Scientific Annals of Economics and Business
71 (3), 2024, 353-380
DOI: 10.47743/saeb-2024-0021

Assessment of Cryptocurrencies Integration into the Financial Market by Applying a Dynamic Equicorrelation Model

Graciela Gomes*, Mário Queirós, Patrícia Ramos*****

Abstract: This work aims to contribute to a deeper understanding of cryptocurrencies, which have emerged as a unique form within the financial market. While there are numerous cryptocurrencies available, most individuals are only familiar with Bitcoin. This knowledge gap and the lack of literature on the subject motivated the present study to shed light on the key characteristics of cryptocurrencies, along with their advantages and disadvantages. Additionally, we seek to investigate the integration of cryptocurrencies within the financial market by applying a dynamic equicorrelation model. The analysis covers ten cryptocurrencies from June 2nd, 2016 to May 25th, 2021. Through the implementation of the dynamic equicorrelation model, we have reached the conclusion that the degree of integration among cryptocurrencies primarily depends on factors such as trading volume, global stock index performance, energy price fluctuations, gold price movements, financial stress index levels, and the index of US implied volatility.

Keywords: cryptocurrencies; bitcoin; Blockchain; finance; decentralization; Dynamic Equicorrelation Model.

JEL classification: G11; E44; O33.

* ISCAP, Polytechnic of Porto, Portugal; e-mail: *2160486@iscap.ipp.pt*.
** CEOS.PP, ISCAP, Polytechnic of Porto, Portugal; e-mail: *mqueiros.iscap@gmail.com*.
*** CEOS.PP, ISCAP, Polytechnic of Porto, Institute for Systems and Computer Engineering, Technology and Science, Portugal; e-mail: *patricia@iscap.ipp.pt* (corresponding author).

Article history: Received 4 June 2024 | Accepted 22 September 2024 | Published online 25 September 2024

To cite this article: Gomes, G., Queirós, M., Ramos, P. (2024). Assessment of Cryptocurrencies Integration into the Financial Market by Applying a Dynamic Equicorrelation Model. *Scientific Annals of Economics and Business*, 71 (3), 353-380. https://doi.org/10.47743/saeb-2024-0021.

1. INTRODUCTION

In the last decade, due to significant technological advancements, new and more sophisticated forms of payment and investment have emerged (Wątorek *et al.*, 2023). Supply, demand, macroeconomic conditions, speculation, and even rumors have been significant factors influencing investor behavior (Rudkin *et al.*, 2023). These factors can drive cryptocurrency prices, making it challenging for investors to take precise positions in trading or investment (Boiko *et al.*, 2021). Cryptocurrency is a virtual currency that utilizes advanced encryption techniques to regulate its monetary units. Cryptography has been applied to enhance payment security and verify transactions. This encryption has also instilled confidence among its users. Cryptocurrency can be transacted without interference from a central entity such as a bank (Poongodi *et al.*, 2020). It has potential impacts, including its susceptibility to money laundering. While governments cannot control these virtual currencies, they can regulate and tax them. As new technologies advance and cryptocurrency adoption increases, more and more businesses are compelled to accept this payment method (Andriole, 2020). Bitcoin (BTC) was the first cryptocurrency created and currently accounts for approximately 50% of the total market capitalization and trading volume. Cryptocurrency exchanges operate 24/7 (Borri and Shakhnov, 2020). Ethereum (ETH) is a decentralized platform that executes smart contracts. It utilizes its own currency, Ether, which has also garnered significant attention and holds the second position[1] among over 4,000 cryptocurrencies in terms of market capitalization (Mensi *et al.*, 2019). Ripple (XRP) is the only cryptocurrency that does not use Blockchain[2]. XRP was developed and launched in 2012 by a company with the same name, aiming to create a simplified, decentralized payment system using blockchain-inspired technology to facilitate secure, instant, and cost-effective global financial transactions. This cryptocurrency has been adopted by many banks and consistently ranks among the top five cryptocurrencies by market capitalization (Leising and Robinson, 2018). Despite the existence of thousands of cryptocurrencies on the market, either as substitutes or replicas of BTC, Litecoin (LTC) was the first BTC substitute by presenting a modified version of BTC's core concepts, including the mining algorithm[3] (Tu and Xue, 2019). The first BTC replica was Bitcoin Cash (BCH), which entered a new blockchain ledger on August 1st, 2017. However, BCH shared the same ledger and user base as BTC prior to that date. This replica avoided the high costs associated with attracting new users and, therefore, gained recognition more easily (Tu and Xue, 2019).

This research aims to extend the existing body of literature by providing novel insights into the cryptocurrency market. Instead of focusing solely on established features, the study seeks to identify and highlight the unique factors that position cryptocurrencies as potential alternatives to traditional currencies. The subsequent sections will delve into a detailed analysis of the profitability, volatility, and market integration of the top ten cryptocurrencies, offering a nuanced perspective on their performance.

The main contributions of this study can be summarized as follows:

1. Clarifying the characteristics of cryptocurrencies and their advantages and disadvantages.
2. Identifying novel reasons supporting the potential of cryptocurrencies as alternatives to traditional currencies.
3. Analyzing the profitability and volatility of the top ten cryptocurrencies.

4. Assessing the integration of cryptocurrencies into the financial market using a dynamic equicorrelation model.
5. Investigating the determinants influencing equicorrelation among cryptocurrencies.

These contributions align with the aim of this study to provide a more nuanced and insightful understanding of the cryptocurrency market.

For the study ten top cryptocurrencies were selected and analyzed. We considered the integration of these cryptocurrencies in the market from June 2nd, 2016, to May 25th, 2021. A Dynamic EquiCorrelation (DECO) Model was used to analyze these cryptocurrencies and infer market integration. We also applied this model to calculate the correlation among the cryptocurrencies. This full study consists of two components. The first component involves estimating the dynamic equicorrelation among the cryptocurrencies, which is dynamic because it varies over time. The second component aims to identify the determinants of this equicorrelation.

The paper is divided into five sections. The first section serves as an introduction to the research topic, outlining the objectives, research methodology, and the overall structure of the document. The second section of the paper is dedicated to a literature review, focusing on four specific top cryptocurrencies available in the market: Bitcoin, Ethereum, Ripple, and Litecoin. In the third section, the adopted methodology for the empirical study is discussed, providing an explanation of the DECO model and its estimation process. Moving on to the fourth section, the empirical analysis is presented, which includes details about the data sample, procedure, and results. The analysis primarily revolves around the application of the DECO model to calculate the correlation among the cryptocurrencies. Finally, in the fifth and final section, the paper concludes with the main findings, limitations of the current work, and suggestions for future research.

2. CRYPTOCURRENCIES

Cryptocurrency is a term that is not widely known in general, but it has gradually been capturing the attention of people and potential investors. However, it is a topic that has significant global emphasis. In recent years, there has been a prominent growth in new technologies, which in turn require a restructuring of the economy (Ma *et al.*, 2020). Cryptocurrencies are extremely attractive to investors due to various factors, including their transparency, trading speed, high liquidity, and ease of use (Zhang and Gregoriou, 2020). In 2012, the European Central Bank (ECB) defined virtual currency as a type of unregulated digital money that is electronically generated, issued and controlled by its developers, and used and accepted within a specific virtual community (Paulino and Mendonça, 2019). Cryptocurrencies were designed to become an alternative to the gaps created by financial institutions (Nakamato, 2009). Currently, there are more than 13,000 cryptocurrencies contributing to a total market capitalization of over $574 billion. Ether (ETH), Tether (USDT), Ripple (XRP), Chainlink (LINK), BCH, Litecoin (LTC), and Bitcoin (BTC) are some of the over 4,000 cryptocurrencies existing worldwide. It is worth noting that BTC stands out as having the largest market capitalization and the highest unit value. We can consider cryptocurrencies as a medium of exchange, meaning it is a mechanism that can be used to pay someone or settle a debt or financial obligation.

2.1 Bitcoin

There have been several attempts to create a centralized system to facilitate the exchange of virtual currency. Bitcoin emerged as a decentralized solution, as its creator, who identified themselves by the pseudonym Satoshi Nakamoto, believed that success could only be achieved through the decentralization of digital money (McKay and Peters, 2018). BTC is a peer-to-peer payment system created in 2009 by Nakamoto. It is the first open-source digital currency, operating on a software algorithm that utilizes the global internet network to record and verify transactions (Hanif *et al.*, 2023). As a cryptocurrency, it operates on the principles of cryptography to control the creation and exchange of BTC. Accessing the network requires downloading software and joining the BTC network, enabling participants to perform operations, update transactions, and verify them (Ciaian *et al.*, 2016). On October 9th, 2009, during the early transactions, the exchange rate between BTC and the U.S. dollar was established based on the cost of electricity required to generate 1 BTC. It was estimated that 1 USD would be equivalent to 1309.03 BTC. On January 12, 2009, the first virtual BTC transaction took place between Satoshi Nakamoto, the programmer, and Hal Finney, a cryptographic activist (Paulino and Mendonça, 2019). While Bitcoin is a virtual currency, it resembles traditional money in certain aspects. However, it possesses unique characteristics. Unlike traditional currencies controlled by monetary authorities, BTC challenges this notion. This cryptocurrency is not controlled by any authority; the money belongs 100% to the individual who possesses it, with no possibility of being moved by third parties. To prevent counterfeiting or duplication, an advanced cryptographic system is employed, given that it operates as a decentralized currency (Amoza *et al.*, 2014). There are some differences between the traditional banking payment system and the cryptocurrency payment system, but there are also some similarities. In the banking payment system, one needs to possess an account number with a specific banking institution. The entity provides a bank card and a PIN code to facilitate transactions. The PIN code is essential for using the card, serving as a security measure and a way to prove ownership of the bank account. Additionally, the bank keeps a record of transactions made by its customers. Finally, a person can use an electronic communication system to identify themselves as the account holder and request the transfer of funds associated with their account number to another person's account in a different bank (Silva *et al.*, 2020). On the other hand, in the cryptocurrency payment system, instead of having an account number as in the traditional banking system, a person wishing to make a payment using cryptocurrency has a public address. They control this public address using a private key, similar to a PIN number. To make payments using cryptocurrency, the use of an electronic communication system, specifically the internet, is essential to identify the network and request digital tokens associated with their public address to be transferred to another person's public address. This process is facilitated by changes made in the blockchain ledger by a group of participants known as miners, who use their computational power to validate transactions. In summary, both parties controlling the public addresses can see these changes, providing proof that tokens have been transferred from one address to another (Silva *et al.*, 2020). Despite the various benefits that BTC presents, there are some disadvantages to consider. One of these is its considerable price volatility throughout its existence (Brito and Castillo, 2013; Charfeddine *et al.*, 2022). Public key cryptography requires that each user receives two keys: a private key, which is confidential, and a public key known to all users (Brito and

