DIRECT VERSUS INDIRECT FORECASTING OF THE DEFINED REAL EXCHANGE RATE OF SOUTH AFRICA

Marinda Pretorius and Ilsé Botha
University of Johannesburg, South Africa

ABSTRACT

The real exchange rate of South Africa can be forecasted using the direct or the indirect methods of forecasting. This article compares the forecasting results of direct and indirect forecasting of the real exchange rate by using two univariate models and a multivariate model. The direct models outperformed the indirect models in-sample and the indirect models generally outperformed the direct models out-of-sample. Given the closeness of the forecasting results, the modeller should decide whether it is worth the effort to forecast the real exchange rate indirectly if similar results can be obtained from a (less time-consuming) direct method.

1. INTRODUCTION

The South African economy, like other developing economies, is characterised by a volatile exchange rate, which makes decision-making based on the exchange rate very difficult. This article focuses on the forecasting accuracy of the real exchange rate (RER) of South Africa by using several forecasting methods. The RER can be defined as an exchange rate which has been adjusted for the difference in inflation between two specific countries. The RER is also classified as a defined variable because the value of the RER at any point in time is calculated by taking into consideration three variables: the nominal exchange rate of a country, the domestic price level in that country and the foreign price level of a trading country partner.

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Correspondence to *: Marinda Pretorius, Department of Economics and Econometrics, University of Johannesburg, Auckland Park, P O Box 524, 2006, Tel: +27 11 559 2060, Email: marindap@uj.ac.za*

The RER is highly significant, given the circumstances of increasing globalisation currently experienced in world markets. The most important function of the RER is probably the role that it plays as an indicator of the competitiveness of the foreign trade of a country through the purchasing power parity theory. More specifically, the RER has a significant influence on the monetary policy of a country. Fluctuations in the RER will lead to changes in short-term capital flows, which will have an impact on the net foreign assets of a country's central bank, which in turn will lead to adjustments in "the volume of currency in circulation on the liability side of the balance sheet" (Kipici and Kesriyeli, 1997: 1). Furthermore, according to Moosa and Kim (2001), the RER is the main role-player in various exchange rate determination models and other open economy macroeconomic models, such as Dornbusch's (1976) sticky price monetary model.

The RER is thus an important and very useful variable to forecast in economic modelling. The question now arises what the best method would be to use for forecasting the RER. A modeller can choose between two main methods when forecasting the RER: the direct method or the indirect method. Direct forecasting is based on modelling the RER from a model estimated directly from a time series, using the RER. Indirect forecasting is based on modelling the time series on the individual defining variables of the RER by applying the same model for the three components of the RER.

A variety of studies have empirically tested and compared the forecasts of direct and indirect models of defined variables, like the real gross domestic product per capita (see Stollar, Grubaugh and Thompson, 1987) and the money multiplier (see Moosa and Kim, 2004). The direct and indirect forecast comparison has not been applied extensively to the RER. This article will compare the direct and indirect forecasts of the RER that were done by using two univariate (incorporating a technical analysis approach) models, as well as a multivariate (fundamental and technical analysis approach) model to decide whether it is worth the effort to forecast the RER by way of individual components. The autoregressive integrated moving average (ARIMA) model and the generalised autoregressive conditional heteroskedasticity (GARCH) model were used to represent the univariate approach, while a vector autoregressive and moving average (VARMA) model was incorporated for the multivariate approach. More than one model was used to forecast the RER in order to judge the robustness of the results obtained with respect to the specific forecasting method that was employed.

2. DIRECT VERSUS INDIRECT FORECASTING OF THE REAL EXCHANGE RATE

The choice between direct and indirect forecasting of a variable is commonly known in economics as the problem of aggregation. The direct method is used to obtain forecasts (directly) from the aggregated variable, while the indirect method adds up the forecasts obtained from the individual disaggregated components of the variable (Moosa and Kim, 2001).

Extensive research has been conducted, over a wide-ranging period, on the forecasting ability of aggregated and disaggregated models (Grunfeld and Griliches, 1960, Lütkepohl, 1984, 1987, Van Garderen, Lee and Pesaran, 2000, Hubrich, 2005).

According to Hendry and Hubrich (2006), the theoretical literature demonstrates that forecasting the disaggregated components of a defined variable outperforms the direct aggregate forecast of a variable if the data-generating process is known. If the data-generating process is not known, which is usually the case in practice, the forecasting results are not as clear. The underlying data-generating process of a specific variable will empirically determine whether the disaggregated forecasts will outperform the aggregated variable forecast.

3. THE FUNDAMENTAL VERSUS THE TECHNICAL APPROACH TO FORECASTING THE RER

Fundamentals have traditionally been used to explain the behaviour of exchange rates. A fundamental model is based on various essential variables that explain the behaviour of the exchange rate. The forecasting ability of fundamental models, especially in the short run, was placed in doubt after the publication of a seminal article by Meese and Rogoff (1983). According to Longmore and Robinson (2004), this suggests that macroeconomic fundamentals do not necessarily explain the short-term behaviour of exchange rates. Not only is there a lot of controversy involved in fundamental exchange rate models, but the modeller also needs to consider problems like specification errors and other more complicated simultaneous equation models when trying to fundamentally forecast the exchange rate.

The other mainstream approach that is followed when forecasting the exchange rate is known as the technical approach. This approach is seen as technical because it does not depend on the fundamental economic determinants of the exchange rate, but only on extrapolations of past movements of the exchange rate. Technical approach analysis is therefore considered art rather than science.

