Volatility Behaviour of Bitcoin as a Digital Asset

Evidence of Shock Transmission Dynamics from the South African Financial Markets

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Abstract: The objective of this study is to use the South African financial markets (Johannesburg Stock Exchange or JSE and USD/ZAR) as a case study to understand the volatility spillover dynamics of Bitcoin as a digital asset. Methodologically, the study applies the exponential generalized autoregressive conditional heteroskedastic (EGARCH) model, followed by a robustness check by applying the time-varying conditional correlation multivariate GARCH (VCC-MGARCH) model. The study utilizes the data set for the period 2011 to 2019, a period before the COVID-19 pandemic. The research outcome revealed three interesting observations. First, Bitcoin and the South African stock market are independent of each other. Second, there is a bidirectional shock transmission between Bitcoin and USD/ZAR in the mean returns only, but not variance. Lastly, results confirm the existence of a bidirectional volatility spillover in both the mean and variance between the JSE stock market and the USD/ZAR market. The study outcome should enlighten investors who may want to consider Bitcoin as a diversifier in their investment and portfolio strategies.

Keywords: Bitcoin, cryptocurrency, volatility spillover, foreign exchange, digital asset.

Introduction

The popularity of cryptocurrency in South Africa grows in tandem with global market trends. However, its intermarket relationship with local financial markets is yet to be understood, and the current paper contributes towards closing this gap. The goal of the study is to investigate the dynamic interactions of Bitcoin cryptocurrency in the South African financial markets. In particular, the research should answer the question of whether there is volatility spillover between Bitcoin as a digital asset and the Johannesburg Stock Exchange (JSE) listed equity market, as well as the foreign exchange market of the US Dollar relative to the South African

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Rand (USD/ZAR). Bitcoin is the first and most dominant cryptocurrency with a market share of around 50% in April 2021. Regarding the ongoing market activity in cryptocurrency, the number of alternatives to Bitcoin (known as altcoins) have mushroomed to more than 5,000 and counting. Bitcoin is said to be the speediest asset to cross-over the market capitalization line of USD 1 trillion within 12 years of its existence compared to Google (21 years), Amazon (24 years), Apple (42 years), and Microsoft (44 years).

Regarding its consumer usage, even though it fails the fundamental economics definition of money (Yermack, 2015), Bitcoin was designed to be a virtual currency (Nakamoto, 2008) and to operate as an alternative to conventional in-use money. However, unlike fiat currency (the traditional money in notes and coins), a cryptocurrency payment system is designed to operate digitally through cryptography validation and free of third-party trusted authority like a central bank. Bitcoin also belongs to a family of digital currencies, much like central bank reserves, or the topical concept of Central Bank Digital Currency (Bindseil, 2019; Gopane, 2019a). In general, Bitcoin as cryptocurrency is characterized by pseudo-anonymity, independence, and double-spending protection, along with uneven recognition by national authorities around the world (Lansky, 2018). Further details on Bitcoin properties, including its operational design and historical developments, are discussed elsewhere (Wolfson, 2015; Gopane, 2019b). Users of cryptocurrency, especially early patrons, are said to be influenced by a prospecting instinct for viable alternatives to the increasingly crisis-susceptible financial markets (Danielsson, Valenzuela & Zer, 2018). More notably, investors' curiosity in Bitcoin digital currency is seemingly induced by its nature of speculative investment (Yermack, 2015).

There is ongoing academic research in different dimensions of Bitcoin cryptocurrency, including currency properties (Ali *et al.*, 2014; Bouoiyour & Selmi, 2015), price evaluation (Dyhrberg, 2016), as well as portfolio management (Brière, Oosterlinck & Szafarz, 2015), to mention a few. The focus of the current study is to investigate the less studied case of Bitcoin volatility spillover dynamics in an emerging market like South Africa.

The Nobel Laureate, Robert F. Engle III, is a pioneer of the GARCH (Generalized Autoregressive Conditional Heteroskedastic) econometric model, which has become a work horse for volatility studies. Engle (1982) stressed the importance of understanding volatility spillover dynamics for asset price determination, risk analysis, and portfolio diversification. Since the virtual currency market is relatively new, the study of volatility dynamics for Bitcoin will have a significant value-add if extended to all emerging markets, including Africa, in today's integrated financial markets.

Research on volatility spillover, asset and market relatedness (Carpenter, 2016; Trabelsi, 2018; Corbet *et al.*, 2018; Baumöhl, 2019) has been conducted in different economies in

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Europe, North America, and Asia, but little has been researched in Africa, and with varying results. In general, unresolved questions call for deepening and broadening of empirical work. The current paper contributes to correcting this imbalance in Bitcoin and financial assets research. At present, we are unaware of a similar study that examines the volatility spillover of Bitcoin as a digital asset in the South African financial markets.

