Faculty of Commerce

School of Economics

Honours Thesis 2021

Forecasting the South African Exchange Rate Using Fundamental Methods

Hermanus Bernardus Swart — University of Cape Town

Student Number: SWRHER002

Supervisor: Dr. Kevin Kotze

29 October 2021

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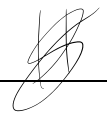
Signature:	
Date:	29 October 2021
Word Count:	7913

ABSTRACT

The objective of this paper is to analyse whether the fundamental methods of determining exchange rates, namely the Uncovered Interest Rate Parity (UIRP), Covered Interest Rate Parity (CIRP), Purchase Power Parity (PPP) and Monetary Approach (MA), are superior in forecasting the USDZAR exchange rate relative to a random walk. This paper concludes that the UIRP, CIRP and PPP models are not statistically more accurate in forecasting the USDZAR exchange rate relative to the random walk at a monthly frequency. Additionally, this paper concludes that the MA model is in fact superior in forecasting the USDZAR exchange rate relative to a random walk at a quarterly frequency. This paper uses a sampling period from January 2000 until August 2021. The out-of-sample forecast horizon used within this paper is a one-step-ahead (h=1) forecast, with the forecasting sample period spanning from January 2016 to August 2021.

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1.) Introduction

The exchange rate is a crucial element in any country's macroeconomic management policy due to the exchange rate determining the price of domestic goods and services in terms of a particular foreign currency. This is crucially important information, as both individuals and governments are generally interested in the price of a foreign good or service specified in their domestic currency. Additionally, the foreign exchange rate outlines the competitiveness of the exported goods and services of a domestic country in relation to other countries.

The above-mentioned features consequently make it desirable to accurately and effectively characterise the behaviour of exchange rates. The ability to accurately forecast the price of a foreign good or service would benefit both governments and individuals, should it be either during the short run or long run (Moosa, 2000; MacDonald, 2007). The ability to forecast exchange rates has several advantages within the domestic economy as it will greatly assist governments in implementing the appropriate and most efficient policies in order to reach their designated economic goals, as well as aiding individuals in making sound business and investment decisions.

The objective of this paper is to analyse whether the fundamental methods of determining exchange rates are more accurate in out-of-sample forecasting the U.S Dollar—South African Rand (USDZAR) exchange rate relative to a random walk for a sampling period from January 2000 until August 2021. This paper will be utilising the Uncovered Interest Rate Parity (UIRP), Covered Interest Rate Parity (CIRP), Purchase Power Parity (PPP) and Monetary Approach (MA) models in to forecast the USDZAR exchange rate. All of the above-mentioned fundamental models will be contrasted to a random walk (without drift) in order to compare the efficacy and efficiency of the implemented models. Furthermore, the aforementioned models will have an out-of-sample forecasting period from January 2016 until August 2021. A model's forecast is regarded as efficient should the forecast be able to accurately predict the future spot exchange rate and simultaneously outperform the forecast made by the random walk. In conclusion, this paper examines whether that the fundamental methods of forecasting exchange rates are superior in forecasting the USDZAR exchange rate relative to a random walk.

The empirical evidence concerning the aforementioned methods of exchange rate estimation vary, but the overall consensus is that these models tend to be worse at predicting exchange rates when contrasted to a random walk (Meese & Rogoff, 1983a, 1983b; Rossi, 2013). Thus, this paper expects that the random walk will be either similar or superior in forecasting the USDZAR exchange rate when compared to the above-mentioned fundamental exchange rate estimation models. The fact that exchange rates are similar in nature to unpredictable assists such as the stock market suggests that the values of exchange rates tend to fluctuate due to unforeseen changes in supply and demand (MacDonald, 2007). Subsequently, there is an element of inherent unpredictability concerning the fluctuations of exchange rates.

This paper concludes that the UIRP, CIRP and PPP models of the fundamental exchange rate determination models are not decisively superior in forecasting the USDZAR exchange rate relative to a random walk at a monthly frequency. Additionally, this paper concludes that the MA model is in fact superior in forecasting the USDZAR exchange rate relative to a random walk for a quarterly frequency. The structure of this paper is as follows: section 2 provides a literature review of relevant literary works; section 3 specifies the data, model specification and methods utilised within the paper; section 4 provides and discusses the results obtained by this study; and section 5 states the conclusions made by this paper and points out areas of further research.

2.) Literature Review

The ability to accurately forecast exchange rates has been a widely researched topic since the ability to accurately predict exchange rates could lead to a wide array of benefits, both at the individual and governmental level (Moosa, 2000; MacDonald, 2007). The fact that numerous different methods of forecasting exchange rates exist exemplifies this fact. This lead towards numerous authors attempting to compare the efficacy of the different methods of forecasting exchange rates. This paper will be utilising Barbara Rossi's paper "Exchange Rate Predictability" (2013) as its foundation in order to compare the various available methods to forecasting foreign exchange rates. Additionally, this paper will be implementing Rossi's (2013) definitions and formulas in order to determine a particular model's exchange rate forecasting ability.

Since the research conducted by Meese and Rogoff (1983a, 1983b, 1988), it is widely known that it is exceptionally difficult to accurately predict the fluctuations of exchange rates by using economic models and that a random walk tends to be more accurate in forecasting exchange rates relative to most economic models (Rossi, 2013); this complication subsequently became known as the 'the Meese and Rogoff puzzle'. Recent literature, however, has determined a series of methodologies/fundamentals that claim to have solved the Meese and Rogoff puzzle (Rossi, 2013). According to Rossi (2013), the predictability of exchange rate relies on numerous factors such as the forecast horizon, chosen predictor, sample period and frequency, chosen exchange rate forecasting model and forecast evaluation method. There have been various studies done that have utilised different frequencies, as well as different time horizons, in order to determine the best possible combination (Mačerinskienė & Balčiūnas, 2013; Barbosa, Jayme & Missio, 2018;

Goda & Priewe, 2019; Wang, Morley & Stamatogiannis, 2019). Additionally, several papers have tried to identify the determinants of exchange rate volatility within specific countries (Mungule, 2004; Villavicencio & Bara, 2008; Kia, 2012; Mirchandani, 2013).

Whereas several studies have been done concerning the emerging countries of Brazil, Russia, India and China (BRIC) (Güriş & Tiraşoğlu, 2018; Prabheesh & Garg, 2020), the South African context has not been studied to the same extent. Within the South African context, the most recent studies concerning the determination of exchange rates include Caporale and Gil-Alana (2010), who reject the hypothesis of PPP holding from 1990 until 2008 utilising daily, weekly and monthly frequencies, and De Bruyn, Gupta and Stander (2013), who find "evidence in favour of the monetary model of exchange rate determination for the South African Rand is, at best, mixed" using annualised data from 1910 until 2010. The most recent paper concerning exchange rate predictability within the BRICS country context was written by Salisu, Gupta and Kim (2021). These authors conclude that the UIRP and PPP models consistently produce superior forecasts relative to the benchmark random walk model, regardless of the regression model implemented. Additionally, Salisu, Gupta and Kim (2021) find that the MA model is considered to outperform the benchmark random walk model in all but one-period-ahead forecasts. This paper will subsequently contribute an updated study towards the existing literature concerning the forecasting of the South African Rand exchange rate.

Rossi (2013) argues that most of the fundamental exchange rate forecasting methods do not perform significantly better empirically when compared to a random walk. The empirical evidence of UIRP and CIRP are not favourable, as concluded by Meese and Rogoff (1988) and Rossi (2013) among several others. PPP tends to perform slightly better empirically relative to UIRP and CIRP in forecasting exchange rates when compared to a random walk, but only at the longest of horizons (Meese & Rogoff, 1988; Rossi, 2013). Empirical evidence concludes that PPP estimations are less accurate relative to a random walk over the short run (Cheung, Chinn & Pascual, 2005). The empirical findings of the MA are somewhat mixed, as in-sample forecasts tend to perform far better than out-of-sample forecasts (Rossi, 2013). Meese and Rogoff (1983a, 1983b) demonstrate that random walk out-of-sample forecasts of exchange rates perform better than any of the MA models. The findings by Meese and Rogoff (1983a, 1983b) has been confirmed by Cheung, Chinn, and Pascual (2005), who conclude that the MA model does not accurately forecast exchange rates even for longer time horizons, and by Chinn and Meese (1995), who conclude that the MA model does not accurately predict exchange rates for short time horizon forecasts (one-month-ahead to one-year-ahead).

2.1.) Uncovered Interest Rate Parity

The UIRP condition states that "in the absence of arbitrage opportunities, the returns from investments in two specific countries should be equalised once they are converted into the same currency" (Ismailov & Rossi, 2017:2). The implication of the UIRP condition is that the bilateral exchange rate appreciations or depreciations could be predicted by the interest rate differentials (Ismailov & Rossi, 2017). The UIRP as described by Lothian and Wu (2011:449) is one of the "key international financial relations that are used repeatedly in the fields of international finance and open-economy macroeconomics in both model construction and other analytical work". Lothian and Wu (2011) further explain that the paradoxical behaviour of a floating exchange rate since its inception in the 1970's after the abolishment of the Brenton Woods system is the propensity for countries with low interest rates to experience a depreciation of their domestic currency rather than an appreciation as the UIRP model would suggest. This UIRP paradox is widely known as the 'forward-premium puzzle', which is extremely widely researched with many papers seeking to to determine the reasons for its existence (Lothian & Wu, 2011).

Furthermore, Lothian and Wu (2011) suggest that much of the empirical research done concerning UIRP centres their attention on the sampling period of the late 1970's and 1980's; an era which is predominantly dominated by the appreciation of the U.S. Dollar. Lothian and Wu (2011) speculate that this specific relationship is largely driven by the distinct properties of this sampling period. They further speculate that even though the market tolerates marginal deviations from UIRP for extended periods of time, mainly caused by market frictions such as transportation costs, the UIRP condition — much like the PPP condition — will perform better in the long run and that revisions of the UIRP condition will become more apparent the larger the deviation becomes.

Stated in its simplest form, the UIRP condition concludes that countries with a low nominal interest rate in relation to interest rates aboard are expected to experience an appreciation in their domestic currency (Lothian, 2015). This issue, however, is that empirical evidence has proven the contrary (Lothian & Wu, 2011; Rossi, 2013). Additionally, another disregarded element of the UIRP is the model's poor predictive performance for small interest rate differentials and over shorter time horizons. It is argued that the assumption of the UIRP condition generally only holds for high-income and/or developed nations over extended time horizons and between currencies that are typically frequently traded within internationally integrated markets (Chinn & Meredith, 2005; Hassan & Simione, 2011).

Additionally, there is substantial evidence that suggests most countries do not experience a one-to-one relationship between interest rate differentials and the future spot exchange rate changes

(Lothian, 2015). This subsequently suggests that the UIRP condition may not hold. Empirical failure of this condition has been documented by several studies that date back to Fama (1984). Burnside, Eichenbaum, and Rebelo (2016) suggest that the failure of UIRP is not surprising from a theoretical perspective, as it would require all participating agents to be risk-neutral.

2.2.) Covered Interest Rate Parity

The CIRP condition states that the interest rate differential between two countries equals the spread between the forward and spot exchange rates and was developed by John Maynard Keynes (1923). As with the UIRP condition, the empirical findings of CIRP is not favourable and many researchers consequently conclude that the CIRP is not significantly better at forecasting exchange rates as opposed to a random walk, with the CIRP only being a superior forecasting model at the longest of horizons (Du, Tepper and Verdelhan, 2018). The CIRP is a fundamental tenet of international finance and plays a fundamental role in illuminating foreign exchange market efficiency due to it being a hypothetical condition in which the relationship between the forward and spot rates and the interest rates are in equilibrium (Su, Wang, Tao & Lobonţ, 2019). Thus, there is no opportunity for arbitrage using forward contracts when the CIRP condition holds.

Skinner and Mason (2011) conclude that the CIRP condition holds in the short and long run for small triple-A rated economies, whereas CIRP only holds for a three-month maturity in emerging markets. Furthermore, Du, Tepper and Verdelhan (2018) find that the CIRP condition has been both systematically and consistently violated among the G10 countries ever since the 2008 global financial crisis, which consequently lead towards various arbitrage opportunities in the currency and fixed income markets.

In addition, the evidence suggests that the forward rate may not provide an unbiased estimate of the future spot rate (Du, Tepper & Verdelhan, 2018). It has been widely noted that the spot exchange rate would usually move by a smaller amount relative to that suggested by the forward exchange rate (Du, Tepper & Verdelhan, 2018). This condition is termed the 'forward bias' and the perceived failure of the unbiasedness hypothesis indicates that the interest rate differentials might possess information concerning the future spot exchange rates that could be exploited in order to make a profit.

2.3.) Purchase Power Parity

The theory of PPP, which was developed by Gustav Cassel in 1916, states that the prices of similar goods and services should be the same in different countries when expressed in a common currency. In other words, the PPP condition is the empirical postulation that national price levels should be equal once expressed in the same currency (Rogoff, 1996). The main postulation is that should goods market arbitrage enforce widespread equality in prices across an acceptable range of specific goods, then there should be a correspondingly high level of correlation in aggregate price levels (Rogoff, 1996). This is otherwise known as the law of one price.

The PPP model is widely considered to be significantly worse in forecasting exchange rates relative to a random walk over the short run (Cheung, Chinn & Pascual, 2005; Caporale & Gil-Alana, 2010). Similar to the aforementioned UIRP and CIRP models, the PPP model could possibly be slightly more accurate in forecasting exchange rates relative to a random walk, but only at the longest of horizons (Rogoff, 1996; Cheung, Chinn & Pascual, 2005). For PPP, empirical evidence suggests that the 'sticky-price' version of the PPP model is a superior method of forecasting relative to the 'flexible-price' version (Rogoff, 1996). Additionally, it is crucial to establish whether PPP holds in order to evaluate the effects of a devaluation within a particular country. Within the USDZAR context, the evidence provided by Caporale and Gil-Alana (2010) strongly reject the hypothesis that PPP holds between South Africa and the U.S.

