



Modeling the Rand-Dollar Future Spot Rates: The Kalman Filter Approach

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Working Paper Number 98

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October 30, 2008

Abstract

A number of studies have contended that it is challenging to explain exchange rate movement with macroeconomic fundamentals. A naïve model such as a random walk forecasts exchange rate movements more reliably than existing structural models. This paper confirms that it is possible to improve the forecast of structural exchange rate models, by explicitly accounting for parameter instability when estimating these models. Making use of the Kalman filter as an estimation method that accounts for time-varying coefficients in the presence of parameter instability, this paper indicates that forward exchange rates with different maturities predict the future spot exchange rates more reliably than the random walk model for the Rand exchange rates.

1 Introduction

Forward exchange rates have traditionally been used as proxies for expected future spot rates. Most of the empirical studies, especially in the 1960s, have supported the ‘Unbiased Forward Rate Hypothesis’ (UFRH). The unbiasedness of the forward rate is important for the construction of macroeconomic models and for testing monetarist theories concerning the asset market approach to the determination of the foreign exchange rate (Bailey *et al*, 1984). However, a large body of statistical work published since the introduction of flexible exchange rates in the early 1970s has established that forward rates for major currencies are not optimal predictors of future spot rates. For example, Hansen and Hodrick (1983), and Agmon and Ahmihud (1981) reported evidence of a risk premium in major forward foreign exchange markets, making the forward rate a biased predictor of the future spot rate. Furthermore, comparing the forecasting accuracy of structural models of the exchange rate and random models, Meese and Rogoff (1983) indicate that structural models perform poorly compared to random walk models and conclude that random walk predictions cannot be outperformed. However, Elliot and Timmermann (2008) show that structural breaks in parameters can cause a forecasting model’s performance to deviate significantly and erratically from the outcome expected on the basis of its in-sample fit. Clements and Hendry (2006) also emphasise parameter instability as a key determinant of forecasting performance and suggest the exploration of nonlinear models as a way to improve the forecasting performance of linear models.

Traditional linear models are based on constant parameters and fail to accurately account for parameters instability. With regards to the importance of the use of nonlinear models in improving structural models of exchange rate determination, Clarida *et al* (2002) apply a nonlinear vector error correction framework for exchange rate forecasting. The results of their study provide evidence that the term structure of forward rates is strong in forecasting spot exchange rates. Clarida *et al* (2002) concluded that the nonlinear vector error correction forecasts of the future spot exchange rate from

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the forward exchange rate were strongly superior to the random walk forecasts. Notwithstanding the failure of the UFRH, the authors state that forward rates may contain more useful information to forecast spot exchange rates than do conventional fundamentals and the random walk model.

Wolff (1987) expanded on the study by Meese and Rogoff (1983) and implements an empirical methodology based on recursive application of the Kalman filter in order to deal with parameter variation in the structural models of the flexible-price and sticky-price monetary models. Wolff concludes that the introduction of time-varying parameters enhances the forecasting performance of the structural models. Nevertheless, the performance of these structural models relative to the random walk varies for different exchange rates. Wesso (1999) investigated the empirical issue of market efficiency for the South African currency from January 1987 to November 1998. The results of Wesso's study rejected the UFRH in the Rand-US dollar exchange market and the current spot rate was superior to the forward rate in predicting future spot rates. Wesso's empirical study was based on constant coefficients assumption. Nonetheless, the author suggests that further research be devoted to the analysis of the time-variant coefficients considering a number of structural breaks or regime shifts present in the Rand exchange rates.

This paper expands on the study by Wesso (1999) by making use of the recursive application of the Kalman filter method in order to deal with the issue of parameters instability in the forecast of the Rand-US dollar future spot rates based on the unbiasedness of the forward rate. The forecasting accuracy of this structural model is compared with the random walk. The root mean square error (RMSE) and mean absolute error (MABE) are used to compare the forecasting accuracy of the different methods.

The remainder of this paper is organised as follows. Section 2 provides a brief review of the literature on exchange rate modeling and forecasting. Section 3 provides a theoretical background for the unbiased hypothesis. Section 4 describes the Kalman filter methodology. The empirical results are reported and analysed in section 5. Section 6 compares the forecast performance of the models used. The final section presents the conclusion and main findings of this paper.

2 Literature Review

A number of estimations that tested the unbiased forward rate hypothesis in the context of the asset market approach to the determination of the exchange rate have rejected the hypothesis and many reasons have been advanced. For example, Fama (1984), testing for the UFRH, offered an explanation as to why the estimate of coefficient β was less than zero. Fama argues that the rational expectations risk premium on foreign exchange rates must be extremely variable. However, McCallum (1994) provides a different explanation. For McCallum, the failure of the forward rate unbiased hypothesis is explained by a neglect to take into account the fact that a number of monetary authorities pursue interest rate smoothing and avoid exchange rate changes. Therefore the activities of the central bank in the foreign exchange market would have an influence on how foreign exchange market participants formulate expectations on the change in the spot rate. Given this assumption, market participants will cease to be risk neutral and will require a premium because of the wedge between the interest rate differential and the expectations of the change in the spot rate.