Castillo, 2013). The owner transfers a certain amount of BTC to a specific person by digitally signing a hash of the previous transaction and the public key of the next owner. A recipient can validate the signatures to verify the chain of ownership (Nakamato, 2009). In conclusion, Bitcoin, as the pioneering cryptocurrency, boasts a decentralized and transparent ledger system based on blockchain technology. Its decentralized nature, achieved through a proof-of-work consensus mechanism, enhances security and mitigates the risk of centralized control. Bitcoin's fixed supply and deflationary nature contribute to its appeal as a store of value. However, concerns arise regarding its scalability and environmental impact due to energy-intensive mining processes (Karaömer, 2022).

2.2 Ether

Blockchain is one of the largest public platforms that supports smart contracts. ETH, known as Ether, was introduced to facilitate the implementation of smart contracts as this cryptocurrency introduces the concept of an account, which is formally an address. ETH is used to compensate the mining nodes of participants (Hasan *et al.*, 2022). Currently, the interactive relationship between users and smart contracts is still unknown, as current research on this cryptocurrency is centralized around security and performance issues of blockchain technology (Lin *et al.*, 2020). After the implementation of smart contracts on the blockchain, and also due to the immutability of the code, security becomes a particularly serious concern. Therefore, the presence of a bug or vulnerability in the code can be very critical, as it cannot be corrected and may result in financial losses for the owner of the buggy contract (Staderini *et al.*, 2020). In 1997, Szabo introduced the concept of smart contracts. These smart contracts, due to their ability to automatically execute computerized transactions according to external and internal conditions, were considered the major innovation presented in the second generation of blockchain technology (Staderini *et al.*, 2020). Smart contracts differ from traditional contracts because they are computable, meaning they are programs used to verify and enforce the terms of a particular agreement, which improves their security and reduces costs (Bistarelli *et al.*, 2020). Through a complete Turing language, ETH smart contracts can be programmed, including a powerful set of tools for their development. In the Ethereum platform, an immutable version of a compiled smart contract can be deployed and executed using the ETH virtual machine (Correas *et al.*, 2021). The unit of measurement used for the execution of smart contracts is gas units. Miners receive a certain amount of ether that comes from applying a gas price to the total amount of gas required to complete a transaction (Correas *et al.*, 2021). In conclusion, Ether operates on the Ethereum blockchain and distinguishes itself by facilitating smart contracts. This feature enables the creation of decentralized applications (DApps) and decentralized autonomous organizations (DAOs). While Ethereum's programmability enhances its utility, challenges include scalability issues and the transition to a proof-of-stake consensus, aiming to address environmental concerns associated with proof-of-work.

2.3 Ripple

Just like BTC, XRP is a peer-to-peer network, but it operates on a mutual credit system. Ripple is not only the name of the cryptocurrency, but also the name of the company that acquired the Ryan Fugger's Ripple project. Fugger transferred the rights of the name Ripple to the start-up OpenCoin in 2012, but in 2013 the name was changed again to Ripple Labs, and finally in 2015 to Ripple (Rella, 2020). In 2013, the founders of the Ripple developed the Ripple Ledger, which combined with Fugger's credit network, resulted in a distributed currency exchange on a ledger inspired by blockchain technology. In 2015, Ripple shifted its focus to cross-border interbank payment services for financial institutions (Rella, 2020). According to "Global: Another Cryptocurrency Causes Ripples"[4], XRP is a cryptocurrency not tied to the dollar, allowing the XRP platform to seek the shortest path through numerous clients buying and selling their distinct currencies[5] to complete the transaction. XRP and its potential successors will drive the adoption of blockchain technology with the goal of processing international payments. In 2017, according to Leising and Robinson (2018), there was a surprising increase in the value of the XRP cryptocurrency between late September and early January 2018. Ripple began exploring business ideas around XRP at a time when there was little guidance on digital tokens[6] (Jeff, 2020). XRP offers faster transaction processing for transfers between two countries and aims to reduce or even eliminate fees for cross-border transfers (Adams, 2021). One advantage of XRP over BTC is that XRP can typically complete transfers in three to five seconds, while BTC can take up to forty minutes to process a transfer (Kauflin, 2014). Nowadays, international payments are generally made using the SWIFT network[7], which is the international mechanism through which most banks communicate to conduct transactions. However, banks show little interest in using XRP due to the low likelihood of their customers trusting cryptocurrency payments (Leising and Robinson, 2018). In conclusion, Ripple stands out with its focus on facilitating fast and cost-effective cross-border transactions. The Ripple network employs a consensus algorithm, providing quick settlement times. However, centralization concerns arise due to a more controlled validation process involving trusted nodes. The XRP cryptocurrency is designed to minimize volatility in value during transactions, emphasizing stability but raising questions about decentralization.

2.4 Litecoin

Currently, in the cryptocurrency market, there are several replicas of BTC. However, LTC was created with the intention of replacing BTC by implementing an alternative platform to attract its own users (Tu and Xue, 2019). LTC is based on an open-source protocol and is also not governed by any central authority. This cryptocurrency was introduced on October 7th, 2011, and is currently one of the largest cryptocurrencies, with a total market capitalization of over 15 billion U.S. dollars[8]. However, LTC has some gaps in terms of privacy protection (Zhang *et al.*, 2020). LTC is a peer-to-peer cryptographic currency inspired by BTC. Both do not require the assistance of financial organizations, making them similar. LTC is electronically transferred with significantly reduced transaction fees (Padmavathi and Suresh, 2019). However, according to (Zhang *et al.*, 2020), it has three distinct differences from BTC:

- It provides faster transaction confirmation times than BTC since the block time interval is 2.5 minutes.
- LTC issues four times more coins than BTC.
- LTC uses the encryption algorithm proposed by Percival, making it more accessible to common computer miners.

The creation of LTC involves the mining process, which consists of solving mathematical problems using computers, and the successful computer receives the LTC

(Padmavathi and Suresh, 2019). Just like BTC, LTC transactions are also recorded on the blockchain. LTC uses the scrypt algorithm, as the initial purpose of using this algorithm was to allow miners to mine both cryptocurrencies simultaneously. This algorithm utilizes a sequential memory-hard function, meaning it contains more memory than a memory-less algorithm. Although the scrypt algorithm offers dual resistance to attacks within the same time frame, it has the drawback of increasing orphaned blocks and the size of the blockchain (Padmavathi and Suresh, 2019). In conclusion, often considered the silver to Bitcoin's gold, Litecoin shares similarities with Bitcoin but offers faster transaction confirmation times. Its adoption of the Scrypt algorithm aims to make mining more accessible. While Litecoin provides a faster and more scalable alternative, questions persist about its ability to differentiate significantly from Bitcoin and secure a distinct market niche.

A critical examination of leading cryptocurrencies reveals common challenges (Kumar *et al.*, 2022). Scalability concerns, energy consumption in proof-of-work systems, and centralization risks underscore the need for continuous innovation. Additionally, the speculative nature of cryptocurrency markets and price volatility present challenges for their mainstream adoption. Regulatory uncertainties and potential governance issues further contribute to the complex landscape. Ultimately, while leading cryptocurrencies offer unique features, their limitations and challenges warrant a critical perspective. Ongoing efforts to address scalability, environmental impact, and governance issues are crucial for the sustained evolution and broader acceptance of cryptocurrencies in the financial landscape. A balanced approach that acknowledges both strengths and weaknesses is essential for informed discussions on the role of cryptocurrencies in the future of finance (Łęt *et al.*, 2023).

2.5 Blockchain

There are two types of blockchains: public and private. In the public blockchain anyone can participate, unlike in the private blockchain. This decentralized system has a ledger that records all transactions, which can be referred to as nodes or parties (Lucas and Paez, 2019). Originated from the cryptocurrency BTC, Blockchain[9] aims to provide anonymous exchange of digital money through its decentralized system (Prybila *et al.*, 2020). Validating transactions in this decentralized system posed a challenge since there is no centralized entity or authority. As mentioned, blockchain is a public ledger that stores all transactions since the creation of BTC. A payment transfer can be made by deducting the balance in the ledger of the person making the payment while increasing the balance in the ledger of the recipient (Prybila *et al.*, 2020). Blockchain is a new type of infrastructure that integrates technologies, including data storage, forming a chain of blocks, each containing a set of transactions that provide transaction confirmations to users and verify ownership rights of BTC. Once a block is added to the blockchain, it is extremely difficult to alter or remove. As new transactions are processed, the blockchain is extended (Zaghloul *et al.*, 2020). The main characteristics of a blockchain network are consensus, provenance, and immutability. Consensus is necessary for a transaction to be valid, requiring agreement among all participants. Provenance ensures that all participants know the history of the asset. Lastly, immutability means that a transaction cannot be altered once recorded in the ledger. In the case of an incorrect transaction, the only way to reverse it is by creating a new transaction, and both transactions will be visible (Case *et al.*, 2020). This cryptographic technology is used to ensure the security of data transmission and access. Smart contracts, composed of automated script codes, are used to program the data. Due to the integration of various technologies, the cluster jointly maintains the security and operation of the blockchain network and builds trust with machines (Li and He, 2020). To carry out a double-spending attack, an attacker would need to control more than 51% of the computational power of the internal network. Otherwise, executing a double-spending attack becomes infeasible. A miner is a computer connected to the internet that verifies the transactions that have been conducted. Miners assess the legitimacy of each transaction as part of the mining process by timestamping each transaction and determining if there has been any double-spending (Ferreira *et al.*, 2017). Virtual currencies need to achieve price stability in the market if they are intended to be used as a means of payment and not just for investment purposes. Due to their significant price volatility, which tends to rise in the long term and fluctuate widely in the short term, they are not considered the most suitable method of payment. Because of this volatility, people are incentivized to hold these currencies with the intention of gaining profits in the future. If used as a means of payment, there is a risk of losing money due to their instability (Saito and Iwamura, 2018).

