Which Rand Hedges Have Provided The Best Hedging?

Nico Katzke[a], Jason Dolan[a], Sibusiso Mnisi[a,1]

[a] *Department of Economics, Stellenbosch University, South Africa.*

Abstract

This paper provides a comprehensive empirical investigation into which assets are the best rand hedges. Using daily data over the period of 2003 to 2016, the aim is to determine which assets have provided investors with the best protection from rand weakness. A regression model including dummy variables for when rand depreciation exceeds a certain quantile is used to this effect. Subsequently, a DCC model is fitted to study the dynamic correlations between asset returns and currency movements, in order to identify which assets are most effective at hedging against the rand. The results are consistent in suggesting that gold has acted as the best rand hedge by a significant margin, while locally listed equities have differing degrees of hedging potential.

Keywords: Multivariate GARCH DCC Gold Stocks Hedging Currency

JEL classification L250, L100

1. Introduction

A hedge refers to an investment intended to offset the gains or losses associated with the returns of another asset. This paper provides an investigation into which traditional rand hedge instruments have provided investors with the best hedging. Specifically, we aim to determine which assets have provided investors with the best protection from rand weakness. Therefore, the econometric techniques employed in this paper aim at the identification of assets most strongly negatively correlated with the rand i.e. assets that perform the best during periods of rand depreciation. Two econometric methods are used for the purposes of this investigation. Firstly, a regression

*Corresponding author: Nico Katzke
Email addresses: `nfkatzke@gmail.com` (Nico Katzke), `jason1dolan@gmail.com` (Jason Dolan), `sibu.mnisi@gmail.com` (Sibusiso Mnisi)

model with a quantile factor variable is run in order study the hedging potential of assets, and their behaviour during times of rand stress. Secondly, a Dynamic Conditional Correlation (DCC) model is run in order to study the time-varying correlations between the assets and the rand, in order to conclude which are the best rand hedges.

2. Literature Overview

The South African exchange rate has historically been subject to significant exchange rate volatility, with fairly long periods of rand depreciation (refer to figure 7.1 in the appendix for a visual depiction of the rand-dollar exchange rate from 2003 to 2016). Consequently, the question of how to protect capital against rand weakness has become a topic of interest for many South African investors.

In this paper we follow Baur and Lucey (2010) in defining ‘hedges’ and ‘safe havens’. Consequently, a hedge is defined as an asset that is negatively correlated with another asset, or group of assets, *on average*. A safe haven, on the other hand, is defined as an asset that is negatively correlated with another asset, or group of assets, during times of *market stress*.

Theoretically, there should be a number of South African equities that have rand hedge potential, due to the fact that a fairly large proportion of the companies listed on the JSE either have substantial offshore operations, or sell goods denominated in foreign currencies. Given these characteristics, when the rand depreciates, the revenue of such companies translated into rands will then be higher. The increase in revenue should, in turn, make the companies more valuable and subsequently increase their share prices - culminating in a positive correlation between rand *depreciation* and share price *appreciation* (i.e. these equities will provide hedging against the rand for investors). Another theoretical avenue for hedging (or finding a safe haven) against the rand is through commodities, as they are priced in dollars - and therefore become worth more, in rand terms, when the rand depreciates.

The literature on rand hedges in South Africa is currently both dated and limited. The main contribution is by Barr, Holdsworth, and Kantor (2006), who use a regression model in order to study the relationships between the top 40 JSE listed shares and the rand-dollar exchange rate. These authors find evidence to suggest that it is possible to construct domestic portfolios, consisting wholly of locally listed equities, that provide consistent and effective protection against rand depreciation. Subsequently, in Barr, Kantor, and Holdsworth (2007), the same authors use a GARCH regression approach to investigate the relationship between the top 40 JSE listed shares and the rand-dollar exchange rate. These authors find a wide range of heterogenity in the correlations between the rand and different shares, with some shares individually acting as effective rand hedges. More recently, Ward and Terblanche (2009) conducted an investigation into the feasibility, and effectiveness, of market timing the JSE using exchange rate fluctuations. The method these authors use is to switch between 'rand hedge' and 'rand play' portfolios based on exchange rate fluctuations. The results of these authors suggest that potentially significant excess returns, over and above the benchmark, can be generated by employing this method.

In the international literature, there have been various applications to the co-movements of financial returns series when attempting to hedge an investment position against currency movements. The perceived co-movements between currency depreciation and stock market returns investigated by Fang and Miller (2002), using a bivariate GARCH-M model, reveals evidence that the conditional variance of stock returns and currency depreciation rate exhibit time-varying characteristics. This result is supported by Mukherjee and Naka (1995) and Kearney (1998) who find a cointegrating relationship between the stock market and the exchange rate.

Bauwens, Laurent, and Rombouts (2006) stress that understanding and predicting the temporal dependence in the second-order moments and being able to control for the second order temporal persistence of assets return has numerous financial econometric applications. Chief among those applications are hedging and risk management in options pricing and volatility modeling. Tse and Tsui (2002) along with Bae, Karolyi, and Stulz (2003) in turn apply GARCH models in their investigation of volatility and correlation transmission to the spillover effects inherent in the study of contagions. Kennedy and Nourzad (2016) conclude that once the major drivers of financial volatility are controlled for, increased exchange rate volatility exerts a positive and statistically significant effect on the volatility of stock returns. Baur and Lucey (2010) study the time-varying correlations between gold and various other assets in the UK, US and Germany. The findings of Baur and Lucey (2010) suggest that gold acts as a safe haven for stocks in all three countries considered. Finally, Ciner, Gurdgiev, and Lucey (2013) conduct an investigation into the hedging potential of various assets against both the US dollar and the pound, using the DCC model due to R. Engle (2002) with a GARCH specification. These authors find that gold acts as a hedge against exchange rate fluctuations for both the UK pound and the US dollar.

In terms of methodology, the GARCH-DCC method offers a simple and relatively parsimonious means of modeling multivariate volatility estimations, which allows for the modeling of time varying correlations. The caveat in the quest for parsimonious model estimation is that the simplification required at times fails to capture the dynamics entrenched in the covariance structure[1].

The use of a GARCH-DCC model has two further advantages when compared to other estimation methods. Firstly, DCC models estimate the correlation coefficients of the standardized residuals, in doing so the heteroskedasticity inherent in the series is taken into account directly. The model also allows for the inclusion of additional explanatory variables in the mean equation to ensure that the model remains well specified. The model does not, however, account for the asymmetries within the conditional variances, covariances and the correlations (Chittedi 2015, 6), these asymmetries are adressed further in Cappiello, Engle, and Sheppard (2006).

3. Data

Equities, bonds and commodities easily accessible to the South African investor are considered for their rand hedge potential. In particular, the 30 largest locally (JSE) shares are included in the ensuing investigation. In addition we incorporate two bond indices, one ETF as well as

[1] See Silvennoinen and Teräsvirta (2009) for further analysis hereon.

one commodity - in the form of physical gold - into the analysis. The two bond indices are the ALBI and the GOVI. Finally, the ETF is the NewGold ETF, which tracks the rand gold price, effectively giving investors the opportunity to invest in gold bullion. We expect the hedging potential of physical gold and the Newgold ETF to be very similiar; we nonetheless include both as contrasting the performance between the two may be interesting to an investor in and of itself. It is of a similiar motivation that we include two bond indices. A complete list of all assets included in the analysis, which includes both tickers and full names, are included in an appendix (see table 7.1).

Daily data, over the period 2003 to 2016, obtained from Bloomberg, are used in the proceeding investigation. Where applicable we use total return index data (returns with dividends reinvested). Daily log returns are then calculated, and subsequently used, for all statistical analyses. Each series has a total of 3564 observations - execpt for British American Tobacco and the NewGold ETF which were only listed in 2008 and 2004 respectively. Dataset characteristics - for each included series - can be seen in the descriptive table included in the appendix (see table 7.2).

