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Predictability of Foreign Exchange Rates with the AR(1) Model

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Abstract

Many authors have investigated the possibility of predictability in asset returns, but very little supportive evidence has so far been found in exchange rate returns. This empirical study uses the econometric model ARIMA (1,0,0) to study three different foreign exchange rates, namely the euro and the dollar, the euro and the Hungarian forint and the euro and the Korean won. The results show that it is not possible to explain and predict all three foreign exchange rates using the autoregressive model. Specifically, the technical rule on transactions ARIMA(1,0,0) is not effective in the case of euro vs dollar but it is effective in the case of euro vs the Hungarian forint and euro v-s the Korean won. Fairly accurate predictions can be made regarding the last two foreign exchange relationships.

Keywords: Foreign Exchange Market; Exchange Rate, Technical Trading, Forecasting.

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Introduction

During recent years, volatility predictions of time series, like for example on foreign exchange, have been the subject of extensive discussions and research. Volatility is a very important aspect of financial markets as it reflects uncertainty and therefore currency or investment portfolio risk. The greater the volatility the greater the currency exchange risk between a pair of currencies. Investors, fund managers and investment analysts use different volatility models in order to predict maximum returns on foreign currency exchange (Engle and Patton, 2001). Currency exchanges are largely influenced by interrelationships of economic, political and psychological factors (Yao and Tan, 2000). Prediction of foreign exchange movements is very difficult and professionals make serious attempts to explain such movements thus establishing fundamental and technical analysis as the most basic and important financial prediction methodologies.

Fundamental analysis evaluates wealth based on national economic conditions without taking into account price fluctuations (DAILYFX, 2014). Technical Analysis studies past price behavioural patterns in order to arrive at optimum asset allocation decisions. These decisions are usually based on the application of simple rules using historical price data (Neely, 1997). Technical analysis predicts foreign exchange rate fluctuations or other asset price fluctuations through inductive analysis of past movements using quantitative and qualitative techniques or a combination of the two. During the last 20 years, economists pay more attention to technical analysis in an attempt to comprehend the foreign exchange fluctuation patterns as well as the behavioural patterns of foreign exchange market participants (Menkhoff and Taylor, 2007). As a result, literature on the application of technical analysis on FOREX markets has been adequately developed although on certain occasions this literature is about the application of technical analysis on financial markets and more specifically on equity markets. Yet foreign exchange markets are significantly different to equity markets. Firstly, the total daily volumes on FOREX are much higher than those of the largest equity markets in the world, exceeding four trillion dollars per day. Additionally, the foreign exchange market is made up, almost exclusively, of professional traders and therefore any impact is merely affecting private investors rather than the whole (Sager and Taylor, 2006). Finally, one may claim that there is less confidence among traders in fair value models in FOREX than in equity markets (Taylor, 1995). Lack of trust in fair value models by FOREX participants and the main emphasis on transactions with a short-term time horizon, would lead to the conclusion that the use of technical analysis is far more popular in foreign exchange markets although the high percentage of professional traders and the bigger liquidity in the foreign exchange market could suggest the opposite (Menkhoff and Taylor, 2007).

This empirical study investigates the predictive capacity of one of the most popular and important time series prediction models, the ARIMA (Autoregressive Integrated Moving Average) model. It also considers the various types of technical analysis used in the FOREX industry, both by FOREX companies, academics and practitioners. The purpose is to examine whether technical analysis, through the application of the ARIMA(1,0,0) model, is sufficiently rewarding for the participants of FOREX trading. The methods and models used by FOREX companies in predicting currency fluctuations are also examined. It is worth mentioning that based on our literature review this is the first time of applying the autoregression model. The testing of how efficiently the future foreign exchange prices of the dollar (USD), the Hungarian forint (HUF) and the South Korean won(KRW) against the euro (EUR) can be predicted is carried out using data for the five year period 2009-2014 extracted from the Archives of the European Central Bank.

The various conclusions regarding the application of technical analysis in FOREX trading give rise to a number of questions. The technical approach reflects the principle that prices move in trends that are established by the changing attitudes of investors according to various economic monetary policies but also psychological factors. Given that technical analysis is based on the theory that prices reflect investor psychology, it attempts to predict the movement of prices in the future, assuming that crowd psychology moves between panic, fear and pessimism on the one hand and self confidence, optimism and greed on the other hand.

Analysing and predicting future exchange rates using a single isolated model (ARIMA) raises a number of questions. This is because there should have been comparison between the results of the model under examination and the results obtained using some other model, like for example the econometric model GARCH(1,1). Comparing the two models one can conclude which is more appropriate to predict future prices but also which of the two gives a higher return. Similar questions arise regarding predictions over two time periods. In the current research a time period of 5 years is used. However, the results from this time period could have been compared to those from a bigger time period (e.g. 10 years) or even from a short term period (e.g. 1 year) to add confidence in these results.

The remainder of the paper is organized as follows. In the second section various econometric methods are examined that could be used for the prediction of the movement of exchange rates of various foreign currencies. In the third section, the ARIMA model is applied to predict foreign exchange rates of the US dollar and the Hungarian and the S. Korean currencies against the euro in order to extract results. In a final section this study draws some conclusions from the various findings.

