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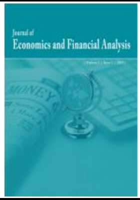

The Spill-over Effects of Cryptocurrencies on Equity and Bonds Market

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Abstract

This study examines the extent to which crypto assets have moved to the mainstream by estimating the potential for spillovers crypto on bond and equity markets using daily data on price volatility and returns. The analysis reveals that the coefficients of the constant variance term, the ARCH and the GARCH parameters are positive and statistically significant at the 1% level across all models. In respect of the mean equation, the results suggest that the spill-over effects of bitcoin on equities and long-term bonds are ambiguous. Spillovers from price volatility of the oldest and most popular crypto asset, Bitcoin, to the S&P 500 and MSCI emerging markets indices have increased by about 12-16 percentage points since the onset of the COVID-19 pandemic, while those from its returns have increased by about 8-10 percentage points. This clearly indicates that the persistence of volatility shocks, as represented by the sum of the ARCH and GARCH parameter is large. Moreover, this suggests that the effect of today's shock remains in the forecasts of variance for many periods in the future.

Keywords: *GARCH Model; Cryptocurrencies; Financial Markets.*

JEL Classification: *B41, C01, C58, D53.*

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1. Introduction

Financial markets present various opportunities for investors such as selecting different asset classes. For instance, green investors can choose to invest in either S&P global clean energy index (GCEI), S&P green bonds index (GB), or DJ sustainability world index (DJSWI). However, elevated energy consumption coupled with carbon footprints triggers sustainability and environmental concerns for investors thereof. Furthermore, as postulated by Inzamam (2022), there is a nexus between the three green and socially responsible financial assets (GCEI, GB, and DJSWI) and cryptocurrency uncertainties (Hassan, Hasan, Halim, Maroney, and Rashid, 2022). That is, the evidence of inverse coherences demonstrates that higher uncertainties in cryptocurrencies lead to lower returns as far as the green financial assets are concerned.

Cryptocurrencies are considered safe havens and investment tools used for protection against economic uncertainties. The objective of this study is to assess the influence of cryptocurrency volatility on the traditional asset classes. Cryptocurrencies have gained significant attention and popularity over the past few years, with Bitcoin being the most well-known cryptocurrency. While cryptocurrencies were initially viewed as a niche investment, they have gradually gained mainstream acceptance, and their use as a medium of exchange has increased. As a result, the cryptocurrency market has grown to a market capitalization of over $2 trillion, with several other cryptocurrencies, such as Ethereum and Dogecoin, gaining significant market share. Notwithstanding their growing popularity, the impact of cryptocurrencies on other financial markets, particularly equity and bond markets, remains a subject of much debate. Some argue that cryptocurrencies have spill-over effects on equity and bond markets, while others believe that there is no such correlation. The potential spill-over effects of cryptocurrencies on equity and bond markets have become a topic of interest for policymakers, investors, and researchers alike.

Despite the growing body of research on this topic, the spill-over effects of cryptocurrencies on equity and bond markets remain a subject of debate. As such, there is a need for further research to understand the relationship between these markets and cryptocurrencies better. This research is important as it can help policymakers and investors make informed decisions about the role of cryptocurrencies in their investment portfolios and overall financial strategy.

2. Literature Review

Cryptocurrencies have grown in popularity and market capitalization over the past decade. The impact of cryptocurrencies on traditional financial markets, such as equity and bonds, has become a topic of interest among scholars and practitioners. This section provides the review and discussion of literature pertaining to cryptocurrency volatility and the influence on the equity and bond markets.

2.1. Theoretical literature

In every academic study, theoretical literature forms an integral part of research. To this study, four theories concerning the cryptocurrencies, equity and bond markets have been identified. The first theory is called Efficient market Hypothesis (EMH), followed by Informational Cascades Theory. The discussion for each of these theories is presented in the sub-sections below.

2.1.1. Efficient Market Hypothesis (EMH)

The Efficient Market Hypothesis theory is a cornerstone in financial economics. The theory states that financial markets are efficient and that prices reflect all available information. According to Malkiel (2003), the EMH theory is based on the notion that investors behave rationally, and the stock market is efficient in processing and reflecting all available information. Therefore, the market is always in equilibrium, and prices are always at their fair value. Nonetheless, Fama (1991) argues that while the EMH theory has some empirical support, it is not without its limitations. One major limitation is that it assumes that all investors have access to the same information and possess the same level of rationality. In reality, investors have different levels of access to information, and irrational behaviour can affect market prices. Also, the EMH theory assumes that there are no transaction costs or taxes, which is not always the case in reality. Overall, the EMH theory has been the subject of much debate and criticism in the finance community. While some researchers and practitioners believe in the theory's validity, others argue that the market is not always efficient, and there are opportunities for skilled investors to achieve above-average returns. Nevertheless, the EMH theory remains a fundamental theory in finance and has contributed significantly to the development of financial economics.