Also, Taylor and Sarno (2003) note that a change in policy from the monetary authority will cause foreign exchange market participants to continually learn about the effects of a given policy and consequently adjust their expectations. Continual adjustment of expectations can generate forecast errors displaying serial correlation. This argument supports the view that agents in the foreign exchange market derive their expectations of the future exchange rate, under the assumption of adaptive expectations rather than rational expectations. For instance, they will revise their expectations of future spot rates upwards if they under-predicted these rates in the past. Therefore, The Kalman filter method, through its recursive procedure for computing estimators, will be adequate to model the actions of foreign exchange market participants who continually adjust their prediction

errors.

Wolff (1987) uses recursive applications of the Kalman filter in order to deal with parameter variation to forecast structural models of exchange rate determination. The structural models include a class of monetary exchange rates of flexible-price and sticky-price models. Wolff justifies the use of a varying-parameter estimation technique by a number of different factors. These include the instability of conventional money demand functions, the occurrence of changes in policy regimes and other factors such as changes in oil prices and global trades. The set of exchange rates analysed by Wolff include the US Dollar-German Mark, US Dollar-Japanese Yen and US-Dollar British Pound exchange rates. Wolff finds that both structural models for the determination of US Dollar-Mark exchange rate outperform the random walk model in a number of cases at horizons within 12 months. Nevertheless, the structural models' forecasts for the US Dollar-Yen and US Dollar-Pound exchange rates at longer horizons are very poor compared with the results for the random walk.

Clarida *et al* (2002) indicate that the forward exchange rate may contain more useful information to forecast spot exchange rates compare to other conventional fundamentals. By exploiting the presence of nonlinearity in the context of exchange rate modeling and with the use of a multivariate three-regime Markov-Switching vector error correction model (MS-VECM), the authors contend that nonlinear VECM strongly outperforms a linear VECM as well as the random walk model in forecasting the future spot dollar-yen exchange rate.

In comparison to the forecast performance between a linear and a nonlinear model, Elliot and Timmermann (2008) state that it is less evident for a linear relationship to exist between the data and the predicted variables. In fact, most empirical tests for various forms of nonlinearity often reject linear benchmark models. Thus, nonlinear models can improve the forecasting performance of linear models. Nonetheless, the authors contend that nonlinear models can generate poor forecasts due to their sensitivity to outliers and susceptibility to estimation error. Another important issue concerning nonlinear models is the choice of the type of nonlinear model among many models. In this context, Elliot and Timmermann (2008) advise that in the presence of historical breaks in a time-series model, a popular approach is to parameterise coefficients of the model as a random walk and use a Kalman filter to estimate the path for the coefficients and produce a forecast.

Wesso (1999) suggests that the analysis of the time-variant coefficients be considered in testing for the efficiency of the exchange rate market and forecasting exchange rates in South Africa in view of a number of structural breaks present in the Rand exchange rates series. Specifically, casual inspection of data on the Rand exchange rate from January 1987 to November 1998 by Wesso reveals a marked increase in the variability of the Rand, particularly during 1996 and 1998. The author has noted that the weakness of the Rand during 1996 was a combination of several factors such as large-scale speculation triggered by unfounded rumours about the health of the previous president Mr. Nelson Mandela, and negative views on the South African socio-political situation. According to Wesso, the major depreciation of the Rand in 1998 was due to emerging market contagion from the Asian crisis as well as the increase in the South African Reserve Bank's net open forward position that inspired important speculation against the Rand.

3 Foreign exchange market efficiency and the unbiased forward rate hypothesis

The asset market approach with regards to the determination of the exchange rate views currencies as asset prices traded in an efficient financial market. Asset prices respond immediately to changes in expectations and interest rates (Krugman and Obstfeld, 2003). The important characteristics of an efficient market is that prices should fully reflect information available to market participants and it should be impossible for a trader to earn excess returns to speculation (Taylor & Sarno, 2003). Therefore, any arbitrage opportunity that presents itself in the market will quickly cancel out, with the change in the conditions of supply and demand. In an efficient market, the forward rates, as with

all derivatives products, are priced under the hypothesis of non-arbitrage opportunity. Assume F_t^K is the K period's forward exchange rate (the rate agreed now for an exchange of currency K periods ahead), S_t is the spot exchange rate (domestic price of foreign currency). If r and r_f represent the domestic and foreign interest rate respectively prevailing at time t , the fair price of the forward contract expressed in term of continuous compounding and under risk-neutrality hypothesis will then be:

$$F_t^K = S_t e^{(r-r_f)} \quad (1)$$

Under these conditions, any risk-free arbitrage opportunity cancels out. Expressed in terms of a natural logarithm, expression (1) becomes:

$$f_t^K - s_t = r - r_f \quad (2)$$

Where $f_t^K = \log_e F_t^K$ and $s_t = \log_e S_t$ and use has been made of the conventional expression $\log_e(1 + X) \approx X$ for small X . So here $X = r, r_f$.