1. *Econometric Models*

1.1 The Autoregressive Integrated Moving Average (ARIMA) model

In general, the ARIMA(p,q) procedure is written as follows:

$$z_t = \alpha_1 z_{t-1} + \alpha_2 z_{t-2} + \cdots + \alpha_p z_{t-p} + u_t + \theta_1 u_{t-1} + \theta_2 u_{t-2} + \cdots + \theta_q u_{t-q} \quad (1)$$

It is worth noting that the specific procedure can be expressed in different ways. Firstly, it is possible to be formulated as a function of its past values and the values of the disturbance term of the past and present. In other words, the difference equation form is used. For example, if $z_t = Y_t - Y_{t-1}$, the difference equation for the ARIMA(p,1,q) model is:

$$Y_t = (1+\alpha_1)Y_{t-1} + (\alpha_1 - \alpha_2)Y_{t-2} + \cdots + (\alpha_p - \alpha_{p-1})Y_{t-p} - \alpha_p Y_{t-p-1} + u_t + \theta_1 u_{t-1} + \cdots + \theta_q u_{t-q}$$
(2)

This relation is the result of the ARMA(p,q) equation that replaces z_t with its equivalent, that is $z_t = Y_t - Y_{t-1}$.

Furthermore, this procedure can also be a function of its past values and the current value of the disturbance term, in other words to be inverted (Inverted form). For example, the inverted form of the ARIMA(0,1,1) model is as follows:

$$Y_t = (1+\theta_1)Y_{t-1} - \theta_1(1+\theta_1)Y_{t-2} + \theta_1^2(1+\theta_1)Y_{t-3} - \theta_1^3(1+\theta_1)Y_{t-4} + \cdots + u_t \quad (3)$$

The relation is based on the difference equation with consecutive substitutions of u_{t-1}, u_{t-2}, etc.

In addition, the ARIMA(p,d,q) procedure is possible to be expressed as a function only of the values of the disturbance term, past and present. The specific form is the random shock form. For example, the ARIMA(0,1,1) model assumes the following form:

$$Y_t = u_t + (1+\theta_1)u_{t-1} + (1+\theta_1)u_{t-2} + \cdots \quad (4)$$

The relation is based on the difference equation with consecutive substitutions of Y_{t-1}, Y_{t-2} etc.

As the present work is a study of the first-order autoregressive model, AR(1), it is important to note that this is the ARIMA(1,0,0) model in the form of:

$$Y_t = \alpha_0 + \alpha_1 Y_{t-1} + \varepsilon_t \quad (5)$$

where $\alpha_0 = (1-\alpha_1)\mu$ και $\mu = \frac{\alpha_0}{1-\alpha_1}$

1.2 The Autoregressive Conditional Heteroscedasticity (ARCH) model

ARCH is the simplest model where AR stems from the fact that this type of model is autoregressive in squared returns. Conditionality results from the fact that in these models the variability of the following period is based on data of this period. In a standard linear regression analysis where,

$$y_i = \alpha + \beta\chi_i + \varepsilon_t \quad (6)$$

when the variation of residuals ϵ_i is stable, there exists homoscedasticity and the Ordinary Least Squares (OLS) method is employed for the estimation of α and β parameters. On the other hand, if the variation of residuals is unstable, there is heteroscedasticity and in this case the Weighted Least Squares (WLS) method is used for the estimation of the regression coefficients.

1.3 Generalized AutoRegressive Conditional Heteroskedasticity GARCH(1,1) model

The GARCH(1,1) model is widely used as a parametric test for predicting the variability of foreign exchange rates. This model is an extension of the ARCH model (Bollerslev, 1986). The equation of this model is

$$r_t = \alpha + \sum_{i=1}^{p} \beta_i \, S_{t-i}^{n1,n2} + \varepsilon_t \quad (7)$$

where $\epsilon_t \sim N(0, h_t)$ and $h_t = \delta_0 + \delta_1 h_{t-1} + \delta_2 \epsilon_{t-1}^2$

The GARCH modeling assumes a two period conditional relationship where returns are auto-correlated (Gencay, 1999). In other words, periods of high variability are possible to be followed again by periods of high variability. The same is true in times of low variability that are followed by periods of low variability. In his research during 1994, Taylor applied the exchange rule ARIMA(1,0,2), which is usually used for in-sample data where the expected return exceeds the «band of inactivity». Taylor selected the ARIMA series and chose the size of the band so as to maximize the in-sample profitability (Taylor, 1994). Brailsford and Faff, used various complicated fluctuation prediction models for shares listed on the Australian Stock Exchange (Brailsford and Faff, 1996). Although the various rankings of the model are sensitive to the statistical error, they are used for assessing the forecasting accuracy. Their results indicate that the ARCH model and the simple regression model provide the best prediction of fluctuations. (Brailsford and Faff, 1996).

Wang and Leu in 1996, developed a useful prediction system for medium term trends of stock prices on the Taiwanese stock exchange based on a repetitive neural network data extracted from the ARIMA sample analysis (Wang and Leu, 1996). Analyzing differences of primary data from the Taiwan stock exchange weighted stock index-TSEWSI and then studying the auto regressions and partial auto regressions of the time series led to the conclusion that this series follows the ARIMA(1,2,1) model. Subsequently, applying second differences on the data, led to improved predictions compared to previous ones (Wang and Leu, 1996). In conclusion, the econometric model ARIMA is efficient and relatively accurate in predicting market trends.

