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Cryptocurrency Returns, Cybercrime and Stock Market Volatility: GAS and Regime Switching Approaches

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ABSTRACT

This study examines the behaviour of cryptocurrencies' returns to stock market volatility and cybercrime in the South African economy. The study makes use Generalized Autoregressive Score Model (GAS) investigate the time-varying correlation between cryptocurrencies' returns and cybercrime, and cryptocurrencies' returns and stock market volatility by making use of daily time series data on different four types of Cryptocurrencies, Bitcoin, Ethereum, Tether and BNB from January 2019 to December 2021. The study also makes use of the regime-switching approach to regime-switching impacts on the cryptocurrencies' returns. The empirical results obtained showed that cybercrime, on average, has negative impacts on the cryptocurrencies' returns and the time-varying correlation between stock market volatility and each of the cryptocurrencies' returns is largely positive. The stock market volatility impact is found to be regime-switching dependent. The study recommends that efforts to reduce cybercrime activities must be reinforced to deepen the use of digital currencies and policy measures must be taken to ensure reduced or moderate stock market volatility.

Keywords: Cryptocurrencies, Cybercrime, Stock Market Volatility, South Africa
JEL Classifications: D53; E44; C01

1. INTRODUCTION

Cryptocurrencies are undoubtedly one of the biggest financial innovations in recent times. Cryptocurrencies are decentralized virtual currencies that are often traded through online exchanges with traditional fiat currencies, like the U.S. dollar and the Euro. It can also be used to purchase goods and services online (Levin et al., 2014a, b, c). The term virtual or digital currency refers to electronic money that runs like a currency but does not possess all the characteristics of real currency (Levin et al., 2014a, b, c). Digital currencies can be created by an individual, corporation, or organization, and might even arise from acceptance by people as currency (Turpin, 2014). It is customary to distinguish cryptocurrencies or digital currencies from electronic money that is produced by the central government, endorsed by the apex banks and backed by national currency. Conventional currencies are backed by the faith and credit of the national governments that identify the currency (the fiat system) or by real assets or hard commodities, such as gold, silver, or minerals (the commodity system). On the other hand, digital currencies such as bitcoin are neither backed by fiat nor a commodity and mainly exist as bits of computer code (Yermack, 2014). Digital currencies are not controlled by the apex bank or by any other form of government regulation. The supply of cryptocurrencies is largely based on an algorithm that structures a decentralized peer-to-peer system of the transaction (Nakamoto, 2008; Turpin, 2014). Cryptocurrencies are not like previous online payment systems as there is no middleman between the buyer and the seller as obtainable under the online payment system such as PayPal, traditional payment cards, bank wires, or other payment systems. No wonder, cryptocurrencies are referred to as decentralized or virtual currency. No company is responsible for the management and control of its operation. The cryptocurrency transaction network comprises computers around the globe running the software, and this software operates the standard of practice for administering cryptocurrency transactions. The software is downloadable and can be run by anyone, while any computer running the software automatically can join the network. Any computer on the network sustains a copy of the public ledger (Levin et al., 2014a, b, c). The ledger contains the record of all the transactions that run in the system. The ledger is divided into transaction blocks, and the blocks are linked to each other, thereby accounting for the name "blockchain."

The underlying aim of cryptocurrencies as noted above is to avoid dependence on the authority of financial institutions and apex banks, while also cutting costs and deepening the safety and the security of transactions and payments. All of these had widened and deepened the popularity of cryptocurrencies globally, but the susceptibility of cryptocurrency markets to cyberattacks and manipulation has been a great source of worry and concern. Several factors have been noted in the literature as being responsible for the susceptibility of cryptocurrency markets to cyberattacks and manipulation. The factors mainly include the absence of a regulatory framework, the operations of cryptocurrencies within cyberspace, lack of relevant financial literacy and, an increase in cryptocurrency prices. These factors have undoubtedly made cryptocurrencies a serious target for cyber-hackers (Fang et al., 2021; Umar, 2021; Panos et al., 2020; Caporale et al., 2020; Schipor, 2019).

Some studies such as Kara and Aydos (2022), Kshetri and Voas (2017) and Kok et al. (2020) among others have associated the increased cyberattacks, especially ransomware to the inception of cryptocurrencies. Ransomware is malicious software, or malware which steals data and encrypts the data, and holds it for ransom. Ransomware attacks commonly deny the victims access to their data except the ransom is paid and a short timeframe is given to pay the ransom before the data is forever gone. They are of the position that ransomware could rarely occur in the absence of cryptocurrencies because all other payment mechanisms are easily traceable. Empirical studies have confirmed that cyber-attacks on cryptocurrencies accounted for a loss of $445 billion for global markets (Benjamin et al., 2019) and thereby affecting the cryptocurrency's returns. Similarly, Fang et al. (2021) argued that 10 confirmed cyberattacks on cryptocurrency markets led to the loss of 244 million euros in 2019. From the foregoing, it is clear that there exists a relationship between cyber-attacks and cryptocurrencies and their returns. This study investigates the impact of cyber-attacks on cryptocurrencies' return to the South African economy. The study specifically contributes to the discussion on the impact of cyber-attacks on cryptocurrencies' return as available evidence in the South African economy is still very lean. Also, this study is different from the available evidence in the literature (Fang et al., 2021; Umar, 2021; Panos et al., 2020; Caporale et al.) in its approach as this study employs Dynamic Conditional Correlation (DCC-GARCH) to investigate the time-varying correlation between cyberattacks and cryptocurrencies' return. Our study employs the Generalized Autoregressive Score Model (GAS) to investigate the time-varying correlation between cryptocurrencies' returns and cybercrime, and cryptocurrencies' returns and stock market volatility. GAS is employed because of its superiority over earlier proposed volatility models. Specifically, GAS is developed to capture jumps/outliers effects in the returns series. Also, the use of GAS possesses the capacity to capture asymmetry with occasional jump detection. The GAS model combines other foremost volatility models such as the Generalized Autoregressive Conditional Heteroscedasticity (GARCH), the Autoregressive Conditional Duration (ACD), the Autoregressive Conditional Intensity (ACI), and the single source of error models.

Also, it has been argued that there is tremendous growth in the value and popularity of cryptocurrencies because many people consider them as an alternative financial assets. This is because these people believe that cryptocurrencies unlike stocks or share have no association with any central authority and has no physical representation and are infinitely divisible (Corbet et al. 2019). Like the cryptocurrency markets, the stock market is one of the markets with a high degree of volatility. The current study also contributes to the literature by examining the impact of stock market volatility on cryptocurrencies' returns. The remainder of the study is structured as follows. Section 2 reviews the theoretical and empirical literature, while section 3 discusses the empirical method. Section 4 discusses the empirical results. The conclusion is provided in section 5.

2. REVIEW OF LITERATURE

Relevant theories that explain how the stock market and cybercrime impact cryptocurrency are explained in section 2.1 while section 2.2 outlines the previous empirical attempts on the subject matter.

2.1. Theoretical Framework

The current study reviews the following theories that connect financial markets with cryptocurrencies. Theories such as Capital Asset Pricing Model (CAPM)/The Arbitrage Pricing Theory (APT) and Behavioral Portfolio Theory (BPT) are briefly reviewed.

