Is forecasting inflation easier under inflation targeting?

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Abstract

This paper investigates whether monetary policy regime changes affect the success of forecasting inflation. The forecasting performance of some linear and nonlinear univariate models are analyzed for 14 different countries that have adopted inflation-targeting (IT) monetary regimes at some point in their economic history. The results show that forecasting performance is generally superior under an IT monetary regime compared to NIT periods. In more than half of the countries covered in this study, superior forecasting accuracy can be achieved in IT periods regardless of the model used. In contrast, among most of the remaining countries, the results remain ambiguous, and the evidence on the superiority of NIT is limited to very few countries.

Keywords: Inflation targeting, forecasting inflation, forecast accuracy

JEL classification: C45, C53, E31, E37, E42, E47, E52, E61, E65

1 Introduction

Inflation targeting (IT) has been adopted by several industrialized and emerging market economies, and it appears to have been successful in terms of stabilizing both inflation and the real economy (Svensson, 2010). IT is a monetary-policy strategy that is characterized by (1) an announced numerical inflation target, (2) a particular implementation of a monetary policy that has been called forecast targeting and to a considerable extent relies on an inflation forecast, and (3) a high degree of transparency and accountability. Hence, forecasting inflation constitutes an important part of this monetary-policy strategy and directly influences its ultimate success[1].

Despite its importance, to the best of our knowledge, no study has analyzed the relative performance of inflation forecasts in IT periods compared to non-IT (NIT) periods, i.e., periods in which an alternative monetary policy regime has been implemented. In this study, we fill this gap by systematically analyzing the predictive performance of several time-series models for a group of countries in the IT and NIT periods of their economic

[1] In addition to the special role given to IT, the prominence of inflation forecasting has been raised by the recent formalization of the New Keynesian optimal policy. The New Keynesian model has been used to demonstrate that the optimal choice of policy will depend on the optimal forecasts (see Svensson, 2005; Faust and Wright, 2012).

history. In general, the empirical evidence that is presented in this paper supports the notion that IT provides a more suitable environment in which to forecast inflation.

The performance of inflation forecasting in different time periods has already been analyzed for the US. The evidence that has been gleaned from US data suggests that the success of inflation predictions seems to differ in the different monetary-policy regimes that have been implemented in different periods of time. In some periods, US inflation appears to be more predictable in this sense: the forecasts that are generated by multivariate models are more accurate than the forecasts that are based on simple "naïve" models, such as random walk. Whereas virtually no model seems to improve upon the "naïve" models in other periods (see Stock and Watson, 2007, 2009; Rossi and Sekhposyan, 2010; D'Agostino et al., 2006, 2011), a recent paper D'Agostino and Surico (2012) provides evidence that a policy regime that successfully stabilizes inflation in the US makes it harder to improve upon those forecasts that are based on "naïve" models.

Indeed, the US has not yet adopted all of the explicit characteristics IT, and although America seems to be taking steps in that direction, it can be classified as a non-targeter country. Therefore, the time periods considered in the above studies do not match the division that we use in this study. In contrast, this strand of literature methodologically focuses on the effect of a period of time on the forecasting performance of time-series models that are measured relative to a "naïve model" such as random walk. However, in this paper, we use a class of linear and nonlinear time-series models and focus on the effect of a period of time on the forecasting performance of each of these models. We conclude that an IT period increases the likelihood of "correct" forecasts.

Since its inception in the early 1990s in New Zealand, Canada, the U.K., and Sweden, the success of IT has been questioned. Ball and Sheridan (2004) showed that the available evidence for a group of developed economies does not lend credence to the belief that adopting an inflation-targeting regime (IT) was instrumental in reducing inflation and inflation volatility. Lin and Ye (2007) showed that inflation targeting has no significant effects on either inflation or inflation variability in seven industrial countries. In contrast, Gonçalves and Salles (2008) extended Ball and Sheridan's analysis to emerging market economies, and they found that compared to non-targeters, developing countries that adopted the IT regime experienced greater declines not only in inflation but also in growth volatility. Recently, the findings of de Mendonça and de Guimarães e Souza (2012) suggested that although IT is successful in developing economies in terms of both reducing inflation volatility and driving inflation down to internationally acceptable levels, the adoption of IT does not appear to represent an advantageous strategy in advanced economies. These findings are consistent with the previous literature[2].

For the group of countries considered in this paper, IT seems to be successful in terms of reducing and stabilizing inflation, which is suggested by the descriptive statistics presented in the following section. Hence, our evidence can also be interpreted in the following manner: any policy regime that successfully stabilizes inflation (i.e., an IT

[2] See Brito and Bystedt (2010) for a counter argument that claims that there is no evidence that an inflation-targeting regime (IT) improves economic performance, as measured by the behavior of inflation and output growth in developing countries.

policy regime) makes inflation easier to forecast[3].

The rest of the paper is organized as follows: the following section describes the data and forecasting models and discusses the methodology used to compare the accuracy of the forecasts that are made with these models in IT and NIT regimes. Section 3 illustrates the results, and section 4 concludes.

2 Data and Forecasting Models

To compare forecasting performance of the time series models, presented below, we use consumer price index (CPI) inflation data obtained from International Financial Statistics for 14 countries. The time span of the inflation data, the adoption date of IT, mean and coefficient of variation of inflation regarding IT and NIT periods for each countries are displayed in Table 1 below.

Table 1: *Inflation in countries under IT and NIT regimes*

Country	NIT period	IT period	μ_{NIT}	μ_{IT}	CV_{NIT}	CV_{IT}
Canada	1957M02 - 1991M01	1991M02 - 2010M01	0.004	0.002	1.0000	2.0000
Chile	1973M02 - 1989M12	1990M01 - 2010M01	0.039	0.006	2.2564	1.1667
Colombia	1957M02 - 1999M12	2000M01 - 2010M01	0.014	0.005	1.4286	1.0000
Hungary	1976M02 - 2000M12	2001M01 - 2010M01	0.011	0.004	1.2727	1.5000
Israel	1975M05 - 1991M12	1992M01 - 2010M01	0.042	0.004	1.8333	1.5000
S. Korea	1970M02 - 1999M12	2000M01 - 2010M01	0.008	0.003	1.1250	1.6667
Mexico	1980M01 - 1998M12	2000M01 - 2010M01	0.018	0.005	2.5556	0.8000
Norway	1957M02 - 2001M02	2001M03 - 2010M01	0.004	0.002	1.5000	2.5000
Poland	1988M02 - 1997M12	1998M01 - 2010M01	0.047	0.003	1.6809	1.6667
S. Africa	1957M02 - 1999M12	2000M01 - 2010M01	0.007	0.005	1.0000	1.2000
Sweden	1957M02 - 1992M12	1993M01 - 2010M01	0.005	0.001	1.2000	4.0000
Thailand	1965M02 - 1999M12	2000M01 - 2010M01	0.005	0.002	1.4000	3.0000
Turkey	1983M03 - 2000M12	2001M01 - 2010M01	0.038	0.014	1.7368	1.1429
UK	1957M02 - 1991M12	1992M01 - 2010M01	0.006	0.002	1.1667	2.0000

Note: Inflation is computed using the log-difference of the CPI index; μ and CV refer to the mean and coefficient of variation, respectively, for the IT and NIT periods.

As can be observed in the table, the mean of inflation in IT regimes is lower than the same mean in NIT regimes for all 14 of the countries that are examined. However, the results for volatility as measured by CVs are ambiguous, and as a result, it is not possible to assert that IT is successful in reducing volatility[4]. We use seasonally adjusted data to estimate time-series models. Seasonal adjustment is performed by the X12-ARIMA filtering methodology of the U.S. Census Bureau. Therefore, we forecast seasonally adjusted

[3] This interpretation is not directly in contrast with D'Agostino and Surico's results, which are mentioned above. These results provide evidence that a policy regime that successfully stabilizes inflation in the US makes it harder to improve upon the forecasts that are based on "naïve" models. However, the evidence that we provide here can be interpreted thusly: a policy regime that successfully stabilizes inflation (i.e., an IT regime) makes it easier to forecast inflation irrespective of the underlying model that is used for forecasting.

[4] The effect of IT regimes on inflation volatility will be studied in future research.

inflation figures, and to evaluate their success, we first "deseasonalize" them using the estimated additive seasonal adjustment factors of X12-ARIMA. Then, we compare these forecasts with the actual figures.

In our out-of-sample forecasting exercise, we concentrate exclusively on univariate models, and we consider three types of linear univariate models and four types of nonlinear univariate models. The linear models are random walk (RW), autoregressive (AR), and autoregressive moving-average (ARMA) models; the nonlinear ones are logistic smooth transition autoregressive (LSTAR), self-exciting threshold autoregressive (SETAR), markov-switching autoregressive (MS-AR), and autoregressive neural networks (ARNN) models.

Let $\hat{y}_{t+h|t}$ be the forecast of y_t that is generated at time t for the time $t+h$ $(h \geq 1)$ by any forecasting model. In the RW model, $\hat{y}_{t+h|t}$ is equal to the the value of y_t at time t.

The ARMA model is

$$y_t = \alpha + \sum_{i=1}^{p} \phi_{1,i} y_{t-i} + \sum_{i=1}^{q} \phi_{2,i} \varepsilon_{t-i} + \varepsilon_t. \tag{1}$$

Where p and q are selected to minimize Akaike Information Criterion (AIC) and with a maximum lag of 24. After estimating the parameters of equation (1) one can easily produce h-step $(h \geq 1)$ forecasts by the following recursive equation:

$$\hat{y}_{t+h|t} = \alpha + \sum_{i=1}^{p} \hat{\phi}_{1,i} y_{t+h-i} + \sum_{i=1}^{q} \hat{\phi}_{2,i} \varepsilon_{t+h-i} \,. \tag{2}$$

When $h > 1$, to obtain forecasts we iterate on a one-period forecasting model, by feeding the previous period forecasts as regressors into the model. That means when $h > p$ and $h > q$, $y_{t+h-i|t}$ is replaced by $\hat{y}_{t+h-i|t}$ and ε_{t+h-i} by $\hat{\varepsilon}_{t+h-i|t} = 0$. An obvious alternative to iterating forward on a single-period model would be to tailor the forecasting model directly to the forecast horizon, i.e., estimate the following equation by using the data up to t.

$$y_t = \alpha + \sum_{i=0}^{p} \phi_{1,i} y_{t-i-h} + \sum_{i=0}^{q} \phi_{2,i} \varepsilon_{t-i-h} + \varepsilon_t, \tag{3}$$

for $h \geq 1$. We use the fitted values of this regression to directly produce h-step ahead forecast [5].

