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Full Length Research PapeR

Forecasting the exchange rate in South Africa: A comparative analysis challenging the random walk model

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Literature shows that exchange rates are largely unpredictable, and that a simple random walk outperforms structural exchange rate models. In order to determine whether fundamentals explain exchange rate behaviour in South Africa, the two approaches to exchange rate forecasting - the technical and fundamental approach - will be compared. Various univariate time series models, including the random walk model, will be compared to various multivariate time series models (using the MAD/mean ratio), combining the two approaches. The determinants of the South African exchange rate are identified, and these determinants are used to specify multivariate time series models for the South African exchange rate. The multivariate models (VARMA) outperformed the univariate models (except for the Random walk model) in the short-run forecasts, one step ahead, while the multivariate models, performed better in the longer-run forecasts. To improve the accuracy of especially the multivariate models, it is recommended that multiple frequencies be used to capture the dynamic behaviour between variables in a Structural VAR framework.

Key words: Evaluation forecasts, cointegration, error correction models, ARIMA models, VAR models, VARMA models.

INTRODUCTION

Since the breakdown of the Bretton-Woods system, there has been more interest in predicting exchange rates. Exchange rate economics has seen a number of important developments over the last decade, with substantial contributions being made to both the theory and the empirical understanding of exchange rate determination. Important developments in econometrics, together with the increasing availability of high-quality data, have also stimulated a large output of empirical work on exchange rates. While this has served to improve the understanding of exchange rates, a number of challenges still need to be addressed, one of which being the question as to why monetary models of exchange rate determination cannot forecast much of the variation in exchange rates. The monetary approach to exchange rate determination emerged as the dominant exchange rate model; however, the finding of Meese and Rogoff (1983) that monetary model forecasts could not outperform a simple random walk model was devastating, marking a watershed in exchange rate economics. A large number of puzzles have not been resolved since the findings by Meese and Rogoff, and this attract the attention of academics, policy makers and practitioners (Sarno, 2003).

The aim of this paper is an attempt to add some value to this debate by using time series techniques instead of theoretical exchange rate models to forecast the exchange rate. Firstly the determinants of exchange rates in South Africa will be identified to be applied in a multivariate context. Forecasts from multivariate models and univariate models will be compared, in order to establish whether fundamentals do indeed play an important role in explaining and forecasting exchange rates in South Africa, or whether a simple random walk model will suffice.

The paper is organised as follows. Section 2 provides a brief discussion of the determinants of exchange rates. Section 3 will present a brief literature review followed by a discussion on the two approaches to forecasting exchange rates. Section 4 explains the multivariate model theoretically and in section 5 the R/$ exchange rate and its determinants will be analysed. Section 6

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concludes with a comparison between univariate and multivariate models.

Determinants of the South African exchange rate

The monetary approach uses money supply, the price level, income and the level of interest rates as determinants for the exchange rate. The model by Meese and Rogoff used M3, output, interest rates, expected inflation and the trade balance as determinants.

The findings of Aron, Elbadawi and Kahn (1997) point out that the trade policy, terms of trade (including gold), long and short term capital flows, foreign exchange reserves, government expenditure and productivity growth differentials are determinants of the R/$ exchange rate.

According to Piana (2001) changes in floating rates or pressures on fixed rates will be derived, as in the case of other financial assets, from three broad categories of determinants:

- Variables on the "real" side of the economy.
- Monetary and financial variables determined in cross-linked markets.
- Past and expected values of the same financial market with its autonomous dynamics.

Various studies on exchange rate determination were considered in this article, and a combination of the monetary model, Reese and Rogoff's model and the determinants of Aron et al., 1997 were applied. The variables used in this analysis can be classified according to the three broad categories proposed by Piana, 2001. The real side variables included in this analysis were the government expenditure to GDP ratio and the current account balance to GDP ratio. For the monetary variables; total credit extension, CPI and the prime rate were used, while the balance on the financial account was used for the financial variables.

