ASECU South-Eastern Europe Journal of Economics 1 (2015) 85-100 SEEJE

NOWCASTING GDP IN GREECE: A NOTE ON FORECASTING IMPROVEMENTS FROM THE USE OF BRIDGE MODELS

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Abstract
In the recent literature on nowcasting, the use of the so-called bridge models is advocated. These are simple regression models that use data on mixed frequencies, usually with the lower frequency data serving as dependent variables and the higher frequency data as explanatory variables. In this note we investigate whether the use of such models can lead to performance enhancements in forecasting real GDP growth for Greece. This is an interesting and instructive exercise because of the obvious break in Greek real GDP growth during the crisis but also, and more importantly, because of the potential usefulness of such models in forecasting the anticipated recovery in Greek growth. Since many monthly activity indicators are released in advance of GDP growth it is interesting to see how the structure and timing of bridge models can lead to potential improvements in forecasting growth. Our results indicate that by using three of the most important monthly activity indicators such performance enhancements are indeed possible.

JEL Classification: C52, C53, E01, E27
Key words: bridge models, nowcasting, GDP, Greece, growth

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1. Introduction

Decision-makers in different parts of the economy such as business, government, the central bank, financial markets and others, are in need of an accurate and timely assessment of economic growth. The main problem is that since most macroeconomic series of interest are only available at a quarterly frequency and are released three to six weeks after the close of the quarter, many institutions are faced with the problem of using monthly information in order to obtain an early estimate of the last quarter and the current quarter results, as well as a forecast for one quarter ahead.

The aim of this paper is to attempt a nowcasting exercise for the Greek real growth rate by exploiting the particular structure of data on the Greek economy and their release. What makes our exercise particularly interesting is the problems of the data themselves and the importance of growth assessments and forecasts in the context of the deep fiscal crisis faced by the Greek government and productive sectors.

Nowcasting is a relatively new method whose main advantage is the use of new information as it comes in, and the generation of updates at a higher frequency than the frequency of observation of the variable of interest. Until recently, nowcasting had received very little attention in the academic literature, although it was routinely conducted in policy institutions either through a judgmental process or on the basis of simple models. It was first introduced by Evans (2005) for a limited number of time series and evolved by Giannone, Reichlin, and Small (2008) for a larger number of series. In recent years, there have been many applications of this method for several countries and variables thus enhancing and expanding this methodology, such as Antonello *et al*. (2008) for Ireland.

In order to have better forecasts, factor models have proved to be a very useful tool for short-term forecasting of real activity. The use of dynamic factor models has been further improved by recent advances in estimation techniques proposed by Stock and Watson (2002a, 2002b), Forni *et al*. (2004, 2005) or Giannone, Reichlin, and Small (2008), who have put forward the advances in estimation techniques that allow improving their efficiency. This type of model is particularly appealing as it can be applied to large data sets [e.g., Angelini, Camba-Mendez, Giannone, Reichlin, & Rünstler (2011); Barhoumi, Darné, & Ferrara (2010); Schumacher & Breitung (2008); Schumacher (2007)].

The DFMs are based on static and dynamic principal components. The static principal components are obtained as in Stock and Watson (2002a, 2002b). The dynamic principal components are based on either time domain methods, as in Doz, Giannone and Reichlin (2011, 2012), or frequency domain methods, as in Forni *et al*.

(2004, 2005). To the best of our knowledge, Banerjee, Marcellino, and Masten (2005), Banerjee and Marcellino (2006), Antipa *et al*. (2012) are the only studies that compare the forecasting performance of the automatically selected BMs and the DFMs – for Eurozone, US and German GDP growth, respectively. These studies, however, only use factor models following Stock and Watson (2002a, 2002b), for which results are not conclusive in favor of one or the other. DFMs have so far never been used for forecasting Greek GDP growth rates. While the econometric performance of DFMs is very satisfactory, an important caveat of this approach is that the economic content of factors is difficult to interpret from an economic point of view. For that reason we complete this analysis by several bridge models which allow for a more straightforward interpretation of the data used.