In addition, and by way of further motivation, Figure 1 plots (on the vertical left scale) the Google search index as a proxy of general user interest in Bitcoin (a form of connectedness). The graph reveals strong harmony in patterns of Bitcoin user interest for South Africa compared with the rest of the world. The secondary vertical axis (on right) measures the price of Bitcoin in USD, and its historical trend displays a lead-lag relationship with the cryptocurrency user-interest. Overall, the graphs provide *prima facie* evidence that South Africa is connected in some way to the global Bitcoin market. This observation inspires further analytical investigation in the context of the current study.

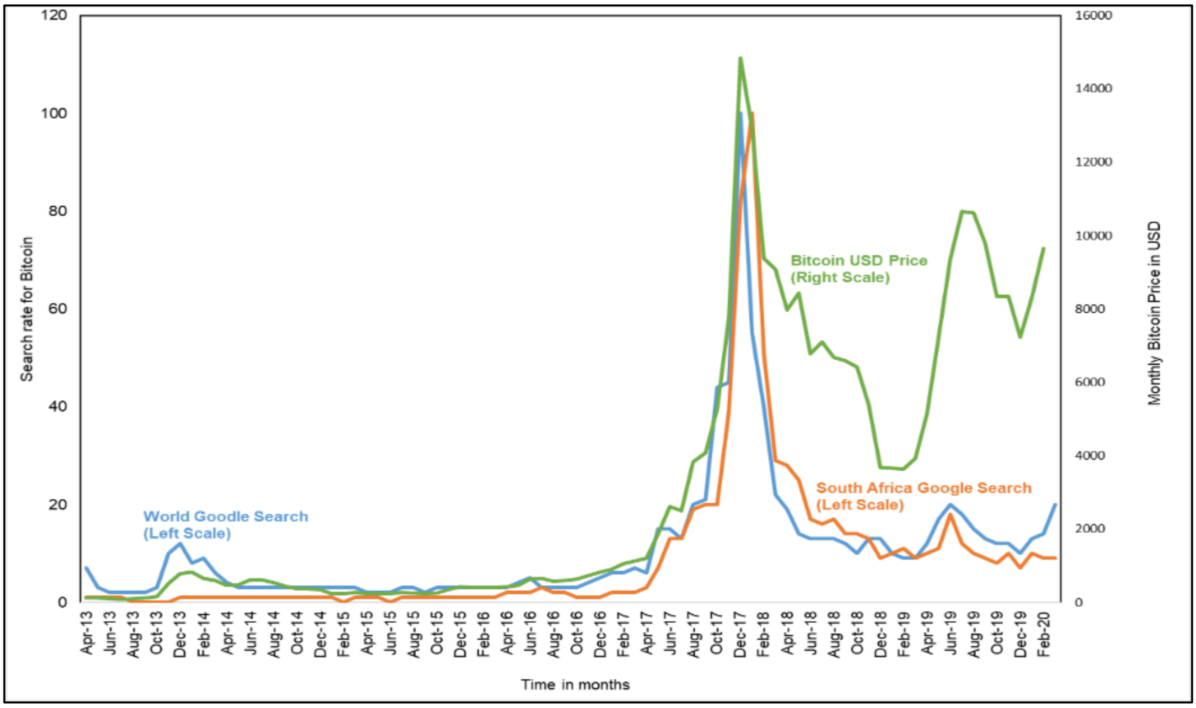

Figure 1. Google's Bitcoin Search Index (Left Scale) for the World and South Africa, and Monthly Bitcoin Price in USD (Right Scale). ***Source: Author's own graphics.***

There is other supportive evidence on the adoption of cryptocurrency in South Africa and its connectedness to global markets. Jankeeparsad and Tewari (2018) have empirically examined the end user take-up of cryptocurrency and found that perceived usefulness, as well as availability of facilitating resources, were some of the important determinants of Bitcoin take-up adoption in South Africa. The South African government (Intergovernmental Fintech Working Group, 2021) estimates that daily trading values of crypto assets exceed two billion South African Rands. Unlike in other countries (such as Algeria, Egypt, and Morocco) where

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cryptocurrency is banned, the South African authorities have not imposed any direct restrictive usage, and therefore cryptocurrency adoption can grow in tandem with market forces. However, as a member of the Financial Action Task Force (FATF), South Africa is expected to introduce some regulatory framework for cryptocurrency; and they have announced the initiation of this project in April 2021 (Intergovernmental Fintech Working Group, 2021).

The rest of the paper is organized and sequenced into the following sections: literature review, methodology including econometric methods and data description, empirical results and interpretation, discussion of results, as well as conclusion and policy implications of the research outcomes.

