Uncovering Systematic Risk in Crypto currency Markets: An Empirical Investigation Using DCC-GARCH Model.

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Abstract: This study presents an analysis of the occurrence of structural flaws and spillovers of volatility among eight popular digital currencies, such as Bit coin (BTC), Litecoin (LTC), Ripple (XRP), BNBPrice, DOGECOINPrice, ETHEREUMPrice, TETHERPrice, and USDCOINPrice. The analysis covers the period from December 25, 2019, to August 25, 2022, utilizing various statistical tests such as the Chow Breakpoint Test, Cumulative Sum test, The Granger Causality Test, the LM test for ARCH, and Dynamic Conditional Correlation (DCC) GARCH model. The results of this research reveal being present structural breaks in all the evaluated cryptocurrencies, highlighting the unpredictable nature of the cryptocurrency market. Additionally, these cryptocurrencies exhibit notable volatility spillovers and substantial positive correlations, which point to limited benefits of diversification within the cryptocurrency market. (Chowdhury, 2020; Treiblmaier, 2018; Quispe, 2023). These results have implications for investors, policymakers, and other stakeholders in the cryptocurrency market. The study recommends including cryptocurrencies as an important component in investment portfolios to stimulate returns and reduce overall portfolio risks, it is noted that direct investment in cryptocurrencies can generate higher abnormal returns, but this comes with increased risk due to their inherent volatility. Investor preference for firms involved in cryptocurrency is influenced by factors such as legal protection and familiarity. Thus, policymakers should prioritize financial stability and implement careful regulation of cryptocurrency-related announcements to prevent artificial premiums and fraudulent activities (Chowdhury, 2020; Treiblmaier, 2018; Quispe, 2023). Furthermore, the analysis highlights the presence of high volatility spillover effects among certain cryptocurrencies, particularly Bitcoin, Ethereum, and Litecoin.. While volatility offers diversification advantages, concerns arise due to the lack of intrinsic value and dividends in cryptocurrencies (Özdemir, 2022). The presence of systematic structural breaks suggests the possibility of manipulative behaviors and potential trading strategies that warrant further investigation. The DCC GARCH analysis reveals a high correlation and significant volatility spillover effects among most cryptocurrencies. These findings emphasize the need for a more diversified cryptocurrency market to mitigate risk and promote stability within this emerging financial sector.

Keywords: Crypto currencies, Structural break, Volatility, Systematic risk, Spillovers, DCC-GARCH. JELcode: Q02 G12 G15 G23

1. Introduction

In this research work, the structural breaks and volatility spillovers of cryptocurrencies are investigated in order to assess their potential as a class of financial asset. Crypto-currencies rely on cryptography to secure financial transactions recorded in an electronic ledger known as a block chain, and they offer advantages such as lower transaction costs and greater flexibility in transferring money.

We investigate whether investors can diversify their holdings among multiple cryptocurrencies to reduce risk and analyze the market integration and advantages of variety that result from structural breaks. Specifically, we study eight cryptocurrencies, including Bitcoin (BTC), Litecoin (LTC), Ripple (XRP), BNBPrice, DOGECOINPrice, ETHEREUMPrice, TETHERPrice, and USDCOINPrice, during the period from 25 December 2019 to 25th August 2022 using various econometric models. Our findings suggest that structural breaks exist in the cryptocurrency market and spread from smaller to larger cryptocurrencies, with significant volatility spillovers and positive correlatios among crypto-currencies.

According to several recent studies (Alvarez-Ramirez et al., 2018, Balcilar et al., 2017, Brandvold et al., 2015, Brauneis and Mestel, 2018, Jiang et al., 2018, Koutmos, 2018, Takaishi, 2018, and Van Vliet, 2018), understanding of cryptocurrency investing is still in its infancy. However, investors can diversify away from Bitcoin-specific risk by examining cryptocurrencies alongside other asset classes in their portfolios. Nevertheless, understanding the price fluctuations and interconnections of cryptocurrencies is necessary before engaging in such investments. Our analysis indicates that the conditional quasi-correlations between eight cryptocurrencies, as determined by the DCC-GARCH model results, are highly significant and positive (Brandvold et al., 2015; Polasik et al., 2015).

Objective of this study

Within eight well-known cryptocurrencies, this study will look into the prevalence of structural fractures and volatility spillovers. The goal of the study is to evaluate the possible advantages of market diversity in cryptocurrencies and to examine market integration and the benefits of structural breaks. Bitcoin (BTC), Litecoin (LTC), Ripple (XRP), BNBPrice, DOGECOINPrice, ETHEREUM Price, TETHER-Price, and USDCOINPrice are among the individual crypto-currencies being examined. The study aims in order to clarify the price patterns, volatility spillovers, and correlations among different crypto-currencies by utilising several econometric models. The research's findings are anticipated to offer new information to investors, decision-makers, and other market participants in the bitcoin space.

