Determinants of INR/USD Exchange Rate: Modelling and Forecasting

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Why Study Exchange Rates?

- **Exchange rates affect decisions made by:**
  - foreign exchange investors and traders
  - businesses
  - financial institutions
  - professional investors and
  - policymakers
- **Movements in exchange rates affect:**
  - economy’s business cycle
  - trade and capital flows
  - financial developments
  - economic policy

Exchange Rate Policy in India

- **Up to 1990, the exchange rate regime in India is best described as an adjustable nominal peg to a basket of currencies of major trading partners with a band**

- **After the BOP crisis of 1991 a two-step downward adjustment in the exchange rate was undertaken in July 1991 followed by a transitional 11-month period of dual exchange rates**

- **A market determined exchange rate system was set in place in March 1993. Since then, the exchange rate is largely determined by demand and supply conditions in the market**

Exchange Rate Policy in India cont'd

- **Policy of managed floating is still followed by the Reserve Bank of India**

- **Direct intervention in the foreign exchange rate market through purchases and sales in both spot and forward markets is frequently undertaken**

- **Regime can be interpreted to be "more flexible" during normal market conditions and "managed" when chaos prevails**

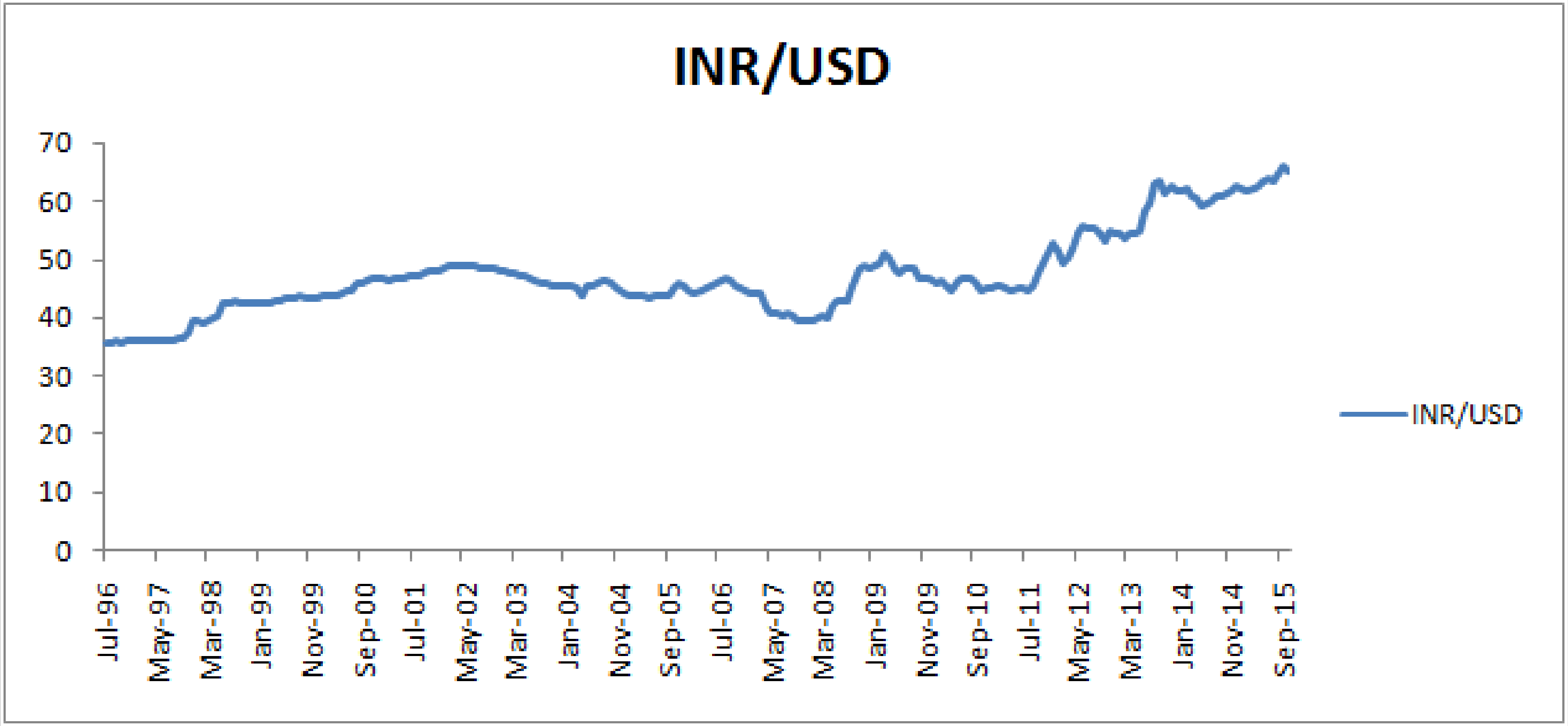
- **Policy response in India has hitherto been to thwart abnormal appreciation or depreciation pressures upon the real exchange rate**

Exchange Rate Policy in India cont'd

- **Since the market determined exchange rate has been in place since March 1993, our analysis will focus on the post March 1993 period.**

- **The period of estimation for this study is July 1996 to December 2012. The period January 2013 to December 2014 is used for forecasting the exchange rate.**

The INR/USD exchange rate



Summary Statistics for the INR/USD Exchange rate

Time Period	mean	Maximum	Minimum	Std. Dev.
Jul 1996 to Dec. 2014	46.44	63.75	35.51	19.26
Jul 1996 to Dec. 2012	44.82	56.03	35.51	4.24
Jan 2013 to Dec. 2014	59.87	63.75	53.77	3.11

Economic Theory

- Flexible-price and sticky-price monetary model
- Real interest differential model
- Hooper-Morton's extension of the sticky price model
- Portfolio approach
- Hybrid approach encompassing all above models
- Extension of above models
    - Capital flows
    - Volatility of capital flows
    - Forward premium
    - Order flows (Microstructure approach)
    - Central Bank Intervention
    - Stock price differential

Economic Theory cont'd

- **The first four models can be derived from the following equation specified in logs with starred variables denoting foreign counterparts:**

$$e = \gamma + \delta(m-m^*) + \phi(y-y^*) + \alpha(i-i^*) + \beta(\pi-\pi^*) + \eta(tb-tb^*) + \mu$$

where e = price of foreign currency in domestic currency
m = money supply
y = real output
r = nominal interest rate
π = inflation
tb = trade balance

The alternative testable hypotheses are as follows:

- **Flexible-price monetary model:** $\delta>0, \alpha>0, \phi<0, \beta=\eta=0$
- **Sticky price monetary model:** $\delta>0, \alpha<0, \phi<0, \beta=\eta=0$
- **Real interest differential model:** $\delta>0, \alpha<0, \phi<0, \beta>0, \eta=0$
- **Hooper-Morton model:** $\delta>0, \alpha<0, \phi<0, \beta>0, \eta<0$

Economic Theory cont'd

- ***Portfolio approach*** **introduces the current account in the above equation**

- **Use a hybrid model as follows on the basis of the fit of the model:**

  $e = f\{(m-m^*), (y-y^*), (i-i^*), (\pi-\pi^*), (tb-tb^*), (ca-ca^*), Z\}$

  where ca denotes current account balance and Z accounts for any other variable not captured above.