Literature Review

It is an accepted position in financial economics that knowledge of asset volatility is critical in today's open economies (Bouri *et al.*, 2018), integrated financial markets (Obadan, 2006), digitalization (IMF, 2018; OECD, 2019), and globalization (Boshoff & Fourie, 2017). The literature has shown that there is increased propagation and transmission of economic shocks during financial crises in South Africa (Boshoff, 2006) and other countries (Kaul & Sapp, 2006; Danielsson, Valenzuela & Zer, 2018). Also, it is not surprising that established models (Vasicek, 1977; Cox, Ingersoll & Ross, 1985; Hull & White, 1990) of sensitive monetary variables, such as interest rates, include volatility measure as an important input in their design.

Since its inception in 2009, Bitcoin has attracted studies in different dimensions of academic research. For instance, there is antagonistic research on the politics of Bitcoin, questioning the claims of trust-free money (Dodd, 2017) and critiquing its ethnography (Maddox *et al.*, 2016). Regarding general economic matters, studies evaluate Bitcoin's monetary policy connectedness (Blundell-Wignall, 2014; European Central Bank, 2015) owing to its potentially disruptive nature in financial regulatory systems (Financial Action Task Force on Money Laundering, 2015). Also, economists became equally interested in Bitcoin, partly due to its volatile behaviour (Baek & Elbeck, 2015) and to interrogate its relatedness to conventional financial markets. This line of research sought to find answers to questions related to Bitcoin's potential role in risk hedging (Bouri *et al.*, 2017), speculative investment (Baek & Elbeck, 2015), portfolio diversification (Brière, Oosterlinck & Szafarz, 2015; Carpenter, 2016), or asset selection and allocation (Platanakis & Urquhart, 2020). The current study extends the critical research of volatility studies to emerging markets where Bitcoin has shown visible expansion (Bouri *et al.*, 2018), but in which empirical volatility studies lag behind, especially in Africa. Economists express divergent views on the financial classification of Bitcoin, that is, whether

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Bitcoin is currency, commodity, synthetic commodity or gold (Selgin, 2015). For instance, some see Bitcoin as a hybrid between precious metals and fiat currency (Baur, Dimpfl & Kuck, 2018), or between gold and dollar (Dyhrberg, 2016), while others maintain that Bitcoin is not a currency (Yermack, 2015) but an asset (Smith, 2016). The current study follows the latter definition and takes this a step further in Dyhrberg's (2016) perspective, who conceived of Bitcoin as a digital asset much like gold. For this reason, and similar to Smith (2016) and Gopane (2019b), this paper will compare Bitcoin's product price with its (cross-rate) exchange rate. Further details are discussed in the methodology section.

A number of studies have investigated Bitcoin's volatility spillover dynamics in relation to stock market, foreign exchange, commodities, and against its fellow cryptocurrencies. Although most findings (Carpenter, 2016; Trabelsi, 2018; Corbet *et al.*, 2018) declare Bitcoin independent of financial markets, this is not conclusive, since there are some contradictory results, like those of Baumöhl (2019), among others. Brière, Oosterlinck & Szafarz (2015) examined cryptocurrencies' relationships with other assets (bonds, shares, currency, commodities, hedge funds, real estate) for weekly data from 2010–2013 and found low correlations. A similar study in Ireland by Corbet et al. (2018) also concluded that cryptocurrencies are rather isolated from the other financial markets. In a broad scope of asset classes, Trabelsi (2018) explored the subject of volatility spillover among cryptocurrencies and other actively traded asset classes and found no significant spillover effects. Nevertheless, in the Slovakian context, Baumöhl (2019) examined the connectedness of cryptocurrencies in relation to foreign exchange markets and observed a link between the two markets. The moral of the story is that the breadth and depth of cryptocurrency knowledge is still a work in progress and, more importantly, its inter-market behaviour and stylized facts are far from being a closed chapter (Gozgor *et al.*, 2019; Zeng, Yang & Shen, 2020; Wang *et al.*, 2021; Kayal & Rohilla, 2021; Zhao, 2022). The current study advances the ongoing research into the under-studied emerging market of South Africa.

Methodology

The goal of the model design in this study is to conduct an empirical enquiry on whether Bitcoin cryptocurrency has a volatility spillover relationship with JSE stock and foreign exchange (USD/ZAR) markets. The analysis will follow a two-step econometric procedure of univariate modelling explained within the current section followed by a robust check of results with a multivariate time series model discussed under the section on empirical results.

Economic Model

In the first step of the two-stage econometric procedure, a GARCH (1, 1) model (see Equation Box 1) is estimated with three replications for each of the log returns of stock, Bitcoin, and USD/ZAR exchange rate. On each occasion, a series of standardized residuals is retrieved to be used as input in the next stage.

