DEPARTMENT OF ECONOMICS

TESTING RANDOM WALK HYPOTHESIS IN PRE-REFERENDUM PERIOD: THE CASE OF THE GBP/USD EXCHANGE RATE

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ABSTRACT

This study aims to test out-of-sample forecasting performance of a simple random walk model using an ARIMA model in the case of GBP/USD exchange rate. We conduct this analysis on the basis of the seminal paper of Meese and Rogoff (1983). Short time span forecasts which are less than six months are investigated. The pre-referendum period data is selected in order to avoid the fluctuation in GBP/USD exchange rate. Out-of-sample forecasts of the random walk and the ARIMA models are compared by the forecast evaluation statistics; RMSE, MAE, and MAPE. The ARIMA model is built by the Box-Jenkins approach. Each model generates six separate out-of-sample forecasts, starting from one month ahead forecast up until to six months ahead forecast. We evaluate aggregate RMSE, MAE, and MAPE values for the forecast comparison. The Diebold-Mariano (DM) test with HLN adjusted also examines whether both forecasts have the same accuracy or not. The results indicate that in the case of GBP/USD exchange rate, the ARIMA (1,0,2) model outperforms the naïve random walk model for the pre-referendum time period. However, the DM test statistics are not significant. If we consider the severity of this test, we can still point out the validity of our results.

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1. INTRODUCTION

Central banks, market practitioners, and academics regularly monitor exchange rate movements to determine the future plans of countries and investors (Corte, Sarno, and Tsiakas, 2011). Therefore, exchange rate forecasting plays an important role in international finance.

In 1973, the collapse of Bretton Woods system resulted in floating major exchange rates. Afterwards, forecasting exchange rate behaviours started to draw researchers' attention. Following the floating exchange rate period, some authors stated that spot exchange rate follows a naïve random walk process (Cornell and Dietrich, 1978; Mussa, 1979). In other words, the changes in value occur unexpectedly. Seminal study of Meese and Rogoff (1983) also supported the same hypothesis. In their work, it is demonstrated that a simple random walk model significantly outperforms monetary and sophisticated statistical exchange rate models in short and medium time horizons (Meese and Rogoff, 1983a,b).

In this study, we examine out-of-sample forecasting accuracy for Great British Pound (GBP) against United States Dollar (USD) on the basis of the classical paper of Meese and Rogoff (1983). Our aim is to test the forecasting performance of a simple random walk model using only one statistical model that is an Autoregressive Integrated Moving Average (ARIMA) model. We investigate these models' short time horizon forecasts which are less than two quarters. It is the fact that monetary models, which Meese and Rogoff (1983) used, hold in the long run. We investigate short time horizon forecasts this is why we do not employ economic based exchange rate models in this study. The pre-referendum[1] period is specifically chosen in order to avoid high volatile GBP/USD exchange rate data. A simple random walk and an ARIMA models are compared by the forecast evaluation statistics; these are the root mean squared error (RMSE), the mean absolute error (MAE), and the

[1] It is the Brexit (Britain Exit) referendum. On June 23, 2016, the UK witnessed one of the most important political incidents in its history. In the referendum, the UK decided to withdraw its 'associated membership' from the European Union. Following the referendum, there was a remarkable mean shift in the exchange rate. See appendix ***Graph 1*** for the mean shift.

mean absolute percentage error(MAPE).

In the first step of our analysis, we try to build an appropriate ARIMA model corresponding to the GBP/USD exchange rate series. This model construction is carried out by the help of the Box-Jenkins (1976) methodology. Afterwards, a naïve random walk model is estimated. We evaluate several specifications of the estimated random walk and ARIMA models such as the significance of model coefficients, the goodness-of-fit of the models, information criterions, etc,. Both models seem plausible in terms of those specifications. As a last step, six separate out-of-sample forecasts of each model are generated, starting from one month ahead forecast up until to six months ahead forecast. Aggregate forecast evaluation statistic values (RMSE, MAE, and MAPE), which consist of one to six months ahead forecasts respectively, are assessed between these two forecasts.

At the end of the analysis section, we find the best performing model and also HLN adjusted Diebold-Mariano (DM) test checks whether both forecasts have the same accuracy or not. According to the results, the ARIMA (1,0,2) model beats the naïve random walk model for GBP/USD exchange rate in the short run that is pre-referendum time period. The DM test results are not statistically significant but this test is actually very severe. If we consider DM test's severity specification, we can still conclude that in the short time spans, the ARIMA model can be superior to the simple random walk model for the GBP/USD exchange rate.

This thesis is organised as follows: ***First section*** consists of the introduction, ***the second*** literature review. ***Section three*** gives research question, aims and objectives of this study. ***Section four*** explains the methods used for the analysis. ***Fifth section*** consists of analysis, results, and discussion parts. ***Section six*** presents conclusion and limitations part are presented in the ***section seven***. References and appendix are ***section eight*** and ***nine*** respectively.

2. LITERATURE REVIEW

The behaviour of exchange rate movements is quite complicated in terms of modelling (Frenkel, 1981). Therefore, forecasting exchange rate movements draws a great deal of attention in the field of finance. There are many exchange rate models in the literature, which attempts to achieve out-of-sample accuracy. However, there is no one appropriate model which will be able to capture all the information of exchange rate movements in the forecasting accuracy context (Lam, Fung, and Yu, 2008).

In this study, we will categorise the models in two main groups which are economic based models (monetary approach) and statistical (time series) based models. Three mainstream economic based models are the sticky price monetary (Dornbusch-Frankel) model, the flexible price monetary (Frenkel-Bilson) model, and the sticky price asset (Hooper-Morton) model (Bilson, 1978, 1979; Frenkel, 1976; Dornbusch, 1976; Frenkel, 1979, 1981a; Hooper and Morton, 1982). There are also other economic based models; covered and uncovered interest rate parity (CIP, UIP), relative purchasing power parity (RPPP), behavioural equilibrium exchange rate (BEER) model, Taylor rule fundamental, yield curve slope, etc, (Cheung, Chinn, Pascual, 2005). On the other hand, the main statistical or time series based models are the ARIMA model, Random Walk model, ARCH/GARCH family models, Artificial Neural Network (ANN) model and Fuzzy Logic model[2].

In this section, we will discuss the previous studies which have been done in the light of the classical paper of Meese and Rogoff (1983). In particular we will include the works that are more related to random walk and ARIMA models.

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[2] There are also many more models out of our classification. However, we mention the most frequently used models in the literature. Also, we note that ANN and Fuzzy Logic models are more related to computer science field.

2.1. Related literature of Random walk model

In the forecasting accuracy context of exchange rate models, some economists believe that new generation economic based models (e.g. BEER, Taylor rule fundamental, yield curve slope, etc,.) could generate robust forecasts as much as a simple random walk model can (Engel and West, 2005; Molodtsova and Papell, 2009; Byrne, Korobilis, and Ribeiro, 2016). However, monetary models may not achieve out-of-sample forecasting accuracy under flexible exchange rate regime (Boothe and Glassman, 1987). Balke and Fomby (1997) argue that poor performance of structural models stems from the linearity assumption between the data but in reality, majority of data are nonlinear. At that point, computer scientists assert that artificial intelligence and chaotic processes would be a good alternative in modelling exchange rate movements such as ANN and Fuzzy Logic models (Wu and Dou, 1995). This is because they have the ability of modelling nonlinear processes.

Nevertheless, random walk model has usually beaten most of other models in the short time horizons. Seminal work of Meese and Rogoff (1983) tested the performance of random walk model during the floating-rate period[3] in the 1980s.

2.1.1. Seminal study of Meese and Rogoff

Meese and Rogoff (1983) are the prominent researchers who investigate out-of-sample forecasting accuracy using time series and structural exchange rate models. They test the naïve random walk hypothesis using several time series (univariate autoregression and vector autoregression models) and the three mainstream economic based models (the sticky price monetary model, the flexible price monetary model, and the sticky price asset model). In their research, these models with the various exchange rates between 1973-81 (monthly data) are examined by the values of statistics which are the mean error (ME), the mean absolute error (MAE), and the root mean square error (RMSE). What they found is that the best performing forecasts are generated by the simple random walk model at the short time horizon.

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[3] Global economic recession caused high unemployment rates, affecting developed countries in the early 1980s.

In addition, they attempt to improve poor performing models by the means of taking first difference and adding more explanatory variables to the models. In spite of these modified new models, none of them still outperforms the simple random walk model. In another study, Meese and Rogoff (1983a,b) point out that the naïve random walk model still yields better results than the structural exchange rate models in short and medium time horizons.

2.2. Criticism of the performance of Random walk model

After the keystone study of Meese and Rogoff (1983) on the accuracy of out-of-sample forecasting, a number of authors agree on high forecasting performance of random walk model at short and medium time horizons (MacDonald and Taylor, 1992; Cheung, Chinn, and Pascual, 2005; Moosa, 2013; Moosa and Burns, 2014). In addition to this, the studies which had carried out before Meese and Rogoff (1983) also underpin high performance of random walk model against the alternative models in the out-of-sample forecasting (Cornell and Dietrich, 1978; Mussa, 1979).

Cheung et al. (2005) are in favour of random walk model, saying that random walk model may systematically yield better forecasts at short and medium time spans compared with the main monetary and time series models. Engle (1992) conducts a research on 18 different currencies and found that only in-sample forecast of the Markov-switching model could beat a simple random walk model but this does not necessarily mean it is going to outperform in out-of-sample forecasts as Engle (1992) found the superiority of a naïve random walk model in out-of-sample.

Having said that some other studies do not totally agree with this idea, saying the performance of random walk model depends on the forecast time horizon, data, different countries' currencies, etc. (Rossi, 2013; Della Corte and Tsiakas, 2011). Chinn & Meese (1995) and Mark (1995) assert that while the period span goes beyond twelve months, the simple random walk model fails to keep generating the minimum ME, MAE, and RMSE statistics. According to Pantusson (2005), random walk model may generate poor forecasts in the very short time span, which is less than two quarters. Anaraki (2007) also criticises

Meese and Rogoff's analysis, saying that their work's time horizon does not include economic crisis years. Therefore, their results could be unreliable due to not covering the floating-rate period.