2.1.1. Capital Asset Pricing Model/The Arbitrage Pricing Theory (APT)

The capital asset pricing model (CAPM) was originally introduced in the early 1960s. The theory specifically bothers on how the risk that could not be diversified affects returns. The theory is concerned with the diversification and identification of risks which can be mitigated by diversification and the risks that diversification cannot handle. In the framework of CAPM, two types of risk were identified; systemic risk and unsystemic risk. The systemic risk is also known as market risk it arises from socio and economic factors that impact the overall economy and all investment assets. Factors such as interest rates, recessions, inflations and geopolitical events like war have been identified as factors that impact negatively on traditional financial assets such as stocks and shares. Systemic risk is called market risk because all traditional financial assets are impacted. This makes the investors think of portfolio diversification in the cryptocurrency market as a means of mitigating this risk. Unsystemic risk is also known as a specific risk they are risks that are specific to each asset. For instance, the stock market faces risks of high volatility which often arise from adverse developments that may not impact the entire market, and hence investors' attempts to maximize their returns might be considered an alternative investment option in the crypto market. This is the heart of the Modern Portfolio Theory (MPT). The Arbitrage Pricing Theory (APT) is also known as a theory of asset pricing. The theory postulates that asset returns are a function of the expected returns and the macroeconomic factors that affect the asset's risk. The APT provides an investor with a multi-factor pricing model for securities, conditioned upon the relationship between a financial asset's expected return and macroeconomic factors associated with risks. CAPM emphasizes a single factor, the APT considers multiple factors other than the return of an asset. Li and Wang (2017) argued that cryptocurrencies are influenced by multiple macroeconomic factors. Consequently, APT may better capture the cryptocurrency analysis. Mehta and Afzelius (2017) made use of CAPM on four different assets from different sectors (Google, silver, bitcoin and Pokémon cards). They found that CAPM explains the return on Google and silver. They submit that bitcoins return cannot be predicted using CAPM. They conclude that the APT would be better for any meaningful analysis of the bitcoin (BTC).

2.1.2. Behavioural Portfolio Theory (BPT)

Behavioural portfolio theory (BPT) was encapsulated in the year 2000 by Shefrin and Statman. The theory tries an alternative to the general assumption that maximizing the value of portfolios is the ultimate motivation for investors. The theory probes how investors invest in real life. The traditional finance theory assumes that investors diversify portfolios based on the mean-variance efficient frontier while behavioural portfolio theory, on the other hand, argues that investors are rather known for constructions of the portfolio in layers with each layer portraying varying returns and risk expectations. The objectives and the goals of the investors are fully considered in allocation between different layers. Behavioural Finance theory is a five-factor process and the process can be highlighted as follows: determination of investors' goals and the importance of the goals. This will help in determining the allocation to each layer. For instance, a high return goal means a high return layer will be created while low-risk goals mean more funds are allocated to low-risk layers. Other components of the five-factor process are asset allocation, the number of assets in each layer, and this will determine the risk aversion of the investors. Information advantage at the disposal of the investors and this will determine if more concentrated positions would be created. Lastly, if the investor is risk-averse, more cash would be held to avoid selling off assets when liquidity is needed. Consequently, it is clear that investors have different aims and as a result create an investment portfolio that suits a broad range of goals.

2.2. Empirical Evidence

The subject matter of cryptocurrencies has attracted moderate research attention from various stakeholders ranging from investors, regulators and academia since bitcoin first came into being by Nakamoto (2008). A growing body of literature has regarded cryptocurrency as an alternative financial asset that is largely different from traditional financial assets and most of these studies are concerned about the mechanisms of the operations of the cryptocurrencies (Corbet et al., 2019). In other words, the majority of these studies are concerned about the intrinsic features of cryptocurrencies such as their market inefficiency, facts, anomalies and price clustering (Urquhart, 2016; Urquhart, 2017; Zargar and Kumar, 2019; Phillip et al., 2018; Li et al., 2019; Ma and Tanizaki, 2019). Some studies have also focused on the relationships between cryptocurrencies and some exogenous variables like properties of hedges and safe haven (Urquhart and Zhang, 2019; Wang et al., 2020). Urquhart (2016) examined the market efficiency of Bitcoin which is the most popular of all the cryptocurrencies, he concluded that Bitcoin was inefficient. Recent empirical findings have continued to reorganize cryptocurrencies as an asset class that exhibits a high degree of high levels of volatility about other forms of financial assets (Corbet et al., 2019). Chu et al. (2017) and Phillip et al. (2018) provided evidence in support of the volatility of cryptocurrencies. However, the most worrisome issue of cryptocurrencies is the provision or allowance of a platform for criminality. Foley et al. (2019) submit that about $76 billion of criminal activity per year is involved in Bitcoin which is estimated to be about 46% of Bitcoin transactions. However, empirical studies on the effects of cybercrime on cryptocurrency returns are quite scanty, and studies on the effects of stock market volatility on cryptocurrency returns are unknown to us, especially in the South African economy. Umar (2021) investigated the impact of cyber-attacks on cryptocurrency price, return and liquidity. The empirical conclusions showed that cyber-attacks on cyber-attacks on cryptocurrency significantly affect the returns cyber-attacks on other assets enhance the cryptocurrencies' returns. This is consistent with Fang et al. (2021). Fang et al. (2021) concluded that an increase in cryptocurrency prices is associated with a higher number of cyber-attacks on cryptocurrencies and increased cybercrime has negatively impacted the cryptocurrencies' returns. Recently, Almaqableh et al. (2022) investigate the impact of terrorist attacks on the risk and return of cryptocurrencies. Their findings suggest that terrorist attacks positively impact the returns of cryptocurrencies while the attacks also result in short-term risk-shifting behaviour for different cryptocurrencies.

Most of the available studies found have focused on the effects of cryptocurrencies on the economy or other variables. For instance, Ahannaya et al., (2021) investigate the effect of cryptocurrencies on Nigeria's economy. The study reveals that blockchain technology has benefitted the economy to an extent as a moderate number of people are fully convinced that digital Currency-Bitcoin is legitimate, safe, and has value. Despite the increasing popularity of cryptocurrencies, both the acceptance and legal status vary largely across borders. While some countries have allowed their use and others have outrightly proscribed them. Similarly, there has been debate about whether cryptocurrencies are separated from conventional financial and economic assets (i.e., stock markets). Akyildirim et al. (2020) believe that there is a contagion network between stock markets and crypto markets such that changes in corporate names to blockchain and crypto-related names significantly affect the performance of the stock. Liu and Tsyvinski (2018) argued that there seems to be no correlation between cryptocurrency returns and traditional asset classes. Klein et al. (2018) could not establish any evidence to support the role of cryptocurrencies serving as hedging functions. While other findings such as Dyhrberg et al. (2018), Demir et al. (2018) and Guesmi et al. (2019) contradict the findings of Klein et al. (2018) and concluded that cryptocurrencies can serve as a hedging tool and can be adopted as a diversifier with short-term investment horizons (Corbet et al. 2018). Wang et al. (2022) examine if investors' informed trading behaviour can significantly predict cryptocurrency returns using machine learning algorithms to substantiate the contribution of informed trading to the predictability of cryptocurrency returns. Their findings showed that informed trading contributes to the prediction of some individual cryptocurrency returns, but it cannot largely improve the prediction accuracy. The absence of market supervision of the cryptocurrency market may be responsible for the relatively low efficiency of this market. In conclusion, while there has been a moderate research effort on cryptocurrencies, empirical research on the impacts of cyber-attacks on its returns is lean in the literature, and the empirical research attention on the impact of stock market volatility on cryptocurrencies' returns could not be found in the literature hence, this study.