Expression (2) is known as the covered interest rate parity (CIP), and the reason why CIP should hold is that market deviation from expression (2) will result in arbitrage opportunity which will force the equality to hold.

If the risk-neutral efficient market hypothesis holds, then the expected foreign exchange gain from holding one currency rather than another (the expected exchange change) must be just offset by the opportunity cost of holding funds in this currency rather than the other (the interest rate differential). This condition is known as uncovered interest rate parity (UIP), expressed as:

$$\Delta_k s_{t+k}^e = r - r_f \quad (3)$$

Where $\Delta_k s_{t+k}^e = s_{t+k} - s_t$, expression (3) refers to the market expectations of the change in the spot price between time t and $t + k$.

By combining expressions (2) and (3), the covered and uncovered interest parity, respectively, one would then arrive at the conclusion that:

$$f_t = E(s_{t+k}/I_t) \quad (4)$$

It implies that the forward rate at time t should be equal to the market expectations of the future rate, given information at time t .

Expression (4) provides a basis for the testing of an unbiased forward rate hypothesis by estimating the following equation:

$$s_{t+k} = \alpha + \beta f_t + \eta_{t+k} \quad (5)$$

η_{t+k} is the rational expectations forecast error with $E[\eta_{t+k}/I_t] = 0$. To test the hypothesis that the forward exchange rate is an unbiased predictor of the spot exchange rate, the restriction $\beta = 1$ is tested. A strong form of an unbiased market efficiency hypothesis and no risk premium implies testing $\alpha = 0$ (a constant risk premium equals zero) and $\beta = 1$ and the errors are serially uncorrelated and homoscedastic.

4 Kalman Filter Approach

The Kalman filter is a recursive procedure for computing the optimal estimator of the state vector at time t , based on information available at the same time (Harvey, 1989). The Kalman filter provides an estimation method for equations represented in a state space form. An estimation problem can be put into state-space form by defining the state vector represented by a certain parameter. The equation representing the state vector is known as the transition equation. The state vector is not observed directly; instead the state of the system is conveyed by an observed variable called signal

equation, which is subject to contamination by disturbance or measurement error. The equation representing an observable variable is known as a measurement equation.

An example of the state-space model underlying the Kalman filter can be represented as follows:

$$Y_t = H_t \xi_t + \eta_t \quad (6)$$

This equation represents the observation, signal or measurement equation. The transition or state equation is expressed as:

$$\xi_t = \Phi_t \xi_{t-1} + v_t \quad (7)$$

where Y_t is the observation on the system, H_t is the vector of regressors and ξ_t is the state vector. The random variables η_t and v_t represent the measurement and state disturbance or noise respectively. These variables are assumed to be independent of each other, also white noise and with normal probability distribution, meaning that:

$$p(\eta) \approx N(0, Q)$$

and

$$p(v) \approx N(0, R)$$

where $p(\eta)$ and $p(v)$ represents probability distribution of the errors η and v respectively and Q is the covariance of the measurement while R is the covariance of the state noise.

Because of its recursive character, the estimation of the equations of the Kalman filter requires the determination of the initial estimate of the state vector ξ_0 at time $t = 0$ and of its variance matrix. It is assumed that H_t , Φ_t , Q and R are known for all $t = 1, \dots, n$, the same as the initial estimate for the state vector and its variance matrix. With a set of information at time t given as $I_t = Y_1, \dots, Y_t$ and given the initial estimate, for example x_0 , for the state vector ξ_0 . The Kalman filter equation determines the state vector estimates:

$$X_{t/t-1} = E(\xi_t / I_{t-1}) \quad (8)$$

and

$$X_t = E(\xi_t / I_t) \quad (9)$$

and their associated variance matrices.

The mechanics of the Kalman filter present a relevant foundation for modeling the behaviour of economic agents faced with signal extraction problems. In signal extraction problems, agents slowly adjust their expectations due to different policy changes in their environment (Lewis, 1989). This adjustment results in a forecast error and an updating rule similar to the Kalman filter process as presented in Equation 6 and Equation 7. As with adaptive expectations where expectations of the future value of economic variable are based on past value, the Kalman filter process, as represented in Equation 6 and Equation 7, shows that the measurement or signal equation is constantly revised in proportion to the systematic error associated with previous level of expectations. This indicates that there is a gradual learning process taking place at the root of the Kalman filter process. It is worth noting that in the case of rational expectations, there is no systematic error and the forecast of the future is the best guess that uses all available information (Muth, 1960).