4. Methodology

The two methodologies used in this paper are discussed here, namely: the regression model (4.1) and the DCC model (4.2). The regression model is used in order to identify assets with the best rand hedge and safe haven characteristics, those assets are then incorporated into a DCC model; in order to conclude which assets are the best rand hedges. The aim is then to compare the results of the two different methods to see if they are consistent.

4.1. Regression

In order to investigate which assets are effective rand hedges, the following regression model is specified:

$$Return_t - RF_t = \beta_0 + \beta_1 Rand_t + \beta_2 Rand90_t + \beta_3 Rand95_t + \beta_4 Rand99_t + \epsilon_t \quad (4.1)$$

The model specified here is similiar to the model used by Iqbal (2017), who uses this method to study whether gold is an effective hedge against both the Indian and Pakastani currencies. In equation 4.1, $Return_t$ is the log returns of the assets, RF_t is the risk free rate (for which we use the Johannesburg interbank average rate), $Rand_t$ denotes log rand returns (depreciation), $Rand90_t$ represents log rand returns that exceed the 90% quantile; correspondingly, $Rand95_t$ and $Rand99_t$ represent log rand returns that exceed the 95% and 99% quantiles. We subtract the risk free rate from asset returns in order to obtain excess returns ($Return_t$ - RF_t). $Rand90_t$, $Rand95_t$ and $Rand99_t$ are dummy variables that equal one if rand depreciation exceeds the specified quantile and are zero otherwise. The dummy variables are included to account for extreme foreign exchange market shocks, which enables us to study the behaviour of the included assets during periods of rand stress.

4.2. DCC Model

For this study, the time-varying correlations are calculated using the Dynamic Conditional Correlation (DCC) model of R. Engle (2002). DCC models offer a simple and more parsimonious means of doing multivariate volatility modelling. In particular, it relaxes the constraint of a fixed correlation structure (assumed by the CCC model), to allow for estimates of time-varying correlation. Therefore, an advantage of this model is that it allows for the detection of changes in correlations over the sample period, which allows us to assess whether the hedging potential of our included assets have been static, or contrarily dynamic, over time.

The first step in this method is to obtain GARCH estimates for the univariate volatility estimates for each series. For this purpose a standard GARCH(1,1) specification is used. The standard GARCH(1,1) specification model is written in equation 4.2 as follows:

$$
\begin{aligned}
&r_t = \mu + \varepsilon_t \\
&\ varepsilon_t = \sigma_t . z_t \\
&\ sigma_t^2 = \alpha + \beta_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \\
&z_t \sim \mathcal{N}(0,1)
\end{aligned}
\tag{4.2}
$$

The standardized residuals extracted from the GARCH (1,1) model are then used to estimate dynamic conditional correlations using a log-likelihood approach. The DCC model can be defined as in equation 4.3 below:

$$
H_t = D_t . R_t . D_t . \tag{4.3}
$$

Equation 4.3 splits the variance covariance matrix into identical diagonal matrices and an estimate of the time-varying correlation. Where R_T now refers to time varying conditional correlations. Estimating R_T requires it to be inverted at each estimated period, and thus a proxy equation is used, as represented by equation 4.4 below (R. Engle 2002, 10):

$$
\begin{aligned}
Q_{ij,t} &= \bar{Q} + a\left(z_{t-1} z_{t-1}' - \bar{Q}\right) + b\left(Q_{ij,t-1} - \bar{Q}\right) \\
&= (1 - a - b)\bar{Q} + a z_{t-1} z_{t-1}' + b . Q_{ij,t-1}
\end{aligned}
\tag{4.4}
$$

Equation 4.4 above is similar in form to a GARCH(1,1) process, with non-negative scalars a and b, and with the following features: $Q_{ij,t}$ is the unconditional (sample) variance estimate between series i and j and $\bar{Q}$ is the unconditional matrix of standardized residuals from each univariate pair estimate. Equation 4.4 is then used to estimate R_t as:

$$R_t = diag(Q_t)^{-1/2} Q_t . diag(Q_t)^{-1/2} \tag{4.5}$$

Which has bivariate elements, as shown in equation 4.6 below:

$$R_t = \rho_{ij,t} = \frac{q_{i,j,t}}{\sqrt{q_{ii,t} . q_{jj,t}}} \tag{4.6}$$

The resulting complete DCC model is then formulated as shown in the statistical specification 4.7 below:

$$\begin{aligned}
\varepsilon_t &\sim N(0, D_t.R_t.D_t) \\
D_t^2 &\sim \text{Univariate GARCH(1,1) processes } \forall \text{ (i,j), i} \neq \text{j} \\
z_t &= D_t^{-1}.\varepsilon_t \\
Q_t &= \bar{Q}(1 - a - b) + a(z_t' z_t) + b(Q_{t-1}) \\
R_t &= Diag(Q_t^{-1}).Q_t.Diag(Q_t^{-1})
\end{aligned} \tag{4.7}$$

5. Results

5.1. Regression Results

From the regression output, the aim is to identify the best rand hedges, which will then be used as inputs for the DCC model. The regression results for each individual asset are included in an appendix (see appendix 7.4 for the results of each individual regression seperately).

If an asset is a hedge against rand depreciation, there must be a positive relationship between asset returns and exchange rate returns (or, equivalently, rand depreciation) on average. In terms of interpretation, if only β_1 for a patricular asset is positive then the asset acts as a hedge against rand exchange rate risk. If the sum of β_2, β_3 and β_4 for a particular asset is greater than zero then the asset acts as - what we will refer to as - a 'safe haven' against rand exchange rate depreciation at the 99% quantile. Table 5.1 below shows the top ten best, and from number 6 onward least worst, rand hedges.

Table 5.1: Top Ten Rand Hedges

	Asset	β_1 Coefficient
1	Physical Gold	0.5395
2	NewGold ETF	0.4080
3	British American Tobacco	0.3029
4	South African Breweries	0.1271
5	Intu Properties	0.0852
6	Richemont	-0.0294
7	GOVI	-0.0776
8	Anglo Gold	-0.1433
9	ALBI	-0.1619
10	Capitec	-0.1651

The results suggest that out of the 33 assets included, only five have acted as effective rand hedges (rand values that rise with rand weakness on average). Generally, gold appears to be the best rand hedge, with physical gold and the NewGold ETF occupying the first two spots on the top ten list. Some of the shares traditionally known as 'rand hedges' also make the list, including: British American Tobacco[2], South African Breweries, Intu Properties and Richemont. Though others, such as Steinhoff and Naspers fail to make the top ten. Interestingly, both bond indices make the

[2]It should be noted that BTI only listed on the JSE in 2008, and therefore the sample period is not the same as the other equities (and also excludes much of the financial crisis period). The reader should therefore place caution before interpreting BTI to be unequivocally the best rand hedge share - time will be the ultimate judge.

top ten, though they are not rand hedges as per our definition given their negative β_1 coefficients, rather they are among the 'least worst' rand hedges. These results may come as surprising to the investor, in that only three of the 30 included equities have actually acted as rand hedges. Which goes contrary to the popular belief that the JSE is populated with rand hedge shares. This does not appear to be true in absolute terms (individual equities do not generally provide protection against the rand), though in relative terms there is great variation in the hedging potential of different equities. The analysis further elucidates that just because a company sells goods in foreign denominated currencies, or has substantial offshore operations, does not necessarily make it an effective rand hedge.

We now take a look at the 'worst rand hedges', or alternatively the best 'rand play' shares, i.e shares that benefit the most from rand appreciation on average. Table 5.2 below shows the ten worst rand hedges (assets that perform the most poorly during periods of rand depreciation).