Economic Theory cont'd

- **Extension of model & specification of Z**

e = f{(m-m*), (y-y*), (i-i*), (π-π*), (tb-tb*), (ca-ca*), Z}

Z = for, cap, vol, of, int

implies

e = f{(m-m*), (y-y*), (i-i*), (π-π*), (tb-tb*), (ca-ca*), for, cap, vol, of, int}

Economic Theory Cont'd

- The model discussed above can be summarised as under (Dua and Ranjan,2010)
- $e_t = \gamma + \delta(m_t - m_t^*) + \varphi(y_t - y_t^*) + \alpha(i_t - i_t^*) + \beta(\ (\pi_t - \pi_t^*) + \eta(tb_t - tb_t^*) + v(cap_t) + \rho(vol_t) + \omega(for_t) + \psi(of_t) + \xi\ (int_t) + u_t$

Economic Theory cont'd

- **We extend the model due to Dua and Ranjan (2010) by including the difference between rate of return on stocks in India and rate of return on stocks of the foreign economy.**
- **This inclusion is based on Hau and Rey (2006); Aggarwal(1981); Branson (1986). With increasing integration of capital flows, changes in the stock market conditions across the globe can influence the exchange rate.**

Theoretical Model cont'd

- The extended model is summarised by the following equation
- $e_t = \gamma + \delta(m_t - m_t^*) + \varphi(y_t - y_t^*) + \alpha(i_t - i_t^*) + \beta(\,(\pi_t - \pi_t^*) + \eta(tb_t - tb_t^*) + \theta(ca_t - ca_t^*) + v(cap_t) + \rho(vol_t) + \omega(for_t) + \psi(of_t) + \xi\,(int_t) + \vartheta(ror_t - ror_t^*) + u_t$

Empirical Model

- Model 1
- $e_t = \gamma + \delta(m_t - m_t^*) + \varphi(y_t - y_t^*) + \alpha(i_t - i_t^*) + \rho(vol_t) + \omega(for_t) + \psi(of_t) + \xi\,(int_t) + u_t$

Empirical model

- Model 2
- $e_t = \gamma + \delta(m_t - m_t^*) + \varphi(y_t - y_t^*) + \alpha(i_t - i_t^*) + \rho(vol_t) + \omega(for_t) + \psi(of_t) + \xi\,(int_t) + \sigma(ror_t - ror_t^*) + u_t$

Definition and expected signs of the variables

Variable	Definition	Expected Signs of variables
e_t	Nominal exchange rate (INR/USD)	
$i_t - i_t^*$	Interest rate differential	+/-
$y_t - y_t^*$	Output differential	-
$m_t - m_t^*$	Money supply differential	+
for_t	Forward rate (INR/USD)	+
vol_t	Volatility of capital inflows	+/-
of_t	Order flows	+/-
int_t	Official intervention by the central bank	+/-
$ror_t - ror_t^*$	Rate of return on Indian stocks less rate of return on US stocks	+/-

Empirical Methodology

1. **Nonstationarity**
2. **Cointegration, vector error correction model**
3. **Granger Causality**
4. **Innovation Accounting – Generalized Decomposition**
5. **Forecasting with Univariate and Multivariate (VECM, VAR and BVAR) Models**

Nonstationarity: DF-GLS Unit Root test

- **The DF-GLS test has substantially improved power when an unknown mean or trend is present (Elliot et al., 1996).**
- **The DF-GLS procedure relies on demeaning and/or detrending a series prior to the implementation of the auxiliary ADF regression.**

Nonstationarity: Bayesian Unit Root Test

- **Bayesian unit root tests are superior to the classical approach as the null and the alternative hypothesis are treated symmetrically.**

- **The initial Bayesian analysis of unit root models was by Sims (1988). We use this model to test for the presence of unit roots in the variables under consideration.**

Empirical Methodology Cont'd

Granger Causality:

- **One variable is said to Granger cause the other if lags of the latter improve the forecasting performance of the former.**

- **In a vector error correction model, the RHS variable does not Granger cause the LHS variable if the lags of the RHS variable *and* the error correction term are jointly not significantly different from zero.**

Empirical Methodology Cont'd

Innovation Accounting

- **Dynamic relationships among variables in VAR models can be analyzed using innovation accounting methods that include impulse response functions and variance decompositions.**
- **An impulse response function measures the time profile of the effect of shocks at a given point in time on the future values of variables of a dynamical system.**
- **The forecast error variance decompositions provide a breakdown of the variance of the n-step ahead forecast errors of variable *i* which is accounted for by the innovations in variable *j* in the VAR.**

Empirical Methodology Cont'd

Orthogonalized vs. Generalized Analysis

- **Orthogonalized Impulse Responses and Forecast Error Variance Decompositions are sensitive to ordering of the variables in the VAR.**

- **Generalized Impulse responses and Forecast Error Variance Decompositions overcome this shortcoming.**

Empirical Results

Unit Root test Results (DF-GLS)

variable	DF-GLS
e	I(1)
i-i*	I(1)
y-y*	I(1)
m-m*	I(1)
for	I(1)
vol	I(1)
of	I(0)
int	I(0)
ror-ror*	I(0)

Unit Root test Results (Bayesian odds ratio test ***)***

variable	**Bayesian odds ratio test**
e	I(1)
i-i*	I(1)
y-y*	I(1)
m-m*	I(1)
for	I(1)
vol	I(1)
of	I(0)
int	I(0)
ror-ror*	I(0)

Granger causality: Model 1

Null	Lags	CHSQ(2)	Inference
e_t is not granger caused by $i_t - i_t^*$	1	4.75(.093)	Reject the null hypothesis
e_t is not granger caused by $y_t - y_t^*$	1	6.025(.049)	Reject the null hypothesis
e_t is not granger caused by $m_t - m_t^*$	1	7.07(.029)	Reject the null hypothesis
e_t is not granger caused by for_t	1	11.11(.004)	Reject the null hypothesis
e_t is not granger caused by vol_t	1	5.08(.079)	Reject the null hypothesis
e_t is not granger caused by of_t	1	.001(.002)	Reject the null hypothesis
e_t is not granger caused by int_t	1	.74E-3(.251)	Do not reject the null hypothesis
***t- statistics from the error correction model. All inferences carried out at 20% significance levels**			

Granger Causality :Model 2

Null	Lags	CHSQ(2)	Inference
e_t is not granger caused by $i_t - i_t^*$	1	5.63[.06]	Reject the null hypothesis
e_t is not granger caused by $y_t - y_t^*$	1	7.22[.027)	Reject the null hypothesis
e_t is not granger caused by $m_t - m_t^*$	1	7.54[.023]	Reject the null hypothesis
e_t is not granger caused by for_t	1	12.93[.002]	Reject the null hypothesis
e_t is not granger caused by vol_t	1	5.84[.054]	Reject the null hypothesis
e_t is not granger caused by of_t	1	.0025[.002]	Reject the null hypothesis
e_t is not granger caused by int_t	1	.866E-3[.176]	Reject the null hypothesis
e_t is not granger caused by $ror_t - ror_t^*$	1	-.308(.03)	Reject the null hypothesis

*t- statistics from the error correction model. All inferences carried out at 20% significance levels

Generalized Forecast Error Variance Decomposition for the INR/USD exchange rate (Model 1)

- At the end of 24-month forecast horizon, around 50% of forecast error variance of INR/USD exchange rate is explained by its own innovations.

- Money supply differential explains about 39% of total variation after 24 months. And the volatility of capital flows explains 7% of the same.

- The three month ahead forward rate explains 2.7% of the forecast error variance and the difference in the rates of interest and the difference in output account for .18% and .10% respectively.

Generalized Forecast Error Variance Decomposition for the INR/USD exchange rate (Model 2)

- At the end of 24-month forecast horizon, around 50% of forecast error variance of INR/USD exchange rate is explained by its own innovations.

- Money supply differential explains about 38% of total variation after 24 months. And the volatility of capital flows explains 8% of the same.

- The three month ahead forward rate explains 3.2%, the rate of interest differential explains .26% and the differential in output explains .03% of the forecast error variance.

Forecasting the Exchange Rate

Benchmark Model

- The benchmark model for each interest rate is a naïve model or a random walk model as described below:

$$e_t = e_{t-1} + \varepsilon_t$$

with $E(\varepsilon_t)=0$ and $E(\varepsilon_t\varepsilon_s)=0$ for $t \neq s$.