3. METHODOLOGICAL APPROACH

3.1. Data Description and Summary

Bitcoins were developed in 2008 by a computer programmer known as "Satoshi Nakamoto." The successfully mined complex computer algorithm is known as Bitcoin. Being the first cryptocurrency, the market began slowly, and a rapid rise in the price of bitcoin in 2013 provoked a wider interest in cryptocurrency. Bitcoin became the pillar and foundation for what is later known as programmable money because developers started coming up with methods to build on top of it, and subsequently build new blockchains. Tether came into being after several developments on bitcoins such as coloured coins, tokens and omni layer. The most popular project that was built on Omni is known as Tether. It consists of a use case which is vital in the world of cryptocurrency. It presents how to epitomise a stable asset class in an ecosystem of volatile tokens. Tether is a digital blockchain cryptocurrency, to provide a stable reserve currency that is pegged to the US dollar. Ethereum signifies progress in the design of and thinking about cryptocurrency networks. It's a functional and computation protocol that rests upon the concepts from Bitcoin and Masterpoint, along with other projects. The concept of Ethereum was advanced in 2013 by Vitalik Buterin. Buterin started working with Gavin Wood and a few others to create Ethereum after his failed effort at persuading the Mastercoin Foundation to make changes to its protocol with a view of adding more functionality. The central objective of Ethereum was to take Mastercoin to a higher level to create a decentralized open computer system secured with consensus. Although security model in the future-an ambitious project that changes the mining paradigm within the protocol. Binance Coin (BNB) is a type of cryptocurrency which can be employed to trade and pay fees on the Binance cryptocurrency exchange. In 2018, the Binance Exchange is the largest cryptocurrency exchange in the world with more than 1.4 million transactions per second. BNB came into being in 2017 and initially worked on the Ethereum blockchain before it became the native currency of Binance's blockchain, the Binance Chain. BNB can be traded with other cryptocurrencies like Bitcoin, and Ethereum, among others.

The study employed Bitcoin, Ethereum, Tether and Binance Coin (BNB) because of their transaction volumes and frequency in the South African economy and data availability. Daily time series data on four types of Cryptocurrencies; Bitcoin, Ethereum, Tether and Binance Coin (BNB) from the first January 2019 to December 2021 were obtained from CoinMarketCap. Data on cybercrime is taken from the Hackmageddon database on cybercrime. Daily data on the All Share Price index is obtained from Johannesburg Stock Exchange.

3.2.1. Generalized Autoregressive Score Model (GAS)

The important characteristic of GAS approach is the adoption of the score of the conditional density function to obtain time-varying parameters of nonlinear models. Assuming that $y_t \in R^N$ is N-dimensional random vector at time t with conditional distribution:

$$y_t|y_{1:t-1} \sim p(y_t;\theta_t) \tag{1}$$

$y_{1:t-1} \equiv (y_t' \ldots\ldots\ldots y'_{t-1})'$ has all the previous values of y_t up to time t–1, and $\theta_t \in \ominus \subseteq R^J$ is a vector of time-varying parameters and fully characterizes our probability density function, and depends on $y_{1:t-1}$ and some static parameters ξ, by implication, $\theta_t \equiv \theta(y_{1:t-1},\xi)$. It should be noted that the main characteristic of GAS is the evolution in the time-varying parameters vector θ_t, and is motivated by the score of conditional distribution expressed in equation (1). And the autoregressive component is given as:

$$\theta_{t+1} \equiv \varkappa + As_t + B\theta_t, \tag{2}$$

ϰ, A, B, are coefficients in matrix form, with proper dimensions taken in ξ, and s_t is a vector and is proportional to the score of equation (1) and is expressed as:

$$s_t \equiv S_t(\theta_t)\, \nabla_t\, (y_t,\theta_t),$$

S_t is $J \times J$ matrix of positive definite scaling of the matrix, known at time t, and is expressed as:

$$\nabla_t\left(y_t,\theta_t\right) \equiv \frac{\partial log\mathrm{P}\left(y_t,\theta_t\right)}{\partial\theta_t},$$

Creal et al. (2013) suggest setting the scaling matrix S_t to a power $\gamma > 0$ of the inverse of the Information Matrix of θ_t to account for the variance of ∇_t. This can be stated as:

$$S_t\left(\theta_t\right) \equiv \mathcal{I}_t\left(\theta_t\right)^{-\gamma}$$

With $\mathcal{I}_t\left(\theta_t\right) \equiv E_{t-1}\left[\nabla_t\left(y_t,\theta_t\right)\nabla_t\left(y_t,\theta_{tt}\right)'\right]$ (3)

And the expectation is taken concerning the conditional distribution of given y_t assuming that $y_{1:t-1}$ is given.

An important characteristic of GAS models is that, given the past information and the static parameter vector ξ, the vector of time-varying parameters, θ_t, is predictable and the log-likelihood function can be easily evaluated through the prediction error decomposition. The samples of the observations and the vectors of the parameter can be estimated by Maximum Likelihood (ML).

3.2.2. Multivariate Markov regime-switching model

The Regime switching model is also known as Markov switching model. It is a class of models that involves multiple structures (equations) that can be used to model the time series behaviours in different regimes. Consequently, the model is adopted to look at the behaviour of cryptocurrency's return in the presence or otherwise of cybercrime, and in the presence of high and low stock market volatility. We follow Hamilton (1989). The probabilities of switching from one regime to another one are computed in a Markov switching model (Tong, 1983 and Hamilton, 1989).

The model is given as:

$$y_t = \begin{cases} c_1 + \sum_{i=1}^{p} \varphi_{i,1} y_{t-i} + \varepsilon_{1t} \,; If\ s_t = 1 \\ c_2 + \sum_{i=1}^{p} \varphi_{i,2} y_{t-i} + \varepsilon_{2t} \,; If\ s_t = 2 \end{cases},$$

Where S_t assumes values in {1, or 2} and is a first-order Markov chain with transition probabilities. The state transition model is determined by the transition probabilities and given as follows:

$$P\left(S_t = 2 \setminus S_{t-1} = 1\right) = p_{11}, \ldots \left(S_t = 1 \setminus S_{t-2} = 2\right) = p_{22},$$

Where $0<p_{ii}<1$. In matrix notation, the transition probability matrix is given as:

$$P = \begin{bmatrix} p_{11} & 1-p_{22} \\ 1-p_{11} & p_{22} \end{bmatrix}$$

It is also of economic importance to calculate the steady-state probabilities which are the unconditional probabilities that the system is in regime one (p_1) and the system is regime two (p_2) and are stated as follows:

$$p_1 = {\left(1-p_{22}\right)} \Big/ {\left(2-p_{11}-p_{22}\right)},$$

$$p_2 = {\left(1-p_{11}\right)} \Big/ {\left(2-p_{11}-p_{22}\right)}$$

4. EMPIRICAL FINDINGS

4.1. Descriptive Analysis

We present the results of the descriptive behaviour of all our variables in Table 1. The means of returns of all the selected cryptocurrencies (BNB, Tether, Bitcoin and Ethereum), cybercrimes and stock market volatility are all positives. This shows a bullish trend during the period under investigation. The mean of Tether returns indicates a reduction in the volatility because it is negative. The graphical presentation of all the variables is also contained in Figure 1.