Table 5.2: Ten Worst Rand Hedges

	Asset	β_1 Coefficient
1	Anglo American	-0.5488
2	Anglo American Platinum	-0.5050
3	Firstrand	-0.4998
4	RMB Holdings	-0.4743
5	Standard Bank	-0.4437
6	Barclays Africa	-0.4421
7	MTN	-0.4290
8	Nedbank	-0.4089
9	BHP Biliton	-0.3968
10	Woolworths	-0.333

It is interesting to note that South Africa's 'big four' banks - Firstrand, Standard Bank, Barclays

Africa and Nedbank - all make the list of the ten worst rand hedges. Showing that in South Africa banking share returns are generally negatively related to exchange rate returns (rand depreciation). In addition, two of the biggest JSE listed diversified miners - Anglo American and BHP Biliton - also make the list. Finally, RMB Holdings, MTN and Woolworths complete the list of the worst rand hedge assets.

Table 5.3 shows the best 'safe havens' against rand depreciation at the 99% quantile. In other words, assets that perform the best during extreme bear periods for the rand.

Table 5.3: Top Ten Safe Havens

	Asset	$\beta_2 + \beta_3 + \beta_4$
1	Goldfields	0.0248
2	Anglo Gold	0.0240
3	Anglo Platinum	0.0156
4	Richemont	0.0100
5	Anglo American	0.0100
6	NewGold ETF	0.0096
7	Sasol	0.0078
8	Remgro	0.0076
9	Physical Gold	0.0046
10	Aspen Pharmacare	0.0044

In terms of the best safe havens, table 5.3 shows that the two gold miners come out a fair margin ahead of the others on the top ten list, followed by a platinum miner. It is interesting to note that Anglo Platinum, the second worst rand hedge, is also the third best safe haven as per our definition. Showing that the relationship between Anglo Platinum's returns and the exchange rate are highly non-linear. In other words, Anglo Platinum generally performs poorly when the rand depreciates (on average), but performs well during severe bear periods for the rand (extreme foreign exchange market conditions). Assets that made it concommitantly onto both the 'best rand hedge' list as well as 'best safe haven' list are the following: Richemont, NewGold ETF and Physical Gold.

5.2. DCC Model Results

As inputs for the DCC model, we take the best rand hedges as identified by the regression model, as well as, for the sake of interest, the two best safe havens which aren't already included on the best hedges list. British American Tobacco is excluded from the analysis since it was only listed on the JSE in 2008, and the DCC model requires all sample sizes to be the same. The sample period for the analysis is now starting from 2004/11/03, the NewGold ETF listing date. The complete list of assets used as inputs for the DCC model are listed in table 5.4 below.

Table 5.4: Inputs to the DCC model

	Ticker	Description
1	Gold	Physical Gold
2	Newgold	NewGold ETF
3	Rand	Rand dollar exchange rate
4	SAB	South African Breweries
5	ITU	Intu Properties
6	CFR	Richemont
7	GOVTR	GOVI Bond Index
8	ANG	Anglo Gold
9	GFI	Goldfields
10	AMS	Anglo Platinum

Before running the DCC model, we first center the daily returns data and then clean it using Boudt's technique. Thereafter, the first step is to run a MV Heteroskedasticity test. Table 5.5 below shows the output of the MV Heteroskedasticity test which is run on the data frame.

Table 5.5: MV Heteroskedasticity test

Test	Test-statistic	p-value
LM test	7236.353	0
Rank based test	3456.305	0
Q of squared series	9018.816	0
Robust test	9018.816	0

The MV Heteroskedasticity test output in table 5.5 indicates that all the MV portmanteau tests reject the null of no conditional heteroskedasticity, motivating our use of MVGARCH models. The output for the next step, the fitting of the VAR(1) mean model is included in an appendix (see appendix 7.5). In the proceeding step, a MV Heteroskedasticity test is then conducted on the residuals of the VAR(1) mean model, in order to test for any remaining heteroskedasticity. Table 5.6 shows the output of the MV Heteroskedasticity test on the VAR(1) mean model.

Table 5.6: MV Heteroskedasticity test

Test	Test-statistic	p-value
LM test	6766.355	0
Rank based test	3406.295	0
Q of squared series	8382.189	0
Robust test	4546.586	0

The MV Heteroskedasticit output in table 5.6 shows the presence of remaining MV heteroskedasticity, which motivates the use of Exponentially Weighted Moving Average (EWMA) using Multivariate volatility models. The next step is to fit a univariate GARCH model to each asset, in order to get a volatility estimate of each included asset. For this purpose we fit a GARCH(1,1) model as specified in equation 4.2.

After fitting the standard univariate GARCH (1,1) model, an estimate of valatility for each asset is obtained. Graph 5.1 below shows the volatility of each asset. It is evident from graph 5.1 that Gold fields, Anglo American Platinum and Anglo Gold are all amongst the most volatile assets - this is unsurpsing given that they are all single commodity stocks, subject to commodity price swings. While, as would be expected, the bond index fund is the least volatile.

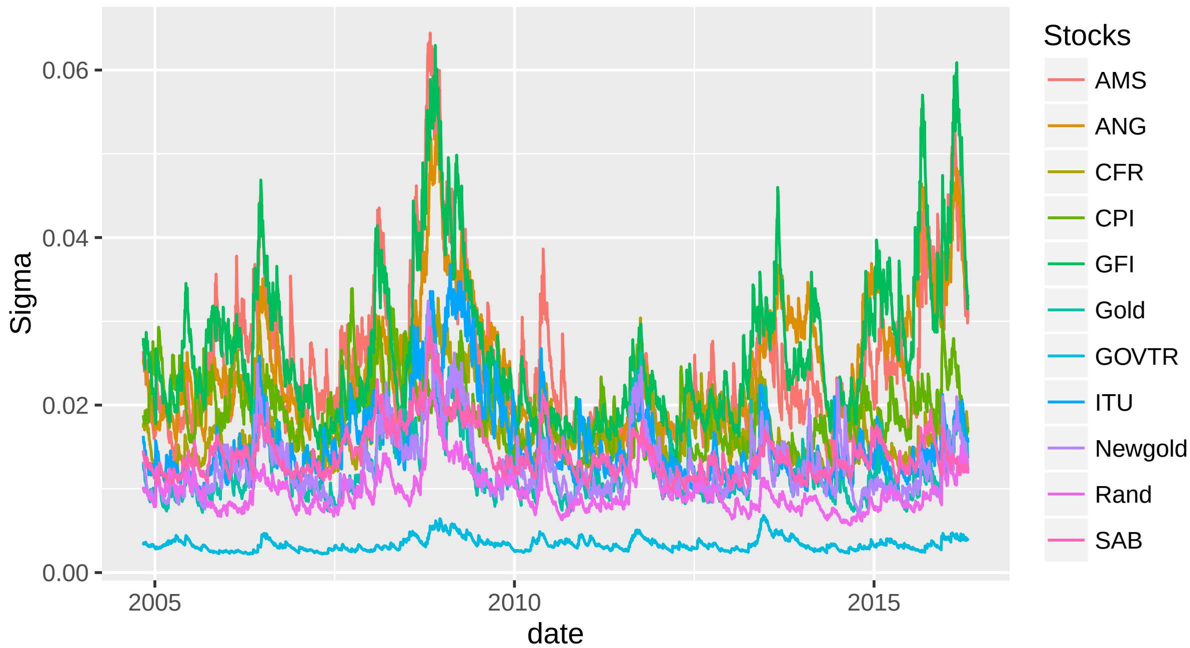

Figure 5.1: Volatility for Each Asset

The next step is to fit the DCC model using the standardized residuals that were obtained by fitting the univariate GARCH model. Finally, we have a graph of the dynamic correlations between all the included assets and the rand. The dynamic correlations are plotted in figure 5.2 below.