2.1.2. Informational Cascades Theory

The Informational Cascades theory suggests that people often make decisions based on the actions of others rather than their own personal knowledge or beliefs. This theory explains how individuals in a group may follow the behaviour of others, even if they do not fully agree or understand the reasoning behind the actions. According to Bikhchandani, Hirshleifer, and Welch (1992), an informational cascade can occur when individuals observe the actions of others and use this information to make their own decisions. In situations where there is uncertainty or incomplete information, people may rely on the actions of others to guide their behaviour, even if the information is imperfect. This can lead to a situation where individuals abandon their own beliefs and preferences in favour of following the crowd. Similarly, Banerjee (1992) argues that informational cascades can arise when individuals prioritize social conformity over their own personal preferences, leading to a situation where groupthink dominates decision-making.

Overall, the Informational Cascades theory highlights the importance of social influence and conformity in shaping individual behaviour and decision-making. However, it is important to note that the theory has also been subject to critique. Some researchers have questioned the assumption that individuals will always follow the actions of others without question, suggesting that there may be instances where people are willing to deviate from the group norm (Anderson and Holt, 1997). Additionally, scholars have noted that the theory may be limited in its ability to account for individual agency and the role of context in shaping decision-making processes (Goldman, 1999). Despite these criticisms, the Informational Cascades theory remains a valuable framework for understanding the role of social influence and conformity in shaping group behaviour.

2.2. Empirical literature

Over the past years, the evolvement of research in cryptocurrencies has become popular among the academics and scholars. Several studies have examined the spill-over effects of cryptocurrencies on equity and bonds markets, providing empirical evidence on the interconnectedness of these markets. Therefore, it is important to review and discuss empirical studies concerning the topic under investigation thereof. The study by Bouri et al. (2018) investigated the spill-over effects of Bitcoin, the largest cryptocurrency by market capitalization, on global equity markets. A quantitative research methodology was applied with cross-sectional design. The authors collected daily data on Bitcoin prices and returns as well as on global equity indices from January 2014 to September 2017, covering a period of 45 months. They used the vector Autoregression (VAR) methodology, which is a statistical method used to analyse the relationship between multiple variables over time. The study found that Bitcoin had a significant and positive impact on the global equity market, suggesting that cryptocurrencies could serve as a diversification tool for investors.

According to Al-Shboul, Assaf and Mokni (2022), the dominance of Bitcoin as a “safe-haven” asset disappeared during Covid-19 health crisis, while Litecoin gained strength as the key “safe-haven” asset hedger prior and during the pandemic period. The study investigated the spill overs among major cryptocurrencies under different market conditions, with a focus on the impact of the Covid-19 pandemic and cryptocurrency policy and price uncertainties. The study adopted Quantile-VAR approach to capture the lower and upper tails of the distributions corresponding to return spill overs under different market conditions. It was also shown that cryptocurrency uncertainties significantly impact the spill overs among the five cryptocurrencies and that the Covid-19 pandemic crisis plays a crucial role in the nexus amid cryptocurrency policy and price uncertainties and the dynamic connectedness across all market conditions.

Hassan, Hasan, Halim, Maroney, and Rashid (2022) explored the dynamic spill-over impact of cryptocurrency environmental attention (ICEA) on green bonds, commodities, and environment-related stocks. The authors have conducted an empirical analysis using econometric models, applied in a secondary data. The ICEA data was obtained from Google Trends, in addition to the daily closing prices of green bonds, commodities, environment-related stocks collected from Bloomberg Terminal for the period between January 2016 and December 2020. This 5-year period is relevant because it includes the rise of cryptocurrencies and their increasing attention to environmental concerns.

Similarly, Khalfaoui, Mefteh-Wali, Dogan and Ghosh (2023), provided the empirical study that covered the role of the most traded cryptocurrencies on the green bond market volatilities. The daily data applied in the study thereof spans from the 1st of January 2020 to 31st of January 2022, which was incorporated into to time domain spill-over approach and quantile regression framework to examine the time-frequency spill-over connectedness among markets, and to also measure the direction and intensity of the net transmission impact under extreme negative and positive event conditions, and normal states. As far as the network connectedness analysis is concerned, the results revealed a robust net information spill-over transmission among the markets, particularly when the market is bearish. The sensitivity to quantile analysis indicated a time-varying and quantile-dependent net shock dynamic transfer mechanism. The MSCI Euro green bond was found to be the largest net shock receiver (Khalfaoui, et al, 2023).