This article concentrates mainly on the technical approach models in order to forecast the RER. A very powerful and popular technical approach model, the ARIMA model, was applied first. The ARIMA modelling approach, also known as the Box-Jenkins methodology, allows a variable to be explained by past values of that specific variable as well as stochastic error terms, making it univariate in nature (Box and Jenkins, 1976).
Since exchange rates, including the RER, are generally characterised by volatility clustering, it was decided that the ARCH or GARCH models would be used for the second comparison of the direct and indirect forecasting methods of the RER. The ARCH model introduced by Engle (1982) is unique in the sense that it states the variance of the error term in a regression model as conditional on squared past errors. Engle's ARCH(q) model can be specified as:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 \tag{1}$$

Bollerslev (1986) introduced the GARCH model, which generalised the ARCH model. In the GARCH(q,p) model the conditional variance is a function of past squared error terms as well as its own past values:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{p} \sigma_{t-i}^2 \tag{2}$$

Empirical results show that incorporating ARCH and GARCH effects in economic models increases their ability to explain the higher moments of volatile financial time series (McKenzie and Brooks, 1999). ARCH and GARCH models are also examples of univariate models, given that only the variable itself is used in the forecasting of the RER.

After the successful application of univariate ARIMA models in practice, practitioners extended the model to the multivariate VARMA case (Lütkepohl, 2004). According to Lütkepohl (2004), a VARMA(p,q) model where the data-generating process is stationary can be represented as follows:

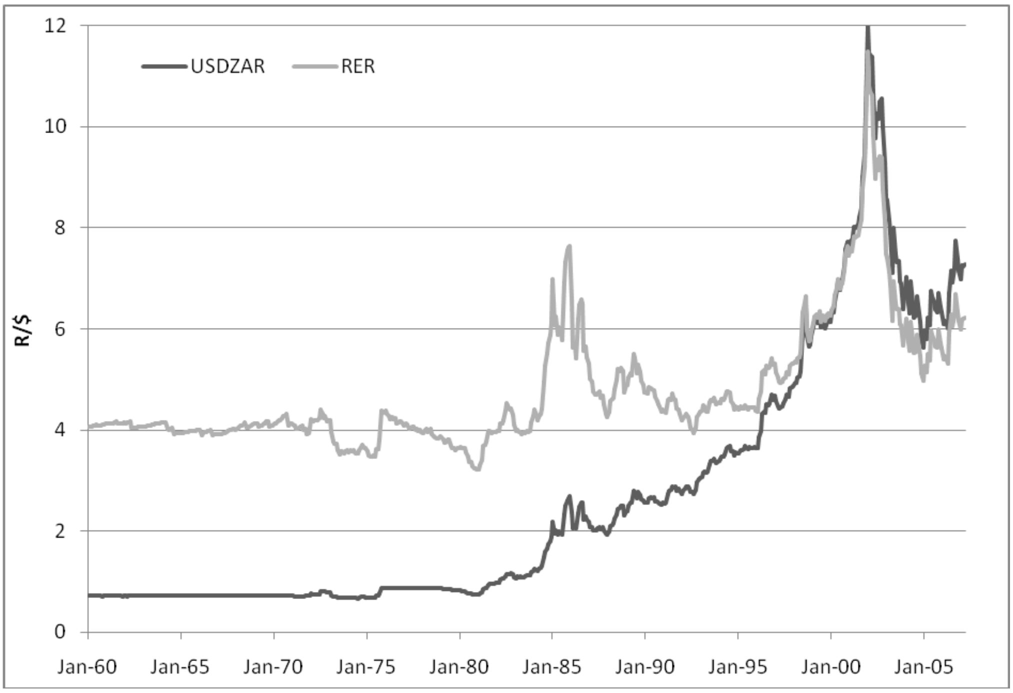
$$Y_t = \alpha_0 + \alpha_1 Y_{t-1} + ... + \alpha_p Y_{t-p} + \beta_0 u_t + \beta_1 u_{t-1} + ... + \beta_q u_{t-q} \tag{3}$$

VARMA models take past values of specific variables (the technical analysis part) as well as influences of other related variables (fundamentals) into account, giving them their multivariate status. The robustness of the direct and indirect forecasting techniques will thus be thoroughly tested by incorporating univariate as well as multivariate forecasting approaches.

4. DATA SOURCES AND PERIOD OF ESTIMATION

The RER was calculated by multiplying the nominal R/$ exchange rate (USDZAR) by the ratio of United States of America prices (USCPI) to the prices of the South African Consumer Price Index (SACPI). The nominal exchange rate was measured as the price of one US dollar in terms of the rand. The price levels of the two respective countries were represented by the consumer price index (CPI) of each. Other alternative measures that are frequently used to represent price levels, include the wholesale price index (WPI), the gross domestic product (GDP) deflator and the producer price index (PPI). Each measure has its own advantages and disadvantages (see for example Kipici and Kesriyeli, 1997). It was decided that the CPI would be used in this study mainly because it is readily available and adequately represents South Africa's competitiveness level.

