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RISKMETRICS METHOD FOR ESTIMATING VALUE AT RISK TO COMPARE THE RISKINESS OF BITCOIN AND RAND

Abstract

In this study, the RiskMetrics method is used to estimate Value at Risk for two exchange rates: BitCoin/dollar and the South African Rand/dollar. Value at Risk is used to compare the riskiness of the two currencies. This is to help South Africans and investors understand the risk they are taking by converting their savings/investments to BitCoin instead of the South African currency, the Rand. The Maximum Likelihood Estimation method is used to estimate the parameters of the models. Seven statistical error distributions, namely Normal Distribution, skewed Normal Distribution, Student's T-Distribution, skewed Student's T-Distribution, Generalized Error Distribution, skewed Generalized Error Distribution, and the Generalized Hyperbolic Distributions, were considered when modelling and estimating model parameters. Value at Risk estimates suggest that the BitCoin/dollar return averaging 0.035 and 0.055 per dollar invested at 95% and 99%, respectively, is riskier than the Rand/dollar return averaging 0.012 and 0.019 per dollar invested at 95% and 99%, respectively. Using the Kupiec test, RiskMetrics with Generalized Error Distribution ($p > 0.07$) and skewed Generalized Error Distribution ($p > 0.62$) gave the best fitting model in the estimation of Value at Risk for BitCoin/dollar and Rand/dollar, respectively. The RiskMetrics approach seems to perform better at higher than lower confidence levels, as evidenced by higher p-values from backtesting using the Kupiec test at 99% than at 95% levels of significance. These findings are also helpful for risk managers in estimating adequate risk-based capital requirements for the two currencies.

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INTRODUCTION

The RiskMetrics methodology was first developed by Morgan in 1989 and later on launched in its technical document form in 1996. It is based on the conditional variance estimation based on the Exponentially Weighted Moving Average (EWMA). It is a type of weighted estimate of variance in which recent observations are given more weight (influence) than earlier observations. The merits of this method lie in its simplicity and ease of implementation. It is very easy for people to understand and bring it into the financial market when measuring the riskiness of an asset. Also, it makes financial risk management much easier to clarify.

Value at Risk (VaR) is widely recommended by the Basel Committee on Banking Supervision (BCBS) to be a measure of market risk. It must be computed and reported regularly. BCBS is responsible for developing supervisory guidelines for banks and financial trading institutions. Value at Risk is a statistic that quantifies the riskiness of a

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financial portfolio of assets. It is the largest value or amount expected to be lost over a specified time horizon i.e. daily, weekly, or ten days, at a pre-defined statistical confidence level. Hull (2006, p. 198) defined VaR as the value that "compresses all Greek letters for all the market variables underlying a portfolio into a single number". This statistic is commonly used to inform capital requirements and formulation of investment diversification and hedging strategies.

BitCoin is on top of the list of traded cryptocurrencies in terms of traded volume. Cryptocurrencies are decentralized currencies that are transacted without the regulations of a reserve bank or financial intermediaries. Blockchain technology is used to process transactions. Since BitCoin is not backed by any central bank or government, its users and traders are expected to be vulnerable to higher risk (volatility). As with the global trend, cryptocurrency trading particularly BitCoin has gained a lot of traction in South Africa. This implies that there is a steady increase in movements of people's savings and investments between the Rand and the BitCoin.

Cryptocurrencies are said to be very risky, and so are developing countries' currencies. The purpose of this study is to use RiskMetrics to estimate VaR and compare the riskiness of the two currencies. The model's adequacy is confirmed using backtesting techniques.