Sovbetov (2018) examines factors that influence prices of most common five cryptocurrencies such as Bitcoin, Ethereum, Dash, Litecoin, and Monero over 2010-2018 using weekly data. The study employs ARDL technique and documents several findings. They build crypto-50 index with the biggest 50 cryptocurrencies in cryptomarket. They asses index price, volume, and volatility. Using ARDL technique, they document that cryptomarket-related factors such as market beta, trading volume, and volatility appear to be significant determinant for all five cryptocurrencies both in short- and long-run. They also examine whether S&P500 has impact on Bitcoin prices or not. They find that S&P500 index seems to have weak positive positive long-run impact on Bitcoin, Ethereum, and Litcoin, while its sign turns to negative losing significance in short-run, except Bitcoin that generates an estimate of -0.20 at 10% significance level.

Corbet et al. (2018) analysed the spill-over effects of Bitcoin and other cryptocurrencies on the stock markets of five European countries. A multivariate GARCH model was applied to analyse the volatility of financial markets, particularly the interdependence of financial assets. The study found that the spill-over effects of cryptocurrencies were positive and significant, indicating that cryptocurrencies could provide diversification benefits to investors in these markets. The study also found that the spill-over effects were stronger during periods of high volatility in the cryptocurrency market. The study used daily stock market data from five European countries (Germany, France, Italy, Spain, and the UK) and the daily cryptocurrency prices of Bitcoin and four other cryptocurrencies (Ethereum, Ripple, Litecoin, and Bitcoin Cash) over the period of January 2015 to September 2017.

Another study by Bouri et al. (2019) employed a vector autoregression (VAR) model to examine the spill-over effects of Bitcoin on emerging and developed stock markets. The study used daily data from January 2013 to October 2018, with a total of 1,917 observations. The study found that Bitcoin had a significant and positive impact on emerging stock markets, while the impact on developed stock markets was negative. The study also noted that the spill-over effects were stronger during periods of high volatility in the Bitcoin market. The type of data used was time-series, which consisted of daily stock market indices of emerging and developed economies, as well as the daily Bitcoin price index. The study also included control variables like VIX (volatility index), oil prices, and gold prices to capture the effect of other macroeconomic factors on stock market returns.

Finally, a study by Ji et al. (2021) examined the spill-over effects of Bitcoin on the US equity market during the Covid-19 pandemic. This is a quantitative empirical study that used statistical analysis techniques. The study found that the spill-over effects of Bitcoin on the US equity market were positive and significant during the pandemic, suggesting that Bitcoin could serve as a hedging tool during times of crisis. The period used in the study is not explicitly mentioned, but it is likely to be focused on the Covid-19 pandemic period.

2.3. Research Gap

As indicated by several studies in the literature reviewed, cryptocurrencies are more volatile than any other asset classes. Several studies have examined the spill-over effects of cryptocurrencies on equity and bonds markets, providing empirical evidence on the interconnectedness of these markets. The findings suggest that cryptocurrencies can have a significant impact on traditional financial markets and can provide diversification benefits and serve as a hedging tool during times of market volatility and uncertainty. However, there is a lack of research on the spill-over effects of cryptocurrencies on other financial markets, such as the green bond market, commodities, and environment-related stocks. In addition, there is a need for further research on the effectiveness of hedging against spill-over risks associated with cryptocurrencies, especially during periods of high volatility and economic crisis such

as Covid-19.

Moreover, the existing literature primarily focuses on the spill-over effects of Bitcoin and other dominant cryptocurrencies on global equity and bond markets, whereas there is a need for research on the spill-over effects of other cryptocurrencies on various financial markets. Also, majority of thestudies made use of traditional statistical methods, and there is a need for more sophisticated econometric methods to capture the dynamic and complex nature of spill-over effects in cryptocurrency markets.

Against this background, research gap at the back of empirical literature thereof stems from the lackof research on the spill-over effects of cryptocurrencies on other financial markets such as the green bond market, commodities, and environment-related stocks. There is also a need for further research on the effectiveness of hedging against spill-over risks associated with cryptocurrencies, especially during economic crises such as Covid-19, using more sophisticated econometric methods to capture the dynamic and complex nature of spill-over effects in cryptocurrency markets.

3. Methodology and Results

The first step in estimating a GARCH model is to analyse the trend of the variable overtime. This involves comparing the trend in raw data format and log difference format.