Overview of the literature

With 20 years of hindsight, evidence that monetary models can outperform a random walk is elusive (Neely and Sarno, 2002). Exchange rate forecasting, with regard to both the univariate and multivariate time series models, has been a subject of keen interest among eco-nomists over the past two decades. Many articles have compared the forecasting abilities of alternative multiva-riate time series models of exchange rate determination (Cuaresma and Hlouskova, 2004). They used a battery of multivariate time series models which has been compared to the random walk model in terms of forecasting accuracy in predicting Central and Eastern European currencies. The results confirm the conclusions of Meese and Rogoff (1983), except in the case of Slovenian Tolar /Euro, where linear multivariate models presented signify-cantly better forecasting properties even in the short-run. In the long-run, however, multivariate time series models do in some cases present better forecasting accuracy than the simple random walk.

Frank and Preminger (2007) proposed robust regression, using the S-estimation method to reduce the impact of outliers (a characteristic of exchange rate data) on the regression estimators. They found that robust estimation outperform non-robust estimation, but could not outperform the random walk model, even when incorporating time varying parameters or time varying autoregressive models.

Engel, Mark and West (2007) found in contrast to previous studies that monetary models do help to forecast changes in exchange rates. They use panel techniques and their findings are that the model generally produces better forecasts than the random walk.

Sarno (2003) in an overview regarding non linear exchange rate models found that it is not a solution to every puzzle in exchange rate economics, but it showed scientific support for PPP and provide forecasts of exchange rate movements which are better than a model that simply assume no change - the random walk.

Two approaches to forecasting the exchange rate

One of the goals of studying the behaviour of exchange rates is to facilitate the forecasting of exchange rates. Exchange rate forecasts are essential for evaluating the foreign denominated cash flows involved in international transactions. For this reason exchange rate forecasting is of crucial importance for evaluating the benefits and risks attached to the international business environment.

The fundamental approach is based on a wide range of data which is regarded as fundamental economic variables, which in turn determine the exchange rates. These fundamental economic variables are taken from economic models. Misspecification can occur when using these models. The technical approach focuses on a smaller subset of available data, which is based on price information. This is a technical matter, as it does not rely on a fundamental analysis (a theoretic, and sometimes seen as a problem) of the underlying economic determinants of exchange rate, but on the extrapolation of past price trends and the repetition of specific price patterns. The most popular time series models are simple and rely on filters, moving averages or momentum indicators (Anon, 2007).

Econometric models are generally based on some underlying economic model. A popular alternative to econometric models, especially for short-run forecasting, is known as time series models. These models relate a dependent variable to its past, and to random errors that may be serially correlated. It is usually not based on the underlying economic behaviour (Anon, 2007). Many forecasters use a combination of the fundamental and technical approach. On theoretical grounds the dependent variable might depend on a set of independent variables, while on empirical grounds it has been established that the dependent variable shows a high degree of autocorrelation. Although this autocorrelation is not present in the economic model, an economist might combine an economic model with an ARMA model to produce a better forecast (Anon, 2007).

One key to improving forecast performance based on economic fundamentals lies in the introduction of equation dynamics. This has been accomplished in various ways, such as using dynamic forecasting equations, forward looking variables, the rational expectations version of the flexible-price monetary model, by incorporating dynamic partial adjustment terms into the estimating equation, and by using time-varying parameter estimation techniques and by using dynamic error correction forms (Sarno, 2003).

Theoretical framework of the multivariate model

According to Lütkepohl (2004), linear models for the conditional mean of a stochastic process are useful for producing linear forecasts of time series variables. Supposing that K related time series variables are considered:

$y_{1t}, \dots y_{Kt}$

Defining y_t – $(y_{1t}, \dots y_{Kt})'$, a linear model for the conditional mean of the data generating process of the observed series with the vector autoregressive (VAR) form:

$$y_t - A_i y_{t-i} | \dots | A_p y_{t-p} | u_t$$

Where the A_i's (i - 1,…p) are (Kx K) coefficient matrices and u_t is a K-dimensional error term. If u_t is independent over time, the conditional mean of y_t, given past observations, is

$$y_{t\ t-i} = E(y_t | y_{t-1}, y_{t-2} \dots) - A_i y_{t-i} | \dots | A_p y_{t-p} |$$

The model can be used directly for forecasting one period ahead, while forecasts with larger horizons can be computed recursively. The simple VAR model of order p may have disadvantages, however. The A_i parameter matrices will be unknown and need to be replaced by estimators. For an adequate representation of the data generating process (DGP) of a set of time series of interest, a rather large VAR order p may be required. Hence, a large number of parameters may be necessary for an adequate description of the data. Given limited sample information, this will usually result in low estimation precision, and also forecasts based on VAR processes with estimated coefficients may suffer from the uncertainty in the parameter estimators. Therefore it is useful to consider the larger model class of vector autoregressive moving-average (VARMA) models which may represent the DGP of interest in a more parsimonious way.