Equation Box 1: Empirical Modelling — Stage 1	
GARCH (1, 1)	$y_t = cy_{t-1} + \varepsilon_t, \ \forall\, t = 1, 2, 3 \ldots N$ $where \quad \varepsilon_t \sim iid(0, h_t)$ $\log h_t = \omega + \ a\varepsilon_t^2 + b\log h_{t-1}$
GARCH (1, 1) is represented by the above equations together. The first expression is the mean equation, where y_t represents returns, while ε_t is the error term. The second equation provides the variance estimation and h_t captures the variance innovations. The parameters, a, b, c and ω are estimated in this model. Further interpretation and intuition are given in the text.	

The second stage implements the main econometric model, EGARCH. The EGARCH model was proposed by Nelson (1991) as an innovation of and extension to the GARCH family, following the pioneering foundations of Engle (1982) and Bollerslev (1986). This model has important advantages that makes it a preferred analytical model for the current study. In addition to its attractive parsimony, EGARCH captures the usual *stylized facts* of financial returns (Enders, 2003) such as volatility clustering, fat-tailedness, leverage, as well as leptokurtic distribution, and, in particular, it relaxes the restriction of symmetry in the basic GARCH (1, 1) model. More specifically and for the benefit of the current study, EGARCH comes with a built-in capacity to guarantee the non-negativity condition of variance. Nelson's (1991) EGARCH (1, 1) model is presented in the framework of two equations, (1) and (2):

$$y_t = \phi y_{t-1} + \delta_1 x_{1t} + \delta_2 x_{2t} + \varepsilon_t, \ \forall\, t = 1, 2, 3 \ldots N \tag{1}$$

$$where \quad \varepsilon_t \sim N(0, h_t)$$

$$\log h_t = \omega + \ \alpha|\eta_{t-1}| + \gamma\eta_{t-1} + \beta\log h_{t-1} + \ \lambda_1 x_{1t} + \lambda_2\, x_{2t} \tag{2}$$

$$where \ \ \eta_t = \frac{\varepsilon_t}{\sqrt{h_t}} \quad \text{and} \quad \eta_t \ \sim \ iid\ (0, \omega)$$

The first expression in (1) is the mean equation, where y represents returns calculated as the first log difference of the price data, $\ln\left(\frac{P_t}{P_{t-1}}\right)$, for each of the time series, namely, implied Bitcoin exchange rate, JSE All Share Index, and USD/ZAR foreign exchange rate. The regressors, x_1 and x_2, are residuals from the GARCH (1, 1) model computed in the first stage (Equation Box 1). The error terms (ε) are assumed to follow a normal distribution. In Equation

(2), the variable h is the conditional variance. In both equations, the subscript t represents time in days, while the parameters to be estimated are α, β, γ, δ, η, λ, ϕ and ω.

A methodological framework of using two-step econometric modelling to examine shock transmission is a known procedure with theoretical motivation (Sefcik & Thompson, 1986), and widespread empirical application. For instance, Boshoff (2006) employed a similar framework to investigate the transmission of imported financial crises to South Africa. A similar model design for related empirical investigation was previously employed by several researchers, including, Hamao, Masulis & Ng (1990), Theodossiou & Lee (1993), Jebran & Iqbal (2016), and Jebran (2018), among others.

Data Characteristics

The empirical analysis was conducted using secondary data for three variables, namely, JSE All Share Index, USD/ZAR, and Bitcoin exchange rates. This study adopts a digital asset definition of Bitcoin exchange rate as elaborated in Smith (2016) and applied in Gopane (2019b). In this context, Bitcoin (much like gold) prices quoted in trading platforms and valued in diverse currencies like the USD, Euro, and British pound sterling (*inter alia*) are conceived as asset prices, and not exchange rates. Therefore, in order to derive the implied exchange rate of Bitcoin, we choose a triangle of stable currencies, USD, and Euro. So, to obtain the implied Bitcoin exchange rate from its USD price, we divide USD/BTC by EUR/BTC to arrive at the implied Bitcoin exchange rate. A graphical distinction between Bitcoin price (BTC) and the implied Bitcoin exchange rate is illustrated in Figure 2.