The review of literature and data is presented in Section 3, while the process is demonstrated in Part 4. We present our results and comments in Section 5 and conclude our discussion in Section 6

2. Review of Literature

Billio et al. investigated financial institutions' interconnectedness in 2012. Finding banks to be more crucial in transmitting shocks. Granger-causality networks and principal-components analysis were used. Vliet (2018) developed a new model for Bitcoin's market capitalization, outperforming Metcalfe's Law. Takaishi (2018) found that Brexit minimally affected Bitcoin. Koutmos (2018) identified Bitcoin's significant impact on return and volatility spillovers among cryptocurrencies. Brauneis and Mestel (2018) found a positive effect of market capitalization on efficiency, while the bid-ask spread had a negative impact. Balcilar et al. (2017)

emphasized nonlinearity and tail behavior in Bitcoin return-volume analysis. Brandvold et al. (2015) investigated Bitcoin exchange's impact on price discovery. Polasik et al. (2015) identified factors influencing the percentage of sales attributed to Bitcoin. Various financial models and methods were used, considering nonlinearity, tail behavior, and conditional heteroscedasticity (Alaoui et al., 2019; Bera et al., 1992; Bollinger & Pagliari, 2019; Corbet, Lucey, et al., 2018; Demir et al., 2018; Dyhrberg, 2016; Gronwald, 2021; Nascimento et al., 2019; Wolff, 1988). Other studies explored return persistence, adoption, and price behavior (Bera & Higgins, 1992; Corbet & Katsiampa, 2020; Dash, 2020; Hidajat, 2019; Wang et al., 2022; Huyen et al., 2023; Canh et al., 2019; Luu Duc Huynh, 2019; Meng & Chen, 2023; Özdemir, 2022; Quispe, 2023; Trinh & Squires, 2022). These findings have implications for policymakers, investors, and risk management.

3. Data

To conduct our study, we collected the daily closing prices of eight cryptocurrencies (Bitcoin, Litecoin, Ripple, BNBPrice, DOGECOINPrice, ETHEREUM Price, TETHERPrice, and USDCOINPrice) and matched them. This allowed us to determine the longest time span that covered the most coins. We analyzed the prices from December 25th, 2019 to August 25th, 2022. In our study, we also took into account the specific technical aspects and filters necessary for the econometric models used.

3.Methodology

Assuming each cryptocurrency (Crypto) is a function of constants.

Crypto=α0+ t,

This includes the following information: t is the date; Crypto is the daily adjusted recorded the coefficient of the closing prices of each coin, and is the residual term. For each coin's price, the Chow Breakpoint Test is employed to validate structural fractures. The Granger test (Granger, 1969) is then used to assess the causality of cryptocurrency pair correlations and project each cryptocurrency's future worth. Finally, we employ the Multivariate Autoregressive Conditionally Heteroskedastic (Multivariate GARCH) model to represent both volatility clusters and the contemporaneous inter connection of crypto currencies (Engle, 2002a). It is possible to discover linkages inside the cryptocurrency market using the estimated results of conditional correlations between crypto currencies (Billio et al., 2006). In comparison to the conditional correlation GARCH model, the DCC GARCH model is more adaptable. When there are structural discontinuities among the variables, the DCC GARCH excels above other models (Engle, 2002b).

The DCC-GARCH model can be expressed in the form of equations as follows:

For a k-dimensional time series $\{Y_t\}$, where Y_t is a vector of k variables at time t, the model is given by: GARCH equation for each variable i:

$$Y_{i,t} = \mu_i + \varepsilon_{i,t}$$
$$\varepsilon_{i,t} = \sigma_{i,t} * \quad _{i,t}$$
$$\sigma_{i,t}^2 = \omega_i + \sum_{j=1}^k \alpha_{i,j} * \varepsilon_{j,t-1}^2 + \sum_{j=1}^k \beta_{i,j} * \sigma_{j,t-1}^2$$

where μ_i is the constant, $\varepsilon_{i,t}$ is the standardized error term, $\sigma_{i,t}^2$ is the conditional variance, ω_i is the constant term, $\alpha_{i,j}$ and $\beta_{i,j}$ are the coefficients for the squared standardized residuals and the past conditional variance, respectively.

DCC equation for the conditional correlation matrix:

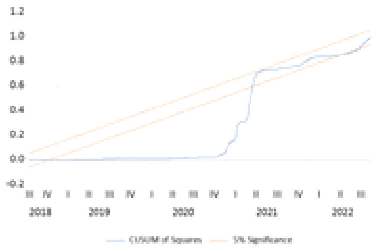
$$R_t = D_t * Q_t * D_t$$
$$Q_t = (1-\lambda) * Q_{t-1} + \lambda * \varepsilon_{t-1} * \varepsilon_{t-1}^T$$
$$D_{i,i,t} = (\sigma_{i,t}^2)^{-1/2}$$

4. Results and Discussions

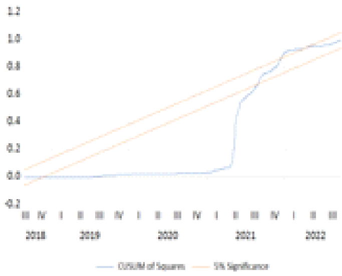
Table1: Structural break test (The Chow Breakpoint Test)

