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Prediction of Unemployment Rates with Time Series and Machine Learning Techniques

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Abstract
In this paper, are explored and analyzed time series and machine learning models for prediction of unemployment in several countries (Med, Baltic, Balkan, Nordic, Benelux) for different forecasting horizons. FARIMA is a suitable model when long memory exists in a time series and has been applied successfully for predicting unemployment. To overcome the potential issue of heteroskedasticity, we explore whether FARIMA models with GARCH errors achieve more accurate results. To further improve forecasting accuracy, we consider models with non-normal errors. The above models however cannot take into account the non-linearity of the data and due to this fact, we employ three machine learning techniques to forecast unemployment rates, i.e. fully connected feed forward neural networks, support vector regression and multivariate adaptive regression splines. ARIMA and Holt-Winters are considered as benchmark models. Finally, the effects of different forecasting horizons and different geographic locations in terms of forecasting accuracy of the models are explored.

Keywords FARIMA/GARCH · FARIMA · Neural networks · Support vector machines · Multivariate adaptive regression splines · Multiple steps ahead predictions · Forecasting accuracy

1 Introduction

Accurate forecasting of unemployment is central to economic decision-making and to the design of policy-making in order to recognize early and reduce the problem. Many time series models have been employed extensively for the forecasting of macroeconomic variables, including unemployment. ARIMA models have been used in empirical studies such as for Czech Republic (Stoklasová 2012), for Roma-

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nia (Dobre and Alexandru 2008) and for Nigeria (Etuk et al. 2012). In Mladenovic et al. (2017) seasonal ARIMA model is used to forecast unemployment at the EU28 level. In Floros (2005) many variations of ARMA and GARCH models for forecasting UK unemployment were compared. GARCH model assumes heteroskedasticity which depends on past values and offer additional insight in the case of heteroskedastic time series. ARIMA models cannot allow for persistent effects of shocks in unemployment—evidence for hysteresis (Blanchard and Summers 1986)—and fractional ARIMA (FARIMA) models which take into account the long-memory effect seem more suitable for unemployment prediction. These models have been used in papers as in Gil-Alana (2001) for the forecasting of the UK unemployment rate, in Kurita (2010) for forecasting of the Japan's unemployment rate and in Katris (2015) for the forecasting of Greece's unemployment rate.

Another issue is non-linearity and when is present other approaches are more suitable. The forecasting performance of a variety of linear and nonlinear time series models using the U.S. unemployment rate was compared in Montgomery et al. (1998). In Rothman (1998) six nonlinear models were compared according to their out-of-sample forecasting accuracy, while in the paper of Proietti (2003) is examined the forecasting accuracy of several linear and nonlinear forecasting models for the US monthly unemployment rate and in Johnes (1999) are reported the results of a forecasting competition between linear autoregressive, GARCH, threshold autoregressive and neural network models of the UK monthly unemployment rate series. Artificial Neural Networks (ANN) appear promising in modeling more accurately data which display non-linearity, thus to give better forecasts. The paper of Aiken (1996) shows how a neural network may be used to forecast unemployment rates in the United States. More recently, in Olmedo (2014) neural network techniques are used for the forecasting of unemployment in Spain. In Katris (2019), FARIMA and FARIMA/GARCH time series models and Multilayer feed-forward neural network models have been used for the 1-step ahead forecasting of unemployment in nine Mediterannean countries. Support Vector Machines (specifically, Support Vector Regression—SVR) is another popular machine learning method for time series prediction (Sapankevych and Sankar 2009). A tutorial on SVR can be found on Smola and Schölkopf (2004), while in Basak et al. (2007) are discussed SVR applications and in Trafalis and Ince (2000) SVR is used for financial forecasting. Moreover, is employed the modern data mining method of multivariate adaptive regression splines (MARS) (Friedman 1991) which is a form of non-parametric regression analysis and can be seen as an extension of linear models which take into account and "automatically" models nonlinearities and interactions between variables. When the method is used in a time series context and lagged variables are used as the predictors, such as in this work, then the term TSMARS (Time Series multivariate adaptive regression splines) is used. This extension of MARS to a time series context is discussed in the paper of Lewis and Stevens (1991). The method has been used widely in many fields including economy and finance, for example in De Gooijer et al. (1998) where MARS model is used to estimate and forecast non-linear structure in weekly exchange rates for four major currencies during the 1980s and in Yüksel and Adali (2017) where MARS model is used to determine influencing factors of unemployment in Turkey. There are also extensions of the MARS model, such as CMARS (Weber et al. 2012) where the backward pass of MARS is replaced by Tikhonov Regularization and Conic Quadratic Programming. The CMARS method extended in order to cope with data uncertainty, by using robust optimization under polyhedral uncertainty and ellipsoidal uncertainty and RCMARS introduced (Özmen et al. 2010, 2011). A modification of RCMARS in order to reduce computational complexity is the RMARS model which introduced in 2014 (Özmen and Weber 2014) and the MARS and RMARS methods applied to a financial dataset and although RMARS displayed smaller variance under different uncertainty scenarios, the MARS method produced slightly more accurate forecasts.

This paper is a comparison of time series, neural network, support vector machine and multivariate adaptive regression splines models to forecast unemployment of twenty-two countries using monthly seasonally adjusted data for unemployment (Eurostat database). For each one of the considered forecasting approaches, we consider multiple models and we adopt a searching strategy to decide the best. For the FARIMA and FARIMA/GARCH models we have set the rules for the selection of the order and we are searching between models with different error distributions. For the feed-forward fully connected feed forward neural networks (ANN approach) we consider models with 1–4 lagged variables as inputs and 1–10 hidden nodes, for SVR and MARS models we consider 1–4 lagged variables as inputs while ARIMA and Holt-Winters are considered as benchmark models. The comparison of models is performed with the RMSE and MAE criteria for each country. To compare the performance of models overall, we consider some metrics which are based in the RMSE and MAE criteria. Furthermore, to decide the suitability of models for each case we perform the Model confidence set procedure (Hansen et al. 2011).

Finally, is performed a comparison of models in different time horizons and geographic regions to decide if a unique approach is better in all cases and to detect if either forecasting horizon and/or geographic location of a country affects the performance of a model. These comparisons are performed via Friedman tests and posthoc comparisons.

In Sect. 2 are described the characteristics of the unemployment data and potential problems of heteroskedasticity, non-linearity, non-normality and long-memory, while in Sect. 3 are presented FARIMA, FARIMA/GARCH, ANN, SVR and MARS modeling approaches and their application in this paper. Section 4 presents the criteria for the comparison of models for multiple series and Sect. 5 the methodology for testing the effects of geographic location and of forecasting horizon to the performance of models. Section 6 contains the data analysis and Sect. 7 the summary and conclusions of the paper.

2 Unemployment Data Characteristics

In this work we consider approaches for the prediction of univariate time series. Approaches which take into account the specific characteristics of data can offer more accurate predictions. According to past research on monthly unemployment rates, we observe that models such as FARIMA and GARCH have been used, thus characteristics such as long-memory and heteroskedasticity have been taken into account. The Ljung-Box test is applied to check autocorrelation of the time series, thus time series models which model the dependence structure of the data are useful for predictions. Heteroskedasticity of data is checked through the Ljung-Box test on squared residuals of a fitted FARIMA model. This displays if the volatility of the next period depends on the volatility of past periods and the use of a FARIMA/GARCH model seems suitable. For the detection of long-memory we compute the Hurst exponent (Hurst 1951) with three methods: the R/S method (Mandelbrot 1972), the aggregate variance method and the Higuchi method (Taqqu et al. 1995) and we consider the smaller of the values as a conservative approach. A value of the Hurst exponent in (0.5, 1) suggests the existence of long memory and values closer to 1 indicates stronger long memory. Values from 0 to 0.5 indicate antipersistence, i.e. larger values are followed by smaller values and vice versa, while a value equal to 0.5 could be considered as independence of the data or exponential decay of their autocorrelation function.

Other potential characteristics are the departure from normality and the non-linearity of the dependence structure of the data in some cases. To take into account non-normality, FARIMA and FARIMA/GARCH models with non-normal errors are considered. Furthermore, when non-linearity exists, approaches such as neural networks, support vector machines and multivariate adaptive regression splines seem suitable. We are testing for normality and non-linearity characteristics using statistical tests, i.e. Jarque–Bera test for normality (Jarque and Bera 1980; Cromwell 1994) and White neural network test for non-linearity (Lee et al. 1993).

3 Forecasting Approaches

In this section, each of the considered forecasting approaches is presented and its application for unemployment forecasting in this paper is discussed.

3.1 FARIMA Models

The FARIMA forecasting models (Granger and Joyeux 1980; Hosking 1981) are extensions of the ARIMA (p, d, q) models where the fractional parameter d is allowed to take real, instead of only integers, values. A FARIMA model is given by the equation

$$\Phi_p(L)(1-L)^d(Y_t) = \Phi_q(L)\epsilon_t,$$

where L is the lag operator, $\Phi_p(L) = 1 - \Phi_1 L - \cdots - \Phi_p L^p$, $\Theta_q(L) = 1 + \theta_1 L + \cdots + \theta_q L^q$,

$$(1-L)^d = \sum_{j=0}^{\infty} \binom{d}{j} (-1)^j L^j \quad \text{with} \quad \binom{d}{j}(-1) = \frac{\Gamma(-d+j)}{\Gamma(-d)\Gamma(j+1)}$$

and $\epsilon_t \sim N\big(0, \sigma^2\big)$ are the error terms.

Alternatively, there can be considered a model where error terms are following other than the normal distribution (N). To further improve the results, we consider FARIMA (and FARIMA/GARCH) models with student-t (t), GED, Normal Inverse

Gaussian (NIG) and Generalized Hyperbolic (GH) error distributions. Details of the distributions can be found in Ghalanos (2013).

When the error terms are considered to follow a student-t distribution t(0, σ, ν), where ν > 2, the pdf in its location-scale version is

$$f(x;\alpha,\beta,\nu)=\frac{\Gamma\left(\frac{\nu+1}{2}\right)}{\sqrt{\beta\nu\pi}\,\Gamma\left(\frac{\nu}{2}\right)}\left[1+\frac{(x-\alpha)^2}{\beta\nu}\right]^{\left(-\frac{\nu+1}{2}\right)},$$

with location parameter α, scale parameter β and shape parameter ν. The mean equals to α and here is 0, while the variance is $\frac{\beta\nu}{(\nu-2)}$.

The Generalized Error Distribution (GED) is a 3 parameter distribution belonging to the exponential family with conditional density

$$f(x;\alpha,\beta,k)=\frac{ke^{-0.5\left|\frac{x-a}{\beta}\right|^{\kappa}}}{2^{1+\kappa^{-1}}\beta\Gamma\left(\kappa^{-1}\right)},$$

with location parameter α, scale parameter β and shape parameter κ. The mean (and mode and median) of the distribution is α, while the variance is $\beta^2 2^{2/\kappa}\frac{\Gamma(3\kappa^{-1})}{\Gamma(\kappa^{-1})}$.