2.3. Results of other relevant studies

Lam, Fung, and Yu (2008) attempt to find some evidence for the predictability of exchange rates in long time horizons. They compare the forecast accuracies of the PPP, UIP, the sticky price monetary model, the Bayesian model averaging method, and all these models' a combined forecast with the benchmarks which is a simple random walk model. Their study is conducted for GBP, EUR, and Japanese Yen against the USD from one to eight quarter ahead in out-of-sample environment. According to their results, the combined one outperforms the others and also the benchmark. They suggest the sticky price model for GBP/USD exchange rate. Briefly, they point out the goodness of combined models.

Ozdemir (2017) examines out-of-sample forecasting accuracy of random walk model for the United States dollar against the Turkish lira (TL) in the pre-crisis period[4]. Similarly, Smoluk, Vasconcellos, and Kramer (1998) study on whether the GBP/USD exchange rate follows a random walk or not. Although they test the same hypothesis with various alternative models, the results are different from each other. The random walk hypothesis cannot be rejected for GBP/USD exchange rate whilst it is rejected in the case of USD/TL exchange rate. Smoluk et al. (1998) point out that failing to reject the random walk hypothesis indicates the efficiency of exchange rate markets in the UK. In their study, they also emphasise the mean reverting effect of the purchasing power parity in the long run. On the other hand, Ozdemir (2017) examines the hypothesis with other structural models. The findings indicate that Frenkel-Bilson (in one month ahead forecasting period) and Dornbusch-Frankel (in 3 month ahead forecasting horizon) models have a superiority compared with random walk model. However, random walk model dominates these models beyond the six month forecasting period.

[4] The crisis mentioned above is the 2008 US Mortgage Crisis.

Darrat and Zhong (2000) intend to test the random walk hypothesis for the two different Chinese stock returns. They apply a model comparison and the variance ratio test to compare several models: GARCH, ARIMA, ANN, and a naïve random walk. Theil's U, RMSE, and MAE statistic values are utilised for their analysis. They emphasise the high performance of the ANN model for stock prices. One similar study with ours was carried out by Newaz (2008) for Indian Rupee against US dollar. Monthly data between 1985 and 2006 is taken and then several time series models' forecasts (ARIMA, exponential smoothing, and naïve random walk) are compared in the exchange rate forecasting context. The random walk hypothesis is rejected. It is found that the ARIMA model yields better results than the others in the out-of-sample environment.

2.4. Consensus of the literature

Most of the authors which we mentioned at the above compares the performances of models using the three most common evaluation statistics; the root mean squared error (RMSE), the mean absolute error (MAE), and the mean absolute percentage error (MAPE). Some other authors add also to the Theil's U statistics or the mean squared error (MSE) statistics as an extra forecast evaluation statistic parameter.

Majority of authors' consensus view is that in terms of out-of-sample forecasting, a simple random walk model exhibits high performance at short and medium time spans, while economic based models are more efficient for longer time horizons (MacDonald and Marsh, 1997; Cheung, Chinn, and Pascual, 2005; Moosa and Burns, 2014). Hence, it may be said that economic based models does not make sense in the short run.

3. RESEARCH QUESTION, AIMS, AND OBJECTIVES

Consensus view of the literature is in favour of high performance of random walk model in short and medium time horizons. However, if the time span is very short for out-of-sample (4,8,12,…,24 weeks). What happens?

In this study, random walk hypothesis is tested using an ARIMA model in short run. Our study is inspired by Meese and Rogoff (1983)'s seminal work on random walk hypothesis. What we are investigating is that 'Can an ARIMA model outperform a simple random walk model for the GBP/USD exchange rate in short time horizons which are less than two quarters?'.

Aim of this study is to test random walk hypothesis for the GBP/USD exchange rate in out-of-sample environment using only ARIMA model.

Objectives of the study are,

- We will try to first build an appropriate ARIMA model and then the simple random walk model will be estimated for the exchange rate data.
- As a next step, we will generate out-of-sample forecasts using the estimated models.
- Afterwards, both of the models' out-of-sample forecasts will be compared by RMSE, MAE, and MAPE forecast evaluation statistics.
- Identifying the best performing model in the out-of-sample forecasting environment, we will test whether both forecasts have the same accuracy or not by the help of the Diebold-Mariano test.

4. METHODOLOGY

4.1. Data

We take weekly GBP/USD exchange rate data to analyse the out-of-sample forecasting accuracy for the period between 07/02/2010 and 01/03/2014, which is 184 observations (obs.) in total. The source of weekly GBP/USD exchange rate data is the St. Louis Federal Reserve Bank electronic data delivery system. The form of the data is taken as 'not seasonally adjusted values'. The sample period is selected the dates between 7/02/2010 and 5/31/2013 with 153 obs. Forecasts are generated for the forecast sample that is between 5/31/2013 and 1/03/2014 with 31 obs.

Pre-referendum period data is chosen to avoid fluctuations in the exchange rate. As Moosa (2013) stated that if exchange rate volatility rises, any model's forecasting error increases faster than a simple random walk model's forecast error. For this reason, the observation period we included is one of the most suitable period to analyse the out-of-sample accuracy of different models in zero level.

GBP/USD exchange rate data is analysed by the help of EViews database. We use static forecasting method in EViews because dynamic forecasting method has a tricky, it yields forecasts in out-of-sample to catch up the mean of series. It does not follow the series, it just tries to track on the average of series.

4.2. WHY TIME SERIES MODELS ARE SELECTED FOR THIS ANALYSIS?

In terms of forecasting ability, monetary and time series exchange rate models have some pros and cons in different time spans. For instance, while statistical based models focus on to generating much more weekly, daily, hourly and even minutes wise (short time horizon) forecasts in financial markets, economic based models usually concentrate on long time horizon forecasts which are based on monthly, quarterly or annually data[5]. In this study, we are investigating short time horizon forecasting accuracies of the time series models. Therefore, we are going to use statistical based models.

4.3. Augmented Dickey-Fuller unit root test

The stationary process is ensured if a series displays a constant mean and a constant variance over the time. It is the fact that the majority of real-world time series data is non-stationary such as exchange rates, asset prices, inflation and other macroeconomic indicators. Non-stationary time series are mostly unpredictable with trends and/or seasonal variations. Initially, a non-stationary series needs to be transformed into a stationary series. One widely used way of removing seasonal variations and/or trends is to take the differences of time series data(Martin, Hurn, and Harris, 2011, p. 493).

[5] Purchasing Power Parity (PPP) does hold in the long run. This can be thought as an example of long run usage of monetary models.

Augmented Dickey-Fuller (ADF) unit root test can be used in order to identify whether the series is stationary or not (Dickey and Fuller, 1979). The null hypothesis of ADF unit root test is defined as 'the series has a unit root (non-stationary)' against the alternative hypothesis which is the null of the unit root (stationary). The formula of an ADF test is shown at the below equation (1):

$$\Delta y_t = \alpha_0 + \alpha_1 t + \gamma y_{t-1} + v_t \qquad (1)$$

where

$\Delta y_t = yt - yt\text{-}1 = v_t$

α_0 is a constant, α_1 is a trend term, and γ is the parameter that is tested in the null hypothesis. Absolute test value of variables should be greater than MacKinnon critical value or values to ensure stationarity condition.

4.4. ARIMA models

ARIMA is an acronym, standing for Autoregressive (AR) Integrated (I) Moving Average (MA). It is also named after the Box-Jenkins (1984) approach. Each component's order is defined by (p,d,q) respectively. p and q represent autoregressive (AR) and moving average (MA) orders respectively whilst the integrated part is defined by d. ARIMA models use a variable's past values in order to predict its present values. One of the functions of ARIMA models is to test serial correlation in a series. It can also capture the correlation of present value using some of the series' past values. General equation of ARIMA (p,d,q) model is given at the below equation (2):

$$\Delta X_t = \varphi_1 \Delta X_{t-1} + \varphi_2 \Delta X_{t-2} + \ldots + \varphi_p \Delta X_{t-p} + e_t - \theta_1 e_{t-1} - \theta_2 e_{t-2} - \ldots - \theta_q e_{t-q} \qquad (2)$$

In the general equation model, $\varphi_1, \varphi_2, \ldots \varphi_p$ and $\theta_1, \theta_2, \ldots \theta_q$ are the coefficients of the AR and MA parts. Δ represents the integrated part, which is d. If data is not stationary, we need to take the differences of series until stationary condition is achieved.

Identification of orders of AR and MA terms can be done by the correlogram of autocorrelation and partial autocorrelation functions. However, it is hard to identify the right orders using only this tool. In addition to this, researchers use iterative model estimation method to select the best model on the basis of information criteria; Akaike (AIC), Schwarz (BIC), and Hannan-Quinn (HQ) information criterions. The lowest values of criteria mean the best performing model corresponding to actual series (Brooks, 2008, p. 233).

4.5. Random walk model without drift

Moosa (2013) recommends the use of random walk model without drift (no intercept or constant) for yielding better results. Therefore, we apply random walk without drift. The simple random walk model without drift in level, which is suggested by Meese and Rogoff (1983), is defined at the below equation (3):

$$e_{t+h} = e_t + \varepsilon_t \tag{3}$$

Basic idea of random walk is that today's value is equal to yesterday's value plus a random shock (Verbeek, 2004, p.266). In other words, the change in values occurs unexpectedly. This model is a benchmark in evaluating the predictability of exchange rates and stock prices (Corte and Tsikias, 2011).

4.6. Forecast evaluation statistics (RMSE, MAE, and MAPE)

The root mean squared error (RMSE), the mean absolute error (MAE), and the mean absolute percentage error (MAPE) are three of most common measures for examining the out-of-sample forecasting performance. The formulas of the forecast evaluation statistics are given at the below equations (4,5,6):

$$\text{RMSE} = \sqrt{\frac{1}{T-(T-1)} * \sum_{t=T_1}^{T} (y_{t+s} - f_{t,s})^2} \tag{4}$$

$$\text{MAE} = \frac{1}{T-(T-1)} * \sum_{t=T_1}^{T} | \frac{y_{t+s}-f_{t,s}}{y_{t+s} + f_{t,s}} | \tag{5}$$

$$\text{MAPE} = \frac{100}{T-(T_1-1)} * \sum_{t=T_1}^{T} | \frac{y_{t+s}-f_{t,s}}{y_{t+s} + f_{t,s}} | \tag{6}$$

where

Total sample size is T, first out-of-sample forecast observation is T_1, $f_{t,s}$ is s-step-ahead forecast, and y_{t+s} is actual value.