The successful use of univariate ARMA models for forecasting has motivated researchers to extend the model class to the multivariate case. It is plausible to expect that using more information, by including more interrelated variables in the model, improves the forecast precision (Lütkepohl, 2004). Lütkepohl and Poskitt (1996) noted a few good reasons for choosing models from the more general VARMA (vector autoregressive moving average) class. Firstly, they may permit more parsimonious representations of the DGP. This may lead to improvements in estimation and forecast precision. Secondly, there are theoretical reasons why the pure VAR class may be too narrow for many economic data sets. Temporal and contemporaneous aggregation leads directly to mixed VARMA models. Trend and seasonal adjustment may also change the DGP in such a way that pure VAR models are inadequate. The VARMA class has the further advantage of being closed with respect to linear transformations, while a linearly transformed finite order VARMA process has a finite order VARMA representation. Therefore linear aggregation issues can be studied within this class (Lütkepohl, 2004). VARMA models can be parameterised in different ways. In other words, different parameterisations describe the same stochastic process. Although this is no problem for forecasting purposes, because only one adequate representation of the DGP is needed, nonunique parameters present a problem at the estimation stage (Lütkepohl, 2004).

The major problems in VARMA modelling are related to the specification of unique representations. For univatiate time series in which just one variable is modelled, these problems were addressed and more or less solved in the seminal work by Box and Jenkins in 1976. A unique model is essentially found by specifying the smallest possible AR and MA orders on the basis of sample autocorrelations and partial autocorrelations, or other quantities that may be helpful for that purpose. In multiple time series analyses, attempts have been made to proceed in a similar way, but this was problematic (Lütkepohl and Poskitt, 1996). Firstly, it is rather difficult to read the orders of many operators from a vast number of autocorrelations, cross-correlations and partial correlations if more than two or three time series are involved. Secondly, for finding a parsimonious, uniquely identified VARMA structure, it is not sufficient to require that minimal orders be chosen for the AR and MA operators. Therefore, requiring that no further cancellation is possible, as in the univariate case, is insufficient for unique identification in multiple time series analyses (Lütkepohl and Poskitt, 1996).

The VARMA process in its general form:

$$A_0 y_t - A_i y_{t-i} | \dots | A_p y_{t-p} | M_0 u_t | M_j u_{t-j} | \dots | M_q u_{t-q}$$

Table 1. Unit root test results.

Variable	Specification	Level	1^{st} difference
R/$	None	0.34	-6.83*
CPI	Trend and intercept	-2.47	-6.84*
Balance on financial account	None	-1.05	-10.87*
Government expenditure/GDP	Intercept	-2.12	-3.97*
Current account/GDP	None	0.74	-8.69*
Prime rate	Trend and intercept	-2.95	-5.62*
Credit	None	4.36	-5.27*

*Rejection of Ho: series contain a unit root, at the 95% confidence level.
Critical values: None: -1.95; Intercept: -3.48; Trend and intercept: -3.48.

Where A_0, A_i …,A_p are (KxK) autoregressive parameter matrices while M_0,M_j,…,M_q are moving average parameter matrices also of the dimension (KxK). Defining the VAR and MA operators respectively.

The zero order matrices A_0 and M_0 are assumed to be non-singular. They will often be identical, A_0-M_0, and in many cases they will be equal to the identity matrix, A_0-M_0-I_K. To indicate the orders of the VAR and MA operators, the process is sometimes referred to as a VARMA (p,q) process. No assumptions are made regarding the parameter matrices, so that some or all of the elements of the A_i's and M_j's are included. In other words, there may be a VARMA representation with the VAR or MA orders being less than p and q respectively.

Empirical analysis of the R/$ exchange rate and its determinants

The analysis was based on quarterly data from 1990q1 - 2006q4. The data was obtained from the I-net Bridge data base. The data used from I-net was sourced from the South African Reserve Bank. The determinants of the South African exchange rate were evaluated in a VAR framework. The relationship between the R/$ exchange rate (the spot rate), CPI (2000 base year), Balance on the financial account (Rand millions), government expenditure to GDP ratio, current account balance to GDP ratio, the prime rate and total credit extended (R million) was analysed. After considering the various models of exchange rate determination, the abovementioned variables were chosen because they were integrated to the same order and cointegration was present.