The Generalized Hyperbolic distribution was introduced by Barndorff-Nielsen (1977). It is a normal variance-mean mixture with a continuous mixing distribution and carries five parameters, μ for the location, α for the shape, β for the skewness, λ for the kurtosis and δ for scaling. Following Aas and Hobæk Haff (2005) if the random variable X follows a GH distribution, then the probability density function takes the form:

$$f(x;\mu,\alpha,\beta,\delta,\lambda)=\frac{(a^2-\beta^2)^{\frac{\lambda}{2}}K_{\lambda-\frac{1}{2}}(\alpha\sqrt{\delta^2+(x+\mu)^2})e^{\beta(x-\mu)}}{\sqrt{2\pi\alpha}^{\lambda-\frac{1}{2}}\delta^{\lambda}K_{\lambda}(\delta\sqrt{\alpha^2-\beta^2})(\sqrt{\delta^2-(x-\mu)^2})^{\frac{1}{2}-\lambda}},$$

where K_λ is the Bessel function of 3rd kind with index λ (Abramowitz and Stegun 1972). The following relations are valid if: $\begin{cases}\lambda<0, & \text{then } \delta>0 \text{ and } |\beta|\le\alpha\\ \lambda=0, & \text{then } \delta>0 \text{ and } |\beta|<\alpha\\ \lambda>0, & \text{then } \delta\ge0 \text{ and } |\beta|<\alpha\end{cases}$. When kurtosis parameter λ = − 1/2, then is arising the subclass of the Inverse Gaussian distribution.

To fit a FARIMA model to a time series the following procedure is applied:

At first we *convert data to a zero-mean series.* Then we specify the *order of the model.* The order (p, q) of the corresponding ARMA model is first determined. For this study, we restrict the autoregressive and moving average orders to be less than or equal to 5 ($0\le p\le5$, $0\le q\le5$) and use the lowest Bayes Information Criterion (BIC) for selecting the best combination. The same order (p, q) is used for the FARIMA model. Finally, we *estimate the parameters of the model.* After the order of the model has been fixed, the rest of the parameters d, Φ_i and θ_j are estimated. The Geweke and Porter-Hudak (GPH) estimator (Geweke and Porter-Hudak 1983) is our choice for d and is computed using R package *fracdiff* (Fraley et al. 2012), while a recursive Maximum Likelihood (ML) procedure is used for the estimation of the other parameters. The ML procedure suggested in Sowell (1992) goes through nonlinear optimization using the nlminb optimizer or augmented Lagrange method and it is all implemented in the R package *rugarch* (Ghalanos 2013).

3.2 FARIMA/GARCH Models

The FARIMA/GARCH models are extensions of FARIMA, in the sense that in addition to all previously discussed assumptions they also assume conditional heteroskedasticity for the errors and then it is possible to give better results than FARIMA. These models were developed and used initially for the prediction of inflation (Baillie et al. 1996) where often the variance appears to be non-stationary. A FARIMA/GARCH model is given by the equation:

$$\Phi_p(L)(1-L)^d(Y_t-\mu)=\Theta_q(L)\epsilon_t,$$

where $\epsilon_t|\Omega_{t-1} \sim$ probability distribution $\left(p_1,\ldots,p_k\right)$ and $\sigma_t^2 = \omega + \sum_{i=1}^{q}\alpha_i\epsilon_{t-i}^2 \sum_{i=1}^{p}\beta_i\sigma_{t-i}^2$.

The new element here, comparing with the description of the FARIMA model, is the fact that given an information set Ω_{t-1}, the error terms e_t follow a probability distribution with parameters $\left(p_1,\ldots,p_k\right)$. This distribution is usually assumed to be Normal with zero mean and σ_t^2 variance (Bollerslev 1986). Here, we assume student-t, GED, Normal Inverse Gaussian and Generalized Hyperbolic error distributions.

The fitting of a FARIMA/GARCH model for this paper will follow the same steps as for the FARIMA, so that the autoregressive and moving average orders (p, q) and the fractional parameter d would be the same as in the corresponding plain FARIMA. Additionally, we will consider a GARCH(1,1) model, which in most applications is sufficient for capturing the conditional variance of the errors. The fitting of a FARIMA/GARCH model can also be performed with the use of the R software package *rugarch* (Ghalanos 2013).

3.3 Artificial Neural Networks (ANN)

Since their introduction, neural networks have been successfully applied to many disciplines, including forecasting (Lippmann 1987; Zhang et al. 1998). They can handle non-linear phenomena more successfully than traditional time series models. ANN forecasting models for time series use sliding windows in the sense that a window with the n most recent values with resampling rate k is used to predict the next one. More specifically, the forecasting model is expressed as in Eq. (3):

$$x(t+1)=f(\mathbf{x}(t)), \tag{3}$$

where $\mathbf{x}(t)=(x(t), x(t-1k), \ldots, x(t-(n-1)k)$ is the vector of the lagged variables to be used as input for the forecast. The process of the information is the following: the input nodes contain the value of the explanatory variables (in our case lagged variables with past values). Each node connection represents a weight factor and the information reaches a single hidden layer node as the weighted sum of its inputs. Each node of the hidden layer passes the information through a nonlinear activation function and passes it on to the output layer if the calculated value is above a threshold.

There have been a number of different architectures for ANNs and in this paper will be used the fully connected feed forward neural networks. In order to construct an ANN for time series one-step ahead prediction, one needs to decide about the input variables, the number of hidden layers and number of nodes for each layer. Empirical research has shown that one hidden layer is sufficient in most cases; therefore we only have to define the number of input nodes and number of hidden nodes. The neural network used in this paper is a fully connected feed-forward ANN comprising of an input layer, one hidden layer and an output node. Each layer is fully connected to the next one and the activation function used in the hidden layer is the sigmoid:

$$\mathrm{S(t)} = \frac{1}{1 + \mathrm{e}^{-\mathrm{t}}}.$$

Moreover, a linear function is used in the output layer in order to transform the previous inputs to final outputs. The training of the network has been done with the adaptive back-propagation with momentum technique (Pernía-Espinoza et al. 2005). The goal is to find a function that best maps a set of inputs to their correct output, thus determine final neuron weights. The weights of the connections in the neural network are updated using the adaptive gradient descent optimization algorithm (Haykin 1999).

In summary, for the construction of an ANN network for an unemployment time series, the following steps are performed:

1. *Determine the resampling rate k* In this paper, is considered $\mathrm{k} = 1$, i.e. no resampling is taking place and we apply the neural network model to the full time series.
2. *Determine the number of input variables* We consider all models with one to four lagged variables as input nodes.
3. *Determine the hidden layer nodes and training epochs* We consider one hidden layer and decide from 1 to 10 nodes. The training is performed using adaptive back-propagation with momentum technique, using the adaptive gradient descent optimization algorithm and for 500 periods of training. The activation function is sigmoid for the hidden layer and linear for the output.

For the multistep ahead prediction of an ANN there is no unique approach and a review of approaches can be found on (Boné and Crucianu 2002). In this work for the 3 step and 12 step ahead forecasts we use the iterative method: we construct an ANN model using the training data, each forecast of the model is considered as a new value and we predict the next value with the constructed neural network model. For the 3 step ahead forecasts the estimated model is updated per 3 months, i.e. four times a year while for the 12 step ahead forecasts, the same model applies for the whole year. Finally, the data are normalized using a z-score normalization with the mean and standard deviation of the training sample. The implementation of the neural networks is performed using the R package *AMORE* (Limas et al. 2014).

The final topology of the ANN will consist of an input layer with I nodes, one hidden layer with H nodes and an output layer with one node, denoted as (I, H, 1). The searching strategy of the neural network models plays a vital role, i.e. how many different models we consider for achieving the best possible result. In this work, the following applies: $I \in \{1, 2, 3, 4\}$, $H \in \{1, \ldots, 10\}$and $I, H \in \mathbb{Z}$.

3.4 Support Vector Regression

Support vector machines (SVM) has been first introduced by Vapnik (1995) and support vector regression machines by Drucker et al. (1997). There are two main categories for support vector machines: support vector classification (SVC) and support vector regression (SVR). The model produced by SVR only depends on a subset of the training data, because the cost function for building the model ignores any training data that is close (within a threshold ε) to the model prediction. A detailed analysis and description of support vector regression can be found in Smola and Schölkopf (2004), Basak et al. (2007) and an application to the prediction of unemployment in Stasinakis et al. (2016). SVR have been used widely for time series prediction (Sapankevych and Sankar 2009) and application areas are many, with financial forecasting (Trafalis and Ince 2000) among others.

Following Sapankevych and Sankar (2009) we briefly present the idea of Support Vector Regression. Given a set of time series data x(t), where t is a series of N discrete samples: $t = \{0, 1, 2, \ldots, N - 1\}$ and $y(t + \Delta)$ is some predicted value in the future $(t \geq N)$. For a time series prediction algorithm, f(x) defines a function that will have an output equal to the predicted value for some prediction horizon. By using regression analysis, $f(x) = (w \cdot \phi(x)) + b$, where $\varphi(x)$ is the non-linear function that maps the input data vector x into a feature space where the training data exhibit linearity. The goal is to find “optimal” weights w and threshold b as well as to define the criteria for finding an “optimal” set of weights.

The overall goal is then the minimization the regularized risk $R_{reg}(f)$ which is defined as:

$$R_{reg}(f) = R_{emp}(f) + \frac{\lambda}{2}w^2,$$

where (f is a function of $\mathbf{x}(t)$) and the empirical risk is defined as:

$$R_{emp}(f) = \frac{1}{N}\sum_{i=1}^{N-1} L\big(x_i, y_i, f(x_i), w\big),$$

where i is an index to discrete time series, y_i is the training set and L(.) is a “loss” function to be defined.

Vapnik defined the e-insensitive loss function and in order to solve for the optimal weights and minimize the regularized risk, a quadratic programming problem is formed used this function:

$$\text{Minimize} \quad \frac{1}{2}w^2 + C\sum_{i=1}^{n} L\big(x_i, y_i, f(x_i), w\big),$$

where $L\left(x_i, y_i, f(x_i), w\right) = \begin{cases} \left|y_i - f(x_i, w)\right| - \epsilon, & \text{if } \left|y_i - f(x_i, w)\right| \geq \epsilon \\ 0, & \text{otherwise} \end{cases}$

Solving for the optimal weights and bias values is an exercise in convex optimization, which is made much simpler by using Lagrange multipliers and forming the dual optimization problem which is formed as:Maximize

$$-\frac{1}{2}\sum_{j=1}^{N}\left(\alpha_i - \alpha_i^*\right)\left(\alpha_j - \alpha_j^*\right)x_i, x_j - \epsilon\sum_{j=1}^{N}\left(\alpha_i - \alpha_i^*\right) + \sum_{i=1}^{n}\gamma_i\left(\alpha_i - \alpha_i^*\right)$$

Subject to

$$\sum_{i=1}^{n}\left(\alpha_i - \alpha_i^*\right) = 0 : \alpha_i, \alpha_i^* \in [0, C]$$

The solution is based on the Karush–Kuhn–Tucker conditions and resulting the function

$$f(x) = \sum_{j=1}^{N}\left(\alpha_i - \alpha_i^*\right)x, x_i + b. \tag{1}$$

The data points on or outside the ε tube with non-zero Lagrange multipliers α, are defined as Support Vectors.