According to Haidar (2011), the main reasons for the violation of PPP are that the indexes of consumer goods and services might differ between countries, protectionist policy rules might be applied to the countries in question and that the economies of the relevant countries are not comparable. Haidar (2011) further explains that researchers cannot compare a developed country to a developing one — as is the case between South Africa and the U.S. Haque & Boger (2013) prove this statement by concluding that the PPP condition does not hold between emerging Asian countries and the U.S.

An advantage of employing the PPP model is that it is relatively easy to utilise, as the model does not contain numerous independent variables. There are two forms of PPP; namely absolute PPP and relative PPP. Several papers argue that the usage of relative PPP is preferred to absolute PPP due to relative PPP being easy to seamlessly compare between countries who utilise varying definitions of the consumer price index (CPI) (Froot & Rogoff, 1995; Güriş & Tiraşoğlu, 2018).

2.4.) The Monetary Approach

The MA model was first introduced by Mussa (1976) and Frenkel (1976), where the intuition underlying the MA model is analytically appealing: the demand and supply of money within a specific country determines that country's price level, and that the price level in separate countries should be equivalent when denoted in the same currency (De Bruyn, Gupta and Stander, 2013). The empirical findings in favour of the MA model in determining exchange rates —including the South African context — are, at best, mixed (Meese & Rogoff, 1983a, 1983b; Rossi, 2013; De Bruyn, Gupta & Stander, 2013). Meese and Rogoff (1983a, 1983b) demonstrate that the random walk determines exchange rates better than any of the implemented monetary models. These findings were additionally confirmed by Cheung, Chinn and Pascual (2005), who conclude that the MA model does not accurately predict exchange rates even at long horizons (i.e. five years) and by Chinn and Meese (1995), who conclude that the MA model does not predict well for short horizon forecasts (one-month-ahead to one-year-ahead).

There are two variants of the MA model: the 'flexible-price' version (Frenkel, 1976; Bilson, 1981) and the 'sticky-price' version (Dornbusch, 1976; Frankel, 1979). In the former, PPP holds throughout the entire sampling period, while in the latter, it only holds in the long run. Similar to PPP, the sticky price version has empirically been more accurate in forecasting exchange rates relative to the flexible price version (Frankel, 1979; Chinn, 2012). Additionally, Papell (1984, 1988) estimates that the MA's extent of undershooting and overshooting is directly correlated to how the monetary policy is being conducted. Chinn (2012) concludes that it is reasonable to assume that the empirical results of the 1980's are not entirely robust to the addition of new data, as the previously identified relationships often break down with the addition of new data.

The empirical characteristics of the MA to determining exchange rates can be characterised by constraints implemented on the parameters utilised within the general model. The general MA model consists of the following five assumptions: the PPP holding over a relevant time horizon; UIRP holding throughout the sampling period; money supply is determined by a stable process; the demand for real money balances being a stable function of real variables; and that expectations are broadly rational (Boughton, 1988). This subsequently often leads to the rejection of the model's assumptions themselves rather than a rejection of the empirical results of the model (De Bruyn, Gupta & Stander, 2013).

3.) Data, Model Specification and Methods

3.1.) Data

The data utilised within this paper is the nominal exchange rate for the South African Rand relative to the U.S. Dollar (termed USDZAR). Furthermore, this paper utilises the 90-day Treasury Bill, inflation rate, M1 money supply and the real GDP (at constant 2010 prices) of the respective countries, as well as the forward spot rate of the USDZAR exchange rate. The data sample spans for the period of January 2000 until August 2021. The utilised data was collected from the IMF (2021), the SARB (2021) and the FRED (2021). This paper opted to use the U.S. as a comparison currency due to the U.S. Dollar being the most widely traded currency in the world and is consequently considered as the standard comparison currency worldwide (Carbaugh & Hedrick, 2009; Costigan, Cottle & Keys, 2017). In this analysis, South Africa is considered as the domestic country and the U.S. as the foreign country.

This paper opted for commencing the study from the year 2000, even though a longer data frame was available, since data before the year 2000 simply does not accurately represent a similar global economic climate relative to that of the 21st century. This is especially true within the South African context. This paper consequently argues that data available before the year 2000 simply would not significantly improve the forecasting power of the utilised forecasting methods due to it not being similar in nature to the current global economic climate.

This paper opted to utilise a monthly frequency for the UIRP, CIRP and PPP models instead of shorter frequencies — such as daily or weekly — due to these shorter frequencies tending to possess more market noise, consequently distorting long run trends. Furthermore, this paper opted to utilise a quarterly frequency for the MA model due to the GDP measurements only being available at quarterly intervals. These aforementioned models will be compared to a random walk denoted in the same frequency as the models they're compared to.

3.2.) Descriptive Statistics and Diagnostics

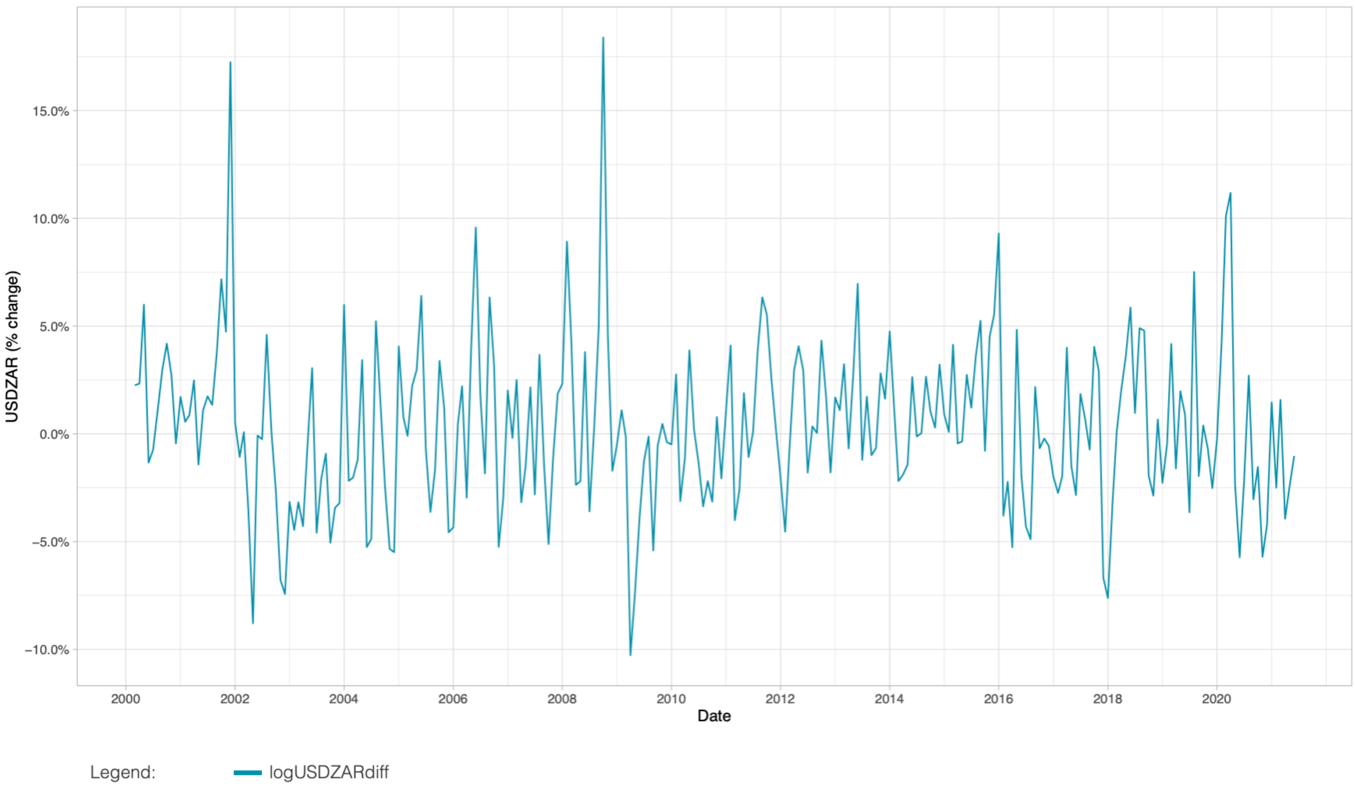
It is well documented that both the exchange rate and its economic determinants are I(1) (Stein & Allen, 1998). When a time series is non-stationary, forecasts, confidence intervals and conventional hypothesis tests can be deceptive due to sound econometric analysis depending on the series being stationary, or I(0) (Wooldridge, 2016). When the series exhibits trends or structural breaks, the assumption of stationarity is violated. The relationship between two stochastically trending time series when regressed onto each another may seem to be highly significant when using conventional critical values, even though the series are not necessarily related (Wooldridge, 2016). Economists call this a spurious relationship.

Consequently, it is vitally important that the variables utilised within this paper be examined for non-stationarity. In order to formally test whether the relevant variables are stationary, an augmented Dickey-Fuller (ADF) test will be implemented. This paper will make use of the constant, no trend variant of the ADF test. In order to correct for non-stationarity, this paper will be implementing a log differenced transformation that will likely result in the exchange rate and its economic determinants becoming I(0). Transforming variables into their log differenced versions has the added advantage of the relatively simple interpretation of percentage changes, as $\log(X_t) - \log(X_{t-1}) \approx \%\Delta x$.

There appears to be a positive upward trend included in the USDZAR exchange rate (see Figure 1). This is primarily due to the South African Rand consistently depreciating against the U.S. Dollar over the past two decades, ranging from a minimum of USDZAR 5.73 in late 2004 to a maximum of USDZAR 18.58 in early 2020 (see Table 1). The Rand experiences periods of drastic deprecation relative to the U.S. Dollar in the 2001 collapse of the Rand (Gidlow, 2005), in 2008 due to the global financial crisis (Deloitte, 2016) and in 2020 due to the COVID-19 pandemic. An ADF test was implemented to formally test the presence of a unit root in the USDZAR exchange rate variable. The ADF test returns an unacceptably high P-value of 0.4109 (see Appendix 1). This consequently rejects the hypothesis that the USDZAR exchange rate is stationarity.

Figure 1.) USDZAR

Figure 2.) Log differenced USDZAR



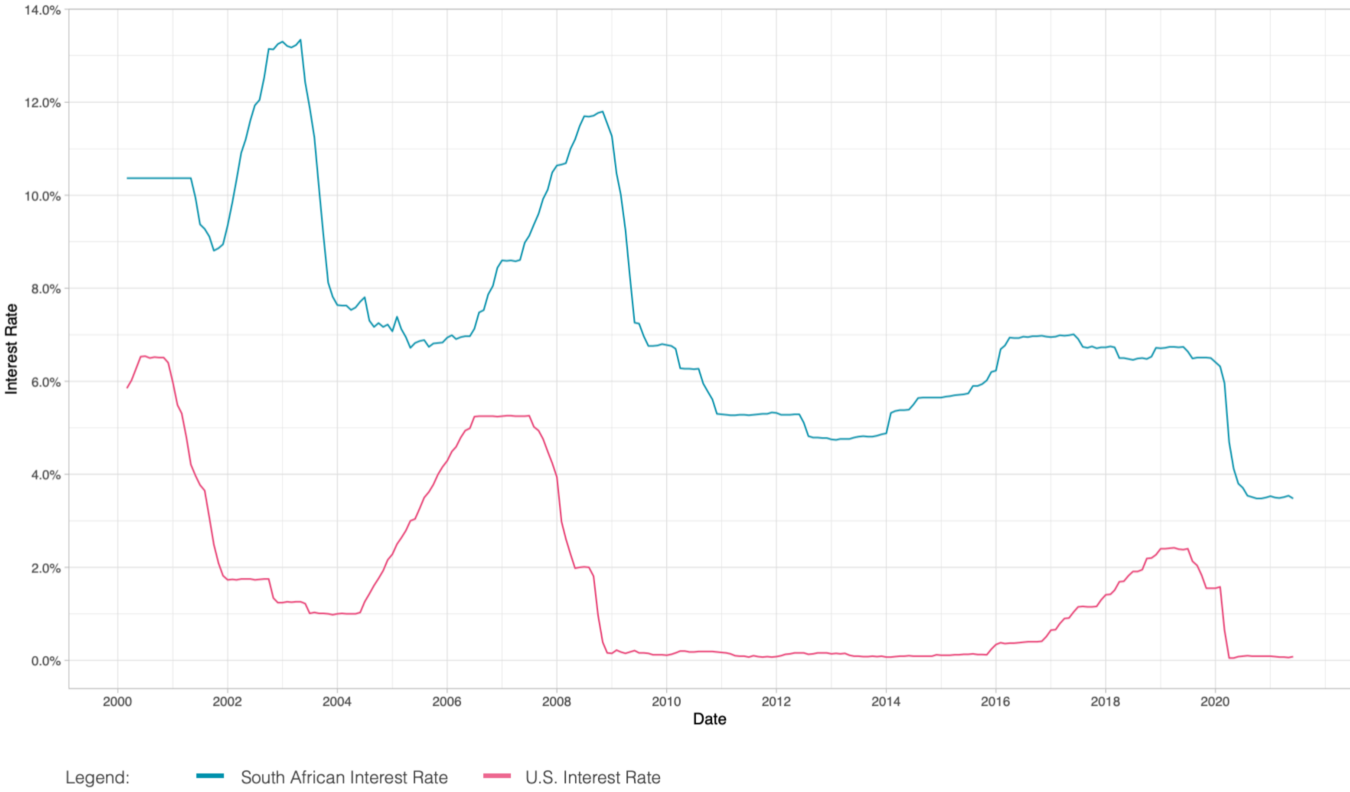
The mean log differenced value of USDZAR indicates that the USDZAR spot rate increases, on average, 0.3% per month (see Table 1). This supports the notion that there exists an upward trend over time for the USDZAR exchange rate. The implementation of a log difference transformation to the USDZAR exchange rate appears to have visually removed most of the non-stationarity (see Figure 2). The implementation of an ADF test returns a P-value of 0.01, thus implying that the null hypothesis of a unit root being present is rejected (see Appendix 1). Thus concluding that it is very likely that the log differenced version of the USDZAR exchange rate is stationary.