1. LITERATURE REVIEW

To correctly estimate VaR, a distribution that captures all volatility stylized facts is required (Danielsson & Vries, 1997). Engle (1982) proposed the auto-regressive conditional heteroscedasticity (ARCH) model. Other models include the Generalized ARCH (GARCH) model proposed by Bollerslev (1986), the Integrated Generalized Auto-Regressive Conditional Heteroscedasticity (IGARCH) model developed by Engle and Bollerslev (1986), the Exponential Generalized Auto-Regressive Conditional Heteroscedasticity (EGARCH) model proposed by Nelson (1991), the GJR-Generalized Auto-Regressive Conditional Heteroscedasticity(GJR-GARCH) model by Glosten et al. (1993), the Asymmetric Power Auto-Regressive Conditional Heteroscedasticity (APARCH) model of Ding et al. (1993), the Fractionally Integrated Generalised Auto-Regressive Conditional Heteroscedasticity (FIGARCH) model by Baillie et al. (1996), the Fractionally Integrated Exponential Generalized Auto-Regressive Conditional Heteroscedasticity (FIEGARCH) model by Bollerslev and Mikkelsen (1996), the Fractionally Integrated Asymmetric Power Auto-Regressive Conditional Heteroscedasticity (FIAPARCH) model by Tse (1998), and The Hyperbolic Generalised Auto-Regressive Conditional Heteroscedasticity (HYGARCH) model proposed by Davidson (2004). These models were proposed in an effort to better understand and capture the stylized facts in financial assets' returns. To obtain a good estimate of VaR for risk management, an appropriate model that sufficiently captures volatility clustering and non-normality features that are common among stock returns must be chosen. RiskMetrics is a constrained GARCH-type approach to estimating VaR. It is a Probabilistic Metric of Market Risk (PMMR), a type of weighted estimate of the variance, where the recent observations have more weight (influence) than those further in the past.

Studies have been done to assess the performance of RiskMetrics against symmetric and asymmetric models in the estimation of VaR. While comparing the performance of RiskMetrics against symmetric and asymmetric models in both developed and emerging markets, Brailsford and Faff (1996), and McMillan et al. (2000) concluded that asymmetric models outperform RiskMetrics in the out-of-sample estimation of VaR. McMillan and Kambouroudis (2009) confirmed the adequacy and effectiveness of RiskMetrics in modelling both volatility and VaR estimation in emerging markets rather than in developed markets. So and Yu (2006) observed that in both GARCH and RiskMetrics, the Student's error models gave better results than the normal distribution. This led to the suggestion that asymmetric (heavy-tailed) error-distributed models could improve the RiskMetrics approach. In the literature, there is little if any heavy-tailed distribution type that significantly outperforms

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others or better captures the non-normality of the residuals of the GARCH-type models.

Other non-Normal distribution models like the extreme value theory based distributions (Jakata & Chikobvu, 2019; Tabasi et al., 2019; Makatjane & Moroke, 2021), stochastic models (Chifurira & Chinhamu, 2019), and the more recent machine learning models, like neural networks (Zhang et al., 2022) have been employed to model volatility, the dependence of financial assets and the estimation of VaR. Paolella (2016) used the stable APARCH model to model four stocks from the DJIA index in the USA. Sin et al., (2017) used the TGARCH combined with the generalized error distribution (GED) to model the crude oil index.

On the other hand, there has been an increase in the number of research to ascertain whether the stylized facts of cryptocurrency are similar to that of other financial assets. Kaseke et al (2021) showed that cryptocurrencies have similar distributional characteristics with Gold and the FTSE/JSE 40, though the cryptocurrency is more volatile. Takaishi (2018) noted the presence of heavy-tailedness and excess kurtosis in the one-minute returns data of BitCoin. Bouri et al. (2017) observed a high negative skewness and volatility in BitCoin in comparison to other stock returns.

Dyhrberg (2016) argued that the shocks that are prevalent in the financial market do not affect BitCoin and gold returns; hence they can be used for hedging. Conversely, Shanaev and Ghimire (2021) noted a relative stability in the BitCoin and Ethereum using asymmetric power-law distributions.

Ndlovu and Chikobvu (2022) concluded that BitCoin is riskier (highly volatile) than Rand using GARCH-GPD and recommended that BitCoin traders and investors should be cautious, especially when the market enters turbulent times. Their findings tally with that of Dasman (2021) who used a statistical tests approach in comparing the average returns and volatility of BitCoin against the Indonesian Composite Index, and gold. Also, the BitCoin average returns are significantly higher than the financial assets studied. This would be consistent with mean-variance portfolio theory, which suggests a higher yield for riskier assets Markowitz (1959).

Other studies that confirmed the high volatility nature of cryptocurrency include Zhang et al. (2018), Katsiampa et al. (2019), and Hu et al. (2019). This feature has been suggested to be caused by speculation, insufficient regulatory measures, and spurious issues, amongst others by Dowd (2014) and Cheah and Fry (2015). However, Blau (2017) found no evidence of speculation as the reason for the high volatility amongst cryptocurrencies.