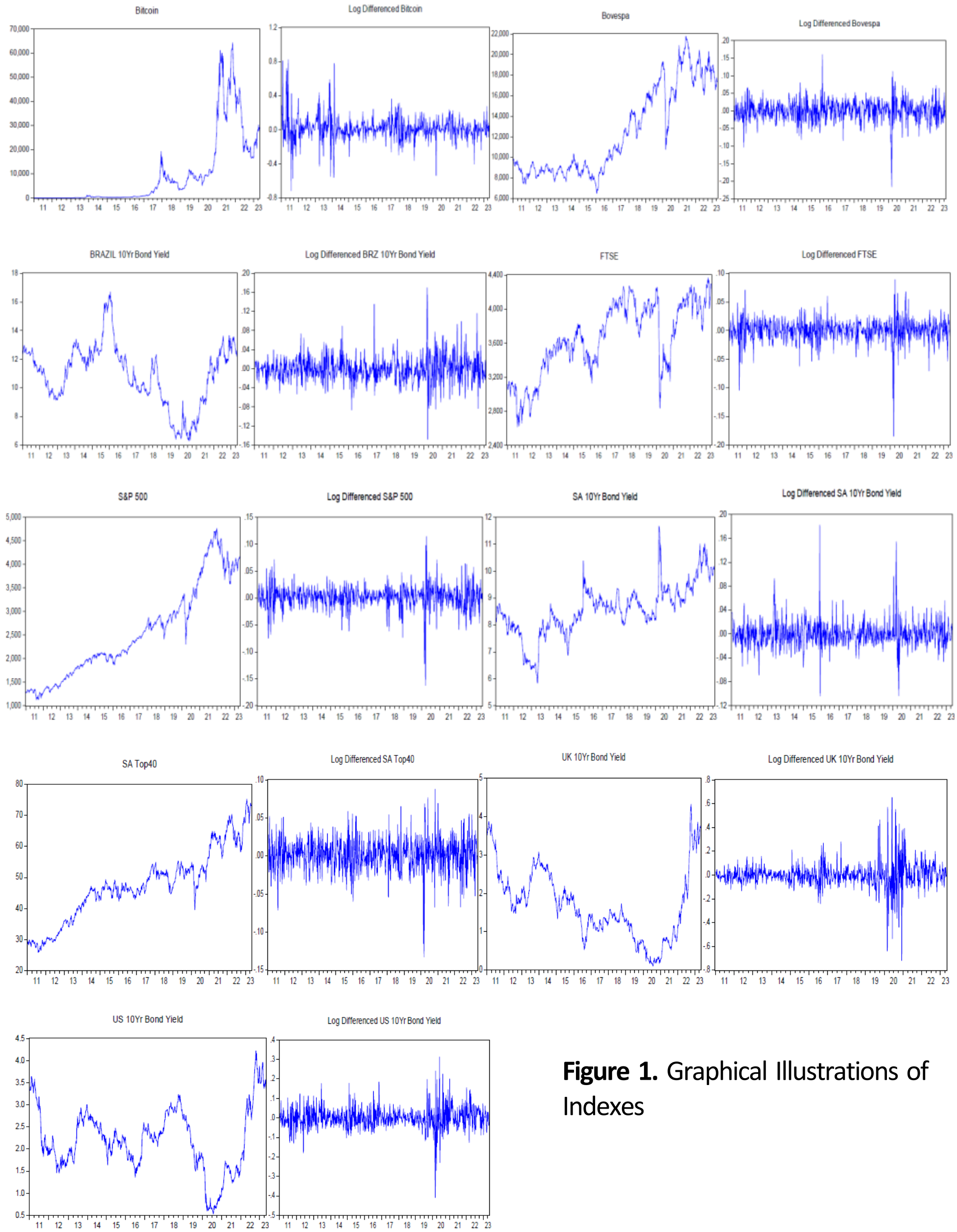

Figure 1. Graphical Illustrations of Indexes

The second step in estimating a GARCH model involves determining the presence of arch effects within the variable of interest. This is achieved first by estimating a linear question which can be expressed as follows:

$$r_t^x = \mu + \lambda r_{t-1}^{bitcoin} + \varepsilon_t \quad (1)$$

Where r_t^x represents returns of the dependent variable at time "t" and the α represents the constant term. The $r_{t-1}^{bitcoin}$ is the lagged value of the bitcoin stock and the ε_t is the residual of the model.

As our data are time-series, we can apply Ordinary Least Squares (OLS) technique in order to estimate responsiveness of bitcoin to its previous period value. Table 1 shows OLS estimations of bitocin for model (1).