Coin name	F-statistic	probability value	The log-likelihood ratio	probability value	Wald statistic	probability value	Conclusion
Bitcoin	5060.212	0.0000	2209.943	0.0000	5060.212	0.0000	Break
DOGECOIN	2754.763	0.0000	1850.775	0.0000	5509.527	0.0000	Break
XRP	1210.173	0.0000	1441.141	0.0000	2420.347	0.0000	Break
USDCOIN	3791.904	0.0000	2121.524	0.0000	7583.808	0.0000	Break
TETHER	2861.811	0.0000	2355.548	0.0000	5723.623	0.0000	Break
LITECOIN	1621.775	0.0000	1726.445	0.0000	3243.550	0.0000	Break
ETHEREUM	206.8908	0.0000	366.1016	0.0000	413.7816	0.0000	Break
BNB	213.0745	0.0000	375.7741	0.0000	426.1489	0.0000	Break

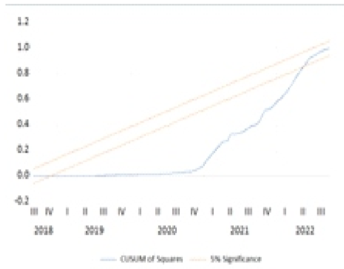
Source: Authors' own calculations



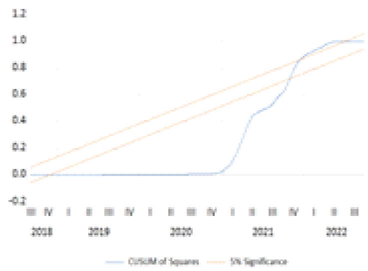
BNB



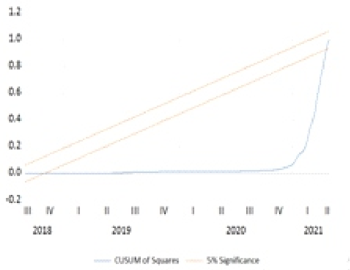
ETHEREUM



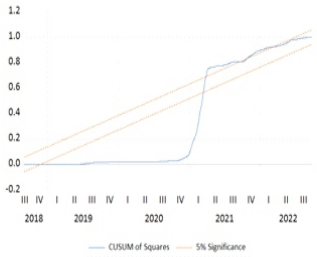
LITECOIN



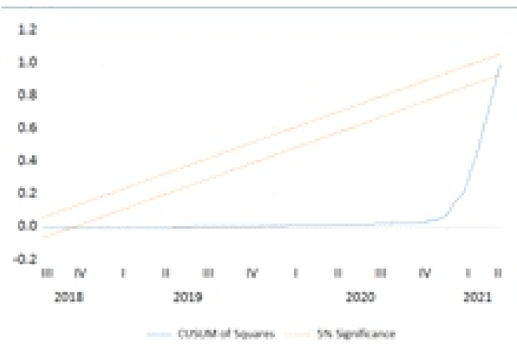
TETHER



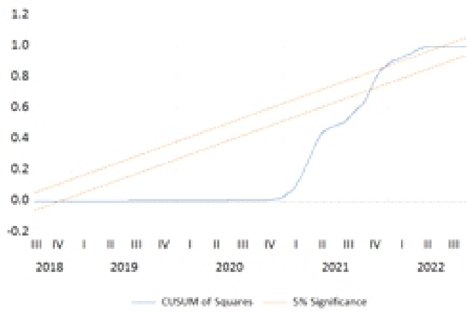
USDCOIN



XRP

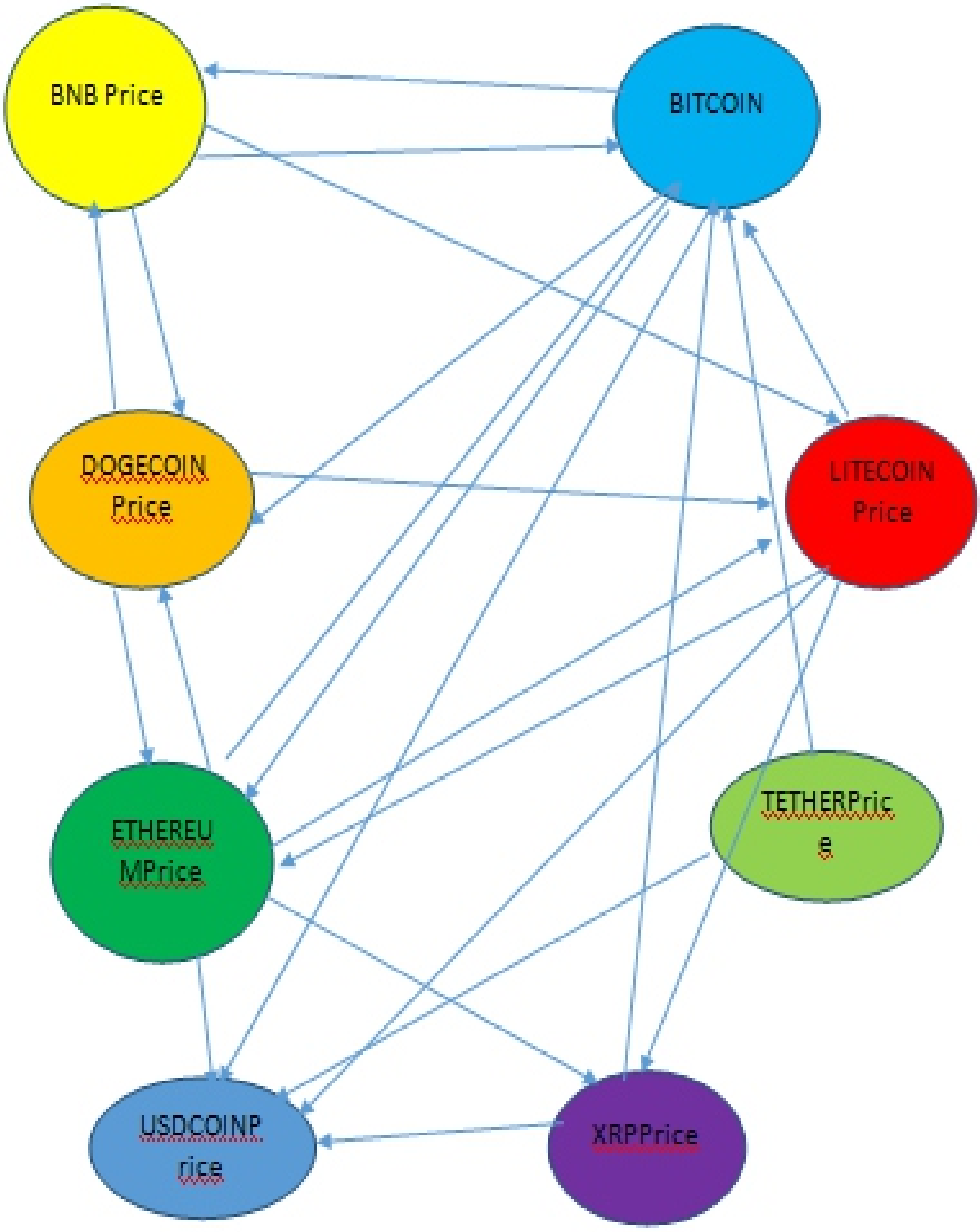


DOGECOIN



Bitcoin

Figure.3. Granger causality between various cryptocurrencies.
Note: The arrow is the significant Granger causality from cryptocurrency to others



* DCC GARCH Fit *				
Optimal Parameters				
	Estimate	**Std. Error**	**t value**	**Pr(>|t|)**
[rbit].mu	**-0.001814**	**0.001130**	**-1.605120**	**0.108467**
[rbit].omega	**0.000087**	**0.000038**	**2.288488**	**0.022109**
[rbit].alpha1	**0.117025**	**0.052879**	**2.213062**	**0.026893**
[rbit].beta1	**0.836443**	**0.045115**	**18.540232**	**0.000000**
[rDOG].mu	**-0.000183**	**0.001941**	**-0.094478**	**0.924729**
[rDOG].omega	**0.000947**	**0.000257**	**3.691521**	**0.000223**
[rDOG].alpha1	**0.783699**	**0.178162**	**4.398792**	**0.000011**
[rDOG].beta1	**0.215301**	**0.074091**	**2.905905**	**0.003662**
[Joint]dcca1	**0.000000**	**0.000012**	**0.000188**	**0.999850**
[Joint]dccb1	**0.903514**	**0.210009**	**4.302271**	**0.000017**