As noted in past research, there is no coherence in some of the findings; hence the properties and distributions of cryptocurrency need further investigations as more data is availed. This will help in more accurate modelling/characterization and estimating Value at Risk for this class of assets. Although RiskMetrics does not fully capture the fat tails, it does allow the incorporation of heavy tail models in the error distribution, hence, it could lead to insightful results and sober decisions when choosing to invest between the BitCoin and the South African Rand. This collected information is also beneficial in risk-based asset portfolio allocation and diversification. Considering that cryptocurrency is a fairly new form of currency, it would not be surprising to discover new or different properties from those found in past studies when comparing BitCoin to the South African Rand.

2. METHODS

The RiskMetrics approach to estimating VaR was developed by Morgan in 1989. It is based on the assumption that the continuously logarithmic daily returns of an asset follow a conditional Normal Distribution (Bachelier, 1900).

$$y_t \mid f_{t-1} \sim N\left(\mu_t;\sigma_t\right), \tag{1}$$

where $y_t = \log(P_t) - \log(P_{t-1})$ and f_{t-1} = information set available at time $t-1$. P_t is the price of an asset at time t.

Two assumptions are that:

1) the conditional mean of y_t, $\mu_t = \mathbb{E}(y_t) = 0$; and

2) the conditional variance of y_t, $\sigma_t^2 = \mathbb{E}(y_t^2)$ since $\mathbb{E}(y_t) = 0$.

The conditional variance is estimated based on the Exponentially Weighted Moving Average (EWMA). It is a type of weighted estimate of variance, where recent observations have more weight (influence) than those further in the past.

Let λ, with $0 < \lambda < 1$, denote the weighting parameter for the EWMA process. It is sometimes called the forgetting factor.

It is known that:

$$\sum_{j=0}^{T}\lambda^{j} = \frac{1-\lambda^{T+1}}{1-\lambda} \approx \frac{1}{1-\lambda}, \tag{2}$$

since $0 < \lambda < 1$, larger T implies that $\lambda^{T+1} \to 0$.

For the RiskMetrics method, a weighted variance is calculated where the weight of y_{t-j} is λ^{j}.

The derivation of σ_t^2 for the RiskMetrics is as follows:

$$\widehat{\sigma_t^2} = \frac{\sum_{j=0}^{T}\lambda^{j}y_{t-j}^2}{\sum_{j=0}^{T}\lambda^{j}}, \tag{3}$$

$$\widehat{\sigma_t^2} = \frac{\left(y_t^2 + \lambda y_{t-1}^2 + \ldots\right)}{\left[\frac{1-\lambda^{T+1}}{1-\lambda}\right]}, \tag{4}$$

$$\widehat{\sigma_t^2} = \frac{\left(y_t^2 + \lambda y_{t-1}^2 + \ldots\right)}{\left[\frac{1}{1-\lambda}\right]}, \quad \text{for large } T \tag{5}$$

$$\widehat{\sigma_t^2} = (1-\lambda)\left(y_t^2 + \lambda y_{t-1}^2 + \ldots\right), \tag{6}$$

$$\widehat{\sigma_t^2} = (1-\lambda)\,y_t^2 + \lambda(1-\lambda)\left(y_{t-1}^2 + \lambda y_{t-2}^2 + \ldots\right) \tag{7}$$

$$\widehat{\sigma_t^2} = (1-\lambda)\,y_t^2 + \lambda\widehat{\sigma_{t-1}^2}, \tag{8}$$

The optimal λ is found by minimizing the objective function

$$\mathbb{E}(\lambda) = \sum_{j=1}^{T}\left(y_t^2 - \widehat{\sigma_t^2}\right)^2, \tag{9}$$

RiskMetrics in equation (2) resembles a restricted Integrated GARCH (IGARCH(1,1)) filter for returns, with zero constant and predefined parameters α and β, where $\alpha = \lambda$ and $\beta = (1 - \lambda)$, summing to unity. According to Morgan (1996), a financial risk management company urged that lambda (λ) be fixed at 0.94, or 94%, when estimating VaR, while Mina and Xiao (2001) recommended that the forgetting parameter be set to 0.97 in an estimate of monthly volatility.