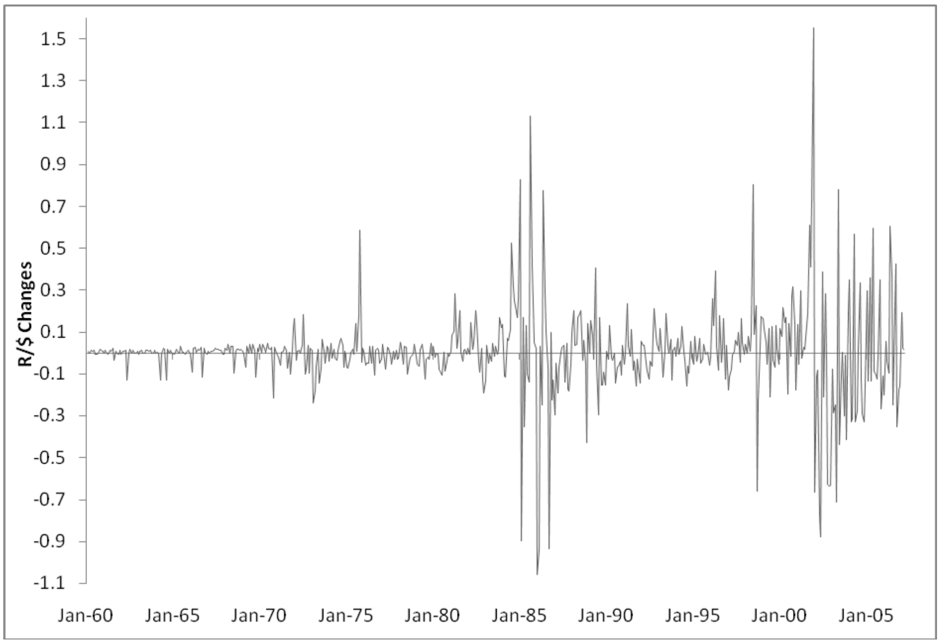
The monthly data was obtained from the I-net Bridge data provider over the period January 1960 and April 2007, a total of 568 trading months. The period between January 1960 and December 2006 was used as part of the in-sample period, while the period between January 2007 and April 2007 was considered out-of-sample for all models. The individual consumer price indices were recalculated so that they both had the same base year of 2000. Figure 1 shows the comparison of the nominal and the real R/$ exchange rate.



Source: I-net Bridge Data

Figure 1: The Nominal (USDZAR) vs. Real R/$ Exchange Rate (RER)

The period (1960 to the beginning of 1971) when South Africa had a fixed exchange rate can clearly be seen in Figure 1. Consequently the RER in this period was also fairly stable. Furthermore, it is noted that the RER is generally as volatile as the nominal exchange rate. The general trend of the RER follows that of the nominal exchange rate. On investigating the first-order differences of the RER (Figure 2) one sees that the series became more volatile in the 1980s and even more so after 2000.



Source: Own calculations, I-net Bridge Data
Figure 2: Volatility of the RER

The individual series were all tested for unit roots with the use of the Augmented Dickey-Fuller (ADF) test (Table 1). The USDZAR, SACPI and USCPI were all integrated to the order of one, whereas the RER was stationary on the level. The results were incorporated into the different forecasting models that were used.

Table 1: Results of the ADF test

Variable	Specification	Level	1st Difference
RER	Trend and Intercept	-3.83*	
USDZAR	None	0.50	-5.91*
SACPI	Trend and Intercept	-0.37	-6.48*
USCPI	Trend and Intercept	-3.01	-3.33**

*Rejection of H_0: Series contain a unit root, at the 95% confidence interval.
Critical values: None: -1.94; Trend and Intercept: -3.42.
**Rejection of H_0: Series contain a unit root, at the 90% confidence interval
Critical values: Trend and Intercept: -3.13.

5. EMPIRICAL RESULTS

5.1 Direct Forecasting ARIMA Models Of The RER

The correlograms (see Figure 1 in the Appendix) of the autocorrelation function (ACF) and the partial autocorrelation function (PACF) were investigated on the level (because the RER is stationary on the level) in order to identify the appropriate autoregressive moving average (ARMA) model for the RER. After an iterative estimation process a suitable ARMA model (see Table 1 in the Appendix) was identified to describe the behaviour of the RER.

The residuals confirmed that the specific model is satisfactory in explaining the behaviour of the RER. The correlogram of the residuals did not contain any significant lags indicating that the residuals of the specified ARMA model is white noise and can be used for forecasting.

5.2 Indirect Forecasting ARIMA Models For The Components Of The RER

For the indirect forecasting of the components of the RER the correlograms (see Figures 2, 3 and 4 in the appendix) of the autocorrelation function (ACF) and the partial autocorrelation function (PACF) were again investigated, but this time on the first difference (because the USDZAR, SACPI and USCPI are stationary on the first difference) in order to identify the appropriate ARIMA model for the RER. The appropriate models were chosen (see Tables 2, 3 and 4 in the appendix) on the basis of the residuals exhibiting white noise. The individual forecasts of the components of the RER were used to compile the indirect forecast of the RER.

5.3 Comparison of the Forecasting Results from the ARIMA Models

The results of the in-sample and out-of-sample forecasting will be evaluated using the mean absolute deviation to the mean ratio (MAD/Mean). Kolassa and Schütz (2007) have shown that the MAD/Mean ratio can be seen as a weighted alternative to the mean of absolute percentage errors (MAPE). They identify one of the ratio's main advantages as the "absence of bias in method selection" (Kolassa and Schütz, 2007: 40), which is very important in this article, since different forecasting models were compared to each other. The smaller the MAD/Mean ratio the better the forecasting results of the specific model. The MAD/Mean ratio for the ARIMA model is represented in Table 2.