Information Criteria				
Akaike	**-2.5532**			
Bayes	**-2.4980**			
Shibata	**-2.5534**			
Hannan-Quinn	**-2.5322**			
Elapsed time :	**4.013455**			

Table 2: LM test to detect ARCH-type disturbances

Coin	Chi^2	p-value	Conclusions
Bitcoin	228.9149	0	**ARCH-disturbances**
DOGECOIN	171.8284	0	**ARCH-disturbances**
BNB	66.30777	0	**ARCH-disturbances**
XRP	20.69165	0	**ARCH-disturbances**
USDCOIN	15.51747	0	**ARCH-disturbances**
TETHER	161.5776	0	**ARCH-disturbances**
LITECOIN	13.57551	0	**ARCH-disturbances**
ETHEREUM	36.89487	0	**ARCH-disturbances**

Source: Authors' own calculations

Table 3a: Dynamic conditional correlation to rbit and rBNB.

* DCC GARCH Model *				
Optimal Parameters				
	Estimate	Std. Error	t value	Pr(>|t|)
[rbit].mu	-0.001814	0.001129	-1.6058	0.108309
[rbit].omega	0.000087	0.000038	2.2884	0.022116
[rbit].alpha1	0.117025	0.057477	2.0360	0.041749
[rbit].beta1	0.836443	0.047517	17.6029	0.000000
[rBNB].mu	-0.001960	0.001313	-1.4929	0.135466
[rBNB].omega	0.000205	0.000088	2.3444	0.019060
[rBNB].alpha1	0.275182	0.079821	3.4475	0.000566
[rBNB].beta1	0.682549	0.080127	8.5183	0.000000
[Joint]dcca1	0.124625	0.025826	4.8255	0.000001
[Joint]dccb1	0.778378	0.063070	12.3415	0.000000
Information Criteria				
Akaike	-7.8127			
Bayes	-7.7576			
Shibata	-7.8130			
Hannan-Quinn	-7.7917			
Elapsed time :	2.173035			

Source: Authors' own calculations

The DCC(1,1) model captures the correlation structure between rbit and rBNB. Both series have negative mean returns and volatility clustering. They impact their own volatility, and past volatility shocks persistently affect future volatility. The dynamic correlation between the two series is positive and higher during high volatility periods. The Multivariate normal distribution matches the DCC(1,1) model. The data well, providing insights for forecasting and risk management.