2.1. Error distribution

Financial time series data often reveal a fat-tail property. This has led to researchers considering alternative distribution assumptions for error terms to the Normal Distribution. Although the Normal Distribution is still widely used as the error distribution in GARCH models, more complex distributions, such as skewed-Normal Distribution, Student's *T*-Distribution (STD), skewed-STD, Generalized Error Distribution (GED), skewed-GED and the Generalized Hyperbolic (GHYP) Distribution. The STD in GARCH models was initially popularized by Bollerslev (1987). Nelson (1991) showed the usefulness of the GED in modelling financial time series with GARCH models.

Table 1. Error distribution functions

Name	Density function
Normal Distribution (μ = location, σ = scale)	$f(\varepsilon_t) = \frac{1}{\sigma\sqrt{2\pi}}e^{-\frac{1}{2}\left(\frac{\varepsilon_t-\mu}{\sigma}\right)^2}$
Skewed Normal Distribution (μ = location, σ = scale and α = shape)	$f(\varepsilon_t) = \frac{1}{\sigma\pi}\exp\left(\frac{(\varepsilon_t-\mu)^2}{2\sigma^2}\right)\int_{-\infty}^{\left(\alpha\left(\frac{\varepsilon_t-\mu}{\sigma}\right)\right)} e^{-\frac{t^2}{2}}dt$
Student's *T*-Distribution v is the number of degrees of freedom	$f(\varepsilon_t) = \frac{\Gamma\left(\frac{v+1}{2}\right)}{\Gamma\left(\frac{v}{2}\right)\sqrt{v\pi}}\left(1+\frac{\varepsilon_t^2}{v}\right)^{-\frac{v+1}{2}}$

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Table 1 (cont.). Error distribution functions

Name	Density function
Skewed Student's *T*-Distribution *v* is the number of degrees of freedom, and *α* = shape	$f(\varepsilon_t)=\frac{2}{\alpha+\frac{1}{\alpha}}f(\alpha\varepsilon_t)$ for $\varepsilon_t<0,$ $f(\varepsilon_t)=\frac{2}{\alpha+\frac{1}{\alpha}}f\left(\frac{\alpha}{\varepsilon_t}\right)$ for $\varepsilon_t\geq 0$
Generalized Error Distribution	$f(\varepsilon_t)=\frac{\sigma\cdot\alpha}{2\Gamma\left(\frac{1}{\alpha}\right)}\exp\left(-\sigma^{\alpha}.\lvert\varepsilon_t-\mu\rvert^{\alpha}\right)$
Skewed GED *u* = excess above mode, *k* = kurtosis, λ = skewness *sgn* = sign function taking −0 for *u* < 0 and 1 for *u* > 0	$f(\varepsilon_t)=\frac{k^{1-\frac{1}{k}}}{2\sigma}\Gamma\left(\frac{1}{k}\right)^{-1}\exp\left(-\frac{1}{k}.\frac{\lvert u\rvert^k}{(1+\text{sgn}(u)\lambda)^k.\sigma^k}\right)$
Generalized Hyperbolic Distribution	The Generalized Hyperbolic Distributions are part of a larger family with nice properties called the Normal Mean Variance Mixture distributions. There are at least five alternative definitions leading to different parameterizations influenced by the shape of the distribution

One of the objectives of this paper is to ascertain which error distribution gives a better estimation of VaR for the univariate RiskMetrics model, in the case of the two exchange rates data. In this paper, as mentioned, seven distributions for error terms shall be employed, namely, Normal Distribution, skewed-Normal Distribution, STD, skewed-STD, GED, skewed-GED, and the GHYP Distribution. Table 1 presents the density functions of these error distribution functions. The table summarizes the distribution functions for the error distributions used in this study.

2.2. Value at Risk (VaR)

VaR is one of the most commonly used market risk measures. For a log return variable *y* of some risky financial asset with distribution function *F* over a specific time-interval period, VaR (for a given probability *p*) is defined as the p^{th} quantile of *F*, i.e.

$$VaR_t=\widehat{\sigma}_t F^{-1}(1-p), \tag{10}$$

where F^{-1} is the quantile function, e.g. the inverse cumulative Normal Distribution.

2.3. Backtesting

To validate the model adequacy when estimating VaR, the Kupiec unconditional coverage test (Kupiec, 1995) is used.

The null hypothesis, H_0: $E[x_p/N]=p$, i.e. (the expected proportion of violations is equal to *p*).