To carry out the non-linear regression using SVR, it is necessary to map the input space x_i into a (possibly) higher dimension feature space $\phi(x_i)$. The solution of the SVR is based on the dot products of the input data, a kernel function that satisfies Mercer's conditions: $k(x, x_i) = \phi(x), \phi(x_i)$ and can be directly substituted to Eq. (1) and the optimal weights w can be computed in feature space using the same procedure.

Several kernel functions satisfy Mercer's conditions (such as polynomial and tangent hyperbolic), but Gaussian kernels appear to be the most popular choice. Quadratic Programming (QP) methods can be used for training SVMs with the Sequential Minimization Optimization (SMO) algorithm to be one of the most popular methods.

We consider as inputs 1, 2, 3 and 4 lagged values to construct models and we select the one with minimum RMSE. The implementation of SVR performed using the R package *e1071* (Meyer et al. 2017).

3.5 Multivariate Adaptive Regression Splines

The method of multivariate adaptive regression splines (MARS) introduced by Friedman (1991) and the extension of MARS to a time series context is discussed in the paper of Lewis and Stevens (1991).

The system which generated the data is supposed to have the form:

$$y = f(x) + \epsilon,$$

where y is the dependent variable, in our case $\mathbf{x} = \left(y_{t-1}, y_{t-2}, \ldots, y_{t-p}\right)^T$ is a vector of predictors which are the lagged time series variables and ε is an additive stochastic component with zero mean and finite variance.

In MARS method, nonparametric models are developed locally, in certain sub-regions of the data and by this way increases flexibility of a global modeling approach to the data. The detection of the optimal number of sub-regions and the fitting of different regression lines for each sub-region is the key for the achievement of flexibility and non-linearity. For each predictor variable, the method detects 'knots' (i.e. breakpoints) which define the intervals where the regression slope changes. The predictor variables which are included in the final model and their corresponding 'knots' are determined through an intensive search procedure.

The MARS model is a weighted sum of basis functions $B_m(x)$ and has the form:

$$\hat{f}(x) = \sum_{m=1}^{M} \alpha_m B_m(x),$$

where $B_m(x) = I[x \in R_m]$ with $\{R_m\}_1^M$ to be a set of disjoint sub-regions representing a partitioning of D and I is an indicator function with value 1 if argument is true and zero otherwise. The $\{\alpha_m\}_1^M$ are the coefficients of the expansion and their values are adjusted at the same time in order to obtain the best fit to the data.

Using the recursive partitioning procedure, the MARS algorithm builds the model using two stages: the forward and the backward pass. At first—in the forward step is considered the entire domain, all sub-regions are split into two sibling sub-regions and the split is optimized using a goodness of fit criterion. The procedure is continued iteratively until a large number of disjoint subregions is generated along with the basis functions of each sub-region. The resulted model from this step intentionally over fits the data and a backward stepwise procedure follows to remove basis functions that not contribute sufficiently to the accuracy of the fit. This is achieved through the recombination of the sub-regions (merge sibling regions when needed) until a good set of non-overlaping sub-regions is obtained through a criterion which penalize both lack-of-fit and increasing number of regions. In this step the complexity of the model is reduced with respect to the ability of the data to fit.

In this work, MARS model with lagged variables as predictors is implemented in the earth package of R statistical software (Milborrow 2018). In this work, lagged variables with 1, 2, 3 and 4 lagged values consider as inputs to construct models and we select the one with minimum RMSE.

4 Comparison of Models

There is no globally accepted best criterion for comparison of forecasting accuracy of models. The comparison of the forecasting accuracy of the models is performed with the well-known RMSE and MAE criteria. In case we want to compare models in more than one country, there are considered six different metrics to assess their aggregated performance.

1. Average RMSE.
2. Average MAE.
3. Number of times when a model is the best choice for forecasting with RMSE.
4. Number of times when a model is the best choice for forecasting with MAE.
5. Average position according to RMSE.
6. Average position according to MAE.
7. Number of times a model is included in the superior set of models.

To calculate the values of criteria 4 and 5, for every dataset we rank the models according to their performance and we specify their position and then we calculate the average value of the positions for each model. Additionally, is used the formal test of Model Confidence Set (MCS) (Hansen et al. 2011), which implemented in R package *MCS* (Catania and Bernardi 2017) to extract a superior set of models for every country. The consideration of different metrics allows a more complete comparison of models. A model is considered preferable than another in a head to head comparison if it prevails with larger number of criteria.

5 Exploration of Effects

It is known that the forecasting horizon could play an important role to the performance of a model. Moreover, the rationale behind analysis of effect of geographic locations is that there could be common factors (such as climatic, political etc.) which affect neighbor countries.

In this section we explore two different kinds of effects: whether forecasting horizons and different geographic locations affect the performance of each forecasting approach.

To achieve that, we use Friedman tests as a non-parametric alternative of Randomized Complete Block Design (Natrella 2010; Hollander et al. 2013). For each model we consider the number of times when a model is included in the superior set of models with Hansen test and we test if is independent from the forecasting horizon considering geographic areas as block. Then, we perform the test for the geographic areas considering forecasting horizons as block. Again, as performance variable we consider the number of times when a model is included in the superior set of models with Hansen test. The tests are performed in FARIMA, FARIMA/GARCH, ANN and MARS approaches. In case significant differences between groups are detected, then by using Conover and Nemenyi posthoc tests (Conover and Iman 1979; Conover 1999; Demšar 2006) we perform pairwise comparisons.

6 Data Analysis

Data are monthly seasonally adjusted unemployment rates of 22 Mediterranean, Nordic, Baltic, Benelux and Balkan countries. Source of the data is the publicly available Eurostat database, the time period is from 2000 M1 to 2014 M12 to train the data and are considered 1 step, 3 steps and 12 steps ahead predictions for the next 12 months, i.e. until 2017 M12 to compare the performance of the models. For Esto-

Table 1 Descriptive statistics

Country	Mean	SD	Skewness	Kurtosis	CV
Belgium	7.775	0.7147	− 0.4856	− 0.8357	0.0919
Bulgaria	11.7933	3.9754	0.4047	− 0.5052	0.3371
Denmark	5.4972	1.4352	0.1775	− 1.3569	0.2611
Estonia	10.1	3.5137	0.2180	− 0.5178	0.3479
Greece	13.7744	6.6856	1.1875	− 0.2610	0.4854
Spain	15.2044	6.3126	0.5560	− 1.3027	0.4152
France	8.955	0.7892	0.0478	− 0.3793	0.0881
Croatia	13.5444	2.7388	− 0.3571	− 0.9816	0.2022
Italy	8.7672	1.8548	0.7189	− 0.3441	0.2116
Cyprus	6.7978	4.2169	1.4025	0.4435	0.6203
Latvia	12.3661	3.8356	0.1751	− 0.4306	0.3102
Lithuania	11.8706	4.2491	− 0.3567	− 0.9147	0.3579
Luxemburg	4.3483	1.2099	− 0.7830	− 0.3975	0.2783
Malta	6.7311	0.5958	0.3878	− 0.1039	0.0885
Netherlands	4.9683	1.2668	0.5220	− 0.4911	0.2550
Romania	7.1078	0.7259	− 0.1276	0.1051	0.1021
Slovenia	6.95	1.6408	0.5541	− 0.3977	0.2361
Finland	8.2639	0.8789	− 0.3907	− 0.3370	0.1064
Sweden	7.1278	1.0241	− 0.1130	− 1.1723	0.1437
Iceland	4.6313	1.8665	0.2547	− 1.5140	0.4030
Norway	3.4789	0.5700	0.1054	− 0.4532	0.1638
Turkey	9.8358	1.3684	1.3685	1.0846	0.1391

nia, Iceland and Turkey we have fewer data available and we train the models with smaller number of observations.

6.1 Exploratory Analysis of Data

For the training set, Table 1 displays descriptive statistics of data, i.e. mean, standard deviation (sd), skewness (excess) kurtosis and coefficient of variation (CV) and Table 2 displays statistical tests for data characteristics, i.e. Ljung–Box test for autocorrelation, Jarque–Bera test for Normality, Ljung–Box test on squared residuals of a FARIMA model (noted on Table 3) for heteroskedasticity, White neural network test for non-linearity and the estimation of Hurst exponent (following methodology of Sect. 2) to measure the long memory of the time series. For the statistical tests, in parenthesis there are reported the p values.

The data have different levels of heterogeneity with CV from 0.0881 for France to 0.6203 for Cyprus. Moreover, only in three cases (the absolute value of) the skewness parameter exceeds 1 and three series are leptokurtic.

We consider the 5% significance level and the conclusions are the following:

Table 2 Statistical tests and hurst exponent

Country	Auto-correlation (Ljung–Box)	Normality (Jarque–Bera)	Heteroskedasticity (Ljung–Box on sq.res.)[a]	Non-linearity (white test)	Hurst exponent
Belgium	167.2948 (<0.01)	12.133 (<0.01)	6.595 (0.0102)	3.8653 (0.1448)	0.6192
Bulgaria	181.6766 (<0.01)	6.7042 (0.035)	9.046 (<0.01)	0.7415 (0.6902)	0.8559
Denmark	180.0896 (<0.01)	14.3974 (<0.01)	0.0927 (<0.01)	2.4537 (0.2932)	0.7147
Estonia	175.902 (<0.01)	3.2315 (0.1987)	2.183 (0.13953)	0.2504 (0.8823)	0.7043
Greece	179.1899 (<0.01)	43.4128 (<0.01)	0.8400 (0.3594)	78.4777 (<0.01)	0.6929
Spain	180.7667 (<0.01)	21.7901 (<0.01)	0.2637 (0.6076)	18.2704 (<0.01)	0.8267
France	175.8938 (<0.01)	0.988 (0.6102)	0.007713 (0.93)	0.6191 (0.7338)	0.6629
Croatia	180.7159 (<0.01)	10.7873 (<0.01)	0.1653 (0.6843)	1.739 (0.4192)	0.7196
Italy	176.4001 (<0.01)	16.5048 (<0.01)	0.1948 (0.6589)	3.7144 (0.1561)	0.7791
Cyprus	176.4567 (<0.01)	61.7456 (<0.01)	1.603 (0.2055)	29.5193 (<0.01)	0.6717
Latvia	179.9232 (<0.01)	2.1456 (0.342)	24.68 (<0.01)	0.2062 (0.902)	0.7759
Lithuania	180.7968 (<0.01)	9.8391 (<0.01)	1.642 (0.200)	0.2759 (0.8712)	0.7721
Luxemburg	176.5282 (<0.01)	19.7188 (<0.01)	0.4862 (0.4856)	9.2216 (<0.01)	0.6802
Malta	158.8769 (<0.01)	4.6264 (0.099)	0.1864 (0.6659)	0.0575 (0.9717)	0.7924
Netherlands	177.9859 (<0.01)	9.9193 (<0.01)	0.08801 (0.7667)	1.8304 (0.4004)	0.5866
Romania	158.0743 (<0.01)	0.6436 (0.7248)	0.7121 (0.3987)	1.6495 (0.4383)	0.8577
Slovenia	178.5908 (<0.01)	10.3857 (<0.01)	0.05375 (0.8167)	5.2069 (0.074)	0.7233
Finland	176.1429 (<0.01)	5.3652 (0.068)	3.837 (0.05012)	3.6282 (0.163)	0.8288
Sweden	164.158 (<0.01)	10.34 (<0.01)	0.06287 (0.80202)	2.5864 (0.2744)	0.6267
Iceland	145.5893 (<0.01)	14.966 (<0.01)	0.004335 (0.9475)	0.1523 (0.9267)	0.9670
Norway	175.5136 (<0.01)	1.692 (0.4291)	0.4081 (0.5229)	0.4099 (0.8147)	0.7548
Turkey	118.849 (<0.01)	45.0639 (<0.01)	1.782 (0.1819)	0.4286 (0.8071)	0.7679