In 1999 Gencay predicted the returns on current exchange rates using historical buy-sell signals of simple technical transaction rules, applying the GARCH(1,1) model (Gencay, 1999). He arrived at the conclusion that in the case of the GARCH(1,1) model, the mean squared error of the prediction is close to 1 and the observed confidence level of the prediction is 0,5 in the case of the British pound and the Swiss Franc and 0,51 in the case of the German mark, the French franc and the Japanese Yen (Gencay το 1999).

Yao and Tan in 2000, using neural networks and the ARIMA model compared their prediction results for various currencies. The results looked promising for most currencies except for the Japanese yen (Yao and Tan, 2000). With the use of neural networks in applying technical prediction rules more accurate results were obtained for the Australian dollar, the Swiss franc and the pound sterling. Results for the Japanese yen were not statistically significant and this may be due to technical analysis not being the appropriate prediction tool for this specific currency (Yao and Tan, 2000). They concluded that concentrating on gradients is only 50% correct as opposed to neural networks that exceed 70% (Yao and Tan, 2000).

Professionals have a different opinion to the above. They believe that returns are more important than gradients (Yao and Tan, 2000). Neural networks provide better results irrespective of the normalized mean squared error (NMSE), the gradient or the profit. Thus, in the case of foreign currency predictions, researchers concluded that neural networks can function as an alternative prediction tool.

Appiah and Adetunde in 2011, using time series analysis attempted to predict future rates of exchange (Appiah and Adetunde, 2011). They collected data on the rate of exchange of Ghanaian Cedi in relation to the dollar from January 1994 to December 2010 using the ARIMA method. Applying the Box-Jenkins methodology, they concluded that the most appropriate prediction model for future prices is the ARIMA(1,1,1) model.

2. ***Data and Results***

In this section the degree of predictability in the intertemporal structure of daily exchange rates (returns) is analysed using the econometric auto-regressive AR(p) method, one of the most important time series models. Additionally, AR(p) models are examined in relation to their performances and their effectiveness regarding time series prediction. The data used in this study consist of observations of daily frequency for the rate of exchange of the dollar, the Hungarian and Korean currencies in relation to the euro for the period 01/09/2009 - 29/08/2014 (N = 1282). The time series included observations on a five day basis covering this period.[2] Initially, the data were transformed into continuously compounded returns by taking the first logarithmic difference as such type of time series are usually exposed to exponential growth. So, the logarithms can smooth out (linearization) the series and the differences help stabilize the variance of the time series. The main motivation to work with logs, instead of levels is that they are usually stationary (covariance-stationary) and they represent the behaviour of the conditional volatility of the series in a more intuitive manner.

Table 1 presents the descriptive statistics of the dollar, Hungarian and Korean currencies against the euro.

Insert table 1 about here

The sample consists of 1282 observations respectively. The mean exchange rate for the dollar vs euro is 1.346, with a standard deviation of 0.063. The corresponding values for the Hungarian currency are 287.281 and 14.536 and for the Korean currency, 1500.767 and 86.267. From the table, we can also detect skewness and kurtosis for the three exchange rates. In all three cases there is positive asymmetry as skewness is greater than zero. It can also be established that the variables are not in line with normal distribution by observing the Jarque-Bera statistic and also the p-value which in all three cases is close to zero thus rejecting the null-hypothesis of normality. Regarding kurtosis, the Korean currency exhibits leptokyrtosis in its distribution (positive kyrtosis) as the kyrtosis coefficient is 4.775 (kurtosis > 3). On the other hand, the other two exchange rates show platykyrtosis (negative kyrtosis) as the kyrtosis coefficients are 2.839 και 1.837, respectively (kurtosis < 3).

Table 1 also shows the statistical measures of the first logarithmic differences of the original USD (DLUSD) series. This is because the time series that is important in determining the results is not the original one but the first logarithmic differences. It is

[2] All data series were obtained from the European Central Bank's database.

made up of 1281 data points as compared to 1282 of the other two series. This can be explained by the equation $\Delta(Y)_t = Y_t - Y_{t-1}$. Therefore, the time series has one less observation. The average value approaches zero with a standard deviation of 0.006. Furthermore, there exists negative asymmetry as the indicator of asymmetry is less than zero (skewness = -0.28). Regarding kyrtosis there is leptokyrtosis as the coefficient of kyrtosis is 3.935 (kurtosis > 3).

2.1 ARIMA(1,0,0) MODEL

2.1.1 Dollar vs Euro

Table 1 in appendix gives the unit root test of the USD series that covers the time period 01/09/2009-29/08/14. It can be observed that at statistical significance level of 5% (α = 0.05), the null hypothesis is not rejected. In other words, as the p-value is greater than 0.05 (p-value = 0.388) the unit root alternative hypothesis of the USD series is true. The existence of a unit root, i.e. no stationarity in the time series is due to the fact that the time series exhibits strong tendency. For this reason it is useful to transform the original series by using logarithms. The table of the stationarity test of the transformed series is given in appendix where the series continues to exhibit strong tendency. Specifically, it shows that the null hypothesis is not rejected since the p-value is still greater than 0.05 (p-value = 0.388).

Table 3 of appendix shows the stationarity test results of the first differences of the logarithms of the exchange rate between dollar and euro (DLUSD) over time where it is obvious that series DLUSD exhibits stationarity since the p value approaches zero (p-value < 0.05). Hence, the first differences of the logarithms of the exchange rate between dollar and euro can be analyzed using ARMA, applying the Box-Jenkins procedure.

