanian (2001), Stock and Watson (2007), etc., demonstrate that though a sharp fall in the volatility of the US economy over time, forecasting has not become easier. In contrary, they find that increasing use of more sophisticated methods which is made possible by advances both in theory and practice is not accompanied by their rising superiority over simple naïve models. To researchers' surprise, naïve models have started to gain sizeable forecasting advantage over time.

In this study, we investigate the performance of different forecasting tools including univariate and multivariate methods, for predicting inflation in Azerbaijan, and compare them with naïve models. Our inflation forecasting experiment is mainly designed for the post-oil boom years *(September, 2010-June, 2014)* and we test the forecast ability of our models vis-à-vis naïve ones.

We find that despite significant decline in the volatility of the economy, the forecasting models employed in our study have harder time to beat naïve models during that period. According to the forecast accuracy criteria (relative Root Mean Squared Forecast Error (RMSFE)) that we have chosen in our comparisons, the forecasting ability of our models cannot be distinguished from that of naïve models. Further analysis show that all forecasting models are performing very poorly in predicting inflation during that period.

To check whether unpredictability of inflation is a new phenomenon, we re-run our forecast experiment using the sample data *January, 2003-October, 2006* and construct our forecasts for the period *November, 2006-August, 2010.* Using the same forecast accuracy criteria and naïve models, we find that our forecasts models exercise nontrivial forecast advantage over naïve ones. This result show that the deterioration in the ability of forecasting methods relative to naïve ones is in fact a recent phenomenon. In other words, it emphasizes that naïve models have increased their relative forecasting ability over the sophisticated ones in the post oil boom years. We show that this results from a major change in the inflation process itself and its dynamics over time. Because, inflation behaves like a white noise during that period, the predictability of inflation is not far better than a bet on possible outcomes of tossing a fair coin.

The structure of the paper is designed as follows: the Section II discusses data, Section III introduces forecasting methods employed in this study, Section IV presents results from forecast comparison experiment, Section V discuss probable implications and causes of the change in inflation process, and finally, Section VI concludes.

II. Data

In this paper, we draw on 30 monthly variables (2003.01-2014.12) in forecasting analysis, describing economic dynamics in the domestic and global (foreign) markets. Global variables include price of oil, price index of food, Russian, Turkish and Chinese CPI as well as bilateral nominal exchange rate vis-à-vis these countries. The prices of oil and food are obtained from IMF database whereas foreign country CPI and exchange rate data is collected from CBAR database. The panel on domestic variables covers oil production, real non-oil GDP and its expenditure components, real industrial production index, real wage, budget capital and current expenditures, short and long term interest rates as well as volume of credits lent out by the banking sector, monetary aggregates, reserve money, NFA, NEER, industrial PPI and CPI. All data on the domestic variables except monetary aggregates and exchange rates are collected from the State Statistics Committee (SSC) bulletins. The SSC provides approximate data on monthly real GDP calculated using the previous year as the base period. In addition, it has recently started publishing quarterly real GDP figures computed using the year 2005 average prices. In this paper, we use the latter figures on real GDP and exclude mining and extraction sector to obtain quarterly real non-oil GDP. We also appeal to Chow and Lin (1971) procedure to get monthly figures from their quarterly counterparts. All data except interest rates employed in the forecasting analysis are seasonally adjusted.

III. Forecast Models and Methodology

We use various univariate and multivariate models, in difference as well as in levels, for forecasting analysis. For multivariate models, we also consider the forecasting performance of numerous models with different number of variables, namely with 4, 8 and 30 variables. We label them as small, medium and large scale models respectively in this paper. In a small model, we include data on the price of oil, real non-oil GDP, M1 and CPI, in difference as well as in levels in corresponding specifications. In a medium model, in addition to these variables we also introduce the world food price, short term interest rate, volume of long term credits, and NEER.

We take natural logarithm of each variable (multiplied by 100) except interest rates in our regression analysis. Because we have 138 monthly observations for each variable, we employ only the period covering 2003.01-2010.08 in our estimation (92 observations) and keep the last 46 observations (2010.09-2014.06) for testing the out-of-sample forecasting performance of a model. We use an iterated forecasting approach and recursive scheme to conduct an out-of-sample experiment for the horizons $h = \{1, 3, 6, 12, 18\}$ and measure the forecast accuracy of a model in terms its Root Mean Squared Forecast Error (RMSFE). Since we compare models in terms of their forecasting performance, we select the optimal lag for the corresponding model by minimizing its RMSFE.