Because it is a special case of ARMA, the estimation and forecasts of the AR model can be obtained by simply setting $q = 0$ in (1) and (3).

[5] Deciding whether the direct or the iterated approach is better is an empirical matter because it involves a trade off between the estimation efficiency and the robustness-to-model misspecification; see Elliott and Timmermann (2008). Marcellino et al. (2006) address these points empirically using a dataset of 170 US monthly macroeconomic time series. They find that the iterated approach generates the lowest MSE-values, particularly if lengthy lags of the variables are included in the forecasting models and if the forecast horizon is long.

The LSTAR model is

$$y_t = \left(\alpha_1 + \sum_{i=1}^{p} \phi_{1,i}\, y_{t-i}\right) + d_t \left(\alpha_2 + \sum_{i=1}^{q} \phi_{2,i}\, y_{t-i}\right) + \varepsilon_t, \tag{4}$$

where $d_t = (1 + \exp\{-\gamma(y_{t-1} - c)\})^{-1}$. Whereas ε_t are regarded as normally distributed i.i.d. variables with zero mean, α_1, α_2, $\phi_{1,i}$, $\phi_{2,i}$, γ and c are simultaneously estimated by maximum likelihood.

In the LSTAR model, the direct forecast can be obtained in the same manner as with ARMA, which is also the case for all of the subsequent nonlinear models[6], but it is not possible to apply any iterative scheme to obtain forecasts that are multiple steps in advance, as in the linear models. This impossibility follows from the general fact that the conditional expectation of a nonlinear function is not necessarily equal to a function of that conditional expectation. In addition, one cannot iteratively derive the forecasts for the time steps $h > 1$ by plugging in the previous forecasts (see, for example, Kock and Teräsvirta, 2011)[7]. Therefore, we use the Monte Carlo integration scheme suggested by Lin and Granger (1994) to numerically calculate the conditional expectations, and we then produce the forecasts iteratively. Some computational details about the algorithmic steps of this Monte Carlo scheme are presented in Appendix.

When $|\gamma| \to \infty$ LSTAR model approaches two-regime SETAR model, which is also included in our forecasting models. Alike LSTAR and most nonlinear models, in forecasting with SETAR, it is not possible to use simple iterative scheme to generate multi period forecasts. In this case, we employ a version of the Normal Forecasting Error (NFE) method suggested by Al-Qassam and Lane (1989) to generate multistep forecasts[8]. NFE is an explicit form recursive approximation to calculate higher step forecasts under normality assumption of error terms and is shown by De Gooijer and De Bruin (1998) to perform reasonably accurate compared with numerical integration and Monte Carlo method alternatives.

The two-regime MS-AR model that we consider here is as follows:

$$y_t = \alpha_s + \sum_{i=1}^{p} \phi_{s,i} y_{t-i} + \varepsilon_t, \tag{5}$$

where s_t is a two-state discrete Markov chain with $S = \{1, 2\}$ and $\varepsilon_t \sim$ i.i.d. $N(0, \sigma^2)$. We estimate MS-AR using the maximum likelihood algorithm expectation-maximization.

Although MS-AR models may encompass complex dynamics, point forecasting is less complicated in comparison to other non-linear models. The h-step forecasts from the MS-AR model is

[6] This process involves replacing y_t with y_{t+h} on the left-hand side of equation (4) and running the regression using data up to time t to fitted values for corresponding forecasts .

[7] Indeed, d_t is convex in y_{t-1} whenever $y_{t-1} < c$ and $-d_t$ is convex whenever $y_{t-1} > c$. Therefore, by Jensen's inequality, naïve estimation underestimates d_t if $y_{t-1} < c$ and it overestimates d_t if $y_{t-1} > c$.

[8] A detailed exposition of approaches for forecasting from a SETAR model can be found in van Dijk et al. (2003)

$$
\begin{aligned}
\hat{y}_{t+h|t} &= P\left(s_{t+h}=1 \mid y_t,...,y_0\right)\left(\alpha_{s=1}+\sum_{i=1}^{p}\hat{\phi}_{s=1,i}y_{t+h-i}\right)\\
&+P\left(s_{t+h}=2 \mid y_t,...,y_0\right)\left(\alpha_{s=2}+\sum_{i=1}^{p}\hat{\phi}_{s=2,i}y_{t+h-i}\right),
\end{aligned} \tag{6}
$$

where $P\left(s_{t+h}=i \mid y_t,...,y_0\right)$ is the ith element of the column vector $\mathbf{P}^h\hat{\xi}_{t|t}$. In addition, $\hat{\xi}_{t|t}$ represents the filtered probabilities vector and $\mathbf{P}^h$ is the constant transition probabilities matrix (see, for example, Hamilton, 1994). Hence, multistep forecasts can be obtained iteratively by plugging in $1, 2, 3, \ldots$-period forecasts that are similar to the iterative forecasting method of AR processes.

ARNN, which is the autoregressive single-hidden-layer feed-forward neural network model[9] that is suggested in Teräsvirta (2006), is defined as follows:

$$
y_t = \alpha + \sum_{i=1}^{p}\phi_i y_{t-i} + \sum_{j=1}^{h}\lambda_j d\left(\sum_{i=1}^{p}\gamma_i y_{t-i} - c\right) + \varepsilon_t, \tag{7}
$$

where d is the logistic function, which is defined above as $d(x) = (1+\exp\{-x\})^{-1}$. In general, the estimation of an ARNN model may be computationally challenging. Here, we follow the QuickNet method, which is a type of "relaxed greedy algorithm"; it was originally suggested by White (2006). In contrast, the forecasting procedure for ARNN is identical to the procedure for LSTAR.

To obtain pseudo-out-of-sample forecasts for a given horizon h, the models are estimated by running regressions with data that were collected no later than the date $t_0 < T$, where t_0 refers to the date when the estimation is initialized and T refers to the final date in our data. The first h-horizon forecast is obtained using the coefficient estimates from the initial regression. Next, the time subscript is advanced, and the procedure is repeated for t_0+1, t_0+2,...,$T-h$ to obtain $N_f = T - t_0 - h - 1$ distinct h-step forecasts. In our applications, N_f differs between 17 and 40 for different values of h, which are between 1 and 24 for each of our countries in both the IT and NIT periods. Therefore, t_0 is defined to meet these requirements for each of the countries and as indicated in Table 1 above.

In particular, there are 40 distinct point forecasts for $h = 1$, 39 distinct point forecasts for $h = 2$ and so on.

For each of these h-step forecasts, we calculate N_f forecast errors for each of the above models. Then, we calculate the models' out-of-sample mean-squared errors (MSE) for both the IT (MSE_{IT}) and NIT (MSE_{NIT}) periods.

[9] See Franses and Dijk (2000) for a review of feed-forward-type neural network models

3 Results

Figure 1 displays the out-of-sample forecasting MSE ratios; these ratios were computed separately as

$$MSE_R = \frac{MSE_{NIT}}{MSE_{IT}}$$

for seven time-series models, for each horizon from 1 to 24, and for all 14 of the studied countries[10]. In these figures, the MSE_Rs are plotted against the forecast horizon h, which is placed on the horizontal axis. Hence, the higher MSE_R plots are placed above the horizontal "1" line, which indicates the superior forecast accuracy that is achieved in an IT regime for the corresponding h.

[Figure 1 is here.]

The information given in these figures are summarized in Table 2 below.

[Table 2 is here]

As can be observed in Table 2, whereas all of the models have superior forecasting power in the IT periods of Colombia, Israel, South Korea, Mexico, Poland, Sweden, and Turkey, all of the models appear to be superior in the NIT periods of Norway and South Africa in terms of forecast accuracy. All models, except the RW model which is ambiguous in general, also better forecast in Canada. In Chile, all of the models have better forecast accuracy in the IT periods except for ARMA and SETAR. The results for Thailand and the United Kingdom are ambiguous for all of the models (except for ARMA). For Hungary, although the results vary across the forecasting models, the majority of the results remain ambiguous. Hence, the overall forecast accuracy in IT periods appears to be superior to the forecast accuracy in NIT periods. For half of the countries covered in this study, the IT periods provide better forecast accuracy irrespective of the model used. In contrast, NIT provides better forecast accuracy in two or three countries irrespective of which forecasting model is employed.

We also use Diebold and Mariano (1995) (DM test) to test the statistical significance of the results that were obtained above. Although the DM test is frequently used to assess the relative accuracy of forecasts that are derived from two competing models, we use the DM test to compare forecasts that were derived from two different periods using the same model[11]. In our case, the DM test is used to compare IT forecasts using the NIT forecasts as benchmarks. The null hypothesis is that the IT forecast is no better than the benchmark forecast (ie. the NIT forecasts), against the alternative of the superiority of IT forecasts over the benchmark forecast. We use MSEs as the loss functions in our DM tests[12].

[10] For the sake of brevity, we only provide the results of the iterative forecasts. The results that were obtained with direct forecasts are qualitatively similar and available upon request.

[11] As long as we assume the same variance for both periods, the DM test is still valid in this case. However, one may object to this assumption by indicating that IT can reduce the variance of the inflation.

[12] Monthly inflation forecasts are scaled by 100. As a caveat, one should keep in mind that comparing two MSE series via Diebold-Mariano statistics is a scale-dependent process, i.e., the statistics change

[Table 3 is here]

The $p-$values of the DM tests are illustrated in Table 3. In most cases where IT is already established as the better period for forecasting in Table 2, we are able to reject the null hypothesis of equal forecast accuracy. Therefore, the superiority of IT forecasts is confirmed by these DM tests. The cases for which IT is found to be superior are indicated by the emboldened numbers in the table.

We have found clear evidence that forecasts are superior in IT periods compared to NIT periods, which was the main goal of this paper. Additionally, we test the relative forecast accuracy of the utilized models in each period against the benchmark of the random walk model. The results are shown in Tables 4 and 5 for the NIT and IT periods, respectively. The null hypothesis is that the forecasts of the model under consideration are no better than those of the random walk model; the alternative is that random walk forecasts more accurately than the model under consideration. As can be observed in Tables 4 and Tables 5 , the DM tests' statistics indicate mixed results that vary across countries and forecasting horizons. Therefore, we cannot assert that forecasts from a particular model are superior to random-walk forecasts in most countries and horizons. Furthermore, comparing the results in IT and NIT periods does not lead us to conclude that one or more models overwhelmingly provide better forecasts in one period in comparison to other periods.

[Tables 4 and 5 are here.]

4 Conclusion

In this paper, we investigated whether monetary-policy regime changes have an effect on the success of forecasting inflation. The forecasting performance of some linear and non-linear univariate models are analyzed for 14 different countries that adopted an IT regime at some point in their economic history. The results show that forecasting performance is generally superior under IT monetary regimes compared to periods of NIT. In more than half of the countries covered in this study, an IT period provides better forecasting accuracy regardless of the model used. In contrast, among the remaining countries, whereas the results remain ambiguous for most cases , the evidence on the superiority of NIT is limited to very few countries.