3. METHODOLOGY

In the early 1980s, the first volatility models were developed. In fact, volatility has always attracted significant attention in finance (Aboura and Chevallier, 2014). The search for reliable correlation estimates between financial variables has been a motivation for the development of academic papers, professional conferences, among others (Engle, 2002). Currently, in terms of risk management, it is highly significant to have the ability to estimate high-dimensional asset matrices. However, several numerical problems arise for classical multivariate Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models (Aboura and Chevallier, 2014). The Dynamic Conditional Correlation (DCC) model aims to be implemented in large-scale systems. This model has only been successfully applied in studies containing up to 100 assets, as the estimation becomes increasingly challenging with the increase in the system's size (Engle and Kelly, 2012). The DCC first estimates univariate GARCH models to calculate conditional variances and standardized residuals. In the second stage, it estimates the conditional correlation. Thus, this model is estimated in two steps (Aboura and Chevallier, 2014). The Dynamic EquiCorrelation (DECO) model was chosen for the present study. Unlike the DCC model, the DECO model can support a large set of variables without encountering estimation issues due to numerical problems (Bouri *et al.*, 2021). GARCH models are ubiquitous for estimating the conditional volatility of time series data. This model is particularly important because it continues to generate extensions of existing models. These extensions allow researchers to choose the model that best fits their needs (Yelamanchili, 2021). DECO model is a competitor of DCC model as it possesses features that the DCC lacks. The correlations in the DECO model are based on broader information, while the DCC model falls short in that regard as it relies on a more limited set of information (Engle and Kelly, 2012). The DECO model assumes that the mean of the conditional correlation can vary over time and is equal to the average of all correlation pairs. By applying this model, a correlation between cryptocurrencies is obtained, which can vary over time. This model first adjusts the individual volatility of cryptocurrencies and then estimates the correlations (Engle and Kelly, 2012).

3.1 Dynamic Equicorrelation Model

Let R_t be an n × 1 vector of cryptocurrency returns, i.e. $R_t = [R_{1t,}R_{2t}, \dots, R_{nt}]'$, assumed to have a normal distribution.

$$R_t | I_{t-1} \sim N(0, H_t) \tag{1}$$

According to Engle (2002), the conditional covariance matrix H_t can be decomposed as follows:

$$H_t = D_t R_t D_t \tag{2}$$

$$\varepsilon_t = H^{1/2} z_t \tag{3}$$

$$R_t = [diag(Q_t)^{-1/2}] Q_t [diag(Q_t)^{-1/2}] \tag{4}$$

where D_t is a diagonal matrix containing the conditional standard deviations from the univariate GARCH models, R_t corresponds to the time-varying conditional correlation matrix, ε_t is an n × 1 vector of conditional residuals based on information up to time *t-1*, z_t denotes an n × 1 vector of standardized residuals, and Q_t is the conditional correlation matrix of the standardized residuals.

In the first stage, it is necessary to estimate the matrix $D_t = diag\sqrt{\{H_t\}}$, a diagonal matrix with the conditional variances of each of the returns along the main diagonal. The elements of the matrix H_t are calculated using the following univariate GARCH (1,1) model:

$$h_{i,t} = \omega_i + \alpha_i \varepsilon_{i,t-1}^2 + \beta_i h_{i,t-1} \tag{5}$$

where $h_{i,t}$ corresponds to the conditional variance of each return series, ω_i is a constant term, α_i controls the ARCH effect, and β_i measures the persistence of the volatility process. To ensure that the conditional variances are positive and stable, the following conditions must be satisfied: $\alpha_i > 0$ and $\alpha_i + \beta_i < 1$. After estimating the univariate GARCH process, the standardized residuals z_t are used to estimate the parameters of the conditional correlation.

The dynamics of Q in the DCC process is given by:

$$Q_t = (1 - \theta_1 - \theta_2)\bar{Q} = \theta_1 z_{t-1} z'_{t-1} = \theta_2 Q_{t-1} \tag{6}$$

where θ_1, θ_2 and φ are parameters, $n_t = I(z_t < 0) \circ z_t$ is a functional indicator that takes the value 1 if the argument is true and 0 otherwise, and "○" denotes the Hadamard product.

$\bar{Q}_j = E[z_t z'_t]$ and $\bar{N}_j = E[n_t n'_t]$ are the unconditional correlation matrices of z_t and n_t, respectively.

The time-varying conditional correlation matrix R_t is given by:

$$R_t = Q_t^{*-1} Q_t Q_t^{*-1} \tag{7}$$

where Q_t^* is a diagonal matrix with the square root of the i-th diagonal of Q_t in the i-th position of its diagonal, and can be written in the following form:

$$R_t = \begin{pmatrix} 1 & \bar{\rho}_t & \cdots & \bar{\rho}_t \\ \bar{\rho}_t & 1 & \cdots & \bar{\rho}_t \\ \vdots & \vdots & \ddots & \vdots \\ \bar{\rho}_t & \bar{\rho}_t & \bar{\rho}_t & 1 \end{pmatrix}$$

or alternatively, in the following equivalent form,

$$R_t = (1 - \bar{\rho}_t) I_n + \bar{\rho}_t J_n \tag{8}$$

where I_n is the identity matrix of order n, J_n denotes the n-by- n matrix of ones, and $\bar{\rho}_t$ represents the equicorrelation given by:

$$\bar{\rho}_t = \frac{2}{n(n-1)} \sum_{i \neq j} \rho_{ij,t} = \frac{2}{n(n-1)} \sum_{i \neq j} \frac{q_{ij,t}}{\sqrt{q_{ii,t} q_{jj,t}}}. \tag{9}$$

The scalar DECO model is defined as follows:

$$Q_t = (1 - \alpha - \beta)\bar{Q} + \alpha e_{t-1} e'_{t-1} + \beta Q_{t-1} \tag{10}$$

By modeling the equicorrelation of returns in this way, we obtain a time series that can be used to determine the main factors that affect this equicorrelation. This analysis can be carried out using a multiple linear regression model, where these factors are included as explanatory variables:

$$Equicorrelation_t = b_0 + \sum_{i=1}^{n} b_i X_{i,t} + e_t \tag{11}$$

3.2 Data Description

The empirical study focused on the analysis of ten cryptocurrencies, namely Bitcoin, Dash, Dogecoin, Ether, Litecoin, Monero, Nem, Ripple, Stellar and Waves. The first and most well-known cryptocurrency, Bitcoin (BTC) operates on a decentralized network using blockchain technology. It serves as a peer-to-peer digital currency without the need for intermediaries. Dash (DASH), short for "digital cash," focuses on fast and private transactions. It offers features like PrivateSend and InstantSend, aiming to make cryptocurrency transactions both secure and quick. Originally started as a meme, Dogecoin (DOGE) has become a popular cryptocurrency. It features a Shiba Inu dog from the "Doge" meme and is often used for tipping and charitable donations. The native cryptocurrency of the Ethereum platform, Ether (ETH) is not just a digital currency but also fuels smart contracts and decentralized applications (DApps) within the Ethereum ecosystem. Created as the "silver to Bitcoin's gold," Litecoin (LTC) is a peer-to-peer cryptocurrency that offers faster transaction confirmation times. It shares many similarities with Bitcoin but with some technical differences. Monero (XMR) focuses on privacy and anonymity. It employs advanced cryptographic techniques to ensure private, untraceable transactions, making it a preferred choice for users seeking enhanced privacy. NEM (New Economy Movement) (XEM) is a blockchain platform that aims to provide customizable blockchain solutions. It offers features like the harvesting of coins and a unique consensus algorithm. Ripple (XRP) is both a cryptocurrency and a technology designed for seamless, fast, and cost-effective cross-border payments. It aims to facilitate international transactions between financial institutions. Stellar (XLM) is a decentralized platform designed to facilitate fast, low-cost cross-border payments and transactions. It aims to connect people, banks, and payment systems to make money more fluid. Waves (WAVES) is a blockchain platform that enables the creation and transfer of custom blockchain tokens. It emphasizes user-friendly token creation and decentralized exchange capabilities.

4. EMPIRICAL STUDY

4.1 Data Analysis

The empirical study focused on the analysis of ten cryptocurrencies, namely Bitcoin, Ether, Dash, Ripple, Stellar, Waves, Monero, Dogecoin, Litecoin, and Nem, as presented in Table no. 1. The daily prices of these cryptocurrencies were extracted from the website https://coinmarketcap.com/. These cryptocurrencies were chosen from the more than 13,000[10] virtual currencies existing in the cryptocurrency market, conditioned by the start of Ether's price history. The sample period spans from June 2nd, 2016, to May 25th, 2021, considering a relevant period of ups and downs in the cryptocurrency market. The empirical analysis was conducted using logarithmic returns multiplied by 100, resulting in a total of 1819 observations.