Table 3b: Dynamic conditional correlation of rbit and rDOG.

[rDOG].omega	0.000947	0.000257	3.691521	0.000223
[rDOG].alpha1	0.783699	0.178162	4.398792	0.000011
[rDOG].beta1	0.215301	0.074091	2.905905	0.003662
[Joint]dcca1	0.000000	0.000012	0.000188	0.999850
[Joint]dccb1	0.903514	0.210009	4.302271	0.000017
Information Criteria				
Akaike	-2.5532			
Bayes	-2.4980			
Shibata	-2.5534			
Hannan-Quinn	-2.5322			
Elapsed time :	4.013455			

Source: Authors' own calculations

We used a DCC GARCH model to analyze the relationship between two assets, rbit and rDOG. The model estimates the dynamic correlation between the assets and their volatility behavior. Results suggest a strong positive correlation between the two assets, with rDOG having a statistically significant negative mean return. Both assets are highly volatile and respond more strongly to positive shocks. The model fits the data reasonably well and can inform investment decisions or risk management strategies.

Table 3c: Dynamic conditional correlation of rbit" and "rETH".

Optimal Parameters				
	Estimate	Std. Error	t value	Pr(>|t|)
[rbit].mu	-0.001814	0.001141	-1.5890	0.112071
[rbit].omega	0.000087	0.000038	2.2919	0.021911
[rbit].alpha1	0.117025	0.057421	2.0380	0.041550
[rbit].beta1	0.836443	0.047600	17.5723	0.000000
[rETH].mu	-0.003921	0.001484	-2.6427	0.008224
[rETH].omega	0.000265	0.000157	1.6874	0.091527
[rETH].alpha1	0.164146	0.074890	2.1918	0.028393
[rETH].beta1	0.747902	0.105616	7.0813	0.000000
[Joint]dcca1	0.150761	0.039511	3.8156	0.000136
[Joint]dccb1	0.679448	0.109807	6.1877	0.000000
Information Criteria				
Akaike	-8.0771			
Bayes	-8.0220			
Shibata	-8.0773			
Hannan-Quinn	-8.0561			
Elapsed time :	2.654194			

Source: Authors' own calculations

The results are from fitting a DCC GARCH model to two financial time series, "rbit" and "rETH". The estimated parameters for the mean and volatility equations of both series suggest that their returns have negative means, which implies they are expected to be negative in long run. Additionally, the parameter estimates suggest that the returns of both series are positively correlated with each other. The estimated values of alpha and beta indicate that there is significant persistence in the conditional volatility of both series.

Table 3d: Dynamic conditional correlation of rbit" and "rLIT".

Optimal Parameters				
	Estimate	Std. Error	t value	Pr(>|t|)
[rbit].mu	-0.001814	0.001150	-1.57648	0.114916
[rbit].omega	0.000087	0.000038	2.28292	0.022435
[rbit].alpha1	0.117025	0.060410	1.93717	0.052725
[rbit].beta1	0.836443	0.049233	16.98948	0.000000
[rLIT].mu	-0.000687	0.001514	-0.45387	0.649922
[rLIT].omega	0.000228	0.000100	2.27949	0.022638
[rLIT].alpha1	0.133404	0.044609	2.99053	0.002785
[rLIT].beta1	0.799280	0.054061	14.78471	0.000000
[Joint]dcca1	0.098943	0.037350	2.64906	0.008072
[Joint]dccb1	0.595490	0.183238	3.24982	0.001155
Information Criteria				
Akaike	-7.9063			
Bayes	-7.8511			
Shibata	-7.9065			
Hannan-Quinn	-7.8853			
Elapsed time :	3.614601			

Source: Authors' own calculations

DCC-GARCH model with rbit and rLIT has a good fit, suggested by the log-likelihood and information criteria. The mean estimates for both series are negative, and there is persistence in their volatility. The DCC parameters indicate a significant positive correlation between the conditional volatilities of the two series, implying inter-dependence.