- The one-period-ahead forecast is simply the current value as shown below:

$$e^e_{t+1} = E(e_t + \varepsilon_{t+1}) = e_t$$

- Similarly the k- period-ahead forecast is:

$$e^e_{t+k} = e_t$$

Forecasting Techniques (Univariate Models)

- Univariate OLS
- Univariate BVAR
- Univariate GARCH

Bayesian Univariate

- ***Bayesian Univariate***
  - **Provides a scientific way of imposing prior or judgmental beliefs**
  - **Imposes prior beliefs on the relationships between own lags of a particular variable**
  - **Lag structure and hyperparameters can be pre-specified or determined by data**

* This is undertaken to test if adding priors improves the forecasting results for the univariate model.

GARCH Model

- **The GARCH model is estimated as an additional univariate model to see if the forecasts improve when the volatility of the exchange rate is taken into account.**

Forecasting Techniques (Multivariate Models)

- **Vector Error Correction Models**
- **Vector autoregressive models**
- **Bayesian vector autoregressive models**

Vector Autoregressive Model (VAR)

- The VAR technique uses regularities in the historical data on the forecasted variables.
- Economic theory only selects the economic variables to include in the model.
- An unrestricted VAR model is written as follows:

$y_t = C + A(L)y_t + e_t$, where

y = an (nx1) vector of variables being forecast;

$A(L)$ = an (nxn) polynomial matrix in the back-shift operator L with lag length p,

$= A_1L + A_2L^2 + \ldots\ldots\ldots\ldots + A_pL^p$;

C = an (nx1) vector of constant terms; and

e = an (nx1) vector of white noise error terms.

Vector Autoregressive Model cont'd

- ***Limitations of VAR***

  - **Overparameterization produces multicollinearity and loss of degrees of freedom.**
  - **This can lead to inefficient estimates and large out-of-sample forecasting errors.**
  - **One solution is to exclude insignificant variables/lags based on statistical tests.**
  - **Alternative approach is to use a Bayesian VAR that imposes restrictions on these coefficients**

Bayesian Vector Autoregressive Model

- ***Bayesian VAR***
  - Provides a scientific way of imposing prior or judgmental beliefs
  - Imposes prior beliefs on the relationships between different variables as well as between own lags of a particular variable
  - Lag structure and hyperparameters can be prespecified or determined by data

Bayesian Vector Autoregressive Model—cont'd

- ***Restrictions on Coefficients***
  - **Restrictions on the coefficients are imposed by specifying normal prior distributions with means zero and non-zero standard deviations for all coefficients the exception being the coefficient on the first own lag of a variable that has a mean of unity.**
  - **Decreasing standard deviation are imposed on increasing lags.**
  - **This is referred to as the "Minnesota prior" due to its development at the Federal Reserve Bank of Minneapolis and the University of Minnesota.**

Bayesian Vector Autoregressive Model—cont'd

- **Another advantage of BVAR approach is that "…the Bayesian approach is entirely based on the likelihood function, which has the same Gaussian shape regardless of the presence of nonstationarity, [hence] Bayesian inference need take no special account of nonstationarity".**

  Sims et. al (1990)

Selection of the "Best" Forecasting Models

- The "best" forecasting model is one that produces the most accurate forecasts.

- This means that the predicted levels should be close to the actual realized values.

- Furthermore, the predicted variables should move in the same direction as the actual series.
  - If a series is rising (falling), the forecasts should reflect the same direction of change. If a series is changing direction, the forecasts should identify this.

Selection of the "Best" Forecasting Models

- **To select the best model, the alternative models are estimated using monthly data from July 1996 through December 2012 and tested for accuracy from January 2013 to December**

- **By continuously updating and re-estimating, we conduct a real world forecasting exercise to see how the models perform. The model that produces the most accurate one- through twelve-month ahead forecasts over January 2013 to December 2014 is designated the "best" model for the exchange rate.**

Forecast Accuracy

- The out-of-sample forecast accuracy is measured by the Theil U-statistic. If At+n denotes the actual value of a variable in period (t+n), and tFt+n the forecast made in period t for (t+n), then for T observations the Theil U-statistic is defined as follows:

$$U = [(A_{t+n} - {}_{t}F_{t+n})^2/(A_{t+n} - A_t)^2]0.5.$$

- The U-statistic therefore measures the ratio of the root mean square error (RMSE) of the model forecasts to the RMSE of naive, no-change forecasts. The U-statistic, therefore, implicitly compares forecasts to the naive model.
- When the U-statistic equals 1, then the model's forecasts match, on average, the naive, no-change forecasts.
- A U-statistic greater than 1 indicates that the naive forecasts out perform the model forecasts.
- A U-statistic less than 1 demonstrates that the model's forecasts out perform the naive forecasts.
- We also examine the root mean square error.

Forecast Accuracy cont'd

- **The Modified Diebold Mariano test is also conducted to compare the forecast performance of alternative models, i.e., it tests the null hypothesis of no difference in the accuracy of two competing forecasts.**

Forecasting

- ***Caveat*: Estimation and selection of "best"model on the basis of the criteria discussed does not ensure "best" ex ante forecasts!**

Empirical Multivariate Models

- Benchmark model
- ${}_{t}e_{t+n} = e_t$
- Model 1
- ${}_{t}e_{t+n} = f((m_t - m_t^*),(y_t - y_t^*),(i_t - i_t^*),(vol_t),(for_t),(of_t)+,(int_t))$
- Model 2
- Model 1 + rate of return on stocks difference.
- ${}_{t}e_{t+n} = f((m_t - m_t^*),(y_t - y_t^*),(i_t - i_t^*),(vol_t),(for_t),(of_t)+,(int_t),(ror_t - ror_t^*))$

Forecasting Results for the Univariate Models

- **The Univariate BVAR for the exchange rate is superior to the univariate OLS providing evidence that inclusion of priors improves the forecasting performance of time series models.**

- **The ARCH(1) model fitted to the ARIMA(1,1,0) model for the exchange rate forecasts better than the univariate OLS and the Univariate BVAR. This is because the ARCH model picks up the volatility in the exchange rate .**

Forecasting Performance of VAR,BVAR and VECM Models : Jan 2013 –Dec.2014 -Model 1 vs 2

- The multivariate models are superior to the univariate models in this forecasting exercise.

- The VECM Forecasts reveal that Model 2 outperforms Model 1 for longer term forecasts.

- A comparison of the VAR estimates for Model 1 and Model 2 also reveals that Model 2 is better than Model 1 at longer term horizons.

- Model 2 performs consistently better than Model 1 at all forecast horizons for the BVAR estimation . This result is stronger than the result for the VAR and the VECM models where Model 2 was superior only at longer horizons.

- Therefore the inclusion of rates of return on stock differential is validated by the BVAR forecasting results.

Forecasting Performance of VECM vs VAR vs BVAR Models : Jan 2013 –Dec.2014

- The forecasting results from the univariate models point at the superiority of Bayesian models over standard OLS models.

- The results of the forecasting exercise for the linear models is further strengthened for the multivariate models as BVAR models yield more accurate forecasts than their VAR counterparts especially at longer forecast horizons.

- VAR models yield more accurate forecasts than VECM.