According to diagram 1 of appendix B΄ which depicts auto-correlations and partial auto-correlations of the first differences of the logarithm of the exchange rate between dollar and euro and specifically the statistical function Q, it is concluded that there is no auto-correlation. This can be explained by the fact that function Q has a value of 14.488 for the first auto-correlation coefficients (m = 22). This value is less than the critical X^2 value which is 33.9 for significance level $\alpha = 0.05$ και m = 22 degrees of freedom. Moreover, by observing the p-value, which is equal to 0.88 and therefore greater than the significance level $\alpha = 0.05$, it can be concluded that the null hypothesis is not rejected for the existence of auto-correlation.

Table 2 shows the results of applying various ARIMA models, regarding the significance of the model's parameters. The estimated parameters are not statistically significant since the absolute value of the t statistic is less than 1.96 for a significance level $\alpha = 0.05$

Insert table 2 about here

2.1.2 Hungarian Forint to Euro Foreign Exchange Rates

Table 4 of appendix shows the results of the stationarity test (unit root test) of the time series HUF which consist of 1282 observations and spans the period 01/09/2009 - 29/08/14. Based on these observations and at a significance level $\alpha = 0.05$ the null hypothesis is rejected. In other words, as the p-value is less than 0.05 (p-value = 0.029) the stationarity hypothesis of the HUF time series holds. The non-existence of a unit root, ie the stationarity of the time series, is due to the fact that the series does not exhibit some form of tendency.

Observing diagram 2 of appendix, depicting auto-correlations and partial auto-correlations of the exchange rate between the Hungarian currency and the euro and more specifically the Q statistical function, leads to the conclusion that there exists auto-correlation. This is simply because the Q function has a value of 23856 for the first coefficients of autocorrelations (m = 22). This value is much higher than the critical X^2 value which equals 33.9 for a significance level of $\alpha = 0.05$ and m = 22 degrees of freedom. Furthermore, the autocorrelations of time series HUF diminish geometrically approaching zero and the partial auto-correlations become zero after a time lag of 1. This behavior is characteristic of the auto-regressive AR(1)model. In other words the HUF time series follows the ARIMA(1,0,0) model.

Table 3 shows the results relating to the significance of the model parameters. The first column of the table relates to ARIMA(1,0,0) model for the time series under examination. The second and fourth columns show the estimation of the parameters and more specifically the constant term and the auto-regressive parameter respectively. Also the table provides the p-values of the parameters and the t values in brackets.

Insert table 3 about here

As was established by the absolute values of the t statistic, the estimated parameters are statistically significant since the absolute vales of the t statistic are greater than the critical t value (|t > 1.96) for a significance level $\alpha = 0.05$. The same result can be obtained from the p-values, given in the third and fifth columns of the table. As a result the parameters of the ARIMA(1,0,0) model are statistically significant.

However, for the hypothesis testing of the model parameters to be valid, the assumption of the independence of the residuals of the estimated model must hold. The auto-correlation testing of the residuals can be carried out using a diagram of auto-correlations and partial auto-correlations given as diagram 3 in appendix. For the first 22 auto-correlation coefficients the value of the Q_{LB} statistic is 29.957 which is less than the X^2 value which equals 33.9 for a significance level of $\alpha = 0.05$ and m = 22 degrees of freedom.

Also, based on the p-value that is greater than the level of significance (p-value > 0.05), the null hypothesis is not rejected, i.e. the residuals are not auto-correlated. The Durbin-Watson value in the table is 1.976 which is very close to a value of 2 which means that the residuals are not auto-correlated.

The testing for the order of the model can be done by comparing the model under examination against another model of higher order. In this case the ARIMA(1,0,0) model is compared against ARIMA(2,0,0) και ARIMA(1,0,1) models. From table 5 in appendix it can be observed that the addition of a second auto-regressive term as well as moving average term is statistically insignificant since the absolute t values of the two parameters are smaller than the critical t value of 1.96 for a significance level of $\alpha = 0.05$. In other words the additional coefficients in the higher order models are statistically insignificant and therefore the original model is the one that can describe the procedure that produces the estimates.

On the basis of the above findings and as the assumption of the independence of residuals holds, the model can be validly used to predict future exchange rates. The predictions relate to the period 01/09/2009 - 29/08/2014, and also to September which is an out-of-sample month and spans the period 01-30/09/2014. It is worth mentioning that these predictions are based on the static approach, in other words actual and not anticipated values are used as the actual data is available.

Table 4 shows the square root of the mean square error (RMSE), the mean absolute error (MAE), the mean absolute percentage error (MAPE), the Theil coefficient of inequality, as well as its biasness, variance and co-variance.

Insert table 4 about here

The errors are insignificant and the Theil coefficient approaches the value of zero (0.003). This indicates that the predicted values match the actual values. On the basis of non-existent biasness in combination with the variance of 0.004 it can be claimed that there are no systematic errors. Therefore, the largest percentage of the error (99.6%) is due to co-variance. Based on these criteria the ARIMA(1,0,0) model is appropriate and able to predict future exchange rates.

2.1.3 The exchange rate between the Korean won and the euro

Using the exchange rate of the Korean won as compared to the euro, the same time period (01/09/2009-29/08/2014) is analyzed, where the sample consists of 1282 observations. As evidenced by the examination of the time series HUF, the time series KRW (see table 6 in appendix) is also characterized by stationarity without strong tendency.