The MAE statistic is based on taking absolute values of errors. If absolute value is not taken, it becomes the mean biased error (MBE). The MBE can give useful information but the issue is that negative and positive errors are likely to cancel out each other. Therefore, its results do not make sense in terms of the interpretation of forecast accuracy. On the other hand, the RMSE is square root of the squared errors' average. It can penalise large errors much more than the others. Therefore, the RMSE gives relatively more weight to large errors. If we do not expect large forecast errors, the RMSE could be more useful especially than the MAE (Brooks, 2008, p. 295).

4.7. Diebold-Mariano test

For instance, we have two different forecasts, namely X and Y. We can obtain lower RMSE value from X forecast in comparison with Y. Can we say that the forecast X has a superior performance compared to the forecast Y? Does the difference between the forecasts X and Y occur by chance?

Diebold-Mariano (1995) procedure examines whether two different forecasts statistically have the same accuracy or not. The null hypothesis is defined as both forecasts have the same accuracy, which we always try to reject it. The null hypothesis is given at the equation (7):

$$d_t = E[g(e_t^x) - g(e_t^y)] = 0. \tag{7}$$

where

g(.) is absolute and squared error, e_t^i is forecasting error for the h-step ahead forecasting.

The test statistics is given at the equation (8):

$$S = [\hat{V}(\overline{d})]^{-1/2}\overline{d} \quad (8)$$

where

$$\hat{V}(\overline{d}) = \frac{1}{n}\,[\,\widehat{\gamma_0} + 2\,\sum_{k=1}^{h-1}\widehat{\gamma_k}\,]$$

and

$$\widehat{\gamma_k} = \frac{1}{n}\sum_{t=k+1}^{n}(d_t - \overline{d})(\,d_{t-k} - \,\overline{d})$$

S asymptotically has the normal distribution. If S in the rejection area, the null hypothesis is rejected. In other words, their forecast accuracies are not equal.

5. ANALYSIS, EMPIRICAL RESULTS, AND DISCUSSION

5.1. Checking for stationarity

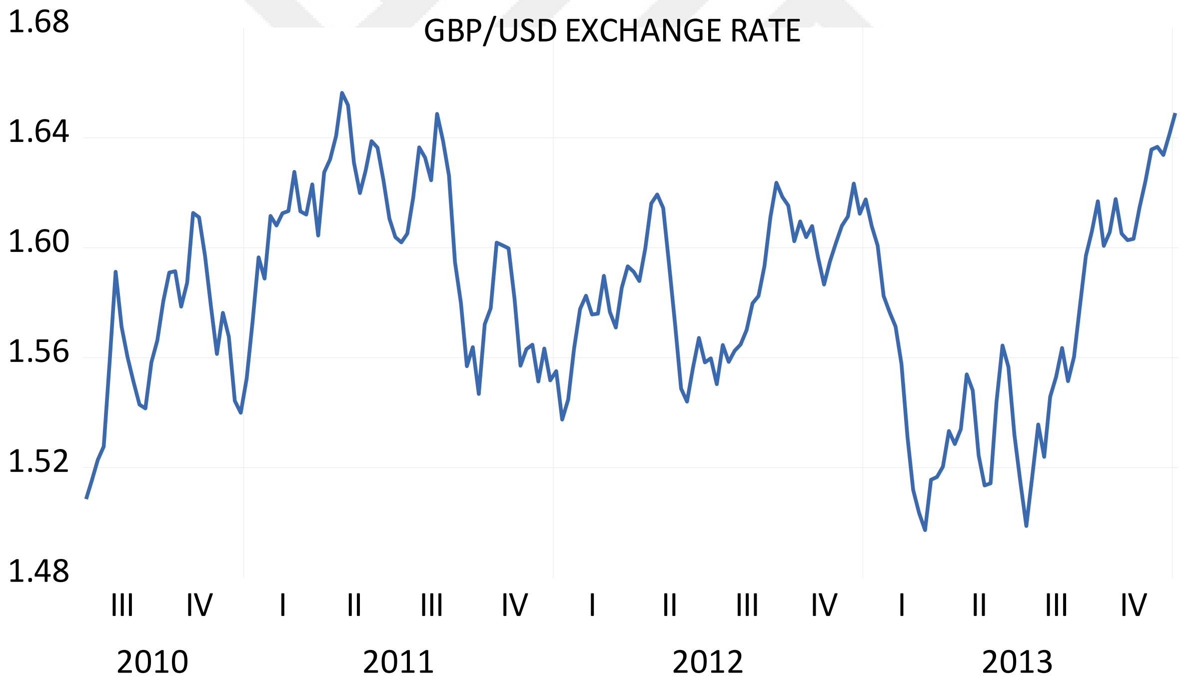
We start our analysis by plotting the GBP/USD exchange rate at the ***Graph 1.*** In the period between July 2010 and January 2014, the band of the exchange rate was approximately between 1.50 and 1.65. The mean of the GBP/USD for the same period was around 1.6[6]. At the graph, the volatility of the exchange rate for the selected period is not as

[6] See appendix ***Table 1*** for the descriptive statistics.

high as the Brexit referendum period[7]. That is the reason why we took this specific time period.

As a first step of our analysis, we need to check whether the series is stationary or not. Looking at the correlogram of the exchange rate may be informative to detect the presence or absence of a unit root. The serial correlations of the exchange rate die away quickly[8] at the ***Table 3***. However, in the case of a non-stationary process, autocorrelations (acf) stay close to unit for many periods. The exchange rate roughly seems stationary from the correlogram and the graph, yet it does not necessarily mean it is stationary. Even if the data looks like a stationary process, we still need to test whether the series is stationary or not.

Graph 1



[7] In this study, the time period between the third quarters of 2014 and 2018 will be referred to the Brexit referendum period this is because in 2014, UK Independence Party (UKIP), whose one of the key policies is the withdrawal from the EU, made a large gain in European Election and later in local elections. This would be thought as a spark of the Brexit referendum. https://www.bbc.co.uk/news/uk-politics-43546199 (See also appendix Graph 1 for a longer period graph)

[8] Autocorrelation decays at the fifteenth lag while partial autocorrelation dies at the third lag.

5.2. Augmented Dickey-Fuller test

In this study, the stationary condition of the exchange rate variable is examined by the ADF unit root test. Test results indicate that the null hypothesis that is defined as the presence of a unit root is rejected. The test statistic for the ADF unit root test is -3.30062 with the p-value of 0.0163, meaning the absence of unit root in the series *(see **Table 1**).* In other words, the ADF test results say that the zero level exchange rate data is stationary in 90 and 95 per cent confidence intervals. There is no need for first order differencing. Therefore, we will use the GBP/USD exchange rate data at the zero level[9]***.

Table 1

	Null Hypothesis: STERLING has a unit root	t-Statistic	p-value*
	Augmented Dickey-Fuller test statistic	-3.300620	0.0163
	Test critical values:		
	5% level	-2.877274	
	10% level	-2.575236	

*MacKinnon (1996) one-sided p-values.

Author estimation

5.3. ARIMA MODEL BUILDING (BOX-JENKINS APPROACH)

ARIMA models are not based on a theory. Therefore, the selection of the best ARIMA model is usually thought by econometricians as an art instead of a science. This is the fact that there might be another alternative ARIMA models. Different researchers could come up with various alternatives (Verbeek, 2004, p.281). In this section, we will attempt to find the best fitted ARIMA model corresponding to the GBP/USD exchange rate series for the sample period. To find the best ARIMA model, the three stages of Box-Jenkins (1976) methodology will be used.

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[9]*** It is important to note in here that according to the ADF unit root test, the series is a stationary process. However, the series is not stationary if we apply to the Kwiatkowski-Philips-Schmidt-Shin (KPSS) and Philips-Perron (PP) tests in order to examine the stationary case (see the KPSS and PP test results in the appendix ***Table 2***). Different tests can give different results. Nevertheless, we will stick with the ADF unit root test because it is such a standard test for the stationarity case. We use the zero level series this is because random walk forecast on the change in the exchange rate is unlikely to be a good one. Also, we would like to compare the random walk and ARIMA forecasts on the same dimension (level). Otherwise (random walk at the zero level and the ARIMA at the first level), the forecast comparison of the models may not make sense.

5.3.1. Identification Stage (Model Selection)

Table 2 exhibits the values of the information criterions (AIC, BIC, HQ and Log likelihood) for different models, while ***Table 3*** shows the correlogram of the GBP/USD exchange rate at the zero level. Box-Jenkins (1976) approach basically relies on the choice of parsimonious models (Hamilton, 1994, p. 109). The meagreness of model parameters generates better results than over-parameterised models[10]. Also, it is accepted by many econometricians that parsimonious models generate more robust forecasts (Ibid). Too many variables consume the degree of freedom in a model, meaning that explanatory variables contribute little to the dependent variable. Therefore, we will select our ARIMA model among parsimonious models to avoid overfitting issue.

In the identification stage of the Box-Jenkins (1976) approach, we estimated a great number of different model sequences (p,d,q) in order to select the best ARIMA model. As can be seen at the ***Table 3***, the geometric decline of the autocorrelation function (acf) can be thought as a sign for the presence of an autoregressive (AR) component for the model (Brooks, 2008, p. 224-225). Partial autocorrelation function (pacf) is also important for identifying whether we need a moving average (MA) part in a model or not (Ibid). The pacf displays a significant spike at the second order with the value of -0.212 (***Table 3).*** This may be showing that the MA part would be represented by the second order. We consider as a benchmark; information criterions (AIC, BIC, HQ) as well as the significance of each estimated model's coefficients. We also compare the models' out-of-sample forecasting performances between each other by looking at RMSE, MAE, and MAPE statistics in order to identify the best performing model.