5 Data analysis and empirical results

As outlined earlier, the aim of this paper is to compare the forecast ability of the structural exchange rate model based on the unbiasedness of the forward rate and the random walk model. As far as the structural model is concerned, the forecasting performance of the future spot exchange rate obtained

from the Kalman filter and the ordinary least square (OLS) methods will also be compared. Thus, this paper will compare the forecasting performance of three different estimation methods, that is, the random walk, the OLS and the Kalman filter to predict the future Rand-dollar spot rate. The empirical analysis uses monthly data on Rand-US dollar spot rates (Spot) and the 1-month (Forw1), 3-month (Forw3), 6-month (Forw6) and 12-month (Forw12) forward rates. The data are collected from the I-Net Bridget database and are applied in the log form.

The data cover the period from April 1993 to August 2008, a total of 185 observations. Observations between April 1993 and August 2006 are utilised for parameter estimation and observations between September 2006 and August 2008 are used for out-of-sample forecast. The predictive accuracy of the different forecasting methods of the future spot rates is tested over the out-of-sample forecasting period. Each method will be covered in a separate subsection before a comparison of the methods is made in section 6. On the issue of the sample selection for the comparison of forecast performance, Elliot and Timmermann (2008) remark that a strategy as to whether to adopt an in-sample or out-of-sample forecast comparison very much depends on the purpose of the analysis. If the aim of the study is to test the implication of economic theories, it is advisable to use the in-sample forecast with the use of full sample. In contrast, if indeed the interest of the study is to test for the presence of real time predictability, then the use of out-of-sample forecast may be appropriate. This paper uses the out-of-sample forecast comparison as its aim is to compare the forecast accuracy of the different forecasting methods in predicting the Rand-US dollar future spot rate.

5.1 The OLS method

This section makes use of the OLS method to predict the future spot exchange rate from different maturities of the forward exchange rates. In order to avoid estimating a spurious regression, unit root and cointegration tests are conducted to establish the level of integration of the two series and subsequently to establish if the two series are cointegrated. The results of the Augmented Dickey-Fuller (ADF) unit root tests on the spot and forward rates are presented in Table 1 and Table 2.

The Augmented Dickey-Fuller test indicates that the two series are integrated at order 1 and they are stationary after the first difference. The null hypothesis of a unit root is rejected at the 1% level of significance.

The Engle-Granger two-step procedure was used to test for cointegration between each pair of the spot rate and the forward rate. The residuals obtained from these estimation regressions are $I(0)$. These results confirm that there is a cointegration relationship between the spot rate and each forward exchange rate series.

The OLS estimation of the relationship between the future spot rate and each forward rate is represented in Table 3. This estimation stems from the following equation:

$$Spot_{t+k} = \alpha + \beta Forw_t + \mu_{t+k} \quad (10)$$

Where $k = 1, 3, 6, 12$. $Forw_t$ represents $Forw1_t$, $Forw3_t$, $Forw6_t$ and $Forw12_t$.

The results in Table 3 indicate that in the regression between the future spot rate and the 1-month forward rate, the coefficient β is 0.9836. This coefficient decreases when long maturities of the forward rate are used to predict the future spot rate. Also, the coefficients of the regression in Table 3 show that the null hypothesis of $\alpha=0$ and $\beta=1$ are rejected (also supported with the use of the Wald test, computed from the 1-month forward rate equation, as in Appendix Table 1A). This finding indicates support for rejecting the unbiased forward rate hypothesis.

Clarida *et al* (2002) illustrate that the forward rate can contain important information to forecast the future spot rate although the UFRH may be rejected. To exploit the information contained in the forward exchange rate in order to predict the future spot rate, the paper makes use of Kalman filter as a suitable estimation method in the presence of structural breaks.

Wesso identifies structural breaks in the Rand-US dollar in the years 1996 and 1998 and the reasons for these structural breaks have been discussed earlier in the paper. In addition to the two structural breaks discussed by Wesso, this paper notes that another important structural break in the Rand exchange rate happened in the year 2001. In late 2001, deteriorating market and economic conditions in Argentina as well as contagion from events in Zimbabwe contributed to the deterioration of the Rand (Pretorius and De Beer, 2004). As a consequence of these external shocks, the value of the Rand to the US dollar reached an all-time low of R13.00 on December 20, 2001.