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under the multiplication of two series by a constant. Here, we scale the monthly inflation figures by 100 to express them in terms of monthly percentages. See Clark and West (2006) for a detailed discussion on the effects of scaling the out-of-sample MSE-based tests.

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References

Al-Qassam, M. S. and J. A. Lane (1989). Forecasting exponential autoregressive models of order 1. *Journal of Time Series Analysis 91*(2), 95–113.

Ball, L. M. and N. Sheridan (2004). Does inflation targeting matter? In *The Inflation-Targeting Debate*, NBER Chapters, pp. 249–282. National Bureau of Economic Research Inc.

Brito, R. D. and B. Bystedt (2010). Inflation targeting in emerging economies: Panel evidence. *Journal of Development Economics 91*(2), 198–210.

Clark, T. E. and K. D. West (2006). Using out-of-sample mean squared prediction errors to test the martingale difference hypothesis. *Journal of Econometrics 135*(1-2), 155 – 186.

D'Agostino, A., L. Gambetti, and D. Giannone (2011). Macroeconomic forecasting and structural change. *Journal of Applied Econometrics 26*(7), 82–101.

D'Agostino, A., D. Giannone, and P. Surico (2006). (Un)Predictability and macroeconomic stability. Working Paper Series 605, European Central Bank.

D'Agostino, A. and P. Surico (2012). A century of inflation forecasts. *Review of Economics and Statistics 94*(4).

De Gooijer, J. G. and P. T. De Bruin (1998). On forecasting SETAR processes. *Statistics & Probability Letters 37*(1), 7–14.

de Mendonça, H. F. and G. J. de Guimarães e Souza (2012). Is inflation targeting a good remedy to control inflation? *Journal of Development Economics 98*(2), 178 – 191.

Diebold, F. X. and R. S. Mariano (1995). Comparing predictive accuracy. *Journal of Business & Economic Statistics 13*(3), 253–63.

Elliott, G. and A. Timmermann (2008). Economic forecasting. *Journal of Economic Literature 46*(1), 3–56.

Faust, J. and J. H. Wright (2012). Forecasting inflation. Unpublished manuscript.

Franses, P. and D. Dijk (2000). *Nonlinear time series models in empirical finance*. Cambridge University Press.

Gonçalves, C. E. S. and J. a. M. Salles (2008). Inflation targeting in emerging economies: What do the data say? *Journal of Development Economics 85*(1-2), 312–318.

Hamilton, J. (1994). *Time series analysis.* Princeton University Press.

Kock, A. B. and T. Teräsvirta (2011). Forecasting with nonlinear time series models. In M. P. Clements and D. F. Hendry (Eds.), *Oxford Handbook on Economic Forecasting*, pp. 61–87. Oxford University Press.

Lin, J. L. and C. W. J. Granger (1994). Forecasting from non-linear models in practice. *Journal of Forecasting 13*, 1–9.

Lin, S. and H. Ye (2007). Does inflation targeting really make a difference? Evaluating the treatment effect of inflation targeting in seven industrial countries. *Journal of Monetary Economics 54*(8), 2521–2533.

Marcellino, M., J. H. Stock, and M. W. Watson (2006). A comparison of direct and iterated multistep AR methods for forecasting macroeconomic time series. *Journal of Econometrics 135*(1-2), 499–526.

Rossi, B. and T. Sekhposyan (2010). Have economic models' forecasting performance for US output growth and inflation changed over time, and when? *International Journal of Forecasting 26*(4), 808–835.

Stock, J. H. and M. W. Watson (2007). Why has U.S. inflation become harder to forecast? *Journal of Money, Credit and Banking 39*(1), 3–33.

Stock, J. H. and M. W. Watson (2009). Phillips curve inflation forecasts. In J. Fuhrer, Y. K. Kodrzycki, J. Little, and G. P. Olivei (Eds.), *Understanding inflation and the implications for monetary policy: a Phillips curve retrospective.* The MIT Press.

Svensson, L. E. (2010). Inflation targeting. In B. M. Friedman and M. Woodford (Eds.), *Handbook of Monetary Economics*, Volume 3 of *Handbook of Monetary Economics*, Chapter 22, pp. 1237–1302. Elsevier.

Svensson, L. E. O. (2005). Monetary policy with judgment: Forecast targeting. *International Journal of Central Banking 1*(1).

Teräsvirta, T. (2006). Forecasting economic variables with nonlinear models. In G. Elliott, C. Granger, and A. Timmermann (Eds.), *Handbook of Economic Forecasting*, Volume 1 of *Handbook of Economic Forecasting*, Chapter 8, pp. 413–457. Elsevier.

van Dijk, D., P. H. Franses, M. P. Clements, and J. Smith (2003). On SETAR non-linearity and forecasting. *Journal of Forecasting 22*(5), 359–375.

White, H. (2006). Approximate nonlinear forecasting methods. In G. Elliott, C. Granger, and A. Timmermann (Eds.), *Handbook of Economic Forecasting*, Volume 1, Chapter 9, pp. 459–512. Elsevier.

Tables and figures

Table 2: The overall relative forecasting performances of models in IT and NIT periods in terms of their MSE measures for the horizons 1-24.

Countries	Superior forecast accuracy in IT periods	Superior forecast accuracy in NIT periods	Ambiguous
Canada		AR, ARMA, SETAR, LSTAR, ARNN, MS	RW
Chile	RW, AR, LSTAR, ARNN, MS		ARMA, SETAR
Colombia	RW, AR, SETAR, LSTAR, ARNN, MS		
Hungary	RW	ARNN, MS	AR, ARMA, SETAR, LSTAR
Israel	RW, AR, ARMA, SETAR, LSTAR, ARNN, MS		
South Korea	RW, AR, ARMA, SETAR, LSTAR, ARNN, MS		
Mexico	RW, AR, ARMA, SETAR, LSTAR, ARNN, MS		
Norway		RW, AR, ARMA, SETAR, LSTAR, ARNN, MS	
Poland	RW, AR, ARMA, SETAR, LSTAR, ARNN, MS		
South Africa		RW, AR, ARMA, SETAR, LSTAR, ARNN, MS	
Sweden	RW, AR, ARMA, SETAR, LSTAR, ARNN, MS		
Thailand			RW, AR, ARMA, SETAR, LSTAR, ARNN, MS
Turkey	RW, AR, ARMA, ARNN, SETAR, LSTAR, MS		
United Kingdom		ARMA	RW, AR, SETAR, LSTAR, ARNN, MS

Table 3: The overall relative forecasting performances of models in IT and NIT periods in terms of their MSE measures for the horizons 1-24.

	h	Canada	Chile	Colombia	Hungary	Israel	S. Korea	Mexico	Norway	Poland	S. Africa	Sweden	Thailand	Turkey	UK
RW	1	0.371	**0.000**	**0.000**	**0.000**	**0.000**	**0.045**	**0.000**	0.952	**0.000**	0.876	**0.031**	0.960	**0.000**	0.178
	2	0.334	**0.000**	**0.000**	**0.001**	**0.000**	**0.040**	**0.000**	0.967	**0.000**	0.886	**0.042**	0.956	**0.000**	0.192
	3	0.371	**0.000**	**0.000**	**0.002**	**0.000**	**0.039**	**0.000**	0.961	**0.000**	0.921	0.060	0.966	**0.000**	0.215
	12	0.370	**0.000**	**0.000**	**0.017**	**0.000**	0.055	**0.000**	0.935	**0.000**	0.957	0.208	0.959	**0.000**	0.224
	24	0.497	**0.000**	**0.000**	0.073	**0.000**	0.110	**0.000**	0.731	**0.000**	0.884	0.523	0.994	**0.000**	0.611
AR	1	0.999	**0.000**	**0.000**	0.289	**0.000**	**0.001**	**0.000**	0.997	**0.000**	0.539	**0.005**	0.970	0.184	0.626
	2	0.999	**0.000**	**0.000**	0.203	**0.000**	**0.008**	**0.000**	0.997	**0.000**	0.488	**0.005**	0.976	0.280	0.618
	3	0.999	**0.000**	**0.000**	0.229	**0.000**	**0.021**	**0.000**	0.995	**0.000**	0.490	**0.005**	0.970	0.291	0.599
	12	0.993	**0.000**	**0.000**	0.265	**0.000**	0.127	**0.000**	0.985	**0.000**	0.404	**0.002**	0.926	0.209	0.442
	24	0.980	**0.037**	**0.000**	0.994	**0.001**	0.161	**0.001**	0.738	**0.000**	0.601	0.074	0.304	**0.006**	0.609
ARMA	1	0.998	0.065	**0.000**	0.473	**0.000**	**0.000**	**0.000**	0.999	**0.000**	0.540	**0.003**	0.952	**0.000**	0.591
	2	0.999	0.114	**0.000**	0.425	**0.000**	0.091	**0.000**	0.999	**0.000**	0.491	**0.003**	0.966	0.287	0.582
	3	0.999	0.181	**0.001**	0.484	**0.000**	0.114	**0.000**	0.997	**0.000**	0.501	**0.003**	0.946	**0.002**	0.554
	12	0.981	0.242	**0.000**	0.308	**0.000**	**0.023**	**0.000**	0.989	**0.000**	0.416	**0.001**	0.887	**0.020**	0.478
	24	0.966	0.503	**0.000**	0.991	**0.001**	0.244	**0.000**	0.600	**0.000**	0.663	0.140	1.000	**0.003**	0.606
SETAR	1	0.994	0.197	**0.000**	**0.004**	**0.000**	**0.045**	**0.000**	0.983	**0.000**	0.617	**0.004**	0.988	**0.000**	0.908
	2	0.992	0.240	**0.000**	0.893	**0.000**	0.132	**0.000**	0.983	**0.000**	0.712	**0.004**	0.971	**0.000**	0.883
	3	0.990	0.344	**0.000**	0.893	**0.000**	**0.032**	**0.000**	0.983	**0.000**	0.710	**0.004**	0.973	**0.000**	0.927
	12	0.954	0.963	**0.000**	**0.001**	**0.005**	0.237	**0.000**	0.946	**0.000**	0.561	**0.003**	0.943	**0.000**	0.807
	24	0.722	0.096	**0.000**	0.069	**0.021**	0.208	**0.000**	0.795	**0.000**	0.639	0.064	0.941	**0.000**	0.849
LSTAR	1	0.998	**0.000**	**0.000**	0.099	**0.001**	**0.001**	**0.000**	0.955	**0.000**	0.164	**0.018**	0.980	**0.022**	0.855
	2	0.998	**0.000**	**0.000**	0.129	**0.002**	**0.003**	**0.000**	0.957	**0.000**	0.173	**0.019**	0.980	**0.006**	0.848
	3	0.998	**0.001**	**0.000**	0.118	**0.001**	**0.008**	**0.000**	0.935	**0.000**	0.201	**0.019**	0.978	**0.001**	0.824
	12	0.984	**0.014**	**0.000**	0.216	**0.034**	**0.037**	**0.000**	0.928	**0.000**	0.215	**0.040**	0.948	**0.001**	0.715
	24	0.877	0.650	**0.000**	0.763	**0.017**	**0.046**	**0.000**	0.772	**0.000**	0.287	0.069	0.872	**0.001**	0.834