The plots in Figure no. 1 show the evolution of the price of the ten cryptocurrencies under study and the evolution of their returns. In March 2020, due to the COVID-19 pandemic, there was a noticeable decline in the returns of all cryptocurrencies. However, the market has shown the ability to recover quickly (Demiralay and Golitsis, 2021).

Table no. 1 – Cryptocurrencies used in the empirical study

Name	*Acronym*	*Cost (USD)*[11]	*Market capitalization (USD)*
Bitcoin	BTC	61,820.0	1.15T[12]
Dash[13]	DASH	198.41	2.03B
Dogecoin	DOGE	0.30	38.31B
Ether	ETH	2,431.70	281.36B[14]
Litecoin	LTC	318.37	21.21B
Monero[5]	XMR	271.74	4.89B
Nem[5]	XEM	0.2054	1.87B
Ripple	XRP	1.65	74.34B
Stellar	XLM	0.3744	47.87B
Waves[5]	WAVES	26.18	9.04B

Table no. 2 presents the statistical summary of daily returns of the ten cryptocurrencies in the considered period.

The ADF test was conducted with a constant and a lag length determined according to the autocorrelation plot, which is found in Appendix A. In this test, the null hypothesis assumes that the series is non-stationary. In this case, if the test statistic value is less than -2.86 (value for a sample size larger than 500), the null hypothesis is rejected. Looking at Table 2, we can see that the ADF test statistic value is always less than -2.86, thus rejecting the null hypothesis and concluding that the series is stationary.

The Jarque-Bera test is a statistical test that checks whether the sample data has symmetry and kurtosis similar to a normal distribution (null hypothesis: the data follows a normal distribution). The Jarque-Bera test statistics indicates that all return series are not normally distributed.

Table no. 2 – Statistical summary of daily returns and stationarity test.

	Mean	**Min.**	**Max.**	**SD**	**Asymmetry**[15]	**Kurtosis**[16]	**Jarque Bera**	**ADF Statistic**	**ARCH-LM p-value**
Bitcoin	0.235	-46.47	22.51	4.13	-0.80	11.88	10.915***	-44.0***	0.0000
Dash	0.175	-46.55	45.13	6.24	0.50	9.75	7,299.1***	-29.7***	0.0000
Dogecoin	0.402	-51.49	151.62	8.09	4.54	76.66	452,423***	-41.2***	0.0000
Ether	0.291	-55.07	29.01	5.73	-0.54	8.85	6,043.2***	-23.5***	0.0000
Litecoin	0.201	-44.90	51.03	5.96	0.37	11.20	9,563.1***	-43.5***	0.0000
Monero	0.307	-53.42	58.46	6.43	0.40	12.13	11,224***	-30.5***	0.0000
Nem	0.251	-42.27	99.54	7.66	1.80	22.11	38,090***	-32.6***	0.0000
Ripple	0.282	-61.64	102.75	7.44	2.09	32.39	80,962***	-43.8***	0.0000
Stellar	0.311	-41.00	72.32	7.83	1.88	16.33	21,317***	-29.0***	0.0000
Waves	0.143	-73.44	45.03	7.56	-0.70	11.51	10,220***	-42.0***	0.0000

Note: "***" indicates the rejection of the null hypothesis at the 0.1% level for both the Jarque-Bera normality test and the Augmented Dickey-Fuller unit root test.

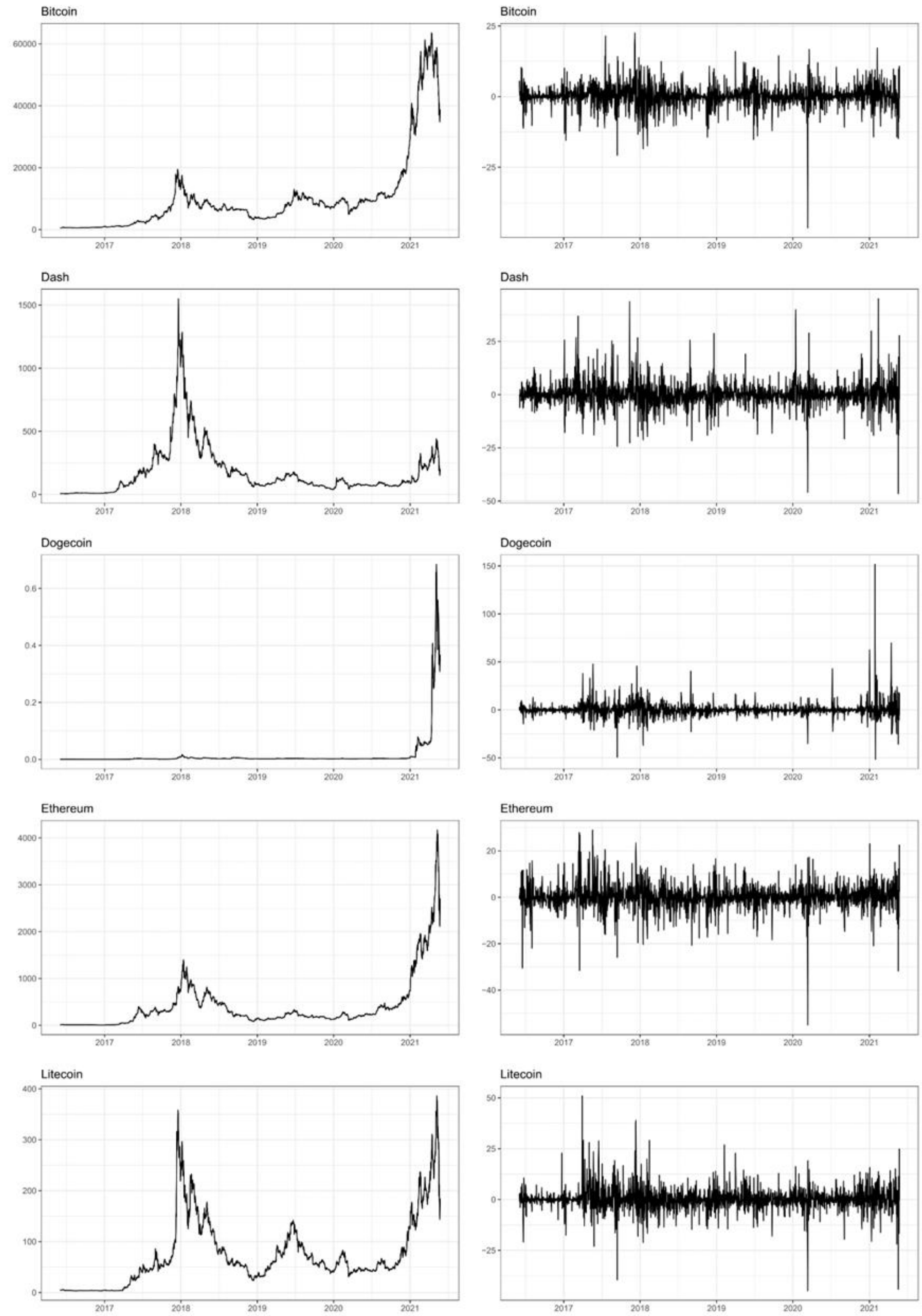


Figure no. 1 – Cryptocurrencies' price (on the left) and return (on the right)

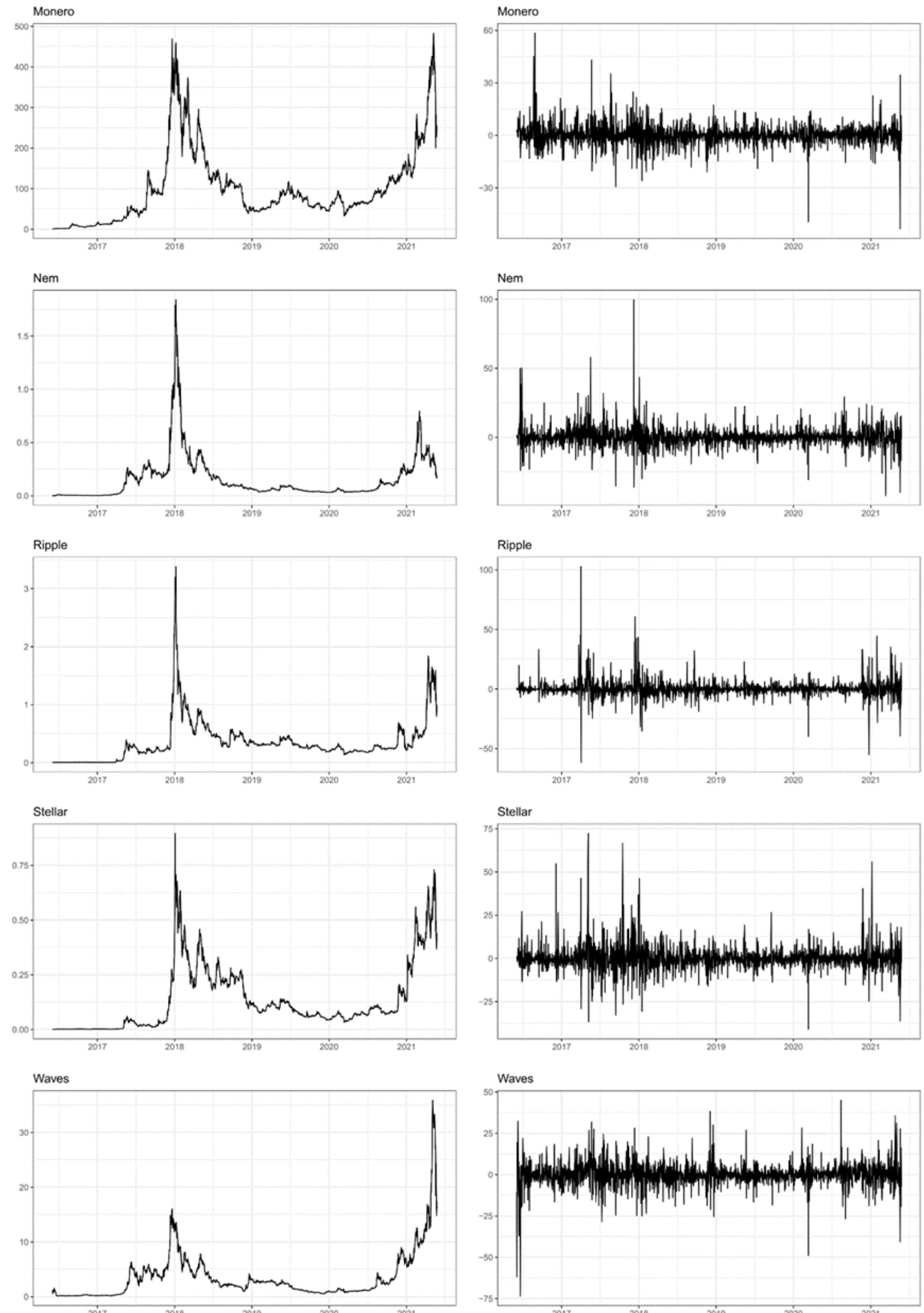


Figure 1 – Cryptocurrencies' price (on the left) and return (on the right) (*continued*)