Next, diagram 4 of appendix depicts the autocorrelations and partial autocorrelations of the time series KRW, for the period 01/09 / 09-29 / 08/14. Function Q has a value of 22522 for the first autocorrelation coefficients (m = 22) of the sample. This value is greater than the critical X^2 value which, for significance level $\alpha = 0.05$ and $m = 22$ degrees of freedom, is 33.9, which proves autocorrelation. Meanwhile, the autocorrelation of the time series KRW declines geometrically approaching zero and the partial autocorrelation approaching zero with time lag 1. Thus, the time series under examination also follows the model ARIMA (1,0,0).

Table 5 shows the results of the ARIMA model for the time series KRW during the relevant period. In the second and fourth columns the estimates of model parameters are given, namely the constant term and the autoregressive parameter. Additionally, the values of the t statistic are shown below the coefficients of the models, which serve to test the statistical significance of the model coefficients.

Insert table 5 about here

In addition to the statistical values t, the testing of the statistical significance of the parameters can be done using the p-value, which can be seen in the third and fifth columns of table 5. As noted, the p-value approaches zero which means that the parameters of the model ARIMA (1,0,0) are statistically significant. Subsequently, the testing of the autocorrelation of residuals of the estimated model is applied. In diagram 5 of appendix it can be seen that for the first 22 autocorrelation coefficients (m = 22) the value of statistical QLB for the period in question is 31.55, which is less than the value of the distribution X^2, which for a significance level = 0.05 and degrees of freedom m = 22, is 33.9. Also, based on the p-value of 0.065 which is greater than the significance level (p-value> 0.05), the null hypothesis cannot be rejected. In other words, the hypothesis that the residuals are not autocorrelated holds true. The same result can be obtained using the Durbin-Watson test. As the values of the test are close to 2 (2.087), it can be inferred that there is no autocorrelation of the residuals.

Next, a test of the ordering of the model is performed, comparing the model under consideration with another of higher order. As in the case of time series HUF, so in this case the model ARIMA (1,0,0) is compared with the model ARIMA (2,0,0) and ARIMA (1,0,1). From Table 7 of Appendix, it can be observed that the addition of a second autoregressive term and a moving average term are statistically insignificant as the absolute values of the two parameters are less than the critical value 1.96 with a significance level a = 0.05. In other words, additional coefficients in the higher-order models are not statistically significant for the model, so the original ARIMA (1,0,0) model defines the process that produced the data.

As the process of over-adjustment has been applied and the requirement of independence of the residuals holds true, the model may be used reliably to forecast future exchange rates. Forecasts relate to the above mentioned periods of time and the immediately following month, namely September, which is a month out of sample. In these forecasts too, the static approach is applied as the actual data are available.

Using the results in table 6 to assess forecasts, the errors are very small. Also, the Theil coefficient is close to zero (0.003), which indicates that the predicted values coincide with the actual. This lack of biasness, in conjunction with the variance (0.003), is an indication of non-systematic errors. Therefore, the greatest part of the error is due to the covariance of 99.7%, which represents the unsystematic (random) factor that cannot be avoided.

Insert table 6 about here

Based on the above results the ARIMA (1,0,0) model can be used to reliably predict future prices in the foreign exchange market.

3. *Conclusions*

Technical analysis according to the Box-Jenkins methodology, namely the application of the model AR(1), is efficient in trading foreign exchange. By using 2009 - 2014 data it has been proved that for some currencies it is feasible to predict future exchange rates using values of the past. As already mentioned, Yao and Tan, while investigating the predictive ability of the ARIMA model for various exchange rates, concluded that in relation to the Japanese yen no reliable predictions can be made. In this research, using the exchange rate of the dollar against the euro proved from the start that applying the ARIMA model cannot give reliable future predictions, as coefficients of the estimated models are statistically insignificant. In other words, technical analysis is not an appropriate tool for forecasting currency trends. That is because the exchange rate of the dollar against the euro is impacted by various economic, political, social, and psychological factors, which makes it quite difficult to forecast. In contrast, the autoregressive AR model with an autoregressive parameter is able to predict future values of the Hungarian Forint and the Korean won against the euro, as the coefficients of the model are statistically significant and residuals not autocorrelated. In other words, the residuals are white noise.

It is important to note that in order to conclude that the model is appropriate and able to make forecasts certain criteria have to be satisfied. The most important is that the Theil inequality coefficient is close to zero. In both cases, namely in the exchange rates of the Hungarian and Korean currencies relative to the euro the value of the coefficient is 0.003. Additionally, the biasness and variance, which make up the systematic error, are almost nonexistent and therefore the greatest percentage of the error is due to non-systematic error as the covariance equals 99.6% and 99.7% respectively. This indicates that the predicted values coincide with the real.

Appiah and Adetude, using the Box-Jenkins methodology concluded that the most appropriate model for future price prediction is the ARIMA (1,1,1) model with an absolute mean percentage error of 0.915 and a square root of mean squared error of 93.873. Instead, this empirical work proves that the most appropriate model for the Hungarian and Korean currencies is the ARIMA (1,0,0). The future exchange rate forecasts for the Hungarian forint have absolute mean percentage error 0.453 and square root of mean squared error 1.748. For the Korean currency the absolute mean percentage error and the square root of the mean squared error is 0.446 and 9.08 respectively. In both cases of the above mentioned currencies, errors are smaller than those derived by Appiah and Adetunde with the ARIMA (1,1,1) model. Hence the predictions of this research are better as the errors are smaller. In conclusion, there is strong evidence to suggest that the ARIMA (1,0,0) model is the most suitable and reliable to forecast future exchange rates of the Hungarian forint and the Korean won against the euro for the period 2009 - 2014.