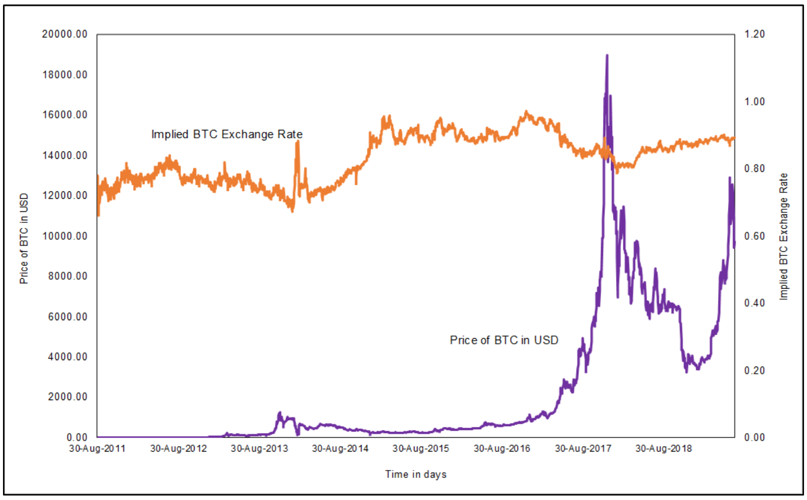

Figure 2. Time Plot BTC Price in USD and Implied BTC exchange rate (Source: Own graphics)

It transpires that, unlike the Bitcoin's USD price, the implied Bitcoin exchange rate trends well with other financial time series for JSE All Share Index (in Panel A of Figure 3), and USD/ZAR exchange rate (in Panel B of Figure 3).

Panel A: Comparison of USD/ZAR and Implied Exchange Rate	**Panel B:** JSE All Share Index and Implied BTC Exchange Rate

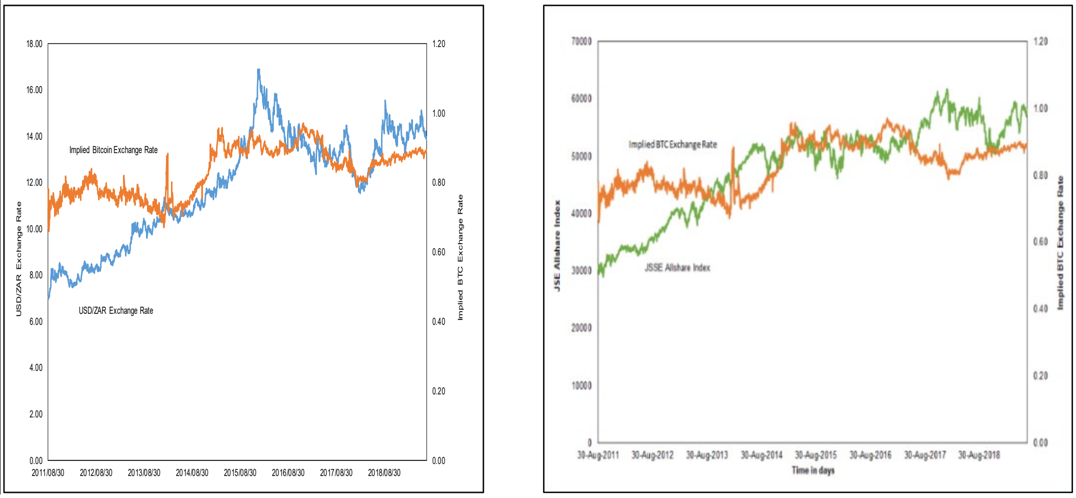

Figure 3. Time Plot of JSE All Share Index, Implied BTC, and USD/ZAR Exchange Rates (Source: Author's own graphics)

The data sets for daily prices were sourced for the period 30 August 2011 to 17 July 2019. The starting date was limited by data availability, while the end of the sample range was purposefully chosen to avoid data contamination risk from the COVID-19 pandemic. The time series data for USD/EUR, BTC/USD and JSE All Share Index were sourced from the online databases of Yahoo Finance and Iress database, respectively. Table 1 presents the descriptive summary statistics of the variables. A sample size of 1,969 for each time series was used. All three variables show a comparable average of approximately 0.03% and consistent standard deviation of around 1%. The evidence of kurtosis and skewness are consistent with the familiar stylized facts of financial return (Enders, 2003).

Table 1. Summary of Descriptive Statistics

Statistics	***JSE All Share Index***	***USD/ZAR Exchange Rate***	***Implied BTC Exchange Rate***
Mean	0.0003	0.0003	0.0002
Standard Deviation	0.0093	0.0101	0.0131
Kurtosis	1.3618	1.8760	9.3486
Skewness	-0.1583	0.4381	-0.3286
Minimum	-0.0362	-0.0338	-0.1055
Maximum	0.0416	0.0625	0.0945
Observations	1969	1969	1969
Source: Own computations			

Empirical Results

EGARCH Model

This section presents the empirical results (in Table 2) regarding Bitcoin's volatility dynamics against the South African stock, and USD/ZAR foreign exchange markets. The empirical model was validated through the standard statistical procedures, including stationarity test using the augmented Dickey–Fuller (ADF) method by Dickey & Fuller (1979). The ADF test was confirmed with the regular alternative test proposed by Phillips & Perron (1988). The post-modelling validation of no-arch effects was tested and yielded satisfactory results displayed in Table 4 (in appendix).

