Foreign exchange rate modeling for the Kenyan market:

Half-life model approach

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DECLARATION

I declare that this work has not been previously submitted and approved for the award of a degree by this or any other University. To the best of my knowledge and belief, the Research Project contains no material previously published or written by another person except where due reference is made in the Research Project itself.

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Abstract

This study is a comparative test of the forecasting ability of the half-life purchasing power parity model and the portfolio-hybrid model used for forecasting exchange rates in Kenya. The United States Dollar and Ugandan Shilling exchange rates are analyzed for the period between 2005 and 2015. The models' forecasting precision assessment is based on three statistical tests; First Diebold and Mariano (1995) null test of equal forecasting ability is used to determine the superior half-life model among the three, four and five year half-life durations of which there is none, the root mean squared forecasting error and Thiel's inequality co-efficient tests are finally used between the three year half-life model for the Ugandan Shilling, the five year half-life model for the United States Dollar and the portfolio-hybrid model. The study concludes that the half-life purchasing power parity model is more precise in forecasting the United States Dollar and Ugandan Shilling exchange rates, albeit in sample. The conclusion of the superiority of the half-life model, which is relatively simple to run, requires no prior forecasts of the economic independent variables and is parsimonious, impacts industry players largely affected by movements in exchange rates who require an efficient exchange rate forecasting model such as portfolio managers.

Keywords; half-life purchasing power parity, forecasting precision, portfolio-hybrid model

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List of Abbreviations

RERs	Real Exchange rates
PPP	Purchasing power parity
UIP	Uncovered Interest rate Parity
CBK	Central Bank of Kenya
USD	United States Dollar
SDR	Special Drawing Rights
UGX	Ugandan Shilling
CNY	Chinese Yuan
JPY	Japanese Yen
GBP	Great British Pound
MSE	Mean Squared Error
MSFE	Mean Square Forecasting Error
D-M	Diebold and Mariano test

1 Introduction

1.1 Background to the Study

The Central Bank of Kenya's Monetary Policy Committee and its Research Department has developed an Econometric Model used to provide consistent short-term forecasts of key macroeconomic variables such as exchange rates (Ndungu & Ngugi, 1999). The structural model used in Kenya is based on two theories UIP-Uncovered Interest Parity which states that the difference in interest rates between two countries is equal to the expected change in exchange rates between the countries' currencies and PPP-Purchasing Power Parity which suggests that the relative price of two identical, domestic and foreign, baskets of goods is constant when expressed in a common currency (Jakub, Michal, & Michele, 2013).

The pioneering structural models of the seventies used to forecast exchange rates include Dornbusch-Frankel, Hooper-Morton and Frenkel-Bilson. The economic variables used in these structural models are money supply, foreign real income, interest rate differential and inflation differential. Over the years, these models were often used relative to the Random Walk Model (Meese & Rogoff, 1983).The random walk hypothesis of exchange rates has often been tested over time with varying conclusions, likely to be caused by the fact that different statistical tests are used to examine the random walk theory. The hypothesis is based on the Efficient Market Hypothesis as founded by Fama (1970) and the existence of a random walk in a market confirms that current prices are independent of past prices, and thus the market is efficient (Fama, 1970).

Authors such as Liu and He (1991) in four out of five nominal exchange rates reject the random-walk hypothesis, Ajayi and Karemera (1996) examine the random-walk hypothesis for the currencies of eight economies of the Pacific Basin, and the results show that the random-walk model is not consistent with market dynamics. Chen (2009) examines the random-walk hypothesis for ten Pacific Basin foreign-exchange markets and rejects the Random Walk hypothesis using the Lo-MacKinlay variance ratio tests. However, authors such as Meese and Rogoff (1983) come out strongly with the conclusion that Structural models fail to improve on the random walk model. This general inconclusiveness of the superior foreign exchange rate forecasting model as supported with recent literature by Barbara Rossi (2005) where forecasts that exploit the time variation in the parameters of structural models (a previous shortcoming) are analyzed and find that, in some cases, they can improve over the random walk, creates the need to reanalyze the portfolio-hybrid model as used by the Central Bank of Kenya.

The exchange rate models of the nineties include; the purchasing power parity model, sticky price model, interest rate parity model, productivity differential model and the composite model. These econometric models as studied by Cheung, Chinn and Pascual (2005) are analyzed as being inconsistently successful in terms of superiority in forecasting over its comparatively paired model among those studied, and further unsuccessful over the random walk model over specifically long horizons. The forecast accuracy tests used in their analysis are the mean squared error, standard mean squared error and the co-integration consistency test.

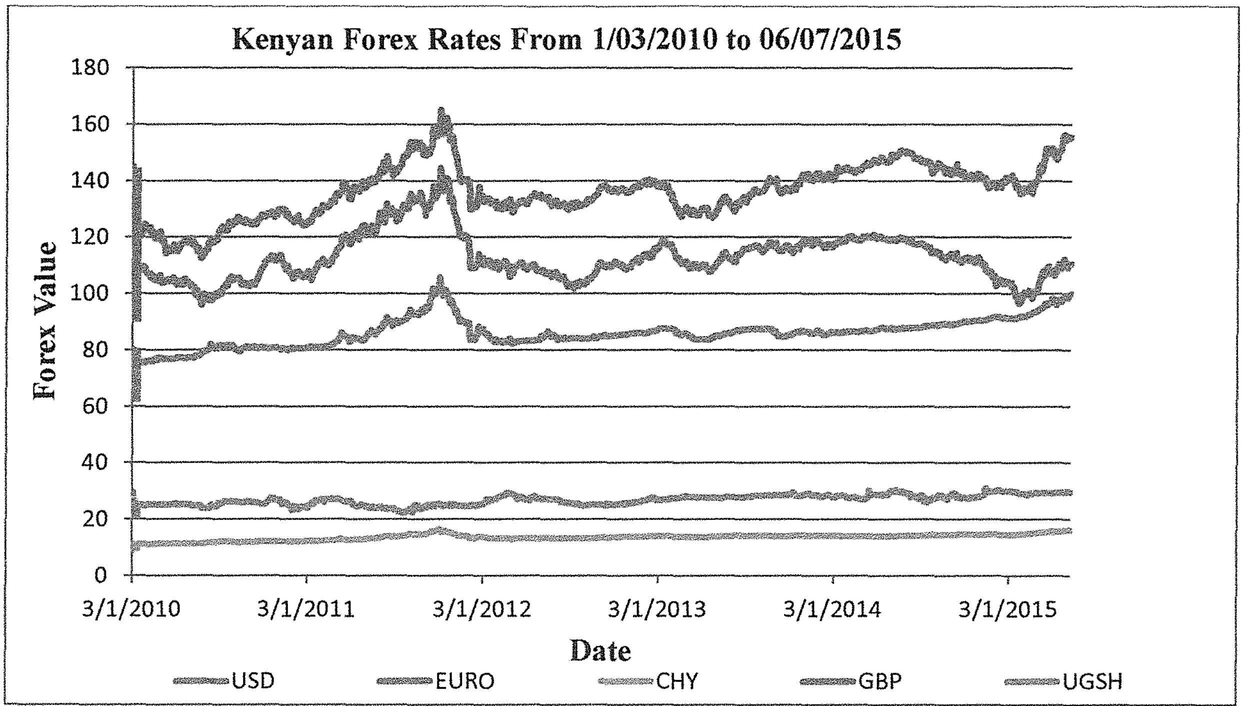
A recent development in the forecasting of exchange rates by Taylor et al (2001) is a mean reverting model of exchange rates based on a pre-estimated half-life calculated through Monte Carlo integration combined with the Purchasing Power Parity theory (Taylor, Peel, & Sarno, 2001).Rogoff (1996) states that consensus estimates of the rate at which Purchasing Power Parity deviations damp suggest a three to five year half-life (Rogoff, 1986). Michele, Michal and Jakub (2013), further establish a Half-Life Purchasing Power Parity Model with a calibrated three to five year half-life to forecast exchange rates. They test the forecast accuracy of this model against the random walk model using the Mean Squared Forecasting Error and correlation co-efficient and conclude that the Half-life Purchasing Power parity model is superior to the random walk.