Under H_0, the Kupiec statistic is given by

$$LR_{UC}=2\ln\left(\left(\frac{x^p}{N}\right)^{x^p}\left(1-\frac{x^p}{N}\right)^{N-x^p}\right)- \tag{11}$$
$$-2\ln\left(p^{x^p}(1-p)^{N-x^p}\right)\sim\chi_1^2,$$

where *N* is total observations, x^p is the number of violations at level *p*.

3. RESULTS

Currency data used in this study were obtained from www.investing.com/currencies. The data were analyzed in an R-programming environment using rugarch, FinTS and PerformanceAnalytics packages. The daily data points were from January 1, 2015 to June 30, 2021. Log returns were calculated as follows: $\log[P_t/P_{t-1}]$, where P_t and P_{t-1} are today's and yesterday's closing prices and used to do the modelling.

Figure 1 and Figure 2 suggest that returns are weakly stationary, around the zero-mean, and volatility clustering is visible, indicating heteroscedasticity, which is common with financial time series data.

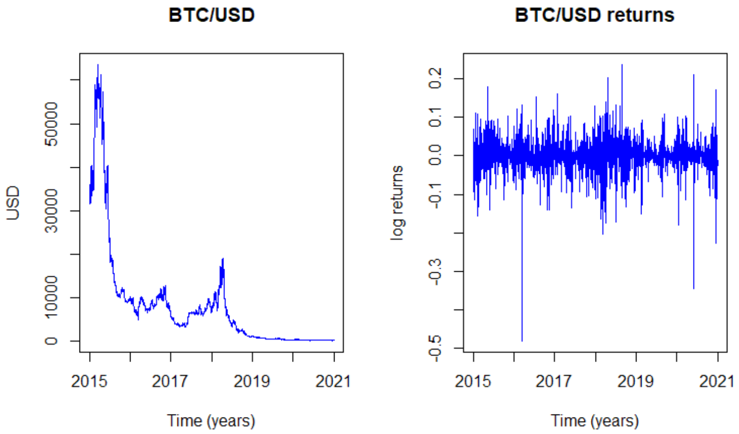

Figure 1. Plot of BTC/USD prices (left) and one-day log returns (right)

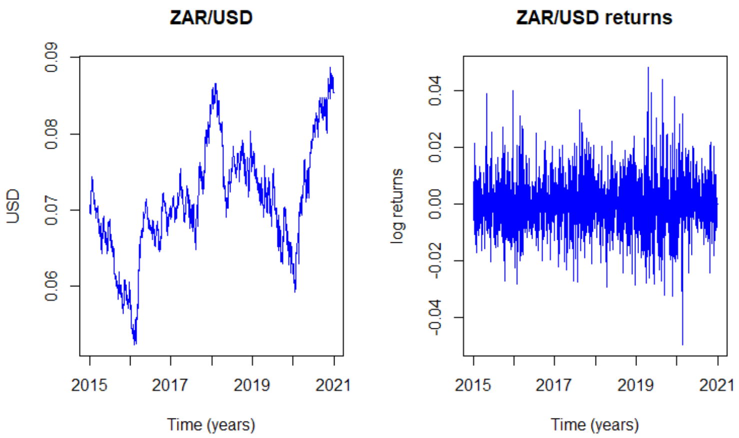

Figure 2. Plot of ZAR/USD prices (left) and one-day log returns (right)

3.1. Descriptive statistics

Table 2 gives the descriptive statistics the for BTC/USD and ZAR/USD log returns.

The positive mean in the BTC/USD log returns suggests that a gain can be realised if one is to invest or keep their investment in BitCoin. The opposite is true when it comes to the ZAR/USD; the

Table 2. Descriptive statistics of exchange rate price returns

Source: Ndlovu and Chikobvu (2022, p. 7).