Similarly, there appears to be an upward trend present in the USDZAR forward rate (see Figure 3). An ADF test confirms that the USDZAR forward rate variable has a unit root present (see Appendix 1). This is expected, as the forward rate tends to mirror the exchange rate. Thus, a log difference transformation was implemented, which caused the variable to become stationary according to the ADF test (see Appendix 1).

Figure 3.) USDZAR Forward Rate

As illustrated by Figure 4 below, the U.S. interest rate is constantly below the South African interest rate throughout the entire sampling period. In other words, the interest differential is always positive throughout the sample period ($i_{SA} - i_{US} > 0$). This is also exemplified by Table 1, as the average interest rate in South Africa throughout the sample is 6.81%, whereas for the U.S. it is merely 1.01% (see Table 1). This is expected as South Africa has a higher risk premium because the country is perceived as a riskier investment relative to the U.S. due to political instability, high unemployment rates and high crime stats (Maveé, Perrelli & Schimmelpfennig, 2016).

Figure 4.) Interest Rates



The implemented ADF-test returned P-values of 0.2192 and 0.0626 for the South African and U.S. interest rates respectively (see Appendix 1). This leads to the conclusion that the South African interest rate is non-stationary, whereas the U.S. interest rate seems stationary, but only at the 10% confidence level. A subsequent ADF test was implemented in order to determine whether the interest rate differential utilised within the models has a unit root present. The ADF-test returned a P-value of 0.0230, thus leading to the conclusion that the interest rate differential used within the models is in fact stationary (see Appendix 1).

As it is widely known that most countries' CPI has a strong upward trend over time, the logged-difference transformation implemented within this paper subsequently transforms the respective non-stationary CPI variables into inflation rates. As illustrated by Figures 5 and 6 below (as well as illustrated by Appendix 2), the U.S. inflation rate is significantly lower relative to the inflation rate in South Africa. This is also exemplified by Table 1, as the mean monthly inflation rate of South Africa is 0.42%, whereas the monthly inflation rate of the U.S. is merely 0.18%. The ADF-test returns a P-value of 0.0380 and 0.01 for the South African and the U.S. inflation rate respectively (see Appendix 1). This leads to the conclusion that both countries' inflation rates appear to be stationary (see Appendix 1).

Figure 5.) The South African Inflation Rate

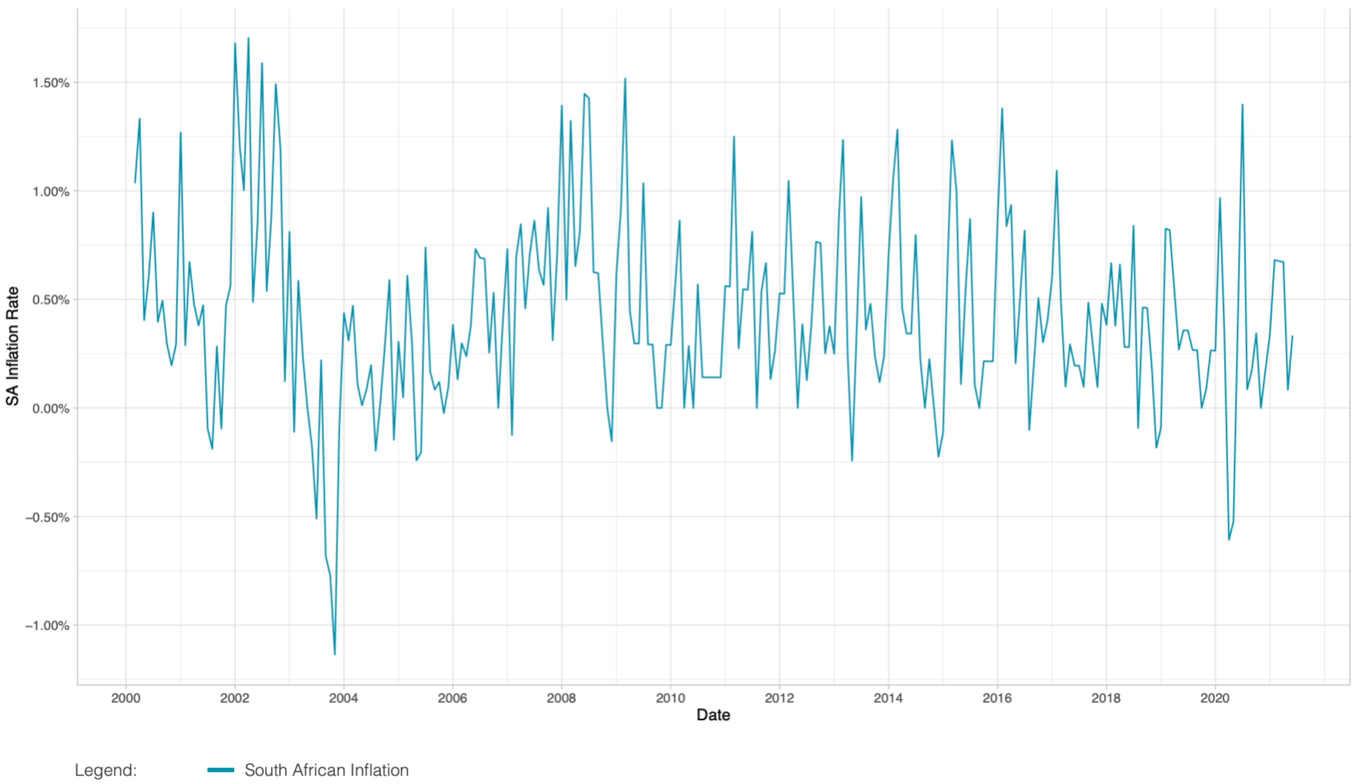


Figure 6.) U.S. Inflation Rate

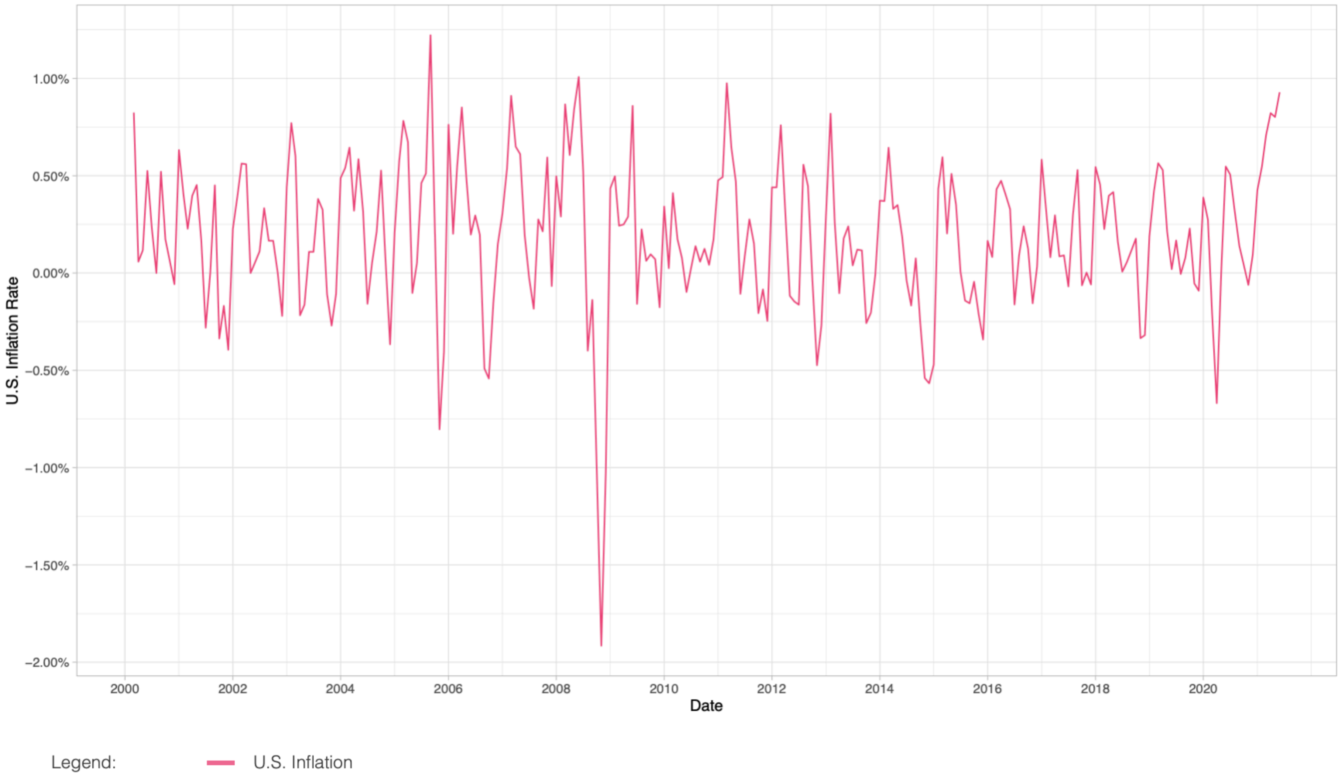
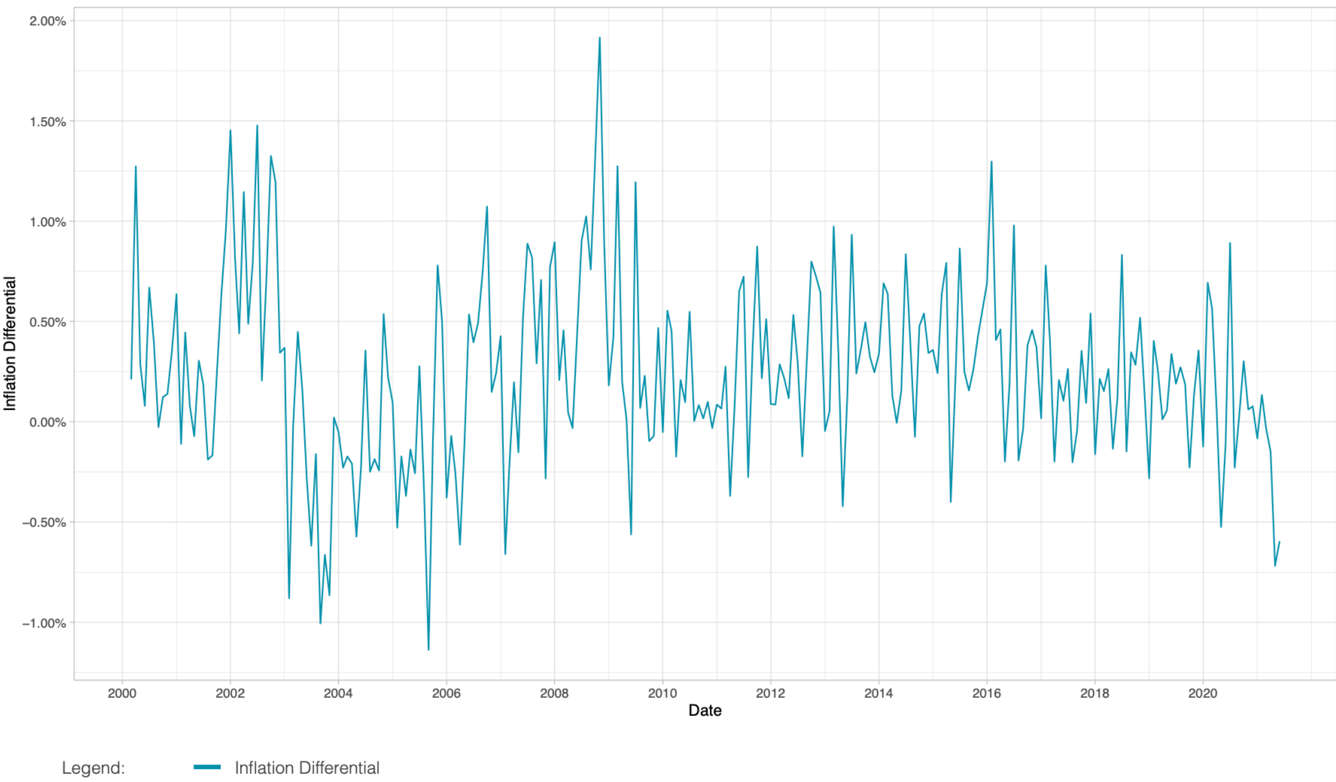


Figure 7.) Inflation Differential



As stated previously, it is well known that the exchange rate and its determinants are non-stationary (Stein & Allen, 1998). The variables utilised within the MA model that are generally considered to be I(1) include the CPI, M1 money supply, and real GDP variables, thus this paper will treat these variables as such. Consequently, a log difference transformation was implemented. Similar to the monthly models, this implementation transformed the aforementioned variables into their respective percentage changes and therefore — according to the implemented ADF tests — eliminated the presence of non-stationarity (see Appendix 1). The only exception was that of the M1 money supply differential, which was still non-stationary when transformed into a log difference — consequently concluding that the M1 money supply variable was I(2). Thus, the log differenced M1 money supply differential was differenced a second time in order to ensure stationarity — as proved by the implemented ADF test (see Appendix 1).