Kenya's economic growth is vulnerable to external shocks, especially developments in the global economy, regional stability and security, and weather-related supply shocks (KIPPRA, 2013). Export supply, import demand, interest rates and the financial sector are dependent upon the signals they get from the real exchange rate movements (Ndungu & Ngugi, 1999). In addition, studies in Kenya show that there is a strong correlation between exchange rate risk and profitability of oil companies and the airline company as listed in the Nairobi Securities Exchange. Kenya's external debt position is not only affected by debt servicing but also exchange rate revaluations, as such exchange rate modeling becomes essential (CBK, Central Bank of Kenya Annual Report, 2013).As such, foreign exchange rates are a vital macro-economic indicator and a key economic variable to any country and it is in line with this that the need to accurately model foreign exchange rates for Kenya arises.

Recent exchange rate market developments and implications of policy stance on exchange rates, a consequence of the model used, include; September 2011 when the committee observed that inflation, exchange rate and money market volatility continued to pose a challenge to the economy and a tight stance was adopted with the expected impact of the currency appreciating until April 2012 when this tight monetary policy measure continued to yield desired results such that exchange rate stability was sustained (Kamau & Ngugi, 2014).

The Graph below shows the average daily foreign exchange rates for the USD, GBP, EURO, UGSH, and CNY from 2010-2015 from the CBK database. There is a sharp depreciation of the Kenyan currency against all currencies examined below which began in December 2012 and is greatly attributed to the pre-election period speculation and foreign investors aversion.

Graph 1; Average Daily Foreign Exchange Rates For the USD, GBP, EURO, UGSH and CNY from 2010-2015.



1.2 Problem statement

Exchange rate forecasts are necessary to evaluate the foreign denominated cash flows involved in international transactions, which often are settled at a future date. Foreign exchange rate forecasting is important in evaluating the benefits and risks attached to the international business environment. It is however important to note that the use of an appropriate model is of essence in ensuring accuracy in forecasts. The Central Bank of Kenya uses a structural exchange rate model- the monetary/portfolio hybrid model. However, based on the development of exchange rate forecasting literature over the years, structural models have been criticized as lacking in significant precision accuracy over other models such as the random walk model (Meese & Rogoff, 1983). It is in consequence to this that this study seeks to compare the forecasting ability of the portfolio hybrid model used by the Central Bank of Kenya against the Half- life purchasing power parity model as supported by literature.

1.3 Purpose of the study

The purpose of the study is to model the Kenyan exchange rate using the existing portfolio-hybrid model and the half-life purchasing power parity model of Jakub et al (2013).

1.4 Research objective

To compare the forecasting ability of the portfolio hybrid model against the Half-life purchasing power parity model in forecasting exchange rates in Kenya.

1.5 Research questions

Which model, between the portfolio hybrid model and the Half-life purchasing power parity model has higher forecast ability for exchange rates in Kenya?

2 Literature review

2.1 Overview

A variety of exchange rate models have been used in forecasting exchange rates. However, a key question in the mind of many is how accurate are these models and worse still are the models empirically applicable. Rogoff (2001) ends his essay by stating a somewhat discouraging remark with regard to the forecasting ability of structural models that incorporate ex-post data "explaining the yen, dollar and euro exchange rates is still a very difficult task, even ex-post" (Rogoff, The Failure of Empirical Exchange Rate Models:No Longer New but Still True., 2001). Meese and Rogoff (1983) introduce a debate that is a good starting point of exchange rate models analysis. The "Meese-Rogoff result" as is commonly known, says that empirical exchange rate models are no better than random walk models. The path of development of foreign exchange rate models entails 3 major structural models; Dornbusch-Frankel Sticky Price Monetary model (1979), Hooper-Morton Sticky Price Asset model and Frenkel-Bilson Flexible Price Monetary model.

The most prominent exchange rate model of the seventies is the Dornbusch model (Dornbusch, 1976).The model used by Dornbusch makes a number of assumptions that are implausible with the current market as critiqued by Meese and Rogoff (Meese & Rogoff, 1983).One of the strongest factors that disqualify structural models according to Meese and Rogoff (1983) is that structural models require forecasts of their explanatory variables which is tautological in nature. This in turn largely impacts on the forecasting precision or accuracy of structural models. However they offer strong explanatory power rather than predictive power (Meese & Rogoff, 1983, p. 10). Further, Cheung, Chinn and Pascal (2005) assess the empirical exchange rate models of the 1990s.A half-life Purchasing Power Parity model by Jakub, Michal and Michele (2013) suggests that empirical models given certain adjustments are better models for real exchange rates in both the long run and the short run than are random walk models.

According to Pherson and Rakovski (2000) there is some difficulty in determining the impact of exchange rates on economic growth due to the fact that most of the important macroeconomic effects are indirect and as such they conclude that improvements in exchange rate management can make a difference to Kenya's growth prospects but only within the context of a broader program of adjustment and reform (Pherson & Rakovski, 2000). Their results show that there is not a statistically significant direct relationship between exchange rates and economic growth and that the indirect link is through several channels, including money, imports, agricultural production, and foreign aid.

In their report, Pherson and Rakovski (2000) mention that nominal exchange rates is a sensitive policy indicator however, real exchange rates defined as the rate at which goods and services produced at home can be exchanged for those produced in another country or group of countries abroad (Jakub, Michal, & Michele, 2013) are key to growth analysis and as such real exchange rate trends should be monitored. The importance of real exchange rate is clearly brought out by overvalued real exchange rate which represents a persistent misalignment of prices between a particular country and the rest of the world such misalignment according to Pherson and Rakovski (2000) has an impact on the pattern and level of production, the allocation and level of expenditure, the distribution and level of factor payments, the composition and size of trade flows, the levels of international reserves and external debt.

In more extreme cases the overvaluation of real exchange rates causes the emergence of parallel foreign exchange markets, currency substitution and capital flight. Persistent real overvaluation which arises from the foreign exchange rate model adopted by a country also erodes business and consumer confidence, thereby lowering the rate of savings and investment. The outcome is a decline in growth and this might be what the Kenyan shilling is currently experiencing against the dollar (Pherson & Rakovski, 2000).

According to Dimitrova (2005) support is found for the hypothesis that a depreciation of the currency (USD) may depress the stock market such that the stock market will react with a less than one percent decline to a one percent depreciation of the exchange rate and consequently implying that an appreciating exchange rate boosts the stock market (Dimitrova, 2005). Consequently, and with regard to the debate of whether the USA should pursue a policy of strengthening the USD, the negative relationship found suggests that such a policy would also be beneficial for the stock market. However, if the country targets exchange rate appreciation in a time of rising stock prices, the policy could remain ineffective.

Moreover, Dimitrova (2005) mentions that multinational companies interested in exchange rate forecasting may consider the stock market as a forecasting indicator such that when the stock market prices rise, the currency is expected to depreciate. He further finds an interesting implication for portfolio managers, that currency and equity have ambiguous correlation, positive when equity prices are the first to fluctuate and negative when currency prices are shocked first.

Finally, Dimitrova (2005) concludes that this correlation relationship proves to be extremely beneficial in a case of financial crisis. If the exchange rate collapses sharply, it will trigger a milder fall of the stock market. Because of the joint causality, a collapse in the stock market will trigger exchange rate appreciation. Similarly, if there is a stock market collapse, the exchange rate will appreciate and cause a rebound in the stock market. Thus the joint relationship between the two markets aids self-recovery during a financial crisis (Dimitrova, 2005).