According to the information criterions and the performances of the models, we come up with the best-fitting models to the series at the ***Table 2***. The ARIMA (2,0,0) and ARIMA (1,0,2) models are the best models and also very close to each other in terms of the criteria. At that point, we check the forecasting performance of both models in order to

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[10]Over-parameterised models cause overfitting issue that means those kinds of models are too complicated for our data set.

select the best model[11]. Indeed the ARIMA (1,0,2) model seems an adequate model with the lowest AIC, BIC, and HQ values and its better forecasting performance

Table 2

Model	LogL	AIC	BIC	HQ
(2,0,0)	521.69	-6.76726	-6.68803	-6.73507
(1,0,2)	522.57	-6.76564	-6.66660	-6.72541
(3,0,0)	522.01	-6.75837	-6.65933	-6.71814
(3,0,1)	522.95	-6.75752	-6.63868	-6.70924
(2,0,1)	521.88	-6.75670	-6.65767	-6.71647
(4,0,0)	522.64	-6.75359	-6.63475	-6.70531

Author estimation

***Table 3** (the correlogram of the GBP/USD)*

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.912	0.912	155.55	0.000
		2	0.796	-0.212	274.72	0.000
		3	0.681	-0.034	362.46	0.000
		4	0.588	0.063	428.29	0.000
		5	0.518	0.041	479.60	0.000
		6	0.469	0.048	521.85	0.000
		7	0.414	-0.095	554.92	0.000
		8	0.370	0.070	581.58	0.000
		9	0.331	-0.007	603.00	0.000
		10	0.291	-0.036	619.67	0.000
		11	0.250	-0.024	632.01	0.000
		12	0.219	0.040	641.54	0.000
		13	0.186	-0.039	648.45	0.000
		14	0.138	-0.128	652.29	0.000
		15	0.090	-0.001	653.91	0.000

5.3.2. Estimation Stage (Parameter Estimation)

ARIMA (1,0,2) model is selected as a best model after trying a great number of different model sequences (p,d,q). Estimated coefficients of the ARIMA model are given at the ***Table 4.*** As can be seen at the table, the constant and estimated model parameter coefficients are statistically significant. We should check the AR term because, if the sum of the AR terms is greater than 1, it can be explosive. The AR term is lower than 1, which is 0.878018. Therefore, it is concluded that the model is not explosive.

Low AIC, BIC, and HQ values are likely to indicate high performance of the ARIMA model in forecasting. High value of adjusted R-squared[12] (86 per cent) shows the goodness-

[11] See the model selection criteria table at the appendix ***Table 3*** and the out-of-sample forecasting performances of both nominated ARIMA models at the appendix ***Table 4***.

of-fit of the model. In other words, the model seems well-fitted to the behaviour of the series in the estimation sample period. We can also say that it is likely to continue chasing the series' behaviour in the out-of-sample period.

Table 4 ***(ARIMA (1,0,2) Model)***

Dependent Variable: GBP/USD Sample period : 7/2/2010 - 5/31/2013

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.575296	0.010789	146.0131	0.0000
AR(1)	0.878018	0.047573	18.45632	0.0000
MA(1)	0.312605	0.084908	3.681706	0.0003
MA(2)	0.179955	0.081444	2.209542	0.0287
SIGMASQ	0.000156	2.12E-05	7.342625	0.0000

R-squared	0.872429	Mean dependent var	1.581766
Adjusted R-squared	0.868982	S.D. dependent var	0.035030
S.E. of regression	0.012680	Akaike info criterion	-5.850462
Sum squared resid	0.023794	Schwarz criterion	-5.751428
Log likelihood	452.5604	Hannan-Quinn criter.	-5.810233
F-statistic	253.0355	Durbin-Watson stat	2.013138
Prob(F-statistic)	0.000000		

Author estimation

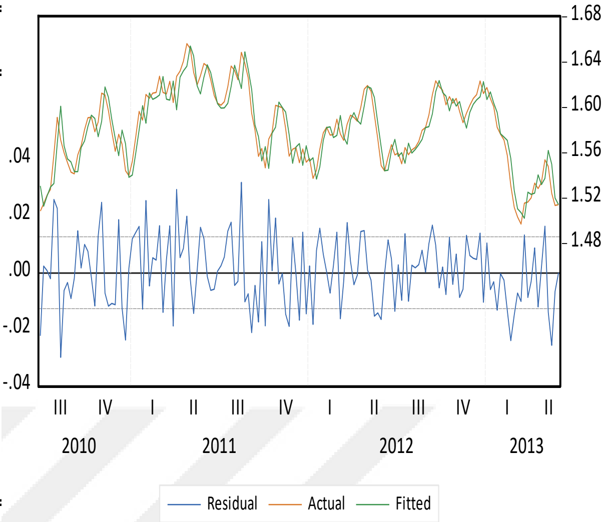
5.3.3. Diagnosis Checking

As a final step of the Box-Jenkins (1976) approach, the residual analysis should be done by looking at the correlogram of residuals including the Q-statistics ***(Table 5)***. The residual correlogram has no a single spike at all the lags that means all the information has been captured. The Q-statistics are also insignificant at all the lags showing that residuals are white noise. Ljung-Box (1978) test results indicate that at no a single lag the null hypothesis (H_0: there is no serial correlation in the residuals) can be rejected. This consolidates the plausibility of the ARIMA (1,0,2) model.

[12] We look at the adjusted R-squared because it is an indicator of whether the variables are relevant or irrelevant. In the case of many irrelevant variables, the difference between R-squared and adjusted R-squared can be quite high. In our model, it is not (R-squared: 0.872, adjusted R-squared: 0.868).

Table 5

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.026	0.026	0.1066	0.744
		2	0.016	0.015	0.1469	0.929
		3	-0.029	-0.030	0.2799	0.964
		4	0.002	0.004	0.2807	0.991
		5	0.094	0.095	1.6971	0.889
		6	-0.056	-0.062	2.2016	0.900
		7	0.096	0.098	3.7052	0.813
		8	0.071	0.074	4.5348	0.806
		9	-0.037	-0.050	4.7592	0.855
		10	-0.030	-0.033	4.9112	0.897
		11	0.011	0.031	4.9303	0.934
		12	0.108	0.085	6.9022	0.864



Author estimation

5.4. RANDOM WALK MODEL

As we know from the classical paper of Meese and Rogoff (1983), it is difficult to beat a simple random walk model in the out-of-sample forecasting. Estimated random walk model is given at the ***Table 6***. To obtain the simple random walk model, only the first lag of the series is used as an explanatory variable. According to the table, the coefficient of the first lag of the series is 0.999988, which is quite close to one. The coefficient is also significantly different from zero. Therefore, it can be said that the GBP/USD exchange rate evolves according to a random walk.

In the model, we do not include the intercept, meaning that we take the random walk model without drift. Moosa (2013) stated that the random walk model without drift can generate more powerful results in predicting and forecasting time series in comparison with the random walk model with drift[13].

[13] We estimated both model (random walk with drift and without drift). We also compared their forecasting accuracies in the out-of-sample and then we selected the best performing one that is random walk without drift (See appendix ***Table 5*** for forecast comparison table).

Table 6

Dependent Variable: GBP/USD Sample period:7/2/2010-5/31/2013				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
GBP/USD (-1)	0.999988	0.000679	1473.606	0.0000
R-square	0.853853	Mean dependent var	1.582247	
Adjusted R-squared	0.853853	S.D. dependent var	0.034634	
S.E. of regression	0.013240	Akaike info criterion	-5.804521	
Sum squared resid	0.026472	Schwarz criterion	-5.784627	
Log likelihood	442.1436	Hannan-Quinn criter.	-5.796440	
Durbin-Watson stat	1.535818			

Author estimation

Giving the simple random walk model at the above table, we will generate out-of-sample forecasts using the random walk and ARIMA (1,0,2) models in the short time horizons, which is up until to 6 month length. Afterwards, the forecasting performances of the simple random walk and the ARIMA models will be compared in the next step.

5.5. COMPARATIVE ANALYSIS OF THE FORECASTS

Two of the most powerful time series models are random walk and ARIMA models. These two models were predicted for a specific estimation sample period in the previous stages. Both models seem plausible from the tables. In this section of the analysis, we will investigate whether the random walk model in a specific time period outperforms the ARIMA model or not.

Detailed results of the forecasting accuracy for each model are given at the ***Table 7***. Forecast performances are examined using the forecast evaluation statistics, namely the root mean squared error (RMSE), the mean absolute error (MAE), and the mean absolute percentage error (MAPE). The out-of-sample forecasts are generated separately for every single time span, starting from the forecast starting point (5/31/2013) to 1 month ahead, 2 months ahead, 3 months ahead, and up until to 6 months ahead (six different forecasts). We consider at the below table the aggregate value of each forecast evaluation statistic this is because while the time horizon rises, the change in values of RMSE, MAE, and MAPE might have negative or positive effects. Therefore, we want to consolidate our results in the short time span by avoiding those changes.

Table 7 ***(Out-of-sample forecasting evaluation statistic values)***

	Random Walk model			ARIMA model		
	RMSE	MAE	MAPE	RMSE	MAE	MAPE
1 month	0.01985	0.01669	1.07946	0.01706	0.01452	0.93964
2 months	0.01887	0.01707	1.11365	0.01556	0.01394	0.90995
3 months	0.01718	0.01551	1.00957	0.01549	0.01347	0.87770
4 months	0.01662	0.01510	0.97650	0.01469	0.01286	0.83347
5 months	0.01585	0.01437	0.92420	0.01446	0.01292	0.83072
6 months	0.01480	0.01306	0.83692	0.01372	0.01217	0.77930
Total	**0.10317**	**0.09180**	**5.94030**	**0.09098**	**0.07988**	**5.17078**

Author estimation[14]

One of the most important goals of econometric analysis is to be able to keep errors as minimum as possible. The success of an econometric work is also evaluated by looking at the degree of minimisation of errors. Therefore, we will assess the out-of-sample forecasting accuracies of the models asking that which model has lower errors at the table.