Table 1.) Descriptive Statistics Table for Monthly Models

	USDZAR	logUSDZAR diff	Fwd Rate	CPI (SA)%	CPI (US)%	S.A Interest Rate (%)	U.S Interest Rate (%)
Obs	256	255	256	256	256	256	256
Mean	9,91	0,0031	10,48	0,42%	0,18%	7,38%	1,65%
Std Dev	3,20	0,0384	3,39	0,0044	0,0038	0,0238	0,019
Min	5,73	-0,1027	5,00	-1,14%	-1,92%	3,48%	0,05%
25th Q	7,18	-0,0218	7,51	0,14%	-0,04%	5,65%	0,14%
Median	8,63	-0,0002	8,99	0,36%	0,18%	6,81%	1,01%
75th Q	12,92	0,0267	13,57	0,67%	0,44%	8,95%	2,38%
Max	18,58	0,1839	19,48	1,70%	1,22%	13,34%	6,54%

Table 2.) Descriptive Statistics Table for Quarterly Model (MA)

	USDZAR	logUSD ZARdiff	CPI SA (%)	CPI US (%)	S.A Interest Rate (%)	U.S Interest Rate (%)	M1 SA (Billion $)	M1 US (Billion $)	GDP SA (Billion $)	GDP US (Billion $)
Obs	86	85	86	86	86	86	86	86	86	86
Mean	9,82	0,0103	1,28%	0,55%	7,47%	1,56%	964,2	2871,0	737,3	16 043,0
Std Dev	3,26	0,0874	0,0089	0,0071	0,0211	0,0178	560,9	3452,5	351,7	1809,87
Min	5,64	-0,1990	1,93%	2,83%	3,61%	0,02%	253,3	1097,0	219,9	12 935,0
25th Q	6,98	-0,0421	0,65%	0,24%	5,90%	0,09%	457,6	1368,0	406,6	14 869,0
Median	8,31	0,0031	1,23%	0,52%	7,17%	0,92%	837,3	1752,0	708,7	15 781,0
75th Q	12,44	0,0578	1,79%	1,03%	8,86%	2,31%	1425,0	3084,0	1049,9	17 456,0
Max	18,15	0,3188	3,42%	2,34%	12,57%	6,06%	2211,1	18 915.80	1351,7	19 358,0

3.3.) Model Specifications and Methods

As mentioned previously, this paper will be using the UIRP, CIRP, PPP and MA models as fundamental methods of forecasting the USDZAR exchange rate. This paper will be comparing each of the fundamental forecasting methods to a random walk, as this comparison method is widely considered to be the most effective comparison method (Rossi, 2013).

The paper will compare the effectiveness of the forecasts made by the models relative to the random walk by referring to each model's respective root mean squared error (RMSE) and mean absolute error (MAE), with a low RMSE / MAE indicating a low forecasting error. Additionally, this paper will be utilising the Diebold-Mariano (DM) test statistic in order to statistically determine whether there is a statistically significant difference in the forecasting errors of the fundamental exchange rate forecasting models and the random walk.

RMSE Formula:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (x_i - \hat{x}_i)^2}{n}}$$

MAE Formula:

$$MAE = \frac{\sum_{i=1}^{n} \mid x_i - \hat{x}_i \mid}{n}$$

Where x_i is the actual observations within the time series, $\hat{x}_i$ is the forecasted values and *n* is the total number of observations.

DM Formula:

$$H_0 : FE_f - FE_{rw} = 0$$
$$H_1 : FE_f - FE_{rw} \neq 0$$

Where the null hypothesis (H_0) states that the difference between the forecasting errors of the model (FE_f) and the forecasting errors of the random walk (FE_{rw}) is not statistically different from zero.

This paper will also be implementing the mean absolute deviation (MAD) and the mean absolute percent error (MAPE) of the relevant variables in level terms compared to the actual realised values of the USDZAR exchange rate. The MAD and MAPE values will provide further information concerning the forecasting accuracy of the utilised models by determining their respective absolute deviations and percentage errors in level terms.

MAD Formula:

$$MAD = \frac{1}{n}\sum_{i=1}^{n}|X_i - \bar{X}|$$

Where X_i is the actual level data point and $\bar{X}$ is the mean value (in level terms) of the dataset.

MAPE Formula:

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{A_t - F_t}{A_t}\right|$$

Where A_t is the actual level data value of the dataset and F_t is the level forecasted data value.

This paper will mathematically and visually compare the differences between the forecasting ability of the above-mentioned models in relation to a random walk and consequently conclude which of the models, if any, are statistically more effective in forecasting exchange rates relative to a random walk. The out-of-sample forecast horizon used within this paper is a one-step-ahead (h=1) forecast, with the forecasting sample spanning from January 2016 to August 2021. Lastly, the monthly models have 66 out-of-sample observations and the quarterly model has 22 out-of-sample observations, which is an out-of-sample forecasting period of about 25% of the total sampling period for both the monthly and quarterly models.

3.3.1.) Uncovered Interest Rate Parity

The UIRP theory claims that the interest rate differential would be offset by the exchange rate differential between two opposing countries. Therefore, the sum of the domestic country's expected currency depreciation — or appreciation — and the foreign interest rate would be equal to the domestic interest rate. UIRP assumes that foreign exchange risk would not be covered by the forward market and that all investors are risk neutral.

UIRP Formula:

$$E_t(s_{t+h} - s_t) = \alpha + \beta(i_{t+h} - i^*_{t+h})$$

Where α=0, β=1, $s_t \equiv \ln(S_t)$, i_{t+h} is the interest rate on domestic bonds, i^*_{t+h} is the interest rate on foreign bonds and *h* is the time horizon. UIRP states that in a society with perfect foresight, one unit of domestic currency enables investors to buy $1/S_t$ units of foreign bonds, where the price of foreign currency in terms of the home currency is denoted by S_t (Rossi, 2013).

3.3.2.) Covered Interest Rate Parity

The CIRP theory suggests that the interest rate differential between risk-free investments should be equal to the forward premium associated with a specific foreign currency (Nirmali & Rajapakse, 2016). This assumes that foreign exchange rate risk is covered by the forward market. CIRP subsequently states that the returns of comparable financial assets should be equivalent when denominated in different currencies when assuming the free flow of capital between countries. The underlying mechanism for CIRP is covered interest arbitrage, which is the hypothetical relationship where the interest rates and spot and forward rates are in equilibrium. Therefore, benefits from covered interest arbitrage would be nonexistent should the CIRP condition hold as the discount on the forward rate between respective currencies will offset any gains from the higher interest rate in any specific country. The main difference between UIRP and CIRP is that CIRP is based on the assumption that exchange rate risk will be covered by the forward market (Nirmali & Rajapakse, 2016).

CIRP Formula:

$$E_t(s_{t+h} - s_t) = \alpha + \beta(F_t - s_t)$$

Similar to UIRP, α=0, β=1, $s_t \equiv \ln(S_t)$ and F_t denotes the *h*-period ahead forward rate at time *t* (Rossi, 2013).

3.3.3.) Purchase Power Parity

The PPP theory has two main approaches: the strong and the weak approach (Barbosa *et a*l, 2018). The former depends on the law of one price, which claims that the price of a particular good or service is equivalent in all countries when expressed in the same currency. The validity of the strong approach depends on the absence of transactional costs such as transport and informational costs (Barbosa *et a*l, 2018). Nevertheless, such costs cannot be neglected, even within perfectly competitive markets. In order to have an equivalent price of a particular good or service in all places simultaneously, it is necessary to irrationally assume that goods can be transported instantly and without any costs involved. The weak approach to PPP loosens the initial restrictions placed by the strong approach and is ultimately the preferred approach. The weak approach to PPP argues that exchange rate changes should be proportional to relative price changes (Barbosa *et al*, 2018). This implies that a rise in domestic relative prices necessitates a domestic currency depreciation. This paper will consequently be making use of the weak approach to PPP.

PPP Formula:

$$s_t = \alpha + \beta(p_t - p_t^*)$$

Where p_t = log(CPI) of the domestic coutnry, $p^*{}_t$ = log(CPI) of the foreign country and α = 0 and β = 1 (Rossi, 2013).

3.3.4.) The Monetary Approach to Flexible Exchange Rates

The MA model regards the exchange rate as the relative price of currencies, where the relative price depends on the relative supply and demand of a country's money stock (Chinn, 2012). As mentioned previously, the general statement of the MA model consists of the following five assumptions: PPP holds over a relevant time horizon; UIRP holds throughout the sampling period; money supply is determined by a stable process; the demand for real money balances being a stable function of real variables; and that expectations are broadly rational (Boughton, 1988).

MA Formula:

$$s_t = \eta(i_{t+h} - i^*_{t+h}) - \phi(y_t - y_t^*) + (m_t - m_t^*) + \zeta(p_t - p_t^*)$$

Where y_t is the logarithm of real output, m_t is the logarithm of nominal money, ' * ' denotes the foreign country and the horizon, *h*, equals 1.

3.3.5.) Diagnostic Tests

For each of the above-mentioned models to be successfully implemented, each individual model needs to satisfy the assumptions of homoskedasticity (constant error variance) and no serial correlation between two different error terms. The Breusch-Pagan (BP) test will be implemented in order to test for heteroskedasticity (where the null hypothesis is that the model is homoskedastic). Additionally, a Durbin-Watson (DW) test will be implemented in order to formally test for autocorrelation in the above-mentioned models. Lastly, the plotted residuals will also be provided in order to visually determine the existence of serial correlation.

In conducting the BP test, the UIRP, PPP and MA models satisfy the assumption of contemporaneous homoskedasticity, whereas the CIRP model does not. The UIRP, CIRP, PPP and MA models yield P-values of 0.0782, 0.0008, 0.1065 and 0.1207 respectively (see Appendix 3). Thus failing to reject the null hypothesis of a constant variance at a 5% level of significance for all models except for CIRP. Robust standard errors were subsequently implemented to the CIRP model since no correlation between independent variables and the variance of the dependent variable is needed due to standard model testing methods relying on this assumption since the presence of heteroskedasticity causes unreliable standard errors. (Note that the BP test does not test for nonlinear relationships between the error variance and the independent variables.)

Furthermore, the implemented DW test for serial correlation returned P-values of 0.3586, 0.5099 0.3636 and 0.6481 for the UIRP, CIRP, PPP and MA models respectively (see Appendix 4). Additionally, the plotted residuals for all the above-mentioned models seem to have no apparent trend present (see Appendix 5). This leads to the assumption that serial correlation is not present in either of the utilised models.

4.) Results

Empirical research tends to indicate that a random walk is often more accurate in out-of-sample forecasting relative to a wide array of economic models (Meese & Rogoff, 1983a, 1983b; Rossi, 2013). This is an interesting conclusion, as a random walk cannot claim to be an economic model due to it not satisfying the three principle criteria for an economic model; namely to explain, to predict and to inform decision-making processes (Schlefer, 2012). As mentioned previously, this paper will be testing whether any of the utilised fundamental models are more effective in predicting the USDZAR exchange rate relative to a random walk for an out-of-sample period of January 2016 to August 2021.

This paper will compare the forecasting accuracy of the relevant models by comparing their respective RMSE and MAE values to that of the random walk. Additionally, this paper will perform a Diebold & Mariano (DM) test statistic to formally determine whether the models' forecasting errors are statistically different to that of the random walk. Furthermore, this paper will visually compare the forecasts made by the respective models relative to that of the random walk. Lastly, this paper will be converting the values forecasted by the fundamental models back into level terms and subsequently implement the mean absolute deviation (MAD) and the mean absolute percentage error (MAPE) in order to compare the forecasting accuracy of the fundamental models relative to the actual realised level values of the random walk.

4.1.) Monthly Fundamental Models

Table 3.) Root Mean Square Error and Mean Absolute Error for the Monthly Models

	UIRP	CIRP	PPP	RW
RMSE	0,03812	0,03628	0,03839	0,03814
MAE	0,03144	0,02963	0,03178	0,03146

It is clear from Table 3 above that both the RMSE and the MAE of all the tested monthly models are similar to the random walk, with only the CIRP model having slightly lower RMSE and MAE values (0.0018 and 0.0019 units for RMSE and MAE respectively) relative to the random walk. Thus, it seems as if the forecasting accuracy of the UIRP, CIRP and PPP models are similar to the random walk. To formally test this hypothesis, a DM test was implemented.

Table 4.) Diebold & Mariano Test Statistic for the Monthly Models

	UIRP	CIRP	PPP
DM-Test P-values	0,8312	0,3531	0,1928

As illustrated by table 4 above, the implementation of the DM test statistic to the UIRP and CIRP models return a P-value of 0.8312 and 0.3531 respectively (see Appendix 6). These test statistics are far beyond the acceptable rejection region of 0.10, thus failing to reject the null hypothesis that the two models have statistically similar levels of forecasting accuracy relative to the random walk. This coincides with the conclusions made by Lothian (2015), and Lothian & Wu (2011) for the UIRP condition, as well as the conclusions made by Su, Wang, Tao & Lobonţ (2019) and Du, Tepper & Verdelhan (2018) for the CIRP condition. Additionally, the CIRP grid (Appendix 7) visually supports the claim that the CIRP model does not hold, as the covered interest differential is not reasonably close to zero.

Similarly, the PPP model returns a P-value of 0.1928, which is lower than the aforementioned UIRP and CIRP models, but still above the acceptable rejection region of 0.10 (see Appendix 6). Thus, the DM test statistic also fails to reject the null hypothesis that the PPP model and the random walk have similar levels of forecasting accuracy. This coincides with the study done by Caporale and Gil-Alana (2010) which strongly rejects the hypothesis that the PPP condition holds within the South African context.

Subsequently, this leads to the conclusion that none of the aforementioned monthly models are statistically superior in forecasting exchange rates relative to a random walk according to the DM test statistic. This confirms the hypothesis stated by Meese and Rogoff (1983), Cheung, Chinn & Pascual (2005) and Rossi (2013) — among several others — that a random walk is more accurate (or just as adequate) in forecasting exchange rates relative to the aforementioned fundamental exchange rate determination models.