Table 3e: Dynamic conditional correlation of rbit and rTETH

Optimal Parameters				
	Estimate	Std. Error	t value	Pr(>|t|)
[rbit].mu	-0.001814	0.001127	-1.609090	0.107597
[rbit].omega	0.000087	0.000038	2.278599	0.022691
[rbit].alpha1	0.117025	0.052326	2.236467	0.025321
[rbit].beta1	0.836443	0.045012	18.582668	0.000000
[rTETH].mu	0.000008	0.000012	0.649365	0.516102
[rTETH].omega	0.000000	0.000000	0.007473	0.994038
[rTETH].alpha1	0.075626	0.016940	4.464454	0.000008
[rTETH].beta1	0.895654	0.026636	33.625095	0.000000
[Joint]dcca1	0.054427	0.019298	2.820389	0.004797
[Joint]dccb1	0.856518	0.056166	15.249823	0.000000
Information Criteria				
Akaike	-16.133			
Bayes	-16.078			
Shibata	-16.133			
Hannan-Quinn	-16.112			
Elapsed time :	2.924669			

Source: Authors' own calculations

The output displays estimated parameters for a model, including mean, volatility, and correlation parameters for two series. The log-likelihood values are also provided. The results show positive and significant omega, alpha, beta, and DCC parameters, indicating volatility clustering and time-varying correlation between the two series. The results can be used to analyze the dynamic behavior of the two series and make forecasts or risk management decisions.

Table 3f: Dynamic conditional correlation of rbit and rUSD

Optimal Parameters				
	Estimate	Std. Error	t value	Pr(>|t|)
[rbit].mu	-0.001814	0.001133	-1.599996	0.109599
[rbit].omega	0.000087	0.000038	2.290032	0.022019
[rbit].alpha1	0.117025	0.053510	2.186958	0.028746
[rbit].beta1	0.836443	0.045447	18.404817	0.000000
[rUSD].mu	-0.000001	0.000011	-0.131420	0.895443
[rUSD].omega	0.000000	0.000000	0.011802	0.990583
[rUSD].alpha1	0.078175	0.013149	5.945374	0.000000
[rUSD].beta1	0.892062	0.015799	56.462261	0.000000
[Joint]dcca1	0.002102	0.003827	0.549165	0.582892
[Joint]dccb1	0.989689	0.012346	80.162128	0.000000
Information Criteria				
Akaike	-16.290			
Bayes	-16.234			
Shibata	-16.290			
Hannan-Quinn	-16.269			
Elapsed time :	3.453407			

Source: Authors' own calculations

The DCC GARCH model was used to model the volatility of rbit and rUSD data. The model with 11 parameters showed a good fit to the data with a log-likelihood of 7944. The mean of rbit is negative and the mean of rUSD is close to zero, with low omega indicating low volatility. However, alpha and beta values indicate significant persistence in volatility. Joint DCC parameters showed a strong correlation between rbit and rUSD. The results indicate that DCC GARCH model is suitable to analyze volatility dynamics and make informed decisions in finance.

Table 3g: Dynamic conditional correlation of rbit and Rxrp

Optimal Parameters				
	Estimate	Std. Error	t value	Pr(>|t|)
[rbit].mu	-0.001814	0.001158	-1.56579	0.117399
[rbit].omega	0.000087	0.000038	2.29140	0.021940
[rbit].alpha1	0.117025	0.063686	1.83752	0.066133
[rbit].beta1	0.836443	0.050874	16.44146	0.000000
[rXRP].mu	-0.000873	0.001524	-0.57293	0.566688
[rXRP].omega	0.000174	0.000122	1.42530	0.154071
[rXRP].alpha1	0.257913	0.104439	2.46952	0.013530
[rXRP].beta1	0.736504	0.107339	6.86148	0.000000
[Joint]dcca1	0.098163	0.038004	2.58298	0.009795
[Joint]dccb1	0.838320	0.076595	10.94483	0.000000
Information Criteria				
Akaike	-7.4535			
Bayes	-7.3984			
Shibata	-7.4538			
Hannan-Quinn	-7.4325			
Elapsed time :	3.141024			

Source: Authors' own calculations

This is a DCC GARCH model with two assets, rbit and rXRP, assuming a multivariate normal distribution with 11 estimated parameters and 974 observations. The model shows a negative mean return for both assets, higher constant variance for rbit, high volatility persistence, and positive dynamic correlation between the assets. The correlation is significant at 1% for dccb1 but not significant at 5% for dcca1, indicating the need for further investigation of the economic and financial factors affecting the assets' dynamics.

Table 3h: Dynamic conditional correlation of rBNB and rbit

Optimal Parameters				
	Estimate	Std. Error	t value	Pr(>|t|)
[rBNB].mu	-0.001960	0.001313	-1.4929	0.135466
[rBNB].omega	0.000205	0.000088	2.3444	0.019057
[rBNB].alpha1	0.275182	0.079821	3.4475	0.000566
[rBNB].beta1	0.682549	0.080126	8.5185	0.000000
[rbit].mu	-0.001814	0.001129	-1.6058	0.108310
[rbit].omega	0.000087	0.000038	2.2884	0.022116
[rbit].alpha1	0.117025	0.057477	2.0360	0.041748
[rbit].beta1	0.836443	0.047517	17.6031	0.000000
[Joint]dcca1	0.124625	0.025825	4.8257	0.000001
[Joint]dccb1	0.778378	0.063065	12.3425	0.000000
Information Criteria				
Akaike	-7.8127			
Bayes	-7.7576			
Shibata	-7.8130			
Hannan-Quinn	-7.7917			
Elapsed time :	1.783381			

Source: Authors' own calculations

A DCC GARCH(1,1) model was applied to rBNB and rbit. Both series exhibit negative mean returns. Volatility is persistent, as indicated by significant beta1 estimates. The DCC parameters suggest a strong contemporaneous correlation and some correlation persistence. The model fits the data well based on the high log-likelihood and low information criteria values.