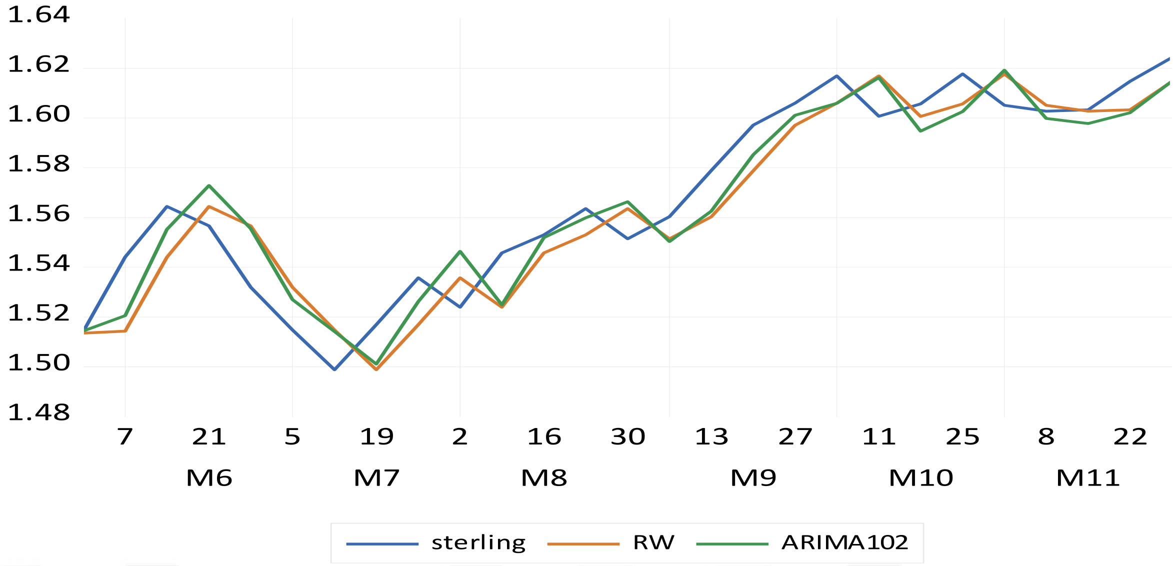
[14] See appendix ***Table 6*** for the actual EViews outputs.

As it is mentioned in the literature review of this study, a simple random walk model usually outperforms time series and/or monetary models in the short and medium time horizons (Meese and Rogoff, 1983). However, the results of our study indicate that the ARIMA model, which we built earlier, outperforms the simple random walk model in the very short time span.

The ARIMA model's aggregate RMSE, MAE, and MAPE forecast evaluation statistics are 0.09098, 0.07988, and 5.17078 respectively, while the same statistics for the simple random walk model are 0.10317, 0.09180, and 5.94030. There is a slight difference between the models' RMSE, MAE, and MAPE statistic values but those slight differences may create large benefits and costs in the financial markets. For this reason, those slight differences cannot be ignored in the financial context.

What is interesting with the results at the ***Table 7*** is the downward tendency of the forecast evaluation statistics while the time horizon increases one by one from one month to six months ahead. The reason behind of it might be that the forecasts cannot be adapted as quickly as possible to the behaviour of the actual series in the very beginning of out-of-sample forecasts (in the very short time horizons such as 2 weeks, 4 weeks, and etc.). The decreases of these values might be showing that both forecasts relatively start to gain adaptation to the actual time series' behaviours while time span is increasing in the short run.

Graph 2 ***Forecast comparison graph***



5.6. DIEBOLD-MARIANO TEST (HLN ADJUSTED)

The aim of Diebold-Mariano (DM) test is to examine whether two different forecasts have the same accuracy or not. However, a number of researchers apply DM type tests for their model comparison purposes in the forecasting context. It is explained that in terms of the DM assumptions[15], DM type tests are not suitable for the model comparison purpose of an empirical study. It was improved only for the forecast comparison purpose (Diebold, 2015, p. 8). In this regard, our study will test whether the out-of-sample 'forecasts' of the random walk and the ARIMA models have the same accuracy or not (not for models). ***Table 8*** shows the Diebold-Mariano test results of this study which consists of the squared error and absolute error statistics and its p values.

Initially, we should point out that statistical tests are actually quite strong. Moreover, Diebold-Mariano test with HLN adjusted modification is stronger than other tests in its class.

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[15] See the article for the assumptions and more information. The title of the article can also make sense for the above paragraph. 'Comparing Predictive Accuracy, Twenty Years Later: A personal Perspective on the Use and Abuse of Diebold-Mariano Tests'.

Thus if we find the errors significant by ~10% at the ***Table 8***, this is practically important. However, we cannot often reject the null hypothesis that is both forecasts have the same accuracy. Having said that statistical inference wants us to make very sure – only a 1 in 20 chance –. We have not mistakenly rejected the null hypothesis except 2 months ahead forecast's squared error statistics with the p value of 0.0434. Even this value is quite close to 0.05. Therefore, we can say that it is very severe.

Table 8

	Diebold-Mariano test (HLN adjusted)			
Null hypothesis:	**Both forecasts have the same accuracy**			
	Squared error statistics	***p value***	***Absolute error statistics***	***p value***
1 month	1.001704	0.1866	0.663969	0.2715
2 months	1.951235	0.0434	1.625412	0.0714
3 months	1.087097	0.1484	1.228751	0.1205
4 months	1.493155	0.0769	1.690618	0.0546
5 months	1.232768	0.1156	1.247642	0.1129
6 months	1.089237	0.1430	0.899604	0.1883

Author estimation

At the end of this analysis, we can conclude that in the case of GBP/USD exchange rate, the ARIMA (1,0,2) model outperforms the simple random walk model for the short time horizon that is the pre-referendum time period. However, it is not significantly better according to the DM test statistics. If we consider the severity of the DM test statistics as it was pointed out earlier, we can say that the ARIMA model is generating better forecasts than the naïve random walk model in our case. Moreover, while the time horizons of the out-of-sample forecasts rise from one month to six months ahead, RMSE, MAE, and MAPE statistic values decrease gradually.

6. CONCLUSION

In terms of macroeconomic future plans and market surveillance purposes, monitoring exchange rate movements is essential especially for central banks, investors, and academics (Lam, Fung, and Yu, 2008). For this reason, exchange rate forecasting is one of the most important field in international finance.

There is a large literature whether a simple random walk model has a superiority performance compared to other models or not. The classical paper of Meese and Rogoff (1983b) accounts for the superiority of a simple random walk model in the exchange rate forecasting context in short and also medium time spans.

In this study, our intention is to investigate out-of-sample forecasting performances of an ARIMA and a naïve random walk models for the GBP/USD exchange rate. We analyse short time horizon out-of-sample forecasts which are less than six months. Therefore, we do not use monetary models due to poor performances of monetary models in the short run. In terms of testing random walk hypothesis properly, we select the period of the pre-referendum time this is because we want to avoid negative effects of the Brexit vote on the domestic currency such as high volatile exchange rate data. Forecasting accuracies of the models are assessed by the forecast evaluation statistics; RMSE, MAE, and MAPE.

According to the results, it is hard to conclude that the naïve random walk model outperforms the ARIMA (1,0,2) model based forecasting for short time spans. In other words, we can say that at least in short time horizons, the ARIMA model for exchange rate determination can have a superiority performance than the simple random walk model in the UK. However, the Diebold-Mariano (DM) test results show that the both forecasts have the same accuracy. If we think about the severity of the DM test, our results still keep its validity. We also find that while time span rises from one month ahead forecast towards six months ahead forecast, the forecast evaluation statistics (RMSE, MAE, and MAPE) decrease slightly for the both forecasts. This downward tendency might be showing that both of the forecasts relatively start to gain adaptation to the exchange rate series' behaviours while time horizon is rising in the short run. In other words, both of the forecasts cannot be adapted as quickly as possible to the behaviour of the actual series in the very beginning of out-of-sample forecasts.

7. LIMITATIONS

In the beginning of our analysis, we decided to study with weekly GBP/USD exchange rate data in a specific time period (to avoid fluctuations). This decision prevented us from using monetary models this is because majority of macroeconomic data are available on a monthly basis such as money supply, interest rate, inflation, etc,. We narrowed down time period and the number of currency on purpose. It could have been carried out for more than one currency and longer time horizons.

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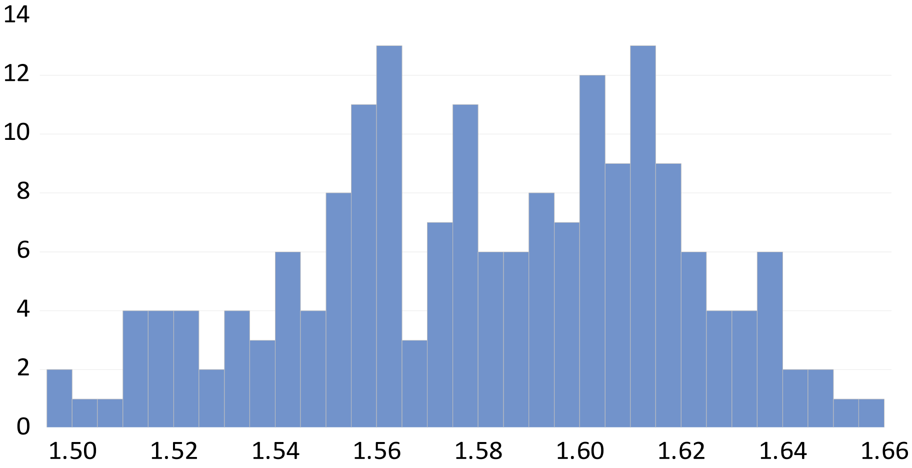
9. APPENDIX

Table 1



Series: STERLING	
Sample 7/02/2010 1/03/2014	
Observations 184	
Mean	1.581747
Median	1.582475
Maximum	1.656380
Minimum	1.497260
Std. Dev.	0.036330
Skewness	-0.230028
Kurtosis	2.296594
Jarque-Bera	5.415977
Probability	0.066671