2.1 Kenya's current CBK exchange rate model

Kenya's current exchange rate model is derived from an analysis of the Dornbusch-Frankel sticky price model and the portfolio balance models leading to a sticky-price hybrid model known as "monetary/portfolio hybrid model" (Were, Kamau, Sichei, & Kiptui, 2013).It is specified as shown below and where all variables are in natural log.

$$s_{t=}\delta(m_t - m_t^*) + \emptyset(y_{t-}y_t^*) + \alpha(i_t - i_t^*) + \varphi(\pi_t e - \pi_t e^*) + \sigma \int TB + e_t \qquad (1)$$

Where; m_t^* -the foreign money supply

m_t - the domestic money supply

y_t^* - the foreign real income,

y_t -the domestic real income

i_t^* - the foreign interest rate,

i_t - the domestic interest rate

π_t^e -the domestic inflation rate

π_t^{e*} -the foreign inflation rate

$\int TB$ - the cumulative trade balance (in current account terms)

e_t - the error term

Furthermore applied studies in Kenya have also tended to adopt the sticky price monetary model approach by using the UIP specification. For example, Ndung'u (2000) and Ndung'u and Ngugi (1999) use a modified UIP, in which the exchange rate is specified as a function of price differentials and real interest rate differentials. They circumvent the PPP notion by arguing that interest differentials will absorb deviations from PPP. They also argue that the observed domestic interest rate partly reflects monetary policy action. Consequently, the formulation for the exchange rate equation need not include money or domestic output, based on the argument that these correlations are embodied in the price level adjustment mechanism. The equation given above can, therefore, be modified accordingly at the estimation stage.

2.2 Exchange rate models of the seventies

Meese and Rogoff (1983) compare time series and structural models of exchange rates on the out of sample forecasting accuracy basis. Their findings reveal that structural models fail to improve on the random walk model. This is in contrast with prior studies based on in sample fit (Meese & Rogoff, 1983). Forecasts are generated for one month to twelve months horizon for the dollar/pound, dollar/mark, dollar/yen and the trade weighted dollar exchange rates. The structural models analyzed are the Dornbusch-Frankel, Hooper-Morton and Frenkel-Bilson.

These models are analyzed against a random walk with a drift and a constrained vector auto regression composed of the exchange rate and all the explanatory variables from the structural models. The variables in the structural model are money supply, foreign real income, interest rate differential and inflation differential. Out of sample accuracy is measured by three statistics, mean error, mean absolute error and root mean square error. Meese and Rogoff note that the dissatisfying results of structural models may be attributed to sampling error ,misspecification of the money demand function, stochastic movements in the true underlying parameters due to oil shocks or changes in global trade patterns or changes in policy regimes, possible non-linearities in the models, simultaneous equation bias and further that it is possible that empirical models do not "adequately capture expectations or other forces which influence exchange rates" (Meese & Rogoff, 1983).

2.2.1 Analysis of the forecasting ability of the seventies' models

The out of sample accuracy of structural and random walk models is analyzed by Meese and Rogoff (1983) using three statistics, mean error, mean absolute error and root mean square error. With regard to variables such as relative money supplies and relative income differentials, Meese and Rogoff note that the variables are treated as exogenous yet they are more endogenous realistically. This affects the consistency of coefficient estimates obtained. They also note that using freely estimated co-efficients as opposed to a grid of constrained coefficients drawn from theoretical and empirical literature on money supply and purchasing power parity makes no difference to the forecasting results obtained.

Further, Meese and Rogoff conclude that although structural models have predictive power they predict badly because their explanatory variables themselves are difficult to predict. This is because structural models require forecasts of their explanatory variables in order to generate forecasts of the exchange rates (Meese & Rogoff, 1983). They find out that the random walk model has the lowest root mean square error, which was their main criterion, over all horizons and across all exchange rates and consequently unambiguously conclude that the 3 structural models analyzed do not perform significantly better than the random walk model.

2.3 Exchange rate models of the nineties

Cheung, Chinn and Pascal (2005) assess the exchange rate models of the nineties by assessing different dimensions of forecast performance such as mean squared error, consistency test of Cheung and Chinn (1998) and direction of change of five structural models against the random walk (Cheung, Chinn, & Pascual, 2005). The models are purchasing power parity model, sticky-price model, interest rate parity model, productivity differential model and composite model. Model performance is evaluated at forecast horizons of 1, 4 and 20 quarters and in two sample periods (post-Louvre Accord and post-1982).

The five models are compared against the random walk. The behavior of US dollar-based exchange rates of the Canadian dollar, British pound, Deutsche mark and Japanese yen are examined. The models are estimated in two ways: in first-difference and error correction specifications. The error correction specification explicitly allows for the long run interaction effect of the variables (as captured by the error correction term) in generating forecast (Cheung, Chinn, & Pascual, 2005). On the other hand, the first differences model emphasizes the effects of changes in the macro variables on exchange rates. If the variables are cointegrated, then the former specification-error correction is more efficient than the latter one-first difference and is expected to forecast better in long horizons.

The analysis uses quarterly data for the United States, Canada, UK, Japan, Germany, and Switzerland over the 1973 quarter 2 to 2000 quarter 4 periods. ''Rolling regressions'' as established by Meese and Rogoff is used. That is, estimates are applied over a given data sample, out-of-sample forecasts produced, then the sample is moved up, or ''rolled'' forward one observation before the procedure is repeated. This process continues until all the out-of-sample observations are exhausted (Cheung, Chinn, & Pascual, 2005). The procedure has the potential benefit of alleviating parameter instability effects over time, a commonly conceived phenomenon in exchange rate modeling. The difference between the error correction specification forecasts and the first-difference specification forecasts is that in first difference specification, ex post values of the right-hand-side variables are used to generate the predicted exchange rate change while in the error correction, predictions are true ex ante forecasts. Hence the first-difference specification has a tremendous informational advantage in forecasting.

To evaluate the forecasting accuracy of the different structural models, the ratio between the mean squared error (MSE) of the structural models and a drift less random walk is used. A value smaller or larger than one indicates a better performance of the structural model or random walks respectively (Cheung, Chinn, & Pascual, 2005). Inferences are based on a formal test for the null hypothesis of no difference in the accuracy in the MSE of the two competing forecasts. In particular, the authors use the Diebold Mariano statistic (1995) which is defined as the ratio between the sample mean loss differential and an estimate of its standard error; this ratio is asymptotically distributed as a standard normal. The loss differential is defined as the difference between the squared forecast error of the structural models and that of the random walk.

Christoffersen and Diebold (1998) point out that the standard mean squared error criterion indicates no improvement of predictions that take into account co-integrating relationships vis a' vis univariate predictions. Hence, the first alternative evaluation metric for the relative forecast performance of the structural models is the direction of change statistic, which is computed as the number of correct predictions of the direction of change over the total number of predictions. A value above (below) 50% indicates a better (worse) forecasting performance than a naive model that predicts the exchange rate has an equal chance to go up or down. Authors like Leitch and Tanner (1991) also argue that a direction of change criterion may be more relevant for profitability and economic concerns, and hence a more appropriate metric than others based on purely statistical motivations (Leitch, 1991).

The third metric used to evaluate forecast performance is the consistency criterion proposed in Cheung and Chinn (1998). This metric focuses on the time-series properties of the forecast. The forecast of a given spot exchange rate is labeled as consistent if (1) the two series have the same order of integration, (2) they are co integrated, and (3) the co integration vector satisfies the unitary elasticity of expectations condition. This means a forecast is consistent if it moves in tandem with the spot exchange rate in the long run. While the two previous criteria focus on the precision of the forecast, the consistency requirement is concerned with the long-run relative variation between forecasts and actual realization (Cheung, Chinn, & Pascual, 2005).