[a]Test in the FARIMA squared residuals

All series are autocorrelated and the majority of them are non-normal. Furthermore, all models exhibit long-memory (Hurst exponent values from 0.5866 for Netherlands to 0.8559 for Bulgaria). Furthermore, only in 4 series can be detected non-linear structure according to White neural network test (Greece, Spain, Cyprus and Luxemburg). Additionally, heteroskedasticity is present only for 4 countries (Belgium, Bulgaria, Denmark and Latvia).

6.2 Comparison of Approaches

The framework for the comparison of the models is constituted of 2 steps:

1. Selection of the best models with the methodologies of Sect. 2.
    - We select the best *FARIMA* model.
    - We select the best *FARIMA/GARCH* model.
    - We select the best *ANN* model.
    - We select the best *SVR* model.
    - We select the best *MARS* model.
2. Comparison of these models with the benchmarks (ARIMA and Holt-Winters) according to the framework of Sect. 4.

Following the methodologies discussed in Sect. 2 we select from each model the best (the results are displayed in "Appendix 1"). For FARIMA and FARIMA/GARCH models we consider errors with normal (N), student-t (t), generalized error (GED), normal inverse Gaussian (NIG) and generalized hyperbolic (GH) distributions and we select the one with the lowest RMSE. For the three considered horizons are constructed tables to display the comparison results.

From the selected models, in Tables 3, 5, 7 are displayed the orders (only in Table 3) and the error distribution of FARIMA and FARIMA/GARCH(1,1), the architectures of ANN, the lagged variables (which are the dependent variables) of SVR and MARS and the orders of ARIMA.

The final comparisons of the approaches are presented in Tables 4, 6 and 8 which display the prediction error of FARIMA and FARIMA/GARCH, ANN, SVR, MARS, ARIMA and Holt-Winters models. Then, the values with the six different performance metrics are reported for each model.

6.2.1 One Step Ahead Predictions (h = 1)

See Tables 3 and 4.

Table 3 Description of models

Country	FARIMA	FARIMA/GARCH(1,1)	ANN	SVR	MARS	ARIMA
Belgium	(2, 0.9257,2)-GH	N	(3,2,1)	4	4	1
Bulgaria	(1, 1.5134,0)-N	N	(4,4,1)	3	4	1
Denmark	(0, 1.5614, 2)-N	N	(2,2,1)	2	2	1
Estonia	(2, 1.1830, 0)-NIG	t	(3,4,1)	3	1	1
Greece	(1, 1.2946, 1)-NIG	N	(4,3,1)	1	4	2
Spain	(1, 1.3557, 1)-NIG	t	(3,4,1)	4	4	2
France	(0, 1.5857, 1)-NIG	NIG	(2,2,1)	1	2	2
Croatia	(0, 1.5819, 1)-GH	NIG	(4,1,1)	4	4	2
Italy	(1, 1.6298, 1)-N	N	(3,3,1)	2	3	2
Cyprus	(0, 1.1654, 2)-N	N	(2,2,1)	1	3	2
Latvia	(3, 1.5277, 3)-NIG	t	(4,5,1)	4	1	1
Lithuania	(1, 1.5211, 0)-N	GH	(4,10,1)	4	1	1
Luxemburg	(1, 1.0895, 2)-N	N	(1,3,1)	1	1	1
Malta	(1, 0.6924, 0)-N	N	(1,4,1)	2	1	1
Netherlands	(1, 1.1769, 2)-N	N	(3,1,1)	3	4	1
Romania	(1, 0.8536, 0)-N	N	(1,2,1)	1	3	1
Slovenia	(2, 1.3716, 2)-GED	GED	(2,2,1)	2	4	1
Finland	(1, 1.4326, 1)-GH	N	(2,3,1)	3	1	2
Sweden	(1, 1.3743, 2)-t	t	(4,1,1)	4	3	1
Iceland	(0, 1.7440, 1)-t	t	(2,1,1)	4	3	2
Norway	(0, 1.2413, 0)-N	N	(2,2,1)	1	1	1
Turkey	(1, 1.3129, 2)-NIG	t	(3,2,1)	3	4	1

Table 4 Prediction accuracy

	FARIMA	FARIMA/GARCH	ANN	SVR	MARS	ARIMA	Holt-Winters
Avg. RMSE	**0.163**	0.164	0.298	0.344	0.209	0.206	0.164
Avg. MAE	**0.130**	0.131	0.250	0.288	0.177	0.165	0.132
Best model with RMSE	**7**	3	1	1	3	3	5
Best model with MAE	**9**	3	1	3	3	3	2
Avg. position RMSE	**2.591**	2.818	5.909	5.091	4.318	4.318	2.864
Avg. position MAE	**2.455**	2.818	5.909	5.136	4.136	4.136	3.182
# Times in superior set	**18**	**18**	4	11	15	13	**18**
# Of best criteria	7	1	0	0	0	0	1

The best values of each criterion (among all models) appears in bold

6.2.2 Three step ahead Predictions (h = 3)

See Tables 5 and 6.

Table 5 Description of models

Country	FARIMA	FARIMA/GARCH(1,1)	ANN	SVR	MARS
Belgium	GH	GH	(2,2,1)	4	2
Bulgaria	GH	GED	(4,3,1)	2	3
Denmark	N	N	(2,9,1)	1	1
Estonia	GED	NIG	(3,4,1)	2	2
Greece	NIG	GED	(3,10,1)	4	3
Spain	N	N	(3,7,1)	4	3
France	GED	GED	(3,8,1)	1	4
Croatia	N	NIG	(4,2,1)	4	4
Italy	GED	NIG	(1,8,1)	1	2
Cyprus	N	GED	(3,1,1)	1	2
Latvia	N	N	(1,4,1)	1	1
Lithuania	GED	NIG	(1,1,1)	1	1
Luxemburg	GED	GH	(2,10,1)	1	2
Malta	N	N	(1,10,1)	1	4
Netherlands	N	N	(4,1,1)	4	4
Romania	t	t	(1,8,1)	1	4
Slovenia	GED	GED	(3,10,1)	2	4
Finland	N	t	(3,10,1)	2	1

Table 5 continued

Country	FARIMA	FARIMA/GARCH(1,1)	ANN	SVR	MARS
Sweden	t	t	(1,5,1)	3	3
Iceland	N	GH	(2,1,1)	3	4
Norway	N	N	(1,10,1)	1	1
Turkey	GED	t	(1,1,1)	2	3

Table 6 Prediction accuracy

	FARIMA	FARIMA/GARCH	ANN	SVR	MARS	ARIMA	Holt-Winters
Avg. RMSE	0.474	0.468	0.269	0.313	0.306	0.375	**0.261**
Avg. MAE	0.425	0.420	0.209	0.245	0.241	0.310	**0.203**
Best model with RMSE	1	1	5	2	2	1	**10**
Best model with MAE	1	2	4	2	2	0	**11**
Avg. position RMSE	5.636	5.545	2.955	3.545	3.045	5.182	**2.182**
Avg. position MAE	5.682	5.500	2.909	3.500	3.000	5.227	**2.136**
# Times in superior set	11	10	**19**	15	18	11	**19**
# Of best criteria	0	0	1	0	0	0	7

The best values of each criterion (among all models) appears in bold

6.2.3 Twelve step ahead Predictions (h = 12)

See Tables 7 and 8.

Table 7 Description of models

Country	FARIMA	FARIMA/GARCH(1,1)	ANN	SVR	MARS
Belgium	NIG	GED	(4,9,1)	4	4
Bulgaria	GED	N	(1,5,1)	1	1
Denmark	N	N	(4,1,1)	2	4
Estonia	GED	GED	(1,9,1)	1	1
Greece	NIG	NIG	(3,10,1)	1	3
Spain	GH	N	(1,3,1)	1	1
France	GED	t	(3,2,1)	1	1
Croatia	GED	NIG	(4,2,1)	2	1

Table 7 continued

Country	FARIMA	FARIMA/GARCH(1,1)	ANN	SVR	MARS
Italy	GED	NIG	(4,10,1)	2	1
Cyprus	t	NIG	(3,1,1)	1	2
Latvia	GH	t	(4,3,1)	1	1
Lithuania	NIG	NIG	(1,1,1)	3	3
Luxemburg	GH	N	(2,9,1)	1	1
Malta	N	N	(2,4,1)	1	4
Netherlands	t	N	(3,3,1)	1	1
Romania	GED	t	(3,10,1)	4	2
Slovenia	N	N	(3,8,1)	1	4
Finland	t	t	(1,2,1)	1	2
Sweden	t	t	(1,5,1)	4	3
Iceland	N	NIG	(2,1,1)	4	1
Norway	N	N	(2,10,1)	1	1
Turkey	NIG	t	(4,4,1)	1	3

Table 8 Prediction accuracy

	FARIMA	FARIMA/GARCH	ANN	SVR	MARS	ARIMA	Holt-Winters
Avg. RMSE	**0.589**	0.598	0.634	0.962	1.016	0.670	0.619
Avg. MAE	**0.496**	0.503	0.517	0.793	0.840	0.527	0.497
Best model with RMSE	6	**7**	3	1	1	3	2
Best model with MAE	4	**5**	**5**	2	0	3	4
Avg. position RMSE	**3.000**	3.045	3.455	5.455	5.545	3.682	3.727
Avg. position MAE	**3.227**	3.409	3.455	5.182	5.636	3.545	3.455
# Times in superior set	**18**	16	**18**	13	12	16	17
# Of best criteria	5	2	2	0	0	0	0

The best values of each criterion (among all models) appears in bold

7 Discussion of Results

From the comparison of models (Tables 4, 6 and 8) we have the following exploratory remarks:

For h=1, FARIMA models are the most suitable approach with all criteria, while FARIMA/GARCH is the second best model. Machine learning approaches are not successful and cannot beat benchmark models. MARS models were more accurate than SVR and neural network models.