The ARCH-LM test was used to test for the presence of heteroscedasticity. When the null hypothesis is rejected, which is the case here, it means there are no ARCH effects, indicating that heteroscedasticity was accounted for by the GARCH model.

We can observe that Dogecoin (DOGE) and Stellar (XLM) provide higher average returns compared to other cryptocurrencies. BTC is the least volatile, unlike DOGE, which is the most volatile. Analyzing the risk-adjusted return, we can see that DOGE and Stellar are more attractive, while Dash and Waves are less attractive. It is notable that the skewness values are mostly positive, indicating that nearly all cryptocurrencies exhibit positive skewness, except for BTC, Ether (ETH), and Waves. Lastly, it is worth mentioning that all return series have high kurtosis, especially DOGE.

Table no. 3 presents the Pearson correlation matrix of the returns for the ten cryptocurrencies studied, during the sampling period. We can observe a generally high linear association among the different cryptocurrencies. The correlations are positive and range from 0.3066 (Waves/Dogecoin) to 0.6776 (Litecoin/Bitcoin).

Table no. 3 – Correlation matrix of daily returns

	Bitcoin	Dash	Dogecoin	Ether	Litecoin	Monero	Nem	Ripple	Stellar	Waves
Bitcoin	1.0000									
Dash	0.5727	1.0000								
Dogecoin	0.4461	0.3645	1.0000							
Ether	0.6440	0.5931	0.4021	1.0000						
Litecoin	0.6776	0.5841	0.4541	0.6332	1.0000					
Monero	0.5984	0.6168	0.3631	0.5699	0.5646	1.0000				
Nem	0.4683	0.4490	0.3422	0.4819	0.4734	0.4326	1.0000			
Ripple	0.4039	0.3823	0.3558	0.4361	0.4691	0.3945	0.3960	1.0000		
Stellar	0.4550	0.4247	0.4153	0.4760	0.4832	0.4703	0.4784	0.6137	1.0000	
Waves	0.5032	0.4408	0.3066	0.4962	0.4830	0.4513	0.3584	0.3180	0.3805	1.0000

4.2 DECO Model Results

Table no. 4 presents the DECO model estimates for the returns of the ten cryptocurrencies. In the first step, the GARCH (1,1) model specified in Equation (5) was estimated for each return, while in the second step, the equicorrelation value was estimated using Equation (11).

Table no. 4 – DECO model estimates for cryptocurrency returns

Step II: DECO	α	β	
Returns	0.0223***	0.9717***	
Step I: GARCH(1,1)	ω	α	β
Bitcoin	0.7982**	0.1570***	0.8187***
Dash	2.0521***	0.2564***	0.7425***
Dogecoin	0.3936	0.0854***	0.9135***
Ether	2.7617***	0.1711***	0.7604***
Litecoin	1.5786	0.0738***	0.8855***
Monero	1.6844***	0.1523***	0.8276***
Nem	4.6333	0,3456	0.6533***
Ripple	4.4816**	0.4078***	0.5911***
Stellar	3.3766*	0.2312***	0.7492***
Waves	2.7221*	0.2717***	0.7241***
Log-likelihood	-51386.82		

Note: ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

The sum of the parameters α (0.0223) and β (0.9717) close to 1 suggests a high persistence of conditional covariance, which indicates a strong correlation between the cryptocurrencies and implies integrated equicorrelation. Additionally, both α and β parameters are statistically significant. Since this study focuses on equicorrelation, we will not delve into the coefficients of the GARCH model. However, it can be generally mentioned that they are positive and statistically significant.

Figure no. 2 displays the estimation results of the DECO model, representing the estimated correlation of returns over time. We can immediately conclude that the estimated equicorrelations are highly volatile and exhibit an increasing trend over time. Note that the term "equi" indicates that the correlation at each moment is equal to the average of all pairs of correlations. By averaging all pairs of correlations, the model assumes that the average correlation represents the global correlation. Between mid-2016 and late 2017, there is a decrease in cryptocurrency returns, which may have been influenced by the Bitfinex hack that occurred in August 2016 (Demiralay and Golitsis, 2021). However, in 2017, there is an upward trend until mid-2018. According to Demiralay and Golitsis (2021), the Coincheck hack occurred in January 2018, leading to an increase in correlation until mid-2018. Subsequently, there is another downward trend that extends until the beginning of 2020. In early 2020, there is a sharp increase, which could possibly be associated with speculative market movements, potentially related to the onset of the COVID-19 pandemic that disrupted the market. However, the market quickly realizes that it is an artificial surge and begins to correct. As a result, there is a sharp decline until the end of 2020. From 2021 onwards, a consistent recovery is observed until May 2021. Overall, there is a high correlation ranging between 0.2 and 0.8.

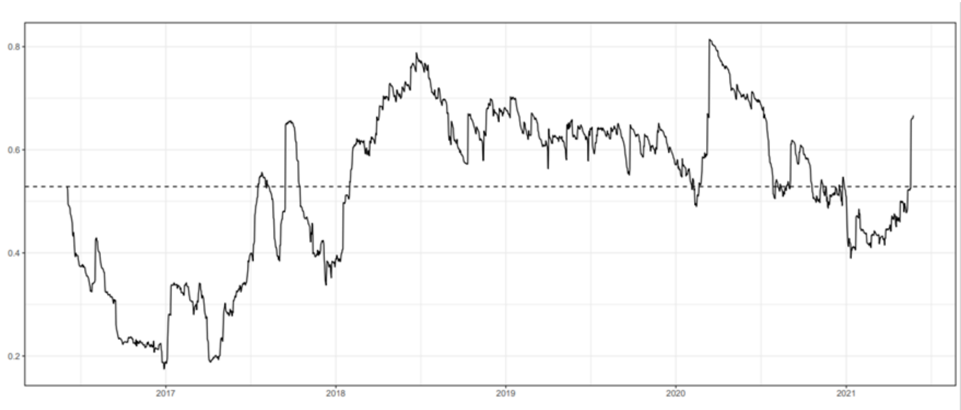


Figure no. 2 – Equicorrelation of returns

4.3 Determinants of the Equicorrelation

To investigate the main determinants/drivers of equicorrelation, a multiple linear regression model was estimated, incorporating several explanatory variables, namely: trading volume, global stock index, energy price, gold price, economic policy uncertainty, financial stress, and US implied volatility index. These variables were motivated by similar previous studies (Balcilar *et al.*, 2017).

$$Equicorrelation_t = b_0 + \sum_{i=1}^{10} b_i \ln(TV_{i,t}) + b_{11}GEI_t + b_{12}EN_t + b_{13}GLD_t + b_{14}EPU_t + b_{15}FSI_t + b_{16}VIX_t + e_t \quad (12)$$

where,

- TV (Trading Volume) represents the trading volume of each of the ten cryptocurrencies (i.e., the amount of assets traded daily).
- GEI (Global Equity Index) denotes the global stock index[17] (evaluated through theoretical portfolios of stocks). It is based on the performance of these stocks, which represent a significant portion of the stocks traded on a particular exchange, allowing the overall performance of the stock market to be measured. In summary, the global equity index serves as a basis for investors to analyze the performance of their business portfolio.
- EN (Energy Price) denotes the price of energy.
- GLD (Gold Price) denotes the price of gold.
- EPU (Economic Policy Uncertainty) denotes the uncertainty of economic policy.
- FSI (Financial Stress Index) denotes the implied volatility index of the United States.
- VIX (US Implied Volatility Index) corresponds to the financial stress index.

This data was extracted from the Thomson Reuters program. Unlike the trading volume of each of the ten cryptocurrencies, which is available daily, seven days a week, the global stock index, gold price, energy price, US implied volatility index, and financial stress index are only available for five days a week. To estimate the value of these variables on weekends, a simple linear interpolation method was used.

Table no. 5 presents the results of the least squares estimation of the equicorrelation's regression: considering all explanatory variables (Model 1); considering only the trading volume of each of the ten cryptocurrencies (Model 2); considering only global financial system indicators (Model 3).

As observed in Table no. 5, Model 1, which considers all explanatory variables, shows the highest Adjusted R-squared value. In this model, all cryptocurrencies are statistically significant at least at the 1% level, except for BTC, which is not statistically significant. The variables GEI, EN, GLD, EPU, FSI, and VIX are also statistically significant at least at the 5% level, which reinforces the findings of Bouri et al. (2021) that state the degree of integration among cryptocurrencies mainly depending on TV, EPU, and VIX. In contrast to Bouri *et al.* (2021), our study includes three additional statistically significant variables related to the financial market, namely GEI, EN, GLD, and FSI.