Figure 8.) Log Differenced Uncovered Interest Rate Parity

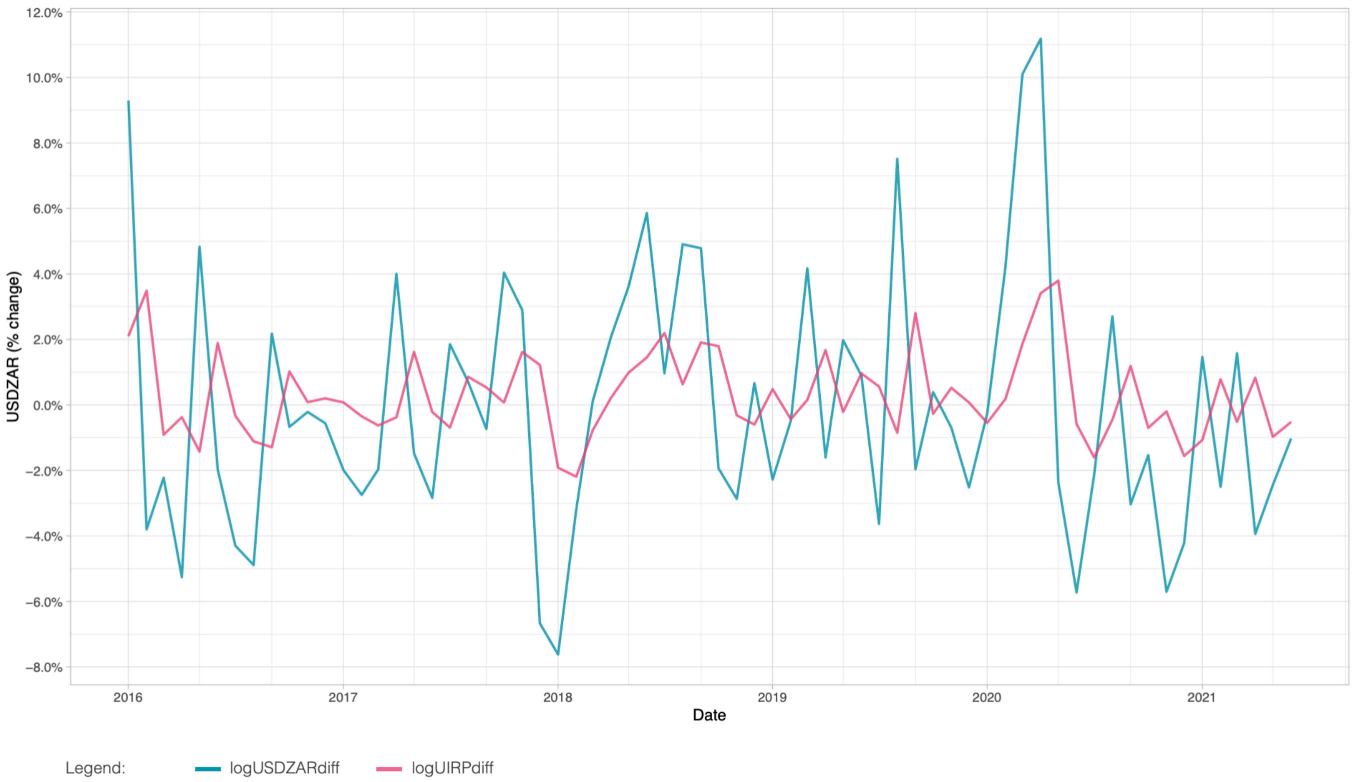


Figure 9.) Log Differenced Covered Interest Rate Parity

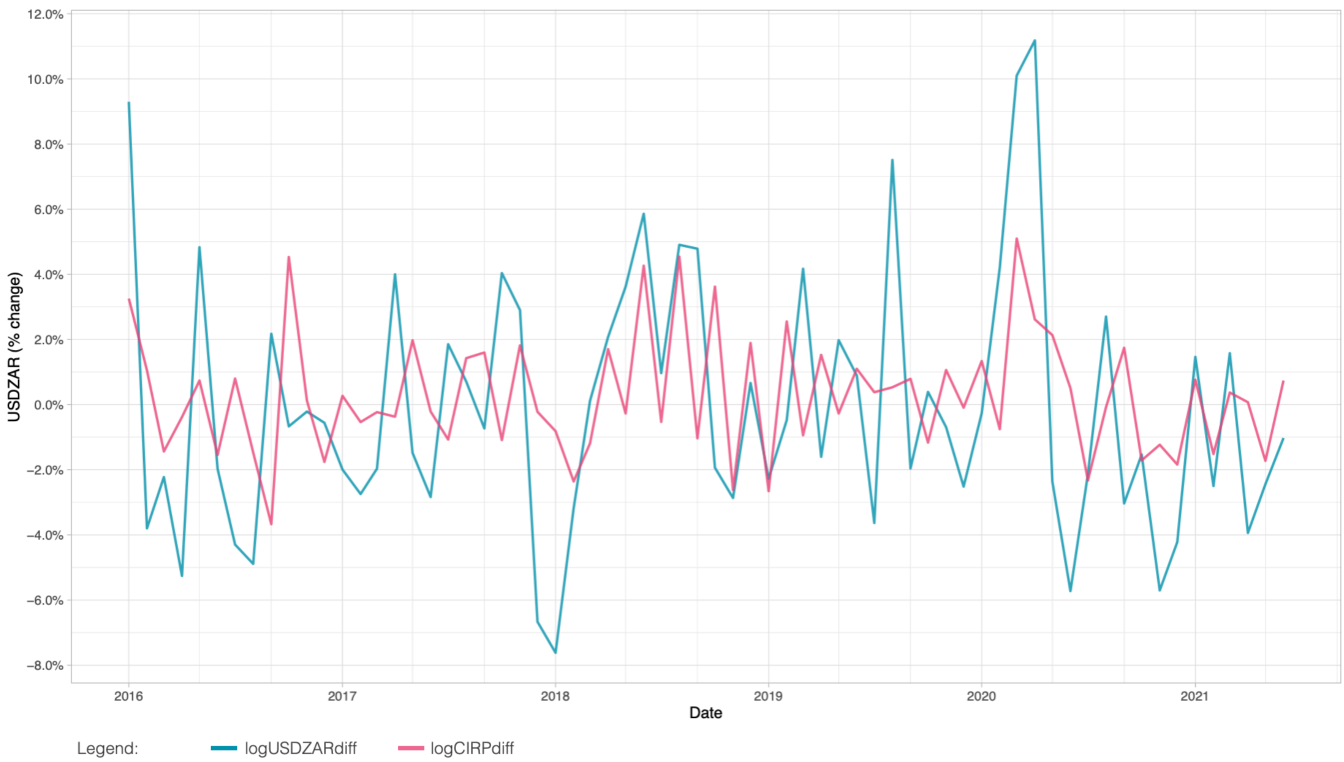


Figure 10.) Log Differenced Purchase Power Parity

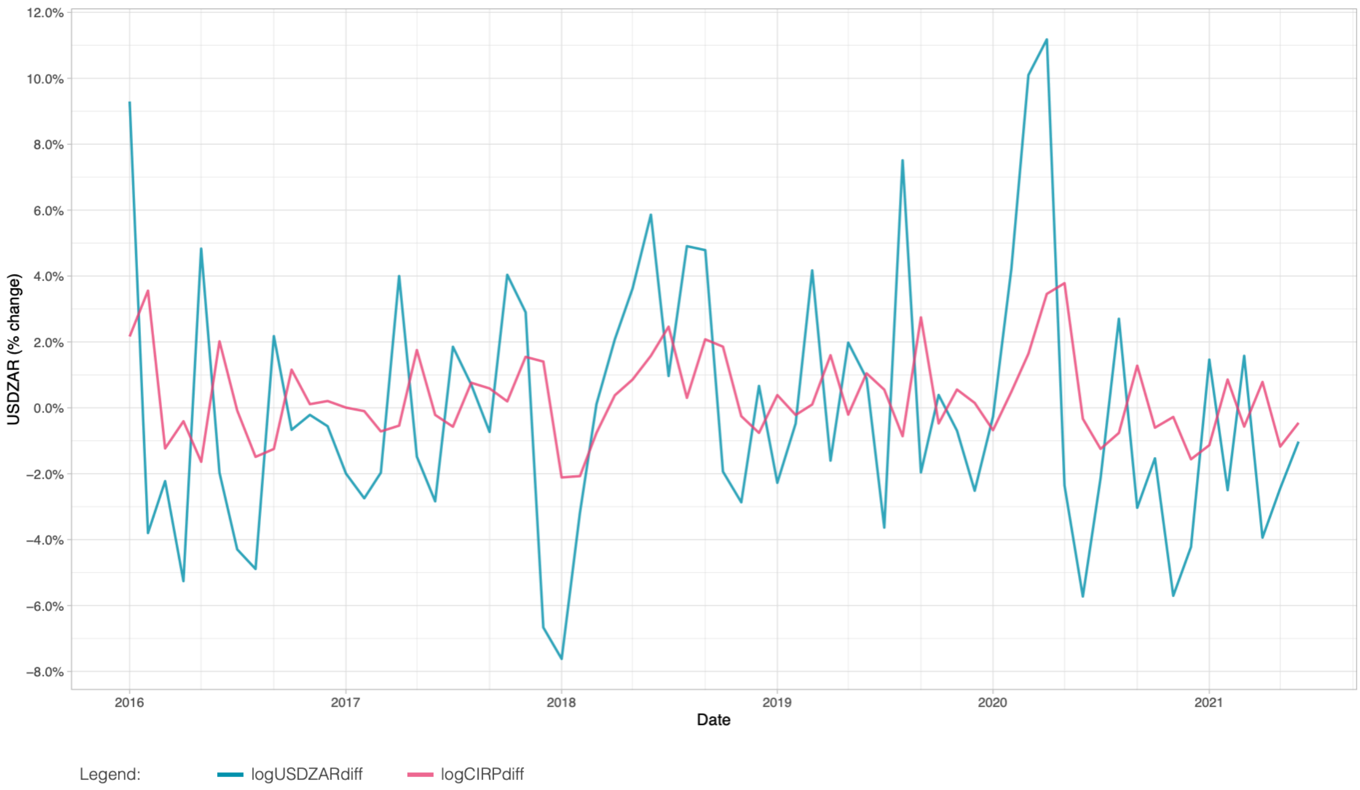
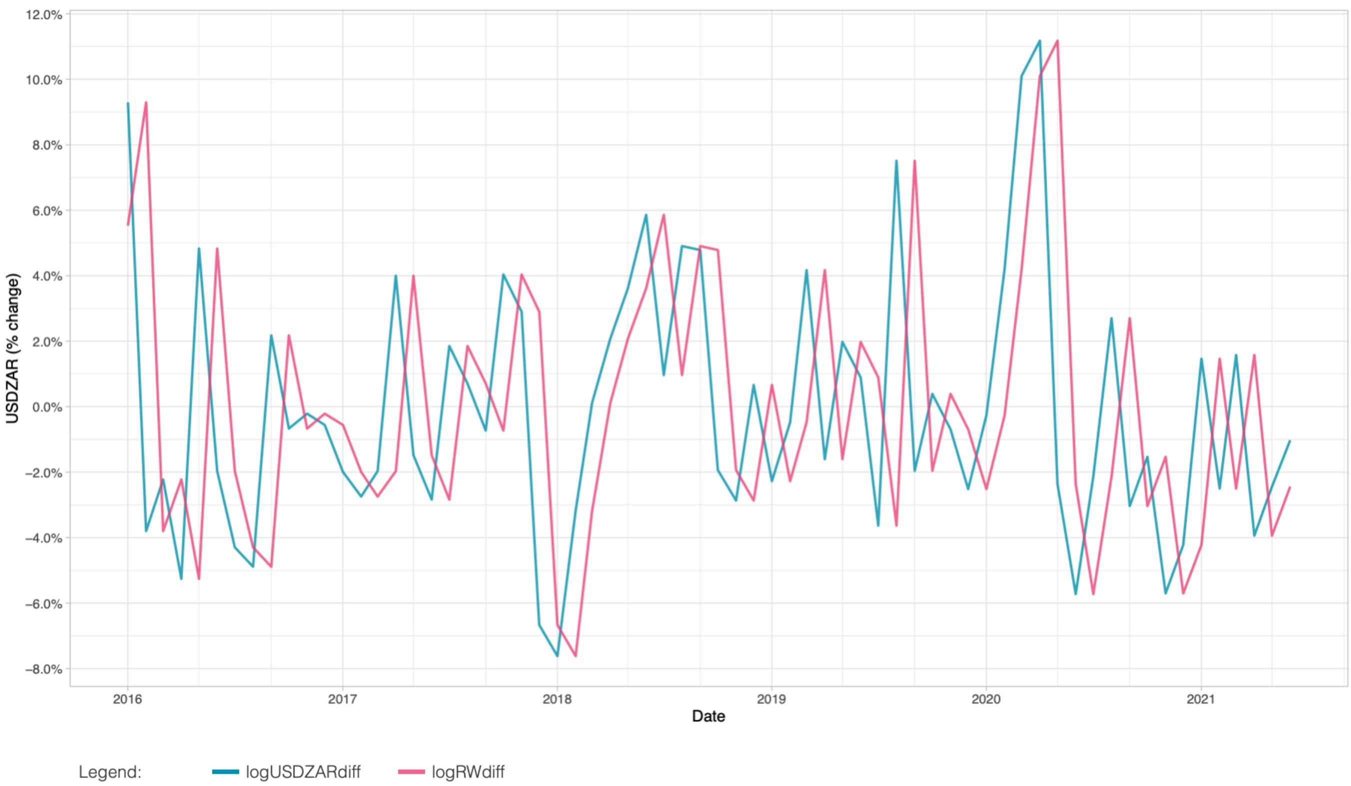


Figure 11.) Log Differenced Random Walk



As illustrated by the figures above, all the log differenced estimations of the fundamental exchange rate forecasting methods constantly underestimated the documented percentage changes of the USDZAR exchange rate over the course of the entire forecasting period. This phenomenon might be attributed to the Rand's increased volatility relative to the U.S. Dollar during this time frame.

According to Maveé, Perrelli and Schimmelpfennig (2016) and Miyajima (2020), the large fluctuations of the Rand during this forecasting period were mainly caused by global market volatility, commodity price volatility, civil unrest and domestic political uncertainty. The large number of domestic shocks within South Africa elevated the Rand's volatility to above the U.S. stock price volatility, or the VIX, which is a widely used indicator of global uncertainty (Miyajima, 2020). These factors caused South Africa to be perceived as an unstable and high-risk investment, which subsequently caused mass international speculation concerning the investment quality of South Africa (Maveé, Perrelli & Schimmelpfennig, 2016; Miyajima, 2020).

In order to easily compare the forecasts made by the monthly fundamental models relative to a random walk, this paper converts the forecasted log differenced values back into level terms. The MAD and MAPE are subsequently calculated to compare the actual values of the forecast relative to a random walk in level terms.