The correlation charts between each of the cryptocurrencies' returns and cybercrime on one hand, and stock market volatility on another hand are contained in Figures 2-5. These correlation charts are generally known as the static correlation coefficient. Our findings show that correlation coefficients between cybercrime and each of the cryptocurrencies' returns are negative except for

Table 1: Descriptive analysis of the variables

Statistics	BNB_RTN	BITC_RTN	ETHER_RTN	TETH_RTN	CYBERCRM	ASP_VOL
Mean	0.006	0.003	0.002	–0.00004	0.213567	0.00006
Median	0.003	0.004	0.002	–0.00045	0.000000	0.0000
Maximum	0.436	0.165	0.2307	0.067	1.000000	0.1012
Minimum	–0.612	–0.565	–0.550714	–0.052570	0.000000	–0.165
Std. Dev.	0.076	0.0523	0.050309	0.00421	0.316041	0.056
Skewness	–0.187	–1.761	–1.467205	0.412	3.67	–0.875
Kurtosis	32.65	12.642	19.14648	84.50	8.497	21.62
Pro.(J.st)	0.00	0.00	0.0	0.00	0.00	0.000
Observations	1280	1280	1280	1280	1280	1280

Figure 1: Movement of the variables over time

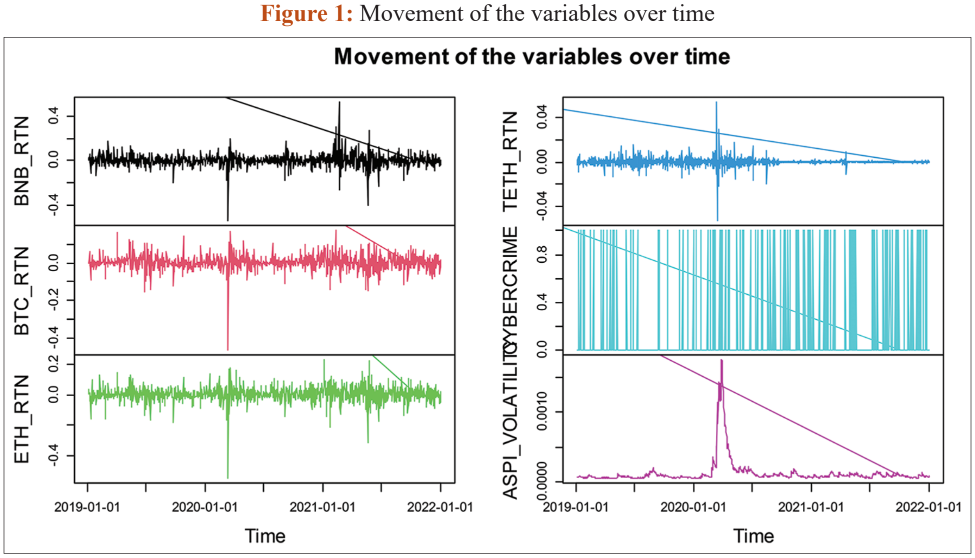


Figure 2: Static correlation between BNB returns and both cybercrime and stock market volatility

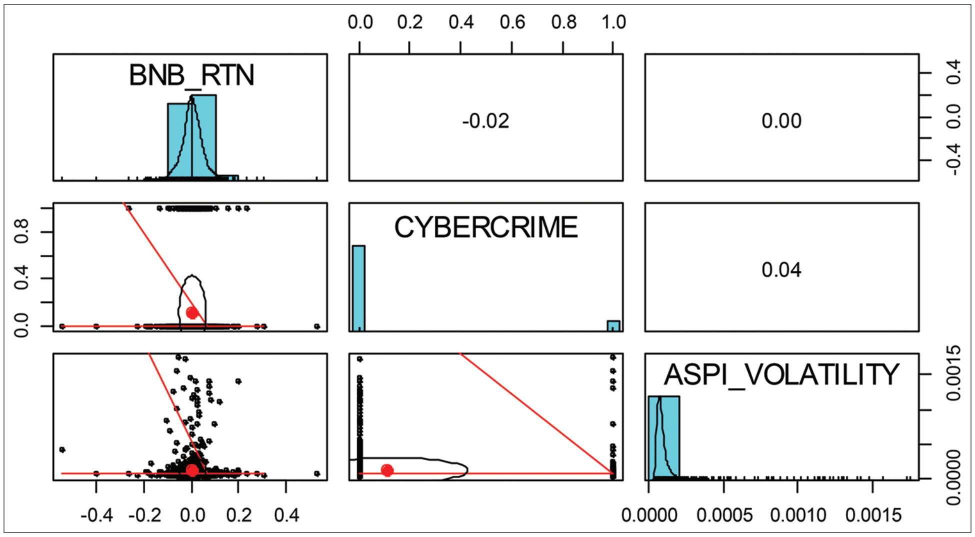


Figure 3: Static correlation between Bitcoin returns and both cybercrime and stock market volatility

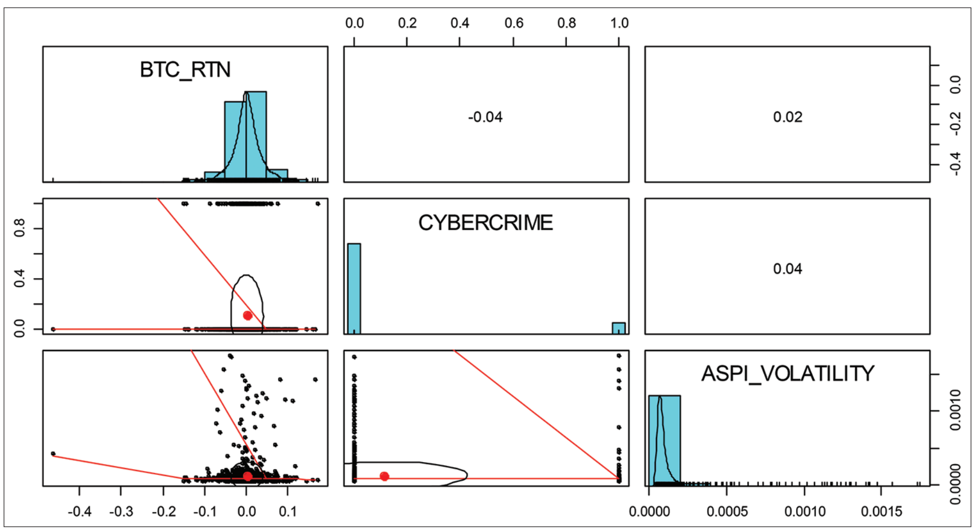
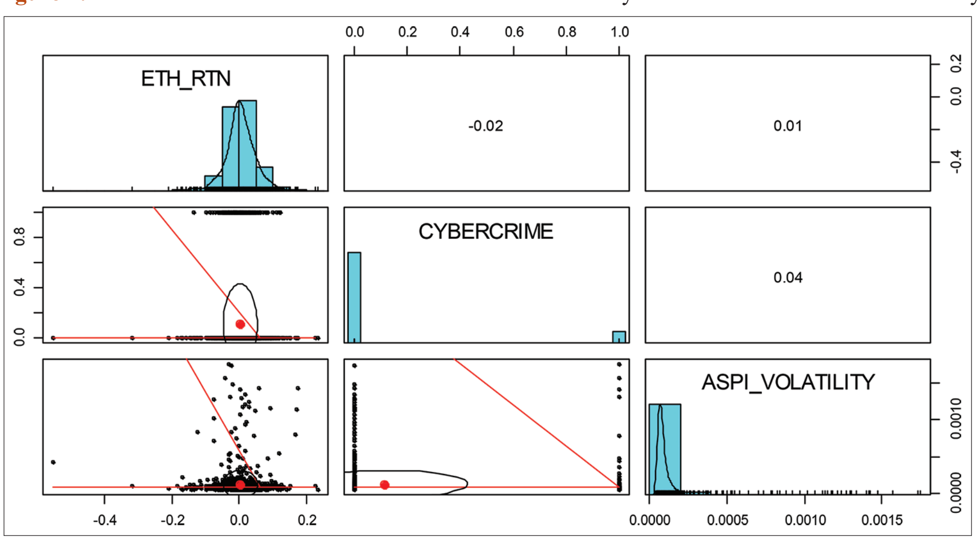


Figure 4: Static correlation between Ethereum returns and both cybercrime and stock market volatility



Tether's returns. On the other hand, the correlation coefficients between all share price index volatility as a measure of stock market volatility, and each of the cryptocurrencies' returns are positive except for Tether's returns. Nonetheless, these coefficients have been accused of being static as they do not account for the changes in correlation that occur over time. This is because static correlation only reflects instant relationships. Thus, the Generalized Autoregressive Score (GAS) framework of Creal et al. (2013) and Harvey (2013) was used to investigate the time-varying correlation between each of the cryptocurrency's returns and cybercrime on one hand, and stock market volatility.