Trading volume is positively related to return equicorrelation for five out of the ten cryptocurrencies. The exceptions are DOGE, LTC, XMR, XEM, and XRP, where the relationship is negative. Thus, our study concludes that the degree of integration among cryptocurrencies primarily depends on trading volume, global stock index, energy price, gold price, financial stress index, and US implied volatility index. This result highlights a weakened association between the integration of the cryptocurrency market and the financial market. Stakeholders are being influenced by the volume traded between cryptocurrencies rather than economic factors such as EN and GLD.

Table no. 5 – Determinants of the returns' equicorrelation

	Model 1	Model 2	Model 3
ln(Bitcoin)	0.00735	0.05464***	
ln(Dash)	0.02310***	0.02350***	
ln(Dogecoin)	-0.01322***	-0.03640***	
ln(Ether)	0.05692***	0.04297***	
ln(Litecoin)	-0.01577***	-0.01808***	
ln(Monero)	-0.01471***	-0.05268***	
ln(Nem)	-0.01055***	-0.01693***	
ln(Ripple)	-0.01106**	-0.00192	
ln(Stellar)	0.01223***	0.01490***	
ln(Waves)	0.01936***	0.02067***	
GEI	-0.00201***		0.00050*
EN	0.02124***		0.03856***
GLD	0.00018***		0.00025***
EPU	0.00006*		0.00037***
FSI	0.03075***		0.01454***
VIX	-0.00270***		0.00662***
Constant	-0.61200***	-0.420539***	-0.70820***
Ajusted R^2	0.7518	0.6188	0.4597
F Statistic	344.9 (0,00000)	296.0 (0,00000)	258.7 (0,00000)

Note: Statistical significance level codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1.

The prices among cryptocurrencies are considerably correlated, but this correlation is not justified by economic factors. Instead, it is primarily driven by the trading volume of these cryptocurrencies, indicating a certain level of market maturity. It was surprising to find that the largest cryptocurrency, BTC, did not contribute to this conclusion. However, these results are explained by all other cryptocurrencies, namely DASH, DOGE, ETH, LTC, XMR, XEM, XRP, XLM, and WAVES.

4.4 Discussion

These findings align with and extend prior literature on the factors influencing the degree of integration among cryptocurrencies. Consistent with the work of Bouri *et al.* (2021), our study underscores the significance of certain key variables in understanding cryptocurrency market integration. Specifically, the inclusion of trading volume, global stock index, energy prices, gold prices, financial stress index, and US implied volatility index as statistically significant factors supports and expands upon the observations made by Bouri *et al.* (2021). In comparison to Bouri *et al.* (2021), our study introduces three additional variables – GEI, EN, and GLD – that exhibit statistical significance, contributing to a more comprehensive understanding of the factors influencing cryptocurrency integration. The positive relationship between trading volume and return equicorrelation for the majority of cryptocurrencies is consistent with the notion that heightened trading activity plays a pivotal role in fostering integration. This finding resonates with prior literature emphasizing the influence of trading volume on market dynamics and inter-asset correlations. Surprisingly, the negative relationship observed in certain cryptocurrencies (DOGE, LTC, XMR, XEM, and XRP) suggests nuanced variations in integration dynamics. This highlights the importance of considering individual cryptocurrency characteristics and behaviors within the broader market context. The conclusion that the correlation among cryptocurrency prices is primarily driven by trading volume rather than economic factors, such as EN and GLD, aligns with existing research emphasizing the distinctive nature of cryptocurrency markets. The unexpected non-significance of BTC in contributing to this conclusion adds an intriguing dimension to the discussion. While BTC is traditionally considered a market leader, its limited influence in this context may indicate that other cryptocurrencies, each with unique attributes, collectively play a more prominent role in determining market correlations. This nuanced insight challenges conventional assumptions and underscores the need for a nuanced understanding of the diverse factors at play in the cryptocurrency landscape. In summary, our results not only confirm but also extend the existing literature on cryptocurrency market integration. The inclusion of additional significant variables and the nuanced relationship between trading volume and correlations contribute to a more comprehensive understanding of the complex dynamics within the cryptocurrency market.

The implications of our findings hold significant relevance for both investors and policymakers in the cryptocurrency space, offering insights that can guide strategic decisions and regulatory considerations. The observed positive relationship between trading volume and return equicorrelation suggests that investors may benefit from diversifying their portfolios based on trading activity. A nuanced understanding of how various cryptocurrencies respond to trading volume can inform investment strategies, allowing investors to optimize risk and return profiles. The finding that price correlations among cryptocurrencies are primarily driven by trading volume rather than economic factors implies a certain level of market maturity. Investors can use this insight to gauge the maturity and stability of the cryptocurrency market, potentially influencing their confidence in allocating assets to this evolving space. The nuanced variations in the relationship between trading volume and correlations for specific cryptocurrencies (DOGE, LTC, XMR, XEM, and XRP) highlight the importance of considering individual cryptocurrency behaviors. Investors may benefit from a tailored approach, taking into account the unique characteristics of each cryptocurrency when constructing their portfolios. Understanding that trading volume plays a central role in driving correlations among cryptocurrencies emphasizes the need for regulators to monitor and potentially regulate trading activities. Policymakers could explore measures to ensure fair and transparent trading practices, mitigating potential risks associated with excessive trading volumes. The observed correlation dynamics provide insights into the factors influencing market stability. Policymakers can use this information to design interventions or measures that enhance market stability, potentially minimizing the impact of extreme price movements and ensuring a more resilient cryptocurrency market. Policymakers could also initiate educational programs to inform investors about the nuanced relationship between trading volume and correlations. This could contribute to a more informed investor base, fostering responsible investment practices and reducing the likelihood of market disruptions driven by uninformed trading behavior.

5. CONCLUSIONS

The present study aimed to assess the integration of cryptocurrencies in the financial market using a dynamic equicorrelation model. The DECO model was applied to ten cryptocurrencies that have significant market value, namely: BTC, ETH, Dash, XRP, XLM, Waves, XMR, DOGE, LTC, and XEM. Among these, DOGE and XLM exhibited higher average returns. BTC was found to be the least volatile, while DOGE was the most volatile.

Through the analysis of daily return statistical summaries and stationarity tests, several conclusions were drawn: (1) the ADF test rejected the null hypothesis, indicating that the return series are stationary; (2) the Jarque Bera test indicated that the returns do not follow a normal distribution; (3) the ARCH-LM test confirmed the presence of heteroscedasticity in the daily returns.

Regarding the results of the DECO model for cryptocurrency returns, it was observed that there is a high persistence of conditional covariance, indicating a strong correlation among them and suggesting integrated equicorrelation. The empirical analysis of return equicorrelation revealed a positive correlation ranging between 0.2 and 0.8, which varies over time and is generally considerably high. The estimated equicorrelations exhibited some oscillations caused by hacking attacks, such as the Bitfinex hack in August 2016, the Coincheck hack in January 2018, and the bans imposed by the Chinese and Indian governments on cryptocurrency operations. All these factors had an impact on the cryptocurrency market.

Determining the factors influencing return’s equicorrelation, various potential drivers were studied, and the results were consistent with those of a study conducted by Bouri *et al.* (2021). It was concluded that the degree of integration between cryptocurrencies primarily depends on trading volume, global stock indices, energy prices, gold prices, financial stress index, and the implied volatility index of the United States. It was found that the cryptocurrency market is not strongly linked to the behavior of the overall financial market but is primarily influenced by transaction volume among cryptocurrencies. It was also observed that prices among cryptocurrencies are highly correlated, which is not explained by economic factors but rather by the volume of transactions, indicating a certain level of maturity in the cryptocurrency market.

It is worth mentioning that cryptocurrencies and blockchain technology have attracted more interest from industry and investment sectors than from academia. Consequently, blockchain technology is one of the few areas of research and investigation led by industry professionals and investors, with few academic works on the subject (Rehman *et al.*, 2020).

For future research, it would be important to understand the driving factor behind the nearly 50% devaluation of the BTC cryptocurrency between April and May 2021. Speculation suggests that this decline in value occurred after Tesla's CEO, Elon Musk, expressed doubts about this asset. Musk had announced that he would suspend the decision, previously announced in March, to accept BTC as a means of payment for Tesla electric cars due to environmental concerns. The reason behind this decision was Musk's realization that BTC consumes a significant amount of energy, much of which comes from fossil fuels. Following this news, there was an immediate impact on the BTC price, leading to a substantial devaluation in a short period of time. However, there is no scientific research that confirms this claim, so it is important to investigate the reasons behind this abrupt decline in BTC. It would also be interesting to investigate the significant price increase in the Dash cryptocurrency between late 2017 and early 2018. There are rumors that the main reason for this price appreciation during that period was the launch of Dash Text[18] in Venezuela, but there is no scientific evidence to support this claim.

References

Aboura, S., & Chevallier, J. (2014). Volatility Equicorrelation: A Cross-m+Market Perspective. *Economics Letters, 122*(2), 289-295. http://dx.doi.org/10.1016/j.econlet.2013.12.008

Adams, J. (2021). Ripple's Blueprint to Modernize Europe's Payments Infrastructure(August). Retrieved from https://www.americanbanker.com/payments/news/ripples-blueprint-to-modernize-europes-payments-infrastructure

Amoza, G., Mercant, S., Presno, N., & Sarto, P. (2014). Características de bitcoin. *IEEM Revista de Negócios, 61*.