Table 3i: Dynamic conditional correlation of rBNB and Rdog

Optimal Parameters				
	Estimate	Std. Error	t value	Pr(>|t|)
[rBNB].mu	-0.001960	0.001320	-1.484637	0.137640
[rBNB].omega	0.000205	0.000086	2.380960	0.017268
[rBNB].alpha1	0.275182	0.081583	3.373024	0.000743
[rBNB].beta1	0.682549	0.079927	8.539619	0.000000
[rDOG].mu	-0.000183	0.001940	-0.094496	0.924715
[rDOG].omega	0.000947	0.000257	3.687141	0.000227
[rDOG].alpha1	0.783699	0.178530	4.389744	0.000011
[rDOG].beta1	0.215301	0.074129	2.904410	0.003679
[Joint]dcca1	0.000000	0.006941	0.000020	0.999984
[Joint]dccb1	0.926114	2.402372	0.385500	0.699867
Information Criteria				
Akaike	-2.1189			
Bayes	-2.0638			
Shibata	-2.1192			
Hannan-Quinn	-2.0979			
Elapsed time :	1.805996			

Source: Authors' own calculations

The DCC GARCH model fits well for rBNB and rDOG financial time series with negative mean returns and significant volatility persistence. The two series exhibit a time-varying positive correlation, which can be modeled using DCC parameters. The model's goodness-of-fit is reasonable, making it a useful tool for conditional covariance modeling.

Table 3j: Dynamic conditional correlation of rBNB and rETH

Optimal Parameters				
	Estimate	Std. Error	t value	Pr(>|t|)
[rBNB].mu	-0.001960	0.001327	-1.4773	0.139594
[rBNB].omega	0.000205	0.000087	2.3577	0.018387
[rBNB].alpha1	0.275182	0.082707	3.3272	0.000877
[rBNB].beta1	0.682549	0.081238	8.4018	0.000000
[rETH].mu	-0.003921	0.001472	-2.6640	0.007723
[rETH].omega	0.000265	0.000160	1.6589	0.097146
[rETH].alpha1	0.164146	0.078214	2.0987	0.035845
[rETH].beta1	0.747902	0.109507	6.8297	0.000000
[Joint]dcca1	0.139714	0.049784	2.8064	0.005010
[Joint]dccb1	0.811907	0.078342	10.3636	0.000000
Information Criteria				
Akaike	-7.5084			
Bayes	-7.4533			
Shibata	-7.5087			
Hannan-Quinn	-7.4875			
Elapsed time :	1.807906			

Source: Authors' own calculations

DCC-GARCH model fit to rBNB and rETH data indicates significant volatility clustering in both series. Positive and significant correlations are found between the two series. The model shows a good fit to the data based on low information criteria values. These findings have implications for risk management and portfolio optimization.

Table 3k: Dynamic conditional correlation of rbit and rXRP

Optimal Parameters				
	Estimate	Std. Error	t value	Pr(>|t|)
[rbit].mu	-0.001814	0.001158	-1.56579	0.117399
[rbit].omega	0.000087	0.000038	2.29140	0.021940
[rbit].alpha1	0.117025	0.063686	1.83752	0.066133
[rbit].beta1	0.836443	0.050874	16.44146	0.000000
[rXRP].mu	-0.000873	0.001524	-0.57293	0.566688
[rXRP].omega	0.000174	0.000122	1.42530	0.154071
[rXRP].alpha1	0.257913	0.104439	2.46952	0.013530
[rXRP].beta1	0.736504	0.107339	6.86148	0.000000
[Joint]dcca1	0.098163	0.038004	2.58298	0.009795
[Joint]dccb1	0.838320	0.076595	10.94483	0.000000
Information Criteria				
Akaike	-7.4535			
Bayes	-7.3984			
Shibata	-7.4538			
Hannan-Quinn	-7.4325			
Elapsed time :	3.141024			

Source: Authors' own calculations

Of the parameters presented, we find that the parameters [rbit].omega, [rbit].beta1, [rXRP].alpha1, [rXRP].beta1, [Joint]dcca1, and [Joint]dccb1 are statistically significant at the 5% level, indicating that they are unlikely to be zero in the population. On the other hand, we cannot reject the null hypothesis for [rbit].mu, [rbit].alpha1, [rXRP].mu, and [rXRP].omega, which are not statistically significant at the 5% level.The information criteria presented suggest that the model may have good fit and predictive performance.