An alternative approach to the analysis of time series with mixed frequencies is the mixed data sampling regression (MIDAS) method proposed by Ghysels, Santa-Clara, and Valkanov (2006). The MIDAS method provides linear projections without specifying the dynamics of the regressors. When the model is specified correctly and the parameters are known, the Kalman filter is superior to MIDAS by construction. Otherwise, the question of whether MIDAS or the state space method is superior is still under investigation; see the study of Bai, Ghysels, and Wright (2011), who consider both MIDAS and state space methods. They show the conditions under which the methods are identical and provide evidence that the Kalman filter is slightly more accurate.

The rest of the paper is organized as follows. In section 2 we give a brief summary of the bridge models. In section 3 we discuss the results of our forecasting analysis and section 4 offers some concluding remarks for future research.

2. The bridge model & data, estimation and forecasting

Bridge models are essentially mixed frequency linear regressions. These models "bridge", i.e. link, monthly variables to quarterly ones − hence their name. In this sense they are unrestricted versions of the MIDAS approach (Ghysels, Santa-Clara, and Valkanov (2006)). Such models have been widely considered in the recent literature, and are especially used to forecast GDP growth in national and international institutions (e.g. Diron, 2008; Golinelli & Parigi, 2005; Parigi & Schlitzer, 1995; Rünstler & Sédillot, 2003; Sédillot & Pain, 2003; Zheng & Rossiter, 2006).

To make things specific, let us consider monthly and quarterly variables in the context of our data. The explanatory variables will be monthly economic activity indicators, namely the index of industrial production (IPI), the total turnover of retail sales (RSTOT) and the volume of retail sales (RSVOL). All variables are from seasonally adjusted indices and expressed in real terms as annual growth rates. The dependent variable is obtained from the, seasonally adjusted, quarterly real GDP series and also expressed as annual growth rate. All variables are obtained from the Greek Statistical Authority website (www.statistics.gr) (Table 1). Data availability is from 2001 for real GDP and this dictates the rest of our analysis: we split the data into a training period up to 2007 and use the post-crisis data as our evaluation period.

Table 1. Data series used in our analysis

Data series	Full-sample period	Data collection period/reporting frequency	Number of observations with reporting lag of 1 month or quarter	Number of observations with reporting lag of 2 months
GDP	1 Q 2001-4Q 2013	Quarterly	52	
Industrial production index	Mar 2001-Dec 2013	Monhtly	106	
Volume of Retail Sales	Mar 2001-Dec 2013	Monhtly		106
Total Turnover of Retail Sales	Mar 2001-Dec 2013	Monhtly		106

Source: ELSTAT

The Real GDP Growth rate varies from -0,0894 at the third quarter of 2010, which is the trough, to the peak 0,0754 at the second quarter of 2006. The variable which is most correlated with the GDP is the Volume of Retail Sales of the previous month of examination, followed by the Total Turnover of Retail Sales of the previ-ous month of examination. As can be seen in Table 2 there is a negative skewness between the variables and the values are wider spread around the mean.

Table 2. Summary of statistics

	Average	Std. Dev.	Min	Max	Skewness	Kurtosis	ACF(1)	ACF(2)	Correlation with GDP
Real GDP Growth	0,0024	0,0490	-0,0894	0,0754	-0,4102	1,7875	0,9199	0,8664	1
IPI (0)	-0,0249	0,0470	-0,1312	0,0748	-0,3578	2,5577	0,4260	0,4724	0,5804
IPI (-1)	-0,0273	0,0401	-0,1183	0,0513	-0,2611	2,3279	0,5382	0,4874	0,6085
IPI (-2)	-0,0256	0,0482	-0,1403	0,0654	-0,4734	2,6163	0,4734	0,5342	0,6301
RSTOT (0)	0,0174	0,0941	-0,1791	0,1813	-0,4599	1,9496	0,8105	0,6013	0,8388
RSTOT (-1)	0,0212	0,0838	-0,1627	0,1317	-0,5707	1,9758	0,8189	0,7412	0,8663
RSTOT (-2)	0,0165	0,0931	-0,1702	0,1580	-0,5672	2,0213	0,7360	0,6443	0,7829
RSVOL (0)	-0,0082	0,0848	-0,1900	0,1359	-0,5483	2,2405	0,8335	0,6148	0,8617
RSVOL (-1)	-0,0062	0,0773	-0,1635	0,0952	-0,5385	1,8410	0,7867	0,7361	0,8789
RSVOL (-2)	-0,0115	0,0854	-0,1755	0,1230	-0,4754	1,8701	0,7075	0,6337	0,8175