Andriole, S. J. (2020). Blockchain, Cryptocurrency, and Cybersecurity. IT Professional. *IT Professional, 22*(1), 13-16. http://dx.doi.org/10.1109/MITP.2019.2949165

Balcilar, M., Bouri, E., Gupta, R., & Roubaud, D. (2017). Can Volume Predict Bitcoin Returns and Volatility? A Quantiles-Based Approach. *Economic Modelling, 64*(August), 74-81. http://dx.doi.org/10.1016/j.econmod.2017.03.019

Bistarelli, S., Mazzante, G., Micheletti, M., Mostarda, L., Sestili, D., & Tiezzi, F. (2020). Ethereum Smart Contracts: Analysis and Statistics of Their Source Code and Opcodes. *Internet of Things : Engineering Cyber Physical Human Systems, 11*(September), 100198. http://dx.doi.org/10.1016/j.iot.2020.100198

Boiko, V., Tymoshenko, Y., Kononenko, A., Rusina, Y., & Goncharov, D. (2021). The Optimization of the Cryptocurrency Portfolio in View of the Risks. *Journal of Management Information & Decision Sciences, 24*(4), 1-9.

Borri, N., & Shakhnov, K. (2020). Regulation Spillovers Across Cryptocurrency Markets. *Finance Research Letters, 36*(October), 101333. http://dx.doi.org/10.1016/j.frl.2019.101333

Bouri, E., Vo, X. V., & Saeed, T. (2021). Return Equicorrelation in the Cryptocurrency Market: Analysis and Determinants. *Finance Research Letters, 38*(January), 101497. http://dx.doi.org/10.1016/j.frl.2020.101497

Brito, J., & Castillo, A. (2013). Bitcoin: A Primer for Policymakers. *Policy, 29*(4), 3-12.

Case, C. J., King, D. L., & Case, J. A. (2020). Blockchain: An Empirical Review of Fortune 500 Website Postings and Usage. *Journal of Business & Behavioral Sciences, 32*(2), 42-52.

Charfeddine, L., Benlagha, N., & Khediri, K. B. (2022). An Intra-Cryptocurrency Analysis of Volatility Connectedness and Its Determinants: Evidence from Mining Coins, Non-Mining Coins and Tokens. *Research in International Business and Finance, 62*(December), 101699. http://dx.doi.org/10.1016/j.ribaf.2022.101699

Ciaian, P., Rajcaniova, M., & Kancs, A. (2016). The Economics of BitCoin Price Formation. *Applied Economics, 48*(19), 1799-1815. http://dx.doi.org/10.1080/00036846.2015.1109038

Correas, J., Gordillo, P., & Roman-Diez, G. (2021). Static Profiling and Optimization of Ethereum Smart Contracts Using Resource Analysis. *IEEE Access : Practical Innovations, Open Solutions, 9*(February), 25495-25507. http://dx.doi.org/10.1109/ACCESS.2021.3057565

Demiralay, S., & Golitsis, P. (2021). On the Dynamic Equicorrelations in Cryptocurrency Market. *The Quarterly Review of Economics and Finance, 80*(May), 524-533. http://dx.doi.org/10.1016/j.qref.2021.04.002

Duong, L. V. T., Thuy, N. T. T., & Khai, L. D. (2020). A Fast Approach for Bitcoin Blockchain Cryptocurrency Mining System. *Integration 74*(September), 107-114. http://dx.doi.org/10.1016/j.vlsi.2020.05.003

Engle, R. (2002). Dynamic Conditional Correlation: A Simple Class of Multivariate Generalized Autoregressive Conditional Heteroskedasticity Models. *Journal of business & economic statistics, 20*(3), 339-350. http://dx.doi.org/10.1198/073500102288618487

Engle, R., & Kelly, B. (2012). Dynamic Equicorrelation. *Journal of business & economic statistics, 30*(2), 212-228. http://dx.doi.org/10.1080/07350015.2011.652048

Ferreira, J., Pinto, F. G. C., & dos Santos, S. C. (2017). Estudo de Mapeamento Sistemático Sobre as Tendências e Desafios do Blockchain. *Revista Eletrónica de Gestão Organizacional, 15*(6), 108-117. http://dx.doi.org/10.21714/1679-18272017v15Ed.p108-117

Hanif, W., Ko, H. U., Pham, L., & Kang, S. H. (2023). Dynamic Connectedness and Network in The High Moments of Cryptocurrency, Stock, and Commodity Markets. *Financial Innovation, 9*(1), 1-40. http://dx.doi.org/10.1186/s40854-023-00474-6

Hasan, M., Naeem, M. A., Arif, M., Shahzad, S. J. H., & Vo, X. V. (2022). Liquidity Connectedness in Cryptocurrency Market. *Financial Innovation, 8*(3), 1-25. http://dx.doi.org/10.1186/s40854-021-00308-3

Jeff, J. R. (2020). Ripple Says It Will be Sued by the SEC, in what the Company Calls a Parting Shot at the Crypto Industry(December). Retrieved from https://fortune.com/2020/12/21/ripple-to-be-sued-by-sec-cryptocurrency-xrp/

Karaömer, Y. (2022). The Time-Varying Correlation between Cryptocurrency Policy Uncertainty and Cryptocurrency Returns. *Studies in Economics and Finance, 39*(2), 297-310. http://dx.doi.org/10.1108/SEF-10-2021-0436

Kauflin, J. (2014). *The Ripple Effect*.

Kumar, A., Iqbal, N., Mitra, S. K., Kristoufek, L., & Bouri, E. (2022). Connectedness among Major Cryptocurrencies in Standard Times and During the COVID-19 Outbreak. *Journal of International Financial Markets, Institutions and Money, 77*(March), 101523. http://dx.doi.org/10.1016/j.intfin.2022.101523

Leising, M., & Robinson, E. (2018). *All Eyes on Ripple*: But What Is It.

Łęt, B., Sobański, K., Świder, W., & Włosik, K. (2023). What Drives the Popularity of Stablecoins? Measuring the Frequency Dynamics of Connectedness between Volatile and Stable Cryptocurrencies. *Technological Forecasting and Social Change, 189*(April), 122318. http://dx.doi.org/10.1016/j.techfore.2023.122318

Li, W., & He, M. (2020). *Comparative Analysis of Bitcoin, Ethereum, and Libra.* Paper presented at the International Conference on Software Engineering and Service Science Beijing.

Lin, D., Wu, J., Yuan, Q., & Zheng, Z. (2020). Modeling and Understanding Ethereum Transaction Records via a Complex Network Approach. IEEE Transactions on Circuits and Systems II: Express Briefs. *IEEE Transactions on Circuits and Systems II: Express Briefs, 67*(11), 2737-2741.

Lucas, B., & Paez, R. V. (2019). *Consensus Algorithm for a Private Blockchain*. Paper presented at the International Conference on Electronics Information and Emergency Communication, Beijing.

Ma, Y., Ahmad, F., Liu, M., & Wang, Z. (2020). Portfolio Optimization in the Era of Digital Financialization Using Cryptocurrencies. *Technological Forecasting and Social Change, 161*(December), 120265. http://dx.doi.org/10.1016/j.techfore.2020.120265

McKay, D. R., & Peters, D. A. (2018). Digital Gold: A Primer on Cryptocurrency. *Plastic Surgery (Oakville, Ont.), 26*(2), 137-138. http://dx.doi.org/10.1177/2292550318777228

Mensi, W., Al-Yahyaee, K. H., & Kang, S. H. (2019). Structural Breaks and Double Long Memory of Cryptocurrency Prices: A Comparative Analysis from Bitcoin and Ethereum. *Finance Research Letters, 29*(C), 222-230. http://dx.doi.org/10.1016/j.frl.2018.07.011

Nakamato, S. (2009). Bitcoin: A Peer-to-Peer Electronic Cash System. *SSRN Electronic Journal*, 1-9. Retrieved from https://metzdowd.com

Padmavathi, M., & Suresh, R. M. (2019). Secure P2P Intelligent Network Transaction using Litecoin. *Mobile Networks and Applications, 24*(2), 318-326. http://dx.doi.org/10.1007/s11036-018-1044-9

Paulino, I. V., & Mendonça, A. (2019). As “Criptomoedas” : Desafios à Regulação. Retrieved from

Poongodi, M., Sharma, A., Vijayakumar, V., Bhardwaj, V., Sharma, A. P., Iqbal, R., & Kumar, R. (2020). Prediction of the Price of Ethereum Blockchain Cryptocurrency in an Industrial Finance System. *Computers & Electrical Engineering, 81*(January), 106527. http://dx.doi.org/10.1016/j.compeleceng.2019.106527

Prybila, C., Schulte, S., Hochreiner, C., & Weber, I. (2020). Runtime Verification for Business Processes Utilizing the Bitcoin Blockchain. *Future Generation Computer Systems, 107*(June), 816-831. http://dx.doi.org/10.1016/j.future.2017.08.024

Rehman, M. H., Salah, K., Damiani, E., & Svetinovic, D. (2020). Trust in Blockchain Cryptocurrency Ecosystem. *IEEE Transactions on Engineering Management, 67*(4), 1196-1212. http://dx.doi.org/10.1109/TEM.2019.2948861

Rella, L. (2020). Steps towards an Ecology of Money Infrastructures: Materiality and Cultures of Ripple. *Journal of Cultural Economics, 13*(2), 236-249. http://dx.doi.org/10.1080/17530350.2020.1711532

Rudkin, S., Rudkin, W., & Dłotko, P. (2023). On the Topology of Cryptocurrency Markets. *International Review of Financial Analysis, 89*(October), 102759. http://dx.doi.org/10.1016/j.irfa.2023.102759

Saito, K., & Iwamura, M. (2018). How to Make a Digital Currency on a Blockchain Stable. *Future Generation Computer Systems, 100*(January), 58-69. http://dx.doi.org/10.1016/j.future.2019.05.019

Silva, W., Martins, N., Miranda, I., Penha, R., & Reina, D. (2020). Cryptocurrencies and Finance: The Relationship between the Return of Bitcoin and the Main Digital Currencies. . *Brazilian Journal of Management / Revista de Administração da UFSM, 13*(2), 394-407. http://dx.doi.org/10.5902/1983465930491

Staderini, M., Palli, C., & Bondavalli, A. (2020). *Classification of Ethereum Vulnerabilities and Their Propagations.* Paper presented at the Second International Conference on Blockchain Computing and Applications (BCCA).