Modified DM Test for VECM vs VAR Models Out-of-sample Period: January 2013 to December 2014

Model 1	
Month Ahead	VECM vs VAR
1	Insignificant
2	.insinificant
3	VAR better than VECM[d]
4	insignificant
5	VAR better than VECM[d]
6	insignificant
7	insignificant
8	insignificant
9	VAR better than VECM[c]
10	VAR better than VECM[a]
11	VAR better than VECM[a]
12	VAR better than VECM[a]

Model 2	
Month Ahead	VECM vs VAR
1	Insignificant
2	.insinificant
3	VAR better than VECM[b]
4	VAR better than VECM[a]
5	VAR better than VECM[d]
6	insignificant
7	insignificant
8	insignificant
9	VAR better than VECM[b]
10	VAR better than VECM[a]
11	VAR better than VECM[a]
12	VAR better than VECM[a]

Modified DM Test for VAR vs BVAR Models Out-of-sample Period: January 2013 to December 2014

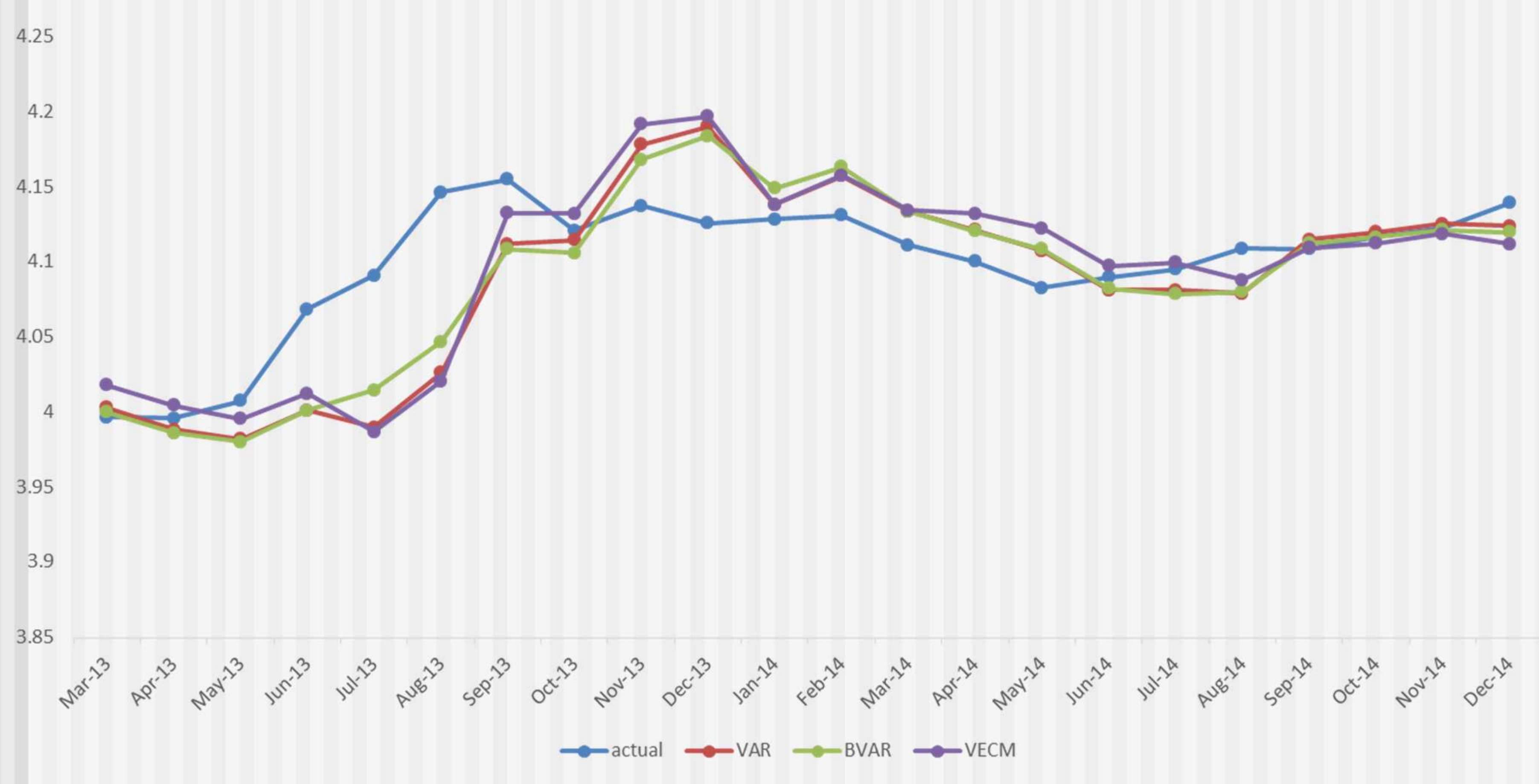
Model 1	
Month Ahead	VAR vs BVAR
1	BVAR better than VAR[d]
2	BVAR better than VAR[b]
3	BVAR better than VAR[b]
4	BVAR better than VAR[a]
5	BVAR better than VAR[a]
6	BVAR better than VAR[a]
7	BVAR better than VAR[a]
8	BVAR better than VAR[a]
9	BVAR better than VAR[a]
10	BVAR better than VAR[a]
11	BVAR better than VAR[a]
12	BVAR better than VAR[a]

Model 2	
Month Ahead	VAR vs BVAR
1	BVAR better than VAR[d]
2	BVAR better than VAR[b]
3	BVAR better than VAR[b]
4	BVAR better than VAR[a]
5	BVAR better than VAR[a]
6	BVAR better than VAR[a]
7	BVAR better than VAR[a]
8	BVAR better than VAR[a]
9	BVAR better than VAR[c]
10	indifferent
11	BVAR better than VAR[c]
12	BVAR better than VAR[b]