As a univariate model, we consider classical AR, AR-GARCH and Bayesian AR (both in levels and differences) specifications for inflation. For Bayesian AR, we impose Litterman (1986) prior on AR coefficients both in levels and differences. For that, we introduce dummy variables and set the value of shrinkage parameter λ, based on the search over the discrete grid $\{0.05, 0.15, 0.25, 0.35, 0.45, 0.55, 0.65, 0.75\}$ to minimize RMSFE after determining the optimal lag order for the model. As λ approaches to zero, the posterior become close to the prior and data has no impact on regression coefficients. However, as λ goes to infinity, the mean of the posterior approaches to the OLS estimates.

For a multivariate model, we first consider a classical small VAR with 4 variables in differences (percentage changes) mentioned in the first paragraph. Another multivariate model is a Bayesian VAR a la Banbura, *et al* (2010), estimated in different sizes (small, medium and large scale models) and in differences as well as in level. As explained in the related paper, we augment our dataset with dummy variables. The first block of dummies imposes prior beliefs on the autoregressive coefficients, the second block introduce priors for the covariance matrix, the third block imposes an uninformative prior for the constant and finally, the fourth block adds prior on the sum of coefficients, described by Doan, Litterman and Sims (1984). We set the values of overall tightness parameter λ by searching a discrete grid {0.05, 0.10, 0.15, 0.20, 0.25} in the large model with 30 variables. The hyperparameter τ which controls the degree of shrinkage for sums-of-coefficients prior is set to the value τ = 10λ. When τ goes to zero, the specification approaches to exact differencing and as τ goes to infinity it approaches to the case of no differencing.

We also estimate a Factor Augmented VAR (FAVAR) model with 3 factors in addition to inflation variable and test its forecasting performance as well. FAVAR models are considered to be a proper specification to exploit valuable information provided by a large dataset without worrying about degrees of freedom, overfitting and increasing parameter uncertainty in our estimations. In other words, these models help us to sidestep the "curse of dimensionality" problem while still preserving the value added information provided by more relevant variables. In our FAVAR specification, we standardize all (29) variables (except inflation) and use them to extract 3 factors in our empirical estimation. We follow Bernanke, Boivin and Eliasz (2005) and estimate the model using Gibbs sampling.

Time Varying Parameter (TVP) VAR model (in different sizes) with stochastic volatility is also estimated to carry out forecasting analysis. Because TVP-VAR models have high computational complexity and are time consuming we will not apply MCMC algorithm in their estimation. Rather, we will apply forgetting factor algorithm proposed by Koop and Korobilis (2013) to estimate large TVP-VARs. Hence, we estimate a TVP-VAR as follows:

$$y_t = Z_t \beta_t + \varepsilon_t$$

$$\beta_t = \beta_{t-1} + u_t$$

where ε_t is i.i.d. $N(0, \Sigma_t)$ and u_t is i.i.d $N(0, Q_t)$. ε_t and u_s are independent of one another for all s and t. y_t is a Mx1 vector containing observations on M time series variables and Z_t is Mxk matrix defined so that each TVP-VAR equation contains an intercept and p lags of each M variables. Koop and Korobilis (2013) propose to use Kalman filter and replace the variance matrix of the state vector in the prediction step by:

$$V_{t|t-1} = \frac{1}{\lambda} V_{t-1|t-1}$$

where $0 < \lambda \leq 1$ is a forgetting factor. We also estimate the forgetting factor λ using the algorithm provided by Koop and Korobilis (2013).

In addition, to model stochastic volatility in the measurement equation they propose using an Exponentially Weighted Moving Average (EWMA) instead of implementing a posterior simulation algorithm. Then the estimator for measurement error covariance matrix is calculated as follows:

$$\hat{\Sigma}_t = \kappa\hat{\Sigma}_{t-1} + (1-\kappa)\hat{\varepsilon}_t\hat{\varepsilon}_t'$$

where $\hat{\varepsilon} = y_t - \beta_{t|t}Z_t$ is produced by the Kalman filter and κ is the decay parameter. In our forecasting exercises, we estimate the model specification in difference and use the last estimated value of parameters for forecasting future values of inflation.

IV. Forecast Comparisions

The forecast accuracy of each model is calculated in terms of Root Mean Squared Forecast Error (MSFE):

$$RMSFE_{m,h} = \sqrt{\frac{1}{T}\sum_{t=1}^{T}(\pi_t - \pi_t^{m,h})^2}$$

where π_t denotes the actual value of monthly inflation at the forecast evaluation period *t*, and $\pi_t^{m,h}$ *h*-period ahead forecast (made *h* periods in the past) for model *m*. The relative forecasting strength of each model for *h* period ahead forecast is calculated based on the relative RMSFE using the Random Walk (RW) specification for CPI as well as 12 months average (12M-average) for monthly inflation as our baseline models:

$$RMSFE_h^{REL} = \frac{RMSFE_{m,h}}{RMSFE_{i,h}}$$

where *i* denotes baseline models of RW or 12M-average specifications. The model with superior forecasting power should possess a relative RMSFE value less than unity.[5]