Table 1. Ordinary Least Squares Output

Variable	Coefficient	Std. Error	t-Statistic	Prob.
μ	0.016922	0.005909	2.863577	0.0043
λ	0.028062	0.039413	0.711992	0.4767

The results indicate that the coefficient for bitcoin is positive but statistically insignificant. It is sufficient to note that at this point, the statistical significance of the variable is not a primary concern. In order to identify the presence of arch effects in the estimated model, we made use of the arch heteroskedasticity test, and the output is provided in table 2 below.

Table 2. Heteroskedasticity output

F-statistic	32.35781	**Prob. F(1,639)**	0.0000
Obs*R-squared	30.89464	**Prob. Chi-Square(1)**	0.0000

The findings in table 2 reveal the presence of arch effects as the null hypothesis that a series of residuals (r_t) exhibits no conditional heteroscedasticity (ARCH effects) is significantly rejected at 1% level. This is determined by the value of the observed R-squared (30.89464) and corresponding probability value (0.00) which is below the 5% significance level. As such, we reject the null hypothesis of no existing arch effects against the alternative hypothesis.

3.1. Estimating GARCH

The error term defined in the model (1), ε_t, has ARCH effect. Thus, we can structure following equation of the ε_t.

$$\varepsilon_t = \sigma_t \omega_t \tag{2}$$

$$\varepsilon_t \backsim P_v(0,1)\ (Normal\ Gaussian\ distribution) \tag{3}$$

$$\omega_t\ \sim i.i.d\ \ (independent, indentical\ distribution) \tag{4}$$

$$E[\omega_t] = 0 \tag{5}$$

$$VAR[\omega_t] = 1 \tag{6}$$

Where σ_t is the conditional standard deviation (i.e. volatility) at time t; and ω_t is the standardized residual. Then, we can define σ_t equation as following.

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 \tag{7}$$

Where α's are the parameters of the ARCH component model, β's are the parameters of the GARCH component model. Likewise, p and q are the orders of the ARCH and GARCH components of the model respectively.

Setting p and q orders to 1, and using Broyden–Fletcher–Goldfarb–Shanno (BFGS) algorithm as optimization methodology, we run model (1) considering different dependent variables such as Bitcoin and stock indices Bovespa, FTSE, South Africa Top 40, and S&P 500 at table 2 and 10-years bonds of Brazil, South Africa, UK, and US at table 3.

Table 2 shows that Bitcoin has average stock return is 0.0103 which is statistically significant at 5% level. While coefficient of $r_{t-1}^{bitcoin}$ is derived statistically insignificant. The variance equation of Bitcoin model implies that it has 0.0012 constant variance which is significant at 1% level. The model also has significant time-varying conditional volatility where ARCH effect is 0.1770 and GARCH effect is 0.7594, both statistically significant at 1% level. These findings clearly establish the presence of time-varying conditional volatility of the returns of the Bitcoin stock. This result also indicates that the persistence of volatility shocks, as represented by the sum of the ARCH and GARCH parameters ($\alpha_1 + \beta_1$) is large. It denotes that the effect of today's shock remains in the forecasts of variance for many periods in the future.

Moreover, it is worth to note that $\alpha_0 + \alpha_1 + \beta_1 < 1$ condition meets. Plus, $\alpha_1 + \beta_1 < 1$ also fulfilled. Thus, we can confirm that our GARCH model is stable and robust. Lastly, we also check diagnostics of our GARCH model. The AC and PAC with Q-statistics and probability show that the null hypothesis of *"no serial correlation"* cannot be rejected.

Table 2. GARCH Estimation for Bitcoin and National Stock Indices

Variable	Bitcoin	Bovespa	FTSE	SA Top40	S&P 500
μ	0.0103** (0.0049)	0.0010 (0.0011)	0.0005 (0.0007)	0.0016* (0.0009)	0.0026*** (0.0006)
λ	0.0433 (0.0450)	0.0065 (0.0062)	0.0134*** (0.0040)	0.0103** (0.0048)	0.0119*** (0.0042)
Variance Equation					
α_0	0.0012*** (0.0001)	0.0001*** (0.0000)	0.0001*** (0.0000)	0.0000*** (0.0000)	0.0000*** (0.0000)
α_1	0.1770*** (0.0266)	0.1387*** (0.0251)	0.1626*** (0.0267)	0.0954*** (0.0216)	0.3098*** (0.0491)
β_1	0.7594*** (0.0192)	0.7112*** (0.0620)	0.7395*** (0.0477)	0.8017*** (0.0440)	0.6521*** (0.0530)
Diagnostics					
F-stat.	0.0023	0.3091	0.6628	0.0245	0.6556
Obs.R^2	0.0023	0.3099	0.6642	0.0246	0.6570
Prob. F	0.9615	0.5784	0.4159	0.8754	0.4184
Prob. χ^2	0.9614	0.5777	0.4151	0.8752	0.4176
AC	0.0450	0.0020	-0.0170	-0.0500	-0.0760
PAC	0.0450	0.0020	-0.0170	-0.0500	-0.0760
Q-stat.	1.2897	0.0016	0.1902	1.6332	3.7086
Q Prob.	0.2560	0.9680	0.6630	0.2010	0.0540