Graph 1

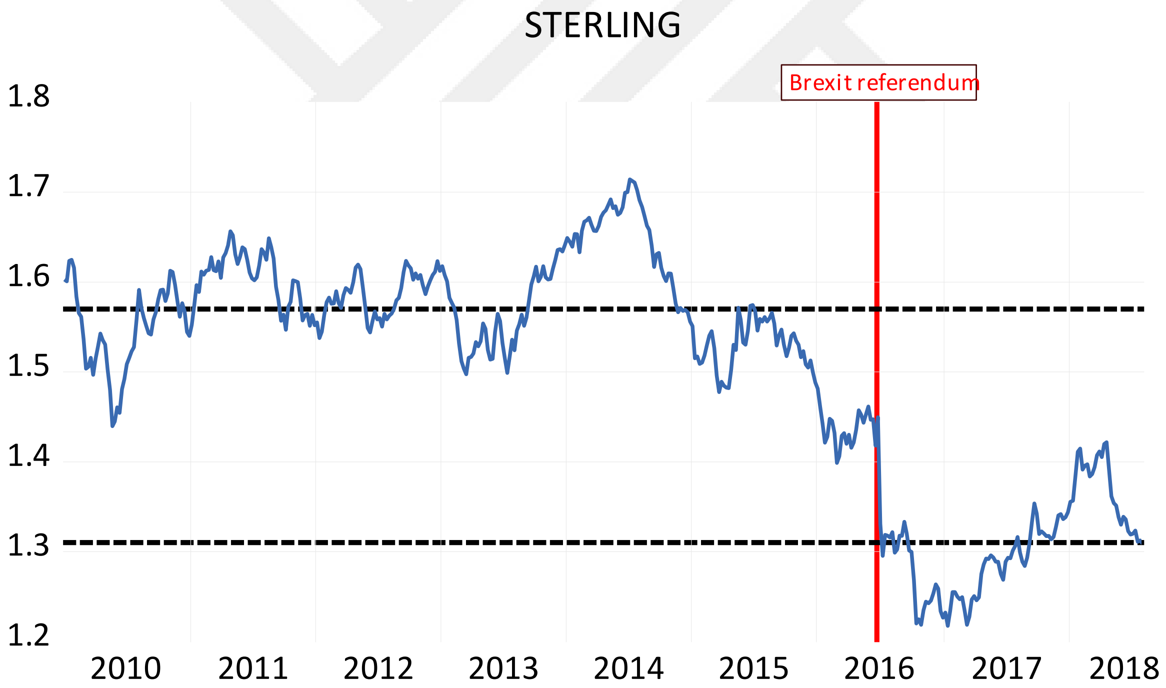


Table 2

Null Hypothesis: STERLING is stationary
Exogenous: Constant
Bandwidth: 9 (Newey-West automatic) using Bartlett kernel

		LM-Stat.
Kwiatkowski-Phillips-Schmidt-Shin test statistic		0.251559
Asymptotic critical values*:	1% level	0.739000
	5% level	0.463000
	10% level	0.347000

*Kwiatkowski-Phillips-Schmidt-Shin (1992, Table 1)

Residual variance (no correction)	0.001219
HAC corrected variance (Bartlett kernel)	0.008040

KPSS Test Equation
Dependent Variable: STERLING
Method: Least Squares
Date: 08/08/18 Time: 19:54
Sample: 7/02/2010 5/31/2013
Included observations: 153

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.581766	0.002832	558.5357	0.0000

R-squared	0.000000	Mean dependent var	1.581766
Adjusted R-squared	0.000000	S.D. dependent var	0.035030
S.E. of regression	0.035030	Akaike info criterion	-3.858723
Sum squared resid	0.186517	Schwarz criterion	-3.838917
Log likelihood	296.1923	Hannan-Quinn criter.	-3.850678
Durbin-Watson stat	0.141927		

Null Hypothesis: STERLING has a unit root
Exogenous: Constant
Bandwidth: 0 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-2.455256	0.1286
Test critical values:	1% level	-3.473672	
	5% level	-2.880463	
	10% level	-2.576939	

*MacKinnon (1996) one-sided p-values.

Residual variance (no correction)	0.000167

HAC corrected variance (Bartlett kernel)	0.000167

Phillips-Perron Test Equation
Dependent Variable: D(STERLING)
Method: Least Squares
Date: 08/08/18 Time: 19:55
Sample (adjusted): 7/09/2010 5/31/2013
Included observations: 152 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
STERLING(-1)	-0.074975	0.030537	-2.455256	0.0152
C	0.118665	0.048327	2.455449	0.0152

R-squared	0.038636	Mean dependent var	3.77E-05
Adjusted R-squared	0.032227	S.D. dependent var	0.013240
S.E. of regression	0.013025	Akaike info criterion	-5.830772
Sum squared resid	0.025449	Schwarz criterion	-5.790984
Log likelihood	445.1386	Hannan-Quinn criter.	-5.814608
F-statistic	6.028282	Durbin-Watson stat	1.483510
Prob(F-statistic)	0.015221		

Table 3

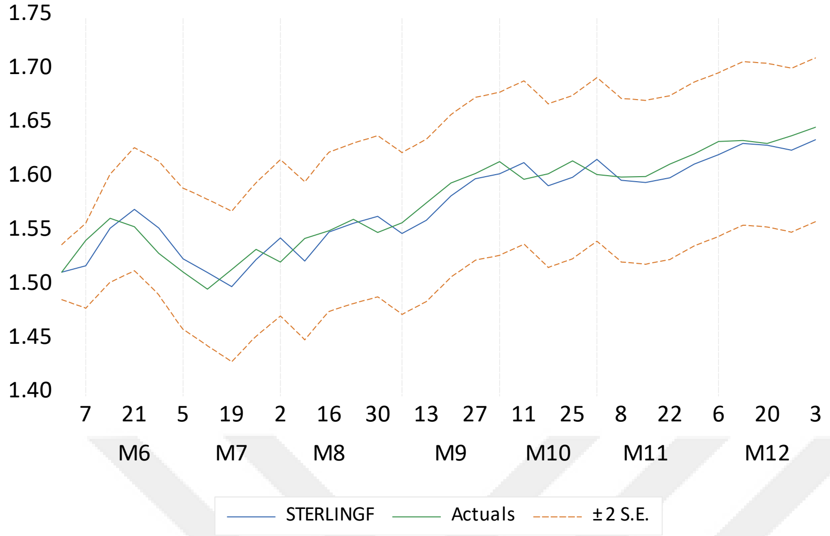
Model Selection Criteria Table
Dependent Variable: STERLING
Date: 08/08/18 Time: 19:57
Sample: 7/02/2010 5/31/2013
Included observations: 153

Model	LogL	AIC	BIC	HQ
(2,1)(0,0)	521.888062	-6.756707	-6.657673	-6.716477
(2,2)(0,0)	522.609347	-6.753063	-6.634223	-6.704788
(4,3)(0,0)	523.750433	-6.728764	-6.550503	-6.656351
(4,1)(0,0)	522.980596	-6.744844	-6.606197	-6.688523
(4,0)(0,0)	522.649673	-6.753591	-6.634750	-6.705315
(3,3)(0,0)	523.694141	-6.741100	-6.582646	-6.676733
(3,2)(0,0)	522.973004	-6.744745	-6.606098	-6.688424
(3,1)(0,0)	522.950324	-6.757521	-6.638680	-6.709246
(2,4)(0,0)	522.640853	-6.727331	-6.568877	-6.662965
(0,1)(0,0)	435.719670	-5.656466	-5.597046	-5.632329
(0,2)(0,0)	479.533585	-6.216125	-6.136898	-6.183942
(2,0)(0,0)	521.695490	-6.767261	-6.688034	-6.735078
(1,4)(0,0)	522.629997	-6.740261	-6.601614	-6.683940
(1,3)(0,0)	522.597703	-6.752911	-6.634070	-6.704636
(1,2)(0,0)	522.571571	-6.765641	-6.666608	-6.725412
(1,1)(0,0)	520.478127	-6.751348	-6.672121	-6.719165
(1,0)(0,0)	515.729299	-6.702344	-6.642923	-6.678206
(0,4)(0,0)	509.496195	-6.581650	-6.462809	-6.533375
(0,3)(0,0)	498.444311	-6.450252	-6.351219	-6.410023
(0,0)(0,0)	365.879857	-4.756599	-4.716986	-4.740508
(3,0)(0,0)	522.015268	-6.758370	-6.659336	-6.718140
(4,2)(0,0)	523.150722	-6.733996	-6.575542	-6.669630
(2,3)(0,0)	522.640853	-6.740403	-6.601756	-6.684082

(4,4)(0,0)	524.303479	-6.722921	-6.524853	-6.642463
(3,4)(0,0)	524.435402	-6.737718	-6.559457	-6.665305

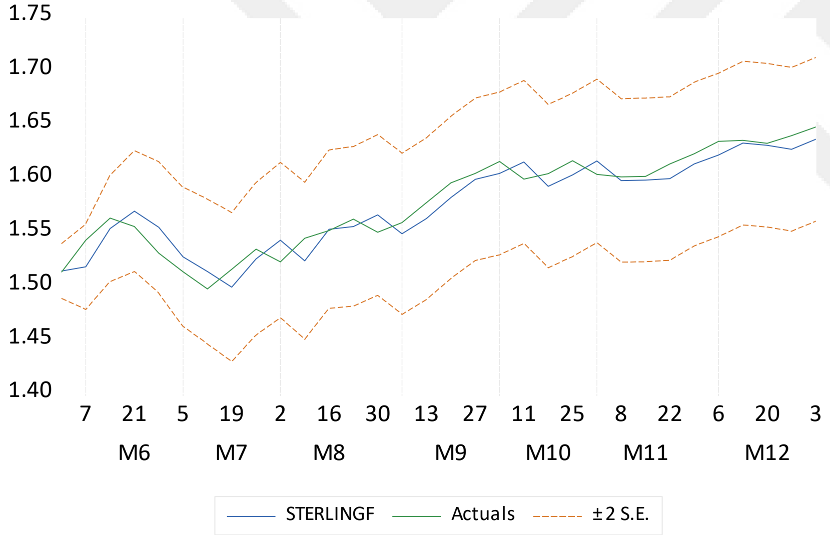
Table 4

ARIMA (1,0,2)



Forecast: STERLINGF	
Actual: STERLING	
Forecast sample: 5/31/2013 1/03/2014	
Included observations: 32	
Root Mean Squared Error	0.013178
Mean Absolute Error	0.011571
Mean Abs. Percent Error	0.736457
Theil Inequality Coef.	0.004174
Bias Proportion	0.057948
Variance Proportion	0.045320
Covariance Proportion	0.896732
Theil U2 Coefficient	0.943584
Symmetric MAPE	0.736920