The results of the out-of-sample experiment for the models are presented in Tables 1 (RW) and Table 2 (12M-average). From both tables, it is evident that except few cases almost all models (except TVP-VARs) perform worse than naïve models in terms of forecasting inflation in nearly all horizons. In contrary, TVP-VAR models with different sizes demonstrate relative forecasting advantage over both naïve models in almost all horizons. In the case of RW as a baseline model, the forecasting gains for the horizon of 1 month is more than 10% in small and

[5] There are more formal methods to test for equal forecast accuracy of different models or forecast encompassing, either nested or non-nested models under different forecasting schemes (see for example, Deibold and Mariano (1995), Giacomini and White (2006), Clark and McCracken (2001), McCracken (2004), etc.).

medium size models, whereas the gains decline as the forecasting horizon becomes longer. In contrary, in the case of 12M average as a baseline model, the forecasting gains of TVP-VAR models of all sizes increase with longer horizons and for the horizon of 18 months it turns out to be more than 25%. However, even for the best performing TVP-VAR model with different sizes, it is apparently harder to beat a random walk forecast for CPI, when horizon becomes longer.

Table 1. Relative RMSFE for different models (RW in levels), 2010.09-2014.06

			1 month	3 months	6 months	12 months	18 months
AR	difference	-	0.95	1.07	1.25	1.52	1.83
AR-GARCH	difference	-	1.02	0.98	1.17	1.50	1.76
Bayes AR	difference	-	0.95	1.09	1.28	1.54	1.83
	level	-	1.02	1.07	1.17	1.35	1.61
VAR	difference	small	0.96	1.15	1.36	1.59	1.88
BVAR	difference	small	0.96	1.11	1.30	1.54	1.80
		medium	0.95	1.09	1.26	1.52	1.83
		large	0.96	1.04	1.25	1.54	1.85
	level	small	1.13	1.20	1.30	1.54	1.85
		medium	1.07	1.16	1.30	1.61	1.85
		large	0.93	0.98	1.13	1.37	1.68
FAVAR	difference	-	1.11	1.22	1.28	1.65	1.93
TVP-VAR	difference	small	0.86	0.93	0.92	0.93	0.98
		medium	0.88	0.95	0.94	0.93	0.98
		large	1.13	0.98	0.98	0.98	0.98

It seems that all models experience difficulties in forecasting inflation, though relative forecasting performance gives some advantage and in longer forecast horizons, marginal advantage for TVP-VAR over naïve models. But checking forecast accuracy of models in terms of their relative RMSFE when all models are performing poorly cannot be a proper forecast model selection criterion. Rather, one can follow Romer and Romer (2000), and Edge and Gürkaynak (2007) and estimate an OLS regression to test the forecasting ability of each model vis-à-vis actual data. Specifically, one can fit the following regression to actual inflation data for each horizon forecast and for each model:

$$\pi_{ht} = \alpha + \beta\hat{\pi}_{ht} + \varepsilon$$

where π_{ht} is actual inflation rate and $\hat{\pi}_{ht}$ denote a forecast of π_{ht} that is made in month *t*. The standard errors are corrected for serial autocorrelation and heteroskedasticity using Newey-West standard errors. A good forecast should have $\alpha = 0$ and $\beta = 1$ as well as a high R^2. If the intercept is statistically different from zero, the forecast has on average been biased over the forecasting period. If the slope coefficient is different from 1, then the corresponding model has been consistently over- or underpredicting actual inflation. If goodness of fit indicator is small, then the forecast weakly explains variations in actual inflation.

Table 2. Relative RMSFE for different models (12M-average), 2010.09-2014.06

			1 month	**3 months**	**6 months**	**12 months**	**18 months**
AR	difference	-	1.06	1.09	1.16	1.25	1.36
AR-GARCH	difference	-	1.14	1.00	1.09	1.23	1.31
Bayes AR	difference	-	1.06	1.11	1.19	1.27	1.36
	level	-	1.14	1.09	1.09	1.11	1.20
VAR	difference	small	1.08	1.17	1.26	1.30	1.40
BVAR	difference	small	1.08	1.13	1.21	1.27	1.35
		medium	1.06	1.11	1.18	1.25	1.36
		large	1.08	1.06	1.16	1.27	1.38
	level	small	1.26	1.22	1.21	1.27	1.38
		medium	1.20	1.19	1.21	1.32	1.38
		large	1.04	1.00	1.05	1.13	1.25
FAVAR	difference	-	1.24	1.24	1.19	1.36	1.44
TVP-VAR	difference	small	0.96	0.94	0.86	0.77	0.73
		medium	0.98	0.96	0.88	0.77	0.73
		large	1.26	1.00	0.91	0.80	0.73