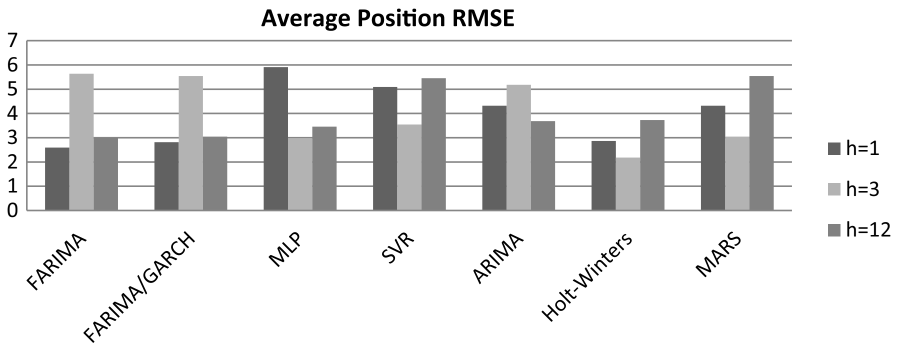

Fig. 1 Average RMSE-based position of models

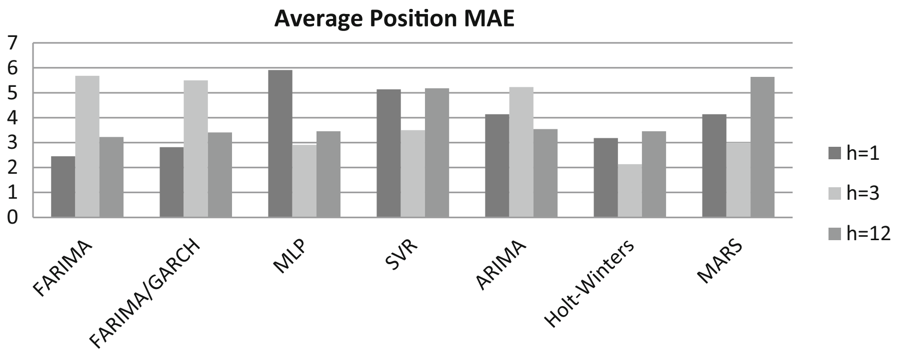

Fig. 2 Average MAE-based position of models

For h=3, simple Holt-Winters outperforms all other approaches with all criteria. Machine learning approaches outperformed FARIMA and FARIMA/GARCH models in this horizon. From these machine learning approaches, neural networks outperformed SVR and MARS models and are included in the superior set of models more times than other models.

For h=12, mainly FARIMA, but also FARIMA/GARCH and ANN forecasting approaches appears as the most suitable. The regression approaches (i.e. SVR and MARS) display the worst performance and cannot beat benchmark models.

Briefly, long-memory found to play important role to the selection of model, and FARIMA model is more accurate than ARIMA in 1-step and 12-steps ahead predictions. The presence of heteroskedasticity led us to FARIMA/GARCH model, but this model did not led to improvement of FARIMA in the majority of cases. The same with the presence of non-linearity, with the machine learning approaches not found to be preferable.

In Figs. 1 and 2 is presented graphically the average position of the models with RMSE and MAE criteria for different forecasting horizons. Only for the ANN and ARIMA approaches the increase of forecasting horizon led to better results, while the average position in the 12 step ahead forecasts worsened for the rest of the models compared to their position in the 1 step ahead forecasts. Overall, FARIMA-based

Table 9 Geographic areas

Region	Countries	Details
Med	Greece, Spain, France, Croatia, Italy, Cyprus, Malta, Slovenia, Turkey	https://en.wikipedia.org/wiki/Mediterranean_Sea
Balkan	Bulgaria, Greece, Croatia, Italy, Romania, Slovenia, Turkey	https://en.wikipedia.org/wiki/Balkans
Baltic	Estonia, Latvia, Lithuania	https://en.wikipedia.org/wiki/Baltic
Nordic	Denmark, Finland, Sweden, Iceland, Norway	https://en.wikipedia.org/wiki/Nordic
Benelux	Netherlands, Belgium, Luxemburg	https://en.wikipedia.org/wiki/Benelux

time series models found preferred for the 1 step-ahead predictions, but when the goal is multiple steps ahead forecasts, then neural network models appear competitive in terms of forecasting accuracy. The FARIMA-based models have mediocre performance in the quarterly forecasting (h = 3) and machine learning approaches appear as a preferable choice.

7.1 Exploration of Forecasting Horizon and Geographical Location Effects

Following the methodology of Sect. 5, we explore the effects of each factor and we discuss them. The factors are the horizons (1-step ahead, 3-step ahead and 12-step ahead) and geographic areas which are presented in Table 9.

We perform Friedman tests with posthoc comparisons when there is detected a significant difference. The results are presented in Tables 10 and 11.

The forecasting horizon is an important factor for the forecasting accuracy of ANN and MARS models (machine learning approaches) at 5% significance level. So, we have to take into account the forecasting horizon for the use of machine learning approaches. The FARIMA/GARCH approach avoids rejection of the null hypothesis of equal performance only marginally and only FARIMA model seems clearly unaffected by the forecasting horizon as a suitable forecasting approach.

Furthermore, geographic areas found to play important role in the performance of all models except from ANN which found to have similar performance across all geographic regions.

8 Summary and Conclusions

In this paper, is made an attempt to apply time series and machine learning approaches to time series prediction of univariate time series of unemployment in several countries. We consider models with respect to the characteristics of long-memory, heteroskedasticity (i.e. FARIMA and FARIMA/GARCH models) and non-linearity (i.e. ANN, SVR and MARS models). For each approach, is provided a framework of application. Additionally, is provided a framework for comparison of models in more than one country. Then, the effects of forecasting horizon and of geographic location to the forecast-

Table 10 Friedman test with geographic area as block

FARIMA		
Friedman test		
Statistic	*df*	*p value*
3.8947	2	0.1426
FARIMA/GARCH		
Friedman test		
Statistic	*df*	*p value*
5.7647	2	0.056
Post-hoc test Conover		
h = 1 versus h = 3		0.022
h = 3 versus h = 12		0.033
ANN		
Friedman test		
Statistic	*df*	*p value*
6.5333	2	0.03813
Posthoc test Conover		
h = 1 versus h = 3		0.011
h = 1 versus h = 12		0.018
MARS		
Friedman test		
Statistic	*df*	*p value*
7.4286	2	0.02437
Posthoc test Conover		
h = 1 versus h = 12		0.0153
h = 3 versus h = 12		<0.01

Table 11 Friedman test with horizon as block

FARIMA		
Friedman test		
Statistic	*df*	*p value*
10.5085	4	0.03268
Posthoc test Nemenyi (Conover cannot be displayed due to NA's)		
Baltic versus med		0.036
FARIMA/GARCH		
Friedman test		
Statistic	*df*	*p value*
9.7544	4	0.04477
Posthoc test Conover		
Balkan versus baltic		<0.01
Balkan versus benelux		0.08474
Balkan versus med		<0.01

Table 11 continued

Baltic versus benelux		0.01081
Baltic versus med		<0.01
Baltic versus nordic		<0.01
Benelux versus med		<0.01
Med versus nordic		<0.01
ANN		
Friedman test		
Statistic	*df*	*p value*
4.5818	4	0.333
MARS		
Friedman test		
Posthoc test Nemenyi (conover cannot be displayed due to NA's)		
Statistic	*df*	*p value*
10.0741	4	0.0392
Benelux versus nordic	0.052	

ing accuracy of models are examined through the use of Friedman non-parametric statistical test and posthoc comparisons where needed.

The main results are that no single model is accepted globally and both the forecasting horizon and the geographic location should be taken into consideration to the selection of an approach. FARIMA models found to be clearly the preferable approach for the 1-step ahead forecasts, while for the longer period (h = 12) neural network approaches achieve comparable results with FARIMA-based models. When h = 3, Holt-Winters model found to be more suitable and the selection of the most suitable forecasting approaches for different forecasting horizons needs further investigation.

Appendix

1-Step Ahead Predictions

See Tables 12 and 13.

Table 12 Positions of models RMSE (MAE)

Country	FARIMA	FARIMA/GARCH(1,1)	ANN	SVR	MARS	ARIMA	Holt-Winters
Belgium	1 (1)	2 (2)	7 (7)	5 (5)	4 (4)	3 (3)	6 (6)
Bulgaria	2 (1)	3 (2)	7 (6)	6 (7)	5 (5)	4 (4)	1 (3)
Denmark	3 (3)	2 (2)	6 (7)	1 (1)	5 (5)	7 (6)	4 (4)
Estonia	5 (4)	3 (5)	1 (1)	7 (7)	2 (2)	4 (3)	6 (6)
Greece	2 (2)	3 (3)	5 (5)	6 (6)	7 (7)	4 (4)	1 (1)
Spain	1 (1)	3 (3)	4 (4)	6 (6)	7 (7)	5 (5)	2 (2)
France	1 (1)	1 (1)	7 (7)	5 (5)	4 (4)	6 (6)	3 (3)
Croatia	1 (1)	2 (2)	6 (6)	5 (5)	4 (4)	7 (7)	3 (3)
Italy	1 (1)	2 (2)	7 (7)	5 (5)	4 (4)	6 (6)	3 (3)
Cyprus	2 (2)	1 (1)	7 (7)	6 (6)	5 (5)	4 (4)	3 (3)
Latvia	6 (5)	5 (3)	4 (4)	2 (6)	1 (1)	7 (7)	3 (2)
Lithuania	6 (6)	7 (7)	3 (3)	2 (2)	1 (1)	5 (5)	4 (4)
Luxemburg	2 (1)	3 (3)	6 (6)	7 (7)	5 (5)	4 (4)	1 (1)
Malta	4 (4)	3 (3)	6 (6)	7 (7)	5 (5)	1 (1)	2 (2)
Netherlands	3 (2)	1 (1)	7 (7)	6 (6)	5 (5)	4 (4)	2 (2)
Romania	4 (5)	3 (4)	6 (6)	7 (7)	5 (3)	1 (1)	2 (2)
Slovenia	1 (1)	2 (2)	7 (7)	6 (6)	5 (5)	3 (3)	4 (4)
Finland	1 (1)	2 (3)	6 (6)	4 (5)	5 (1)	7 (7)	3 (4)
Sweden	4 (6)	5 (5)	7 (7)	3 (1)	6 (4)	2 (3)	1 (2)
Iceland	3 (2)	4 (3)	7 (7)	5 (1)	1 (5)	6 (6)	2 (4)
Norway	2 (2)	2 (2)	7 (7)	6 (6)	5 (5)	4 (1)	1 (4)
Turkey	2 (1)	3 (3)	7 (7)	5 (6)	4 (4)	1 (2)	6 (5)