The variables (0),(-1)(-2) refer to the growth rates of the current month, the previous and two months back, respectively.

The estimation is conducted recursively to fully utilize the relatively small amount of observations available.

The general specification of a bridge model is that of an autoregressive-distributed-lag (ARDL) for q explanatory variables and is given as follows:

$$Y_t = a + \sum_{i=1}^{m} \beta_i Y_{t-i} + \sum_{j=1}^{q} \sum_{i=1}^{k} \delta_{j,i} X_{j,t-1} + \varepsilon_t$$

where m is the number of autoregressive parameters, q is the number of explanatory variables, and k is the number of lags for the explanatory variables. Note that under the restriction that now monthly variables appear above, we see that the equation collapses to a standard autoregression – which thus becomes the natural benchmark to compare forecasting performance. In our analysis we consider models that use each monthly variable, a pair of monthly variables and all three monthly variables together. These models are benchmarked against an AR(1) model and an AR(AIC) model, with maximum lags set to 6.

An important point we should make is that we use our data aligned correctly and taking account of release lags. This is important for making the exercise realistic. For example, we always use a two-month lag on the aligned monthly data: if we are at the end of the 4th quarter we use monthly data for October. So, if the real GDP for the 4th quarter is released, for example, in mid-February and the monthly variable is released in November or December we always use past data correctly in producing the forecasts.

Finally, to evaluate our forecasting results we use the standard measures of mean forecasting error, mean squared error and mean absolute error.

3. Forecasting results

Results in terms of mean error (ME), mean absolute error (MAE), mean-squared error (MSE) and root mean-squared error (RMSE) of the forecasts, as presented in Table 1 as well as the ratio obtained from AR(1) (Ratio1) and AR(AIC) (Ratio 2) benchmarks show that the combination of the IPI, the RSVOL and the RSTOT performed better than the benchmarks. Both Ratio 1 and Ratio 2 showed that almost all models −except for the IPI− perform better than the benchmarks. (Table 2)

Table 3. ME, MAE, MSE, RMSE for the forecast for the period 2008Q3-2013Q4

Model	**AR(1)**	**AR(AIC)**	**RSVOL**	**RSTOT**	**IPI**	**RSVOL & IPI**	**RSTOT & IPI**	**ALL 3**
ME	-0,008	-0,001	-0,003	-0,004	-0,010	-0,005	-0,007	-0,007
MAE	0,018	0,019	0,017	0,018	0,018	0,016	0,017	0,015
MSE	0,001	0,001	0,000	0,000	0,001	0,000	0,000	0,000
RMSE	0,023	0,023	0,021	0,022	0,023	0,020	0,022	0,019
Ratio 1	1,000	1,006	1,085	1,030	0,993	1,117	1,049	1,192
Ratio 2	0,994	1,000	1,079	1,024	0,987	1,111	1,044	1,185

Ratio1 and Ratio2 are computed as the ratios between each RMSE with that obtained from the AR(1) and AR(AIC) models, respectively.