APPENDIX

Table 1: Stationarity test of the USD time series

Null Hypothesis: USD has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=22)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.384004	0.3878
Test critical values:	1% level	-3.965226	
	5% level	-3.413323	
	10% level	-3.128691	

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

Table 2: Stationarity test of the LUSD logarithmic time series

Null Hypothesis: LUSD has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=22)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.383062	0.3883
Test critical values:	1% level	-3.965226	
	5% level	-3.413323	
	10% level	-3.128691	

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

Table 3: Stationarity test of the first differences of the DLUSD time series

Null Hypothesis: DLUSD has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=22)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-36.74499	0.0000
Test critical values:	1% level	-3.965231	
	5% level	-3.413326	
	10% level	-3.128692	

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

Table 4: Stationarity test of the HUF time series

Null Hypothesis: HUF has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=22)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.616744	0.0288
Test critical values:	1% level	-3.965226	
	5% level	-3.413323	
	10% level	-3.128691	

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

Table 5: Over-adjusting the ARIMA(1,0,0) model for the HUF time series

	Constant Term	**AR(1)**	**AR(2)**	**MA(1)**
ARIMA(2,0,0)	292,131	1,005	-0,011	-
	(34,79)	(35,93)	(-0,39)	-
ARIMA(1,0,1)	292,343	0,994	-	0,012
	(35,45)	(289,48)	-	(0,43)

Table 6: Stationarity test of the KRW time series

Null Hypothesis: KRW has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=22)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.596457	0.0304
Test critical values:	1% level	-3.965226	
	5% level	-3.413323	
	10% level	-3.128691	

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

Table 7: Assessed ARIMA models for the KRW time series

	Σταθερός Όρος	**AR(1)**	**AR(2)**	**MA(1)**
ARIMA(2,0,0)	1456,644	0,948	0,044	-
	(41,21)	(33,92)	(1,56)	-
ARIMA(1,0,1)	1456,637	0,992	-	-0,042
	(41,21)	(349,52)	-	(-1,50)

Figure 1: Autocorrelations and partial autocorrelations – DLUSD

Autocorrelation Partial Correlation PAC

1	-0.027	-0.027	0.9568	0.328
2	0.025	0.024	1.7717	0.412
3	0.012	0.014	1.9646	0.580
4	-0.015	-0.015	2.2375	0.692
5	0.020	0.019	2.7588	0.737
6	-0.004	-0.003	2.7826	0.836
7	-0.006	-0.006	2.8226	0.901
8	0.014	0.013	3.0755	0.930
9	-0.001	0.001	3.0764	0.961
10	0.044	0.043	5.6110	0.847
11	-0.008	-0.006	5.6865	0.893
12	0.034	0.032	7.1598	0.847
13	-0.039	-0.039	9.1322	0.763
14	0.005	0.003	9.1637	0.820
15	0.002	0.001	9.1667	0.869
16	-0.005	-0.002	9.1931	0.905
17	0.012	0.009	9.3657	0.928
18	0.028	0.029	10.375	0.919
19	-0.041	-0.040	12.515	0.862
20	-0.005	-0.012	12.543	0.896
21	0.028	0.031	13.549	0.888
22	0.027	0.027	14.488	0.883

Figure 2: Diagram of autocorrelations and partial autocorrelations - HUF

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.991	0.991	1261.9	0.000
		2	0.982	0.003	2502.4	0.000
		3	0.974	0.034	3723.1	0.000
		4	0.966	0.033	4926.0	0.000
		5	0.959	-0.002	6111.2	0.000
		6	0.952	0.016	7279.4	0.000
		7	0.945	0.034	8432.4	0.000
		8	0.938	-0.024	9569.3	0.000
		9	0.931	-0.028	10689.	0.000
		10	0.923	0.007	11792.	0.000
		11	0.916	0.018	12880.	0.000
		12	0.909	-0.012	13951.	0.000
		13	0.902	-0.039	15006.	0.000
		14	0.894	0.010	16044.	0.000
		15	0.887	-0.002	17066.	0.000
		16	0.880	0.048	18074.	0.000
		17	0.875	0.043	19070.	0.000
		18	0.869	-0.033	20052.	0.000
		19	0.863	0.009	21022.	0.000
		20	0.857	0.012	21979.	0.000
		21	0.851	-0.008	22924.	0.000
		22	0.845	0.006	23856.	0.000

Figure 3: Autocorrelations and partial autocorrelations for the residuals of the ARIMA(1,0,0) model