Descriptive statistics

	Total	Average	Median	Max	Min	Skewness	Kurtosis
BTC/USD	2370	0.001990	0.001757	0.237220	–0.480904	–0.994382	16.15451
ZAR/USD	1694	–0.000125	0.000000	0.049546	–0.048252	–0.264130	4.121644

Test for Normality, Autocorrelation and Heteroscedasticity

TEST	BTC/USD Statistic	BTC/USD p-value	ZAR/USD Statistic	ZAR/USD p-value
Jarque-Bera	17,478.40	0.000000	108.4967	0.000000
Ljung-Box	11.7	0.0006249	0.40504	0.5245
ARCH LM Test	52.87	4.345e-07	70.789	2.28e-10

Test for unit root and stationarity

Unit Root Test	BTC/USD Statistic	BTC/USD p-value	ZAR/USD Statistic	ZAR/USD p-value
ADF Test	–52.20130	0.0001	–40.47263	0.0000
PP Test	–52.10963	0.0001	–40.47011	0.0000
KPSS Test	0.092067	0.347000	0.090747	0.347000

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mean return is negative and the losses are likely to be incurred in the long run when one keeps their investment in a Rand account.

The Jarque-Bera test rejected the Normality hypothesis for both currency exchange rates at the 5% level of significance, implying that symmetric models may fail to correctly capture the important features in the above-mentioned return series during the analysis.

The Ljung-Box test for ZAR/USD returns gave a p-value = 0.5245 > 0.05, implying a failure to reject the null hypothesis of no autocorrelation. Therefore, the observations can be assumed to be independent and identically distributed (i.i.d), which is a desirable characteristic in statistical modeling. However, for the BTC/USD returns, the Ljung-Box test's null hypothesis is rejected.

Stationarity tests (ADF and PP) reject H_0 of a unit root, at the 5% level of significance, and it can be concluded that both exchange rate return series are stationary. The KPSS test also confirms stationarity for both returns series.

3.2. Parameter estimation

As stated in section 3, RiskMetrics resembles a restricted Integrated GARCH (IGARCH (1, 1)) filter for returns, with zero constant and $\alpha = \lambda$ and $\beta = (1 - \lambda)$, summing to unity. In this section, the restricted IGARCH (1,1) is fitted to estimate RiskMetrics parameters for the BTC/USD returns data. Table 3 presents optimal parameters using the Maximum likelihood estimation method.

Table 3 shows parameter estimates (Estim), with p-values in brackets for RiskMetrics under the seven error distributions, viz; Normal, skewed Normal, Student's T, skewed Student's T, GED, skewed GED, and GHYP. Akaike's Information Criterion (AIC) suggests that GHYP gives the best fit error distribution model. Conversely, Bayesian Information Criterion (BIC) suggests that GED is the best fit error distribution, model. All error distributions were considered when estimating VaR. λ oscillates around 0.91 in all models suggesting that the more recent returns have a greater influence on the volatility than the distant returns. This value is below the one recommended by Morgan (1996) and Mina and Xiao (2001).

Table 4 shows parameter estimates, with estimated (Estim) p-values in brackets for RiskMetrics parameters of the ZAR/USD returns under the seven conditional error distributions. The Akaike's Information Criterion (AIC) suggests that skewed STD is the best fit error distribution, model. Conversely, Bayesian Information Criterion (BIC) suggests that STD is the best fit error distribution in the model. All error distributions were considered in the estimation of VaR and backtesting was used to evaluate their performances. Table 4

Table 3. Optimal RiskMetrics estimate parameters for BTC/USD

Source: Authors' own work.

Variables	iGARCH (1,1)						
	Normal	Skewed normal	STD	Skewed STD	GED	Skewed GED	GHYP
Variance equation	Estim p–	Estim p–	Estim p–	Estim p–	Estim p–	Estim p–	Estim p–
$1-\lambda$	0.0911	0.0893	0.0932	0.0908	0.0914	0.0892	0.0882
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
λ	0.9089	0.9107	0.9068	0.9092	0.9086	0.9108	0.9118
	(N/A)	(N/A)	(N/A)	(N/A)	(N/A)	(N/A)	(N/A)
Shape	–	–	3.8580	3.84173	0.9528	0.9544	0.2882
	–	–	(0.000)	(0.000)	(0.000)	(0.000)	(0.0284)
Skew	–	0.9734	–	0.9544	–	0.9662	–0.0475
	–	(0.000)	–	(0.000)	–	(0.000)	(0.0119)
Ghlambda	–	–	–	–	–	–	0.6136
	–	–	–	–	–	–	(0.0083)
Goodness of fit							
AIC	–3.7441	–3.7444	–3.9578	–3.9593	–3.9812	–3.9823	–3.9827
BIC	–3.7417	–3.7395	–3.9529	–3.9520	–3.9764	–3.9750	–3.9730

Table 4. Optimal RiskMetrics parameter estimates for ZAR/USD

Source: Authors' own work.