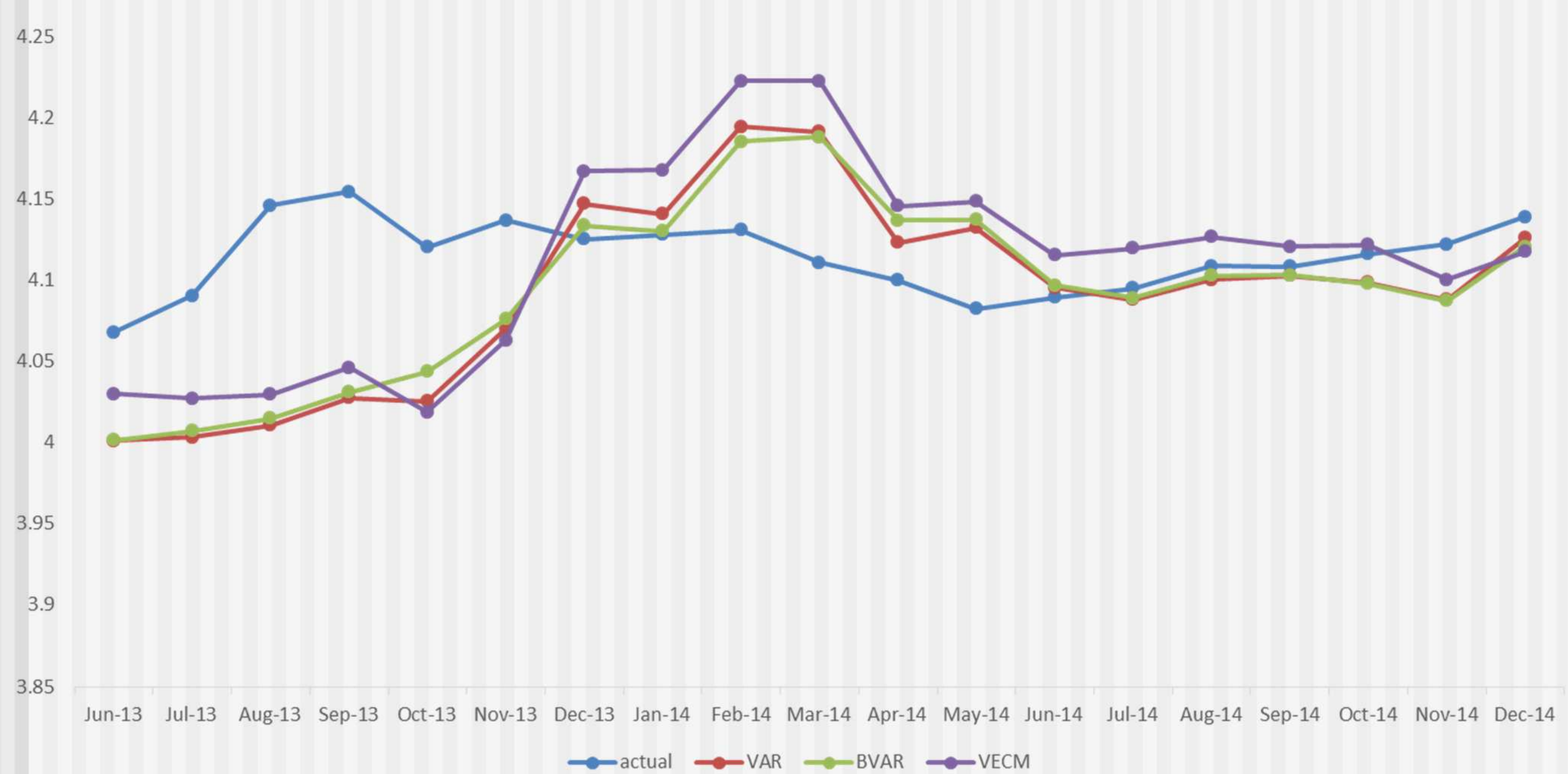
Concluding Observations

- Forecast accuracy can be improved by extending the monetary model to include forward premium, volatility of capital inflows and order flow.
- Information on rates of return on stocks differential helps to improve forecasts at the longer end.
- Bayesian vector autoregressive models generally outperform their corresponding VAR variants.

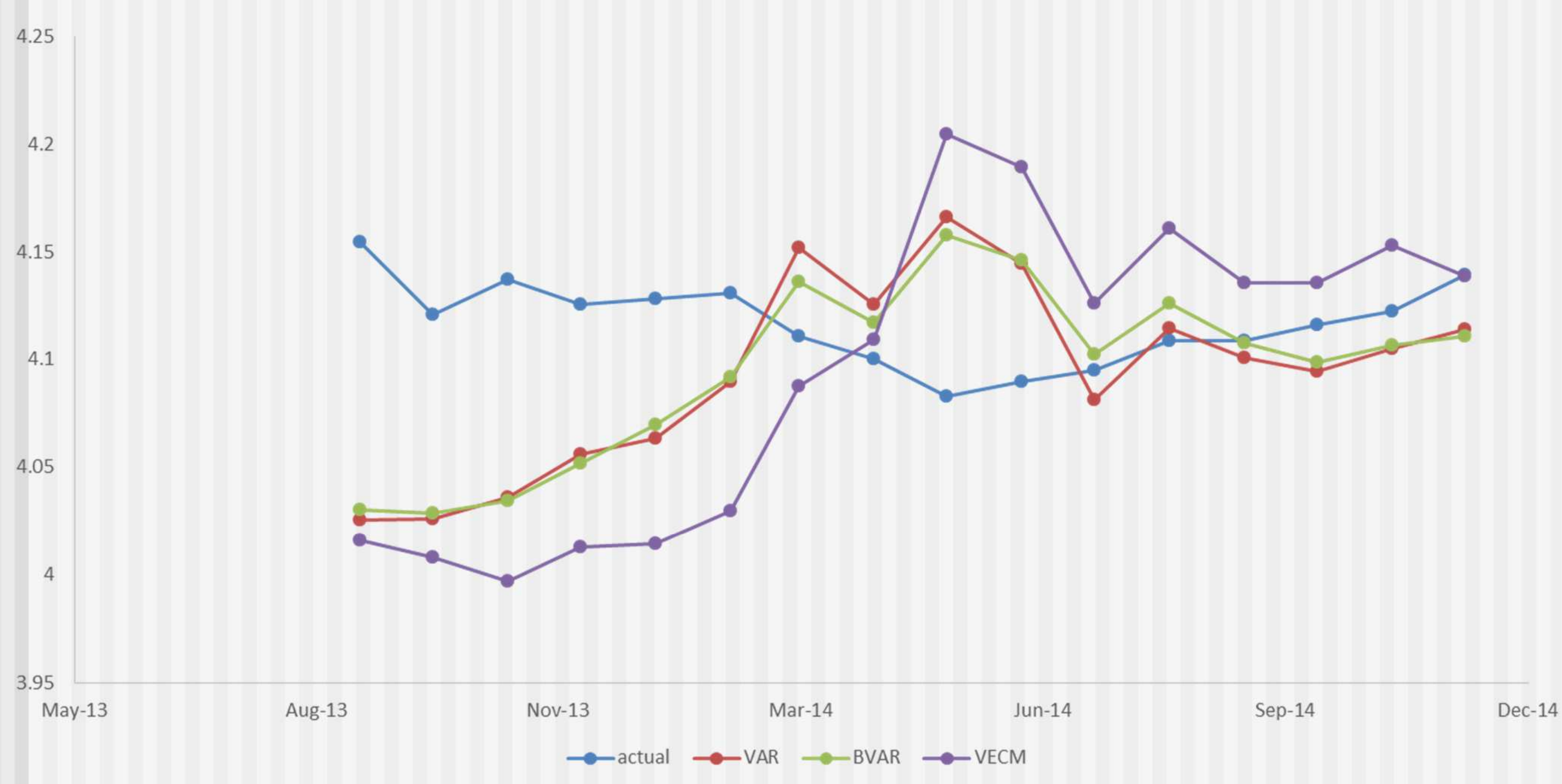
Three step ahead VECM, VAR and BVAR forecasts for Model 1



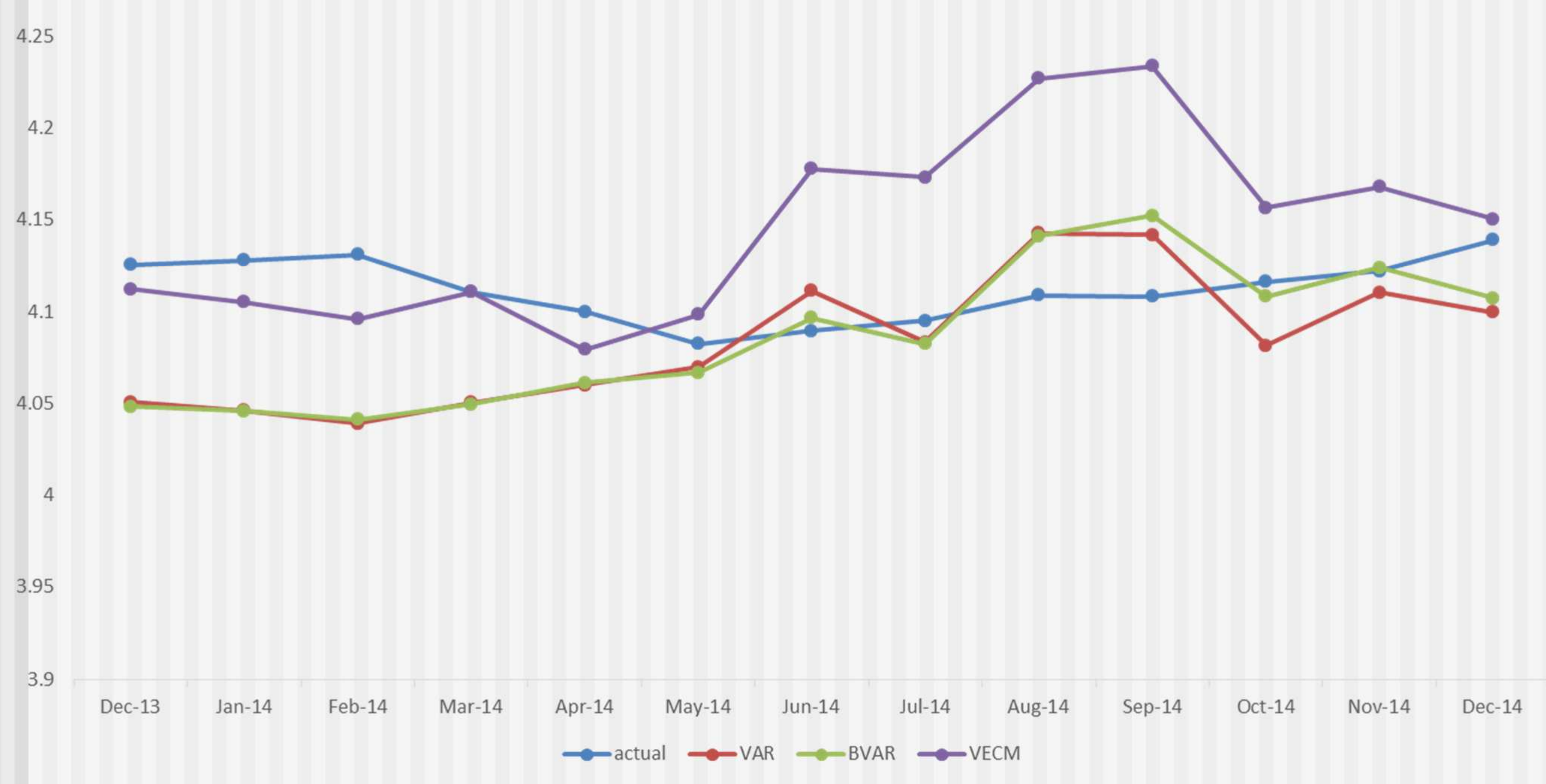
Six step ahead VECM,VAR and BVAR forecasts for Model 1