Table3 – continued from previous page

M	h	Canada	Chile	Colombia	Hungary	Israel	S. Korea	Mexico	Norway	Poland	S. Africa	Sweden	Thailand	Turkey	UK
ARNN	1	0.992	**0.000**	**0.000**	0.233	**0.000**	**0.000**	**0.000**	0.998	**0.000**	0.528	**0.003**	0.937	**0.000**	0.625
	2	0.999	**0.013**	**0.004**	0.098	**0.000**	**0.020**	**0.000**	1.000	**0.000**	0.520	**0.003**	0.931	**0.000**	0.641
	3	0.998	**0.000**	**0.006**	0.728	**0.000**	**0.036**	**0.000**	0.995	**0.000**	0.468	**0.003**	0.928	**0.000**	0.462
	12	0.990	**0.000**	**0.002**	0.563	**0.000**	0.090	**0.000**	0.989	**0.000**	0.393	**0.001**	0.971	0.093	0.614
	24	0.945	0.198	**0.000**	0.875	**0.000**	0.142	**0.045**	0.983	**0.000**	0.542	0.092	1.000	0.602	0.631
MS-AR	1	0.998	0.110	**0.000**	**0.029**	**0.000**	**0.008**	**0.007**	0.998	**0.000**	0.560	**0.021**	0.993	**0.000**	0.696
	2	0.998	**0.050**	**0.001**	**0.027**	**0.000**	**0.003**	**0.012**	0.998	**0.000**	0.589	**0.034**	0.995	**0.003**	0.706
	3	0.998	0.100	**0.010**	**0.020**	**0.000**	**0.007**	**0.010**	0.993	**0.000**	0.623	**0.033**	0.994	**0.021**	0.763
	12	0.999	0.058	**0.000**	0.140	**0.000**	0.691	**0.009**	0.973	**0.000**	0.575	0.097	0.967	**0.019**	0.775
	24	0.993	0.415	**0.000**	0.651	**0.001**	**0.019**	**0.004**	0.991	**0.001**	0.618	0.331	0.986	0.147	0.912

Note: Emboldened items refer to the cases where the null hypothesis is rejected at 5 % level of significance.

Table 4: The p−values of the DM tests where the null hypothesis is that IT forecasts are no better than NIT forecasts.

	h	Canada	Chile	Colombia	Hungary	Israel	S. Korea	Mexico	Norway	Poland	S. Africa	Sweden	Thailand	Turkey	UK
AR	1	0.366	0.682	0.997	0.981	0.395	0.906	1.000	**0.000**	1.000	0.280	0.423	0.054	1.000	0.614
	2	0.229	0.903	1.000	0.993	0.739	0.984	1.000	**0.005**	0.999	0.187	0.085	**0.006**	1.000	0.681
	3	0.259	0.858	1.000	0.998	0.987	0.675	1.000	**0.000**	0.998	0.153	**0.002**	**0.006**	1.000	0.659
	12	**0.031**	0.413	0.984	0.815	0.389	0.500	0.999	**0.002**	0.503	0.064	0.115	**0.005**	0.999	0.155
	24	0.243	0.947	0.659	0.918	0.222	0.517	0.964	**0.018**	0.480	**0.031**	**0.013**	**0.001**	0.998	0.156
ARMA	1	0.366	0.714	0.997	0.981	0.400	0.905	1.000	**0.000**	1.000	0.280	0.422	0.054	1.000	0.614
	2	0.229	0.921	1.000	0.993	0.741	0.984	1.000	**0.005**	0.999	0.187	0.085	**0.006**	1.000	0.681
	3	0.259	0.883	1.000	0.998	0.987	0.673	1.000	**0.000**	0.995	0.153	**0.002**	**0.006**	1.000	0.659
	12	**0.031**	0.580	0.984	0.815	0.423	0.499	0.999	**0.002**	0.552	0.064	0.115	**0.005**	0.999	0.155
	24	0.243	0.983	0.660	0.918	0.261	0.516	0.963	**0.018**	0.485	**0.031**	**0.013**	**0.001**	0.998	0.156
SETAR	1	0.366	0.575	0.997	0.981	0.380	0.906	1.000	**0.000**	1.000	0.281	0.420	0.054	1.000	0.613
	2	0.228	0.915	1.000	0.993	0.754	0.984	1.000	**0.005**	1.000	0.187	0.084	**0.006**	1.000	0.679
	3	0.258	0.886	1.000	0.998	0.988	0.674	1.000	**0.000**	0.999	0.153	**0.002**	**0.006**	1.000	0.655
	12	**0.031**	0.580	0.983	0.809	0.467	0.499	0.998	**0.002**	0.925	0.064	0.115	**0.005**	0.999	0.155
	24	0.242	0.983	0.655	0.916	0.309	0.518	0.890	**0.018**	0.838	**0.031**	**0.013**	**0.001**	0.997	0.157
LSTAR	1	0.366	0.721	0.997	0.981	0.396	0.906	1.000	**0.000**	1.000	0.281	0.419	0.054	1.000	0.614
	2	0.228	0.923	1.000	0.993	0.750	0.984	1.000	**0.005**	1.000	0.187	0.085	**0.006**	1.000	0.677
	3	0.257	0.885	1.000	0.998	0.989	0.672	1.000	**0.000**	0.999	0.152	**0.002**	**0.006**	1.000	0.652
	12	**0.031**	0.562	0.984	0.803	0.286	0.500	0.996	**0.002**	0.902	0.063	0.115	**0.005**	0.999	0.155
	24	0.243	0.965	0.664	0.900	**0.028**	0.518	0.966	**0.018**	0.899	**0.031**	**0.013**	**0.001**	0.998	0.157

Table4 – continued from previous page

M	h	Canada	Chile	Colombia	Hungary	Israel	S. Korea	Mexico	Norway	Poland	S. Africa	Sweden	Thailand	Turkey	UK
ARNN	1	0.366	0.650	0.997	0.981	0.365	0.906	1.000	**0.000**	1.000	0.280	0.423	0.054	1.000	0.615
	2	0.228	0.899	1.000	0.993	0.705	0.984	1.000	**0.005**	0.999	0.187	0.085	**0.006**	1.000	0.681
	3	0.259	0.843	1.000	0.998	0.984	0.674	1.000	**0.000**	0.997	0.153	**0.002**	**0.006**	1.000	0.659
	12	**0.031**	0.482	0.985	0.814	0.079	0.501	0.998	**0.002**	1.000	0.064	0.115	0.005	0.999	0.155
	24	0.243	0.970	0.674	0.917	0.027	0.518	0.886	**0.018**	1.000	**0.031**	**0.013**	**0.001**	0.997	0.156
MS-AR	1	0.365	0.722	0.996	0.981	0.412	0.896	0.361	**0.000**	1.000	0.281	0.421	0.054	1.000	0.609
	2	0.228	0.921	1.000	0.993	0.756	0.984	1.000	**0.005**	1.000	0.187	0.085	**0.006**	1.000	0.677
	3	0.258	0.886	1.000	0.998	0.989	0.668	0.899	**0.000**	1.000	0.153	**0.002**	**0.006**	1.000	0.656
	12	**0.031**	0.582	0.983	0.812	0.391	0.490	1.000	**0.002**	0.969	0.064	0.115	**0.005**	0.999	0.155
	24	0.242	0.983	0.652	0.917	0.178	0.517	1.000	**0.018**	0.902	**0.031**	**0.013**	**0.001**	0.998	0.157

Note: Emboldened items refer to the cases where the null hypothesis is rejected at 5 % level of significance.

Table 5: The $p-$values of the Diebold-Mariano statistics for IT period. (Benchmark Model: Random Walk)

	h	Canada	Chile	Colombia	Hungary	Israel	S. Korea	Mexico	Norway	Poland	S. Africa	Sweden	Thailand	Turkey	UK
AR	1	0.143	0.948	0.992	0.138	**0.043**	0.847	0.968	**0.004**	0.692	0.623	**0.008**	0.237	0.076	0.083
	2	0.157	0.507	0.995	0.210	**0.001**	0.592	0.827	**0.013**	0.154	0.591	**0.000**	**0.020**	**0.009**	0.095
	3	**0.024**	0.354	0.958	0.767	0.058	**0.049**	0.884	**0.010**	0.092	0.743	**0.001**	**0.008**	**0.001**	0.076
	12	0.053	**0.036**	0.231	0.649	0.436	0.289	0.957	0.147	0.677	0.999	**0.042**	0.087	0.134	0.061
	24	0.157	**0.013**	**0.009**	0.172	0.857	0.273	0.925	0.160	0.399	0.909	0.586	**0.034**	0.390	0.280
ARMA	1	0.144	0.956	0.994	0.124	0.104	0.836	0.976	**0.005**	0.813	0.586	**0.007**	0.235	0.497	0.088
	2	0.153	0.540	0.997	0.195	**0.006**	0.621	0.889	**0.017**	0.298	0.560	**0.000**	**0.019**	0.111	0.101
	3	**0.024**	0.388	0.975	0.746	0.235	**0.070**	0.941	**0.010**	0.200	0.717	**0.000**	**0.007**	0.057	0.081
	12	0.054	**0.043**	0.239	0.631	0.752	0.296	0.968	0.151	0.821	0.999	**0.040**	0.088	0.883	0.067
	24	0.155	**0.003**	0.008	0.147	0.883	0.291	0.950	0.163	0.644	0.902	0.625	**0.034**	0.851	0.283
SEETAR	1	0.127	0.948	0.987	0.229	**0.036**	0.816	0.994	**0.009**	0.719	0.729	**0.008**	0.224	0.080	0.119
	2	0.172	0.498	0.991	0.887	**0.001**	0.400	0.942	0.032	0.164	0.760	**0.000**	**0.016**	**0.009**	0.241
	3	**0.036**	0.351	0.937	1.000	**0.044**	**0.027**	0.964	0.014	0.118	0.769	0.001	0.003	0.002	0.070
	12	**0.056**	**0.033**	0.302	1.000	0.423	0.402	0.969	0.048	0.762	1.000	**0.047**	0.141	0.419	0.065
	24	0.131	**0.047**	**0.007**	1.000	0.855	0.436	0.953	0.401	0.538	0.941	0.496	0.029	0.571	0.248
LSTAR	1	0.127	0.974	0.993	0.292	**0.042**	0.728	0.995	**0.001**	0.869	0.727	**0.007**	0.224	0.161	0.091
	2	0.159	0.668	0.998	0.786	**0.002**	0.537	0.968	**0.007**	0.266	0.933	**0.000**	0.297	**0.036**	0.113
	3	**0.027**	0.461	0.992	0.834	0.060	**0.046**	0.992	**0.039**	0.184	0.832	**0.000**	**0.003**	**0.040**	0.059
	12	0.054	0.104	0.384	0.382	0.607	0.202	0.999	0.214	0.852	0.998	**0.039**	0.079	0.927	0.055
	24	0.106	**0.001**	**0.008**	0.666	0.863	0.334	0.989	0.097	0.754	0.967	0.625	0.941	0.859	0.267