Obviously, simply comparing error-values does not take into account the sample uncertainty underlying observed forecast differences. This is why we also applied the test of equality of forecast performance proposed by Diebold and Mariano (1995). Table 4 includes the results of Diebold–Mariano tests for equality of mean squared errors of each pair of forecasts for each individual series for the reported horizons. As can be seen the results are not as accurate as we would have expected, owing to the small amount of observations. The combination of the three models appears to have the best results over the AR(1) model but to have an accurate result we will surely need another test.

Table 4. Diebold-Mariano tests of the forecast accuracies of different methods with the benchmark AR(1) and AR(AIC)

Model	RSVOL	RSTOT	IPI	RSVOL & IPI	RSTOT & IPI	ALL 3
Benchmark the AR(1)	1,11	0,56	-0,07	1,11	0,43	1,36
Benchmark the AR(AIC)	0,76	0,26	-0,08	0,74	0,27	1,23

4. Concluding remarks

In the preceding analysis we have presented the use of bridge models in order to nowcast the GDP growth rate of Greece. We found that it is possible to get reasonably good estimates of current quarterly GDP growth in anticipation of the official release. Our results showed that changing the BM's equations by including newly available monthly information provides generally more precise forecasts and is preferable to maintaining the same equation over the exercise's horizon.

Comparing the BMs with DFMs and the MIDAS approach is in our research agenda. Moreover, it would be very interesting to expand the number of explanatory variables to include other economic activity indicators, experiment with different lags of the explanatory variables and, more importantly, with the timing of the monthly releases before the GDP quarterly release. Our goal is to produce –from now on– forecasts of the Greek GDP and examine their real time performance.

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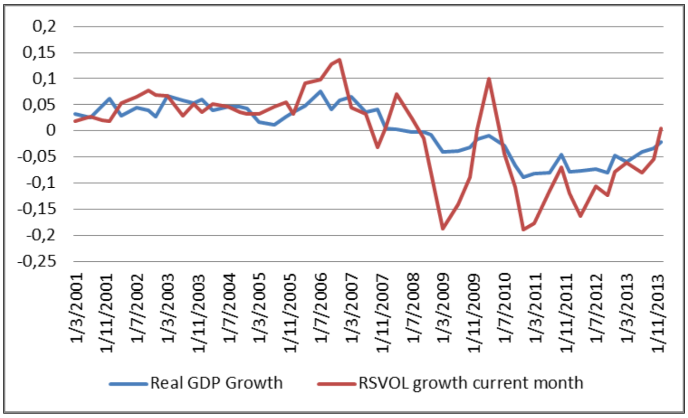
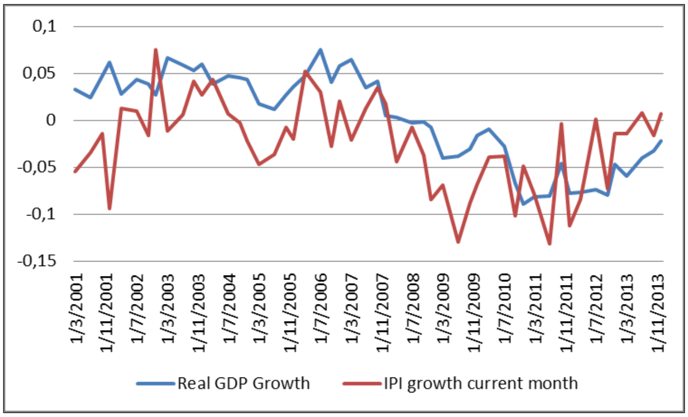
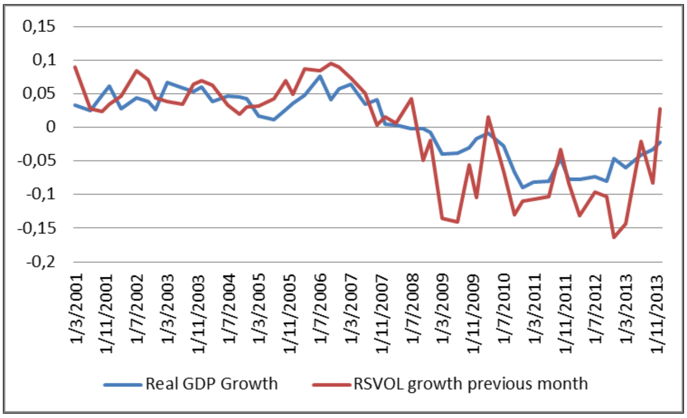
Appendix A.