Variables	iGARCH (1,1)						
	Normal	**Skewednormal**	**STD**	**Skewed STD**	**GED**	**Skewed GED**	**GHYP**
Variance Equation	**Estim p–**	**Estim p–**	**Estim p–**	**Estim p–**	**Estim p–**	**Estim p–**	**Estim p–**
$1-\lambda$	0.0387	0.0362	0.0426	0.0402	0.0402	0.0372	0.0404
	(1e–06)	(4e–06)	(2e–06)	(7.0e–06)	(7e–06)	(1.8e–05)	(0.0000)
Λ	0.9613	0.9638	0.9574	0.9598	0.9598	0.9628	0.9596
	(n/a)	(n/a)	(n/a)	(n/a)	(n/a)	(n/a)	(n/a)
Shape			13.1962	12.9065	1.6600	1.6531	2.0126
			(3e–05)	(2.5e–05)	(0e+00)	(0e+00)	(0.8989)
Skew	–	1.0668	–	1.0730		1.0747	0.3155
	–	(0e+00)	–	(0.0e+00)		(0e+00)	(0.8909)
Ghlambda	–	–	–			–	−6.0000
	–	–	–			–	(0.4920)
Goodness of fit							
AIC	−6.3548	−6.3561	−6.3675	−6.3688	−6.3634	−6.3650	−6.3666
BIC	−6.3516	−6.3497	−6.3611	−6.3591	−6.3570	−6.3554	−6.3538

presents the optimal parameters using Maximum likelihood estimation methods. The forgetting parameter λ oscillates around 0.96 in all models suggesting that the more recent returns have a greater influence on the volatility than the distant returns. This value is close to the one recommended by Mina and Xiao (2001) of 0.97.

3.3. Value at Risk (VaR) and Backtest Results

Table 5. VaR estimates

Source: Authors' own work.

RiskMetrics	BTC returns		ZAR returns	
	95%	**99%**	**95%**	**99%**
Normal	0.03606	0.05100	0.01285	0.01894
sNormal	0.03590	0.05057	0.01327	0.01894
STD	0.03260	0.05787	0.01253	0.01874
sSTD	0.03201	0.05605	0.01297	0.01967
GED	0.03551	0.06130	0.01283	0.01892
sGED	0.03498	0.05997	0.01334	0.01990
GHYP	0.03462	0.06000	0.01286	0.01959

The VaR estimated using RiskMetrics models are summarized in Table 5. The computed values suggest that the BTC/USD is riskier than the ZAR/USD, since it has a higher value at risk per US dollar invested in each currency. Table 5 summarizes the estimates. The 95% level of significance suggests that lower VaR is realized than at 99%; this is due to the fact that, at a higher level of significance, lesser room for error is tolerated. However, too high a level of significance could result in higher than necessary capital requirements, leading to opportunity cost (the potential loss incurred when one forgoes an alternative investment, in this case in favour of keeping a liquid asset).

4. BACKTEST RESULTS

VaR estimates from the fitted RiskMetrics model are backtested using the Kupiec test. The *p*-values greater than 5% suggest that the model adequacy is achieved. Table 6 summarizes the findings.

Table 6. Kupiec's test p-values

Source: Authors' own work.

RiskMetrics	BTC returns		ZAR returns	
	95%	**99%**	**95%**	**99%**
Normal	0.0024	1.7e-11	0.1797	0.6217
sNormal	0.0014	2.2e-12	0.7985	0.8168
STD	2.6e-08	0.0012	0.0968	0.816
sSTD	1.4e-09	9.2e-05	0.3079	0.4592
GED	0.0002	0.070(A)	0.2170	0.8168
sGED	3.4e-05	0.0040	0.9733	0.6290
GHYP	1.1e-05	0.0040	0.3079	0.6290

Based on Table 6, RiskMetrics fits poorly to the BTC/USD currency series, hence model adequacy is rejected as most p-values are below 5%. This could be due to the heavy-tailedness feature of the BitCoin and its high volatility as discovered by

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Takaishi (2018), and the RiskMetrics model fails to fully capture this type of risk. However, it fits fairly well with the ZAR/USD returns since all p-values are greater than 5%. Using as a rule of thumb, "the higher the p-value, the better fit the model", RiskMetrics with GED error distribution is the only appropriate model for estimating VaR for BTC/USD, while RiskMetrics with skewed Generalized Error Distribution gives the best VaR estimates for ZAR/USD. The RiskMetrics approach seems to perform better at higher confidence levels than lower confidence levels, as evidenced by higher p-values at 99% than at 95% levels of significance.