ARIMA (2,0,0)



Forecast: STERLINGF	
Actual: STERLING	
Forecast sample: 5/31/2013 1/03/2014	
Included observations: 32	
Root Mean Squared Error	0.013203
Mean Absolute Error	0.011686
Mean Abs. Percent Error	0.744120
Theil Inequality Coef.	0.004182
Bias Proportion	0.060742
Variance Proportion	0.045670
Covariance Proportion	0.893588
Theil U2 Coefficient	0.946083
Symmetric MAPE	0.744685

ARIMA (1,0,2)

Dependent Variable: STERLING
Method: ARMA Maximum Likelihood (OPG - BHHH)
Date: 08/13/18 Time: 15:36
Sample: 7/02/2010 5/31/2013
Included observations: 153
Convergence achieved after 11 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.575296	0.010789	146.0131	0.0000
AR(1)	0.878018	0.047573	18.45632	0.0000
MA(1)	0.312605	0.084908	3.681706	0.0003
MA(2)	0.179955	0.081444	2.209542	0.0287
SIGMASQ	0.000156	2.12E-05	7.342625	0.0000

R-squared	0.872429	Mean dependent var	1.581766
Adjusted R-squared	0.868982	S.D. dependent var	0.035030
S.E. of regression	0.012680	Akaike info criterion	-5.850462
Sum squared resid	0.023794	Schwarz criterion	-5.751428
Log likelihood	452.5604	Hannan-Quinn criter.	-5.810233
F-statistic	253.0355	Durbin-Watson stat	2.013138
Prob(F-statistic)	0.000000		

Inverted AR Roots	.88	
Inverted MA Roots	-.16+.39i	-.16-.39i

Table 5
Random walk without drift

Dependent Variable: STERLING
Method: Least Squares
Date: 08/13/18 Time: 04:29
Sample (adjusted): 7/09/2010 5/31/2013
Included observations: 152 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
STERLING(-1)	0.999988	0.000679	1473.606	0.0000

R-squared	0.853853	Mean dependent var	1.582247
Adjusted R-squared	0.853853	S.D. dependent var	0.034634
S.E. of regression	0.013240	Akaike info criterion	-5.804521
Sum squared resid	0.026472	Schwarz criterion	-5.784627
Log likelihood	442.1436	Hannan-Quinn criter.	-5.796440
Durbin-Watson stat	1.535818		

Random walk with drift

Dependent Variable: STERLING
Method: Least Squares
Date: 08/14/18 Time: 15:22
Sample (adjusted): 7/09/2010 5/31/2013
Included observations: 152 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.118665	0.048327	2.455449	0.0152
STERLING(-1)	0.925025	0.030537	30.29221	0.0000

R-squared	0.859500	Mean dependent var	1.582247
Adjusted R-squared	0.858564	S.D. dependent var	0.034634
S.E. of regression	0.013025	Akaike info criterion	-5.830772
Sum squared resid	0.025449	Schwarz criterion	-5.790984
Log likelihood	445.1386	Hannan-Quinn criter.	-5.814608
F-statistic	917.6179	Durbin-Watson stat	1.483510
Prob(F-statistic)	0.000000		

Forecast Evaluation
Date: 08/14/18 Time: 15:27
Sample: 5/31/2013 11/29/2013
Included observations: 27
Evaluation sample: 5/31/2013 11/29/2013
Number of forecasts: 2

Combination tests
Null hypothesis: Forecast i includes all information contained in others

Forecast	F-stat	F-prob
RW	0.016746	0.8981
RWDRIFT	0.016746	0.8981

Diebold-Mariano test
(HLN adjusted)
Null hypothesis: Both forecasts have the same accuracy

Accuracy	Statistic	<> prob	> prob	< prob
Abs Error	NA	NA	NA	NA
Sq Error	NA	NA	NA	NA

Evaluation statistics

Forecast	RMSE	MAE	MAPE	SMAPE	Theil U1	Theil U2
RW	0.014273	0.012770	0.818225	0.818671	0.004553	0.960555
RWDRIFT	0.014273	0.012770	0.818225	0.818671	0.004553	0.960555

Table 6

1 month ahead

Forecast Evaluation
Date: 08/20/18   Time: 15:54
Sample: 5/31/2013 6/28/2013
Included observations: 5
Evaluation sample: 5/31/2013 6/28/2013
Number of forecasts: 2

Combination tests
Null hypothesis: Forecast i includes all information contained in others

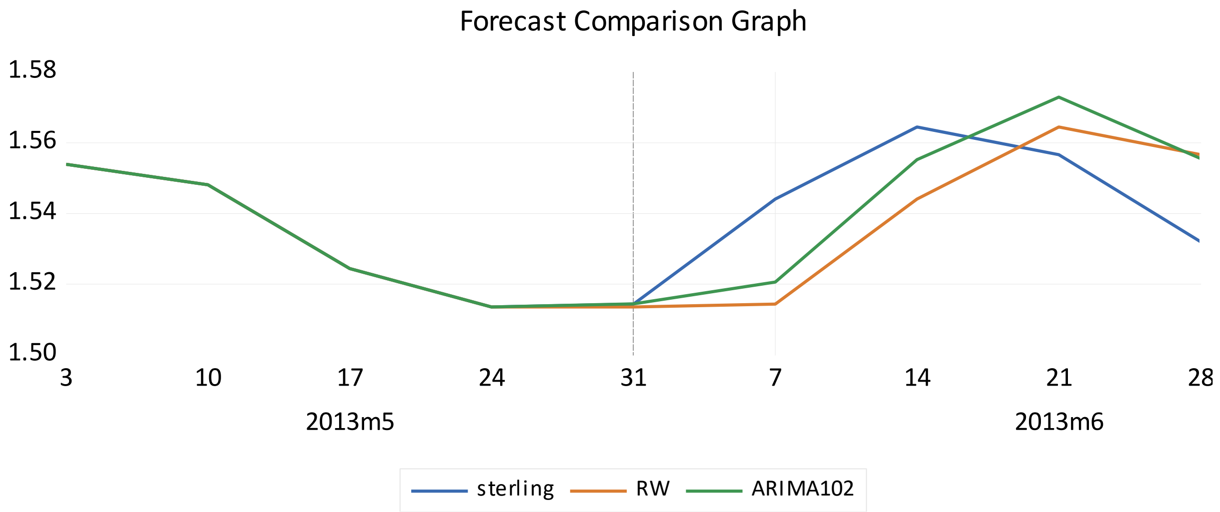
Forecast	F-stat	F-prob
RW	0.784137	0.4411
ARIMA102	4.032056	0.1383

Diebold-Mariano test
(HLN adjusted)
Null hypothesis: Both forecasts have the same accuracy

Accuracy	Statistic	<> prob	> prob	< prob
Abs Error	0.663969	0.5430	0.7285	0.2715
Sq Error	1.001704	0.3732	0.8134	0.1866

Evaluation statistics

Forecast	RMSE	MAE	MAPE	SMAPE	Theil U1	Theil U2
RW	0.019857	0.016691	1.079467	1.082111	0.006445	1.000173
ARIMA102	0.017066	0.014522	0.939644	0.938901	0.005530	0.856415



2 months ahead

Forecast Evaluation
Date: 08/20/18 Time: 22:43
Sample: 5/31/2013 7/26/2013
Included observations: 9
Evaluation sample: 5/31/2013 7/26/2013
Number of forecasts: 2

Combination tests
Null hypothesis: Forecast i includes all information contained in others

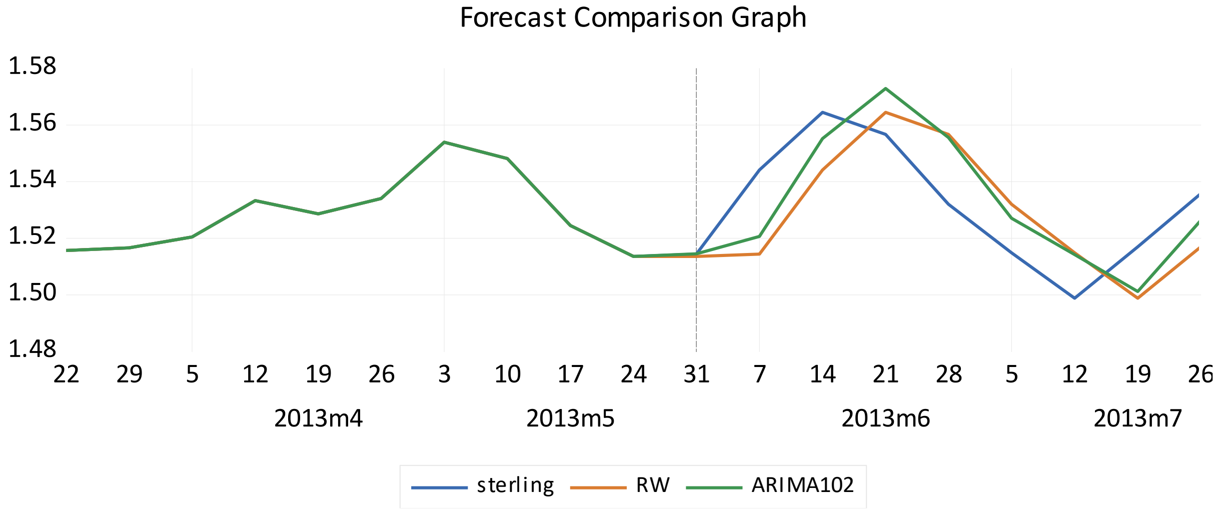
Forecast	F-stat	F-prob
RW	0.615217	0.4585
ARIMA102	4.593288	0.0693

Diebold-Mariano test
(HLN adjusted)
Null hypothesis: Both forecasts have the same accuracy

Accuracy	Statistic	<> prob	> prob	< prob
Abs Error	1.625412	0.1427	0.9286	0.0714
Sq Error	1.951235	0.0868	0.9566	0.0434

Evaluation statistics

Forecast	RMSE	MAE	MAPE	SMAPE	Theil U1	Theil U2
RW	0.018878	0.017071	1.113655	1.115428	0.006170	1.000129
ARIMA102	0.015568	0.013943	0.909956	0.909427	0.005083	0.822588