The results in Table 2 were generated from the EGARCH (1, 1) model presented in Equations (1) and (2). Panel A in Table 2 shows results for the mean equation. The results indicate that all three variables (stocks, USD/ZAR, and Bitcoin) respond to each other's shock in the mean equation (that is, $\delta_1 > 0$ and $\delta_2 > 0$). Panel B shows the regression coefficients of the variance equation, and all parameters are strongly statistically significant, except the asymmetry coefficient for Bitcoin. This insignificant coefficient ($\gamma = 0$) means that own Bitcoin shocks are symmetric. Disturbances of equal magnitude have a similar effect, irrespective of their direction (negative or positive).

The shocks for JSE stocks are asymmetric ($\gamma < 0$), meaning that negative shocks have a higher impact than their equivalent positive disturbances, while USD/ZAR has opposite results in that positive shocks have a higher impact ($\gamma > 0$). The parameter β captures persistence in variance innovations. If β approaches 1, then the system is persistent. This means that a disturbance or shock may prolong its effect before it diminishes. All the three series have persistent shocks.

At this point it is important to reiterate that the objective of this empirical evaluation is to examine the relatedness of Bitcoin's volatility spillover dynamics to JSE stocks and USD/ZAR markets. In this context, volatility is deemed to spill over between markets if either or both λ_1 and λ_2 are statistically significant. In this regard, Panel B (x_i shocks) shows that both JSE stocks and USD/ZAR have bidirectional volatility spillover, while Bitcoin neither gives nor receives volatility shocks to/from the South African financial markets under examination. This is an interesting revelation, since Bitcoin is known to be highly volatile, yet the variances for both stock market and foreign exchange are unaffected by the observed Bitcoin volatility, other things being equal. Panel C displays the rest of the model properties. First, the stability condition of EGARCH model is satisfied for all variables, as evidenced by $|\beta| < 1$. Second, both

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stock and USD/ZAR markets have asymmetric shocks, but not Bitcoin. Lastly, leverage exists only in stock market but none in the exchange markets under consideration.

Table 2. Empirical Results

Details			**Output for EGARCH (1, 1) – (*p*-values in brackets)**		
Panel	**Variables**		**JSE All Share Index**	**USD–ZAR Exchange Rate**	**Implied BTC Exchange Rate**
A	Mean equation	Series' own lag (ϕ)	0.0109 (0.6352)	-0.0193 (0.3945)	-0.2548 (0.0009***)
		JSE All Share Index (x_i)		-0.0017 (0.0009***)	-0.0001 0.3943
		USD/ZAR Exchange Rate (x_i)	-0.0014 (0.0000***)		0.0008 (0.0009***)
		Implied BTC Exchange Rate (x_i)	0.0001 (0.8870)	0.0007 (0.0009***)	
B	Variance equation	ω	-0.2728 (0.0000***)	-0.2831 (0.0000***)	-0.3558 (0.0009***)
		α	0.0497 (0.0005***)	0.1128 (0.0000***)	0.2577 (0.0009***)
		γ	-0.1260 (0.0000***)	0.0379 (0.0000***)	0.0084 (0.5209)
		β	0.9756 (0.0000***)	0.9791 (0.0000***)	0.9830 (0.0009***)
		JSE All Share Index (x_i)		-0.0213 (0.0420**)	0.0040 (0.6981)
		USD–ZAR Exchange Rate (x_i)	0.0637 (0.0000***)		0.0120 (0.3956)
		Implied BTC Exchange Rate (x_i)	-0.0077 (0.5723)	0.0194 (0.1077)	
C	Stability condition	$\lvert\beta\rvert < 1$	Yes	Yes	Yes
	Asymmetry exists	$\gamma \neq 0$	Yes	Yes	No
	Leverage exists	$\gamma < 0,\ \ and\ \ \gamma < \alpha < -\gamma$	Yes	No	No

Notes: Statistical significance at * 1% ** %5**
Source: Own computations

The table provides results for the empirical model, EGARCH (1, 1), as outlined in equations 1 and 2. Overall the model is well validated in row C. Generally, the results indicate that there is some connectivity of Bitcoin with the South African exchange rate but none with the stock market.