They observe that it is not obvious which one of the three evaluation criteria is better as they each have a different focus. The MSE is a standard evaluation criterion, the direction of change metric emphasizes the ability to predict directional changes, and the consistency test is concerned about the long-run interactions between forecasts and their realizations. Therefore, their study considered the use of these criteria as complementary and providing a multifaceted picture of the forecast performance of the structural models. However, they note that depending on the purpose of a specific exercise, one may favor one metric over the other (Cheung, Chinn, & Pascual, 2005).

2.3.1 Analysis of the forecast ability results of the nineties models

Comparison of forecasting performance based on MSE ratios is summarized in a Table (Cheung, Chinn, & Pascual, 2005). The table contains MSE ratios and the p-values from five dollar-based currency pairs, five model specifications, the error correction and first-difference specifications, three forecasting horizons, and two forecasting samples of the Diebold Mariano statistic testing the null hypothesis that the difference of the MSEs of the structural and random walk models is zero (i.e. there is no difference in the forecast accuracy of the structural and the random walk model). Of the 216 MSE ratios, 151 are not significant (at the 10% significance level) and 65 are significant. That is, for the majority cases one cannot differentiate the forecasting performance between a structural model and a random walk model. For the 65 significant cases, there are 63 cases in which the random walk model is significantly better than the competing structural models and only two cases in which the opposite is true. The significant cases are quite evenly distributed across the two forecasting periods.

An important observation is that the MSE ratios of the purchasing power parity and interest rate parity models are less than unity (even though not significant) only at the 20-quarter horizon consistent with the perception that these parity conditions work better at long rather than at short horizons (Cheung, Chinn, & Pascual, 2005). Consistent with the existing literature at that time, Chinn and Woung's results are supportive of the assertion that it is very difficult to find forecasts from a structural model that can consistently beat the random walk model using the MSE criterion.

The proportion of forecasts that correctly predict the direction of the dollar exchange rate movement is also assessed. When the proportion statistic is significantly larger than 1/2, the forecast is said to have the ability to predict the direction of change (Cheung, Chinn, & Pascual, 2005). On the other hand, if the statistic is significantly less than 1/2, the forecast tends to give the wrong direction of change exchange rate behavior. There is mixed evidence on the ability of the structural models to correctly predict the direction of change. Among the 216 direction of change statistics, 50 (23) are significantly larger (less) than 1/2 at the 10% level. The results indicate that the structural model forecasts can correctly predict the direction of the change, while the proportion of cases where a random walk outperforms the competing models is only about what it would in a random case. Among the five models under consideration, the purchasing power parity specification has the highest number (18) of forecasts that give the correct direction of change prediction, followed by the sticky-price, composite, and productivity models (10, 9, and 8, respectively), and the interest rate parity model (5).Proportionately, the purchasing power model does the best (Cheung, Chinn, & Pascual, 2005).

An interesting observation that the success of direction of change prediction appears to be currency specific is made. The cases of correct direction prediction appear to cluster at the long forecast horizon. The 20-quarter horizon accounts for 22 of the 50 cases while the 4 and 1 quarter horizons have 18 and 10 direction of change statistics, respectively, that are significantly larger than 1/2. Mirroring the MSE results, it is interesting to note that the direction of change statistic works for the purchasing power parity at the 4 and 20 quarter horizons and for the interest rate parity model only at the 20-quarter horizon. This pattern is entirely consistent with the findings that the two parity conditions hold better at long horizons (Cheung, Chinn, & Pascual, 2005).

The consistency criterion only requires the forecast and actual realization co-move one-to-one in the long run (Cheung, Chinn, & Pascual, 2005). In assessing the consistency, they first test if the forecast and the realization are co-integrated. If they are co-integrated, then they test if the co-integrating vector satisfies the (1, -1) requirement.67 of 216 cases rejects the null hypothesis of no co-integration at the 10% significance level. Thus, 67 forecast series (31% of the total number) are co-integrated with the corresponding spot exchange rates. The error correction specification accounts for 39 of the 67 co-integrated cases and the first-difference specification accounts for the remaining 28 cases.

There is some evidence that the error correction specification gives better forecasting performance than the first-difference specification. Also of interest is that the sticky-price model garners the largest number of co-integrated cases (Cheung, Chinn, & Pascual, 2005). There are 60 forecast series generated under the sticky-price model. Twenty-six of these 60 series (i.e. 43%) are co-integrated with the corresponding spot rates. The composite model has the second highest frequency of co-integrated forecast series. Thirty-seven percent of the productivity differential model forecast series, 33% of the purchasing power parity model, and none of the interest rate parity model are co-integrated with the spot rates.

The condition of long-run unitary elasticity of expectations that is the (1, -1) restriction on the co-integrating vector is rejected by the data quite frequently: 48 of the 67 co-integration cases (Cheung, Chinn, & Pascual, 2005). The fact that outperformance of the random walk benchmark occurs at the long horizons is consistent with other recent work. However, the basic conclusion that no specific economic model is consistently more successful than the others remains intact.

2.3.2 Weaknesses in the analysis of the nineties' forex models

In using fairly long out-of-sample periods they have given maximum advantage to the random walk characterization. Further, Cheung, Chinn and Pascal (2005) have only evaluated linear models, eschewing functional nonlinearities and regime switching. The study has certain boundaries with respect to models and specifications which include; not employing panel regression techniques in conjunction with long-run relationships, despite the fact that the recent evidence at that time suggested the potential usefulness of such approaches (Cheung, Chinn, & Pascual, 2005).

Further, they did not undertake systems-based estimation that was found in certain circumstances to yield superior forecast performance, even at short horizons for example in MacDonald and Marsh (1997) (MacDonald & Marsh, 1997). However, they noted that such a methodology would have proven much too cumbersome to implement in the cross-currency recursive framework employed in their study. The results do not point to any given model or specification combination as being very successful. However, some models seem to do well predictively at certain horizons, for certain criteria and for a particular exchange rate pair and not for another (Cheung, Chinn, & Pascual, 2005).

Based on their analysis catastrophic failures in prediction performance are distributed across the various structural models estimated in first differences, so (taking into account the fact that these predictions utilize ex post realizations of the right-hand-side variables) the key determinant in this pattern of results appears to be the difficulty in estimating stable short-run dynamics. Finally because it is not easy to determine unambiguously whether the variables are co integrated or not, both first difference and error specifications are considered in forecasting.

2.4 Half-life PPP model

A new perceptive that changes the direction of prior research spear headed by Rogoff(1983) ,that random walk models are superior to empirical models with regard to short run exchange rate modeling, is introduced by Michele ,Michal and Jakub (2013) though with regard to real rather than nominal exchange rates .Where they bring out three new insights into the Purchasing Power Parity debate these are ; a half-life PPP model (an empirical model) is able to forecast real exchange rates (RER) better than the random walk (RW) model at both short and long-term horizons.

For their result to hold the speed of adjustment to the sample mean is calibrated rather than estimated with a half-life of 3 or 5 years (Jakub, Michal, & Michele, 2013).Half-life PPP implicitly assumes that Real Exchange Rates are mean reverting and hence predictable. The paper assesses the predictability of RERs using monthly data for nine major currencies of the following countries: Australia (AUD), Canada (CAD), Euro area (EUR), Japan (JPY), Mexico (MXN), New Zealand (NZD), Switzerland (CHF), the United Kingdom (GBP) and the United States (USD) for the period between 1975:1 and 2012:3.

The out-of-sample forecast performance using rolling regressions for a 15 year window period is analyzed for horizons ranging from one up to sixty months ahead (Jakub, Michal, & Michele, 2013). The first set of forecasts is elaborated with the rolling sample 1975:1-1989:12 for the period 1990:1-1994:12.They then comparatively measure the forecasting performance of half-life models and Auto regressive models with two standard statistics: the mean squared forecast errors (MSFEs) and the correlation coefficient between forecast and realized RER changes.