The results of the forecast efficiency test described above are summarized in Tables 5-8 in the Appendix. The regression results show that in the case of univariate models (in difference) R^2 is very low and most of the regressions slope coefficients are not statistically significant. It seems that all model inflation forecasts cannot explain actual inflation during the forecast evaluation period of *September 2010 - July 2014*. This observation is also applicable to multivariate models (in difference) as well, except large BVAR models of up-to 3 months forecast horizons, yet R^2 still being lower (0.13 and 0.17 for horizons of 1 and 3 months respectively). Forecast models in levels also provide similar picture though with intercept zero and slope close to 1 (statistically significantly), but still with lower explanatory power for variations in actual inflation data.

It is surprising that even TVP-VAR models with relatively good forecasting accuracy (based on relative RMSFE) also perform very poorly in terms of expected values for coefficients and R^2 in the forecast efficiency regression. In addition, they even possess relatively lower R^2 with respect to large BVAR models (in difference) which perform poorly against a baseline RW according to the RMSFE criterion.

Figure 1. Scatter plot of forecasts

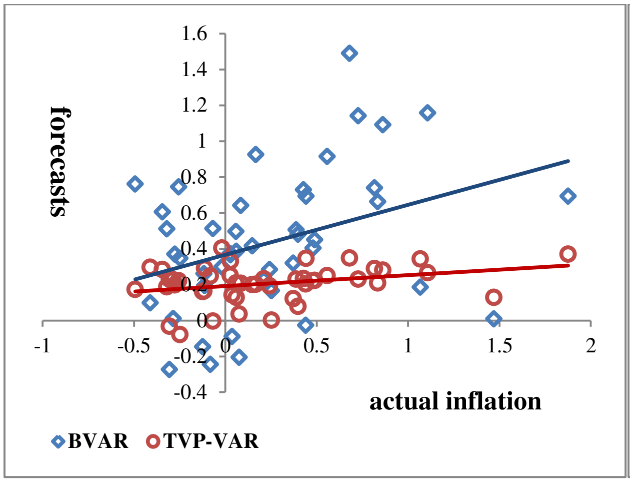
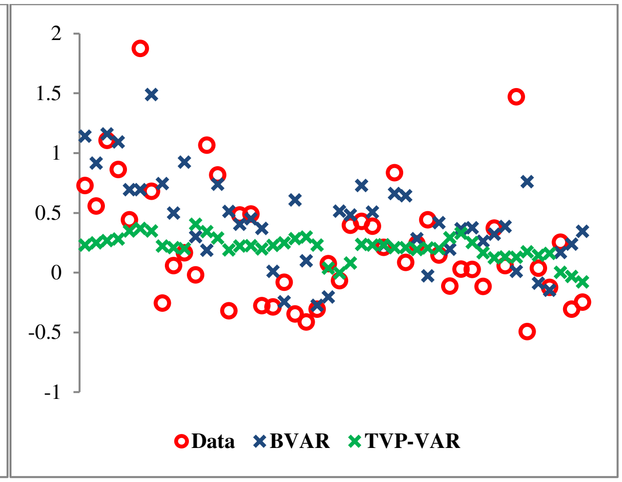


Figure 2. Data vs. Forecasts



The Figure 1 shows scatter plot of the forecasts from the large BVAR and small TVP-VAR against actual inflation data. Figure 2 presents the forecasts of both models against data over the evaluation period. Close inspections of the forecasts from both models reveals reasons of why the small TVP-VAR performs better in terms of relative RMSFE vis-à-vis large BVAR, but rather have less forecast efficiency in explaining actual inflation data. TVP-VAR forecasts exhibit similar dynamics as of a RW for CPI, but with a mean value different from zero. In contrary to the large BVAR and similar to RW, it has no explanatory power, but fits relatively well to actual inflation data. Therefore, it once more emphasizes the claim that a relatively better RMSFE in bad times for a forecasting exercise cannot be a proper model validation criterion.

V. Discussion

It is a tempting and natural question to ask that why all models perform very poor in terms of forecasting inflation in the post-oil boom years. In fact, the results from the forecasting experiment suggest that even naïve models can easily outperform relatively sophisticated models in the forecast evaluation period of 2010-2014. Even explicitly modeling possible parameter instability does not help to improve forecast efficiency of the models employed in the forecasting experiment. This can be attributed to the fact that all models are forced to forecast inflation at times when it behaves like a white noise (or i.i.d.) which is impossible to forecast.