All the variables were I (1), according to the augmented Dickey-Fuller (ADF) test (shown in the Table 1). We followed the sequential procedure for the ADF test when the form of the DGP is unknown. Such a process is necessary, since including the intercept and trend term reduces the degrees of freedom and the power of the test, by implying that it has been concluded that a unit root exists, when in fact this is not the case. Further, additional regressors increase the absolute value of the critical value, making it more difficult to reject the null hypothesis, while inappropriately omitting the deterministic terms may cause the power of the test to go to zero (Dua and Sen, 2006). CPI, the prime rate and total credit extended were I(1), including the trend and intercept. The government expenditure to GDP ratio was I(1), including only the intercept, and the balance on the financial account, R/$ exchange rate and the current account balance to GDP ratio were I(1), excluding the trend and intercept (Table 1).

A VAR model with a lag structure of only 1 lag indicated by the Schwarz information criterion was used. The Johansen cointegration method was applied to the data and the Trace statistic indicated 4 cointegrating relationships (only intercept) and the Max-Eigenvalue indicated 1 cointegrating relationship. The summary of results is shown in Table 2.

In Table 3 one cointegrating relationship is shown where the R/$ exchange rate is normalised (followed the results from the Max-Eigenvalue). All the coefficients are significant except for the prime rate. All the variables, except for CPI, have a positive relationship with the exchange rate, in this case causing depreciation – since the exchange rate is quoted as Rand per Dollar.

The adjustment coefficients of the VECM in the table below show that the exchange rate, the balance on the financial account, and the ratio's of government expenditure and the balance on the current account to GDP comply with the stability condition and will adjust to equilibrium (Table 4).

Since cointegration was present according to the Johansen technique, a VECM could be used to determine the short run dynamics in this model, and the concept of Granger causality can be tested in the VECM framework. If two variables are cointegrated, then causality must exist in at least one direction (Dua and Sen, 2006). The variables jointly cause the R/$ exchange rate on a 75% confidence level. When a pairwise Granger causality was conducted, there was a two-way flow between prices and the exchange rate on an 80% confidence level. A one-way Granger causality was present where the exchange rate caused the prime rate

Table 2. Johansen cointegration results.

Selected (0.05 level*) number of cointegrating relations by model					
Data trend	**None**	**None**	**Linear**	**Linear**	**Quadratic**
Test type	No intercept No Trend	Intercept No Trend	Intercept No Trend	Intercept Trend	Intercept Trend
Trace	4	5	4	4	4
Max-Eig	4	5	1	2	2
*Critical values based on MacKinnon-Haug-Michelis (1999)					

Table 3. Normalised cointegrating coefficients (standard error in parentheses).

RAND(-1)	**1.000000**
CPI(-1)	-0.104674 (0.02985) [-3.50676]
CREPS(-1)	8.18E-06 (3.5E-06) [2.30551]
FA(-1)	0.000265 (3.8E-05) [6.91804]
GOVTOGDP(-1)	0.704021 (0.13970) [5.03946]
CATOGDP(-1)	0.838250 (0.20082) [4.17416]
PRIME(-1)	0.053516 (0.08896) [0.60154]

Table 4. Adjustment coefficients of the VECM (t-statistics in [], standard error in parentheses).

D(RAND)	D(CPI)	D(CREPS)	D(FA)	D(GOVTOGDP)	D(CATOGDP)	D(PRIME)
-0.001495	0.034472	861.8668	-2762.503	-0.552479	-0.078076	0.051551
(0.03890)	(0.06156)	(1007.61)	(502.909)	(0.18122)	(0.08253)	(0.06958)
[-0.03843]	[0.55999]	[0.85536]	[-5.49305]	[-3.04872]	[-0.94609]	[0.74093]

(95%) (vis a vis on 80%) and the current account on a 87%. If the lag length is longer (4), the financial account causes the Rand on a 95% confidence level, and the exchange rate causes CPI on a 95% confidence level.