4.2. GAS Results

The empirical results of the Generalized Autoregressive Score Model (GAS) are presented in this section. GAS IS employed to investigate the time-varying correlations as against static correlation. The model is estimated using Maximum Likelihood Estimation (MLE) techniques.

The time-varying correlations between BNB's returns and cybercrime on one hand, and time-varying correlations between BNB's returns and stock market volatility are presented in Figure 6. As shown in Figure 6, the time-varying correlation between returns on BNB and cybercrime is found to be largely oscillating between –0.0198 and –0.0186. The time-varying correlations between returns on BNB and stock market volatility are found to be positive as it oscillates between 0.00452 and 0.0048 with no cases of negative coefficients. The overall picture is that time-varying correlations between BNB's returns and cybercrime as well as stock market volatility are significantly erratic and largely volatile.

Figure 7 shows the time-varying correlations between bitcoin's returns and cybercrime, as well as time-varying correlations between bitcoin's returns and the volatility of the stock market. The time-varying correlation between returns on bitcoin and cybercrime ranges between –0.0425 and –0.0435. By implication, the time-varying correlation coefficients are negative. The negative coefficients are stronger than that of BNB's return. This simply implies that cyber-attack has stronger negative impacts on bitcoin's returns when compared with BNB. The time-varying correlations between returns on bitcoin and volatility of the stock market range

Figure 5: Static correlation between Tether returns and both cybercrime and stock market volatility

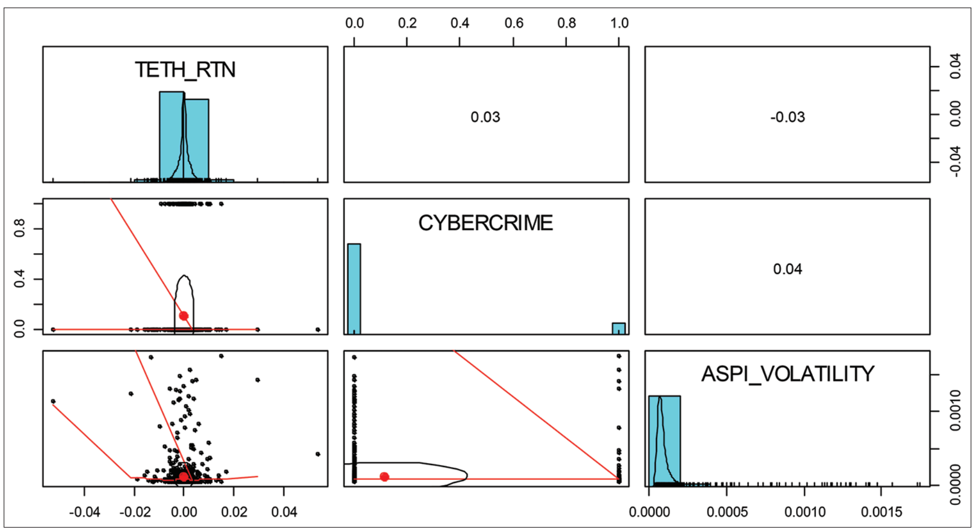
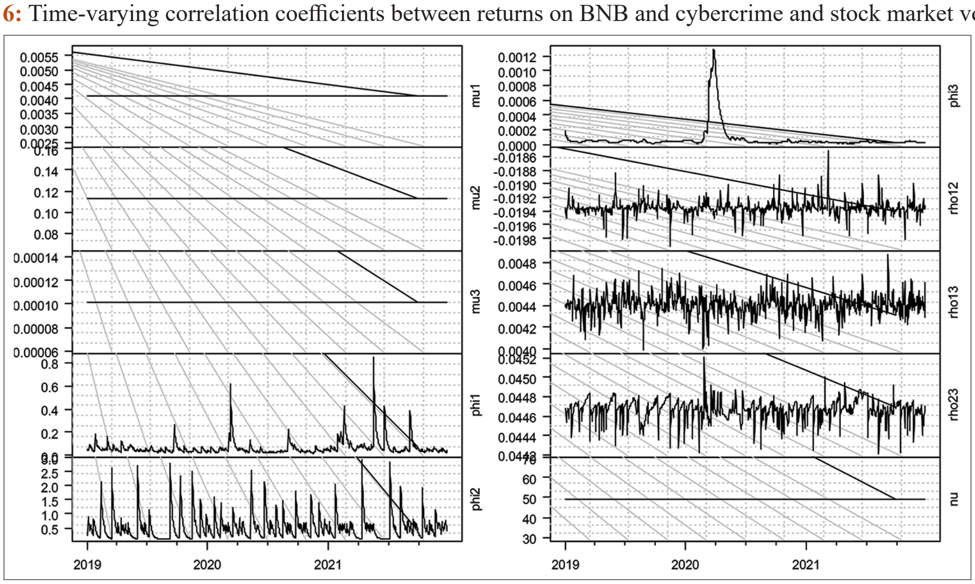


Figure 6: Time-varying correlation coefficients between returns on BNB and cybercrime and stock market volatility



between 0.0156 and 0.0164. We can also see here that time-varying coefficients are stronger than that of BNB's returns.

Figure 8 shows the time-varying correlations between Ethereum's returns and cybercrime, together with time-varying correlations between Ethereum's returns and the volatility of the stock market. The time-varying correlation between returns on Ethereum and cybercrime could be seen to oscillate –0.0195 and –0.0185. The negative coefficients are expectedly negative but coefficients seem to be much lower compared to BNB and bitcoin. On the other hand, the time-varying correlations between Ethereum's returns and the volatility of the stock market range between 0.0452 and 0.0116. The time-varying coefficients are roughly the same as that of bitcoin.

Figure 9 shows the time-varying correlations between tether's returns and cybercrime, as well as time-varying correlations between tether's returns and volatility of the stock market. The time-varying correlation between returns on tether and cybercrime ranges between 0.0275 and 0.0290. Unexpectedly, the time-varying correlation coefficients oscillate within the positive ranges. Similarly, The time-varying correlations between returns on tether and volatility of the stock market range between 0.0260 and –0.0250. The implication here is that returns on tether seem to move in the opposite direction concerning volatility of the stock market. The behaviour of Tether seems to be in sharp contrast when compared with returns on other cryptocurrencies.