Note: μ is average returns of indices; λ is impact of previous period return of Bitcoin onto the indices. The α_0 is constant (persistent) volatility of returns of indices, α_1 (ARCH Effect) and β_1 (GARCH Effect) indicate time-varying conditional volatility on returns of indices. The AC and PAC are auto-correlation and partial auto-correlation statistics respectively. The Q-statistics and its probability assess the H_0 (The residuals are not serially correlated) hypothesis.

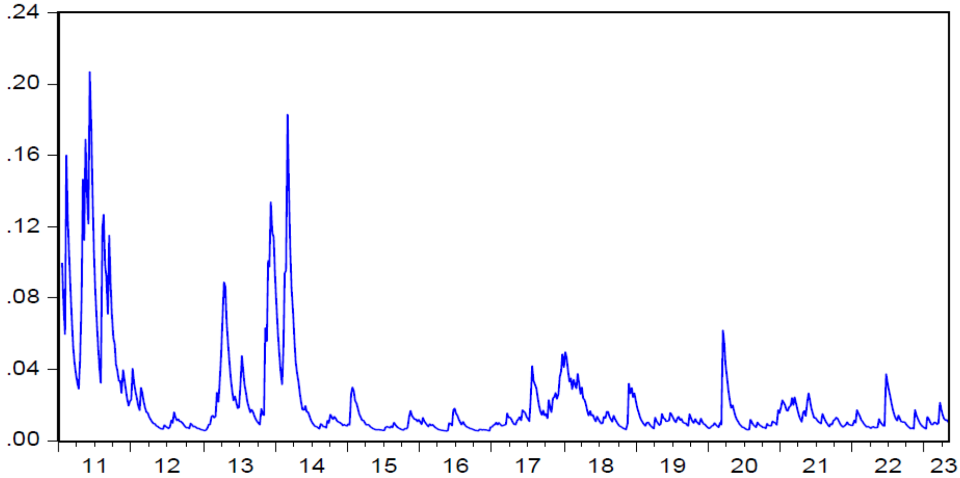

Figure 2. Variance Series of Bitcoin

For Bovespa index, we observe that coefficients of both average return and bitcoin remain insignificant. Nevertheless, its variance equation shows that it has 0.0001 constant variance besides 0.1387 ARCH and 0.7112 GARCH components. The three conditions of stability also works here, plus, probability of q-statistics is greater than 0.05 which confirms stability and robustness of this model.

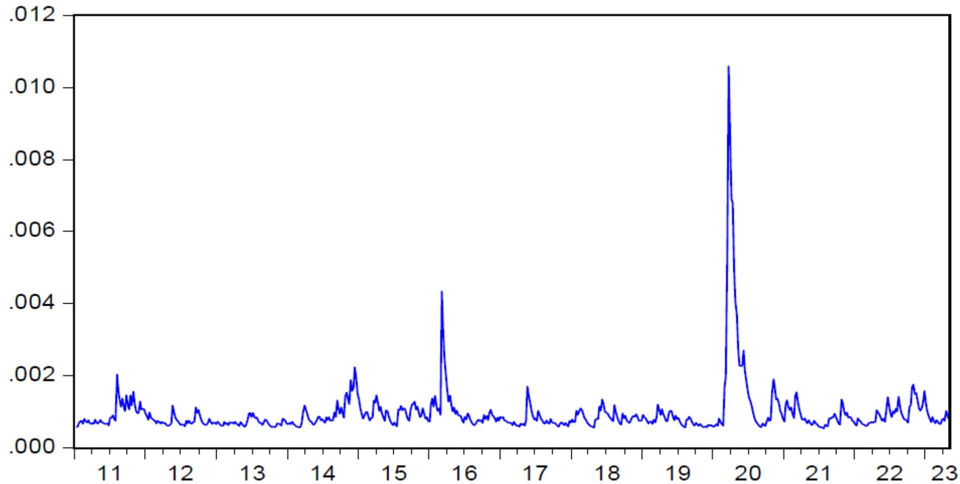

Figure 3. Variance Series of Bovespa

For FTSE, we document positive 0.0134 unit impact running from previous period of Bitcoin returns onto FTSE at 1% significance level. On variance equation part, constant variance, ARCH component, and GARCH component are all positive and statistically significant at 1% level. Meantime, they meet three conditions of stability and diagnostics tests show plausible results. The ARCH heteroskedasticity test and LM autocorrelation test are examined and F-statistic and its probability value imply that the model does not suffer from heteroskedasticity. Regarding autocorrelation, the AC and PAC are found to lie within the confidence intervals while the Q-stat and probability value (0.663) is far away of rejection 5% zone. This suggests that the model is free from autocorrelation.