Dynamic relationships among variables in VAR models can be analysed by using innovation accounting methods that include impulse response functions and variance decompositions. An IRF measures the time profile of the effect of shocks at a given point in time on the future values of a dynamical system. Generalised impulse responses overcome the problem of dependence of the orthogonalised impulse responses on the ordering of the variables in the VAR. The added advantage of generalised impulse response functions (GIRF) is that since no othogonality assumption is imposed, it is possible to examine the initial impact of responses of each variable to shocks with any of the other variables (Dua and Sen, 2006).

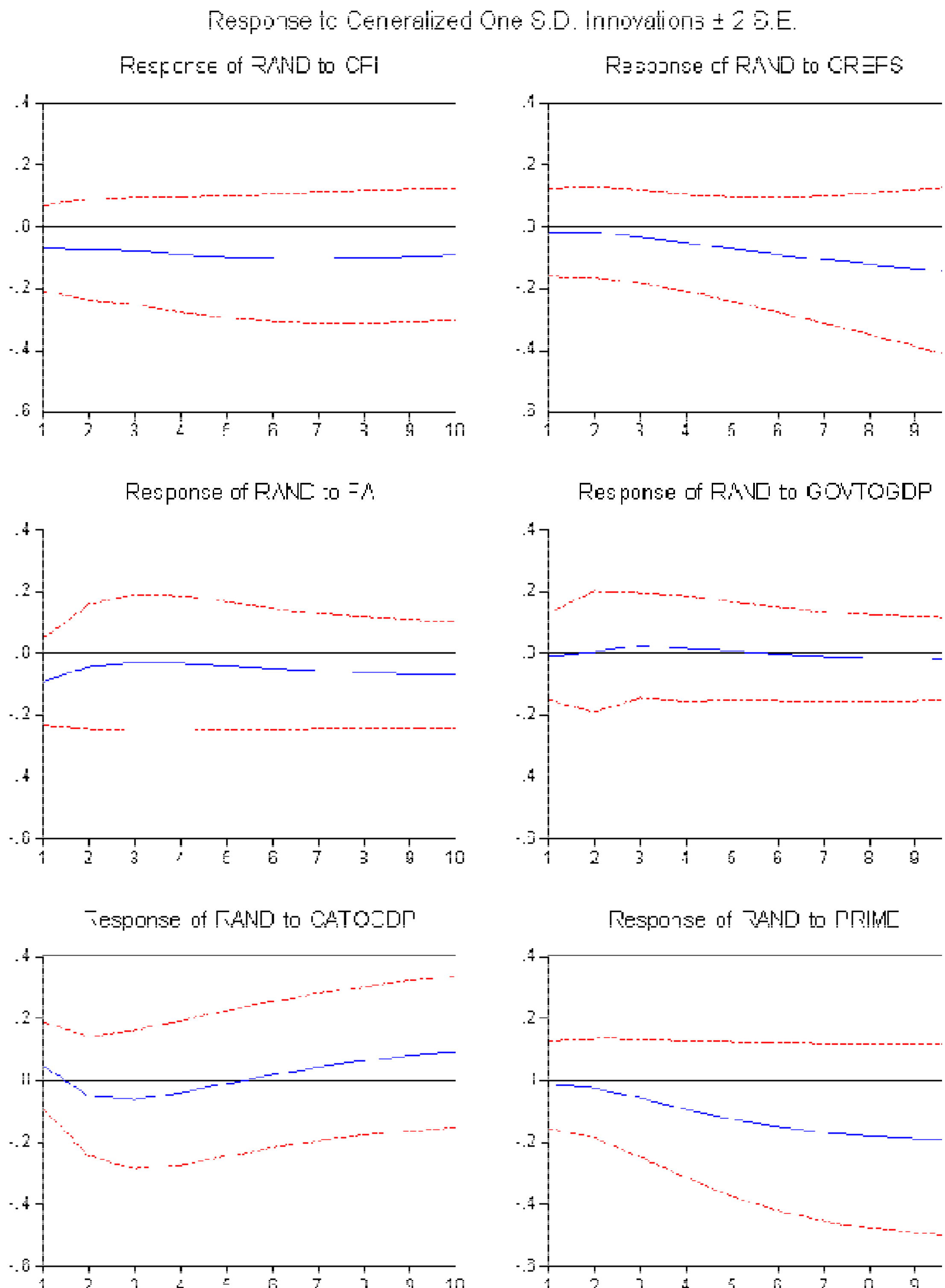

Figure 1. Impulse response functions.