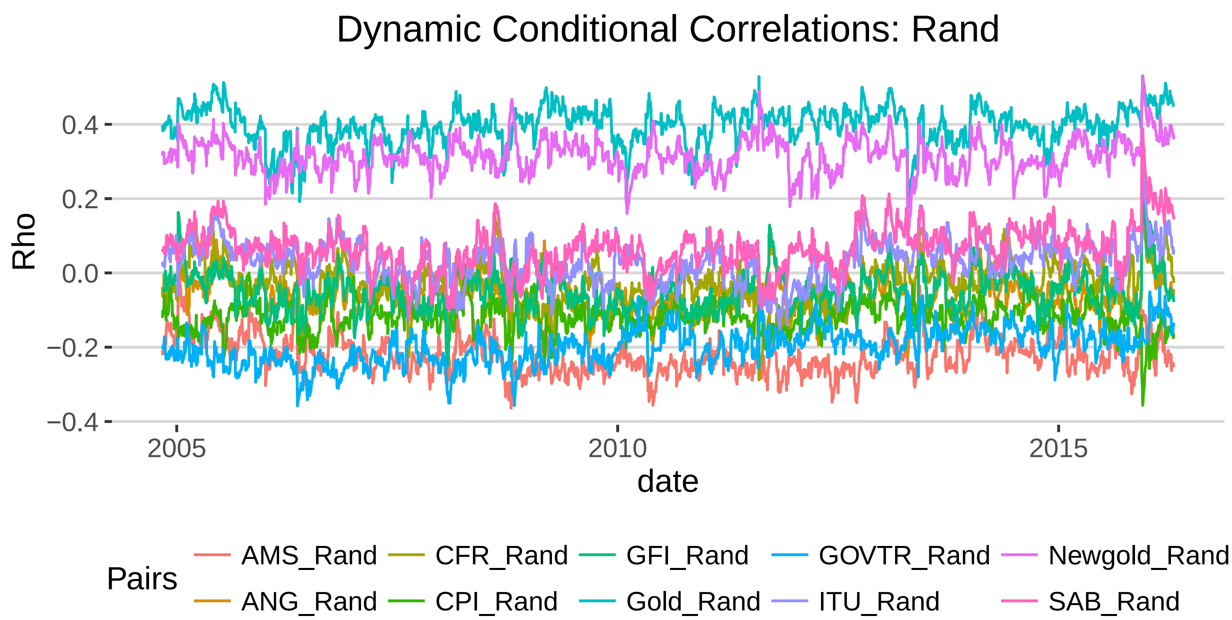

Figure 5.2: Dynamic Conditional Correlations for Each Asset Relative to the Rand

In terms of interpretation, the higher the dynamic correlations, the better the hedge. This is because a positive return on the rand variable represents a depreciation of the rand against the dollar, and a positive return on any asset represents a gain to the investor. Figure 5.2 confirms the inferences of the regression results in suggesting that physical gold is the best rand hedge. In a closely followed second is the NewGold ETF, further confirming that the asset gold is generally the best rand hedge by a fair margin. In third place comes an equity in the form of South African Breweries, seemingly closely followed by Intu Properties. Thereafter comes Richemont, Gold Fields and Anglo Gold who all appear to have similiar hedging potential.

The dynamic correlations elucidate the fact that the hedging potential of the included assets are not completely stable over time. For example Anglo American Platinum (AMS) starts off as a better hedge than the GOVI bond idex. Over time, however, the GOVI starts to move on level with AMS and overtakes it, in terms of being a better hedge, from around 2010 onwards.

In addition, another interesting factor to note from figure 5.2 is how South African breweries (SAB) spiked, and seemed to remain at a structurally higher level, after it was announced that AB Inbev would buy the company. This is likely due to the fact that the purchase price per share was set at a fixed price in pounds - after which SAB effectively became a proxy for the rand pound exchange rate. This fixed price likely acted to increase the conditional dynamic correlations between rand depreciation and the SAB share price - as any rand depreciation made the pound per share offer more valuable in terms of rands.

One thing that is constant, however, is that gold in general - and physical gold in particular - is the best rand hedge. Our results for South Africa are consistent with the aforementioned results of Ciner, Gurdgiev, and Lucey (2013), who find that gold acts as an effective exchange hedge against both the dollar and the pound. Although investing directly in physical gold may not be entirely realisable for the average investor, an asset such as the NewGold ETF gives the investor an opportunity to invest in an asset that tracks the rand gold price. Effectively allowing the investor to invest in gold bullion. The DCC results from figure 5.2 show that the NewGold ETF performs only marginally below physical gold, and a significant margin ahead of the other assets in terms of hedging against the rand.

6. Conclusion

This paper provides an ivestigation into which assets, which are easily available to South African investors, are the best rand hedges. The analysis of both the regression and DCC models suggest that gold is the best rand hedge. In particular, both physical gold and the NewGold ETF outperform the other included assets by a significant margin, and additionally, also act as safe havens. In terms of equities, British American Tobacco appears to be the best rand hedge (with a caveat attached), followed by South African Breweries and Intu Properties. the analysis suggests that only a very small number of shares actually act as rand hedges, meaning that many investors may be being mislead by the belief, which is often touted, that the JSE is full of rand hedge shares. In fact, the bond index funds generally outperform individual equities in terms of their hedging potential, with the GOVI index performing slightly better than the ALBI index. So to the domestic investor who wants to hedge against the rand (without taking money directly offshore) - go for gold.

7. Appendix

7.1. Asset Description

Table 7.1: Description of Assets

No.	Ticker	Description
1	AGL	Anglo American
2	ALBTR	All Bond Composite index
3	AMS	Anglo American Platinum
4	ANG	Anglo Gold
5	APN	Aspen Pharmacare
6	BAT	Brait
7	BGA	Barclays Africa
8	BIL	BHP Biliton
9	BTI	British American Tobacco
10	CFR	Richemont
11	CPI	Capitec
12	DSY	Discovery
13	FSR	Firstrand
14	GFI	Goldfields
15	Gold	Physical Gold
16	GOVTR	GOVI Bond Index
17	GRT	Growthpoint
18	INP	Investec
19	ITU	INTU properties
20	MTN	MTN Group

Continued on next page

Table 7.1 – continued from previous page

No.	Ticker	Description
21	NED	Nedbank Group
22	Newgold	NewGold ETF
23	NPN	Naspers
24	OML	Old Mutual
25	Rand	Rand dollar Exchange Rate
26	REM	Remgro
27	RF	JIBAR 3 month bond rate
28	RMH	RMB Holdings
29	SAB	South African Breweries
30	SBK	Standard Bank
31	SHP	Shoprite
32	SLM	Sanlam
33	SNH	Steinhoff International
34	SOL	Sasol
35	TBS	Tiger Brands
36	WHL	Woolworths