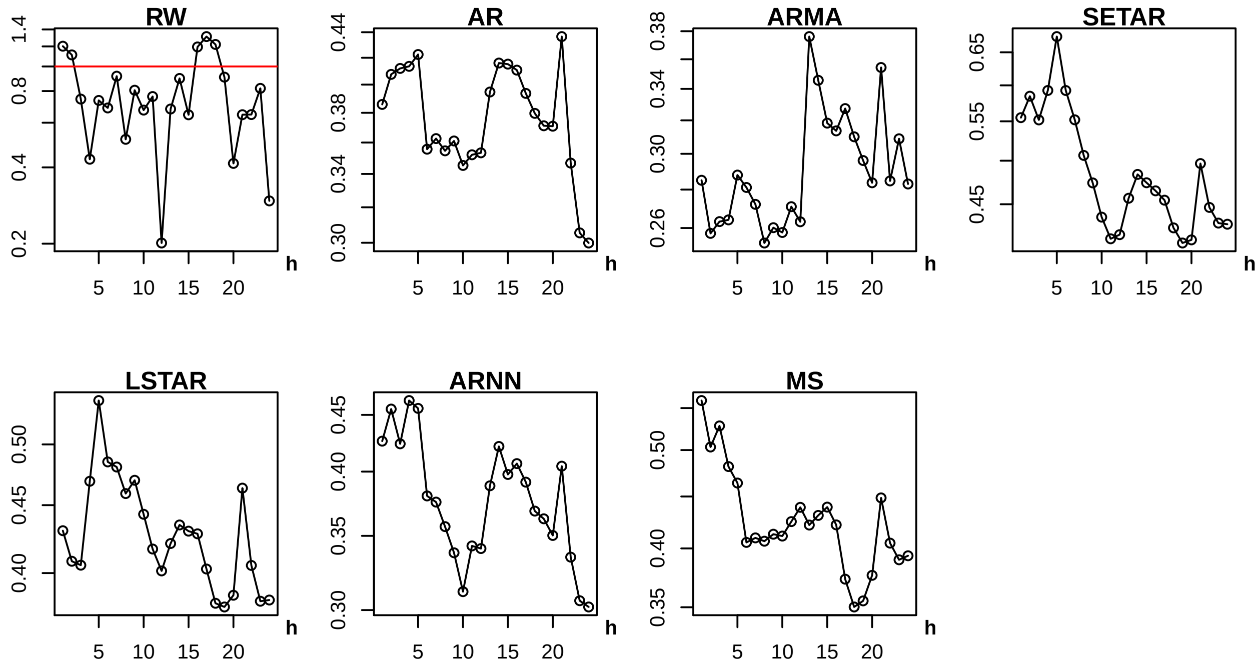
Table5 – continued from previous page

M	h	Canada	Chile	Colombia	Hungary	Israel	S. Korea	Mexico	Norway	Poland	S. Africa	Sweden	Thailand	Turkey	UK
ARNN	1	0.157	0.953	0.996	0.266	**0.040**	0.808	0.979	**0.005**	0.655	0.589	**0.008**	0.231	0.448	0.081
	2	0.167	0.516	0.998	0.478	**0.001**	0.466	0.897	**0.021**	0.134	0.582	**0.000**	**0.016**	0.101	0.091
	3	**0.027**	0.364	0.989	0.917	**0.044**	**0.037**	0.946	**0.015**	0.081	0.757	**0.001**	**0.005**	0.055	0.070
	12	0.058	**0.034**	0.374	0.649	0.377	0.291	0.985	0.128	0.676	1.000	**0.045**	0.104	0.956	0.059
	24	0.145	**0.024**	0.006	0.232	0.868	0.293	0.953	0.220	0.408	0.918	0.527	0.051	0.999	0.291
MS-AR	1	0.120	0.945	0.990	0.141	**0.008**	0.783	0.958	**0.011**	0.679	0.418	**0.006**	0.230	0.156	0.052
	2	0.148	0.541	0.995	0.083	**0.000**	0.691	0.898	**0.022**	0.083	0.767	**0.000**	**0.028**	0.115	0.072
	3	**0.026**	0.420	0.972	0.754	**0.010**	0.137	0.983	**0.019**	0.104	0.889	**0.000**	**0.009**	**0.036**	0.062
	12	0.058	0.069	0.440	0.717	0.392	0.182	0.994	0.093	0.836	0.999	**0.041**	0.096	0.945	**0.049**
	24	0.156	**0.020**	**0.010**	0.259	0.862	0.666	0.995	0.191	0.634	0.916	0.598	**0.023**	0.904	0.275

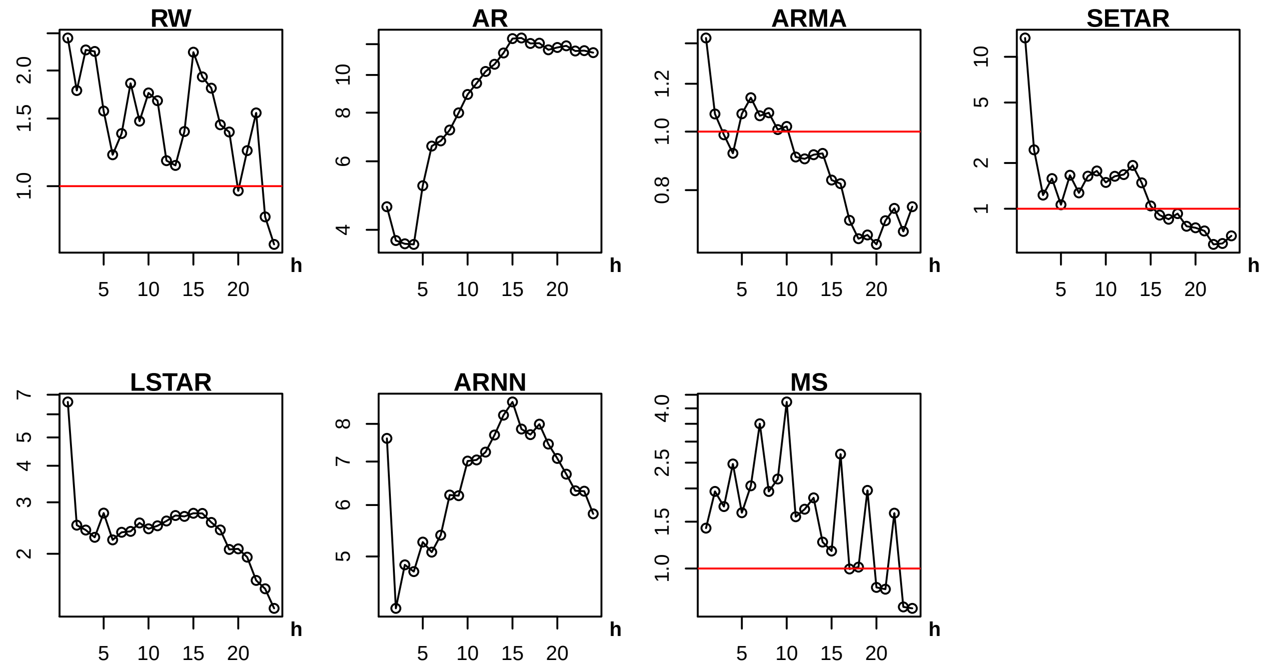
Note: Emboldened items refer to the cases where the null hypothesis is rejected at 5 % level of significance.

Figure 1: MSE ratios computed for 14 IT countries.