From the IRF it seems that the shocks to the exchange rate are persistent, which makes sense, as all the series are non-stationary. The balance on the financial account, and the ratios of government expenditure and the current account to GDP return to equilibrium over time as indicated by the adjustment coefficients of the VECM.

Table 5. In-sample comparison of forecasting methods using the MAD/ mean ratio.

	VARMA	VECM	VAR	ARIMA	ARCH	RW
Static	4.9	6.3	6.0	5.7	5.6	6.0
Dynamic	11.0	19.9	13.1	17.9	17.7	17.4

Table 6. Static, out-of-sample comparison of forecasting methods with different forecast horizons.

Forecast horizon	VARMA	VECM	VAR	ARIMA	ARCH	RW
1 step ahead	1.5	5.7	4.6	7.7	7.3	4.8
2 quarters	10.5	7.9	8.7	9.0	7.5	9.3
4 quarters	19.2	9.6	8.7	7.6	6.8	9.0

The forecast error variance decompositions provide a breakdown of the variance of the n-step ahead forecast errors of variable i, which is accounted for by the innovations in variable j in the VAR. As in the case of the orthogonalised IRF, the orthogonalised forecast error variance decompositions are also not invariant to the ordering of the variables in the VAR. Consequently the generalised variance decomposition will be used (Dua and Sen, 2006). The variance decomposition shows that after 8 quarters, 73% of the forecast variance is explained by the exchange rate, 12% by the CPI and 6% by the prime rate. The other variables are above 2%, and some close to 3% in the 8^{th} quarter, except for the financial account which peaked at 1.24% in the 5^{th} quarter, and declined to 0.8% in the 8^{th} quarter.

Comparison of univariate and multivariate models

Univariate models, for the R/$ exchange rate, such as the random walk model, ARIMA (1,1,1) and ARCH(0,1) model are compared to multivariate models, for the R/$ exchange rate, such as the unrestricted VAR, VECM and VARMA model.

In-sample and out-of-sample techniques will be used to evaluate the forecasts. In-sample evaluation techniques, which permit the use of all the data available to the researcher, provide more precise estimates of statistics of interest, and therefore have more power to reject the null hypothesis of no predictability. The advantage of out-of-sample evaluation procedures is that they implicitly test the stability of the estimated coefficients and there-fore provide a more stringent hurdle for models to overcome (Neely and Sarno, 2002).

To compare the forecasting methods used, the Mean Absolute Deviation (MAD)/mean ratio will be used. Kolassa and Schütz (2007), state that the critical advantage of the Mean absolute Percentage error (MAPE) is scale-free, which allows the comparison of MAPEs across multiple time series with different levels. However, if there are zero's in the data series, the MAPE cannot be calculated, and according to Kolassa and Schütz, (2007) an alternative metric to compare the accuracy of methods across series, is the MAD/mean ratio, which is not only comparable across series, but it can be calculated for intermittent series as well. This ratio will be used to compare the forecasts of the various models in this study.

The results for the in-sample forecasts are shown in Table 5. As a rule of thumb a ratio of 5% is deemed as a good forecast or the lowest ratio as the better model.

For the static forecasts (using the actual as starting point), the VARMA outperforms all the models (lowest value), as well as the dynamic forecasts (using the forecasted value as a starting point). In this case the combination of the fundamental and technical approach in a multivariate case outperforms the univariate models (the atheoretic models, or pure technical models) as well as the simple random walk model, however by a small margin.

To implicitly test the stability of the estimated coefficient, however, it is better to use out-of-sample forecasts. Expost forecasts on a 2-period (2 quarters; 2006q3 - 2006q4)) and 4-period (4 quarters; 2006q1 - 2006q4) forecast horizon were done, and a one step ahead forecast on real time data was done for 2007q1 (Table 6).

The multivariate (VARMA, VECM and VAR) models outperform the univariate models (ARIMA, ARCH), with the exception of the RW model, when a forecast is conducted one step ahead, and the one step ahead forecast was done, truly out of sample for 2007q1. The second and fourth quarter forecast was expost forecasts, and for 2 quarters ahead the VARMA lost power, but the VECM and VAR still outperformed the ARIMA and RW. The ARCH performed well in this forecast horizon. However, it still seems as if the multivariate models outperform the univariate models. For a longer forecast horizon, namely 4 quarters, the multivariate models lost power in favour of the univariate models, especially the

Table 7. Dynamic, out-of-sample comparison of forecasting methods with different forecast horizons.