Table 13 Prediction accuracy

Country	FARIMA	FARIMA/GARCH (1,1)	ANN	SVR	MARS	ARIMA	Holt-Winters
Belgium	RMSE = 0.1351 MAE = 0.1091	RMSE = 0.1363 MAE = 0.1100	RMSE = 0.2443 MAE = 0.2027	RMSE = 0.1601 MAE = 0.1333	RMSE = 0.1475 MAE = 0.125	RMSE = 0.1369 MAE = 0.1104	RMSE = 0.1735 MAE = 0.1441
Bulgaria	RMSE = 0.1122 MAE = 0.0820	RMSE = 0.1126 MAE = 0.0824	RMSE = 0.4230 MAE = 0.3405	RMSE = 0.1234 MAE = 0.0953	RMSE = 0.1156 MAE = 0.0905	RMSE = 0.1136 MAE = 0.0855	RMSE = 0.1121 MAE = 0.0836
Denmark	RMSE = 0.1311 MAE = 0.1049	RMSE = 0.1303 MAE = 0.1036	RMSE = 0.1367 MAE = 0.1175	RMSE = 0.1262 MAE = 0.0951	RMSE = 0.1360 MAE = 0.1121	RMSE = 0.1419 MAE = 0.1166	RMSE = 0.1339 MAE = 0.1065
Estonia	RMSE = 0.4059 MAE = 0.3504	RMSE = 0.4047 MAE = 0.3511	RMSE = 0.3828 MAE = 0.3128	RMSE = 0.4273 MAE = 0.3715	RMSE = 0.3922 MAE = 0.3361	RMSE = 0.4057 MAE = 0.3464	RMSE = 0.4216 MAE = 0.3714
Greece	RMSE = 0.2915 MAE = 0.2358	RMSE = 0.2921 MAE = 0.2363	RMSE = 0.5470 MAE = 0.4695	RMSE = 0.6150 MAE = 0.5559	RMSE = 0.6516 MAE = 0.5812	RMSE = 0.3818 MAE = 0.2838	RMSE = 0.2900 MAE = 0.2321
Spain	RMSE = 0.1020 MAE = 0.0854	RMSE = 0.1024 MAE = 0.0862	RMSE = 0.1392 MAE = 0.1119	RMSE = 0.3281 MAE = 0.3116	RMSE = 0.3831 MAE = 0.3807	RMSE = 0.2383 MAE = 0.2145	RMSE = 0.1022 MAE = 0.0858
France	RMSE = 0.0848 MAE = 0.0696	RMSE = 0.0848 MAE = 0.0696	RMSE = 0.1278 MAE = 0.1024	RMSE = 0.1142 MAE = 0.0923	RMSE = 0.0854 MAE = 0.0721	RMSE = 0.1354 MAE = 0.1028	RMSE = 0.0850 MAE = 0.0702
Croatia	RMSE = 0.1124 MAE = 0.0894	RMSE = 0.1126 MAE = 0.0895	RMSE = 0.2836 MAE = 0.2486	RMSE = 0.1386 MAE = 0.1146	RMSE = 0.1192 MAE = 0.099	RMSE = 0.360 MAE = 0.3308	RMSE = 0.1139 MAE = 0.0923
Italy	RMSE = 0.1755 MAE = 0.1404	RMSE = 0.1756 MAE = 0.1409	RMSE = 0.3217 MAE = 0.2761	RMSE = 0.2493 MAE = 0.1953	RMSE = 0.2053 MAE = 0.1776	RMSE = 0.2679 MAE = 0.1957	RMSE = 0.1774 MAE = 0.1444
Cyprus	RMSE = 0.2261 MAE = 0.1622	RMSE = 0.2216 MAE = 0.1588	RMSE = 0.7333 MAE = 0.6782	RMSE = 0.5788 MAE = 0.5236	RMSE = 0.5579 MAE = 0.4949	RMSE = 0.4872 MAE = 0.3827	RMSE = 0.2394 MAE = 0.1800
Latvia	RMSE = 0.2329 MAE = 0.1490	RMSE = 0.2252 MAE = 0.1456	RMSE = 0.1915 MAE = 0.1482	RMSE = 0.1752 MAE = 0.1503	RMSE = 0.1689 MAE = 0.1376	RMSE = 0.2497 MAE = 0.1636	RMSE = 0.1906 MAE = 0.1383
Lithuania	RMSE = 0.2797 MAE = 0.2280	RMSE = 0.3042 MAE = 0.2474	RMSE = 0.2579 MAE = 0.1920	RMSE = 0.2360 MAE = 0.1781	RMSE = 0.2212 MAE = 0.1683	RMSE = 0.2757 MAE = 0.2246	RMSE = 0.2691 MAE = 0.2183
Luxemburg	RMSE = 0.0735 MAE = 0.0601	RMSE = 0.0749 MAE = 0.0609	RMSE = 0.1373 MAE = 0.1190	RMSE = 0.3437 MAE = 0.2868	RMSE = 0.779 MAE = 0.612	RMSE = 0.0752 MAE = 0.0609	RMSE = 0.0734 MAE = 0.0601
Malta	RMSE = 0.1281 MAE = 0.1060	RMSE = 0.1257 MAE = 0.1043	RMSE = 0.5095 MAE = 0.4296	RMSE = 2.1160 MAE = 1.8395	RMSE = 0.1663 MAE = 0.1459	RMSE = 0.1103 MAE = 0.0899	RMSE = 0.1150 MAE = 0.0942

3-Step Ahead Predictions

See Tables 14 and 15.

Table 14 Prediction accuracy

Country	FARIMA	FARIMA/GARCH (1,1)	ANN	SVR	MARS	ARIMA	Holt-Winters
Netherlands	RMSE = 0.0885 MAE = 0.0749	RMSE = 0.0878 MAE = 0.0747	RMSE = 0.2353 MAE = 0.2132	RMSE = 0.1263 MAE = 0.1061	RMSE = 0.1019 MAE = 0.0828	RMSE = 0.0899 MAE = 0.0758	RMSE = 0.0884 MAE = 0.0749
Romania	RMSE = 0.2288 MAE = 0.1764	RMSE = 0.2285 MAE = 0.1761	RMSE = 0.5992 MAE = 0.4722	RMSE = 0.7874 MAE = 0.5622	RMSE = 0.2201 MAE = 0.1691	RMSE = 0.2096 MAE = 0.1586	RMSE = 0.2141 MAE = 0.1621
Slovenia	RMSE = 0.1129 MAE = 0.0934	RMSE = 0.1136 MAE = 0.0938	RMSE = 0.2561 MAE = 0.2169	RMSE = 0.1812 MAE = 0.1422	RMSE = 0.1467 MAE = 0.1194	RMSE = 0.1306 MAE = 0.1090	RMSE = 0.1402 MAE = 0.1153
Finland	RMSE = 0.0614 MAE = 0.0536	RMSE = 0.0615 MAE = 0.0537	RMSE = 0.0710 MAE = 0.0588	RMSE = 0.0670 MAE = 0.0544	RMSE = 0.0674 MAE = 0.0492	RMSE = 0.0776 MAE = 0.0624	RMSE = 0.0620 MAE = 0.0538
Sweden	RMSE = 0.2534 MAE = 0.2187	RMSE = 0.2537 MAE = 0.2183	RMSE = 0.3395 MAE = 0.2678	RMSE = 0.2386 MAE = 0.1873	RMSE = 0.2595 MAE = 0.2006	RMSE = 0.2353 MAE = 0.1929	RMSE = 0.2340 MAE = 0.1926
Iceland	RMSE = 0.0632 MAE = 0.0526	RMSE = 0.0635 MAE = 0.0529	RMSE = 0.1635 MAE = 0.1387	RMSE = 0.0700 MAE = 0.0511	RMSE = 0.0626 MAE = 0.0544	RMSE = 0.1244 MAE = 0.1028	RMSE = 0.0628 MAE = 0.0532
Norway	RMSE = 0.1172 MAE = 0.0935	RMSE = 0.1172 MAE = 0.0935	RMSE = 0.2388 MAE = 0.2053	RMSE = 0.1807 MAE = 0.1453	RMSE = 0.1201 MAE = 0.0984	RMSE = 0.1189 MAE = 0.0922	RMSE = 0.1170 MAE = 0.0942
Turkey	RMSE = 0.1698 MAE = 0.1297	RMSE = 0.1801 MAE = 0.1363	RMSE = 0.2255 MAE = 0.1826	RMSE = 0.1877 MAE = 0.1516	RMSE = 0.1826 MAE = 0.1410	RMSE = 0.1686 MAE = 0.1336	RMSE = 0.1896 MAE = 0.1468

Table 15 Positions of models RMSE (MAE)

Country	FARIMA	FARIMA/GARCH(1,1)	ANN	SVR	MARS	ARIMA	Holt-Winters
Belgium	3 (3)	2 (1)	6 (6)	5 (5)	1 (2)	7 (7)	4 (4)
Bulgaria	6 (6)	7 (7)	4 (4)	1 (1)	3 (3)	5 (5)	2 (2)
Denmark	6 (6)	7 (7)	1 (1)	2 (2)	3 (3)	5 (5)	4 (4)
Estonia	6 (6)	7 (7)	1 (1)	3 (3)	2 (2)	5 (5)	4 (4)
Greece	7 (7)	6 (6)	2 (2)	4 (4)	5 (5)	3 (3)	1 (1)
Spain	7 (7)	6 (6)	2 (2)	3 (3)	5 (4)	4 (5)	1 (1)
France	6 (7)	5 (6)	1 (2)	4 (3)	3 (4)	7 (5)	2 (1)
Croatia	6 (6)	1 (1)	5 (5)	4 (4)	3 (2)	7 (7)	2 (3)
Italy	6 (6)	7 (7)	1 (1)	4 (4)	3 (3)	5 (5)	2 (2)
Cyprus	6 (6)	7 (7)	2 (2)	3 (3)	4 (4)	5 (5)	1 (1)
Latvia	7 (7)	6 (6)	3 (3)	1 (1)	2 (2)	5 (5)	4 (4)
Lithuania	6 (6)	7 (7)	4 (4)	2 (3)	3 (1)	1 (2)	5 (5)
Luxemburg	7 (7)	6 (6)	3 (3)	5 (4)	2 (2)	4 (5)	1 (1)
Malta	7 (7)	6 (6)	4 (4)	5 (5)	2 (2)	3 (3)	1 (1)
Netherlands	4 (5)	6 (6)	3 (3)	5 (4)	2 (2)	7 (7)	1 (1)
Romania	7 (7)	6 (6)	1 (1)	5 (5)	3 (3)	4 (4)	2 (2)
Slovenia	1 (1)	2 (2)	3 (4)	6 (6)	5 (5)	7 (7)	4 (3)
Finland	5 (5)	6 (6)	5 (2)	4 (3)	3 (4)	7 (7)	1 (1)
Sweden	3 (4)	4 (5)	5 (3)	2 (2)	6 (6)	7 (7)	1 (1)
Iceland	7 (7)	6 (6)	4 (4)	3 (3)	2 (2)	5 (5)	1 (1)
Norway	6 (6)	6 (6)	2 (2)	3 (3)	4 (4)	5 (5)	1 (1)
Turkey	5 (3)	6 (4)	3 (5)	4 (6)	1 (1)	7 (7)	2 (2)

12-Step Ahead Predictions

See Tables 16 and 17.