VCC-MGARCH Model: Robustness check

For robustness check, the results of EGARCH are extended with VCC-MGARCH where the model mathematics are presented in Equation Box 2 (in appendix), and the results are reported in Table 5 (in appendix). The model is appropriately validated with Wald test being statistically significant; and the parameters governing the correlation process (λ_1, and λ_2) are also significant and satisfy the relevant econometric condition, $0 \leq \lambda_1 - \lambda_2 < 1$. Further, the stability condition of the model is validated through the sum of Arch and Garch coefficients. The VCC-MGARCH is a parsimonious model that is suited to study the volatility spillover on a tri-variate system of JSE stock market, Bitcoin, and USD/ZAR exchange rates. Overall, the results of the two sets of models (EGARCH and VCC-MGARCH) are consistent and the original results are confirmed in the main. The results in Table 5 (in appendix) reveal several observations, including that, similar to the univariate models, the mean equations show that the variables are influenced by their own lags but less by the others. Further, the model captures the short- and long-term volatility spillovers well across the three variables. Most importantly, the results show that the correlations for Corr(JSE, USD/ZAR), and Corr(USD/ZAR, BTC) are statistically significant, confirming the bidirectional shock transmission observed in the univariate models. Also, the correlation of Corr(JSE, BTC) is insignificant, which concurs with unrelatedness between the two variables seen in the first round of modelling.

Discussion of Results

The current study was conducted against the hypothesis that South African financial markets are integrated with global markets in view of published empirical evidence (Boshoff, 2006; Heymans & Da Camara, 2013; Boshoff & Fourie, 2017). Therefore, this created anticipation at the outset that a relatively new but very disruptive and volatile digital asset like Bitcoin is likely to be involved in volatility spillover with domestic financial markets. This is an empirical question that was answered in the current study. The study has used EGARCH (1, 1) to examine the spillover dynamics of Bitcoin in relation to the financial markets of South Africa (JSE stocks, and USD/ZAR), and confirmed the outcomes with VCC-MGARCH. Table 3 summarizes results intuitively. The findings highlight three key observations.

Table 3. Summary of mean and volatility spillover for Bitcoin, JSE stock, and USD/ZAR

No.	Details	Mean	Variance
1	Bitcoin vs JSE Stocks	None	None
2	Bitcoin vs USD/ZAR	Bidirectional	None
3	Stock vs USD/ZAR	Bidirectional	Bidirectional
This table provides a summary of results for Bitcoin's interaction relationship with the South African financial markets (stocks, and exchange rate).			

First, Bitcoin is independent of the JSE stock market. This result is comparable with prior studies. Corbet et al. (2018) examined volatility spillover between Bitcoin and the S&P 500 stock market, *inter alia*, using the *frequency domain* analysis introduced by Baruník & Křehlík (2018), and found almost zero bidirectional shock transmission or volatility spillover.

Second, Bitcoin is a giver and recipient to/from USD/ZAR of shocks in the mean returns, and no volatility spillover in the variance. Corbet et al. (2018) studied the volatility spillover of Bitcoin in relation to six global financial markets, including foreign exchange. Consistent with the current study and employing the Total Spillover Index (TSI) proposed by Diebold & Yilmaz (2012), Corbet et al. (2018) found that Bitcoin gives (15.25%) and receives (4.18%) volatility measures to/from foreign exchange markets in the price level. The study also found that the two variables have an equal but very minimal (0.35%) bidirectional volatility spillover effect.

Lastly, the JSE stock market and the foreign exchange market (USD/ZAR) have bidirectional shock transmission, both in the mean and in the variance. Even though not conclusive, this is a very common finding in the literature, both in South Africa (Oberholzer & Von Boetticher, 2015) and in other countries. There is supportive evidence from emerging markets like India (Mishra, Swain & Malhotra, 2007), China (Jebran & Igbal, 2016), as well as from developed economies like the US, UK, Germany, Japan, and Canada (Francis, Hasan & Hunter, 2006; Aloui, 2007).

Even though the study was neither designed nor intended to answer this question, there is value in offering a perspective on why Bitcoin volatility spillover in the South African financial markets (stock and USD/ZAR) is non-existent. Since the South African financial markets are integrated with world markets (Samouilhan, 2006), it is possible that similar explanations given for other economies apply in the current study, as Bitcoin is still relatively small in relation to conventional markets (Gopane, 2019b). Another reason may be its speculative nature as a digital asset, coupled with its disconnectedness with financial market fundamentals.

Overall, our findings reinforce a trend of empirical results reaching a common conclusion that "cryptocurrencies are rather isolated from the other markets" (Corbet *et al.*, 2018, p. 30) and that Bitcoin offers investors potential opportunities for portfolio diversification (Carpenter, 2016) or risk hedging (Bouri *et al.*, 2017).

Conclusions

An empirical analysis of Bitcoin's volatility spillover in the South African financial markets (of JSE equity and USD/ZAR) revealed enlightening outcomes. The findings show that Bitcoin is independent of the JSE stock market but has bidirectional shock transmission with USD/ZAR in the mean return, but not variance. In line with expectations, the domestic financial markets (JSE equity and USD/ZAR) have bidirectional shock transmission in the mean and reciprocate volatility disturbances to each other. These results should be informative to JSE stock market investors who may want to explore Bitcoin as a portfolio diversifier. Monetary policy makers should find the results of volatility dynamics between Bitcoin and USD/ZAR beneficial.