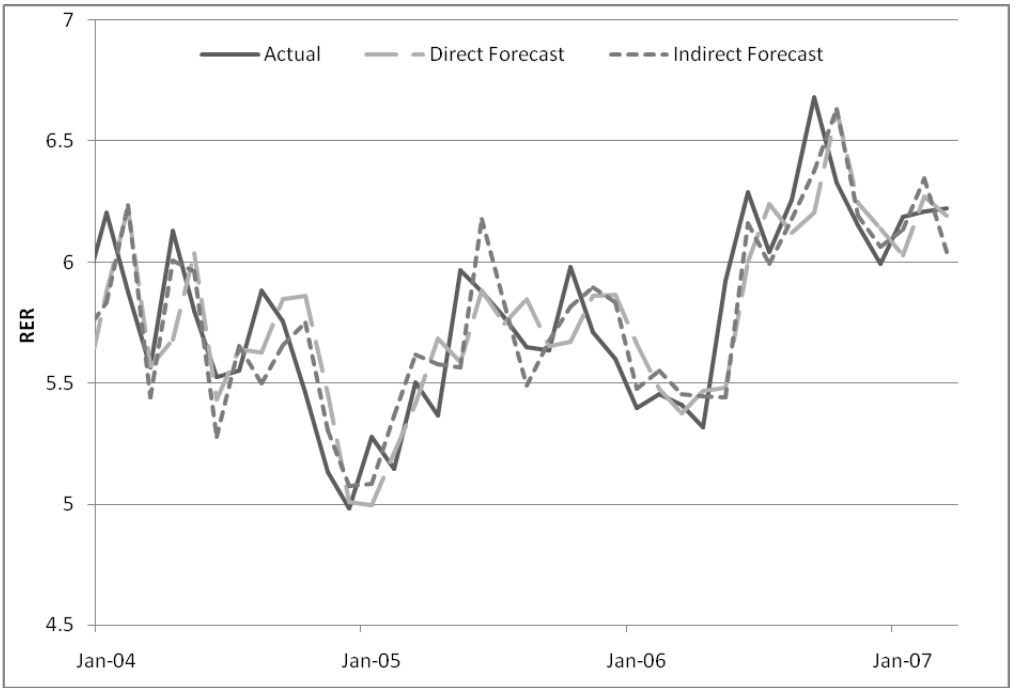
Table 2: Direct vs. Indirect Forecasting Ability of the ARIMA model

	In-sample		**Out-of-sample**	
ARIMA	**Direct**	**Indirect**	**Direct**	**Indirect**
MAD	0.11	0.12	0.17	0.27
Mean of actual	4.79		6.13	
MAD/Mean ratio	2.31	2.60	2.78	4.34

Source: Own calculations

Generally, all the ARIMA models forecasted the RER satisfactorily. Although the in-sample forecasting results are very similar, the direct method outperformed the indirect method. Out-of-sample there was a relative difference between the direct and indirect forecasts and the direct method again outperformed the indirect method.

Figure 3 presents the comparison of the actual value of the RER with the direct and indirect forecasts of the RER (from January 2004). The indirect forecast overestimated the movements in the RER various times, whereas the direct forecast sometimes forecasted the direction of movement of the RER completely incorrectly.



Source: Own calculations

Figure 3: Comparison of the results of the ARIMA models

5.4 Direct Forecasting ARCH/GARCH Models Of The RER

The proposed ARCH and/or GARCH model that was considered for forecasting the RER was based on the ARIMA model of the previous section. After the ARIMA model was constructed it was tested for ARCH effects. Engle (1982) proposed the Lagrange Multiplier (LM) test as a formal method to test for the presence of ARCH effects. Under the null hypothesis of no volatility the p-value of the chi-square statistic can be used to decide whether there is any volatility present in a specific series.

If the p-value of the RER is equal to zero, ARCH effects exist in the RER series. From here an iterative method is used in order to find the optimal ARCH or GARCH model. Various ARCH and GARCH possibilities were identified as possible forecasting models for the RER. The potential models all reached convergence and had relatively significant ARCH and/or GARCH coefficients. In the end the model with the lowest Schwarz information criterion (SIC) was chosen as the optimal model.

The diagnostic adequacy of the chosen GARCH model was confirmed with the correlogram of the squared standardised residuals, which exhibited no significant lags. This indicates that the GARCH model had successfully captured all of the ARCH effects of the variable.

5.5 Indirect Forecasting ARCH/GARCH Models for the Components of the RER

The ARCH and/or GARCH models that will be considered for the different components of the RER are also based on the ARIMA models of the previous section. The same procedure to specify the best ARCH or GARCH model for the RER was incorporated to determine the optimal ARCH or GARCH models for the indirect components of the RER. The individually chosen GARCH models all effectively captured the ARCH effects of the components.

5.6 Comparison of the Forecasting Results from the GARCH Models

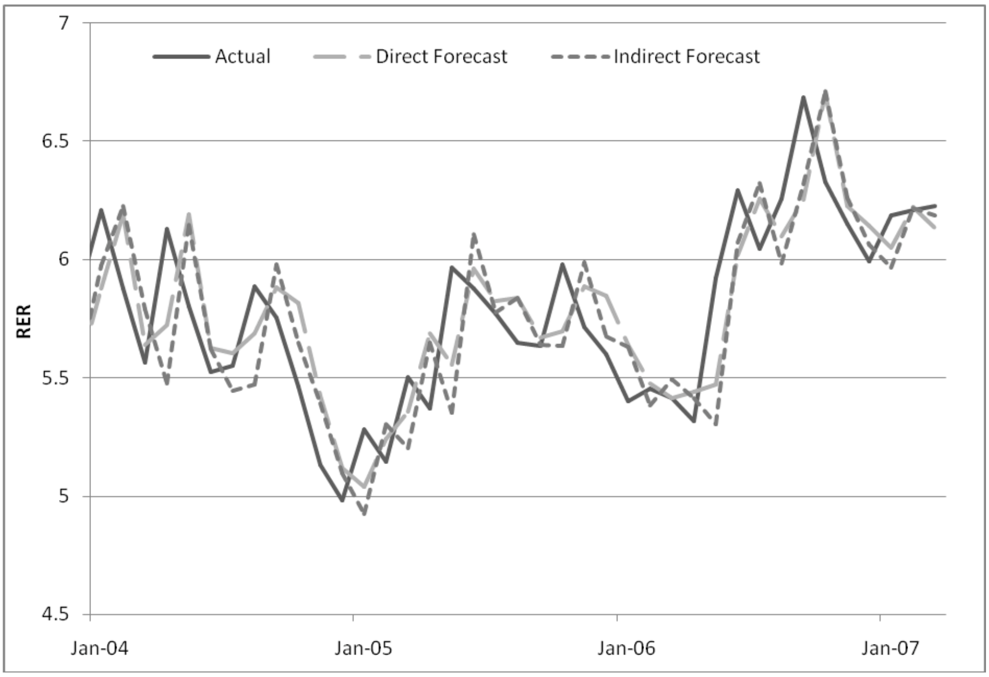
Table 3 presents the direct and indirect forecasting ability statistics of the GARCH models. The results obtained from the various models are satisfactory and in this case the indirect out-of-sample forecast did very well compared to that of the ARIMA model. The direct method again outperformed the indirect model in-sample. This time, however, the indirect out-of-sample forecast outperformed the direct forecast. A reason for this could be that the indirect components capture the volatility present in the RER better than the direct forecast.