To confirm the presence of structural break in the Rand exchange rate in the year 2001, the chow's break point test is applied in Equation (10) between the spot and the 6-month forward rate. The chow's break point test in Table 4 rejects the null hypothesis of no structural break. The reference date used to test for the breakpoint is October 2001. This date corresponds with the start of the 2001 financial crisis (Bhundia and Ricci, 2005).

5.2 The Kalman Filter Estimation

The presence of structural breaks in the period between April 1993 and August 2008, as discussed earlier, should justify the use of the time-varying coefficient method in modeling the relationship between the future spot and forward exchange rates. The Kalman filter method accommodates time-varying coefficients and adaptive expectations (Lansing, 2008). To allow for parameter variation in the relationship between future spot and forward exchange rates, the future spot exchange rate is generated by the following model:

$$Spot_{t+k} = \alpha + \beta_t forw_t + \eta_{t+k} \quad (11)$$

$$\beta_t = \beta_{t-1} + v_{1t} \quad (12)$$

Where α is a fixed coefficient and β_t is a vector of time-varying coefficients. η_{t+k} is a scalar disturbance term, and v_{1t} is a vector of disturbance term. The following properties are assumed for the disturbance term:

$$E(\eta_t) = 0, \text{var}(\eta_t) = Q \text{ (Q is a scalar)}$$

$$E(v_{1t}) = 0, \text{var}(v_{1t}) = R \text{ (R is a } k \times k \text{ matrix)}$$

Where $E(\cdot)$ and $\text{Var}(\cdot)$ stand for expectations and variance, respectively.

Equation (11) represents the measurement or signal equation and equation (12) represents the transition or state equation. These two equations combined, represent the recursive system for modeling the future spot rate with the aid of the Kalman filter. The coefficient β_t is represented as Random walk. This is important to account for time-varying parameters in the presence of structural breaks observed in the relationship between the spot and forward exchange rates. Nonlinearity is introduced in Equation (11) by allowing $forw_t$ to be stochastic (Wolff, 1987). $Forw_t$ represents $Forw_{1t}$, $Forw_{3t}$, $Forw_{6t}$ and $Forw_{12t}$.

Table 5 presents the estimation results of the Kalman filter process as in Equations 11,12. With reference to these equations the results in Table 5 are expressed as:

$$spot_{t+k} = c(1) + SV1 * Forw_t + [Var = \exp(c(2))] \quad (13)$$

$$SV1 = SV1(-1) + [Var = \exp(c(3))] \quad (14)$$

Equation (13) and Equation (14) represent the signal and state equations, respectively. Table 5 provides the final values of the state vectors β_t ($SV1$). For example in the relationship between the future spot rate and the 1-month forward rate, the final value of the coefficient β_t is 0.9836. Appendix Figure 1 shows that this coefficient is time varying and take values between 0.9775 and 0.9932. The variances of the error term of the signal and state equations are given as exponential of the estimated coefficients $c(2)$ and $c(3)$ respectively. These coefficients are not required to be

statistically significant. Indeed, The Kalman filter algorithm computes recursively the posterior mean and covariance matrix given the prior knowledge of the coefficient β as well as the variances of the error term of the signal and state equations. The Akaike information criterion is minimised for the regression between the future spot rate and the forward rate.

5.3 Random Walk Model

Because this paper compares the forecast ability of the OLS, Kalman Filter and random walk estimations of the future spot exchange rates, this section briefly presents the random Walk estimation results of the future spot rate. The random walk model is the benchmark from which the performance of other models of exchange rates is assessed. The model estimated is of the form:

$$Spot_t = Spot_{t-1} + \eta_t \text{ Where } \eta_t \text{ is the error term.}$$

The estimation results of the random walk model presented in Table 6 confirm that the AR (1) representation of the spot rate series depicts a random walk process as the coefficient of spot (-1) is close to unity.

Table 6 presents the statistics of the random walk model after correcting the standard error by using White's heteroskedasticity and autocorrelation consistent covariance in order to account for the heteroskedasticity in the variance of the model. As mentioned previously, the coefficient of the lag of spot rate is close to unity. This result confirms that the rand-dollar exchange follows a random walk process.

6 Comparison of the Models

This section provides insight on which forecasting method best predicts the Rand-US dollar future spot exchange rate. Because this paper is interested in assessing the performance of different forecasting methods in predicting the future spot rate, the out-of-sample forecast comparison is used. The basis for comparison will be the root means square error (RMSE) and the mean absolute error (MABE) for the one-month-ahead forecasts. The results in Table 7 show that the Kalman filter forecasts of the future spot rates estimated from forward rates of different maturities outperform their OLS counterpart forecasts. For example, the value of the RMSE is 0.00243 when the future spot rate is predicted from the 1-month forward rate using the Kalman filter method. This value is 0.04047 if the OLS method is used for the same prediction.