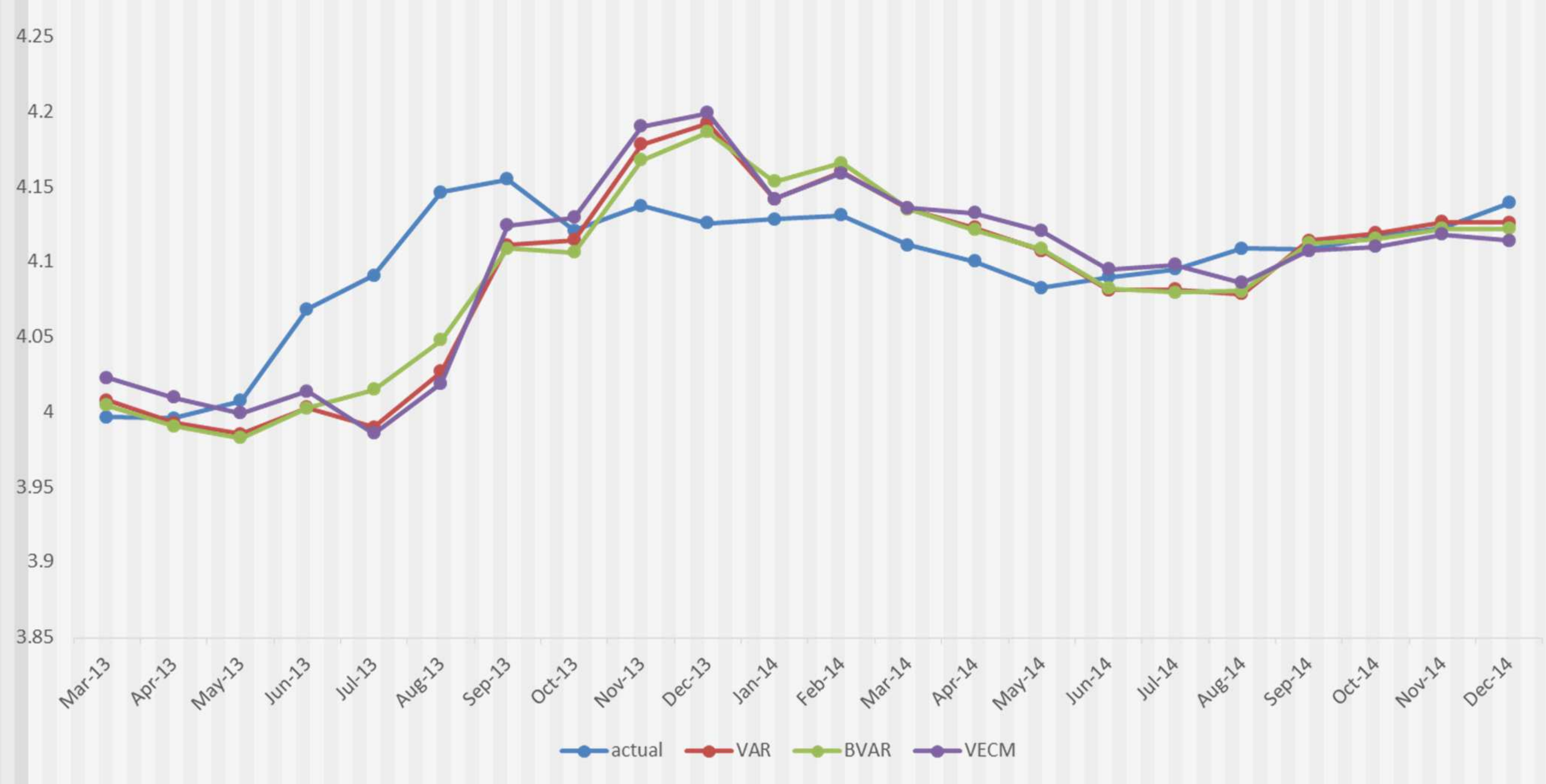
Nine step ahead VECM, VAR and BVAR forecasts for Model 1



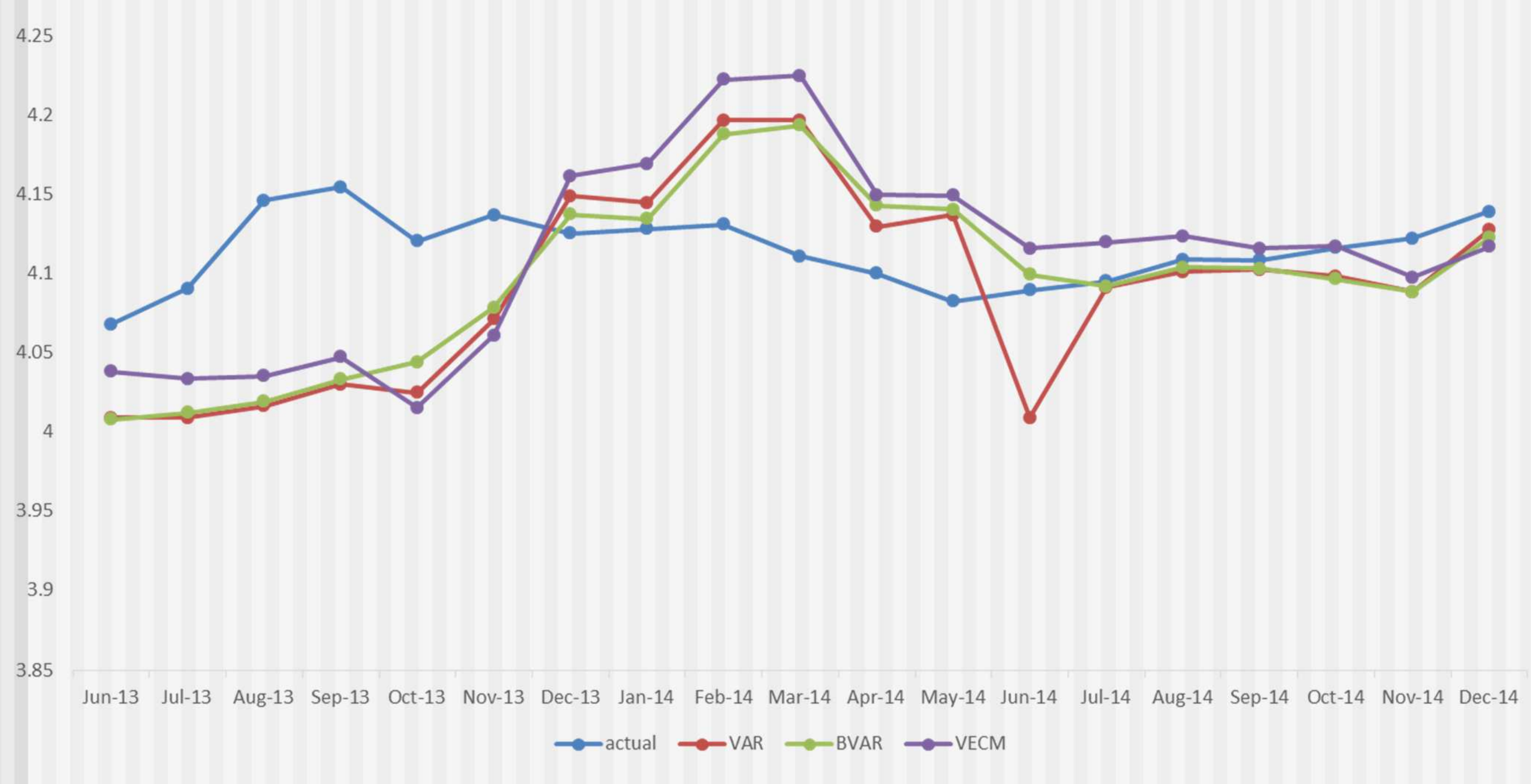
Twelve step ahead VECM, VAR and BVAR forecasts for Model 1