2.4.1 Analysis of the forecast ability results of the PPP half-life model

The results of the two tests, mean squared forecasting errors and correlation co-efficient suggest that RERs of major currencies are mean reverting and forecast able, however the estimated Auto Regressive model performs poorly (Jakub, Michal, & Michele, 2013). They also perform sensitivity analysis to test the validity of the results by varying the rolling window period, using other currencies and by eliciting a prior on the half-life parameter.

2.5 Conclusion

In conclusion, the studies above have used different statistical tests as criteria to determine the forecasting ability of the different models. Conclusions for the 1970's model analysis were drawn from the Root Mean Square Test, Mean Error and the Mean Absolute Error (Meese & Rogoff, 1983). The Root Mean Square Error criteria, being the main criteria concludes that the random walk and the Structural model have rather equal forecasting ability. The 1990's model analysis uses three criteria to determine the forecasting ability these are; direction of change test, Mean Square Error and the consistency test. The overall conclusion based on the results is that none of the models is superior. The 2013 Half-life Purchasing Power Parity model uses two criteria the correlation co-efficient and the Mean Square Forecasting Error, with both criteria concluding that the Half-life PPP is superior to the random walk (Jakub, Michal, & Michele, 2013).

The random walk hypothesis of exchange rates was studied on a developing country's exchange rate, that is the Zambian Kwacha against the dollar where conclusions were drawn that the forex rate was not a random walk and consequently technical analysis for policymakers and fund managers was advised; which is in support of structural models of forex rates (Auret, Chiliba, & Mbululu, 2013).The inconclusiveness of whether the random walk model improves on the structural models seems to cut across most literature with the exception of the recently developed Half-life PPP. The non-unanimous result is further supported by Mark and Choi (1997) in their analysis of real exchange rates over long horizons (Mark & Choi, 1997). Furthermore, Engel et al (2010) find results that lead to the conclusion that a factor model which is essentially a structural model makes no improvement on forecasting relative to the random walk (Engel, Mark, & West, 2010).

3 Methodology

3.1 Introduction

In light of the conclusions from the literature review, it is of essence to note that no one size model fits all such that different models seem to work best for different currencies, different forecast horizons and that forecast results may be sensitive to the particular out of sample period chosen and also to the statistical criteria used to test forecasting ability.

The study analyzes the forecasting ability and precision of two models the portfolio-hybrid model against the half-life PPP Model. The tests used to determine forecasting precision are; Diebold and Mariano test (1995) which is used to determine the most suitable mean reverting rate among the three, four and five year half-life basis, the ratio of the Mean Squared Forecasting Error and Theils' co-efficient upon which conclusions are drawn as to the forecasting ability superiority of the two models.

Data is analyzed over a ten year period pegged on availability and a back test carried out to determine out of sample forecasting accuracy. Rolling regressions as advocated for by Richard and Meese (1983) is also carried out. Sensitivity analysis is also conducted to analyze the impact of changing variables or time spans and to test for the consistency of overall results. Prior to running the regression and model fitting, data is restructured through differencing or the use of logs to avoid non-stationary data that may result in spurious regressions. A stationary series is defined as that which has a constant mean, variance and auto covariance (Brooks, 2008).

3.2 Research design

The study has an exploratory research design as it describes the model used for foreign exchange rates and its forecasting ability.

3.3 Sampling design

The study adopts a non-probabilistic purposive sampling design where the amount of data on the selected model's variables such as interest rate differentials, is left to my discretion. This is in line with the definition of purposive sampling Kothari (2004) where the researcher purposefully chooses the particular units of the population that form the sample on the basis that the small mass that they select will represent the whole population.

3.4 Data collection

Data used is secondary. Data is obtained from The Central Bank of Kenya, Bank of Uganda the National Bureau of Statistics, Index mundi and The United States Federal Reserve databases.

3.5 Choice of currency and period of study

The currencies that will be used in this study are based on the level of trade relations with Kenya as per Table 5. Accordingly, the USD $, GBP £, EUR €, JPY, UGSH are identified as Kenya's key trading partner currencies (CBK, Central Bank of Kenya Annual Report, 2013). Further, based on Kenya's External public debt portfolio exposure, the USD and EUR are currencies of interest. The Asian region as a dominant trading partner accounted for 50.8% of total trade in 2013, with leading countries being China, India, Indonesia and Japan (CBK, Central Bank of Kenya Annual Report, 2013).Furthermore, due to Kenya's increased relations with China the Chinese yuan CNY ¥ would have been included in this study. However, due to time series property similarities of the GBP, EURO and CHY as identified in Graph 1, this study will narrow down to the modelling of the USD and UGSH.

3.6 Data analysis

3.6.1 The Kenyan model

The Kenyan forex rate model is essentially derived from three models the sticky price monetary model, the flexible price monetary model and the portfolio balance models (Were, Kamau, Sichei, & Kiptui, 2013).In the sticky price model, the nominal output prices are assumed to be sticky—that is, they adjust slowly over time such that the asset markets clear continuously in response to new information or changes in expectations. The model thus adopts the principle of Uncovered Interest Parity;

$$s_{t=}\delta(\mathrm{m}-m^{*})+\emptyset(y-y^{*})+\alpha(\mathrm{r}-r^{*})+\beta(\pi-\pi^{t})+u \qquad (2)$$

The assumptions in the sticky price monetary model include; there is perfect capital mobility and substitutability between home and foreign bonds. The domestic economy is small for the rest of the world; with the assumption that the foreign interest rate is exogenous. The flexible price model is where the nominal exchange rate is expressed in terms of current relative money supplies and factors affecting money demands only. The model is specified as;

$$s_{t=}\delta(m_t - m_t^*) + \emptyset(y_{t-}y_t^*) + \gamma(i_t - i_t^*) \quad (3)$$

The final model is the portfolio balance model that regards the exchange rate as the relative price of nominal assets. The portfolio balance approach focuses on the link between the balance of payments and adjustments in asset stocks. These emerged in the late 1960s.Further, based on early drafts by Meese and Rogoff (1983a, 1983b), a specification incorporating cumulative trade account balances became widely adapted. For Hooper and Morton (1982), the cumulative current account (adjusted for cumulative official intervention flows) appears as a risk premium term, and changes in the expected long-run real exchange rate are captured by including a measure of the non-transitory unexpected change in the current account unlike in Meese and Rogoff (1983a, 1993b) where the cumulative trade balance or current account terms are interpreted as variables that allowed for changes in the long-run real exchange rate.

Meese's interpretation is supported by the view that cumulative current account imbalances redistribute wealth internationally, with effects on a country's levels of expenditures, incomes, and current account imbalances, and consequently with implications for the level of the real exchange rate that are consistent with the long-run current account balance (Were, Kamau, Sichei, & Kiptui, 2013).

The analysis of the three models leads to a combination of the monetary/portfolio hybrid model also called a sticky-price hybrid model with variables borrowed from all three models which is specified as;

$$s_{t=}\delta(m_t - m_t^*) + \emptyset(y_{t-}y_t^*) + \alpha(i_t - i_t^*) + \varphi(\pi_t^e - \pi_t^{e*}) + \sigma \int TB + e_t \quad (4)$$

Where; S- exchange rate expressed in units of home currency per foreign currency

m_t^* -the foreign money supply

m_t - the domestic money supply

y_t^* - the foreign real income

y_t -the domestic real income

i_t^* - the foreign interest rate

i_t - the domestic interest rate

π_t^e -the domestic inflation rate

π_t^{e*} -the foreign inflation rate

$\int TB$ - the cumulative trade balance (in current account terms)

e_t - the error term

All variables are in natural log.