7.2. Descriptive Statistics

	vars	n	mean	sd	median	trimmed	mad	min	max	range	skew	kurtosis	se
ALBTR	1	3437.000	0.000	0.004	0.000	0.000	0.003	-0.073	0.038	0.111	-1.704	31.446	0.000
GOVTR	2	3437.000	0.000	0.004	0.000	0.000	0.003	-0.066	0.019	0.085	-1.994	31.503	0.000
Newgold	3	2965.000	0.001	0.014	0.000	0.001	0.010	-0.093	0.104	0.197	0.031	5.016	0.000
RF	4	3564.000	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.000	1.087	0.302	0.000
Gold	5	3563.000	0.000	0.014	0.000	0.000	0.011	-0.091	0.120	0.211	0.304	5.386	0.000
Rand	6	3564.000	0.000	0.011	-0.000	-0.000	0.009	-0.069	0.092	0.162	0.321	4.108	0.000
AGL	7	3564.000	0.001	0.026	0.000	0.000	0.020	-0.159	0.171	0.330	0.269	4.390	0.000
AMS	8	3564.000	0.001	0.027	0.000	0.000	0.021	-0.161	0.196	0.358	0.208	3.467	0.000
ANG	9	3564.000	0.000	0.026	0.000	-0.000	0.020	-0.146	0.192	0.338	0.494	3.613	0.000
APN	10	3564.000	0.001	0.019	0.000	0.001	0.014	-0.094	0.101	0.195	0.193	2.741	0.000
BAT	11	3564.000	0.001	0.018	0.000	0.001	0.012	-0.188	0.154	0.342	0.024	6.991	0.000
BGA	12	3564.000	0.001	0.018	0.000	0.001	0.014	-0.145	0.119	0.264	0.095	3.807	0.000
BIL	13	3564.000	0.001	0.022	0.000	0.001	0.018	-0.108	0.197	0.305	0.375	4.451	0.000
BTI	14	2044.000	0.001	0.012	0.000	0.001	0.010	-0.045	0.063	0.108	0.097	1.613	0.000
CFR	15	3564.000	0.001	0.019	0.000	0.001	0.014	-0.108	0.336	0.445	1.553	28.131	0.000
CPI	16	3564.000	0.002	0.021	0.000	0.002	0.013	-0.133	0.184	0.317	0.446	7.172	0.000
DSY	17	3564.000	0.001	0.017	0.000	0.001	0.012	-0.143	0.104	0.246	0.066	3.940	0.000
FSR	18	3564.000	0.001	0.019	0.000	0.001	0.016	-0.148	0.130	0.279	-0.020	3.550	0.000
GFI	19	3564.000	0.000	0.029	0.000	-0.000	0.022	-0.148	0.214	0.362	0.433	4.296	0.000
GRT	20	3564.000	0.001	0.013	0.000	0.001	0.009	-0.100	0.110	0.210	0.282	6.843	0.000
INP	21	3564.000	0.001	0.020	0.000	0.001	0.015	-0.104	0.166	0.269	0.079	4.893	0.000
ITU	22	3564.000	0.000	0.017	0.000	0.000	0.013	-0.152	0.090	0.242	-0.458	6.341	0.000
MRP	23	3564.000	0.001	0.019	0.000	0.001	0.014	-0.178	0.097	0.275	-0.471	5.976	0.000
MTN	24	3564.000	0.001	0.022	0.000	0.001	0.017	-0.180	0.176	0.357	0.222	5.044	0.000
NED	25	3564.000	0.001	0.018	0.000	0.000	0.015	-0.105	0.126	0.231	0.130	3.005	0.000
NPN	26	3564.000	0.002	0.020	0.000	0.001	0.016	-0.102	0.109	0.212	0.114	1.631	0.000
OML	27	3564.000	0.001	0.020	0.000	0.001	0.014	-0.152	0.158	0.310	0.139	7.480	0.000
REM	28	3564.000	0.001	0.015	0.000	0.001	0.013	-0.088	0.107	0.194	0.340	3.260	0.000
RMH	29	3564.000	0.001	0.020	0.000	0.001	0.016	-0.125	0.122	0.246	0.172	3.020	0.000
SAB	30	3564.000	0.001	0.015	0.000	0.001	0.012	-0.075	0.184	0.258	0.818	8.608	0.000
SBK	31	3564.000	0.001	0.018	0.000	0.001	0.014	-0.135	0.110	0.245	0.136	3.312	0.000
SHP	32	3564.000	0.001	0.018	0.000	0.001	0.014	-0.088	0.113	0.201	0.244	2.337	0.000
SLM	33	3564.000	0.001	0.018	0.000	0.001	0.014	-0.107	0.126	0.233	0.058	2.701	0.000
SNH	34	3564.000	0.001	0.020	0.000	0.001	0.015	-0.107	0.211	0.318	0.365	5.890	0.000
SOL	35	3564.000	0.001	0.021	0.000	0.001	0.017	-0.108	0.121	0.229	0.205	3.072	0.000
TBS	36	3564.000	0.001	0.015	0.000	0.001	0.012	-0.068	0.084	0.151	0.148	2.044	0.000