4.3. Markov Regime-Switching Model Results

We use the multivariate Markov switching regime analysis to investigate the regime-switching behaviour of the impact of cybercrime and stock market volatility on cryptocurrencies' return. Our empirical findings are contained in Table 2. From Table 2, findings show that the effects of the cyberattack on the returns of the cryptocurrencies could be said to be non-regime dependent except for Ethereum and negative except for Tether. More specifical, the effects of a cyberattack on BNB's return are negative and are non-regime dependent. The results are the same

Figure 7: Time-varying correlation coefficients between returns on bitcoin and cybercrime and stock market volatility

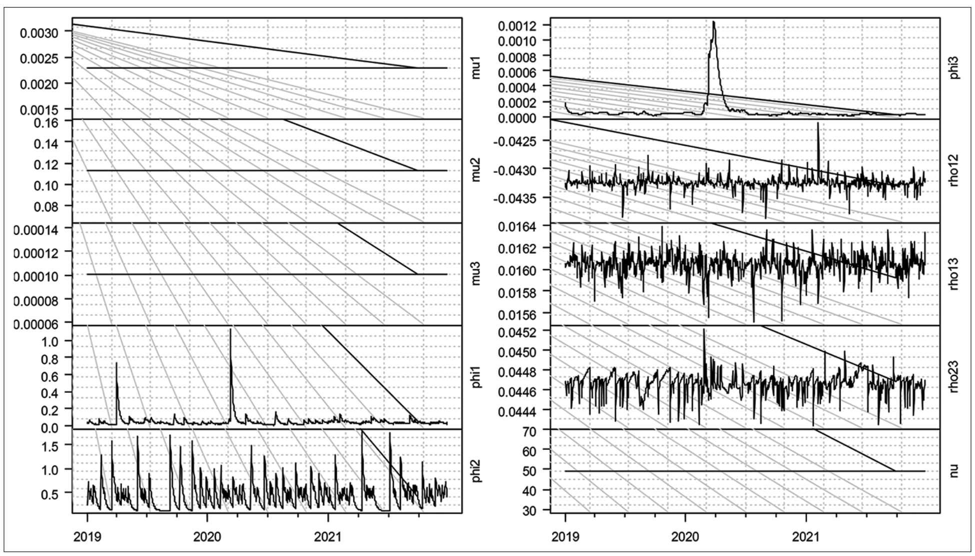


Figure 8: Time-varying correlation coefficients between returns on Ethereum and cybercrime and stock market volatility

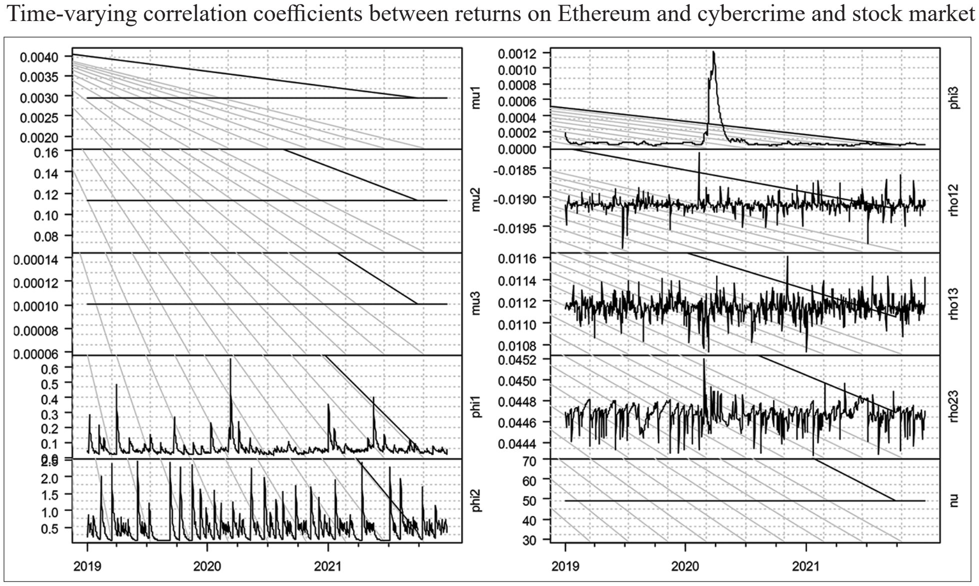
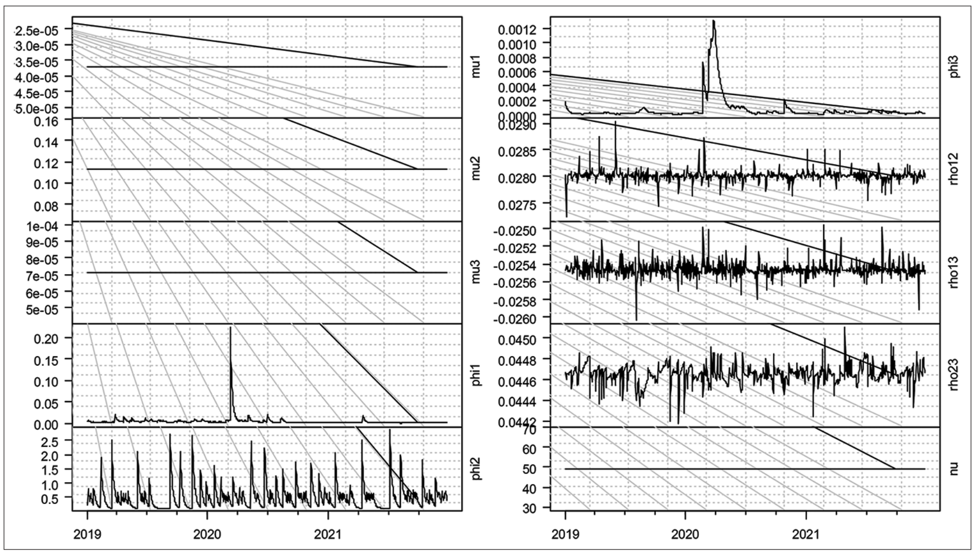


Table 2: Multivariate Markov regime switching results

Dependent variable=BNB_RETURN	Regime 1		Regime 2		Transition probabilities
	Coefficient	P-values	Coefficient	P-values	
Intercept	0.0036	0.002***	0.0089	0.00016***	$\begin{bmatrix} 0.9776 & 0.1409 \\ 0.0224 & 0.8590 \end{bmatrix}$
CYBERCRIME	–0.0047	0.23	–0.065	0.812	
ASPI_VOLA	0.0612	0.001***	–0.0214	0.0016***	
Dependent variable=BITCOIN_RETURN					
Intercept	0.0024	0.0002***	0.028	0.007***	$\begin{bmatrix} 0.4815 & 0.2263 \\ 0.5184 & 0.7736 \end{bmatrix}$
CYBERCRIME	–0.013	0.2950	–0.0020	0.065	
ASPI_VOLA	0.8412	0.000***	–0.54362	0.0019* **	
Dependent varaiable=ETHEREUM_RETURN					
Intercept	0.0057	0.0003***	-0.0091	0.0007***	$\begin{bmatrix} 0.9308 & 0.3025 \\ 0.0691 & 0.6974 \end{bmatrix}$
CYBERCRIME	–0.086	0.004***	0.0207	0.002***	
ASPI_VOLA	3.26	0.001***	–0.2218	0.021***	
Dependent varaiable=TETHER_RETURN					
Intercept	0.0001	0.0005***	–0.000	0.0012***	$\begin{bmatrix} 0.107 & 0.9387 \\ 0.9892 & 0.0116 \end{bmatrix}$
CYBERCRIME	0.0007	0.2433	0.0001	0.3173	
ASPI_VOLA	–0.6332	0.0016***	0.7657	0.004***	