Table 16 Prediction accuracy

Country	FARIMA	FARIMA/GARCH (1,1)	ANN	SVR	MARS	ARIMA	Holt-Winters
Belgium	RMSE = 0.2812 MAE = 0.2345	RMSE = 0.2676 MAE = 0.2254	RMSE = 0.3402 MAE = 0.2658	RMSE = 0.2849 MAE = 0.2365	RMSE = 0.2659 MAE = 0.2328	RMSE = 0.4695 MAE = 0.4063	RMSE = 0.2818 MAE = 0.2328
Bulgaria	RMSE = 0.6856 MAE = 0.6450	RMSE = 0.6875 MAE = 0.6484	RMSE = 0.2689 MAE = 0.2094	RMSE = 0.2048 MAE = 0.1488	RMSE = 0.2246 MAE = 0.1707	RMSE = 0.2840 MAE = 0.2269	RMSE = 0.2244 MAE = 0.1704
Denmark	RMSE = 0.2190 MAE = 0.1895	RMSE = 0.2200 MAE = 0.1908	RMSE = 0.1849 MAE = 0.1457	RMSE = 0.1868 MAE = 0.1474	RMSE = 0.2020 MAE = 0.1588	RMSE = 0.2148 MAE = 0.1730	RMSE = 0.2077 MAE = 0.1680
Estonia	RMSE = 0.8299 MAE = 0.7343	RMSE = 0.8353 MAE = 0.7384	RMSE = 0.4230 MAE = 0.3386	RMSE = 0.5449 MAE = 0.4208	RMSE = 0.5026 MAE = 0.4117	RMSE = 0.7333 MAE = 0.5869	RMSE = 0.6085 MAE = 0.4853
Greece	RMSE = 1.5155 MAE = 1.4403	RMSE = 1.5004 MAE = 1.4241	RMSE = 0.4893 MAE = 0.3725	RMSE = 0.7087 MAE = 0.5697	RMSE = 0.8151 MAE = 0.6931	RMSE = 0.5405 MAE = 0.4104	RMSE = 0.4703 MAE = 0.3381
Spain	RMSE = 0.6896 MAE = 0.6586	RMSE = 0.6835 MAE = 0.6529	RMSE = 0.2513 MAE = 0.1933	RMSE = 0.3991 MAE = 0.3154	RMSE = 0.5553 MAE = 0.4464	RMSE = 0.5315 MAE = 0.4893	RMSE = 0.2184 MAE = 0.1686
France	RMSE = 0.1952 MAE = 0.1697	RMSE = 0.1951 MAE = 0.1696	RMSE = 0.1292 MAE = 0.1038	RMSE = 0.1562 MAE = 0.1104	RMSE = 0.1481 MAE = 0.1207	RMSE = 0.2032 MAE = 0.1541	RMSE = 0.1379 MAE = 0.1063
Croatia	RMSE = 0.3634 MAE = 0.2468	RMSE = 0.2326 MAE = 0.1798	RMSE = 0.3146 MAE = 0.2422	RMSE = 0.2614 MAE = 0.1962	RMSE = 0.2406 MAE = 0.1837	RMSE = 0.6157 MAE = 0.5647	RMSE = 0.2383 MAE = 0.1849
Italy	RMSE = 0.4713 MAE = 0.4263	RMSE = 0.4752 MAE = 0.4354	RMSE = 0.2523 MAE = 0.1773	RMSE = 0.3245 MAE = 0.2464	RMSE = 0.3015 MAE = 0.2120	RMSE = 0.3353 MAE = 0.2711	RMSE = 0.2579 MAE = 0.1969
Cyprus	RMSE = 0.8929 MAE = 0.8133	RMSE = 0.8997 MAE = 0.8206	RMSE = 0.5159 MAE = 0.3781	RMSE = 0.7682 MAE = 0.5715	RMSE = 0.7863 MAE = 0.6137	RMSE = 0.7912 MAE = 0.6552	RMSE = 0.4658 MAE = 0.3509
Latvia	RMSE = 0.6530 MAE = 0.5929	RMSE = 0.6504 MAE = 0.5849	RMSE = 0.2461 MAE = 0.1952	RMSE = 0.2259 MAE = 0.1795	RMSE = 0.2369 MAE = 0.1874	RMSE = 0.2980 MAE = 0.2350	RMSE = 0.3562 MAE = 0.2947
Lithuania	RMSE = 0.7697 MAE = 0.7133	RMSE = 0.7757 MAE = 0.7159	RMSE = 0.3710 MAE = 0.2720	RMSE = 0.3372 MAE = 0.2603	RMSE = 0.3427 MAE = 0.2451	RMSE = 0.3370 MAE = 0.2515	RMSE = 0.3778 MAE = 0.3060

Table 16 continued

Country	FARIMA	FARIMA/GARCH (1,1)	ANN	SVR	MARS	ARIMA	Holt-Winters
Luxemburg	RMSE = 0.2851 MAE = 0.2600	RMSE = 0.2812 MAE = 0.2581	RMSE = 0.1487 MAE = 0.1251	RMSE = 0.2009 MAE = 0.1478	RMSE = 0.1476 MAE = 0.1216	RMSE = 0.1879 MAE = 0.1581	RMSE = 0.1322 MAE = 0.1077
Malta	RMSE = 0.5255 MAE = 0.5050	RMSE = 0.5104 MAE = 0.4895	RMSE = 0.2976 MAE = 0.2411	RMSE = 0.3708 MAE = 0.3277	RMSE = 0.1636 MAE = 0.1352	RMSE = 0.2174 MAE = 0.1628	RMSE = 0.1487 MAE = 0.1246
Netherlands	RMSE = 0.1464 MAE = 0.1236	RMSE = 0.1532 MAE = 0.1302	RMSE = 0.1336 MAE = 0.1023	RMSE = 0.1484 MAE = 0.1180	RMSE = 0.1307 MAE = 0.1010	RMSE = 0.2781 MAE = 0.2399	RMSE = 0.0973 MAE = 0.0743
Romania	RMSE = 0.4631 MAE = 0.4196	RMSE = 0.4630 MAE = 0.4193	RMSE = 0.2573 MAE = 0.2121	RMSE = 0.3858 MAE = 0.3326	RMSE = 0.2781 MAE = 0.2384	RMSE = 0.3643 MAE = 0.3204	RMSE = 0.2794 MAE = 0.2198
Slovenia	RMSE = 0.1779 MAE = 0.1404	RMSE = 0.1809 MAE = 0.1433	RMSE = 0.2834 MAE = 0.2295	RMSE = 0.3541 MAE = 0.2721	RMSE = 0.3426 MAE = 0.2644	RMSE = 0.4379 MAE = 0.3690	RMSE = 0.3051 MAE = 0.2271
Finland	RMSE = 0.1273 MAE = 0.1099	RMSE = 0.1300 MAE = 0.1133	RMSE = 0.1085 MAE = 0.0834	RMSE = 0.1159 MAE = 0.0942	RMSE = 0.1156 MAE = 0.0945	RMSE = 0.1524 MAE = 0.1332	RMSE = 0.1032 MAE = 0.0823
Sweden	RMSE = 0.2498 MAE = 0.1996	RMSE = 0.2501 MAE = 0.2001	RMSE = 0.2518 MAE = 0.1933	RMSE = 0.2496 MAE = 0.1907	RMSE = 0.2703 MAE = 0.2055	RMSE = 0.4281 MAE = 0.3722	RMSE = 0.2441 MAE = 0.1900
Iceland	RMSE = 0.2551 MAE = 0.2447	RMSE = 0.2507 MAE = 0.2345	RMSE = 0.1233 MAE = 0.1043	RMSE = 0.0973 MAE = 0.0744	RMSE = 0.0799 MAE = 0.0605	RMSE = 0.2004 MAE = 0.1682	RMSE = 0.0737 MAE = 0.0554
Norway	RMSE = 0.2244 MAE = 0.1855	RMSE = 0.2244 MAE = 0.1855	RMSE = 0.1668 MAE = 0.1271	RMSE = 0.1728 MAE = 0.1422	RMSE = 0.1882 MAE = 0.1515	RMSE = 0.1997 MAE = 0.1553	RMSE = 0.1532 MAE = 0.1212
Turkey	RMSE = 0.4118 MAE = 0.2869	RMSE = 0.4201 MAE = 0.2879	RMSE = 0.3707 MAE = 0.2880	RMSE = 0.3814 MAE = 0.2908	RMSE = 0.3643 MAE = 0.2520	RMSE = 0.4374 MAE = 0.3443	RMSE = 0.3681 MAE = 0.2565

Table 17 Positions of models RMSE (MAE)

Country	FARIMA	FARIMA/GARCH(1,1)	ANN	SVR	MARS	ARIMA	Holt-Winters
Belgium	3 (2)	1 (3)	2 (4)	7 (7)	6 (6)	4 (1)	5 (5)
Bulgaria	1 (1)	2 (3)	4 (4)	7 (7)	6 (6)	5 (5)	3 (1)
Denmark	6 (6)	7 (7)	1 (1)	3 (3)	4 (4)	5 (5)	2 (2)
Estonia	5 (6)	6 (7)	4 (4)	3 (3)	1 (2)	2 (1)	7 (5)
Greece	1 (1)	2 (4)	5 (5)	6 (6)	7 (7)	3 (3)	4 (2)
Spain	1 (2)	2 (1)	5 (5)	6 (6)	7 (7)	4 (4)	3 (3)
France	1 (2)	1 (1)	4 (4)	7 (7)	6 (6)	5 (5)	3 (3)
Croatia	1 (1)	2 (2)	4 (4)	7 (7)	6 (6)	5 (5)	3 (3)
Italy	3 (3)	2 (2)	1 (1)	7 (7)	4 (4)	6 (5)	5 (6)
Cyprus	2 (3)	1 (2)	3 (1)	5 (5)	7 (7)	4 (4)	6 (6)
Latvia	5 (5)	7 (7)	2 (2)	3 (4)	4 (3)	1 (1)	6 (6)
Lithuania	5 (6)	7 (7)	3 (3)	6 (5)	4 (4)	1 (2)	2 (1)
Luxemburg	2 (3)	1 (1)	6 (7)	7 (5)	5 (6)	3 (2)	4 (4)
Malta	6 (6)	5 (5)	2 (2)	4 (4)	7 (7)	3 (3)	1 (1)
Netherlands	2 (2)	1 (1)	5 (4)	7 (7)	6 (6)	4 (5)	3 (3)
Romania	5 (4)	4 (5)	2 (1)	6 (6)	7 (7)	1 (2)	3 (3)
Slovenia	1 (1)	2 (2)	3 (3)	7 (6)	6 (7)	5 (5)	4 (4)
Finland	2 (3)	1 (2)	6 (6)	3 (1)	7 (7)	4 (4)	5 (5)
Sweden	2 (2)	1 (1)	4 (5)	5 (4)	7 (7)	6 (6)	3 (3)
Iceland	3 (3)	2 (2)	4 (4)	7 (7)	6 (6)	5 (5)	1 (1)
Norway	6 (6)	6 (6)	5 (5)	1 (1)	2 (2)	3 (3)	4 (4)
Turkey	3 (3)	4 (4)	1 (1)	6 (6)	7 (7)	2 (2)	5 (5)

Data for Friedman Tests

Elements of the Model

Dependent variable # of times where the model is included in the MCS superior set of models.