In fact, there are various papers which show that with Great Moderation, the predictability of macroeconomic variables in US declined considerably. Atkeson and Ohanion (2001) found that since 1984, naïve average inflation (of previous 12 months) forecast had gained significant advantage over backward looking Phillips curve forecasts. Similarly, Stock and Watson (2007) demonstrated that in Great Moderation years, despite declining volatility, the predictability of inflation diminished in importance. According to D'Agostino, Giannone and Surico (2006), the ability of models to predict inflation and real activity in US declined remarkably during the Great Moderation. Edge and Gürkaynak (2010) found poor forecasting performance of DSGE models using US data since the onset of the Great moderation.

Though countries in the world may have significantly different economic structures, it is possible that the similar tendencies may take place in different parts of the world and in different times, and in our case, in Azeri economy during post oil boom years. In fact, Huseynov and Ahmadov (2014) show that though an estimated DSGE model for Azeri economy satisfactorily replicates second moments of macroeconomic variables over the period 2003-2010, introducing new observations of later three years leads to a considerable deterioration in the ability of the model in fitting data. Thus, it is reasonable to check whether in reality, forecasting performance of models employed in this paper has declined over time relative to simple naïve models.

Table 3. Relative RMSFE for different models (RW in levels), 2006.11-2010.08

			1 month	**3 months**	**6 months**	**12 months**	**18 months**
AR	difference	-	0.73	0.85	0.86	0.88	1.03
AR-GARCH	difference	-	0.70	0.85	1.07	0.88	1.15
Bayes AR	difference	-	0.72	0.84	0.85	0.88	1.02
	level	-	0.85	0.94	1.11	1.25	1.86
VAR	difference	small	0.74	0.90	0.94	1.37	1.02
BVAR	difference	small	0.71	0.87	0.85	0.89	1.01
		medium	0.70	0.86	0.84	0.90	1.04
		large	0.65	0.82	0.86	0.93	1.13
	level	small	0.82	0.87	0.90	0.95	1.16
		medium	0.82	0.87	0.95	1.03	1.31
		large	0.81	0.87	0.93	1.00	1.23
FAVAR	difference	-	0.78	0.77	1.01	0.98	1.19
TVP-VAR	difference	small	0.89	0.95	0.94	0.95	0.95
		medium	0.93	0.97	0.96	0.97	0.97
		large	1.00	1.00	0.99	1.00	1.00

Therefore, we repeat our forecasting exercises and estimate the models using data over *January, 2003 - October, 2006* and evaluate forecast accuracy of them against two baseline naïve models over the period *November, 2006 – August, 2010*. The forecast accuracy results of the models based on relative RMSFE are provided in Tables 3-4.

The results reveal that surprisingly significant forecast accuracy of naïve models in post-oil boom years is not present in the pre-boom and oil boom years. That is, it confirms our early made claim of declining forecasting ability of more sophisticated models relative to simple naïve ones over years. According to relative RMSFE, both univariate and multivariate models, in levels as well as in differences, demonstrate significant forecast gains over the baseline models of both RW and 12M average. When RW is used as a baseline model, the forecast gain reaches to 35% for the large BVAR model (in difference). Though forecast gains are relatively smaller in the case of 12M average as a baseline model, it reaches to 27% in the case of TVP-VAR for longer horizons.

Table 4. Relative RMSFE for different models (12M-average), 2006.11-2010.08

			1 month	**3 months**	**6 months**	**12 months**	**18 months**
AR	difference	-	0.86	0.93	0.88	0.86	0.79
AR-GARCH	difference	-	0.83	0.93	1.09	0.86	0.88
Bayes AR	difference	-	0.85	0.92	0.86	0.86	0.78
	level	-	1.01	1.03	1.13	1.22	1.43
VAR	difference	small	0.87	0.99	0.96	1.34	0.78
BVAR	difference	small	0.84	0.95	0.86	0.87	0.77
		medium	0.82	0.94	0.85	0.88	0.79
		large	0.77	0.90	0.88	0.91	0.87
	level	small	0.98	0.95	0.92	0.92	0.89
		medium	0.98	0.96	0.97	1.01	1.01
		large	0.96	0.95	0.94	0.98	0.94
FAVAR	difference	-	0.92	0.85	1.02	0.95	0.91
TVP-VAR	difference	small	1.06	1.04	0.95	0.92	0.73
		medium	1.10	1.07	0.98	0.95	0.74
		large	1.18	1.10	1.01	0.98	0.77

To gain further insights why it has happened, we follow Stock and Watson (2007) and estimate stochastic volatility using unobserved component model over the whole period. Figure 3 presents estimated inflation volatility during the period of *January, 2003-June, 2014*. It seems that monthly inflation volatility has declined sharply (more than three times), especially towards the end of the forecast period. The considerable reduction in volatility is not inherent to inflation only, it is observed in most variables. Figure 4 presents stochastic volatility estimate (AR(1)-GARCH(1, 1)) of quarterly reserve money which displays sharp decline in the volatility as well.