The Kalman filter forecast method also outperforms the random walk forecast except for the future spot rate predicted from the 6-month forward rate. Furthermore, the results in Table 7 show that the random walk forecast outperforms all the OLS forecasts of the future spot rates.

With regards to the Kalman filter forecasts, the results indicate that the 1-month forward rates forecast the future spot rates better than any other forward rates maturity. This may indicate the importance of coinciding the forecast period and the maturity of the forward rate for forecast accuracy when modeling the future spot exchange rate from the forward rate. This paper advises further research of this topic, as this paper only makes use of the one-month-ahead forecast period.

With the poor performance of the linear model compared to the nonlinear model, these results indicate that the underlying principle for the determination of the exchange rate in South Africa during the period between April 1993 and August 2008 is nonlinear.

Appendix Figure 2A illustrates the actual and predicted future spot exchange rate estimated with different forecast methods. The poor performance of the OLS prediction of the future spot rates from different forward rates maturity compared to the corresponding Kalman filter prediction is clear from the graph. Appendix Figure 2A also shows that for each forecasting method, the 1-month forward rate forecasts the future spot rate better than any other forward rate maturity.

7 Conclusion

This paper compared the forecasting accuracy of the structural model of exchange rate based on the unbiasedness of the forward rate and the random walk model for the Rand-US dollar exchange rate. The paper indicated that due to a number of structural breaks during the sample period of the analysis (from April 1993 to August 2008) and the encompassing parameters instability, the use of a time-varying coefficient method, the Kalman filter, improves the predictability of the Rand-US dollar future spot rate to a greater extent than the OLS method.

Furthermore, the out-of-sample forecast accuracy of the Kalman filter is compared to the random walk method in predicting the Rand-dollar future spot rates. Using the RMSE and MABE, the paper finds that different maturities of the forward rates predict the Rand-US dollar future spot rate better than the current spot rate during the period of our analysis, except for the 6-month forward rates. This indicates that structural models can outperform the Random walk once use is made of time-varying coefficient methods in the prediction of the exchange rate. In addition, the paper contends that 1-month forward rates predict the future spot rates better than any other forward rate maturities. The forecast period used in the paper is the one-month-ahead prediction.

This paper concludes that this indicates the importance of matching the forecast period and the maturity of the forward rate for improving forecasting performance when modeling the future spot exchange rate from the forward rate. Nevertheless, this is suggested as a topic for further research as this paper only makes use of the one-month-ahead forecast period. The findings of this paper also confirm that the unbiasedness of the forward rate as a structural model based on the asset market approach to the determination of exchange rate is well suited for forecasting exchange rate in the short-term.

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Table 1: Unit root test of different series at the level

Variables	ADF (Adjusted t-statistics)
Forw1	-1.581216
Forw3	-1.574505
Forw6	-1.544155
Forw12	-1.564730
Spot	-1.832022

Note: ADF is Augmented Dickey-Fuller test where the null hypothesis is of a unit root in the series. ** and * indicate the rejection of the null hypothesis at the 90% and 95% level of confidence, respectively. The estimated regressions include a constant and a trend.

Table 2: Unit root test of different series at the first difference

Variables	ADF (Adjusted t-statistics)
Forw1	-12.44641*
Forw3	-12.31794*
Forw6	-12.37625*
Forw12	-12.20795*
Spot	-12.96141*

Note: ADF is Augmented Dickey-Fuller test where the null hypothesis is of a unit root in the series. ** and * indicate the rejection of the null hypothesis at the 95% and 99% level of confidence, respectively. The estimated regressions include a constant and a trend.

Table 3: OLS estimation of the future spot exchange rate

Dependent variable: $spot_t$

	Forw1 _{t-1}	Forw3 _{t-3}	Forw6 _{t-6}	Forw12 _{t-12}
α	0.0273***	0.0878*	0.1845*	0.4195*
β	0.9836*	0.9478*	0.8907*	0.7574*
R ²	0.9848	0.9469	0.8844	0.7259
F-statistic	10248	2783	1170.6	389.31
Probability (F-stat)	0.0000	0.0000	0.00000	0.0000

Note: *, ** and *** mean significant at 1%, 5% and 10%, respectively. The standard errors are corrected using the Newey-West heteroskedasticity and Autocorrelation Consistent Variance (HAC) in the presence of serial correlation and heteroskedasticity in the residuals. Residuals are I (0).