Table 4: Correlation among currencies

	rbit	rBNB	rDOG	rETH	rLIT	rTETH	rUSD	rXRP
rbit	1.00000000	0.74368883	0.15679829	0.82773834	0.82713639	-0.039572547	-0.28363335	0.683660897
rBNB	0.74368883	1.00000000	0.17094794	0.78832127	0.75232860	0.024007951	-0.23464837	0.688106306
rDOG	0.15679829	0.17094794	1.00000000	0.15142619	0.13350689	-0.024982647	-0.05122694	0.151758379
rETH	0.82773834	0.78832127	0.15142619	1.00000000	0.83277615	-0.023262549	-0.28342373	0.742868141
rLIT	0.82713639	0.75232860	0.13350689	0.83277615	1.00000000	-0.051544333	-0.22197060	0.736734637
rTETH	-0.03957255	0.02400795	-0.02498265	-0.02326255	-0.05154433	1.000000000	-0.30317765	-0.007585386
rUSD	-0.28363335	-0.23464837	-0.05122694	-0.28342373	-0.22197060	-0.303177655	1.00000000	-0.240305957
rXRP	0.68366090	0.68810631	0.15175838	0.74286814	0.73673464	-0.007585386	-0.24030596	1.000000000

Source: Authors' own calculations

Correlation analysis of eight cryptocurrencies reveals high positive correlations between rbit and rLIT (0.827), and between rBNB and rETH (0.788). The highest negative correlation is observed between rTETH and rUSD (-0.303). These correlations offer insights into potential co-movements and can inform investment decisions.

Table 5: Covariance among currencies

	rbit	rBNB	rDOG	rETH	rLIT	rTETH	rUSD	rXRP
rbit	8.777869e-04	7.268764e-04	2.496332e-04	9.313419e-04	1.050491e-03	-3.094835e-06	-6.940611e-06	6.792211e-04
rBNB	7.268764e-04	1.088302e-03	3.030436e-04	9.876419e-04	1.063905e-03	2.090638e-06	-6.393492e-06	7.612130e-04
rDOG	2.496332e-04	3.030436e-04	2.887573e-03	3.090217e-04	3.075324e-04	-3.543675e-06	-2.273582e-06	2.734608e-04
rETH	9.313419e-04	9.876419e-04	3.090217e-04	1.442258e-03	1.355722e-03	-2.331996e-06	-8.890037e-06	9.460393e-04
rLIT	1.050491e-03	1.063905e-03	3.075324e-04	1.355722e-03	1.837560e-03	-5.832444e-06	-7.858905e-06	1.059029e-03
rTETH	-3.094835e-06	2.090638e-06	-3.543675e-06	-2.331996e-06	-5.832444e-06	6.967835e-06	-6.609856e-07	-6.714327e-07
rUSD	-6.940611e-06	-6.393492e-06	-2.273582e-06	-8.890037e-06	-7.858905e-06	-6.609856e-07	6.821686e-07	-6.655586e-06
rXRP	6.792211e-04	7.612130e-04	2.734608e-04	9.460393e-04	1.059029e-03	-6.714327e-07	-6.655586e-06	1.124480e-03

Source: Authors' own calculations

Covariance among currencies: The covariance matrix presents pairwise covariances between eight financial assets, indicating the degree of relationship between their returns. Positive covariances such as rBIT-rBNB (0.000727) and rLIT-rXRP (0.001059) suggest positive relationships. Diagonal values represent variances, enabling calculation of standard deviation. This matrix aids in analyzing risk and return characteristics of the assets in a portfolio.

5. Conclusion

Based on the findings of this study, it is evident that the cryptocurrency market exhibits structural breaks and volatility spillovers, highlighting its unpredictable nature. While previous research primarily focused on Bitcoin, this study aimed to address this gap by examining the broader cryptocurrency market. The findings show a strong dynamic link across cryptocurrencies, pointing to the potential for return spillover. Therefore, including crypto-currencies as an essential investment component in portfolios can enhance returns and mitigate overall portfolio risks.

Furthermore, the market demonstrates a preference for public firms' crypto-currency announcements, and direct investment in crypto-currencies generates higher abnormal returns. However, it is crucial to acknowledge that direct investment also exposes firms to increased risk due to the volatile nature of cryptocurrencies. Investor preference for firms involved in cryptocurrency is driven by factors such as legal protection and familiarity. Hence, policymakers must prioritize financial stability and implement careful regulation of crypto currency related announcements to prevent artificial premiums and fraudulent activities.

The data finds considerable volatility spillover effects across several cryptocurrencies, most notably Bitcoin, Ethereum, and Litecoin, when it comes to spillovers in the cryptocurrency market. While volatility offers diversification advantages, concerns arise due to the absence of intrinsic value and dividends in cryptocurrencies. It is important to note that our findings also uncover the presence of systematic structural breaks, suggesting potential manipulative behaviors and trading strategies that warrant further investigation.

Furthermore, the DCC GARCH analysis highlights that most cryptocurrencies exhibit high correlation and significant volatility spillover effects. These outcomes emphasize the necessity for a more diversified cryptocurrency market to mitigate risks and promote stability within this emerging financial sector. In summary, this study contributes to the literature by evaluating the efficiency of the cryptocurrency market, particularly its structural breaks and volatility spillovers. The findings underscore the importance of including cryptocurrencies in investment portfolios to stimulate returns and reduce overall risks. However, it is essential to manage the increased risk associated with direct cryptocurrency investments and prioritize regulatory measures to maintain financial stability. Moreover, a diversified cryptocurrency market is crucial to minimize risk and foster stability in this evolving financial landscape (Chowdhury, 2020; Treiblmaier, 2018; Quispe, 2023; Özdemir, 2022).

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