Graphs of each time series in comparison with the Real GDP Growth.



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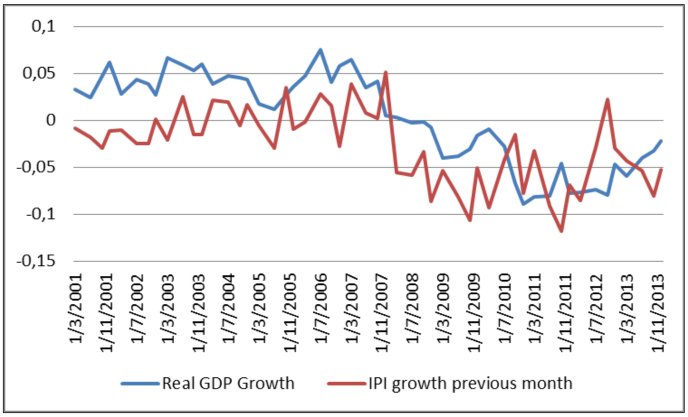
Real GDP Growth
RSVOL growth previous month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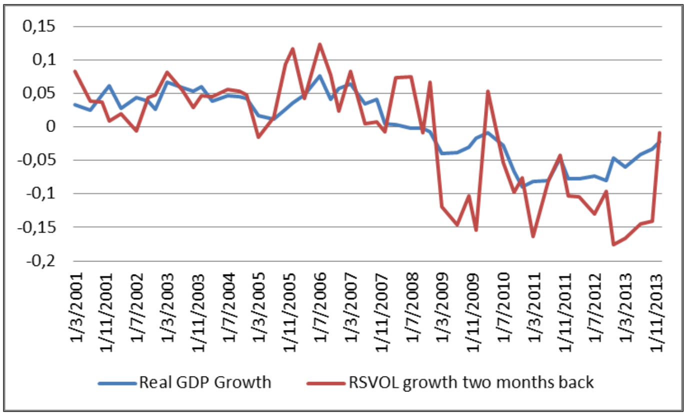
Real GDP Growth
IPI growth previous month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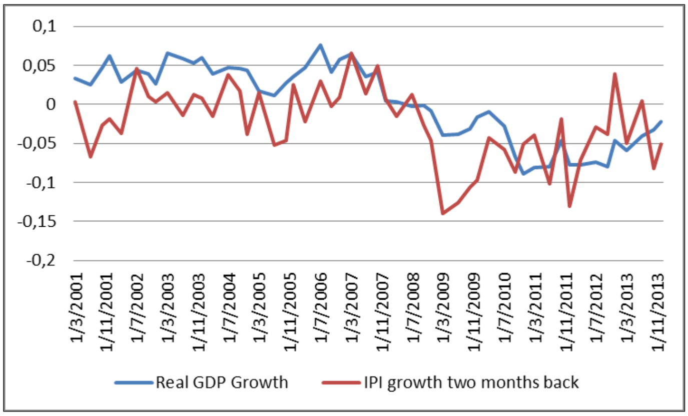
Real GDP Growth
RSVOL growth two months back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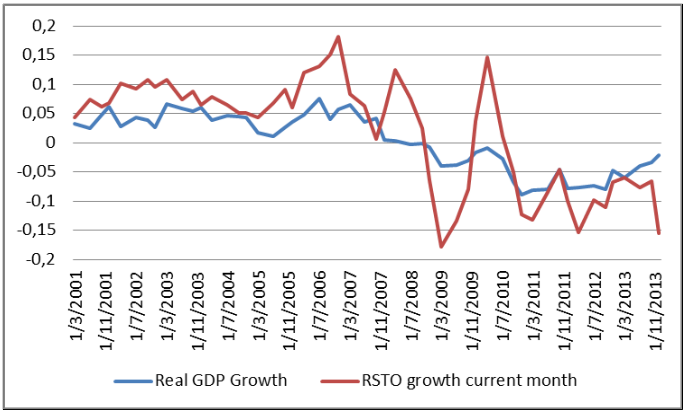