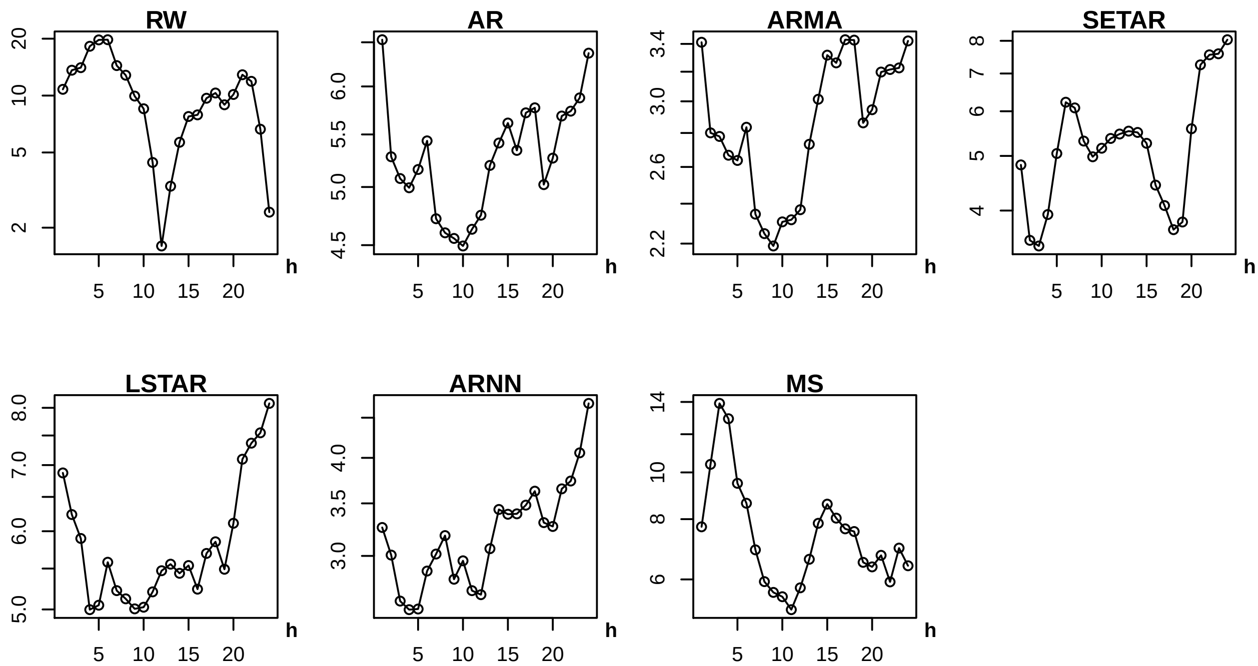
Canada



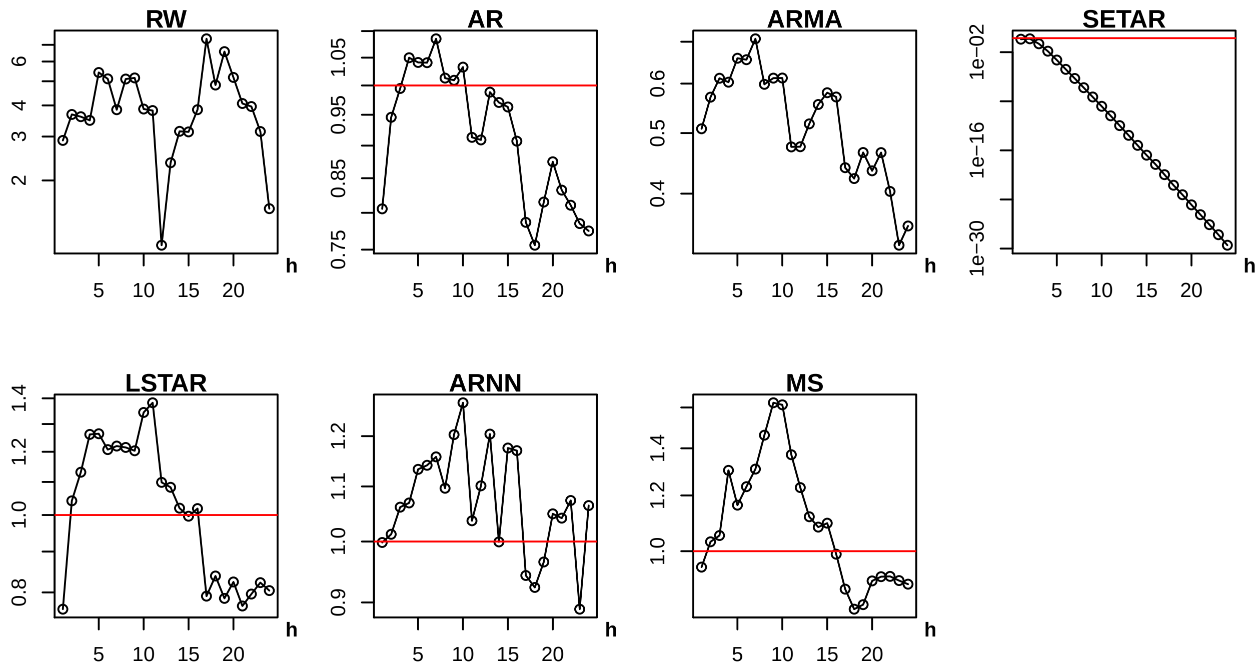
Chile



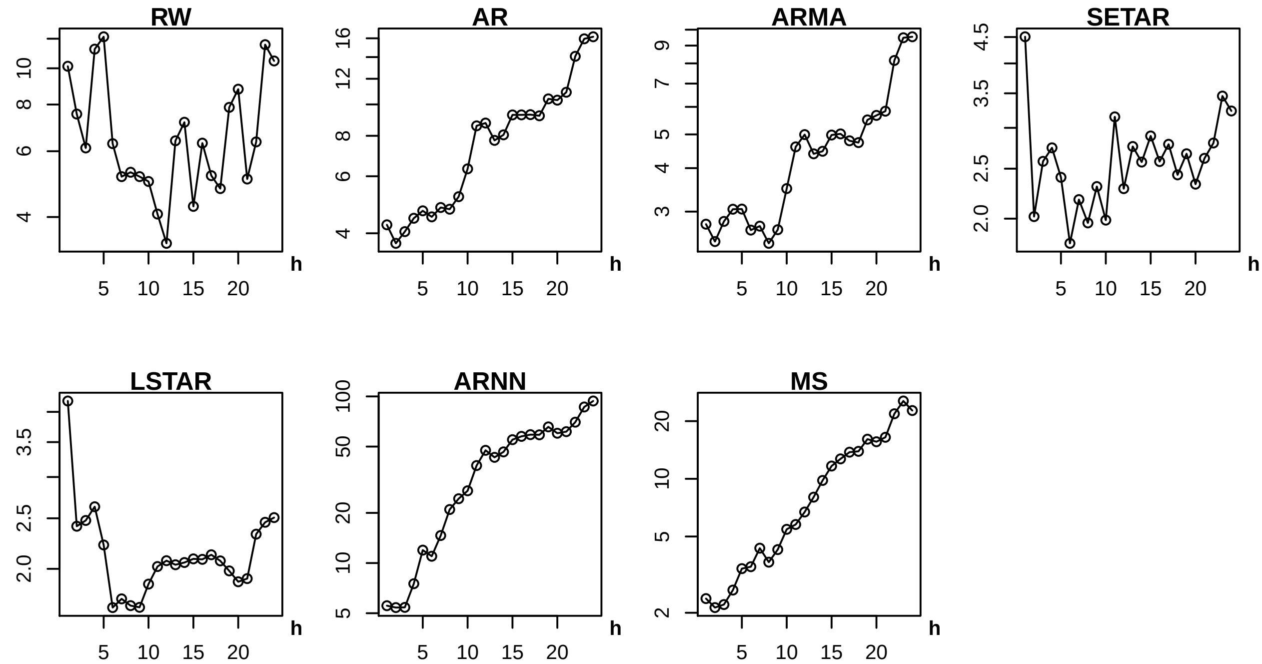
Colombia



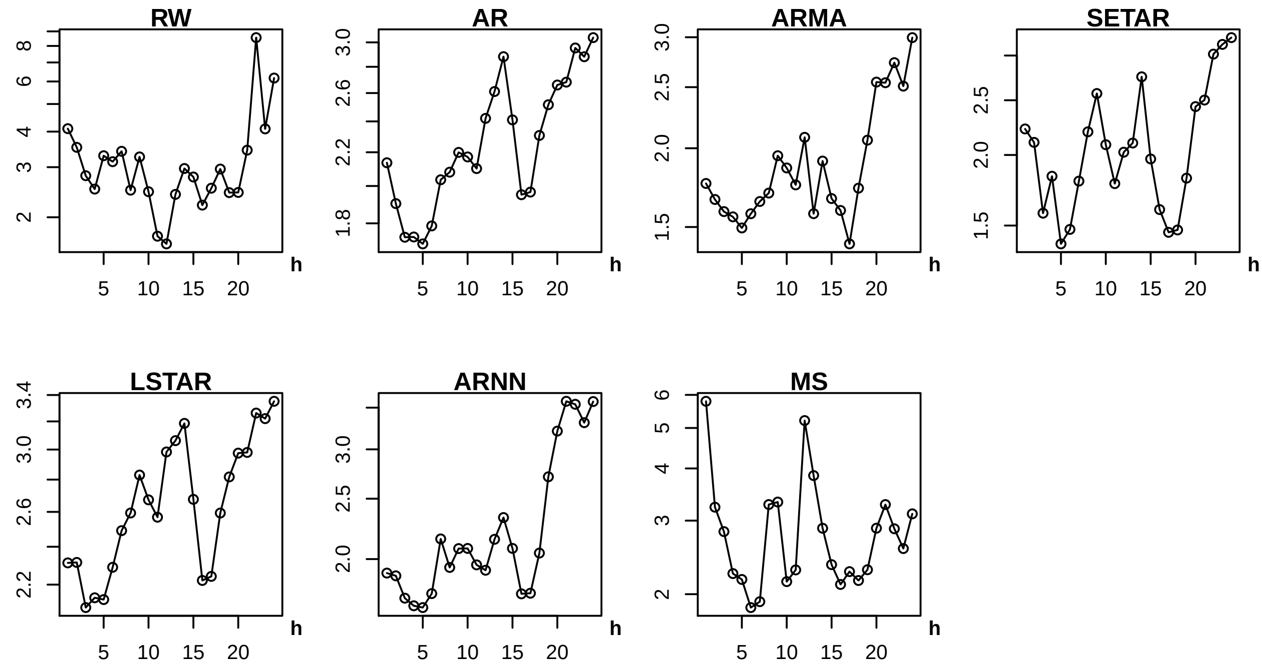
Hungary



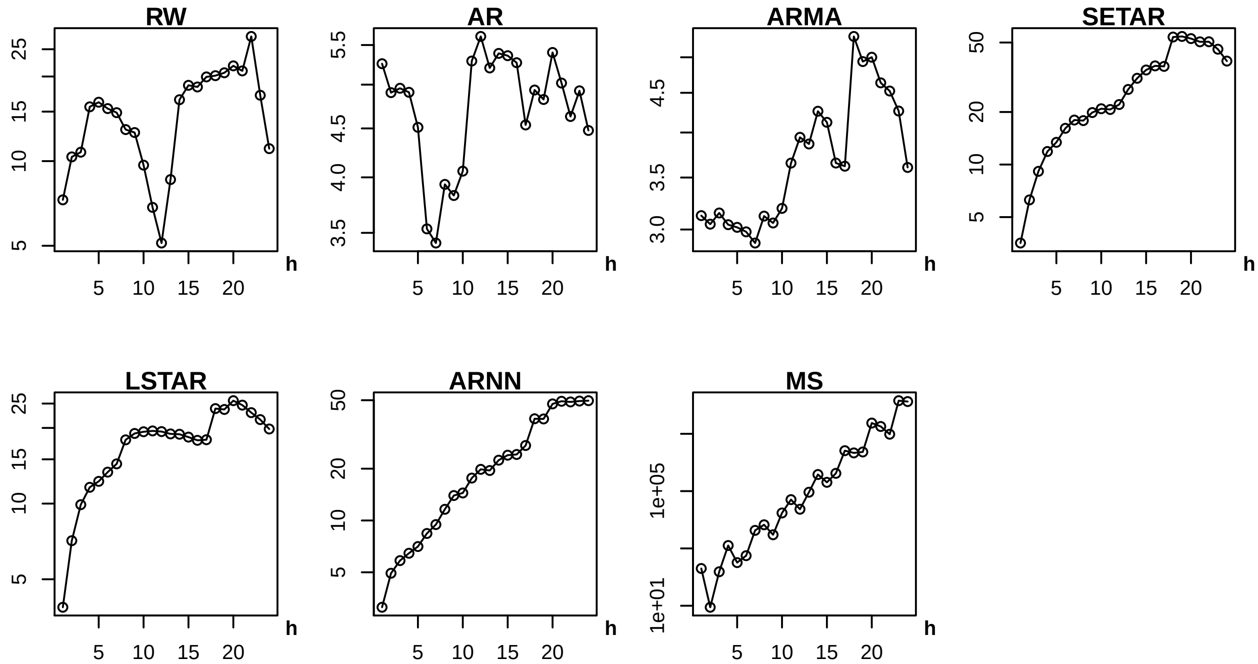
Israel



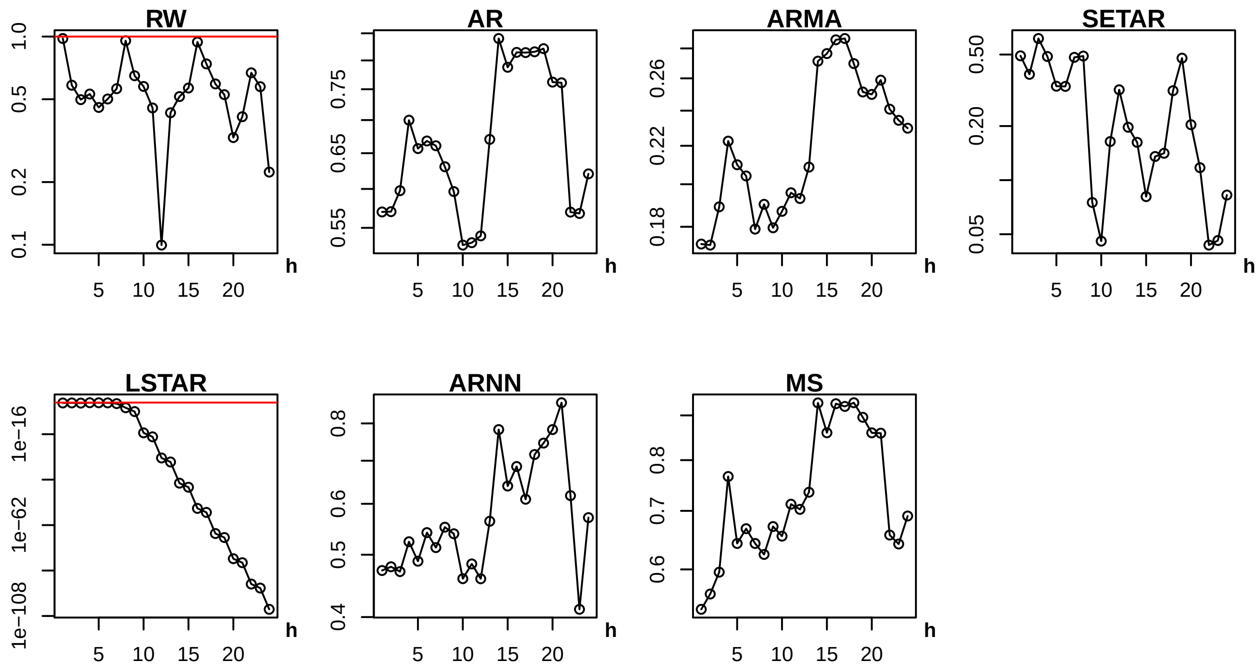