Figure 3. Stochastic Volatility of Inflation

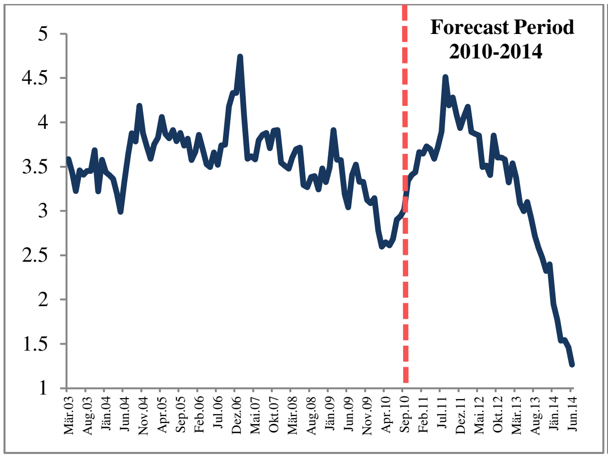


Figure 4. Stochastic Volatility of Reserve Money

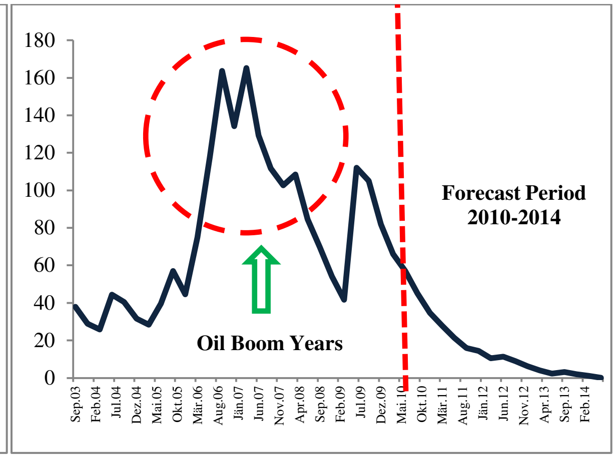


Figure 5. AC and PC for inflation, 2003.01-2010.08

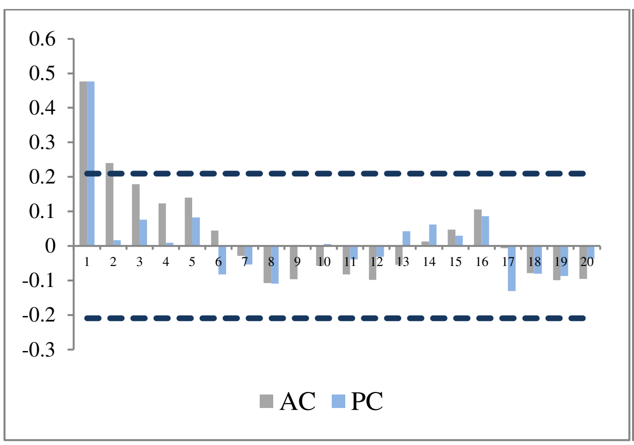
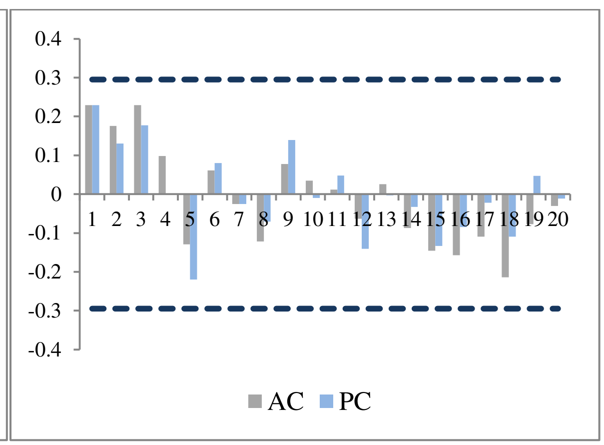


Figure 6. AC and PC for inflation, 2010.09-2014.06



Evidently, important major changes have happened in the inflation process itself and in the ability of its predictors over time. However, these changes turn out to be more than apparently plausible explanation of probable structural changes that allow for easy capturing by models with time varying parameters.