Real GDP Growth
IPI growth two months back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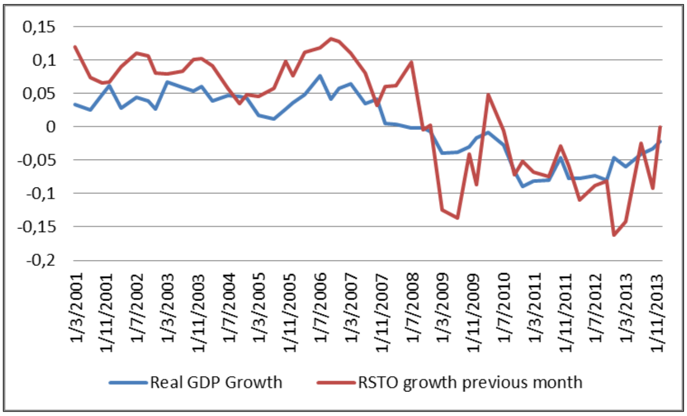
Real GDP Growth
RSTO growth current month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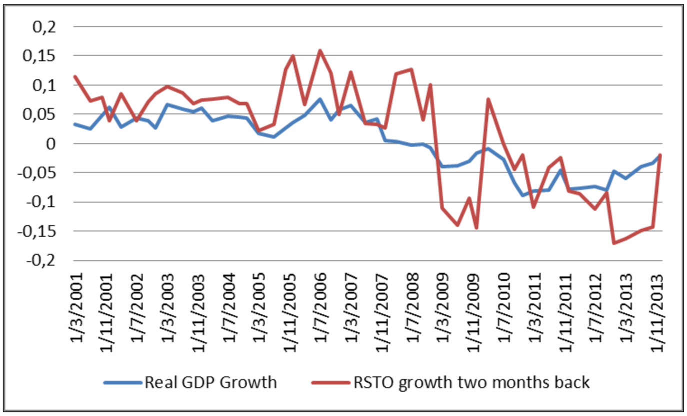
Real GDP Growth
RSTO growth previous month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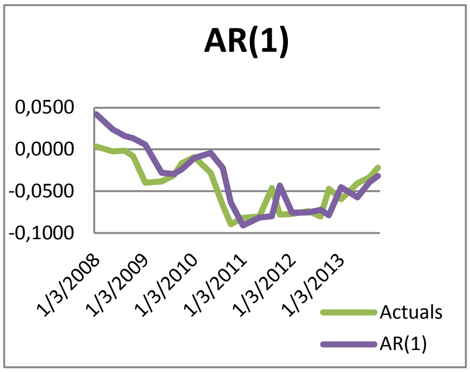
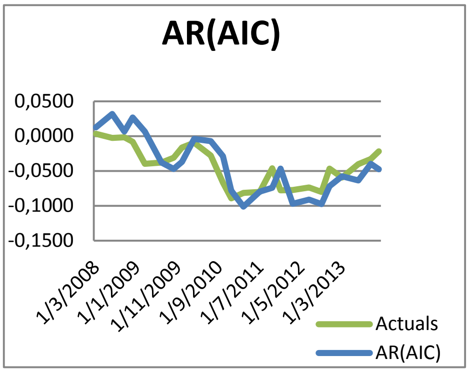
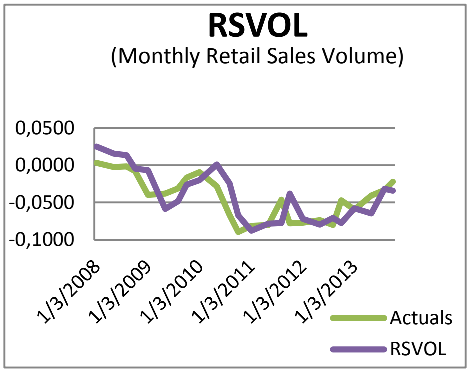
Real GDP Growth
RSTO growth two months back