South Korea



Mexico



Norway



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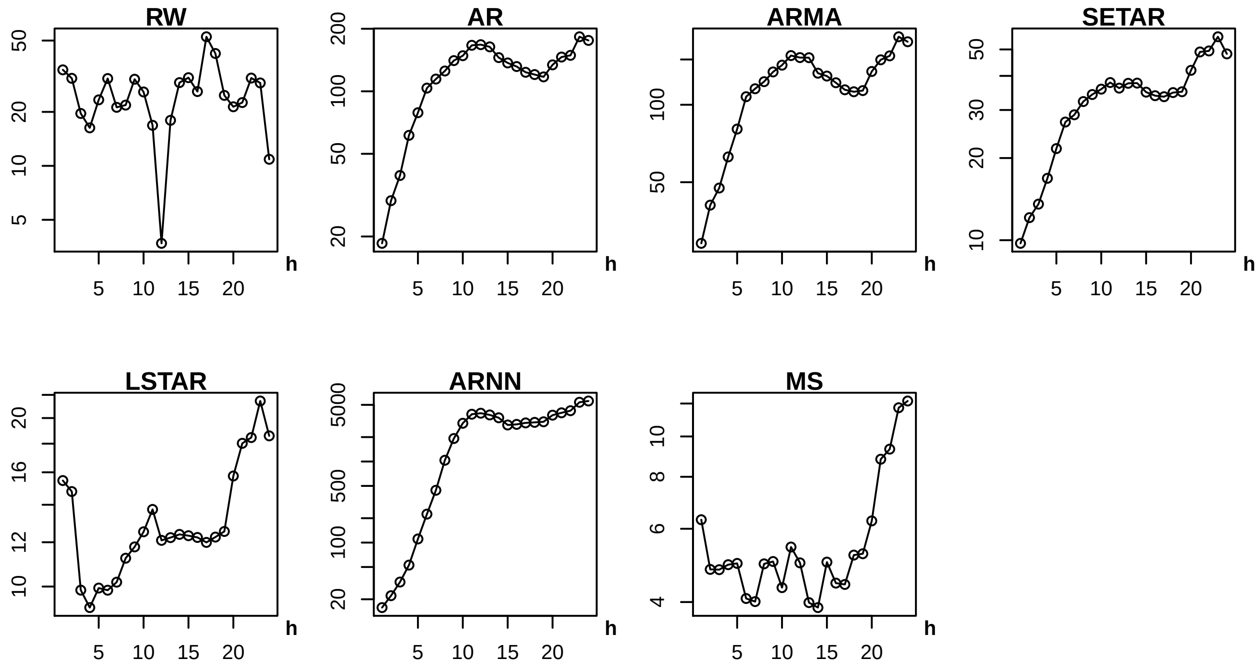

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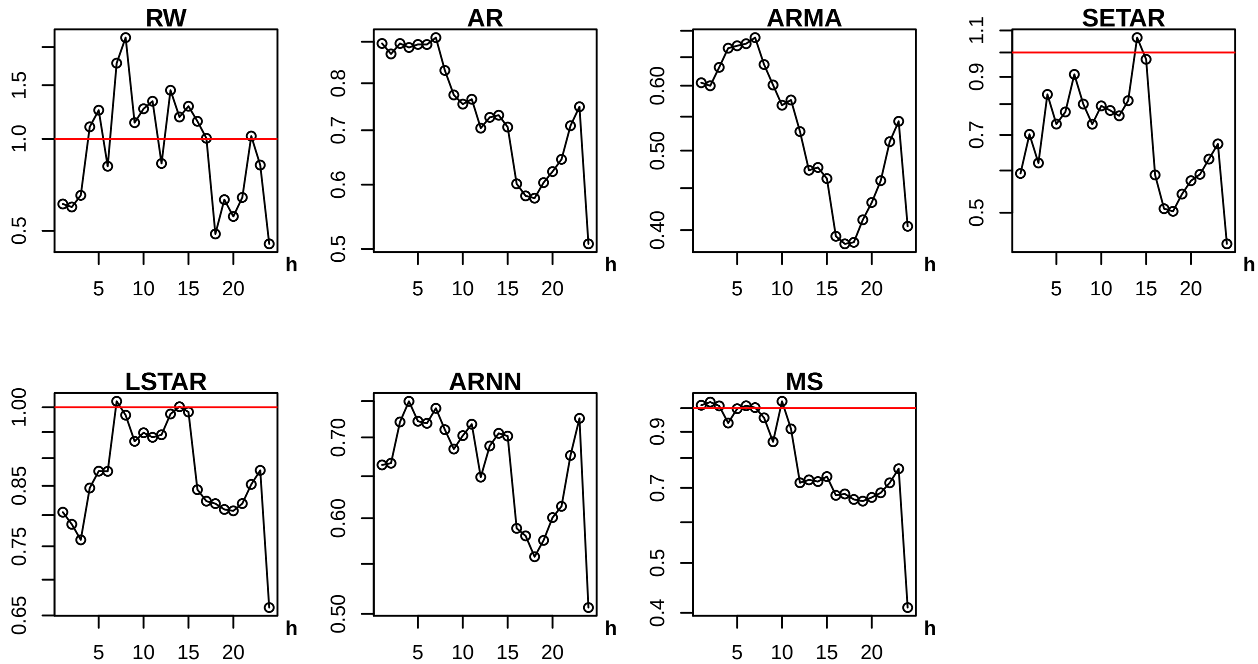
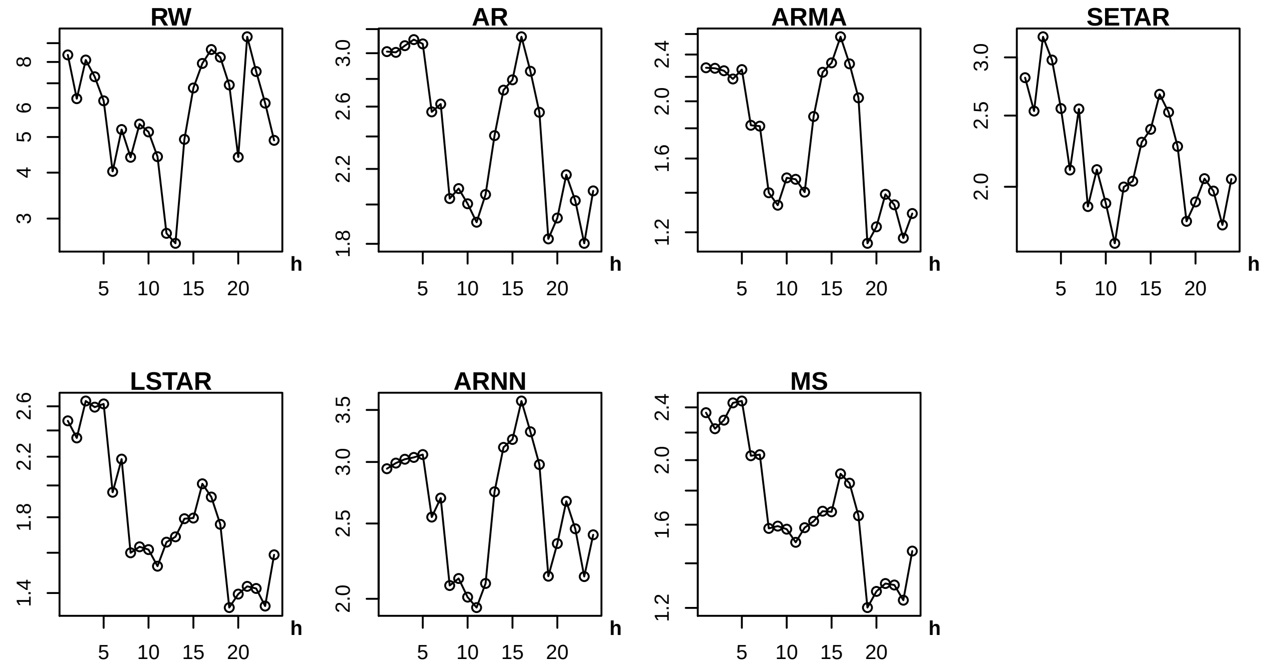
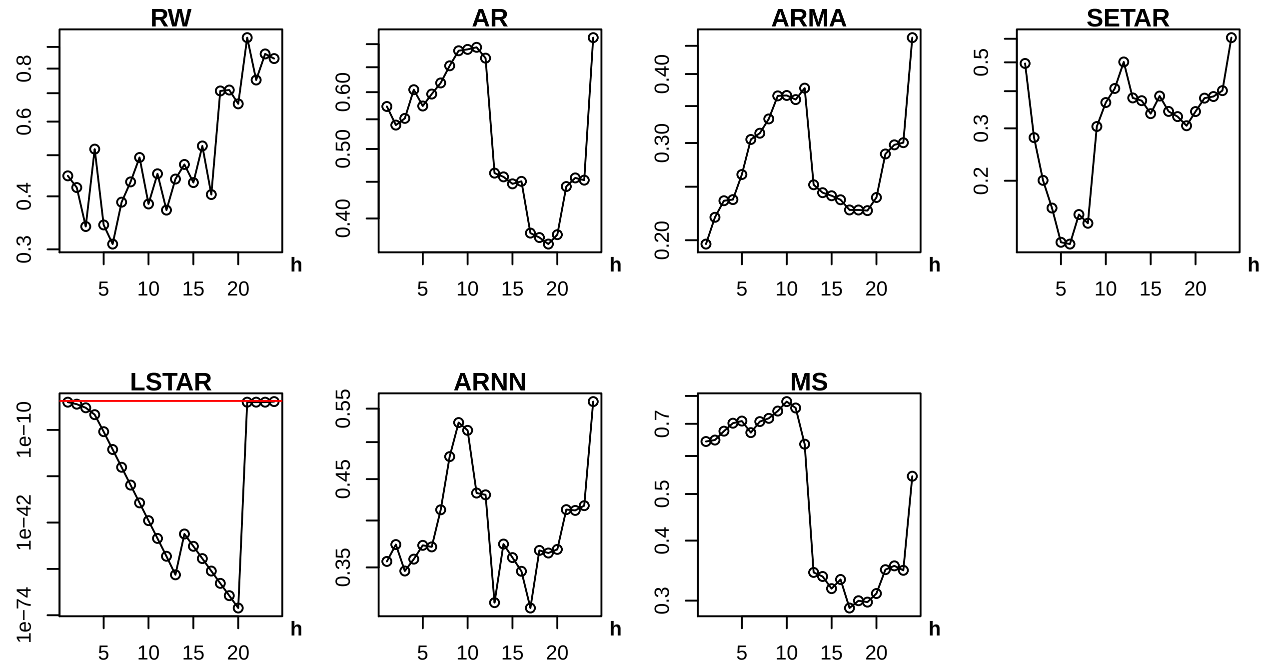