In the Figure 3-4, autocorrelation and partial autocorrelation with 95% confidence intervals for monthly inflation are depicted. The AC and PC clearly show that though inflation was a persistent process until 2010, it has changed its nature since then and started to behave like a white noise.

Therefore, it is not surprising that despite a sharp decline in the volatility of inflation process, it has become harder to predict it over the post-oil boom years. Then it is tempting to question why monthly inflation has started to behave like a white noise process. One can speculate that this might be result of possible changes in the nature of shocks hitting the economy and their effect on the persistence of inflation. Other explanation can be the increase in the ability of the monetary authority to control inflation and thus, reducing its persistence and predictability. However, it seems that this puzzling behavior of inflation will require further investigation and can be considered an interesting direction for future research.

VI. Conclusion

In this paper, we test forecasting performance of numerous models against simple naïve ones for the period of post-oil boom years. We find that forecasting ability of naïve models, namely, RW and 12 month average, is not inferior to relatively sophisticated ones for that period. To test whether surprisingly better forecast performance of naïve models is a relatively new phenomenon, we re-run our experiment and estimate our models using the sample of *January, 2003-October, 2006* and predict inflation for the period of *November, 2006-August, 2010*. The results show that the models employed in this study exhibit significant superiority to naïve ones in terms of forecasting inflation for that period. It seems that increasing forecast performance of naïve models over the years is a relatively new phenomenon. We further extend our analysis and demonstrate that despite a sharp decline in the volatility of monthly inflation over these years, it has started to behave like a white noise. This puzzling behavior of inflation needs further analysis and can be considered an interesting direction for research.

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APPENDIX

Table 5. Accuracy in Forecasting for Inflation (2010.09-2014.06)

(univariate models in difference)

$$\pi_{ht} = \alpha + \beta\hat{\pi}_{ht} + \varepsilon$$

Forecast Horizon (Months)	Intercept	Slope	R^2	N
AR				
1	0.00 (0.15)	0.56* (0.33)	0.09	46
3	-0.23 (0.30)	0.83 (0.59)	0.08	44
6	-0.29 (0.52)	0.74 (0.87)	0.03	41
12	-0.15 (0.90)	0.42 (1.35)	0.00	35
18	0.62 (1.15)	-0.75 (1.61)	0.01	29
AR-GARCH				
1	0.12 (0.10)	0.27 (0.22)	0.04	46
3	0.24 (0.18)	-0.04 (0.34)	0.00	44
6	-0.20 (0.46)	0.59 (0.79)	0.02	41
12	0.21 (0.90)	-0.10 (1.33)	0.00	35
18	-1.76** (0.87)	2.56** (1.20)	0.09	29
Bayes AR				
1	-0.03 (0.16)	0.61* (0.33)	0.10	46
3	-0.33 (0.36)	0.97 (0.67)	0.08	44
6	-0.39 (0.63)	0.89 (1.02)	0.03	41
12	-0.24 (1.02)	0.55 (1.51)	0.01	35
18	0.57 (1.26)	-0.67 (1.76)	0.01	29

Note: *** denotes the significance of the respective coefficient at 1%, ** at 5%, * at 10% significance level. Newey-West standard errors are provided in the parenthesis.

Table 6. Accuracy in Forecasting for Inflation 2010.09-2014.06

(multivariate models in difference)

$$\pi_{ht} = \alpha + \beta\hat{\pi}_{ht} + \varepsilon$$

Forecast Horizon (Months)	Intercept	Slope	R^2	N
VAR				
1	-0.02 (0.11)	0.56** (0.24)	0.11	46
3	-0.27 (0.28)	0.79 (0.52)	0.07	44
6	-0.21 (0.58)	0.55 (0.86)	0.01	41
12	-0.21 (1.21)	0.48 (1.72)	0.00	35
18	0.84 (1.56)	-1.02 (2.12)	0.01	29
$BVAR^S$				
1	-0.01 (0.13)	0.54* (0.28)	0.09	46
3	-0.31 (0.28)	0.89 (0.55)	0.08	44
6	-0.08 (0.65)	0.39 (1.01)	0.00	41
12	-0.12 (1.11)	0.37 (1.65)	0.00	35
18	0.43 (1.45)	0.48 (2.07)	0.00	29
$BVAR^M$				
1	0.01 (0.13)	0.53** (0.27)	0.11	46
3	-0.19 (0.21)	0.73* (0.44)	0.09	44
6	-0.43 (0.52)	0.95 (0.84)	0.05	41
12	-0.29 (0.84)	0.61 (1.24)	0.02	35
18	0.00 (0.63)	0.13 (0.90)	0.00	29
$BVAR^L$				
1	0.03 (0.10)	0.48*** (0.19)	0.13	46
3	-0.21* (0.12)	0.78*** (0.26)	0.17	44

6	-0.34 (0.26)	0.81* (0.44)	0.07	41
12	-0.02 (0.48)	0.23 (0.73)	0.00	35
18	0.55 (0.69)	0.63 (0.95)	0.00	29

Note: *** denotes the significance of the respective coefficient at 1%, ** at 5%, * at 10% significance level. Newey-West standard errors are provided in the parenthesis. Superscript *S* over multivariate VAR specification denotes small model, *M* medium and *L* large models.