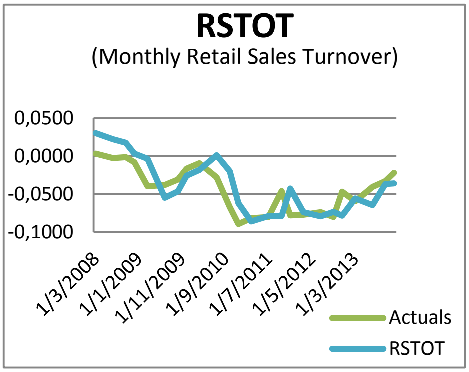
Appendix B.

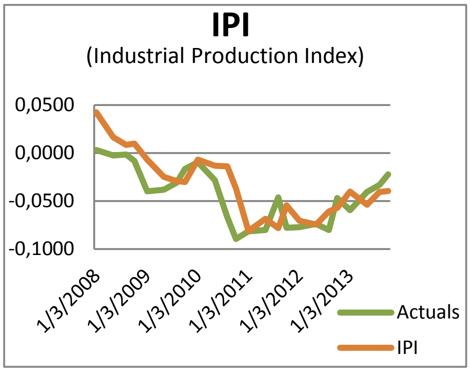
Graphs of each forecast series of each model along with actual values.

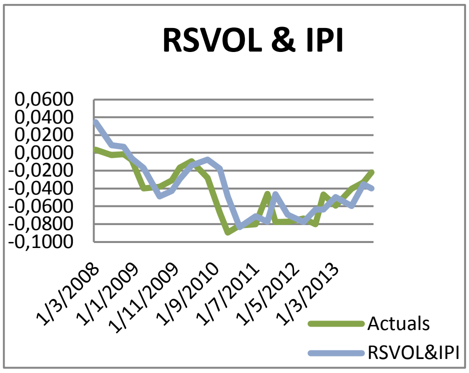


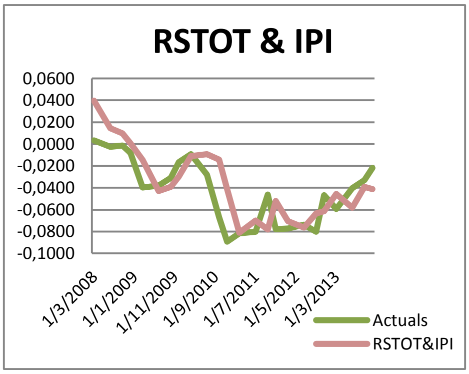








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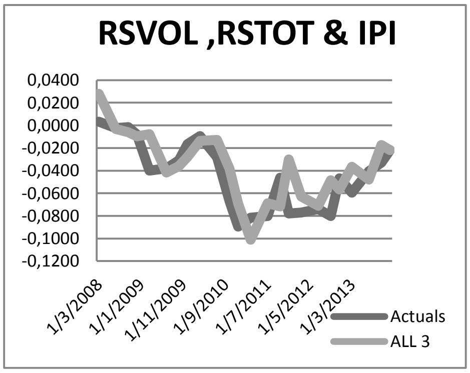
Actuals
RSTOT&IPI


RSVOL ,RSTOT & IPI
0,0400
0,0200
0,0000
-0,0200
-0,0400
-0,0600
-0,0800
-0,1000
-0,1200
1/3/2008
1/1/2009
1/11/2009
1/9/2010
1/7/2011
1/5/2012
1/3/2013
Actuals
ALL 3