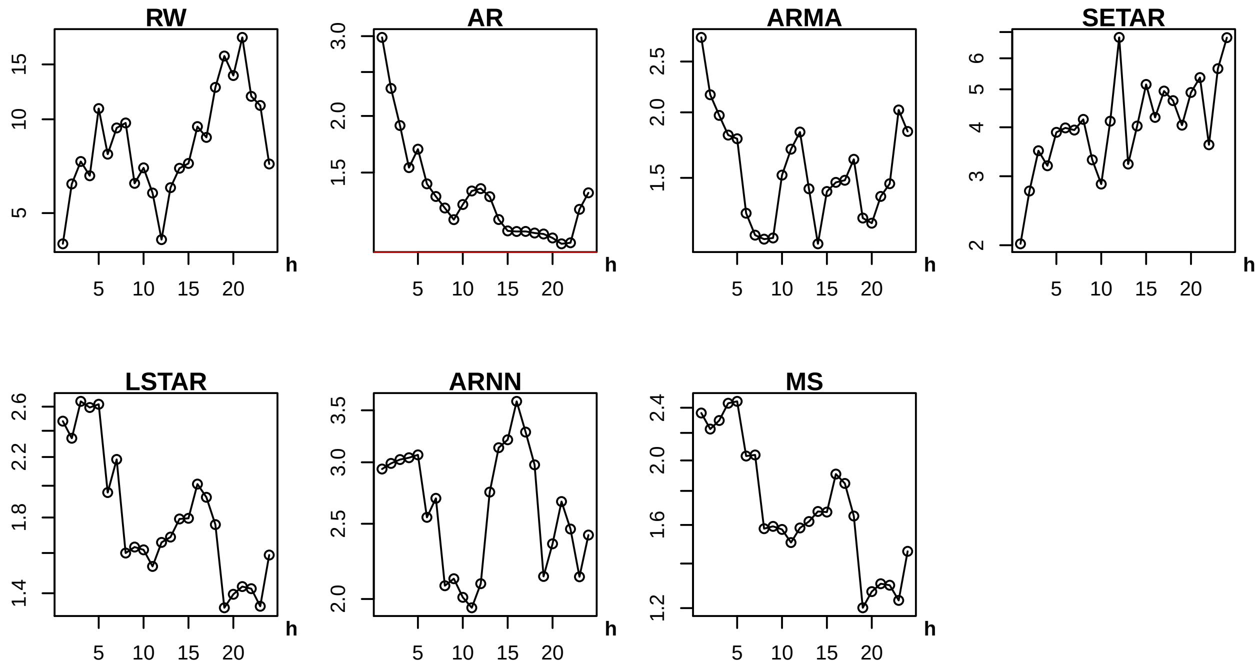
Sweden



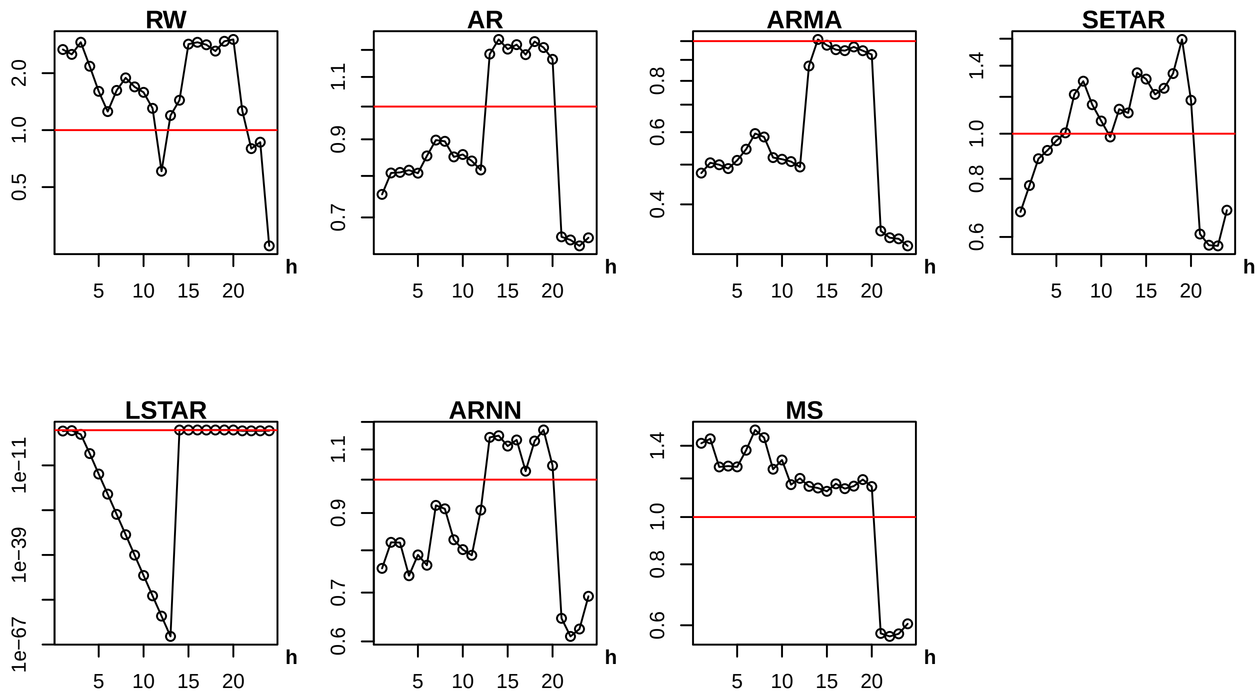
Thailand



Turkey



United Kingdom



Appendix: A note on Monte Carlo numerical method

As mentioned in the text, a version of Monte Carlo approach, which was first suggested by Lin and Granger (1994), is adopted for numerical computation of the multi-step iterative forecasts within LSTAR and ARNN models. The main reason behind this choice is computational speed and accuracy of Monte Carlo simulation against the alternative approach of numerical integration: as the forecasting steps get higher, numerical integration becomes significantly slower.

Computing more than one step forecasts via Monte Carlo framework for nonlinear models in general consists of the following steps:

Step 1: Compute $\hat{y}_{t+1|t}$ by directly plugging in $y_t, y_{t-1}, \dots$ into the estimated equation.

Step 2: Generate n normal random variates with a mean of zero and a variance of $\hat{\sigma}^2$ to form a vector of simulated $\varepsilon_{t+1|t}$ values.

Step 3: Compute simulated $y_{t+2|t}$s by plugging in the simulated values of $\varepsilon_{t+1|t}$ along with $y_{t+1|t}$ and $y_t, y_{t-1}, \dots$ $n-$times.

Step 4: Compute the Monte Carlo estimation of $y_{t+2|t}$ which is $\hat{y}_{t+2|t}$.

Step 5: Repeat Steps 2, 3, and 4 to increase t for getting the higher step forecasts until the end of the forecast horizon.

Notice that, in order to apply a Monte Carlo scheme for forecasting it is necessary to assume a probability distribution for the error terms $\{\varepsilon_t\}$. Here, in all models $\{\varepsilon_t\}$ is assumed to be i.i.d. $N(0, \sigma^2)$ for all t.