Table 7. Accuracy in Forecasting for Inflation 2010.09-2014.06

(models in levels)

$$\pi_{ht} = \alpha + \beta\hat{\pi}_{ht} + \varepsilon$$

Forecast Horizon (Months)	Intercept	Slope	R^2	N
Bayes AR				
1	-0.42 (0.30)	1.21** (0.59)	0.10	46
3	-0.38 (0.35)	1.09 (0.70)	0.08	44
6	-0.29 (0.34)	0.84 (0.68)	0.05	41
12	0.02 (0.41)	0.20 (0.78)	0.00	35
18	-0.13 (0.39)	0.07 (0.69)	0.00	29
$BVAR^S$				
1	-0.48 (0.40)	1.12* (0.69)	0.08	46
3	-0.44 (0.44)	1.01 (0.74)	0.06	44
6	-0.16 (0.38)	0.52 (0.63)	0.02	41
12	-0.07 (0.47)	0.30 (0.74)	0.01	35
18	0.33 (0.66)	-0.33 (0.90)	0.01	29
$BVAR^M$				
1	-0.05 (0.15)	0.51* (0.29)	0.07	46
3	-0.03 (0.20)	0.42 (0.39)	0.03	44

6	-0.08 (0.27)	0.39 (0.45)	0.02	41
12	0.34 (0.41)	-0.29 (0.59)	0.01	35
18	-0.32 (0.40)	0.55 (0.56)	0.03	29
$BVAR^L$				
1	0.09 (0.31)	0.44 (0.11)	0.05	46
3	0.06 (0.11)	0.43 (0.31)	0.05	44
6	0.12 (0.12)	0.12 (0.33)	0.00	41
12	0.08 (0.20)	0.11 (0.40)	0.00	35
18	0.05 (0.29)	0.07 (0.45)	0.00	29

Note: *** denotes the significance of the respective coefficient at 1%, ** at 5%, * at 10% significance level. Newey-West standard errors are provided in the parenthesis. Superscript *S* over multivariate VAR specification denotes small model, *M* medium and *L* large models.

Table 8. Accuracy in Forecasting for Inflation 2010.09-2014.06

(FAVAR and TVP-VAR in difference)

$$\pi_{ht} = \alpha + \beta \hat{\pi}_{ht} + \varepsilon$$

Forecast Horizon (Months)	Intercept	Slope	R^2	N
FAVAR				
1	0.18** (0.09)	0.17 (0.20)	0.02	46
3	0.20 (0.15)	0.04 (0.25)	0.00	44
6	-0.04 (0.17)	0.35 (0.29)	0.03	41
12	0.33 (0.28)	-0.27 (0.32)	0.02	35
18	0.09 (0.27)	0.00 (0.36)	0.00	29
$TVP\text{-}VAR^S$				
1	-0.07 (0.11)	1.49** (0.78)	0.09	46
3	-0.18 (0.45)	2.73 (3.19)	0.02	44

6	-0.33 (0.52)	3.67 (4.06)	0.02	41
12	0.06 (0.62)	0.52 (4.61)	0.00	35
18	0.38 (0.66)	2.02 (4.64)	0.01	29
TVP-VAR^{M}				
1	-0.03 (0.12)	1.55* (0.95)	0.07	46
3	0.09 (0.39)	1.07 (3.44)	0.00	44
6	-0.31 (0.47)	4.37 (4.61)	0.02	41
12	-0.07 (0.67)	1.77 (6.03)	0.00	35
18	0.20 (0.68)	-0.97 (5.74)	0.00	29
TVP-VAR^{L}				
1	0.24** (0.10)	-0.07 (0.24)	0.00	46
3	0.23** (0.10)	-0.13 (0.55)	0.00	44
6	0.18 (0.18)	0.00 (5.35)	0.00	41
12	0.15 (0.12)	-0.54 (12.37)	0.00	35
18	-0.25 (0.20)	13.55* (7.22)	0.07	29

Note: *** denotes the significance of the respective coefficient at 1%, ** at 5%, * at 10% significance level. Newey-West standard errors are provided in the parenthesis. Superscript *S* over multivariate VAR specification denotes small model, *M* medium and *L* large models.