Table 5.) MAD and MAPE for Monthly Models (in Level Terms)

	UIRP	CIRP	PPP	RW
MAD	0,9501	0,9196	0,5854	0,4572
MAPE	6,61%	6,47%	3,98%	3,09%

Contrary to the DM test statistic failing to reject the null hypothesis that the fundamental models are not statistically different in forecasting accuracy relative to a random walk, Table 5 above illustrates that the random walk has the smallest MAD and MAPE values of all the tested monthly models (see Appendix 8). This implies that the random walk has the smallest absolute deviation and the smallest percentage error. Additionally, the random walk (Figure 15) seems to visually represent the movements in the USDZAR exchange rate more accurately relative to the utilised monthly fundamental models' forecasts (Figures 12, 13, 14). This supports the conclusions made by Meese and Rogoff (1983a, 1983b) that the fundamental methods of determining exchange rates are clearly not superior in forecasting the USDZAR exchange rate for a monthly frequency. This is exemplified by the fact that the monthly models consistently underestimated the percentage changes in the USDZAR exchange rate (Figures 8, 9, 10), thus resulting in inaccurate estimations relative to that of the random walk.

Figure 12.) Uncovered Interest Rate Parity Forecast

Figure 13.) Covered Interest Rate Parity Forecast

Figure 14.) Purchase Power Parity Forecast

Figure 15.) Random Walk Forecast

Finding that none of the monthly models have statistically different forecasting errors (proved by the DM Test), as well as the MAD and MAPE values being smaller for the random walk, consequently leads to the conclusion that the UIRP, CIRP and PPP models are not statistically superior in forecasting the monthly USDZAR exchange rate when compared to a random walk.

4.2.) Quarterly Model

Table 6.) Root Mean Square Error and Mean Absolute Error for the Quarterly Model

	MA	RW
RMSE	0,0969	0,1325
MAE	0,0713	0,0990

As illustrated in Table 6 above, the MA model has lower RMSE and MAE values relative to that of the random walk. This is in contrast to the findings of the aforementioned monthly models. Additionally, the implementation of the DM test-statistic on the MA model and the random walk returns a P-value of 0.0334 (see Appendix 6).

Table 7.) Diebold & Mariano Test Statistic for Quarterly Model

	MA
DM-Test P-values	0,0334

This indicates that the forecasting accuracy of the MA model is statistically different relative to a random walk due to the rejection of the null hypothesis stating that the two models have similar levels of forecasting. This coincides with the conclusions made by Salisu, Gupta and Kim (2021). Even though this finding is interesting, it is not completely unsurprising as quarterly models tend to have less volatility and are thus easier to forecast relative to monthly models. Additionally, the MA model is considered to be more accurate relative to a random walk due to the RMSE and MAE values implying that the MA model has a lower forecasting error than the random walk when forecasting the quarterly USDZAR spot rate. This suggests the MA model is likely a superior forecasting method relative to a random walk at a quarterly frequency.

It should be noted however, that the chosen frequency of the MA model has a direct influence on its perceived efficacy and accuracy (De Bruyn, Gupta and Stander, 2013; Rossi, 2013). Consequently, should the output variables (y and y*) in the MA model be proxied by a variable with a monthly frequency, such as industrial production, the findings may have been different.

Figure 16.) Log Differenced Monetary Approach

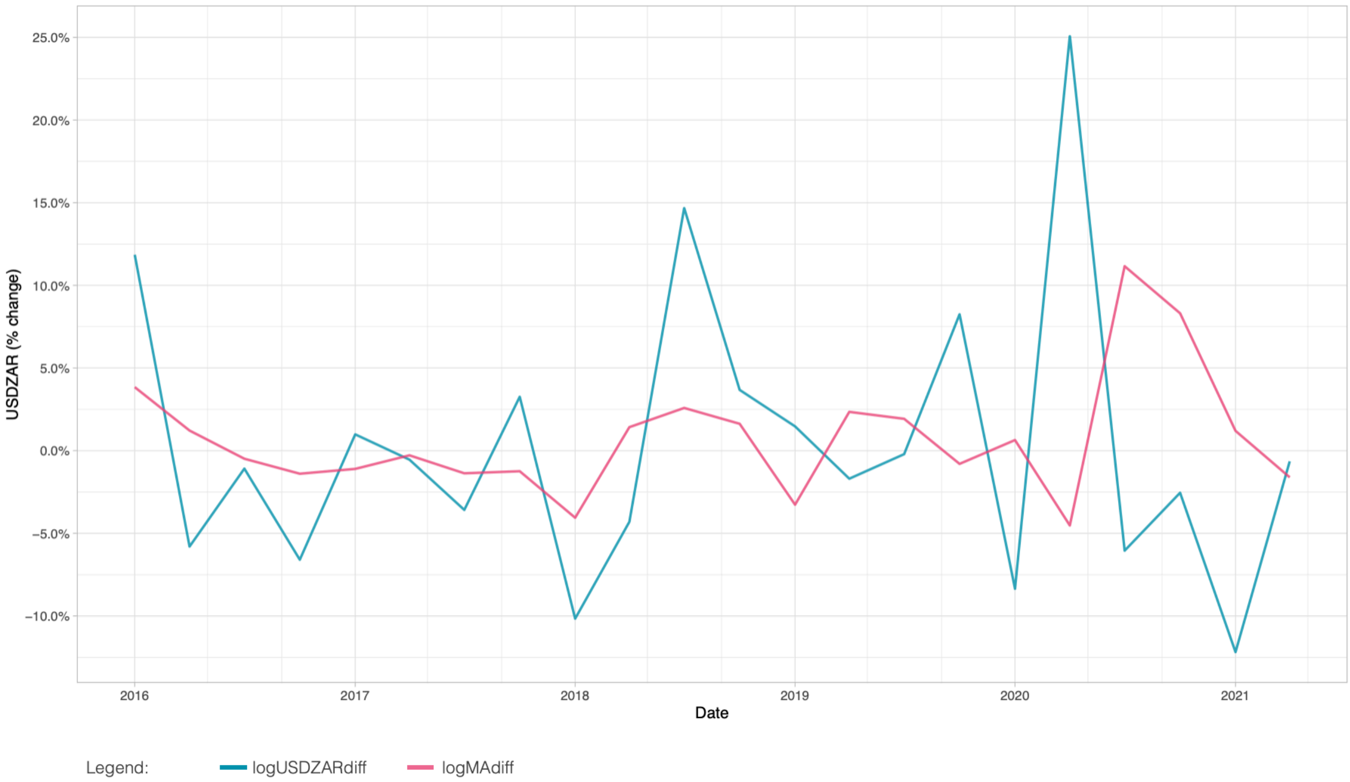


Figure 17.) Log Differenced Random Walk

Similar to the monthly fundamental models, the log differenced estimations of the exchange rate forecasted by the MA model consistently underestimated the documented percentage changes of the USDZAR over the course of the entire forecasting period. This phenomenon could be attributed to the perceived increase in the Rand's volatility relative to the U.S. Dollar due to various domestic and international factors (Maveé, Perrelli & Schimmelpfennig, 2016; Miyajima, 2020).

Similar to the monthly fundamental models, in order to easily compare the forecasts made by the quarterly MA model relative to a random walk, this paper converts the forecasted log differenced values back into level terms. The MAD and MAPE are subsequently calculated to compare the actual values of the forecast relative to a random walk in level terms.

Table 8.) MAD and MAPE for Quarterly Models (in Level Terms)

	MA	RW
MAD	0,4342	0,8871
MAPE	2,84%	5,93%

The fact that the MAD and MAPE values for the MA level forecast is lower relative to the random walk suggests that the MA model is superior in forecasting the USDZAR exchange rate. This coincides with the conclusion made by the DM test statistic that the MA model and the random walk do in fact have statistically different levels of forecasting accuracy. This reinforces the idea that the quarterly MA model is likely superior in forecasting the USDZAR exchange rate relative to a random walk.

This consequently leads to the conclusion that the MA model is more accurate in forecasting the USDZAR quarterly exchange rate relative to a random walk. This is a similar conclusion made by Salisu, Gupta and Kim (2021). Even though the MA model consistently underestimated the percentage changes in the USDZAR exchange rate (Figure 16), the MA model is statistically more accurate in forecasting the quarterly USDZAR exchange rate relative to a random walk (Figure 17). Furthermore, it seems as if the implementation of the quarterly model has eradicated much of the noise perceived in the forecasting sample period. Thus, the quarterly period is considered to be easier to forecast due to quarterly frequencies being less volatile than other shorter frequencies. Hence it is not completely unexpected that the quarterly MA model is superior in forecasting the USDZAR exchange rate relative to the random walk. It should be noted that should the MA model be estimated at monthly intervals, the results may differ.

Figure 18.) Monetary Approach Forecast

Figure 19.) Random Walk Forecast

Contrary to the forecasts made by the monthly fundamental models, the MA model (Figure 18) visually seems to be more accurate in forecasting the USDZAR exchange rate at a quarterly frequency relative to a random walk (Figure 19). Excluding the severe periods of economic uncertainty that occurred after the commencement of the COVID-19 pandemic in 2020, illustrated by the subsequent deviation of the MA forecast relative to the USDZAR exchange rate, the MA model seemed to forecast the fluctuations in the USDZAR exchange relatively accurately compared to that of the random walk. This strong deviation of the MA forecast in 2020 could also partially be due to the U.S exponentially increasing its M1 money supply after the commencement of the COVID-19 pandemic.

The conclusion of the implemented DM-test indicated that the forecasting error of the MA model is statistically different relative to a random walk. The RMSE, MAE, MAD and MAPE values all being significantly lower for the MA model relative to the values for the random walk strongly suggests that the MA model is superior in forecasting the quarterly USDZAR exchange rate. Additionally, the level forecasts made by the MA model arguably reflect the movement in the quarterly USDZAR exchange rate better than the random walk. This leads to the conclusion that the MA model is statistically superior in forecasting the quarterly USDZAR exchange rate when compared to the random walk. As previously mentioned, it should be noted that these conclusions might differ should the quarterly MA model be transformed into a monthly MA model.

5.) Conclusion

The exchange rate determines the price of domestic goods and services in terms of a particular foreign currency. This subsequently makes the ability to accurately forecast the exchange rate an indispensable tool to governments and individuals alike. The exchange rate is considered to be instrumental to any country's macroeconomic decision-making process, as well as informing the business decisions made by individuals and institutions. These features of the exchange rate consequently make the ability to accurately forecast and effectively characterise the behaviour of the exchange rate to be an extremely appealing skill.

The objective of this paper was to analyse whether the fundamental methods of determining exchange rates are more accurate in forecasting the USDZAR exchange rate relative to a random walk for the sample period of January 2000 until August 2021. This paper utilised the Uncovered Interest Rate Parity (UIRP), Covered Interest Rate Parity (CIRP), Purchase Power Parity (PPP) and the Monetary Approach (MA) models in order to forecast the behaviour of the USDZAR exchange rate. Furthermore, the aforementioned fundamental exchange rate models had an out-of-sample forecasting period from January 2016 until August 2021. The forecasts made by the implemented models were considered to be efficient should they be able to accurately predict the future spot exchange rate and simultaneously outperform the forecast made by the random walk.

This paper concluded that neither of the monthly UIRP, CIRP and PPP models of fundamental exchange rate determination are distinctly superior in forecasting the USDZAR exchange rate relative to a random walk. Contrary to the monthly models, the quarterly MA model was found to be statistically superior in forecasting the USDZAR exchange rate relative to the random walk. Possible further research topics include utilising an extended sampling period, implementing weekly or daily frequencies for the UIRP, CIRP and PPP models, transforming the MA model into a monthly frequency by proxying output with industrial production and applying a similar study to other emerging economies.

Words:7913
(incl. headings and references)

6.) Appendix

6.1. Appendix 1 Augmented Dickey Fuller (ADF) Test for Non-Stationarity

Monthly Models:

USDZAR Exchange Rate:

The P-value is larger than a 5% level of significance for level USDZAR (thus indicating non-stationary).

```
        Augmented Dickey-Fuller Test

data:  Data$`Rand to US$`
Dickey-Fuller = -2.3918, Lag order = 12, p-value = 0.4109
alternative hypothesis: stationary
```

Log Differenced USDZAR Exchange Rate:

The P-value is smaller than a 5% level of significance for logUSDZARdiff (thus indicating stationary).

```
        Augmented Dickey-Fuller Test

data:  Data$logExchRateDiff
Dickey-Fuller = -4.1828, Lag order = 12, p-value = 0.01
alternative hypothesis: stationary
```

USDZAR Forward Rate:

The P-value is larger than a 5% level of significance for the USDZAR Forward Rate (thus indicating non- stationary).

```
        Augmented Dickey-Fuller Test

data:  Data$`Fwd Rate`
Dickey-Fuller = -2.5175, Lag order = 12, p-value = 0.3579
alternative hypothesis: stationary
```

Log Differenced USDZAR Forward Rate:

The P-value is smaller than a 5% level of significance for log(USDZARFwdRate)diff (thus indicating stationary).

```
        Augmented Dickey-Fuller Test

data:  Data$`log(Fwd Rate )diff`
Dickey-Fuller = -3.7258, Lag order = 12, p-value = 0.0232
alternative hypothesis: stationary
```

South African Interest Rate:

The P-value is larger than a 5% level of significance for the South African Interest rate (thus indicating non-stationary).

```
        Augmented Dickey-Fuller Test

data:  Data$`S.A Interest Rate`
Dickey-Fuller = -2.8469, Lag order = 12, p-value = 0.2192
alternative hypothesis: stationary
```

U.S. Interest Rate:

The P-value is smaller than a 10% level of significance for the U.S. Interest Rate (thus likely indicating stationary).

```
        Augmented Dickey-Fuller Test

data:  Data$`U.S Interest Rate`
Dickey-Fuller = -3.3541, Lag order = 12, p-value = 0.06262
alternative hypothesis: stationary
```

Interest Rate Differential:

The P-value is smaller than a 5% level of significance for Interest Rate Differential (thus indicating stationary).

```
        Augmented Dickey-Fuller Test

data:  Data$`Interest Rate Differential`
Dickey-Fuller = -3.7297, Lag order = 12, p-value = 0.02301
alternative hypothesis: stationary
```

South African Inflation Rate:

The P-value is smaller than a 5% level of significance for the South African Inflation Rate (thus indicating stationary).

```
        Augmented Dickey-Fuller Test

data:  Data$`CPI (SA)%`
Dickey-Fuller = -3.5543, Lag order = 12, p-value = 0.03803
alternative hypothesis: stationary
```

U.S. Inflation Rate:

The P-value is smaller than a 5% level of significance for the U.S Inflation Rate (thus indicating stationary).

```
        Augmented Dickey-Fuller Test

data:  Data$`CPI (US)%`
Dickey-Fuller = -4.1476, Lag order = 12, p-value = 0.01
alternative hypothesis: stationary
```

Quarterly Model:

Log Differenced USDZAR Exchange Rate:

The P-value is smaller than a 5% level of significance for logUSDZARdiff (thus indicating stationary).

```
        Augmented Dickey-Fuller Test

data:  Data$logExchRateDiff
Dickey-Fuller = -3.738, Lag order = 4, p-value = 0.02638
alternative hypothesis: stationary
```

Interest Rate Differential:

The P-value is smaller than a 5% level of significance for Interest Rate Differential (thus indicating stationary).

```
        Augmented Dickey-Fuller Test

data:  Data$`IntRate Diff`
Dickey-Fuller = -4.179, Lag order = 4, p-value = 0.01
alternative hypothesis: stationary
```

Log Differenced GDP for South Africa:

The P-value is smaller than a 5% level of significance for log(SA GDP)diff (thus indicating stationary).

```
        Augmented Dickey-Fuller Test

data:  Data$`log(SA GDP)diff`
Dickey-Fuller = -4.4001, Lag order = 4, p-value = 0.01
alternative hypothesis: stationary
```

Log Differenced GDP for the U.S.:

The P-value is smaller than a 5% level of significance for log(US GDP)diff (thus indicating stationary).

```
        Augmented Dickey-Fuller Test

data:  Data$`log(US GDP)diff`
Dickey-Fuller = -3.9018, Lag order = 4, p-value = 0.01814
alternative hypothesis: stationary
```

M1 Money Supply:

P-value is smaller than a 5% level of significance for log(M1)diffdiff (thus indicating stationary).

```
        Augmented Dickey-Fuller Test

data:  Data$`log(M1)diffdiff`
Dickey-Fuller = -6.8614, Lag order = 4, p-value = 0.01
alternative hypothesis: stationary
```

South African Inflation Rate:

P-value is smaller than a 5% level of significance for the South African Inflation Rate (thus indicating stationary).

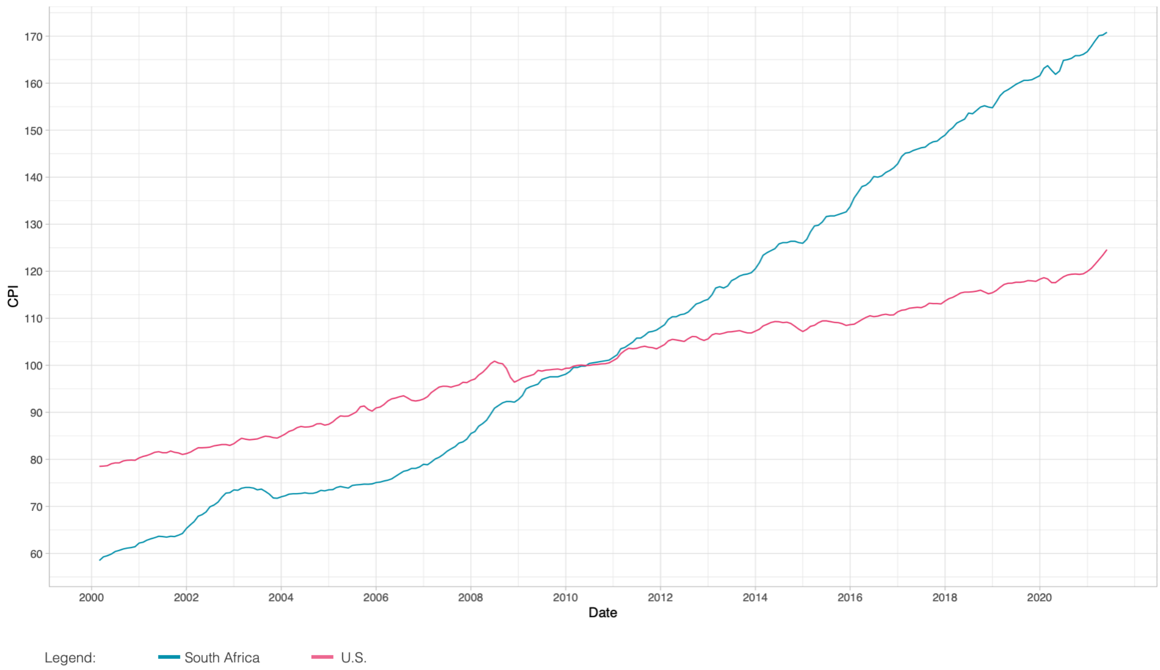
```
            Augmented Dickey-Fuller Test

data:  Data$`CPI SA (%)`
Dickey-Fuller = -3.9603, Lag order = 4, p-value = 0.01543
alternative hypothesis: stationary
```

U.S. Inflation Rate:

P-value is smaller than a 5% level of significance for the U.S. Inflation Rate (thus indicating stationary).

```
            Augmented Dickey-Fuller Test

data:  Data$`CPI US (%)`
Dickey-Fuller = -3.4805, Lag order = 4, p-value = 0.04883
alternative hypothesis: stationary
```

6.2. Appendix 2: CPI for South Africa and the U.S.



There are clear upward trends for both country's CPI variables over the entire sample period, with the South African CPI growing faster relative to the U.S CPI.

6.3. Appendix 3: Homoskedasticity

Implementing the Breusch-Pagan (BP) test for homoskedasticity, the P-value is greater than a 10% level of significance for the PPP and MA models and greater than a 5% level of significance for the UIRP model. Hence we fail to reject the null hypothesis of a constant variance for these three models. Whereas the P-value for the CIRP is less than the 5% level of significance, thus rejecting the null hypothesis of a constant variance.

UIRP Model:

```
        studentized Breusch-Pagan test

data:  UIRP
BP = 3.1021, df = 1, p-value = 0.07819
```

CIRP Model:

```
        studentized Breusch-Pagan test

data:  CIRP
BP = 11.567, df = 1, p-value = 0.0006713
```

PPP Model:

```
        studentized Breusch-Pagan test

data:  PPP
BP = 2.6047, df = 1, p-value = 0.1065
```

MA Model:

```
        studentized Breusch-Pagan test

data:  MA
BP = 7.304, df = 4, p-value = 0.1207
```

6.4. Appendix 4: Durbin-Watson Tests

Due to the P-Value being greater than the 10% significance level for all the models, it is conclusive that serial correlation is not an issue for all four models.

UIRP Model:

```
        Durbin-Watson test

data:  UIRP
DW = 1.9514, p-value = 0.3586
alternative hypothesis: true autocorrelation is greater than 0
```

CIRP Model:

```
        Durbin-Watson test

data:  CIRP
DW = 2.0023, p-value = 0.5099
alternative hypothesis: true autocorrelation is greater than 0
```

PPP Model:

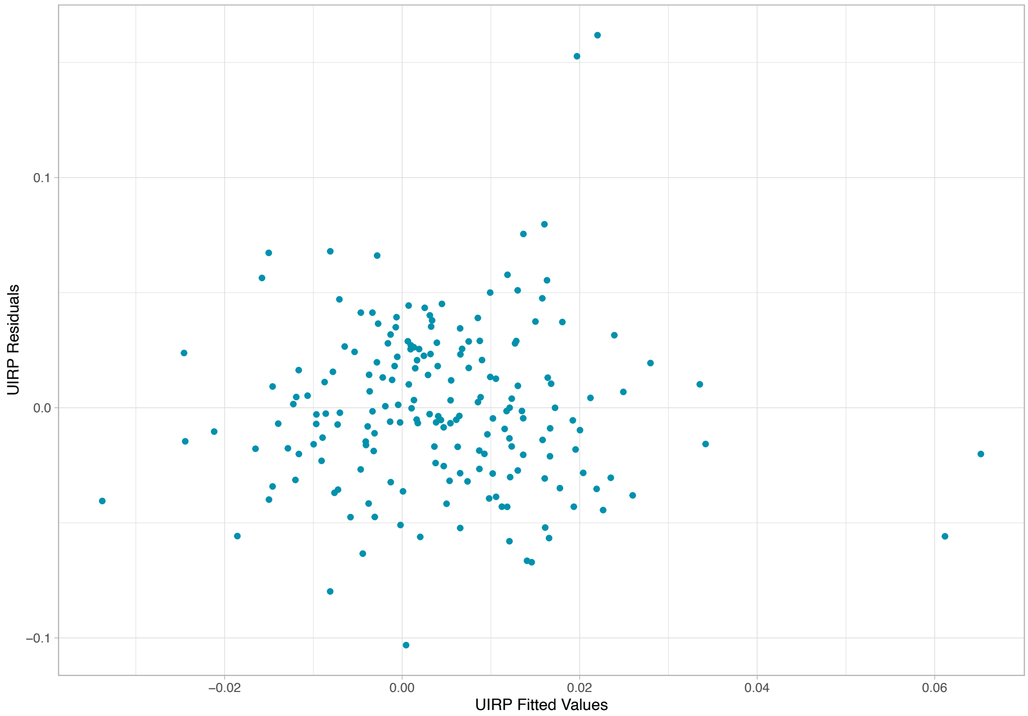
```
        Durbin-Watson test

data:  PPP
DW = 1.9529, p-value = 0.3636
alternative hypothesis: true autocorrelation is greater than 0
```

MA Model:

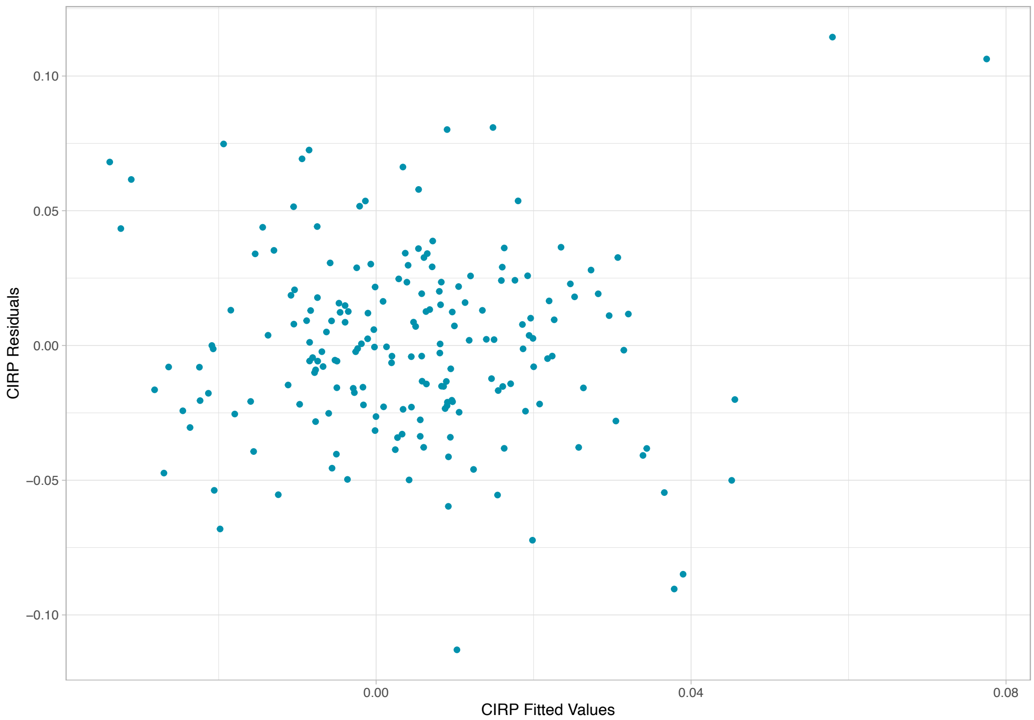
```
        Durbin-Watson test

data:  MA
DW = 2.1813, p-value = 0.6481
alternative hypothesis: true autocorrelation is greater than 0
```

6.5. Appendix 5: Residuals Plots

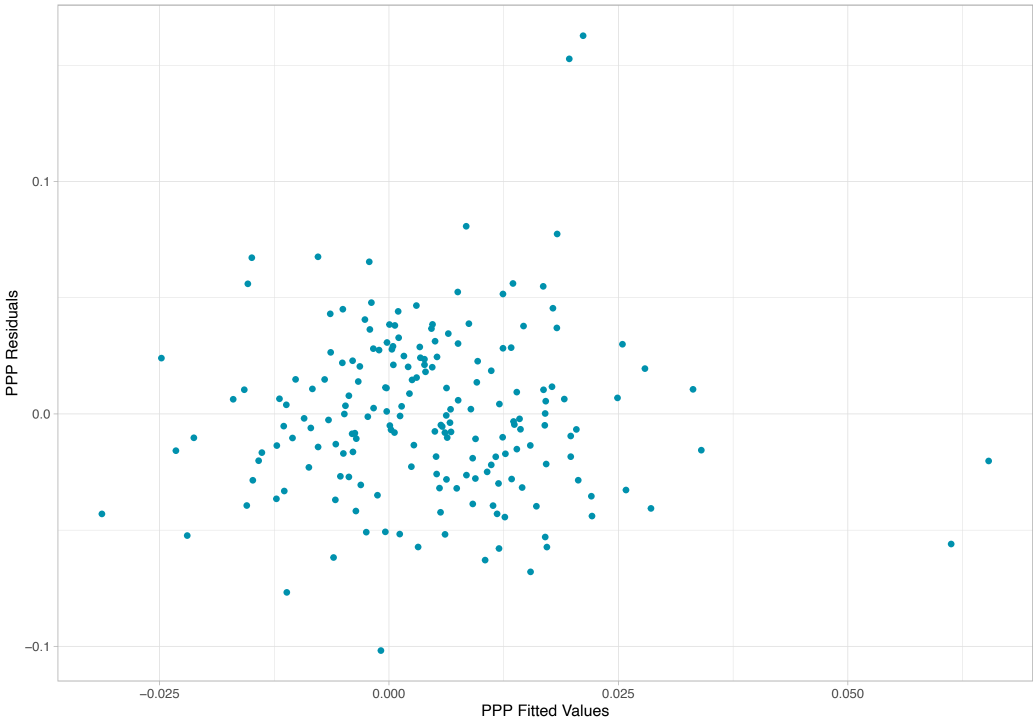
UIRP Model:



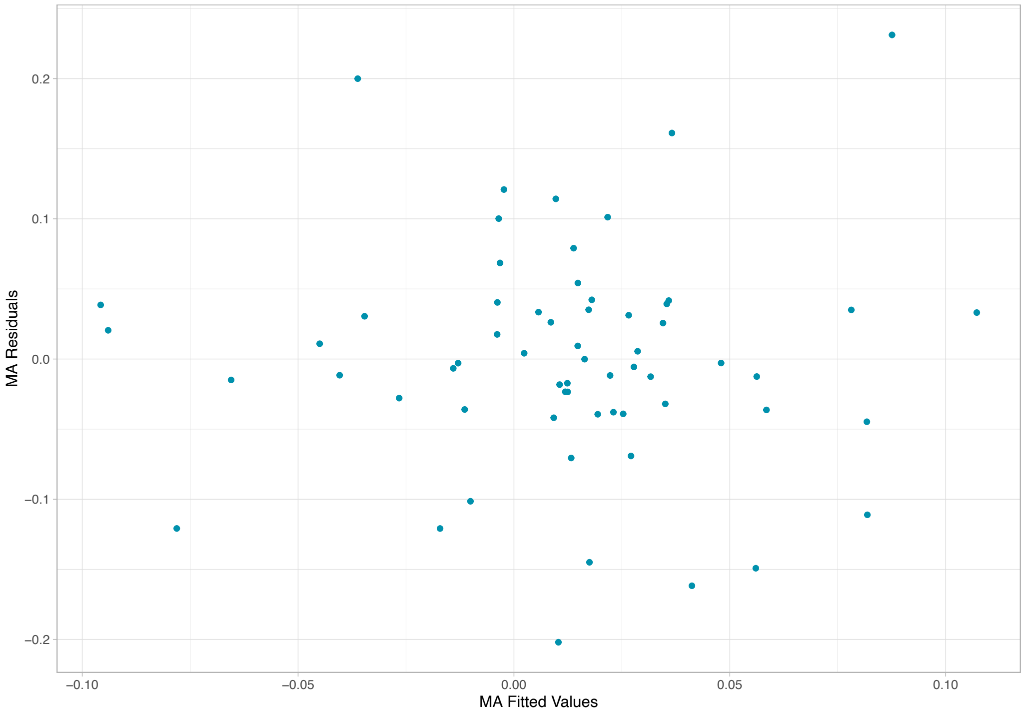
CIRP Model:



PPP Model:



MA Model:



6.6. Appendix 6: Diebold & Mariano Test Statistic

None of the monthly models return a P-value that is smaller than 0.05, thus concluding that none of the monthly models has statistically different levels of forecasting accuracy relative to a random walk. Whereas the quarterly MA model has a P-value smaller than 0.05, thus indicating that the MA model has a statistically different level of forecasting accuracy relative to a random walk.

UIRP:

```
        Diebold-Mariano Test

data:  Forecast_Error_UIRPForecast_Error_RW
DM = -0.21399, Forecast horizon = 1, Loss function power = 2, p-value = 0.8312
alternative hypothesis: two.sided
```

CIRP:

```
        Diebold-Mariano Test

data:  Forecast_Error_CIRPForecast_Error_RW
DM = -0.93526, Forecast horizon = 1, Loss function power = 2, p-value = 0.3531
alternative hypothesis: two.sided
```

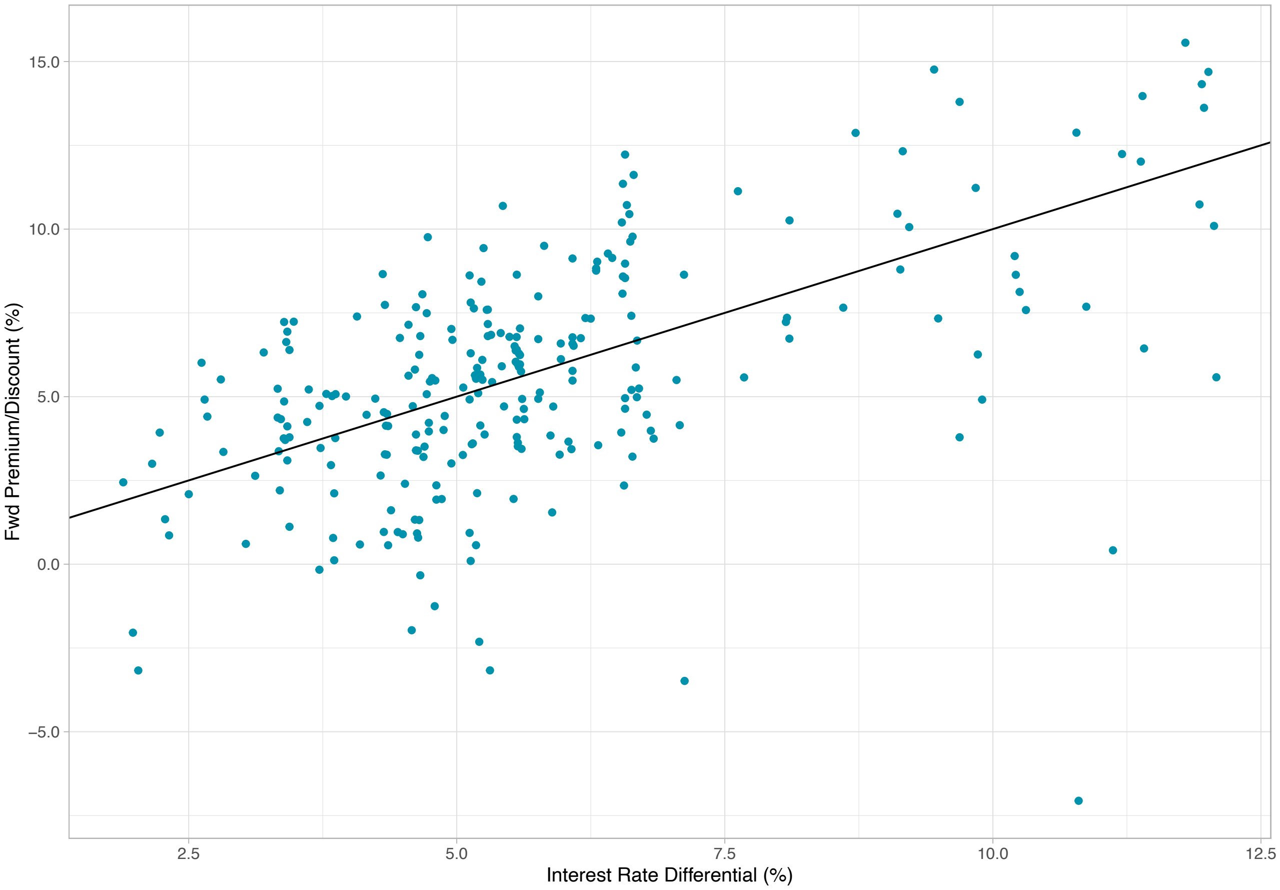
PPP:

```
        Diebold-Mariano Test

data:  Forecast_Error_PPPForecast_Error_RW
DM = 1.3158, Forecast horizon = 1, Loss function power = 2, p-value = 0.1928
alternative hypothesis: two.sided
```

MA:

```
        Diebold-Mariano Test

data:  Forecast_Error_MAForecast_Error_RW
DM = -2.2766, Forecast horizon = 1, Loss function power = 2, p-value = 0.03339
alternative hypothesis: two.sided
```

6.7. Appendix 7: CIRP Grid



As illustrated by the grid above, the CIRP model does not hold within the USDZAR context due to the data points not lying in close proximity to the 45 degree line.

6.8. Appendix 8: MAD and MAPE for Monthly Models (in Level Terms)

Date	USDZAR	UIRP	CIRP	PPP	RW
2016-01-01	16,38	15,28	14,09	14,52	14,93
2016-02-01	15,77	16,37	14,25	15,58	16,38
2016-03-01	15,42	17,26	14,05	16,39	15,77
2016-04-01	14,63	16,71	13,99	15,77	15,42
2016-05-01	15,36	16,21	14,09	15,25	14,63
2016-06-01	15,06	15,89	13,88	14,90	15,36
2016-07-01	14,42	16,31	13,99	15,37	15,06
2016-08-01	13,73	15,87	13,79	14,98	14,42
2016-09-01	14,04	15,17	13,29	14,22	13,73
2016-10-01	13,94	14,78	13,90	13,90	14,04
2016-11-01	13,91	14,97	13,91	14,10	13,94
2016-12-01	13,84	14,89	13,66	14,04	13,91
2017-01-01	13,56	14,83	13,70	13,97	13,84
2017-02-01	13,20	14,66	13,64	13,82	13,56
2017-03-01	12,94	14,33	13,61	13,57	13,20
2017-04-01	13,47	13,96	13,55	13,18	12,94
2017-05-01	13,27	13,95	13,83	13,15	13,47
2017-06-01	12,90	14,26	13,80	13,47	13,27
2017-07-01	13,14	13,96	13,65	13,20	12,90
2017-08-01	13,23	13,76	13,84	13,03	13,14
2017-09-01	13,13	13,94	14,06	13,19	13,23
2017-10-01	13,68	13,98	13,91	13,25	13,13
2017-11-01	14,08	14,09	14,16	13,38	13,68
2017-12-01	13,17	14,61	14,13	13,88	14,08
2018-01-01	12,20	14,56	14,02	13,86	13,17
2018-02-01	11,82	13,57	13,69	12,88	12,20
2018-03-01	11,84	12,75	13,53	12,13	11,82
2018-04-01	12,08	12,46	13,76	11,89	11,84
2018-05-01	12,53	12,53	13,72	11,97	12,08

Date	USDZAR	UIRP	CIRP	PPP	RW
2018-06-01	13,29	12,84	14,32	12,26	12,53
2018-07-01	13,41	13,40	14,25	12,86	13,29
2018-08-01	14,09	13,97	14,90	13,44	13,41
2018-09-01	14,78	14,30	14,76	13,68	14,09
2018-10-01	14,50	15,00	15,30	14,41	14,78
2018-11-01	14,09	15,37	14,90	14,78	14,50
2018-12-01	14,18	15,03	15,19	14,46	14,09
2019-01-01	13,86	14,79	14,79	14,16	14,18
2019-02-01	13,80	14,73	15,18	14,11	13,86
2019-03-01	14,38	14,49	15,04	13,93	13,80
2019-04-01	14,15	14,64	15,27	14,05	14,38
2019-05-01	14,44	14,97	15,22	14,36	14,15
2019-06-01	14,57	14,92	15,39	14,30	14,44
2019-07-01	14,05	15,16	15,45	14,57	14,57
2019-08-01	15,14	15,06	15,53	14,46	14,05
2019-09-01	14,85	15,08	15,65	14,47	15,14
2019-10-01	14,91	15,77	15,47	15,10	14,85
2019-11-01	14,80	15,62	15,64	14,90	14,91
2019-12-01	14,44	15,66	15,62	14,94	14,80
2020-01-01	14,40	15,46	15,83	14,75	14,44
2020-02-01	15,02	15,17	15,70	14,49	14,40
2020-03-01	16,61	15,37	16,52	14,73	15,02
2020-04-01	18,58	16,36	16,96	15,64	16,61
2020-05-01	18,14	18,06	17,32	17,27	18,58
2020-06-01	17,13	19,22	17,40	18,42	18,14
2020-07-01	16,77	18,52	17,01	17,91	17,13
2020-08-01	17,23	17,66	16,99	17,15	16,77
2020-09-01	16,72	17,56	17,28	16,95	17,23
2020-10-01	16,46	17,70	16,99	17,13	16,72
2020-11-01	15,55	17,25	16,79	16,72	16,46

Date	USDZAR	UIRP	CIRP	PPP	RW
2020-12-01	14,91	16,75	16,49	16,21	15,55
2021-01-01	15,13	15,90	16,62	15,39	14,91
2021-02-01	14,75	15,54	16,37	15,03	15,13
2021-03-01	14,99	15,56	16,44	15,06	14,75
2021-04-01	14,41	15,38	16,46	14,87	14,99
2021-05-01	14,06	15,35	16,18	14,79	14,41
2021-06-01	13,92	14,83	16,29	14,23	14,06
	MAD (Mean Abs Deviation	**0,9501**	**0,9196**	**0,5854**	**0,4572**
	MAPE(Mean Abs Percent Error)	**6,614%**	**6,470%**	**3,984%**	**3,093%**

6.9. Appendix 9: MAD and MAPE for Quarterly Model

Date	USDZAR	MA	RW
2016-01-01	15,615	16,299	13,870
2016-04-01	14,735	14,986	15,615
2016-07-01	14,576	14,450	14,735
2016-10-01	13,645	13,300	14,576
2017-01-01	13,780	13,698	13,645
2017-04-01	13,705	13,800	13,780
2017-07-01	13,223	13,111	13,705
2017-10-01	13,660	13,560	13,223
2018-01-01	12,340	11,916	13,660
2018-04-01	11,820	12,060	12,340
2018-07-01	13,688	14,118	11,820
2018-10-01	14,200	14,504	13,688
2019-01-01	14,410	14,014	14,200
2019-04-01	14,168	14,576	14,410
2019-07-01	14,138	14,500	14,168
2019-10-01	15,353	15,100	14,138
2020-01-01	14,122	14,300	15,353
2020-04-01	18,145	17,409	14,122
2020-07-01	17,080	19,174	18,145
2020-10-01	16,650	18,169	17,080
2021-01-01	14,740	14,988	16,650
2021-04-01	14,645	14,479	14,740
	MAD (Mean Abs Deviation	**0,6116**	**0,8871**
	MAPE(Mean Abs Percent Error)	**3,982%**	**5,927%**

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