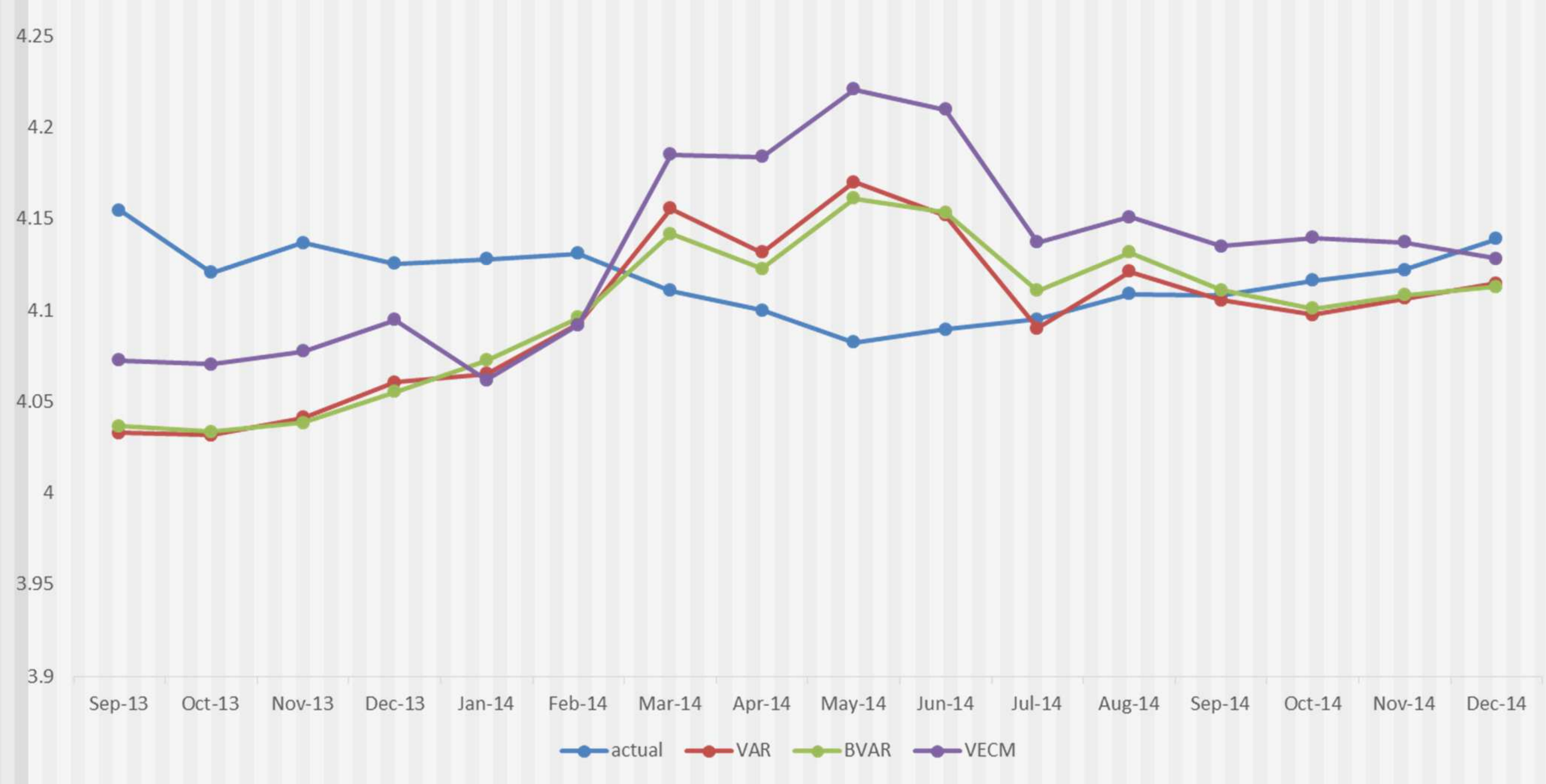
Three step ahead VECM, VAR and BVAR forecasts for Model 2



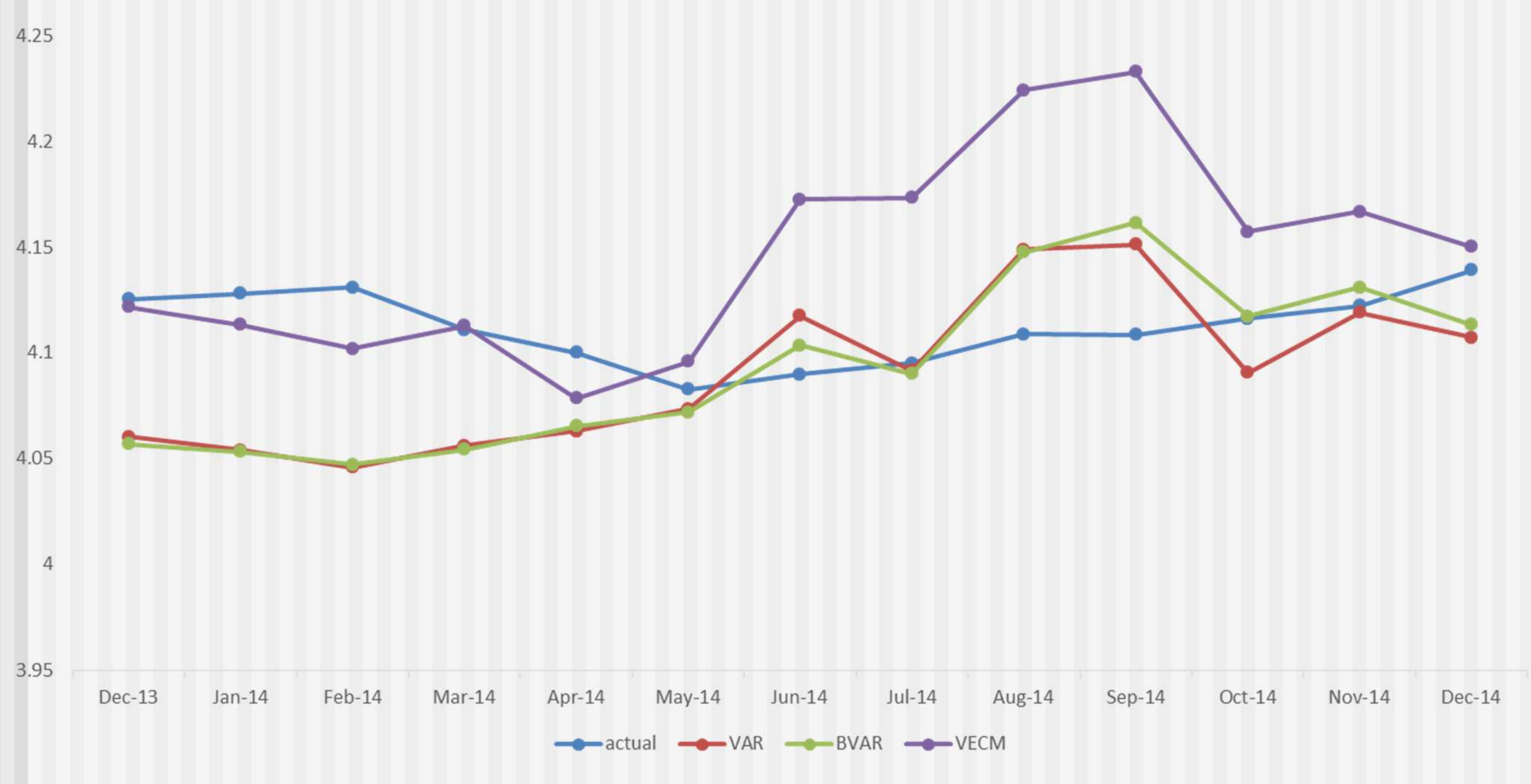
Six step ahead VECM, VAR and BVAR forecasts for Model 2