3 months ahead

Forecast Evaluation
Date: 08/20/18 Time: 15:56
Sample: 5/31/2013 8/30/2013
Included observations: 14
Evaluation sample: 5/31/2013 8/30/2013
Number of forecasts: 2

Combination tests
Null hypothesis: Forecast i includes all information contained in others

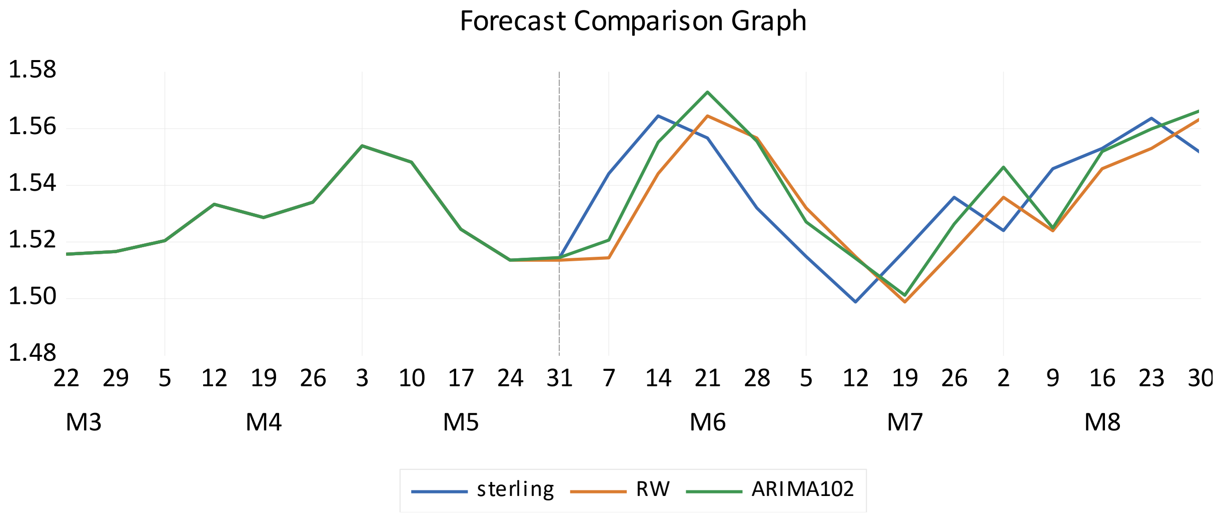
Forecast	F-stat	F-prob
RW	1.317832	0.2734
ARIMA102	5.192681	0.0418

Diebold-Mariano test
(HLN adjusted)
Null hypothesis: Both forecasts have the same accuracy

Accuracy	Statistic	<> prob	> prob	< prob
Abs Error	1.228751	0.2409	0.8795	0.1205
Sq Error	1.087097	0.2967	0.8516	0.1484

Evaluation statistics

Forecast	RMSE	MAE	MAPE	SMAPE	Theil U1	Theil U2
RW	0.017187	0.015515	1.009570	1.011241	0.005596	1.000171
ARIMA102	0.015491	0.013473	0.877700	0.876940	0.005037	0.899217



4 months ahead

Forecast Evaluation
Date: 08/20/18 Time: 22:45
Sample: 5/31/2013 9/27/2013
Included observations: 18
Evaluation sample: 5/31/2013 9/27/2013
Number of forecasts: 2

Combination tests
Null hypothesis: Forecast i includes all information contained in others

Forecast	F-stat	F-prob
RW	0.046678	0.8317
ARIMA102	0.494622	0.4920

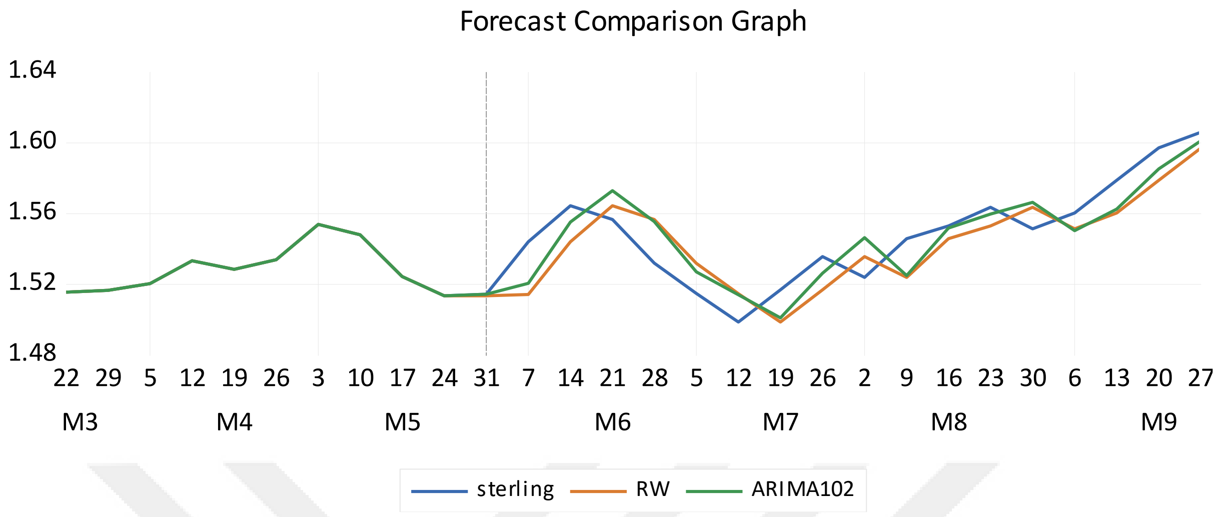
Diebold-Mariano test
(HLN adjusted)
Null hypothesis: Both forecasts have the same accuracy

Accuracy	Statistic	<> prob	> prob	< prob
Abs Error	1.690618	0.1092	0.9454	0.0546
Sq Error	1.493155	0.1537	0.9231	0.0769

Evaluation statistics

Forecast	RMSE	MAE	MAPE	SMAPE	Theil U1	Theil U2

RW	0.016620	0.015102	0.976506	0.978734	0.005378	1.000342
ARIMA102	0.014696	0.012865	0.833472	0.833470	0.004749	0.883723



5 months ahead

Forecast Evaluation
Date: 08/20/18 Time: 22:47
Sample: 5/31/2013 10/25/2013
Included observations: 22
Evaluation sample: 5/31/2013 10/25/2013
Number of forecasts: 2

Combination tests
Null hypothesis: Forecast i includes all information contained in others

Forecast	F-stat	F-prob
RW	0.195485	0.6631
ARIMA102	0.048827	0.8274

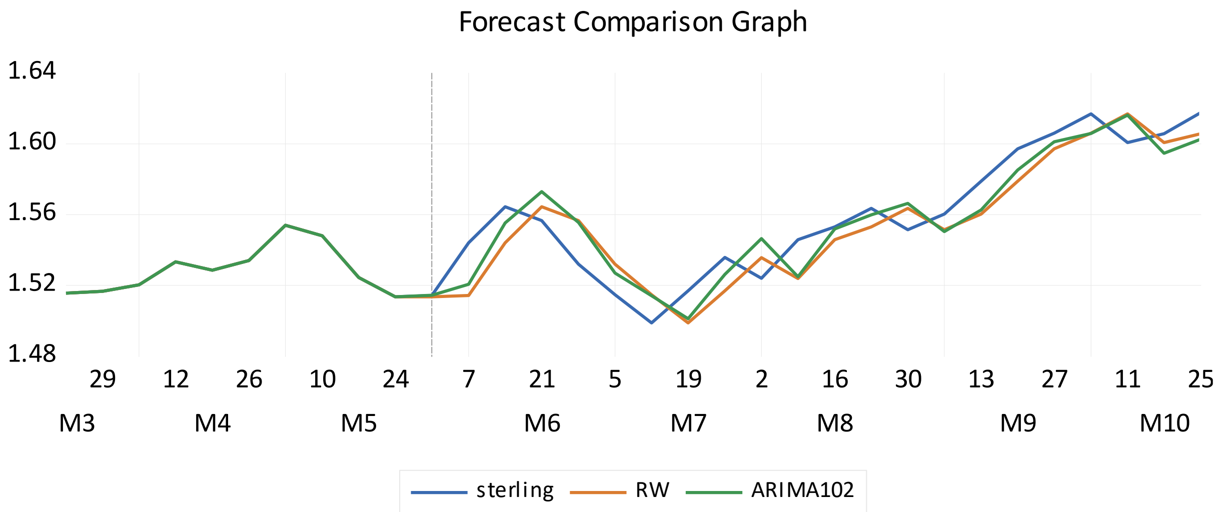
Diebold-Mariano test
(HLN adjusted)
Null hypothesis: Both forecasts have the same accuracy

Accuracy	Statistic	<> prob	> prob	< prob
Abs Error	1.247642	0.2259	0.8871	0.1129
Sq Error	1.232768	0.2313	0.8844	0.1156

Evaluation statistics

Forecast	RMSE	MAE	MAPE	SMAPE	Theil U1	Theil U2
RW	0.015852	0.014372	0.924205	0.926048	0.005090	1.000349

ARIMA102	0.014461	0.012922	0.830729	0.830925	0.004640	0.909717



<u>6 months ahead</u>

Forecast Evaluation
Date: 08/20/18 Time: 15:57
Sample: 5/31/2013 11/29/2013
Included observations: 27
Evaluation sample: 5/31/2013 11/29/2013
Number of forecasts: 2

Combination tests
Null hypothesis: Forecast i includes all information contained in others

Forecast	F-stat	F-prob
RW	0.485909	0.4922
ARIMA102	0.023525	0.8793

Diebold-Mariano test
(HLN adjusted)
Null hypothesis: Both forecasts have the same accuracy

Accuracy	Statistic	<> prob	> prob	< prob
Abs Error	0.899604	0.3766	0.8117	0.1883
Sq Error	1.089237	0.2860	0.8570	0.1430

Evaluation statistics

Forecast	RMSE	MAE	MAPE	SMAPE	Theil U1	Theil U2

RW	0.014800	0.013063	0.836923	0.838467	0.004723	1.000348
ARIMA102	0.013724	0.012179	0.779308	0.779531	0.004377	0.923830