Table 7.2: Descriptive Statistics

7.3. Graphs

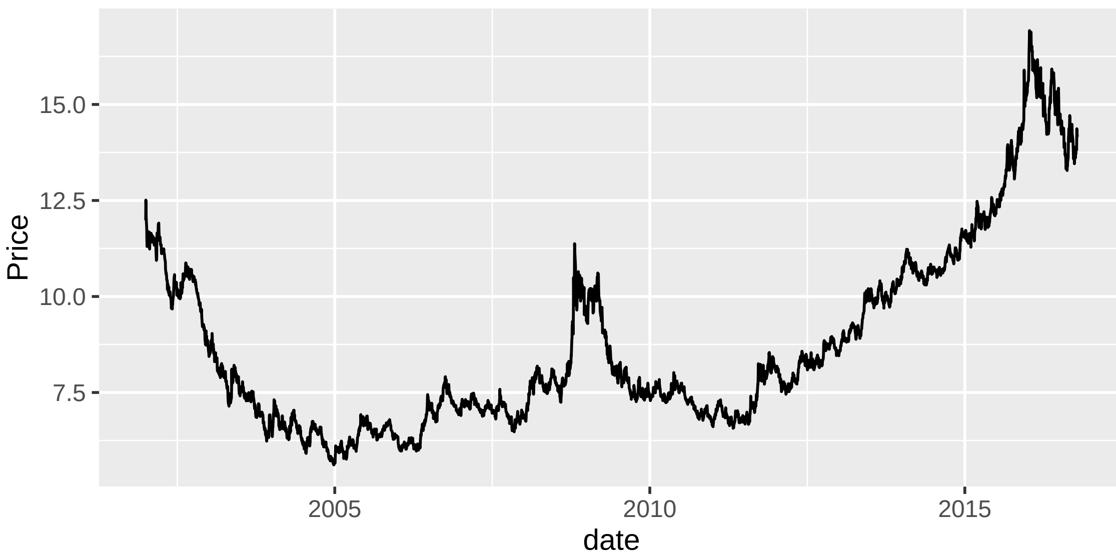

Figure 7.1: Daily Rand Dollar Exchange Rate

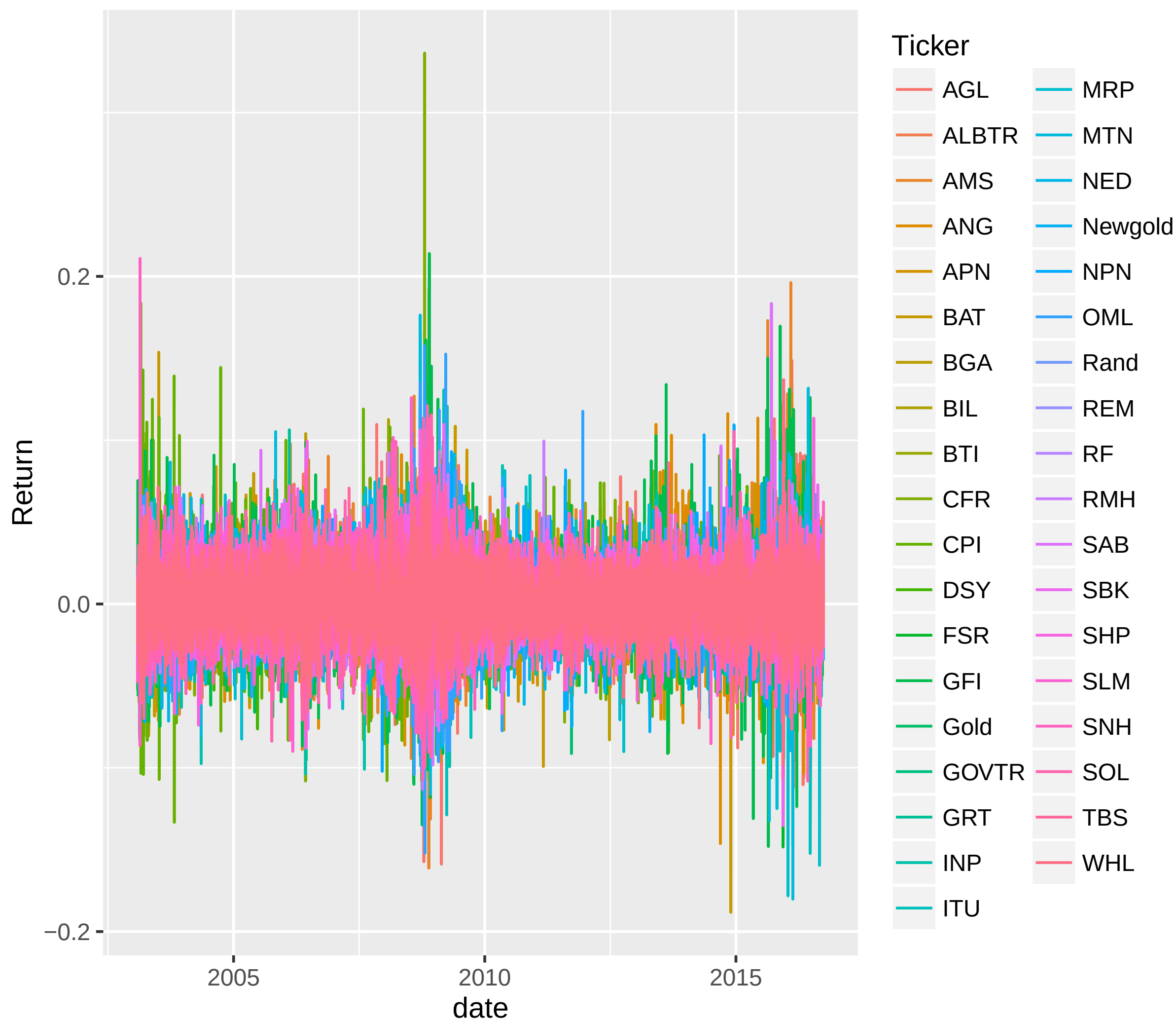

Figure 7.2: Daily Returns

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	0.0005	0.0003	1.81	0.0710
Rand	0.3029	0.0325	9.32	0.0000
rand_stateQ90	0.0011	0.0013	0.87	0.3867
rand_stateQ95	-0.0001	0.0015	-0.07	0.9470
rand_stateQ99	0.0016	0.0034	0.47	0.6398

Table 7.3: BTI

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	0.0006	0.0003	2.26	0.0239
Rand	0.1271	0.0309	4.12	0.0000
rand_stateQ90	0.0023	0.0013	1.81	0.0708
rand_stateQ95	-0.0014	0.0015	-0.96	0.3352
rand_stateQ99	-0.0049	0.0029	-1.69	0.0914

Table 7.4: SAB

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	0.0004	0.0004	1.03	0.3032
Rand	-0.3968	0.0444	-8.94	0.0000
rand_stateQ90	0.0028	0.0019	1.50	0.1327
rand_stateQ95	0.0016	0.0022	0.75	0.4510
rand_stateQ99	-0.0011	0.0041	-0.27	0.7882

Table 7.5: Bhp biliton

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	0.0012	0.0004	3.39	0.0007
Rand	-0.3005	0.0402	-7.47	0.0000
rand_stateQ90	0.0031	0.0017	1.81	0.0701
rand_stateQ95	-0.0030	0.0020	-1.52	0.1297
rand_stateQ99	0.0006	0.0037	0.17	0.8660

Table 7.6: Naspers

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	0.0005	0.0003	1.55	0.1216
Rand	-0.0294	0.0386	-0.76	0.4462
rand_stateQ90	0.0021	0.0016	1.32	0.1878
rand_stateQ95	-0.0018	0.0019	-0.94	0.3485
rand_stateQ99	0.0097	0.0036	2.69	0.0073

Table 7.7: Richemont

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	0.0008	0.0004	2.11	0.0353
Rand	-0.2244	0.0402	-5.58	0.0000
rand_stateQ90	0.0019	0.0017	1.13	0.2594
rand_stateQ95	-0.0013	0.0020	-0.66	0.5092
rand_stateQ99	-0.0047	0.0037	-1.26	0.2093

Table 7.8: Steinhoff

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	0.0007	0.0003	1.97	0.0494
Rand	-0.4998	0.0369	-13.53	0.0000
rand_stateQ90	0.0037	0.0015	2.41	0.0161
rand_stateQ95	-0.0023	0.0018	-1.31	0.1918
rand_stateQ99	-0.0033	0.0034	-0.96	0.3355

Table 7.9: First Rand

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	0.0003	0.0004	0.89	0.3746
Rand	-0.2808	0.0418	-6.73	0.0000
rand_stateQ90	0.0017	0.0017	0.95	0.3422
rand_stateQ95	0.0009	0.0020	0.44	0.6606
rand_stateQ99	0.0052	0.0039	1.34	0.1792

Table 7.10: Sasol

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	0.0008	0.0004	2.05	0.0408
Rand	-0.4290	0.0433	-9.90	0.0000
rand_stateQ90	0.0018	0.0018	0.99	0.3247
rand_stateQ95	-0.0041	0.0021	-1.94	0.0519
rand_stateQ99	0.0028	0.0040	0.69	0.4921

Table 7.11: MTN

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	0.0004	0.0003	1.40	0.1622
Rand	-0.4437	0.0353	-12.56	0.0000
rand_stateQ90	0.0030	0.0015	2.04	0.0412
rand_stateQ95	-0.0001	0.0017	-0.07	0.9451
rand_stateQ99	-0.0047	0.0033	-1.42	0.1564

Table 7.12: Standard bank

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	0.0000	0.0005	0.07	0.9457
Rand	-0.5488	0.0514	-10.68	0.0000
rand_stateQ90	0.0023	0.0022	1.06	0.2874
rand_stateQ95	0.0028	0.0025	1.13	0.2589
rand_stateQ99	0.0049	0.0048	1.02	0.3087

Table 7.13: Anglo

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	0.0003	0.0004	0.70	0.4809
Rand	-0.2221	0.0408	-5.44	0.0000
rand_stateQ90	0.0015	0.0017	0.90	0.3657
rand_stateQ95	0.0019	0.0020	0.96	0.3382
rand_stateQ99	-0.0006	0.0038	-0.15	0.8779

Table 7.14: Old mutual

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	0.0010	0.0003	2.93	0.0034
Rand	-0.2657	0.0372	-7.15	0.0000
rand_stateQ90	-0.0003	0.0016	-0.20	0.8380
rand_stateQ95	-0.0007	0.0018	-0.37	0.7120
rand_stateQ99	0.0054	0.0035	1.55	0.1216

Table 7.15: Aspen

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	0.0008	0.0003	2.56	0.0104
Rand	-0.3084	0.0346	-8.91	0.0000
rand_stateQ90	0.0014	0.0015	0.94	0.3460
rand_stateQ95	-0.0037	0.0017	-2.19	0.0289
rand_stateQ99	-0.0050	0.0032	-1.55	0.1201

Table 7.16: Sanlam

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	0.0005	0.0003	1.95	0.0510
Rand	-0.2717	0.0304	-8.94	0.0000
rand_stateQ90	0.0026	0.0013	2.01	0.0442
rand_stateQ95	-0.0012	0.0015	-0.82	0.4130
rand_stateQ99	0.0062	0.0028	2.19	0.0287