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.011	0.011	0.1510	
		2	-0.043	-0.043	2.5397	0.111
		3	-0.044	-0.043	5.0662	0.079
		4	-0.002	-0.003	5.0734	0.167
		5	-0.027	-0.031	5.9970	0.199
		6	-0.045	-0.047	8.6148	0.125
		7	0.041	0.039	10.784	0.095
		8	0.040	0.033	12.873	0.075
		9	-0.009	-0.011	12.983	0.112
		10	-0.029	-0.023	14.037	0.121
		11	0.007	0.008	14.097	0.169
		12	0.043	0.040	16.466	0.125
		13	-0.018	-0.015	16.863	0.155
		14	0.005	0.011	16.899	0.204
		15	-0.064	-0.067	22.145	0.076
		16	-0.065	-0.067	27.576	0.024
		17	0.035	0.038	29.180	0.023
		18	0.001	-0.007	29.180	0.033
		19	0.000	-0.009	29.180	0.046
		20	0.004	0.002	29.203	0.063
		21	0.008	-0.000	29.286	0.082
		22	-0.023	-0.021	29.957	0.093

Figure 4: Autocorrelations and partial autocorrelations – KRW

Autocorrelation	Partial Correlation		AC		Q-Stat	Prob
		1	.989	0.989	1257.0	0.000
		2	0.979	0.020	2488.6	0.000
		3	0.968	-0.029	3693.8	0.000
		4	0.957	-0.007	4872.8	0.000
		5	0.946	0.015	6026.9	0.000
		6	0.936	-0.015	7155.9	0.000
		7	0.925	0.010	8260.9	0.000
		8	0.915	0.015	9343.1	0.000
		9	0.906	0.032	10405.	0.000
		10	0.897	-0.010	11445.	0.000
		11	0.888	0.022	12467.	0.000
		12	0.879	-0.021	13468.	0.000
		13	0.870	0.008	14451.	0.000
		14	0.862	0.015	15415.	0.000
		15	0.854	0.005	16362.	0.000
		16	0.845	-0.020	17291.	0.000
		17	0.837	0.017	18202.	0.000
		18	0.829	-0.019	19097.	0.000
		19	0.821	0.025	19974.	0.000
		20	0.813	-0.001	20837.	0.000
		21	0.807	0.061	21686.	0.000
		22	0.800	-0.011	22522.	0.000

Figure 5: Autocorrelations and partial autocorrelations for the residuals of the ARIMA(1,0,0) model

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.043	-0.043	2.4187	
		2	0.020	0.018	2.9227	0.087
		3	0.048	0.050	5.8676	0.053
		4	-0.028	-0.025	6.8979	0.075
		5	-0.011	-0.015	7.0428	0.134
		6	-0.021	-0.023	7.5956	0.180
		7	-0.034	-0.033	9.0613	0.170
		8	-0.068	-0.070	15.090	0.035
		9	0.008	0.005	15.173	0.056
		10	-0.046	-0.042	17.958	0.036
		11	0.048	0.049	20.982	0.021
		12	0.003	0.003	20.991	0.033
		13	-0.054	-0.055	24.729	0.016
		14	0.023	0.007	25.407	0.020
		15	-0.000	-0.000	25.407	0.031
		16	0.003	0.002	25.420	0.045
		17	0.026	0.022	26.273	0.050
		18	0.007	0.006	26.334	0.069
		19	-0.027	-0.023	27.316	0.073
		20	-0.048	-0.059	30.346	0.048
		21	0.006	0.000	30.388	0.064
		22	-0.030	-0.024	31.554	0.065

References

Appiah, S.T., & Adetunde, I. A. (2011). Forecasting exchange rate between the Ghana cedi and the US dollar using time series analysis. *Current Research Journal of Economic Theory*, 3(2), 76-83.

Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity. *Journal of Econometrics*, 31(3), 307–327.

Brailsford, T. J., & Faff, R. W. (1996). An evaluation of volatility forecasting techniques. *Journal of Banking & Finance*, 20(3), 419-438.

DAILYFX (2014), DailyFX For Beginners: Trading Tips: Weekly Trading Lesson: Technical Versus Fundamental Analysis in Forex. [Online] Available: http://www.dailyfx.com/forex/education/trading_tips/daily_trading_lesson/2012/01/20/Technical_Versus_Fundamental_Analysis_in_Forex.html (October, 2014).

Dueker, M., & Neely, C. J. (2007). Can Markov switching models predict excess foreign exchange returns?. *Journal of Banking & Finance,* 31(2), 279-296.

Engle, R. F., & Patton, A. J. (2001). What good is a volatility model. Quantitative Finance, 1(2), 237-245.

Fama, E. F., & Blume, M. E. (1966). Filter rules and stock market trading profits. Journal of Business, 39(1), 226–241.

Gencay, R. (1999). Linear, non-linear and essential foreign exchange rate prediction with simple technical trading rules. *Journal of International Economics*, 47(1), 91–107.

Kuan, C-M., & Liu, T. (1995). Forecasting exchange rates using feedforward and recurrent neural networks. Journal of Applied Econometrics ,10(4), 347–364.

LeBaron, B. (1999). Technical trading rule profitability and foreign exchange intervention. *Journal of International Economics*, 49(1), 125-143.

Malkiel, B. G. (1996). A random walk down Wall Street. New York: W.W. Norton.

Marshall, B. R., Young, M. R., & Cahan, R. (2008). Are candlestick technical trading strategies profitable in the Japanese equity market?. *Review of Quantitative Finance and Accounting*, 31(2), 191-207.

Martin, A. D. (2001). Technical trading rules in the spot foreign exchange markets of developing countries. *Journal of Multinational Financial Management*, 11(1), 59–68.

Menkhoff, L., & Taylor, M. P. (2007). The Obstinate Passion of Foreign Exchange Professionals: Technical Analysis. Journal of Economic Literature, 45(4), 936-972.