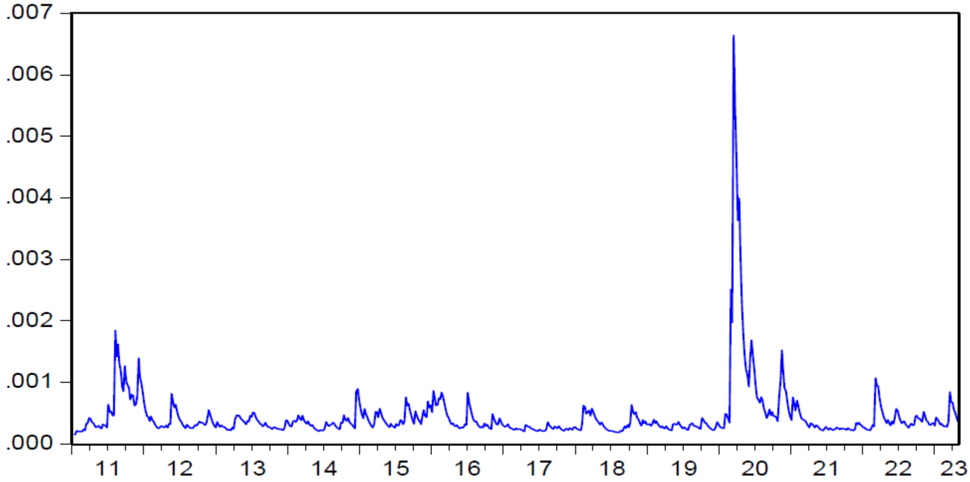

Figure 3. Variance Series of FTSE

In cases of South Africa Top40 and S&P500 indices, both mean value (μ) and Bitcoin coefficient (λ) appear to be positive and statistically significant. This indicates that last period's Bitcoin returns positively affects current period's South Africa Top40 and S&P500 returns. The variance equations of these two models also derive statistically significant estimates. Both models variance coefficients (constant, ARCH, GARCH) obey to three stability conditions as well as they seem to be free of autocorrelation problem.

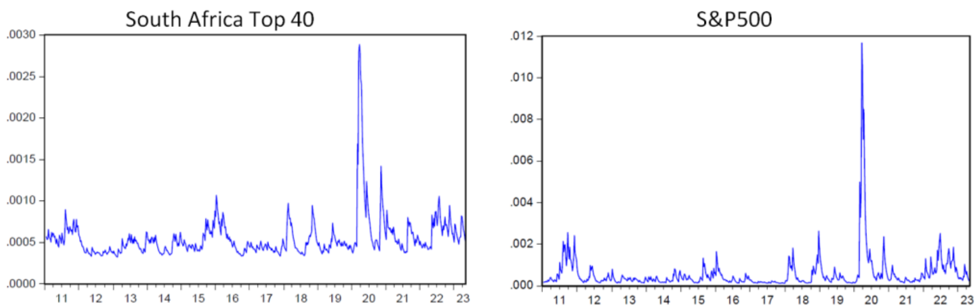

Figure 4. Variance Series of South Africa Top40 and S&P500

Table 3. GARCH Estimation for 10-Year National Bonds

Variable	Brazil Bond	SA Bond	UK Bond	US Bond
μ	-0.0005 (0.0001)	0.0001 (0.0008)	0.0002 (0.0023)	0.0012 (0.0018)
λ	0.0095* (0.0052)	-0.0052 (0.0058)	-0.0001 (0.0140)	-0.0026 (0.0110)
Variance Equation				
α_0	0.0000*** (0.0000)	0.0001*** (0.0000)	0.0000*** (0.0000)	0.0000*** (0.0000)
α_1	0.0119*** (0.0026)	0.1499*** (0.0310)	0.1255*** (0.0177)	0.1233*** (0.0185)
β_1	0.9832*** (0.0036)	0.5930*** (0.0883)	0.8770*** (0.0159)	0.8696*** (0.0194)
Diagnostics				
F-stat.	27.8771	0.3138	1.4785	5.0732
Obs.R^2	26.7970	0.3146	1.4797	5.0490
Prob. F	0.0000	0.5756	0.2245	0.0246
Prob. χ^2	0.0000	0.5749	0.2238	0. 0246
AC	-0.0390	0.0370	-0.0420	-0.0580
PAC	-0.0390	0. 0370	-0.0420	-0. 0580
Q-stat.	0.9615	0.08783	1.1181	2.1452
Q Prob.	0.3270	0.3490	0.2900	0.1430