Table 4: Chow's breakpoint test

F-Statistics	38.70054	Probability	0.00000
Log likelihood ratio	71.27469	Probability	0.0000

Note: Null hypothesis: No structural break

Table 5: Statistics of the Kalman filter model. Final state coefficients

Dependent variable: $Spot_t$

	Forw1 _{t-1}	Forw3 _{t-3}	Forw6 _{t-6}	Forw12 _{t-12}
C (1) or (α)	0.0273**	0.08786*	0.1845**	0.4195**
C (2)	-6.3863**	-5.1597**	-4.4134**	-3.6269
C (3)	-65.683	-65.6839*	-65.6839	-65.6839
SV1 or β_t	0.9836*	0.9478*	0.8907*	0.7574*
Log likelihood	271.167	171.32	110.38	47.45
Akaike criterion	-3.3520	-2.1307	-1.3855	-0.5967

Note: *, ** and *** mean significant at 1%, 5% and 10%, respectively.

Table 6: Statistics of the Random walk model

Dependent Variable: Spot

Variable	Coefficient	Std. Error	T-statistic	Prob
Spot(-1)	1.000595	0.000528	1895.078	0.000
R-squared	0.995773		Mean dep. Var	0.814014
Adjust. R-squared	0.995773		S.D. dep.Var	0.126512
S.E regression	0.008225		Akaike info	-6.760778
Sum Squared res.	0.027874		Schwarz crit.	-6.751036
Log likelihood	1397.101		Durbin Watson stat	1.757306

Table 7: Out-of-sample statistics

Forecast Methods	RMSE	MABE
Kalman Filter		
1-month forward	0.00243	0.00220
3-month forward	0.00837	0.00684
6-month forward	0.04228	0.03377
12-month forward	0.02210	0.02042
OLS		
1-month forward	0.04047	0.03285
3-month forward	0.07098	0.05354
6-month forward	0.09924	0.07562
12-month forward	0.10900	0.09489
Random walk	0.04039	0.03284

Appendix A

Table 1A Wald restriction test

Null Hypothesis: $\alpha = 0$ and $\beta = 1$

Equation from which the null hypothesis is based: $Spot = \alpha + \beta Forw1(-1)$

Test Statistic	Value	degree of freedom	Probability
F-Statistics	19.87183	(2, 158)	0.0000
Chi-square	39.74366	2	0.0000

The null hypothesis is rejected at 99% confidence level

Figure 1A Evolution of β_t from the kalman filter estimation of the future spot rate

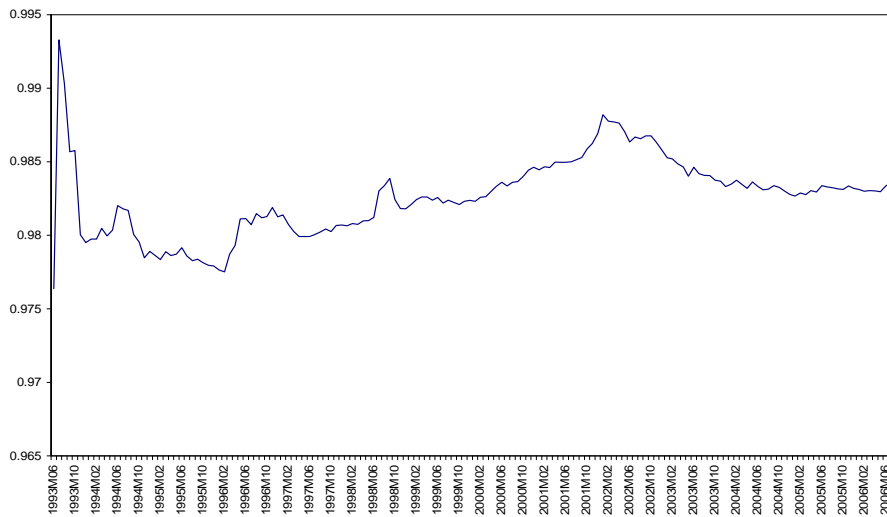


Figure 2A Out-of-sample forecast of the future spot rate: comparison of forecast methods