Table 3: Direct vs. Indirect Forecasting Ability of GARCH models

	In-sample		Out-of-sample	
GARCH	**Direct**	**Indirect**	**Direct**	**Indirect**
MAD	0.11	0.12	0.14	0.13
Mean of actual	4.79		6.13	
MAD/Mean ration	2.33	2.47	2.31	2.14

Source: Own calculations

Figure 4 presents the comparison of the actual value of the RER with the direct and indirect forecasts of the RER (from January 2004). Both the direct and the indirect forecasts followed the actual data with one lag. The indirect forecasts overestimated the value of the RER in some places.



Source: Own calculations
Figure 4: Comparison of the results of the GARCH Models

5.7 Direct and Indirect Forecasting VARMA Models of the RER

The VARMA model process starts with the specification of a vector autoregressive (VAR) model. The RER, USDZAR, SACPI and USCPI were used jointly in the specification of the VAR model. The RER was used on the level and the other variables were used in the first difference form. The optimal lag structure for the model was determined by making use of the lowest Shwarz Information Criterion (SIC) value.

Individual residuals were obtained from the VAR model for each of the variables and their lags were added as exogenous variables in the VAR model to accommodate the moving average element of the VARMA model.

The four variables were thus explained by the first lag of each of the four variables as well as by other significant moving average terms. The forecast of the direct forecasting component was directly obtained from the VARMA model. The indirect forecast of the RER was calculated by using the forecasts of the USDZAR, SACPI and USCPI ($RER = USDZAR\left(\frac{USCPI}{SACPI}\right)$) variables of the VARMA model.

5.8 Comparison of the Forecasting Results from the VARMA Models

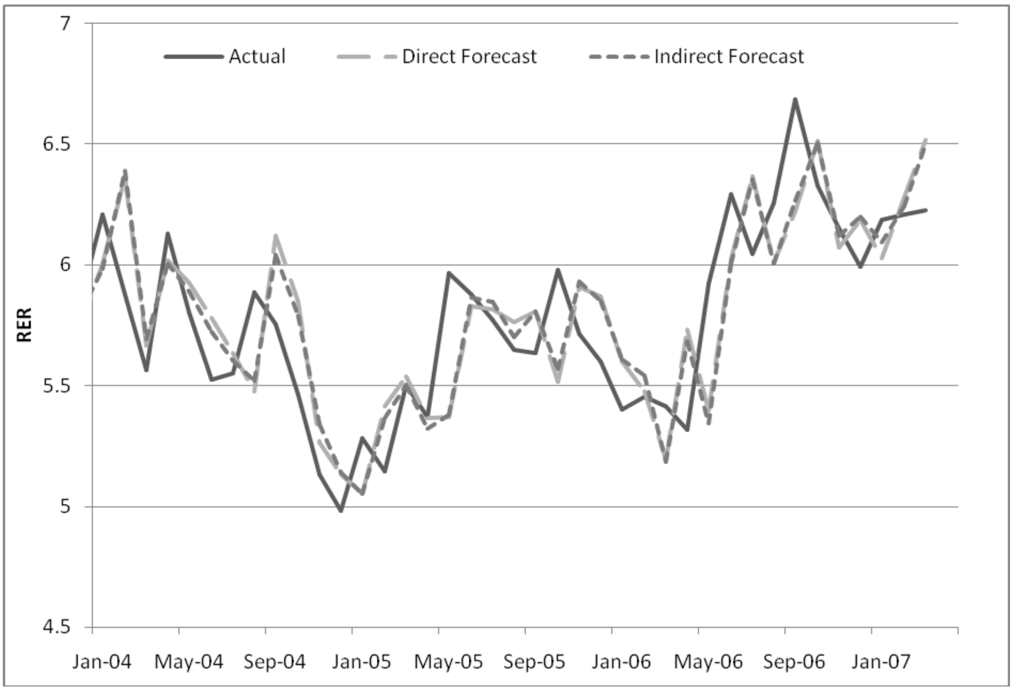
The forecasting results of the VARMA model in Table 4 correspond with the forecasting results of the GARCH models. In-sample the direct method outperformed the indirect method, whereas the indirect method outperformed the direct method out-of-sample.

Table 4: Direct vs. Indirect Forecasting Ability of VARMA models

	In-sample		**Out-of-sample**	
VARMA	**Direct**	**Indirect**	**Direct**	**Indirect**
MAD	0.11	0.14	0.23	0.21
Mean of actual	4.79		6.13	
MAD/Mean ration	2.27	2.97	3.68	3.46

Source: Own calculations

Figure 5 presents the comparison of the direct and indirect forecasts with the actual RER. Here the direct and indirect forecasts are very close to each other, especially when compared to the other two models. As with the GARCH model, it seems that the forecasts are following the actual data with a lag.



Source: Own calculations

Figure 5: Comparison of the results of the VARMA Models

6. GENERAL COMPARISON OF MODELS

Table 5 summarises the forecasting results of the different models used to forecast both the direct and the indirect RER. In-sample the direct VARMA model outperformed all the other direct and indirect models. Out-of-sample the indirect GARCH model outperformed the other direct and indirect models. Overall the direct models outperformed the indirect models in-sample. Out-of-sample, two direct models (GARCH and ARIMA) and one indirect model (GARCH) outperformed the other models. The forecasts of the various models are summarised in Table 5 of the appendix.