Factor 1 Horizon (1, 3 and 12 steps ahead).

Factor 2 Geographic area (Balkan, Med, Nordic, Baltic, Benelux).

See Tables 18 and 19.

Table 18 Prediction accuracy

Country	FARIMA	FARIMA/GARCH (1,1)	ANN	SVR	MARS	ARIMA	Holt-Winters
Belgium	RMSE = 0.6045 MAE = 0.4618	RMSE = 0.6021 MAE = 0.4625	RMSE = 0.6029 MAE = 0.4713	RMSE = 0.7939 MAE = 0.6701	RMSE = 0.7868 MAE = 0.6671	RMSE = 0.6294 MAE = 0.4571	RMSE = 0.7780 MAE = 0.6137
Bulgaria	RMSE = 0.3505 MAE = 0.3052	RMSE = 0.3602 MAE = 0.3193	RMSE = 0.7185 MAE = 0.5556	RMSE = 1.7634 MAE = 1.3650	RMSE = 1.6996 MAE = 1.3285	RMSE = 0.8477 MAE ==0.6151	RMSE = 0.3965 MAE0.3052
Denmark	RMSE = 0.3754 MAE = 0.3361	RMSE = 0.3805 MAE = 0.3419	RMSE = 0.2363 MAE = 0.1928	RMSE = 0.2912 MAE = 0.2309	RMSE = 0.3029 MAE = 0.2374	RMSE = 0.3552 MAE = 0.2669	RMSE = 0.2633 MAE = 0.2093
Estonia	RMSE = 0.5956 MAE = 0.5071	RMSE = 0.6073 MAE = 0.5183	RMSE = 0.5840 MAE = 0.4666	RMSE = 0.5812 MAE = 0.4539	RMSE = 0.5753 MAE = 0.4464	RMSE = 0.5764 MAE = 0.4437	RMSE = 0.6188 MAE = 0.5069
Greece	RMSE = 1.1864 MAE = 1.0161	RMSE = 1.2305 MAE = 1.0576	RMSE = 1.3652 MAE = 1.1121	RMSE = 1.5732 MAE = 1.3092	RMSE = 1.9317 MAE = 1.5174	RMSE = 1.2592 MAE = 1.0504	RMSE = 1.3251 MAE = 1.0323
Spain	RMSE = 0.5801 MAE = 0.4689	RMSE = 0.6036 MAE = 0.4608	RMSE = 1.3660 MAE = 1.1616	RMSE = 2.2557 MAE = 1.9157	RMSE = 2.3038 MAE = 1.9457	RMSE = 1.3256 MAE = 1.1164	RMSE = 1.0137 MAE = 0.8252
France	RMSE = 0.1685 MAE = 0.1366	RMSE = 0.1685 MAE = 0.1357	RMSE = 0.2608 MAE = 0.2137	RMSE = 0.4339 MAE = 0.3868	RMSE = 0.4338 MAE = 0.3721	RMSE = 0.3029 MAE = 0.2198	RMSE = 0.2418 MAE = 0.1750
Croatia	RMSE = 0.7843 MAE = 0.6982	RMSE = 0.7862 MAE = 0.6996	RMSE = 1.4006 MAE = 1.1811	RMSE = 2.4798 MAE = 2.0348	RMSE = 2.4206 MAE = 1.9915	RMSE = 1.4016 MAE = 1.1913	RMSE = 0.8299 MAE = 0.7307
Italy	RMSE = 0.4513 MAE = 0.4057	RMSE = 0.4424 MAE = 0.3990	RMSE = 0.3693 MAE = 0.3030	RMSE = 0.7083 MAE = 0.6226	RMSE = 0.5104 MAE = 0.4390	RMSE = 0.5998 MAE = 0.4735	RMSE = 0.5603 MAE = 0.4814
Cyprus	RMSE = 1.3126 MAE = 1.1661	RMSE = 1.3023 MAE = 1.1567	RMSE = 1.3841 MAE = 1.0992	RMSE = 1.7407 MAE = 1.2585	RMSE = 1.9633 MAE = 1.5371	RMSE = 1.6388 MAE = 1.1962	RMSE = 1.7759 MAE = 1.4524
Latvia	RMSE = 0.6467 MAE = 0.5593	RMSE = 0.7326 MAE = 0.6631	RMSE = 0.5108 MAE = 0.4018	RMSE = 0.5481 MAE = 0.5066	RMSE = 0.5580 MAE = 0.4818	RMSE = 0.4519 MAE = 0.3710	RMSE = 0.6480 MAE = 0.5681
Lithuania	RMSE = 0.9291 MAE = 0.8039	RMSE = 0.9747 MAE = 0.8309	RMSE = 0.7946 MAE = 0.7270	RMSE = 0.9436 MAE = 0.7812	RMSE = 0.9093 MAE = 0.7466	RMSE = 0.5982 MAE = 0.4961	RMSE = 0.6300 MAE = 0.4838

Table 18 continued

Country	FARIMA	FARIMA/GARCH (1,1)	ANN	SVR	MARS	ARIMA	Holt-Winters
Luxemburg	RMSE = 0.2860 MAE = 0.2397	RMSE = 0.2787 MAE = 0.2321	RMSE = 0.3918 MAE = 0.3348	RMSE = 0.4080 MAE = 0.3150	RMSE = 0.3875 MAE = 0.3304	RMSE = 0.3010 MAE = 0.2358	RMSE = 0.3324 MAE = 0.2780
Malta	RMSE = 0.9016 MAE = 0.8348	RMSE = 0.8801 MAE = 0.8134	RMSE = 0.2572 MAE = 0.2098	RMSE = 0.6303 MAE = 0.5703	RMSE = 1.4032 MAE = 1.2497	RMSE = 0.3620 MAE = 0.2850	RMSE = 0.2553 MAE = 0.1859
Netherlands	RMSE = 0.2299 MAE = 0.2243	RMSE = 0.2706 MAE = 0.2193	RMSE = 0.4049 MAE = 0.3404	RMSE = 1.0288 MAE = 0.8860	RMSE = 1.0066 MAE = 0.8706	RMSE = 0.4999 MAE = 0.4000	RMSE = 0.3604 MAE = 0.2816
Romania	RMSE = 0.7951 MAE = 0.6636	RMSE = 0.7950 MAE = 0.6649	RMSE = 0.5281 MAE = 0.3987	RMSE = 0.8326 MAE = 0.7388	RMSE = 0.8486 MAE = 0.7542	RMSE = 0.4867MAE = 0.4049	RMSE = 0.5540 MAE = 0.4825
Slovenia	RMSE = 0.6012 MAE = 0.4260	RMSE = 0.6068 MAE = 0.4294	RMSE = 0.7179 MAE = 0.5525	RMSE = 1.1011 MAE = 0.8836	RMSE = 1.0775 MAE = 0.8969	RMSE = 0.8333 MAE = 0.6312	RMSE = 0.8184 MAE = 0.6167
Finland	RMSE = 0.2815 MAE = 0.2406	RMSE = 0.2806 MAE = 0.2384	RMSE = 0.3245 MAE = 0.2703	RMSE = 0.2975 MAE = 0.2371	RMSE = 0.3856 MAE = 0.3023	RMSE = 0.2978 MAE = 0.2432	RMSE = 0.3059 MAE = 0.2600
Sweden	RMSE = 0.2421 MAE = 0.2075	RMSE = 0.2335 MAE = 0.1942	RMSE = 0.3578 MAE = 0.2922	RMSE = 0.3657 MAE = 0.2894	RMSE = 0.4258 MAE = 0.3467	RMSE = 0.3719 MAE = 0.3133	RMSE = 0.2663 MAE = 0.2186
Iceland	RMSE = 0.2140 MAE = 0.1941	RMSE = 0.2118 MAE = 0.1916	RMSE = 0.2767 MAE = 0.2371	RMSE = 0.7290 MAE = 0.5199	RMSE = 0.7012 MAE = 0.4805	RMSE = 0.3870 MAE = 0.3063	RMSE = 0.1475 MAE = 0.1104
Norway	RMSE = 0.4315 MAE = 0.3513	RMSE = 0.4315 MAE = 0.3513	RMSE = 0.3875 MAE = 0.3101	RMSE = 0.2749 MAE = 0.2336	RMSE = 0.2752 MAE = 0.2409	RMSE = 0.3026 MAE = 0.2415	RMSE = 0.3322 MAE = 0.2542
Turkey	RMSE = 0.9506 MAE = 0.6564	RMSE = 0.9773 MAE = 0.6830	RMSE = 0.7147 MAE = 0.5507	RMSE = 1.3874 MAE = 1.2387	RMSE = 1.4388 MAE = 1.2936	RMSE = 0.9012 MAE = 0.6297	RMSE = 1.1619 MAE = 0.8530

Table 19 # of times where the model is included in the MCS superior set of models

FARIMA	Med	Balkan	Baltic	Nordic	Benelux
h = 1	7	6	3	5	2
h = 3	5	3	0	4	2
h = 12	8	7	2	3	3
FARIMA/GARCH	Med	Balkan	Baltic	Nordic	Benelux
h = 1	7	5	2	5	3
h = 3	4	2	0	3	2
h = 12	7	6	2	2	3
ANN	Med	Balkan	Baltic	Nordic	Benelux
h = 1	0	0	3	1	0
h = 3	7	6	3	4	3
h = 12	8	5	3	4	2
MARS	Med	Balkan	Baltic	Nordic	Benelux
h = 1	4	4	3	5	2
h = 3	6	4	3	5	3
h = 12	3	3	3	4	1

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