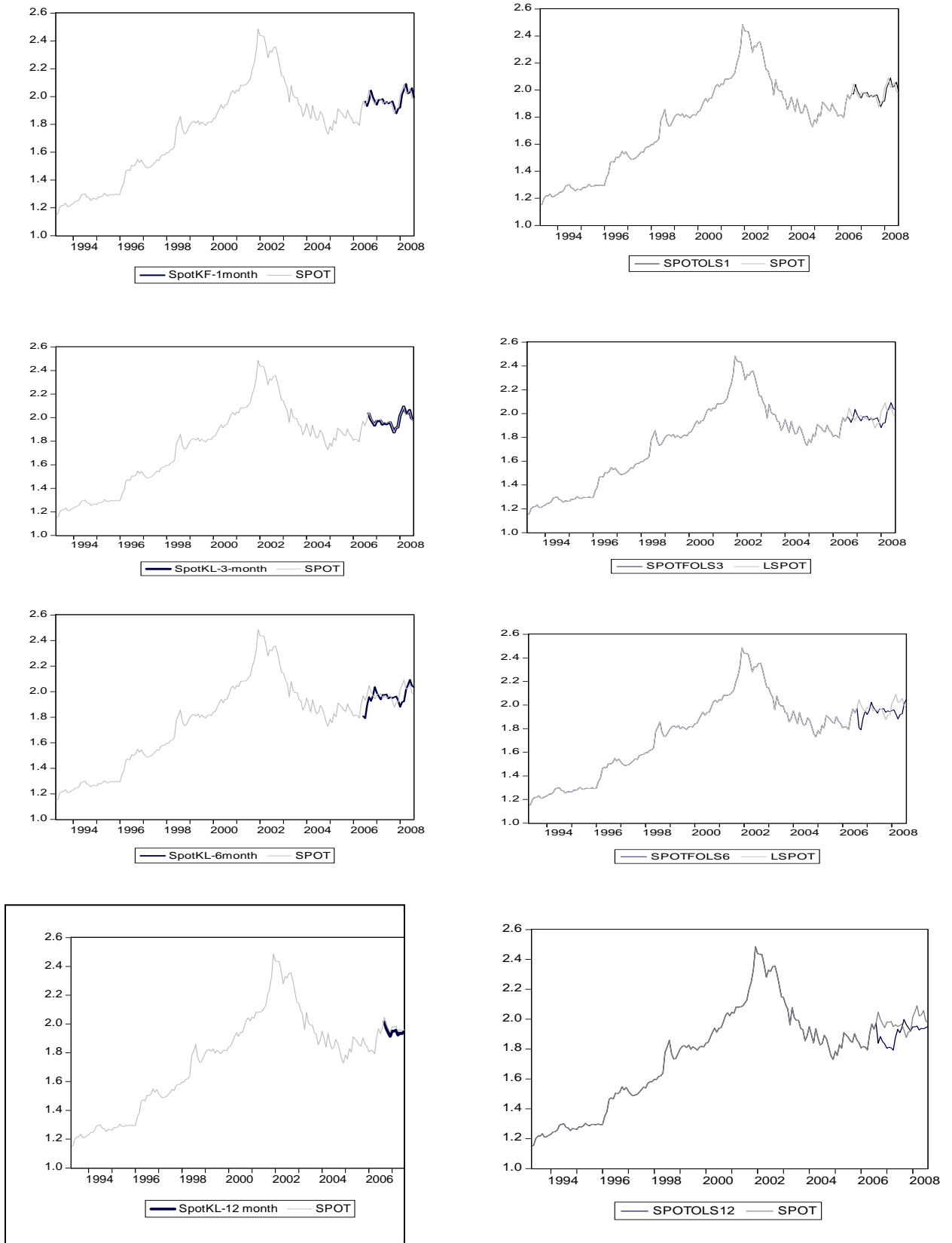
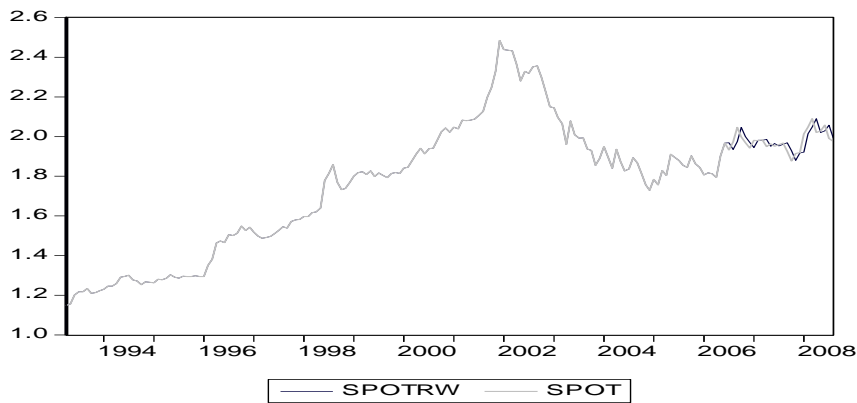


Figure 2A continued:



Note: SPOT is the actual value of the future spot exchange rate. SpotKF-1 month, SpotKL-3 month, SpotKL-6 month and SpotKL-12 month are the out-of-sample forecast of the future spot rates estimated with the Kalman filter method from the 1-month, 3-month, 6-month and 12-month forward rates. SpotOLS1, SpotOLS3, SpotOLS6 and Spot OLS12 are the future spot rates estimated with the OLS method from the 1-month, 3-month, 6-month and 12-month forward rates. SpotRW is the out-of-sample forecast of the future spot rate estimated from the random walk method.