Table 5: MAD/Mean Ratio Comparison of Models

	In-sample		Out-of-sample	
MAD/Mean ratio	**Direct**	**Indirect**	**Direct**	**Indirect**
ARIMA	2.31	2.60	2.78	4.34
GARCH	2.33	2.47	2.31	2.14
VARMA	2.27	2.97	3.68	3.46

Source: Own calculations

7. CONCLUSION

In this article several models were presented to forecast the real exchange rate of South Africa by concentrating on the direct and indirect methods, given that the real exchange rate is a defined variable. Direct forecasting methods involve obtaining forecasts of the real exchange rate directly from a specific model. Indirect forecasting implies that the different components of the real exchange rate be forecasted individually, whereafter the components are aggregated to obtain the indirect forecast of the real exchange rate.

For the purpose of forecasting, it was decided that technical analysis methods would mainly be used. Two univariate technical analysis methods, an autoregressive integrated moving average (ARIMA) model and a generalised autoregressive conditional heteroskedasticity (GARCH) model, were used to forecast the direct and indirect real exchange rate. Furthermore, in order to ensure the robustness of the forecasting results a model containing fundamentals as well as a technical analysis element was incorporated. The last method that was used to forecast the real exchange rate was a vector autoregressive and moving average (VARMA) model.

The purpose of this article was to investigate whether better forecasting results could be obtained from direct or indirect forecasts of the real exchange rate. The results obtained turned out to be mixed. In terms of the in-sample forecasting, the direct VARMA model (marginally) outperformed all the other models. Out-of-sample, the indirect GARCH model was superior, again marginally, compared to the other models. Considering the proximity of the forecasting results of the different methods as well as the different models, the question arises whether there is really a significant enough difference among them all.

The results of this investigation could have turned out differently if other models had been considered. Other models that can be considered to forecast the RER as well as its components include non-linear models like the smooth transition autoregressive (STAR) method, panel and dynamic factor models and models that take more fundamentals into account. Furthermore, the indirect forecast of the RER might also be improved if the best forecasting method for that specific component is used rather than if the same forecasting method is used for each of the individual components.

Although the exchange rate is classified as very volatile it seems that there is a variety of equally acceptable methods that can be used to obtain a comparatively accurate forecast. It seems that the choice lies with the modeller to decide whether it is worth the effort to forecast the real exchange rate indirectly by way of components if similar results can be obtained from a (less time-consuming) direct method. One fact remains: "Prediction is very difficult, especially if it's about the future" (Nils Bohr).

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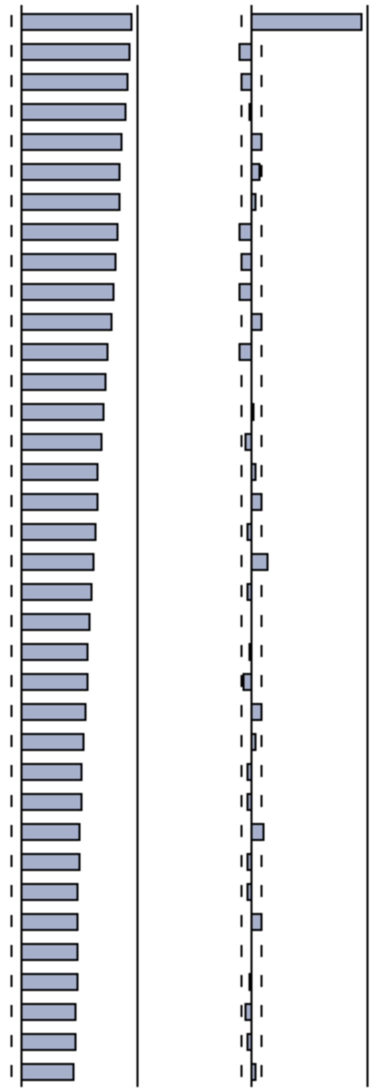
APPENDIX



Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.985	0.985	553.43	0.000
		2	0.968	-0.111	1088.2	0.000
		3	0.947	-0.093	1601.5	0.000
		4	0.926	-0.013	2093.3	0.000
		5	0.908	0.093	2566.8	0.000
		6	0.893	0.079	3025.2	0.000
		7	0.880	0.027	3470.9	0.000
		8	0.865	-0.099	3902.4	0.000
		9	0.847	-0.098	4317.0	0.000
		10	0.825	-0.109	4711.5	0.000
		11	0.805	0.096	5087.3	0.000
		12	0.781	-0.106	5442.2	0.000
		13	0.759	0.003	5777.4	0.000
		14	0.738	0.011	6095.0	0.000
		15	0.716	-0.052	6395.0	0.000
		16	0.696	0.025	6678.9	0.000
		17	0.679	0.098	6948.9	0.000
		18	0.661	-0.035	7205.4	0.000
		19	0.646	0.131	7451.3	0.000
		20	0.632	-0.030	7687.2	0.000
		21	0.618	0.003	7913.1	0.000
		22	0.604	-0.014	8129.3	0.000
		23	0.588	-0.070	8334.5	0.000
		24	0.574	0.093	8530.1	0.000
		25	0.561	0.034	8717.4	0.000
		26	0.549	-0.034	8897.0	0.000
		27	0.537	-0.031	9069.3	0.000
		28	0.530	0.102	9237.3	0.000
		29	0.522	-0.025	9400.4	0.000
		30	0.513	-0.035	9558.4	0.000
		31	0.506	0.089	9712.6	0.000
		32	0.499	0.000	9862.8	0.000
		33	0.493	-0.012	10010.	0.000
		34	0.485	-0.051	10152.	0.000
		35	0.476	-0.035	10290.	0.000
		36	0.469	0.040	10423.	0.000