Table 7.17: Remgro

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	0.0006	0.0003	1.76	0.0784
Rand	-0.4421	0.0349	-12.66	0.0000
rand_stateQ90	0.0009	0.0015	0.64	0.5249
rand_stateQ95	0.0004	0.0017	0.24	0.8110
rand_stateQ99	-0.0062	0.0033	-1.90	0.0571

Table 7.18: Barclays africa

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	0.0010	0.0003	3.26	0.0011
Rand	-0.2568	0.0348	-7.37	0.0000
rand_stateQ90	0.0005	0.0015	0.36	0.7221
rand_stateQ95	-0.0027	0.0017	-1.59	0.1122
rand_stateQ99	-0.0005	0.0032	-0.15	0.8771

Table 7.19: Shoprite

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	0.0000	0.0005	0.06	0.9492
Rand	-0.5050	0.0537	-9.40	0.0000
rand_stateQ90	0.0019	0.0023	0.84	0.4000
rand_stateQ95	0.0002	0.0026	0.07	0.9424
rand_stateQ99	0.0135	0.0050	2.70	0.0070

Table 7.20: Anglo platinum

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	0.0004	0.0003	1.20	0.2304
Rand	-0.4089	0.0357	-11.45	0.0000
rand_stateQ90	0.0010	0.0015	0.66	0.5062
rand_stateQ95	-0.0025	0.0017	-1.44	0.1486
rand_stateQ99	-0.0017	0.0033	-0.51	0.6068

Table 7.21: Nedbank

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	-0.0005	0.0005	-1.04	0.2994
Rand	-0.1433	0.0524	-2.74	0.0063
rand_stateQ90	0.0023	0.0022	1.06	0.2883
rand_stateQ95	0.0059	0.0025	2.34	0.0195
rand_stateQ99	0.0158	0.0049	3.24	0.0012

Table 7.22: Anglo gold

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	0.0010	0.0003	2.99	0.0028
Rand	-0.3330	0.0357	-9.32	0.0000
rand_stateQ90	0.0009	0.0015	0.61	0.5413
rand_stateQ95	-0.0026	0.0017	-1.48	0.1394
rand_stateQ99	0.0001	0.0033	0.04	0.9715

Table 7.23: Woolworths

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	0.0008	0.0003	2.16	0.0308
Rand	-0.4743	0.0388	-12.23	0.0000
rand_stateQ90	0.0041	0.0016	2.51	0.0121
rand_stateQ95	-0.0020	0.0019	-1.07	0.2837
rand_stateQ99	-0.0104	0.0036	-2.88	0.0040

Table 7.24: RMB

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	0.0005	0.0004	1.49	0.1368
Rand	-0.2986	0.0402	-7.43	0.0000
rand_stateQ90	0.0022	0.0017	1.31	0.1911
rand_stateQ95	-0.0013	0.0020	-0.64	0.5212
rand_stateQ99	-0.0084	0.0037	-2.24	0.0252

Table 7.25: Investec

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	0.0001	0.0003	0.21	0.8353
Rand	0.0852	0.0339	2.51	0.0121
rand_stateQ90	-0.0017	0.0014	-1.17	0.2409
rand_stateQ95	0.0011	0.0017	0.67	0.5051
rand_stateQ99	-0.0030	0.0032	-0.95	0.3419

Table 7.26: Intu properties

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	0.0007	0.0003	2.28	0.0228
Rand	-0.2119	0.0334	-6.34	0.0000
rand_stateQ90	0.0022	0.0014	1.55	0.1224
rand_stateQ95	-0.0029	0.0016	-1.79	0.0740
rand_stateQ99	0.0048	0.0031	1.53	0.1259

Table 7.27: Discovery

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	0.0005	0.0003	1.73	0.0830
Rand	-0.2900	0.0301	-9.62	0.0000
rand_stateQ90	0.0033	0.0013	2.65	0.0081
rand_stateQ95	-0.0001	0.0015	-0.10	0.9223
rand_stateQ99	0.0005	0.0028	0.19	0.8499

Table 7.28: Tiger brands

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	0.0006	0.0002	2.37	0.0178
Rand	-0.1922	0.0263	-7.30	0.0000
rand_stateQ90	0.0020	0.0011	1.81	0.0709
rand_stateQ95	-0.0024	0.0013	-1.89	0.0593
rand_stateQ99	-0.0022	0.0025	-0.89	0.3733

Table 7.29: Growthpoint

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	0.0019	0.0004	4.96	0.0000
Rand	-0.1651	0.0430	-3.84	0.0001
rand_stateQ90	-0.0012	0.0018	-0.66	0.5096
rand_stateQ95	-0.0042	0.0021	-2.00	0.0459
rand_stateQ99	-0.0053	0.0040	-1.32	0.1854

Table 7.30: Capitec

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	-0.0005	0.0005	-0.87	0.3833
Rand	-0.1715	0.0579	-2.96	0.0031
rand_stateQ90	0.0032	0.0024	1.31	0.1902
rand_stateQ95	0.0052	0.0028	1.85	0.0644
rand_stateQ99	0.0164	0.0054	3.04	0.0024

Table 7.31: Gold fields

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	0.0010	0.0003	2.89	0.0038
Rand	-0.1685	0.0366	-4.61	0.0000
rand_stateQ90	0.0010	0.0015	0.62	0.5354
rand_stateQ95	-0.0033	0.0018	-1.86	0.0630
rand_stateQ99	0.0012	0.0034	0.35	0.7272

Table 7.32: Brait

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	0.0012	0.0003	3.45	0.0006
Rand	-0.3148	0.0377	-8.36	0.0000
rand__stateQ90	-0.0007	0.0016	-0.44	0.6630
rand__stateQ95	-0.0025	0.0018	-1.37	0.1705
rand__stateQ99	-0.0021	0.0035	-0.61	0.5449

Table 7.33: Mr price

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	-0.0000	0.0002	-0.19	0.8486
Rand	0.5395	0.0247	21.86	0.0000
rand__stateQ90	0.0023	0.0010	2.19	0.0287
rand__stateQ95	0.0009	0.0012	0.77	0.4401
rand__stateQ99	0.0014	0.0023	0.59	0.5546

Table 7.34: Gold (physical)

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	0.0001	0.0003	0.23	0.8207
Rand	0.4080	0.0296	13.78	0.0000
rand__stateQ90	0.0008	0.0012	0.68	0.4972
rand__stateQ95	0.0011	0.0014	0.79	0.4308
rand__stateQ99	0.0077	0.0029	2.65	0.0081

Table 7.35: NewGold ETF

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	0.0001	0.0001	0.72	0.4725
Rand	-0.1619	0.0078	-20.70	0.0000
rand_stateQ90	0.0002	0.0003	0.56	0.5726
rand_stateQ95	-0.0002	0.0004	-0.62	0.5373
rand_stateQ99	-0.0002	0.0007	-0.34	0.7317

Table 7.36: ALBI bond index

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	0.0001	0.0001	0.95	0.3400
Rand	-0.0776	0.0076	-10.25	0.0000
rand_stateQ90	0.0003	0.0003	0.93	0.3541
rand_stateQ95	-0.0001	0.0004	-0.37	0.7129
rand_stateQ99	0.0011	0.0007	1.58	0.1144