**Denotes significance at 5% ***Denotes significance at 1%

Figure 9: Time-varying correlation coefficients between returns on tether and cybercrime and stock market volatility



for bitcoin as the cyberattack is found to pose negative effects on its return but the effect is also found to be non-regime dependent. On the other hand, the effect of cyberattacks on Ethereum is found to be regime dependent while the effect is found to be negative in the low regime but positive in the high regime. Cyberattack effect on tether's returns is positive and non-regime dependent. Our findings also show that the effect of stock market volatility is regime-depending. Stock market volatility has positive effects on the returns of each of the cryptocurrencies with the exception of Tether in the period of low volatility, while a negative effect is observed in the period of high volatility. This shows that during the period of moderate stock market volatility, there will be motivation from the investors to diversify their portfolio into other investment options such as digital currencies, and this in turn improves the returns on the digital currencies due to improved participation. However, the effects are found to be negative as the economy transits from a period of low volatility to high volatility. The implication here is that whatever gains that have accrued to the cryptocurrency market in the period of low volatility are likely to be eroded by the spill-over effects of high stock market volatility. This is not entirely unexpected because most of the factors that cause high stock market volatility such as global economic shocks or global financial crises do not have an effect on the stock market only but on other sectors of the economy. The transition probabilities which show the persistence of the effects on each of the variables are as well contained in Table 2. The Table shows that the probability that the positive impact of stock market volatility on BNB's returns would persist in the low regime is 0.9776. The probability of the negative impacts being persistent in a high regime can also be observed to be very high, which is 0.8590. By implication, stock market volatility be it moderate or high, has very strong persisting effects on BNB's returns in the South African economy. It can also be observed that the probability that the positive impact of stock market volatility on bitcoins' returns would persist in the low regime is 0.4815. The probability of the negative impacts being persistent in a high regime is 0.7736. By implication, the negative effects of high stock market volatility on returns of bitcoins are more persistent when compared to the positive impacts of moderate volatility. Similarly, the probability of the positive impact of moderate stock market volatility on Ethereum's return is 0.9308, while the probability that the negative impacts would persist in a period of high volatility is 0.6974. Both moderate and high stock market volatility pose strong persisting impacts on Ethereum's returns. Lastly, the probability of the negative impact of moderate stock market volatility on tether's return is 0.107, while the probability that the positive impacts would persist in the period of high volatility is 0.0116. From the results, it can be observed that, though low stock market volatility has a negative effect, the probability of persistence of the effect is low and the probability of positive impact of high stock market volatility persisting is also low. These empirical findings are also corroborated by smoothed probabilities, presented in Figures 10-13. Smoothed probabilities present the probability of being in regime *j* at each period that is computed according to the available information of all the samples.

Summarily, the empirical results obtained showed that cybercrime, on average, has a negative relationship with cryptocurrencies' returns. The implication hereby is that the growth of digital currencies is being hindered by the increased rate of cybercrimes in the South African economy. This is consistent with some empirical studies in the literature such as Caporale et al. (2020) and Ciaan et al. (2016). However, the study is at variance with studies such as Umar (2021) and Fang et al. (2021) who are of the opinion that cyber-attacks do not have any effect on cryptocurrency prices and return. Similarly, the time-varying correlation between stock market volatility and each of the cryptocurrencies' returns is largely positive. This is largely not unexpected, as the stock market volatility often motivates investors to diversify their portfolio, and hence, diversification into digital currencies. This is however at variance with Gil-Alana and Abakah (2020) who argued that there is no linkage between the cryptocurrency market and other