Figure 1: Correlogram of RER on the level

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.091	0.091	4.6690	0.031
		2	0.088	0.081	9.0953	0.011
		3	0.078	0.065	12.613	0.006
		4	-0.016	-0.035	12.757	0.013
		5	-0.111	-0.121	19.811	0.001
		6	-0.018	-0.001	20.002	0.003
		7	0.092	0.121	24.817	0.001
		8	0.121	0.131	33.242	0.000
		9	0.138	0.105	44.291	0.000
		10	-0.075	-0.158	47.571	0.000
		11	0.164	0.144	63.227	0.000
		12	-0.128	-0.137	72.788	0.000
		13	-0.028	0.035	73.247	0.000
		14	-0.010	0.004	73.300	0.000
		15	0.016	0.001	73.444	0.000
		16	-0.112	-0.139	80.791	0.000
		17	0.073	0.073	83.931	0.000
		18	-0.078	-0.119	87.481	0.000
		19	-0.032	0.032	88.075	0.000
		20	0.043	0.020	89.168	0.000
		21	-0.074	-0.014	92.364	0.000
		22	0.121	0.085	101.05	0.000
		23	-0.120	-0.119	109.58	0.000
		24	-0.038	-0.037	110.43	0.000
		25	0.026	0.087	110.84	0.000
		26	0.018	0.005	111.04	0.000
		27	-0.214	-0.151	138.35	0.000
		28	0.065	0.014	140.88	0.000
		29	0.042	0.071	141.93	0.000
		30	-0.168	-0.180	158.84	0.000
		31	0.011	0.035	158.92	0.000
		32	-0.002	0.036	158.92	0.000
		33	0.079	0.065	162.70	0.000
		34	-0.037	-0.015	163.52	0.000
		35	-0.095	-0.136	168.93	0.000
		36	-0.091	-0.101	173.91	0.000

Figure 2: Correlogram of USDZAR on the first difference

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.500	0.500	142.11	0.000
		2	0.457	0.276	261.05	0.000
		3	0.461	0.228	382.43	0.000
		4	0.360	0.031	456.74	0.000
		5	0.372	0.099	536.02	0.000
		6	0.444	0.206	649.14	0.000
		7	0.253	-0.146	685.96	0.000
		8	0.273	-0.001	729.03	0.000
		9	0.360	0.166	803.94	0.000
		10	0.291	0.046	853.07	0.000
		11	0.238	-0.091	886.00	0.000
		12	0.365	0.172	963.18	0.000
		13	0.177	-0.113	981.37	0.000
		14	0.263	0.071	1021.6	0.000
		15	0.294	0.024	1072.0	0.000
		16	0.255	0.082	1109.9	0.000
		17	0.225	-0.028	1139.7	0.000
		18	0.369	0.173	1219.7	0.000
		19	0.264	0.030	1260.7	0.000
		20	0.304	0.034	1314.9	0.000
		21	0.365	0.074	1393.6	0.000
		22	0.282	0.004	1440.7	0.000
		23	0.311	0.077	1498.0	0.000
		24	0.514	0.268	1655.0	0.000
		25	0.306	-0.082	1710.8	0.000
		26	0.328	-0.053	1774.8	0.000
		27	0.338	-0.005	1842.9	0.000
		28	0.296	0.046	1895.2	0.000
		29	0.258	-0.092	1935.2	0.000
		30	0.372	0.045	2018.3	0.000
		31	0.209	-0.001	2044.7	0.000
		32	0.200	-0.086	2068.7	0.000
		33	0.280	0.010	2116.1	0.000
		34	0.194	-0.028	2138.8	0.000
		35	0.196	0.018	2162.0	0.000
		36	0.349	0.130	2235.8	0.000

Figure 3: Correlogram of SACPI on the first difference

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.382	0.382	83.153	0.000
		2	0.131	-0.018	92.904	0.000
		3	0.100	0.066	98.667	0.000
		4	0.128	0.081	108.00	0.000
		5	0.194	0.134	129.56	0.000
		6	0.229	0.125	159.76	0.000
		7	0.236	0.118	191.85	0.000
		8	0.151	0.011	205.05	0.000
		9	0.127	0.047	214.39	0.000
		10	0.271	0.210	257.00	0.000
		11	0.370	0.212	336.38	0.000
		12	0.322	0.118	396.45	0.000
		13	0.107	-0.102	403.16	0.000
		14	0.142	0.101	414.90	0.000
		15	0.150	0.014	428.11	0.000
		16	0.150	-0.007	441.23	0.000
		17	0.183	-0.005	460.75	0.000
		18	0.204	0.032	485.10	0.000
		19	0.183	0.035	504.80	0.000
		20	0.088	-0.072	509.40	0.000
		21	0.047	-0.135	510.71	0.000
		22	0.084	-0.102	514.90	0.000
		23	0.169	0.054	531.90	0.000
		24	0.294	0.201	583.31	0.000
		25	0.221	0.023	612.24	0.000
		26	0.142	-0.030	624.17	0.000
		27	0.002	-0.125	624.17	0.000
		28	0.037	0.007	625.01	0.000
		29	0.107	-0.013	631.86	0.000
		30	0.117	-0.042	640.14	0.000
		31	0.120	0.023	648.82	0.000
		32	0.021	-0.024	649.08	0.000
		33	-0.013	-0.035	649.19	0.000
		34	0.024	-0.108	649.54	0.000
		35	0.205	0.078	675.02	0.000
		36	0.250	0.083	712.91	0.000