Nine step ahead VECM,VAR and BVAR forecasts for Model 2



Twelve step ahead VECM, VAR and BVAR forecasts for Model 2



Univariate Models: Forecasting Results

Univariate Models Out-of-sample Forecast Accuracy: January 2013 to December 2014															
		RMSE								Theil's U					
		Naïve model	3-mth av		GARCH 3 mth. Av.	Univariate BVAR	3-mth av	Univariate OLS	3-mth av	GARCH	3 mth. Av.	Univariate BVAR	3-mth av	Univariate OLS	3-mth a
1	24	.021		.0204		.0209		.0217		.961		.9984		1.037	
2	23	.035		.0319		.0351		.0358		.919		1.021		1.042	
3	**22**	**.048**	**.035**	**.0446**	**.032**	**.0495**	**.0352**	**.0497**	**.0358**	**.936**	**.939**	**1.046**	**1.02**	**1.051**	**1.043**
4	21	.06		.0578		.0641		.065		.966		1.073		1.093	
5	20	.069		.0661		.0744		.0753		.961		1.094		1.106	
6	**19**	**.078**	**.069**	**.0749**	**.066**	**.0856**	**.0747**	**.0869**	**.0757**	**.964**	**.964**	**1.113**	**1.09**	**1.129**	**1.109**
7	18	.084		.0815		.0957		.0966		.966		1.129		1.141	
8	17	.089		.0851		.1038		.104		.961		1.145		1.156	
9	**16**	**.088**	**.087**	**.0851**	**.084**	**.1106**	**.1034**	**.1113**	**.1043**	**.962**	**.963**	**1.162**	**1.14**	**1.17**	**1.155**
10	15	.086		.0821		.1118		.1126		.958		1.188		1.197	
11	14	.085		.0811		.1109		.1125		.948		1.221		1.238	
12	**13**	**.074**	**.082**	**.0772**	**.080**	**.1131**	**.1111**	**.1147**	**.1133**	**.934**	**.947**	**1.249**	**1.21**	**1.266**	**1.234**
Average		**.068**		**.0656**		**.0352**		**.0822**		**.953**		**1.121**		**1.136**	

VECM Models : Forecasting results

V ECM Models
Out-of-sample Forecast Accuracy: January 2013 to December 2014

Months ahead	No of .Obs	RMSE: Naive	3-mth avg	RMSE: Model 1	3-mth avg	RMSE: Model 2	3-mth avg	Theil U2: Model 1	3-mth avg	Theil U2: Model 2	3-mth avg
1	24	.021		.0192		.019		.903		.894	
2	23	.035		.0321		.0325		.927		.937	
3	**22**	**.048**	**.035**	**.0449**	**.0321**	**.0455**	**.0323**	**.94**	**.924**	**.957**	**.929**
4	21	.060		.0562		.0566		.94		.947	
5	20	.069		.0606		.0601		.882		.885	
6	**19**	**.078**	**.069**	**.0649**	**.0605**	**.0644**	**.0603**	**.835**	**.885**	**.828**	**.887**
7	18	.084		.0682		.0672		.809		.796	
8	17	.089		.0695		.068		.784		.767	
9	**16**	**.088**	**.087**	**.0682**	**.0686**	**.066**	**.0671**	**.771**		**.752**	**.772**
10	15	.086		.0646		.0631		.755	.788	.737	
11	14	.085		.0629		.0611		.737		.716	
12	**13**	**.074**	**.082**	**.0621**	**.0632**	**.0603**		**.751**	**.747**	**.730**	**.728**
Average		**.068**		**.056**		**.055**		**.836**		**.829**	

VAR Models : Forecasting Results

VAR Models
Out-of-sample Forecast Accuracy: January 2013 to December 2014

Months ahead	No of .Obs	RMSE						Theil U2			
		Naïve Model 3-mth avg		Model 1 3-mth avg		Model 2 3-mth avg		Model 1 3-mth avg		Model 2 3-mth avg	
1	24	.021		.019		.019		.898		.890	
2	23	.035		.032		.032		.911		.911	
3	**22**	**.048**	**.035**	**.043**	**.031**	**.044**	**.031**	**.912**	**.907**	**.914**	**.905**
4	21	.060		.053		.053		.892		.892	
5	20	.069		.058		.058		.844		.841	
6	**19**	**.078**	**.069**	**.063**	**.058**	**.062**	**.058**	**.814**	**.850**	**.803**	**.846**
7	18	.084		.066		.065		.782		.767	
8	17	.089		.066		.064		.744		.726	
9	**16**	**.088**	**.087**	**.062**	**.065**	**.06**	**.063**	**.696**	**.741**	**.677**	**.724**
10	15	.086		.055		.053		.640		.616	
11	14	.085		.053		.05		.615		.581	
12	**13**	**.074**	**.082**	**.05**	**.052**	**.046**	**.049**	**.599**	**.618**	**.554**	**.585**
Average		**.068**		**.052**		**.05**		**.779**		**.765**	

BVAR Models Forecasting Results

BVAR Models
Out-of-sample Forecast Accuracy: January 2013 to December 2014

Months ahead	No of .Obs	RMSE Naive	RMSE Naive 3-mth avg	RMSE Model 1	RMSE Model 1 3-mth avg	RMSE Model 2	RMSE Model 2 3-mth avg	Theil U2 Model 1	Theil U2 Model 1 3-mth avg	Theil U2 Model 2	Theil U2 Model 2 3-mth avg
1	24	.021		.018		.018		.844		.832	
2	23	.035		.028		.028		.820		.817	
3	**22**	**.048**	**.035**	**.038**	**.028**	**.038**	**.028**	**.806**	**.823**	**.804**	**.818**
4	21	.060		.048		.047		.797		.794	
5	20	.069		.054		.053		.781		.776	
6	**19**	**.078**	**.069**	**.060**	**.054**	**.060**	**.053**	**.775**	**.784**	**.766**	**.779**
7	18	.084		.063		.062		.751		.740	
8	17	.089		.064		.062		.718		.705	
9	**16**	**.088**	**.087**	**.059**	**.062**	**.058**	**.061**	**.671**	**.713**	**.657**	**.701**
10	15	.086		.053		.052		.620		.603	
11	14	.085		.051		.049		.602		.578	
12	**13**	**.074**	**.082**	**.048**	**.051**	**..046**	**.049**	**.585**	**.602**	**.553**	**.578**
Average		**.068**		**.049**		**.048**		**.731**		**.719**	

THANK YOU !