5. DISCUSSION

In this study, the estimation and performance of the RiskMetrics methodology are explored using the BTC/USD and ZAR/USD data to contrast the riskiness of the two currencies. Seven error distributions, viz; Normal, skewed Normal, Student's T, skewed Student's T, Generalised Error, skewed Generalised Error, and Generalized Hyperbolic distributions were considered in parameter estimation of the RiskMetrics model.

Both return series have a higher than 3 kurtosis statistics meaning they are leptokurtic in nature. BitCoin has returns with a much higher kurtosis when compared to the South African Rand. This confirms the findings of Kaseke et al. (2021) that cryptocurrencies are more volatile than other financial assets. Both currencies have negative skewness, suggesting the data deviate from the Normality assumption.

The forgetting parameter λ for ZAR/USD oscillates around 0.96 in all models suggesting that the more recent returns have a greater influence on the volatility than the distant returns. This value is close to the one recommended by Mina and Xiao (2001) of 0.97. However, λ for BTC/USD is at around 0.91, way below the recommended ones by Morgan (1996) of 0.94 or Mina and Xiao (2001), suggesting that the BitCoin returns keeps information longer than currencies from an emerging economy, South Africa.

AIC and BIC gave somewhat contradictory conclusions on the best fit model i.e. in the BTC/USD currency exchange rate, the AIC suggested that GHYP is the best fit error distribution for the RiskMetrics model. Conversely, Bayesian Information Criterion (BIC) suggests that GED is the best fit error distribution, model.

VaR estimates suggest that the BTC/USD return averaging 0.035 and 0.055 per dollar invested at 95% and 99%, respectively, is riskier than the ZAR/USD return averaging 0.012 and 0.019 per dollar invested at 95% and 99%, respectively. To ensure the validity and reliability of the findings, the estimated VaR is backtested using Kupiec's likelihood tests, and the outcome shows that the RiskMetrics with skewed Generalized Error Distribution outperformed other models in the ZAR/USD, while on the hand model adequacy is insufficient for the BTC/USD except for the RiskMetrics with skewed Generalized Error Distribution at 99% confidence level. This is contrary to the findings of McMillan and Kambouroudis (2009) that RiskMetrics is better adequate at lower confidence levels than at higher levels.

CONCLUSION

The purpose of this study is to use the RiskMetrics approach to estimate VaR and compare the riskiness of the BitCoin and South African Rand, both indices measured against the US Dollar. The Value at Risk estimate concludes that BitCoin is riskier than the Rand.

The incorporation of heavy tail error distributions to capture fat tails improved the estimation of the Value at Risk in the Rand/dollar, and backtesting procedures confirmed this with high p-values above 0.5 that were obtained using the Kupiec's unconditional coverage test for these currencies.

This information is useful to local foreign currency traders and investors who need to fully appreciate the risk they are exposed to when they convert their savings or investments to BitCoin instead of the South African currency, the Rand. In particular, when the market enters a turbulent time, BitCoin is riskier than a developing country's currency such as the South African Rand. Furthermore, these findings help risk managers make adequate risk-based capital requirements more rational between the two currencies. The argument is for more capital requirements for BitCoin than for the South African Rand.

A hybrid of RiskMetrics with extreme value theory is recommended for further research to improve the estimation of currency risks in cryptocurrencies and exchange rates in emerging markets.

AUTHOR CONTRIBUTIONS

Conceptualization: Delson Chikobvu, Thabani Ndlovu.
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Formal analysis: Thabani Ndlovu, Delson Chikobvu.
Investigation: Thabani Ndlovu.
Methodology: Delson Chikobvu, Thabani Ndlovu.
Project administration: Delson Chikobvu.
Resources: Delson Chikobvu.
Software: Thabani Ndlovu.
Supervision: Delson Chikobvu.
Validation: Thabani Ndlovu.
Writing – original draft: Thabani Ndlovu.
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