Figure 4: Correlogram of USCPI on the first difference

Table 1: Final ARMA model for RER

	Coefficient	Std. Error	t-Statistic	Prob.
Constant	-23.54096	662.4199	-0.035538	0.9717
AR(1)	1.071270	0.021184	50.57048	0.0000
AR(4)	-0.187710	0.036524	-5.139358	0.0000
AR(6)	0.215461	0.031755	6.785055	0.0000
AR(12)	-0.098935	0.015982	-6.190567	0.0000
MA(6)	-0.272712	0.040725	-6.696375	0.0000
MA(10)	-0.234410	0.040167	-5.835958	0.0000
MA(18)	-0.192802	0.040346	-4.778710	0.0000
MA(27)	-0.087314	0.038567	-2.263948	0.0240
MA(30)	-0.173539	0.040662	-4.267820	0.0000

Table 2: Final ARIMA model for USDZAR

	Coefficient	Std. Error	t-Statistic	Prob.
Constant	0.000152	0.000350	0.435844	0.6631
AR(5)	-0.188911	0.044653	-4.230664	0.0000
AR(7)	0.184175	0.037617	4.896047	0.0000
AR(9)	-0.196496	0.053772	-3.654247	0.0003
AR(10)	-0.043803	0.038647	-1.133405	0.2576
AR(11)	0.189166	0.037734	5.013173	0.0000
AR(12)	-0.225640	0.044742	-5.043112	0.0000
AR(18)	-0.105113	0.046214	-2.274500	0.0233
AR(27)	-0.465798	0.069063	-6.744494	0.0000
AR(35)	-0.160126	0.048467	-3.303806	0.0010
MA(5)	0.127356	0.027454	4.638961	0.0000
MA(8)	0.278241	0.032002	8.694400	0.0000
MA(9)	0.536982	0.057003	9.420167	0.0000
MA(12)	0.174636	0.034275	5.095146	0.0000
MA(16)	-0.093797	0.023139	-4.053591	0.0001
MA(27)	0.523494	0.063659	8.223368	0.0000
MA(30)	-0.257792	0.039532	-6.521172	0.0000

Table 3: Final ARIMA model for SACPI

	Coefficient	Std. Error	t-Statistic	Prob.
Constant	1.318274	3.602951	0.365887	0.7146
AR(1)	0.280945	0.029593	9.493496	0.0000
AR(5)	0.076158	0.022798	3.340588	0.0009
AR(6)	0.320777	0.034571	9.278833	0.0000
AR(7)	-0.244668	0.030942	-7.907415	0.0000
AR(24)	0.697105	0.035270	19.76453	0.0000
AR(27)	-0.139436	0.023347	-5.972240	0.0000
MA(2)	0.192992	0.024521	7.870603	0.0000
MA(3)	0.174139	0.034993	4.976433	0.0000
MA(6)	-0.299696	0.038110	-7.863997	0.0000
MA(21)	0.118896	0.031497	3.774762	0.0002
MA(24)	-0.490744	0.043913	-11.17541	0.0000
MA(25)	-0.226569	0.032117	-7.054402	0.0000
MA(36)	0.177930	0.030326	5.868134	0.0000

Table 4: Final ARIMA model for USCPI

	Coefficient	Std. Error	t-Statistic	Prob.
Constant	0.209076	0.037505	5.574564	0.0000
AR(5)	0.192237	0.033799	5.687696	0.0000
AR(10)	-0.292470	0.032072	-9.119046	0.0000
AR(11)	0.214820	0.032806	6.548249	0.0000
AR(24)	0.588772	0.036677	16.05281	0.0000
MA(1)	0.246558	0.035112	7.022045	0.0000
MA(2)	0.090844	0.036404	2.495425	0.0129
MA(4)	-0.101475	0.025156	-4.033811	0.0001
MA(5)	-0.227404	0.044437	-5.117476	0.0000
MA(7)	0.044047	0.029548	1.490707	0.1366
MA(10)	0.458786	0.030044	15.27034	0.0000
MA(11)	0.096963	0.033936	2.857247	0.0044
MA(12)	0.171540	0.036412	4.711098	0.0000
MA(13)	-0.053868	0.025009	-2.153922	0.0317
MA(15)	0.156949	0.037070	4.233898	0.0000
MA(24)	-0.396399	0.029169	-13.58976	0.0000

Table 5: Summary of forecast RER values for 2006 and 2007

		Direct			Indirect		
Date	**Actual**	**ARIMA**	**ARCH**	**VARMA**	**ARIMA**	**ARCH**	**VARMA**
Jan 06	5.398466	5.662388	5.640445	5.383270	5.474879	5.628086	5.585551
Feb 06	5.452936	5.476393	5.475673	5.498233	5.551922	5.384856	5.749447
Mar 06	5.411936	5.373327	5.413945	5.237510	5.453212	5.493935	5.497826
Apr 06	5.316281	5.467040	5.438838	5.523768	5.446987	5.412749	5.725688
May 06	5.922973	5.482266	5.472467	5.667316	5.439668	5.302128	5.802632
June 06	6.290341	6.002496	6.017860	5.715111	6.159454	6.073628	5.842368
July 06	6.043311	6.240973	6.255795	5.779058	5.995009	6.324235	5.900666
Aug 06	6.258533	6.120708	6.099926	5.821881	6.177875	5.982761	5.927597
Sept 06	6.683193	6.202806	6.251340	5.768925	6.377872	6.319873	5.925083
Oct 06	6.329348	6.627523	6.704772	5.494789	6.632561	6.711416	5.678162
Nov 06	6.150422	6.245863	6.225325	5.250836	6.189816	6.261687	5.488716
Dec 06	5.993796	6.137774	6.142154	5.283238	6.065315	6.060908	5.531360
Jan 07	6.188236	6.026006	6.049950	5.359134	6.136292	5.967100	5.656296
Feb 07	6.210232	6.271154	6.220059	5.455819	6.347581	6.219389	5.713207
Mar 07	6.224069	6.192747	6.131432	5.758630	6.039842	6.186357	5.983220
Apr 07	5.960654	6.380052	6.283686	5.875007	6.437949	6.308880	6.093452

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