3.6.2 Half-life purchasing power parity model

The half -life purchasing power parity model is based on the PPP assumption, imposing a speed of adjustment to PPP, which implies that half of the adjustment is completed in 3 or 5 years. This calibration is consistent with the findings of the exchange rate literature on the "PPP puzzle" (Obstfeld & Rogoff, 2001). The "PPP puzzle" literature estimates the speed of mean-reversion of RERs and generally concludes that it takes between 3 and 5 years to halve PPP deviations.

An implicit assumption is made that RERs are mean reverting and hence predictable (Jakub, Michal, & Michele, 2013).Further supported by an analysis of studies on real exchange rate mean reversion of developing countries by Edwards and Savastano (1998) (Edwards & Savastano, 1998).The purchasing power parity assumption used by Jakub et al (2013) is defined in an equation as;

$$y_t = s_t + p_t - p^{t*} \tag{5}$$

Where y_t is the log real exchange rate, s_t is the log nominal exchange rate expressed as the foreign currency price per unit of domestic currency, p_t is the log home price level and p^{t*} is the foreign price level, derived from the monthly Consumer Price Index. Borrowing from Obstfeld and Rogoff (2001) the half-life duration below is as used to estimate the mean reverting rate ρ by Jakub et al (2013) (Obstfeld & Rogoff, 2001).

$$\text{HL}=\frac{\log(0.5)}{\log(\rho)}=3 \text{ to } 5 \text{ years} \tag{6}$$

Building the half-life PPP Model entails specifying a Data Generating Process (DGP) .The DGP used below is assumed to be autoregressive as is in Jakub et al (2013).

$$(y_t - \mu) = \rho(y_{t-h} - \mu) + \varepsilon_t \tag{7}$$

ρ is the speed of reversion to μ ,n is the varying lag duration and ε_t~N(0,σ^2)

The three-year half-life (HL3) and five-year half-life (HL5) models as derived from the Data Generating process above is specified as below;

$$y_{T+h|T}^{HL} = \bar{\mu} + \bar{\rho}(y_T - \bar{\mu}) \tag{8}$$

$\bar{\rho}$ is consistent with the half-life duration of three to five years.

3.6.3 Forecast accuracy test

The Mean Square Forecast Error is a forecast performance indicator that measures the size of forecast deviation from actual values, the lower the statistic the more accurate the forecast is. This will be determined in the statistical software e-views used.

$$\text{MSFE} = \sum_{S=0}^{N_{k-1}} \frac{\{F(t+s+k) - A(t+s+k)\}^2}{N_k} \tag{9}$$

Where; k = h step forward forecasts ranging from 1 month to 36 months.

N_k is the total number of forecasts in projection

A_t is the actual values

F_t is the forecast value

The Diebold Mariano statistic tests the null hypothesis of no difference in the forecast accuracy (as measured by MSEs) of the three year half-life PPP and the four or five year half-life PPP Model (Cheung, Chinn, & Pascual, 2005). Given the exchange rate series X_t and the forecast series Y_t and Z_t from the two comparative half-life models under study, the loss function L for the mean square error is defined as:

$$L(Y_t) = (Y_t - X_t)^2$$

Testing whether the performance of the forecast series from the 3 year half-life PPP Model (Y_t) is different from that of the four or five year half-life PPP Model forecast (Z_t), is equivalent to testing whether the population mean of the loss differential series d_t is zero. The loss differential is defined as;

$$d_t = L(Y_t) - L(Z_t) \tag{11}$$

Under the assumptions of covariance stationarity and short-memory for d_t, the large-sample statistic for the null of equal forecast performance is distributed as a standard normal, and can be expressed as;

$$\bar{d}\left\{2\pi \sum_{\tau=-(T-1)}^{T-1} l\left(\frac{\tau}{S(T)}\right) \sum_{t=|\tau|+1}^{T}\left(d_t - \bar{d}\right)\left(d_{t-|\tau|} - \bar{d}\right)\right\}^{-1/2} \tag{12}$$

Where; $l\left(\frac{\tau}{S(T)}\right)$ is the lag window

S (T) is the truncation lag

T is the number of observations

Another test of relative forecasting accuracy that is used is Theil's inequality coefficient U, estimated as,

$$U = \frac{\left[\frac{1}{n}\sum_{i=1}^{n}(A_i - P_i)^2\right]^{1/2}}{\left[\frac{1}{n}\sum_{i=1}^{n} A_i^2\right]^{1/2} + \left[\frac{1}{n}\sum_{i=1}^{n} P_i^2\right]^{1/2}}$$

Where; A_i is the first model's forecast value

P_i is the second model's forecast value

The Theil coefficient is scale invariant and it lies between zero and one. If the Theil coefficient equals zero then we have a perfect fit and there exists no superior model between the two models under comparison.

4 Findings

4.1 Analysis of forecast results

The Half-life PPP model's in-sample forecasts are based on 10 years monthly data from January 2005 to June 2015 simulated into a five-day week daily data. The model assumes a three year half-life, four year half-life and a five year half-life separately and in turn computes a mean reverting rate ρ=0.7937, ρ=0.840896 and ρ= 0.8706 respectively.

Table 1:Forecasting statistics results

Forecast Results			
Half-life PPP Model			
USD			
Variable	Co-efficient	Standard error	T-statistic
Mean	1.0002	0.0000	14855.7900
Reversion-rate	1.2552	0.0015	840.2424
UGX			
Mean	1.0002	0.0000	27430.4900
Reversion-rate	1.2563	0.0017	732.9050
Portfolio-Hybrid Model			
USD			
Interest rate	0.3422	0.0041	82.8202
M2	-0.1581	0.0078	-20.3953
Inflation	0.0000	0.0000	-1.5290
Trade Balances	-0.2183	0.0059	-37.0953

GDP	-0.1214	0.0038	-31.8900
UGX*			
M2	0.1800	0.0025	71.3171
Inflation	-0.0266	0.0012	-21.7498
Trade Balances	0.0095	0.0035	2.7655
GDP	1.2108	0.0023	536.2040

*The UGX Portfolio-hybrid Model excluded one variable the interest rate differential which was (statistically insignificant to the results obtained) due to perfect collinearity.

The variable log of the real USD and UGX exchange rate is Y_T and Z_T respectively, of which the descriptive statistics displays stationarity, consequently spurious results are avoided. The forecasts are based on a five day lag, which based on the sensitivity analysis resulted in better forecasts than a longer lag period. The statistics of the forecasted values for the USD and UGX are as represented in the table of results Table 1 above. The signs of the co-efficients are consistent with hypothesized literature apart from the inflation rate deemed to be positive (CBK, Central Bank of Kenya Annual Report, 2013).

The forecasts above are based on the three year half-life period that represents a mean reverting rate of ρ=0.7937.Varying the mean reversion rate based on a four year and a five year period yielded similar values for the root mean squared error- the object of our analysis that is a measure of forecast accuracy, as represented in Appendix 2 to 7 for the USD and similar graphs not shown were obtained for the Ugandan shilling. Varying the lag period (h) of the regressor variable Y_{T-h} and Z_{T-h} and simultaneously combining it with different mean reversion rates produced results shown in the matrix Table 2 below, indicating that the forecasting accuracy does not vary with the half-life period used.

However, as the lag period becomes bigger from daily to weekly to monthly and yearly lag ,the model seems to worsen off as the root mean squared error increases regardless of the half-life period used, up to a certain point where the error reduces, up to a 1 year lag for the USD and a 3 year lag for UGX. This indicates that the half-life purchasing power parity model best predicts the USD and the UGX in the long-term, consistent with the findings of Jakub et al (2013) and Dimitrova (2005) where long term exchange rates are easier to forecast.