Figure 10: Smoothened probabilities for parameter impacts on BNB's returns

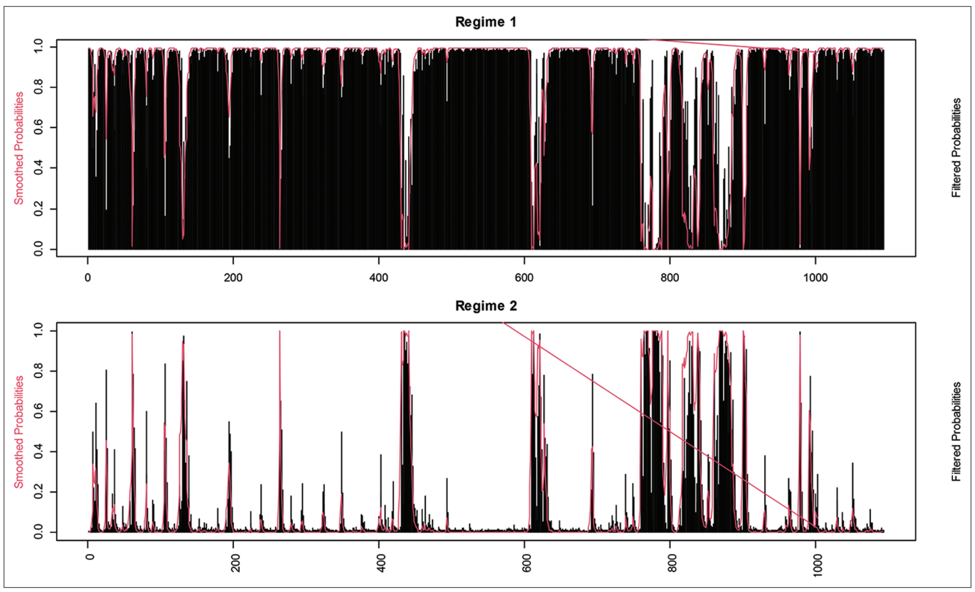


Figure 11: Smoothened probabilities for parameter impacts on bitcoin's returns

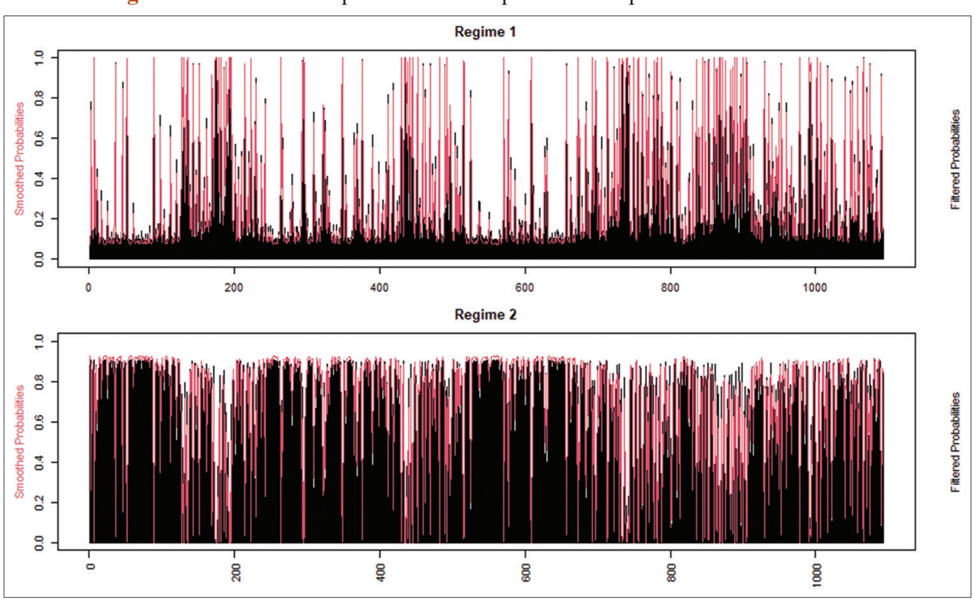


Figure 12: Smoothened probabilities for parameter impacts on Ethereum's returns

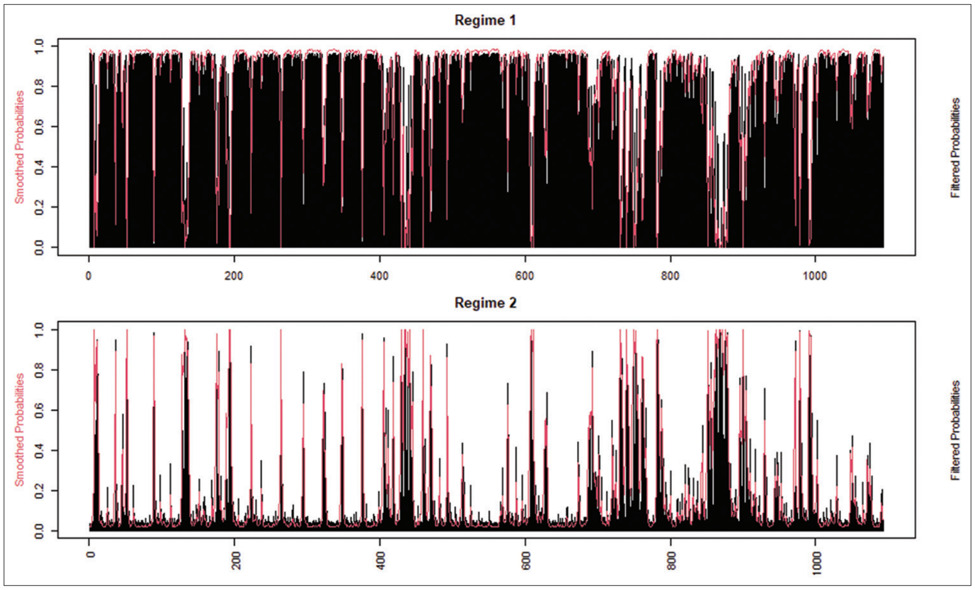
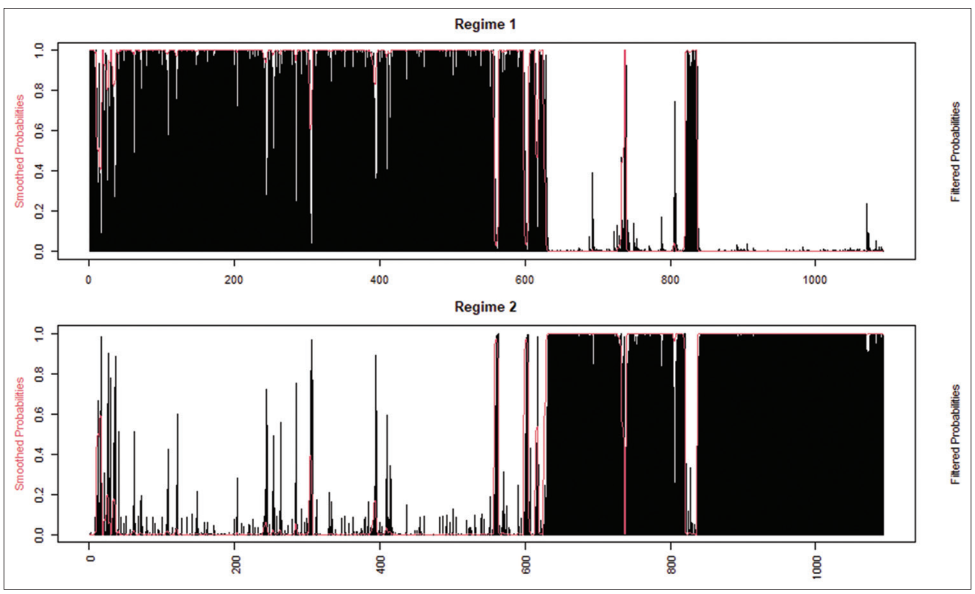


Figure 13: Smoothened probabilities for parameter impacts on tether's returns



financial major assets such as the stock market. Also, the findings from the regime-switching approach show that cybercrime, on average, has a quantitative negative impact on the cryptocurrencies' returns but the impact is said to be non-regime dependent. This finding confirms the position that cybercrime activities have consistently been a major impediment to the growth of FinTech in developing countries. This is because the potential and existing investors in Fin-Tech are being scared away and discouraged from the industry. This has been a major threat to the overall growth and development of digital currencies and financial technology in general. The positive impact of the stock market volatility during the period of moderate volatility follows the theoretical expectation as enunciated by Modern Portfolio Theory as investors look at an asset co-moves with other assets before investing in it. The co-movement between the moderate stock market volatility and investment in cryptocurrencies would undoubtedly motivate the investors to diversify into digital, which in turn pushes up the returns due to increased investment. However, high stock market volatility does not follow the Modern Portfolio Theory, as the effect is found to be negative on cryptocurrencies' returns.

5. CONCLUSIONS

Our study provides empirical evidence on the effects of stock market volatility and cybercrime on cryptocurrencies' returns in the South African economy using time series data on different four types of Cryptocurrencies (Bitcoin, Ethereum, Tether and BMB) were employed. The data covers the period 1 January 2019–31 December 2021. The data were sourced from Coin Market Cap. Data on cybercrime is taken from the Hackmageddon database on cybercrime. Daily data on all share price indexes were obtained Johannesburg Stock Exchange.

This study, in addition to contributing to relatively scarce studies on the effects of stock market volatility and cybercrime on cryptocurrencies' returns in the South African economy, is unique as it employs the Generalized Autoregressive Score Model (GAS) to investigate the time-varying correlation between each Cryptocurrencies' return and cybercrime as well as stock market volatility. Our study also delves into the matter of regime switching approach as claimed by Hamilton (1989) that most financial and macroeconomic series exhibit regime-switching behaviour. Consequently, we investigate the effects of stock market volatility and cybercrime on cryptocurrencies' returns using a regime-switching approach. Our findings show that the time-varying correlation between returns on BNB and cybercrime is found to be largely oscillating between –0.0198 and –0.0186 while time-varying correlations between returns on BNB and stock market volatility are found to be positive as it oscillates between 0.00452 and 0.0048. Also, the time-varying correlation between returns on bitcoin and cybercrime ranges between –0.0425 and –0.0435. The time-varying correlations between returns on bitcoin and volatility of the stock market range between 0.0156 and 0.0164. The time-varying correlation between returns on Ethereum and cybercrime could be seen to oscillate –0.0195 and –0.0185. On the other hand, the time-varying correlations between Ethereum's returns and the volatility of the stock market range between 0.0452 and 0.0116. The time-varying correlation between returns on tether and cybercrime ranges between 0.0275 and 0.0290. Similarly, the time-varying correlations between returns on tether and volatility of the stock market range between 0.0260 and –0.0250.

Our findings show that the effects of the cyberattack on the returns of the cryptocurrencies could be said to be non-regime dependent except for Ethereum and negative except Tether. Also, the cyberattack effect on Tether's returns is positive and non-regime dependent. Our findings also show that the effect of stock market volatility is regime-depending. Stock market volatility has positive effects on the returns of each of the cryptocurrencies except for Tether in the period of low volatility, while a negative effect is observed in the period of high volatility. The study concludes that ongoing efforts to reduce cybercrime activities need to be strengthened to deepen the use of digital currencies. Also, given the negative impacts of excessive or high stock market volatility on cryptocurrencies' returns, policy measures must be taken to ensure reduced or moderate stock market volatility.

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