Forecast horizon	VARMA	VECM	VAR	ARIMA	ARCH	RW
1 step ahead	1.5	5.7	4.6	7.7	7.3	4.8
2 quarters	7.4	6.3	5.7	4.9	4.7	5.8
4 quarters	35.9	8.9	12.5	10.5	10.0	9.5

ARCH.

The results of the one step ahead forecast seem to substantiate the findings by Faust, Rogers and Wright, (2001) that the predictive power of real-time fundamental data is better than when using expost revised fundamental data. It can then be concluded that the multivariate models outperform the univariate models when forecasts are conducted for one period ahead - short term forecasting, with the exception of the RW model.

Where dynamic forecasting is concerned (Table 7), the univariate models outperform the multivariate models for 2 quarters ahead, however the VECM outperforms all on a longer forecast horizon of 4 quarters. In all cases, either the multivariate or ARIMA and ARCH outperform the RW by a small margin. Therefore, although marginally better forecasts can be obtained by other models, the effort to build them against the simplicity of the random walk model will have an impact on the choice of model chosen by the practitioner when making short-term forecasts.

The poor performance of the multivariate models in respect of dynamic forecasting may be due to the fact that various variables have been forecasted, and those forecasted values subsequently being used for the next forecast, causing error propagation.

From these results it can be concluded that the combination of the fundamental approach and the technical approach, in a multivariate model such as the VARMA, performs well in the short term, (1 quarter ahead). This indicates that the economic variables included in the model, fundamentals, do explain some of the variation in the South African exchange rate. It also outperforms the random walk model on the short term, although the MAD/mean ratio is still below 5%, implying that not all information is immediately accounted for.

Conclusion

The dominant approach in exchange rate determination is the monetary approach, despite not being very successful in forecasting the exchange rate. In this paper determinants of the SA exchange rate were classified according to 3 broad categories, namely real, monetary and financial variables, as well as past and expected values. Cointegration was found between these variables. Univariate and multivariate models were compared to the simple random walk model using the MAD/mean ratio. Multivariate models performed well in comparison to the univariate models, specifically the one step ahead, out-of-sample forecast. The VARMA model had a low MAD/mean ratio of 1.5% followed by the VAR and random walk at 4.6% and 4.8% respectively. This was, however, not the case in the dynamic, out-of-sample forecast. With a longer forecast horizon, the univariate models (ARCH and ARIMA) outperformed mostl multivariate models, except for the VECM that outperformed all the models.

Therefore this research suggests that a combination of the fundamental approach and the technical approach, in a multivariate model such as the VARMA, be used for forecasting the South African exchange rate in the short run (although the RW can still be deemed as a good model), and the VECM for the longer forecast horizon. These results are more or less in line with the research of (Cuaresma and Hlouskova: 2004). Since South Africa is an emerging market experiencing a highly volatile currency, it is suggested that only one step ahead or static forecasts be conducted on a short forecast horizon where fundamentals are concerned. This research also confirms the findings of Hlouskova and Cuaresma (2004) that some multivariate models do have good forecast performance in the short-run, but the random walk' performance is also good. From the results of this research the random walk model did well, below 5%, therefore it is up to the practitioner if a more complex model, such as the VARMA, or the simple random walk model should be used to forecast the exchange rate in the short-run.

Recommendations

Short-run movements in exchange rates are primarily determined by changes in expectations, as the standard models say. Engle and West (2005) acknowledge that there are unobserved fundamentals (money demand, shocks, risk premiums), and that the exchange rate may not exactly equal the expected present value of observed fundamentals. However, should exchange rates react to news about future economic fundamentals, exchange rates may possibly help to forecast the observed fundamentals. If the observed fundamentals are the primary drivers of the exchange rate, the exchange rates should incorporate some useful information about future fundamentals. Given the results that fundamental models are not all bad, this research can be improved by using multiple frequencies of the determinants to capture the dynamic behaviour between variables, and the presence of dynamic behaviour could be seen in the good performance of the VECM out of sample. A resticted VARMA echelon form model could improve the results and it is believed that the structural VAR might be even better.

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