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Appendix

Table 4. LM Test for Arch Effects

Variable	Statistic	Value	*P*-value
JSE Allshare Index	F(5,1957)	0.3372	0.8906
	Obs*R-squared, $\chi_{(5)}$	1.6899	0.8902
USD/ZAR Exchange Rate	F(5,1957)	1.0062	0.4124
	Obs*R-squared, $\chi_{(5)}$	5.0335	0.4118
Implied BTC Exchange Rate	F(10,1947)	1.5233	0.1248
	Obs*R-squared, $\chi_{(10)}$	15.2001	0.1249

Source: Own computations

This table provides post-modelling validation results LM Test for Arch Effects. The results are satisfactory.

Equation Box 2: Time-varying conditional correlation multivariate GARCH, (VCC-MGARCH)
$h_{ij,t} = \rho_{ij,t}\sqrt{h_{ii,t}\, h_{jj,t}} \qquad (2a)$ $q_t = \Pi z_t + \mu_t \qquad (2b)$ $\mu_t = H_t^{(1/2)}\, e_t \qquad (2c)$ $H_t = D_t^{(1/2)}\, R_t\, D_t^{(1/2)} \qquad (2d)$ $R_t = (1-\lambda_1-\lambda_2)R + \lambda_1\psi_{t-1} + \lambda_2 R_{t-1} \qquad (2e)$ where $\rho_{ij,t}$ = correlations which vary with time $h_{ii,t}$, *and* $h_{jj,t}$ = variances, and $h_{ij,t}$ are covariances. q_t = *vector of response variables with dimension* $m \times 1$ Π = *coefficient matrix with dimension* $m \times k1$ z_t = *vector of covariates or lags of* q_t *with dimension* $k \times 1$ H_t = *dynamic conditional covariance matrix* e_t = *identically distributed innovations with dimension* $m \times 1$ D_t = *diagonal matrix of conditional variances* R_t = *matrix of conditional correlations* R = *matrix of means responding to the dynamic process* ψ = *rolling estimator of the correlation matrix* λ_1, λ_2 = *constants that control the dynamic conditional correlation process,* $0 \leq \lambda_1 - \lambda_2 < 1$
Notes: In Equation 2a, the $h_{ii,t}$ *and* $h_{jj,t}$ are derived from univariate GARCH systems, while $\rho_{ij,t}$ are computed from an elaborate dynamic process. Equation 2b is the mean equation.
Source: Adapted from Tse & Tsui (2002)

Table 5. Results of Time-Varying Conditional Correlation MGARCH, VCC-MGARCH (2,1)

Equation	Variables	lag	Coeff.	Std. Err.	P-value	
JSE	JSE	L1	-0.0481	0.0258	0.0620	*
	USD/ZAR	L1	0.0000	0.0000	0.2990	
	BTC	L1	0.0121	0.0165	0.4640	
	ARCH	L1	0.0456	0.0327	0.1640	
		L2	0.2127	0.0525	0.0000	***
	GARCH	L1	0.5237	0.1883	0.0050	**
		Const	0.0000	0.0000	0.1740	
USD/ZAR	JSE	L1	0.0322	0.3278	0.9220	
	USD/ZAR	L1	1.0001	0.0003	0.0000	***
	BTC	L1	0.2430	0.2051	0.2360	
	ARCH	L1	0.1396	0.0389	0.0000	***
		L2	0.2109	0.0808	0.0090	***
	GARCH	L1	0.4757	0.2581	0.0650	*
		Const	0.0032	0.0031	0.3110	
BTC	JSE	L1	-0.0506	0.0228	0.0270	**
	USD/ZAR	L1	0.0000	0.0000	0.1760	
	BTC	L1	-0.3222	0.0245	0.0000	***
	ARCH	L1	0.5663	0.0661	0.0000	***
		L2	0.2723	0.0549	0.0000	***
	GARCH	L1	0.0194	0.0760	0.7980	
		Const	0.0000	0.0000	0.0000	***
Corr (JSE, USD/ZAR)			-0.2056	0.0286	0.0000	***
Corr (JSE, BTC)			-0.0220	0.0321	0.4930	
Corr (USD/ZAR, BTC)			0.0619	0.0303	0.0410	**
/Adjustment, Lambda1	λ_1		0.0125	0.0124	0.0081	***
Lambda2	λ_2		0.9021	0.1449	0.0000	***
Wald Test, $\chi^2_{(9)}$				1.65e07	0.0000	***
Number of observations				1524		
Notes: Statistical significance at	***** 1%**		**** %5**			
Source: Own computations						