Table 7.37: GOVI bond index

7.5. VAR(1) Mean Model Results

```
Constant term:
Estimates:  -6.108476e-05 -0.0001188868 -7.956684e-05 7.980628e-07 -9.631207e-05 -1.28799e-
Std.Error:  0.0004811553 0.0004561262 0.0003160992 0.0003408428 0.0004977589 0.0002380207 6
AR coefficient matrix
AR( 1 )-matrix
            [,1]     [,2]     [,3]     [,4]      [,5]     [,6]     [,7]
 [1,]  0.017867  0.06074  0.00507 -0.05691 -0.035650  0.11802 -0.04921
 [2,]  0.020231 -0.01322 -0.01017 -0.04758 -0.004409  0.48353 -0.20833
 [3,] -0.001353  0.04711 -0.05047 -0.00457 -0.020526 -0.04250  0.01930
```

```
 [4,]  0.003053 -0.01762  0.02215 -0.04117 -0.018180 -0.02725  0.14822
 [5,]  0.062521  0.01816 -0.06587 -0.03816 -0.050055  0.63571 -0.11031
 [6,]  0.010100  0.02185  0.01155  0.01580 -0.001873 -0.02266 -0.03632
 [7,] -0.000573 -0.00127  0.00222  0.00372 -0.004307 -0.00854  0.08920
 [8,]  0.005939  0.02886  0.01543 -0.01262 -0.023967 -0.04173  0.00240
 [9,]  0.016204  0.00738  0.00381  0.01489  0.010517  0.55448 -0.00861
[10,]  0.000514 -0.02393 -0.00146  0.02415  0.027783  0.09091 -0.37640
[11,] -0.012442  0.01892 -0.00182  0.00114  0.000551 -0.02009 -0.03472
          [,8]     [,9]   [,10]    [,11]
 [1,] -1.04e-02  0.05349 -0.1653  0.06301
 [2,] -7.71e-03 -0.28612 -0.0557 -0.02614
 [3,] -5.23e-05 -0.03585  0.0514  0.01644
 [4,] -2.40e-02  0.00855 -0.2005  0.05712
 [5,]  1.81e-03 -0.28385 -0.1022 -0.00329
 [6,]  5.70e-03 -0.04970  0.0775 -0.01535
 [7,]  2.97e-03  0.00965 -0.0129 -0.00236
 [8,] -1.41e-02  0.02489  0.0427 -0.04938
 [9,]  1.79e-02 -0.37615  0.0460 -0.04273
[10,]  2.12e-03 -0.05791 -0.0357  0.00536
[11,] -9.17e-03  0.01584  0.0290 -0.04517
standard error
        [,1]    [,2]    [,3]    [,4]    [,5]    [,6]   [,7]    [,8]
 [1,] 0.02124 0.02877 0.03325 0.02615 0.02661 0.04796 0.1420 0.03489
 [2,] 0.02014 0.02728 0.03152 0.02479 0.02522 0.04546 0.1346 0.03308
 [3,] 0.01396 0.01890 0.02184 0.01718 0.01748 0.03151 0.0933 0.02292
 [4,] 0.01505 0.02038 0.02355 0.01853 0.01885 0.03397 0.1006 0.02472
 [5,] 0.02198 0.02977 0.03440 0.02706 0.02752 0.04961 0.1469 0.03610
```

```
 [6,] 0.01051 0.01423 0.01645 0.01294 0.01316 0.02372 0.0703 0.01726
 [7,] 0.00279 0.00378 0.00437 0.00344 0.00350 0.00631 0.0187 0.00459
 [8,] 0.01318 0.01785 0.02063 0.01623 0.01651 0.02976 0.0881 0.02165
 [9,] 0.00950 0.01286 0.01487 0.01169 0.01189 0.02144 0.0635 0.01560
[10,] 0.00795 0.01076 0.01244 0.00978 0.00995 0.01794 0.0531 0.01305
[11,] 0.01176 0.01593 0.01840 0.01448 0.01473 0.02654 0.0786 0.01931
         [,9]   [,10]   [,11]
 [1,] 0.04930 0.05839 0.03900
 [2,] 0.04674 0.05535 0.03697
 [3,] 0.03239 0.03836 0.02562
 [4,] 0.03493 0.04136 0.02762
 [5,] 0.05100 0.06040 0.04034
 [6,] 0.02439 0.02888 0.01929
 [7,] 0.00648 0.00768 0.00513
 [8,] 0.03059 0.03623 0.02420
 [9,] 0.02204 0.02610 0.01743
[10,] 0.01844 0.02184 0.01459
[11,] 0.02729 0.03232 0.02158
```

```
Residuals cov-mtx:
                  AMS           ANG           CFR           CPI
AMS      6.897405e-04  2.233259e-04  1.380428e-04  5.595164e-05
ANG      2.233259e-04  6.198479e-04  6.381437e-05  5.858033e-06
CFR      1.380428e-04  6.381437e-05  2.976884e-04  3.999905e-05
CPI      5.595164e-05  5.858033e-06  3.999905e-05  3.461174e-04
GFI      2.401836e-04  4.894923e-04  7.063267e-05  6.523157e-06
Gold     1.121592e-05  1.022640e-04 -1.013534e-07 -1.283496e-05
```

```
GOVTR    3.214342e-06  2.168993e-06  5.151276e-07  1.928689e-06
ITU      1.145792e-04  3.805167e-05  1.245022e-04  3.223898e-05
Newgold  1.711970e-05  1.149413e-04 -5.847394e-07 -1.128027e-05
Rand    -6.432454e-05 -1.649328e-05 -1.509761e-05 -2.317072e-05
SAB      9.359587e-05  5.009337e-05  1.101406e-04  3.284951e-05
                  GFI          Gold         GOVTR           ITU
AMS      2.401836e-04  1.121592e-05  3.214342e-06  1.145792e-04
ANG      4.894923e-04  1.022640e-04  2.168993e-06  3.805167e-05
CFR      7.063267e-05 -1.013534e-07  5.151276e-07  1.245022e-04
CPI      6.523157e-06 -1.283496e-05  1.928689e-06  3.223898e-05
GFI      7.381645e-04  1.176268e-04  4.740713e-06  3.795026e-05
Gold     1.176268e-04  1.687892e-04 -4.134785e-06 -7.217981e-08
GOVTR    4.740713e-06 -4.134785e-06  1.193134e-05 -1.351651e-06
ITU      3.795026e-05 -7.217981e-08 -1.351651e-06  2.655117e-04
Newgold  1.313990e-04  9.824281e-05 -4.016320e-06 -3.961482e-06
Rand    -1.668623e-05  5.437979e-05 -6.577247e-06 -6.523559e-07
SAB      5.145403e-05  1.128129e-05  1.325680e-06  1.030132e-04
              Newgold          Rand          SAB
AMS      1.711970e-05 -6.432454e-05 9.359587e-05
ANG      1.149413e-04 -1.649328e-05 5.009337e-05
CFR     -5.847394e-07 -1.509761e-05 1.101406e-04
CPI     -1.128027e-05 -2.317072e-05 3.284951e-05
GFI      1.313990e-04 -1.668623e-05 5.145403e-05
Gold     9.824281e-05  5.437979e-05 1.128129e-05
GOVTR   -4.016320e-06 -6.577247e-06 1.325680e-06
ITU     -3.961482e-06 -6.523559e-07 1.030132e-04
Newgold  1.378497e-04  3.814572e-05 1.155275e-05
```

```
Rand     3.814572e-05  9.648152e-05 3.319489e-06
SAB      1.155275e-05  3.319489e-06 2.112920e-04

det(SSE) =  3.052978e-42
AIC =  -95.5116
BIC =  -95.26887
HQ  =  -95.42428

          Length Class  Mode
data      32923  xts    numeric
cnst          1  -none- logical
order         1  -none- numeric
coef        132  -none- numeric
aic           1  -none- numeric
bic           1  -none- numeric
hq            1  -none- numeric
residuals 32912  xts    numeric
secoef      132  -none- numeric
Sigma       121  -none- numeric
Phi         121  -none- numeric
Ph0          11  -none- numeric
```

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