Note: μ is average returns of indices; λ is impact of previous period return of Bitcoin onto the indices. The α_0 is constant (persistent) volatility of returns of indices, α_1 (ARCH Effect) and β_1 (GARCH Effect) indicate time-varying conditional volatility on returns of indices. The AC and PAC are auto-correlation and partial auto-correlation statistics respectively. The Q-statistics and its probability assess the H_0 (The residuals are not serially correlated) hypothesis.

At Table 3, almost all bond models fail to generate statistically significant estimates for mean equations, except Brazilian bond model. That model has dependent variable of Brazilian 10-years bond yield and the regressor is the lagged Bitcoin returns. The results show that mean value is a negative but statistically insignificant. However, the Bitcoin coefficient is estimated as positive at 10% statistical significance level. This means there some weak impact of last period's Bitcoin returns on Brazilian bond yields.

On variance equations side, it is clear that all bond models have time-varying conditional volatility of the returns of the Bitcoin stock. These results also indicate the persistence of volatility shocks, as represented by the sum of the ARCH and GARCH parameters ($\alpha_1+\beta_1$) is large. It denotes that the effect of today's shock remains in the forecasts of variance for many periods in the future.

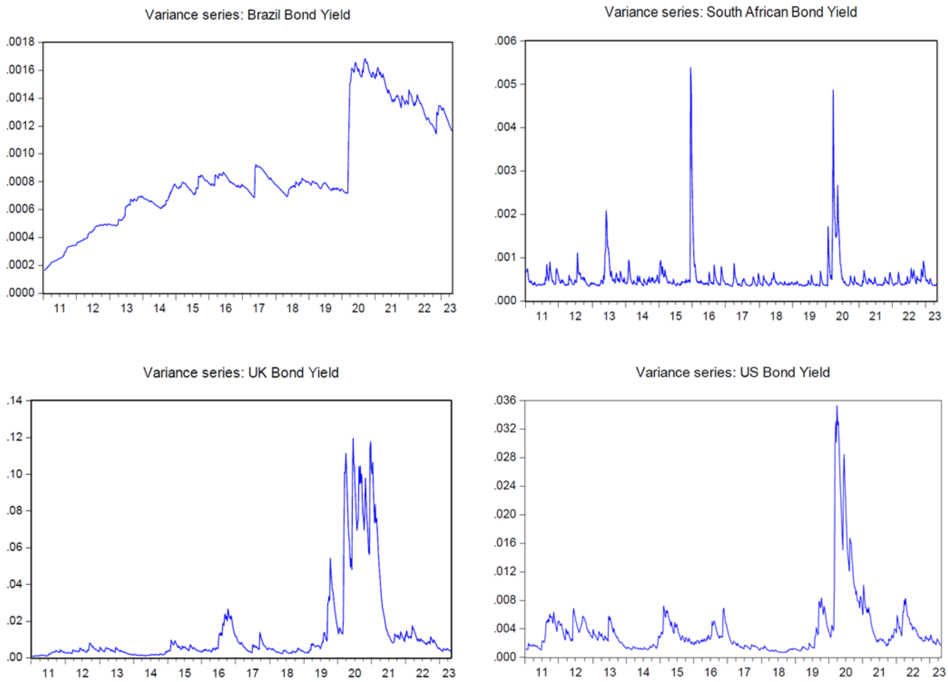

Figure 5. Variance Series of Brazil, South Africa, UK, and US Bonds

5. Conclusion

This paper examines ARCH and GARCH effects of Bitcoin on various stock indices including national long-term bonds. Overall, the results reveal that the coefficients of the constant variance term, the arch and the GARCH parameters are positive and statistically significant at the 1% level across all models. In respect of the mean equation, the results suggest that the spill over effects of Bitcoin on equities and long-term bonds are ambiguous. The findings reveal the presence of time-varying conditional volatility of the returns of the Bitcoin stock. This clearly indicates that the persistence of volatility shocks, as represented by the sum of the ARCH and GARCH parameter is large. Moreover, this suggests that the effect of today's shock remains in the forecasts of variance for many periods in the future.

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