Murphy, J. J. (1986). Technical Analysis of the Futures Markets. New York: Prentice Hall.

Neely, C. J. (1997). Technical analysis in the foreign exchange market: a layman's guide'. Federal Reserve Bank of St. Louis, 79, 23-38.

Neely, C. J., & Weller, P. A. (2011). Technical analysis of the foreign exchange market. Working Paper 2011-001B, Research Division, Federal Reserve Bank of St. Louis.

Neely, C., Weller, P., & Dittmar, R. (1997). Is technical analysis in the foreign exchange market profitable? A genetic programming approach. *Journal of Financial and Quantitative Analysis*, 32(4), 405-426.

Park, C-H., & Irwin, S. H. (2007). What do we know about the profitability of technical analysis?. *Journal of Economic Surveys*, 21(4), 786–826.

Rodriguez, F., Rivero, S., & Felix, A. (2003). Technical analysis in foreign exchange markets: Evidence from the EMS. Applied Financial Economics, 13(2), 113-122.

Rosillo, R., de la Fuente, D., & Brugos, J. A. L. (2013). Technical analysis and the Spanish stock exchange: Testing the RSI, MACD, momentum and stochastic rules using Spanish market companies. *Applied Economics*, 45(12), 1541-1550.

Sager, M. J., & Taylor, M. P. (2006). Under the microscope: the structure of the foreign exchange market. *International Journal of Finance & Economics*, 11(1), 81-95.

Taylor, S. J. (1994). Trading futures using a channel rule: A study of the predictive power of technical analysis with currency examples. Journal of Futures Markets, 14(2), 215-235.

Taylor, M. P. (1995). The Economics of Exchange Rates. *Journal of Economic Literature*, 33(1), 13-47.

Taylor, M. P., & Allen, H. (1992). The use of technical analysis in the foreign exchange market. *Journal of international Money and Finance*, 11(3), 304-314.

Taylor, A. M., & Taylor, M. P. (2004). The Purchasing Power Parity Debate. *Journal of Economic Perspectives*, 18(4), 135-158.

Wang, J. H., & Leu, J. Y. (1996). Stock market trend prediction using ARIMA-based neural networks. IEEE International Conference, 4, 2160 – 2165.

Yao, J., & Tan, C-L. (2000). A case study on using neural networks to perform technical forecasting of Forex. *Neurocomputing*, 34(1-4), 79-98.

Table1: Descriptive Statistics of the three Exchange Rates Descriptive Measures

Descriptive Measures	USD	DLUSD	HUF	KRW
Mean	1.346	-0.000064	287.281	1500.767
Median	1.343	0.0002	286.975	1485.630
Max	1.512	0.018	320.780	1784.750
Min	1.194	-0.027	261.920	1336.710
Standard Deviation	0.063	0.006	14.536	86.267
Skewness	0.300	-0.280	0.107	1.221
Kurtosis	2.839	3.935	1.837	4.775
Jurgue-Bera	20.621	63.501	74.688	486.679
p-value	0.000	0.000	0.000	0.000
N-observations	1282	1281	1282	1282

Table 2: Estimated ARIMA Model – DLUSD

	Constant Term	AR(1)	AR(2)	MA(1)	MA(1)
ARIMA(0,1,0)	-0.00006 (-0.39)	-	-	-	-
ARIMA(0,1,1)	-0.00006 (-0.40)	-	-	-0.026 (-0.93)	-
ARIMA(0,1,2)	-0.00006 (-0.39)	-	-	-0.027 (-0.98)	0.027 (0.96)
ARIMA(1,1,0)	-0.00006 (-0.37)	-0.027 (-0.98)	-	-	-
ARIMA(1,1,1)	-0.00006 (-0.38)	-0.537 (-1.52)	-	0.515 (1.43)	-
ARIMA(1,1,2)	-0.00006 (-0.38)	-0.57 (-1.47)	-	0.546 (1.41)	-0.006 (-0.20)
ARIMA(2,1,0)	-0.00006 (-0.40)	-0.025 (-0.91)	0.024 (0.88)	-	-
ARIMA(2,1,1)	-0.00006 (-0.40)	-0.284 (-0.53)	0.011 (0.34)	0.259 (0.48)	-
ARIMA(2,1,2)	-0.00009 (-0.54)	0.439 (1.16)	0.415 (1.20)	-0.463 (-1.20)	-0.384 (-1.09)

Table 3: Estimated ARIMA Model – HUF

	Constant Term	p-value	AR(1)	p-value	QLS	DW
ARIMA(1,0,0)	292.481 (34.83)	0.0000	0.994 (295.21	0.0000	60.007	1.976

Table 4: Forecasts Assessment

ARIMA(1,0,0	HUF
RMSE	1.748
MAE	1.301
MAPE	0.453
Theil Statistic	0.003
Components:	
Bias	0.000
Variance	0.004
Covariance	0.996

Table 5: Estimated ARIMA Model – KRW

	Constant Term	p-value	AR(1)	p-value	QLS	DW
ARIMA(1,0,0)	1459.144 (42.44)	0.0000	0.992 (336.5)	0.0000	31.554	2.087

Table 6: Forecasts Assessment

ARIMA(1,0,0	**KRW**
RMSE	9.080
MAE	6.736
MAPE	0.446
Theil Statistic	0.003
Components:	
d. Bias	0.000
e. Variance	0.003
f. Covariance	0.997