Table 2:Root Mean squared forecasting results

	Root Mean Square Forecasting Error					
Currency	**USD**	**UGX**	**USD**	**UGX**	**USD**	**UGX**
Lag h (days)	**3**	**3**	**4**	**4**	**5**	**5**
1	0.0015	0.0013	0.0015	0.0013	0.0015	0.0013
5	0.0074	0.0063	0.0737	0.0063	0.0737	0.0063
20	0.0262	0.0225	0.0262	0.0225	0.0262	0.0225
240	0.0816	0.0520	0.0816	0.0520	0.0816	0.0520
720	0.0523	0.0569	0.0523	0.0569	0.0523	0.0569
960	0.0316	0.0504	0.0316	0.0504	0.0316	0.0504
1200	0.0186	0.0429	0.0186	0.0429	0.0186	0.0429

Further, the Diebold and Mariano (1995) null test of equivalent forecasting accuracy between two models is used to compare the forecasting accuracy between the three variations of the half-life model by varying the half-life duration. The comparative test statistic is summarized in Table 3 below. The null hypothesis of equal forecasting ability between the three year and four-year half-life model is rejected at the 5% confidence level since the Diebold and Mariano statistic is greater than 1.96 meaning that the first model with a three year half-life for the USD is better than the second model with either a four or five year half-life, which is statistically significant given the p-value. Similarly, the null hypothesis between the three year and either four or five year half-life is rejected for the UGX since the Diebold and Mariano statistic is less than 1.96, meaning that the three year half-life model best predicts the UGX.

Table 3:Diebold and Mariano test statistic

Diebold and Mariano Test Statistic				
	USD		UGX	
	|DM|	P-value	|DM|	P-value
3 Vs 4*	43.2678	0.0000	17.0448	0.0000
4 Vs 5*	43.2678	0.0000	16.0089	0.0000
3*Vs 5	0.4620	0.6441	16.3386	0.0000

*These values represent the assumed half-life duration between three to four years.

The portfolio hybrid model in-sample forecasts are based on 10 years monthly data from January 2005 to June 2014 simulated and intrapolated into a five- day week daily data. The forecasted values for the USD and UGX respectively based on the Ordinary Least Square method which gives similar root mean squared error as with the Limited Maximum Likelihood method, are as represented in Graph 6.

5 Conclusions and Recommendations

5.1 Comparison of Forecasting Ability Results

The study focuses on three measures of forecasting accuracy/precision the Root Mean Squared Forecasting Error, the Diebold and Mariano (1995) null test of equivalent forecasting accuracy between two models and Theil's Inequality coefficient. The ratio of the root mean squared forecasting error between the two models is computed, with a value less than 1 depicting that the portfolio-hybrid model has higher forecasting accuracy than the half-life PPP model and values greater than 1 show that the portfolio hybrid model has a lower forecasting accuracy than the half-life purchasing power parity model.

From the table below the half-life purchasing power parity model seems to have more accurate forecasts relative to the portfolio-hybrid model. Theil's inequality coefficient is not perfectly zero for both the USD and UGX indicating that one of the models is more superior. Consequently, the half-life PPP model seems to have more accurate forecasts relative to the portfolio-hybrid model with relative root squared mean forecast errors being greater than 1 for both the USD and UGX.

Table 4: Comparative Test Results

Portfolio hybrid model Vs PPP half-life model		
Currency	**USD**	**UGX**
Relative Root Mean Square Forecasting Error	40.0403*	26.3525*
Theil Inequality coefficient(U)	0.0175	0.0123

*The values represent the ratio of the mean squared forecast error of the portfolio-hybrid model to the Half-life PPP model as a percentage.

5.2 Areas for further Study

The above analysis is based on largely simulated and interpolated data of some variables due to the mismatch in frequencies of recorded data, which may have altered the forecasting accuracy of the models. The parameters as estimated in the portfolio hybrid model may be biased due to the use of the same set of data for estimation and for model selection.

A key aspect to note about the study is that models can dominate each other on different measures, or superiority may alter with forecast horizons or the choice of variables. Consequently, this study's conclusion is based on the three measures of forecasting accuracy used and should be considered as such. Further, an out of sample analysis of both models would also make for better empirical results that would reveal the empirical impact and the extent to which the exchange rate models can be used in industry (Meese & Rogoff, 1983).

The mean reverting rate for the Half-life PPP Model is assumed to be continuous and of a constant speed regardless of the size of deviation from the PPP, yet the presence of transaction costs imply a non-linear process of the movement of exchange rates. Therefore, a Smooth Transition Autoregressive Model that allows for the rate of adjustment to vary with the extent of deviation from the parity assumption would be more suitable (Taylor, Peel, & Sarno, 2001).

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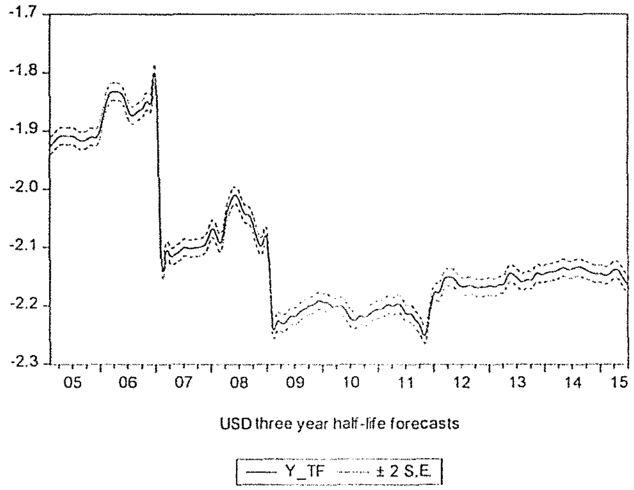
7 Appendices

Appendix 1 Kenya's exports and imports: Main destination countries (US$ millions as %) **(CBK, Central Bank of Kenya Annual Report, 2013)**

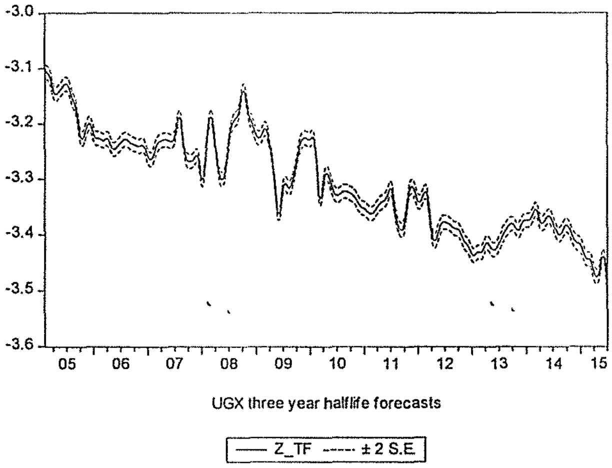
Share of Exports by %				**Share of Imports by %**			
Destination Country	**2010/2011**	**2011/2012**	**2012/2013**	**Destination Country**	**2010/2011**	**2011/2012**	**2012/2013**
Uganda	14.7	13.8	13	South Africa	5.9	4.9	4.4
Tanzania	8	8.8	8.3	Egypt	1.7	1.7	2.1
Egypt	4.1	4.5	3.9	Others	4.1	4.4	3.5
Sudan	4.7	2.8	1.1	Total Africa	11.7	11	10
Somalia	2.8	4	3.5	India	11.7	11.5	15.8
DRC	3.2	3.5	3.7	United Arab Emirates	13.2	13.6	10.4
Rwanda	2.6	2.8	3	China	12.2	11.5	11.9
Others	7.3	8.6	10.5	Japan	5.2	4.4	5.3
Total Africa	47.3	48.9	46	USA	3.6	4.3	4.5
United Kingdom	9.2	8.2	7.8	United Kingdom	4.6	3.2	3.5
Netherlands	6.6	6.1	6.1	Singapore	4.1	0.7	1.4
USA	5.6	5	5.4	Germany	2.6	2.7	2.8
Pakistan	4.2	4.2	4.7	Saudi Arabia	2.6	5.6	3.4
United Arab Emirates	4.1	4.2	6	Indonesia	2.9	4.3	3.3
Germany	1.6	1.8	1.7	Netherlands	1.8	1.4	1.4
India	1.8	1.8	1.6	France	1.8	1.7	1.7
Afghanistan	2.7	2.3	2.8	Bahrain	0.6	1.4	2.8
Others	16.9	17.5	16.9	Italy	1	1.2	1.5
				Others	20.4	21.4	20.4
Total Exports	100	100	100	Total Imports	100	100	100

Appendix 2: Three Year half-life forecasts(USD)



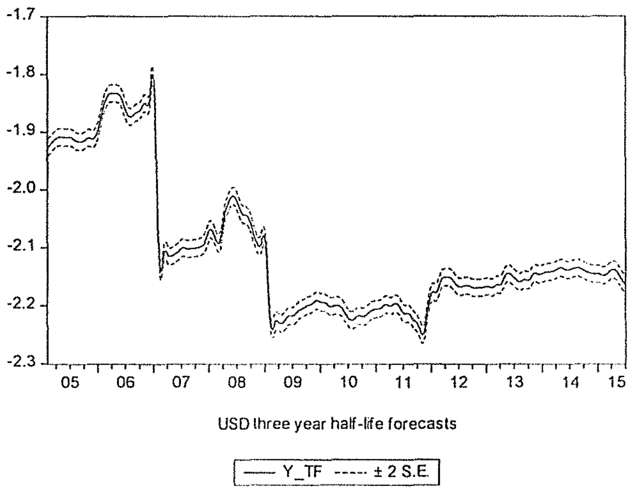
Forecast: Y_TF
Actual: Y_T
Forecast sample: 1/03/2005 6/30/2015
Adjusted sample: 2/07/2005 6/30/2015
Included observations: 2712
Root Mean Squared Error 0.007371
Mean Absolute Error 0.002918
Mean Abs. Percent Error 0.142121
Theil Inequality Coefficient 0.001749
Bias Proportion 0.000000
Variance Proportion 0.000958
Covariance Proportion 0.999042

Appendix 3: Three year half-life forecasts(UGX)



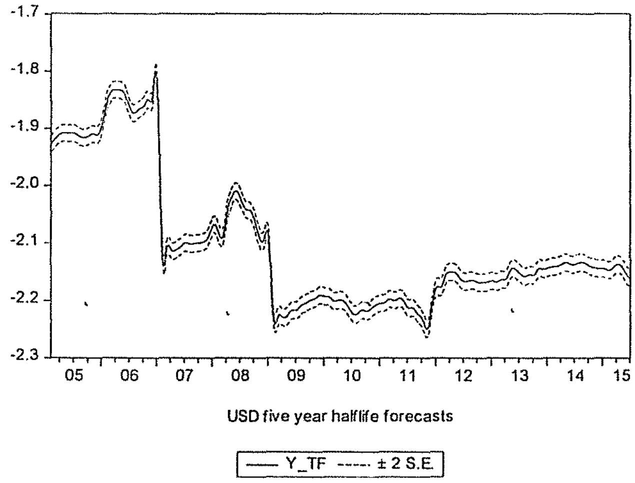
Forecast: Z_TF	
Actual: Z_T	
Forecast sample: 1/03/2005 6/30/2015	
Adjusted sample: 2/07/2005 6/30/2015	
Included observations: 2712	
Root Mean Squared Error	0.006273
Mean Absolute Error	0.004449
Mean Abs. Percent Error	0.135084
Theil Inequality Coefficient	0.000949
Bias Proportion	0.000000
Variance Proportion	0.001258
Covariance Proportion	0.998742

Appendix 4: Three year half-life forecasts(USD)



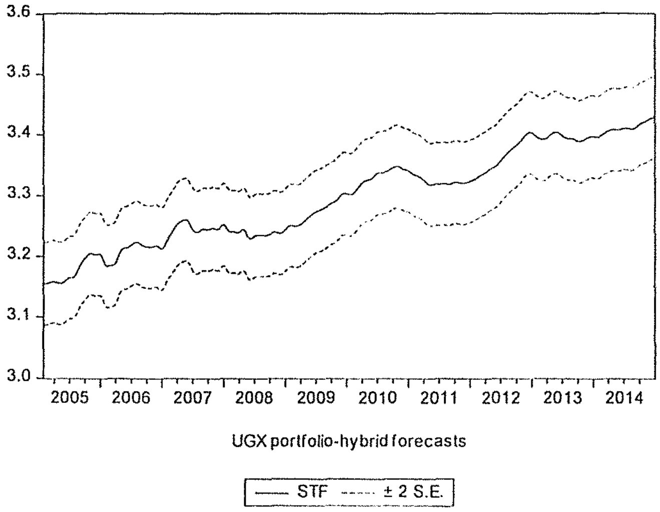
Forecast: Y_TF	
Actual: Y_T	
Forecast sample: 1/03/2005 6/30/2015	
Adjusted sample: 2/07/2005 6/30/2015	
Included observations: 2712	
Root Mean Squared Error	0.007371
Mean Absolute Error	0.002918
Mean Abs. Percent Error	0.142121
Theil Inequality Coefficient	0.001749
Bias Proportion	0.000000
Variance Proportion	0.000958
Covariance Proportion	0.999042

Appendix 5: Five-year half-life forecasts(USD)



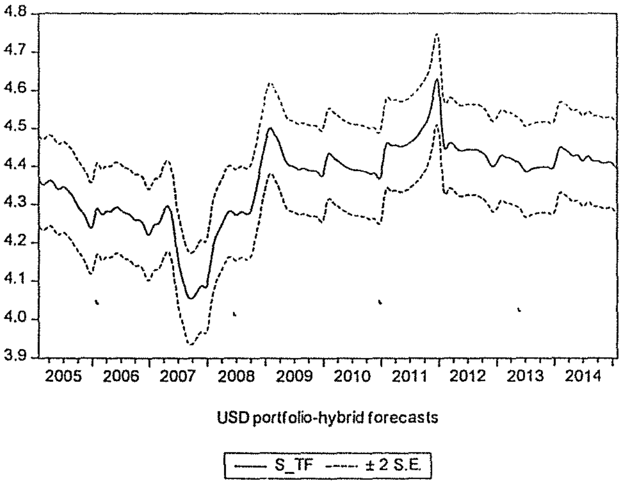
Forecast: Y_TF	
Actual: Y_T	
Forecast sample: 1/03/2005 6/30/2015	
Adjusted sample: 2/07/2005 6/30/2015	
Included observations: 2712	
Root Mean Squared Error	0.007371
Mean Absolute Error	0.002918
Mean Abs. Percent Error	0.142121
Theil Inequality Coefficient	0.001749
Bias Proportion	0.000000
Variance Proportion	0.000958
Covariance Proportion	0.999042

Appendix 6: Portfolio-hybrid forecasts(UGX)



Forecast: STF	
Actual: ST	
Forecast sample: 1/03/2005 12/30/2014	
Adjusted sample: 1/31/2005 12/30/2014	
Included observations: 2587	
Root Mean Squared Error	0.033886
Mean Absolute Error	0.027770
Mean Abs. Percent Error	0.845788
Theil Inequality Coefficient	0.005137
Bias Proportion	0.000000
Variance Proportion	0.044095
Covariance Proportion	0.955905

Appendix 7: Portfolio-hybrid forecasts(USD)



USD portfolio-hybrid forecasts

Forecast: S_TF	
Actual: S_T	
Forecast sample: 1/03/2005 1/30/2015	
Adjusted sample: 1/31/2005 1/30/2015	
Included observations: 2610	
Root Mean Squared Error	0.059540
Mean Absolute Error	0.046395
Mean Abs. Percent Error	1.067762
Theil Inequality Coefficient	0.006823
Bias Proportion	0.000053
Variance Proportion	0.000409
Covariance Proportion	0.999537