Tu, Z., & Xue, C. (2019). Effect of Bifurcation on the Interaction between Bitcoin and Litecoin. *Finance Research Letters, 31*(December). http://dx.doi.org/10.1016/j.frl.2018.12.010

Wątorek, M., Kwapień, J., & Drożdż, S. (2023). Cryptocurrencies are Becoming Part of the World Global Financial Market. *Entropy (Basel, Switzerland), 25*(2), 377. http://dx.doi.org/10.3390/e25020377

Yelamanchili, R. K. (2021). Stock Market Returns, Data Frequency, Time Horizon, Return Distribution Density and GARCH Models. *IUP Journal of Applied Economics, 20*(1), 29-46.

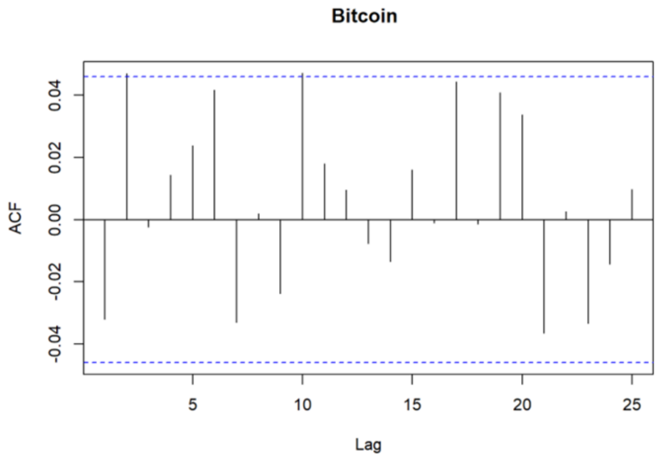
Zaghloul, E., Li, T., Mutka, M. W., & Ren, J. (2020). Bitcoin and Blockchain: Security and Privacy. *IEEE Internet of Things Journal, 7*(10), 10288-10313. http://dx.doi.org/10.1109/JIOT.2020.3004273

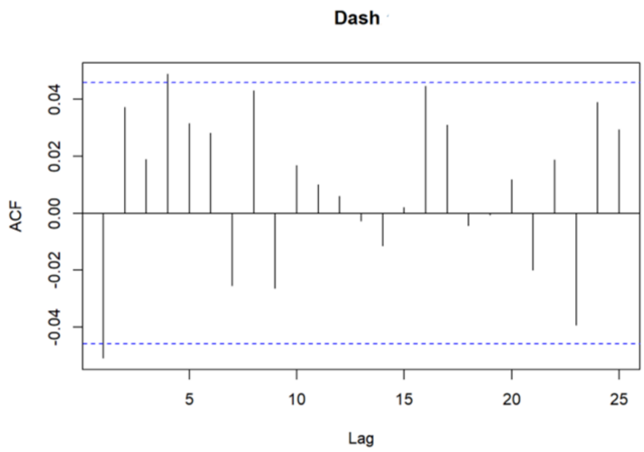
Zhang, S., & Gregoriou, A. (2020). The Price and Liquidity Impact of China Forbidding Initial Coin Offerings on the Cryptocurrency Market. *Applied Economics Letters, 27*(20), 1695-1698. http://dx.doi.org/10.1080/13504851.2020.1713979

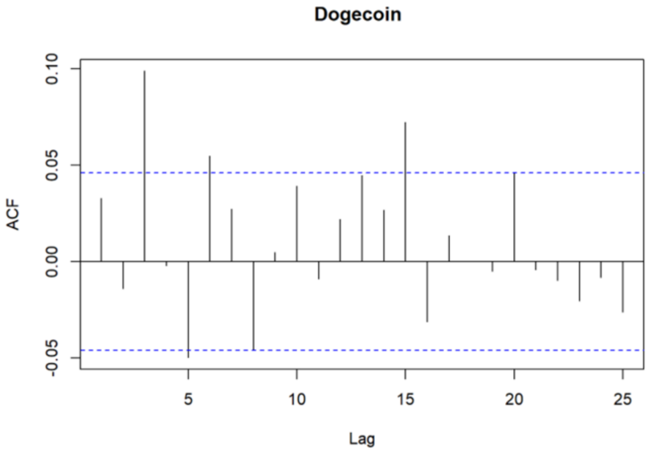
Zhang, Z., Yin, J., Liu, Y., & Liu, J. (2020). *Deanonymization of Litecoin through Transaction-Linkage Attacks.* Paper presented at the International Conference on Information and Communication Systems.

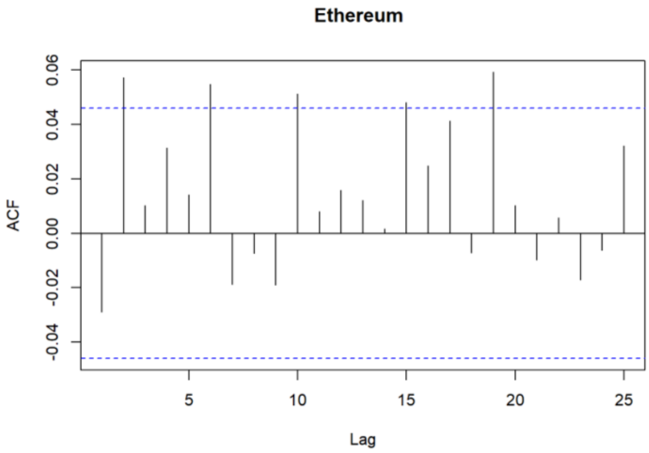
ANNEX

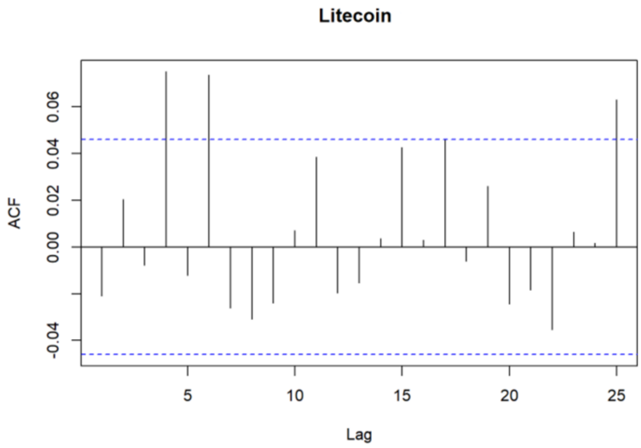
Autocorrelation function of cryptocurrencies return

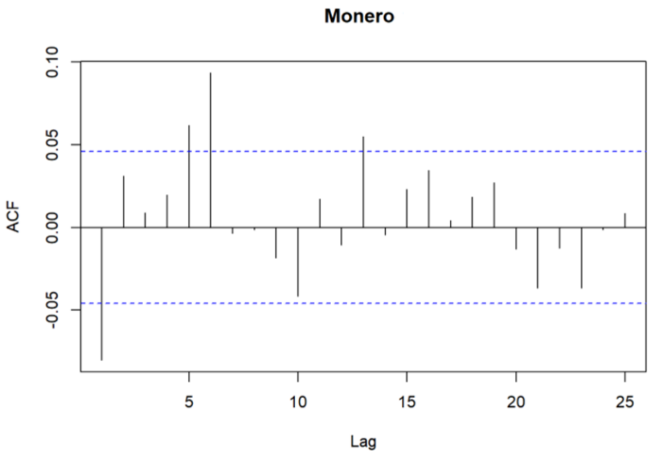


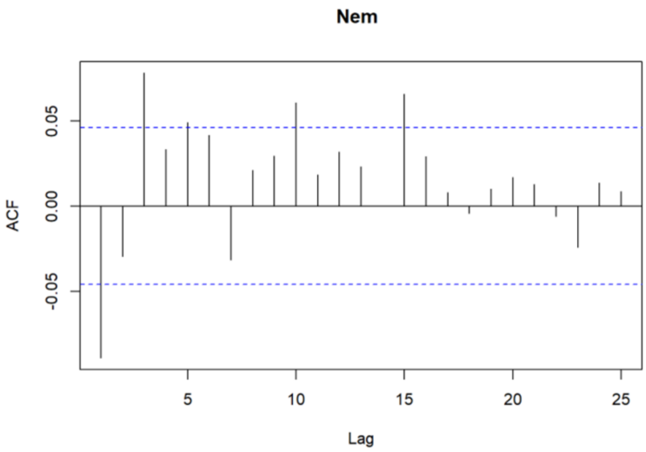


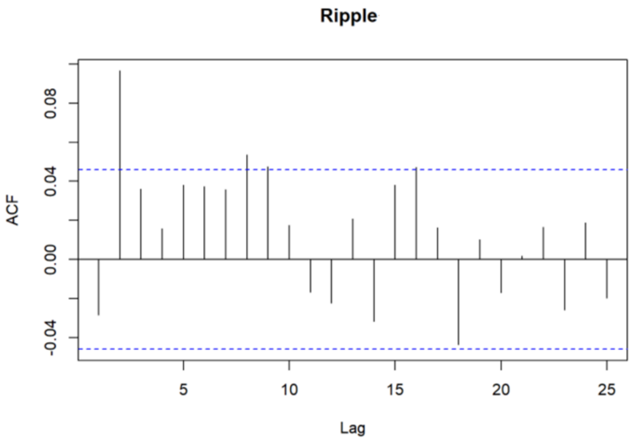

Dogecoin
ACF
0.10
0.05
0.00
-0.05
5
10
15
20
25
Lag

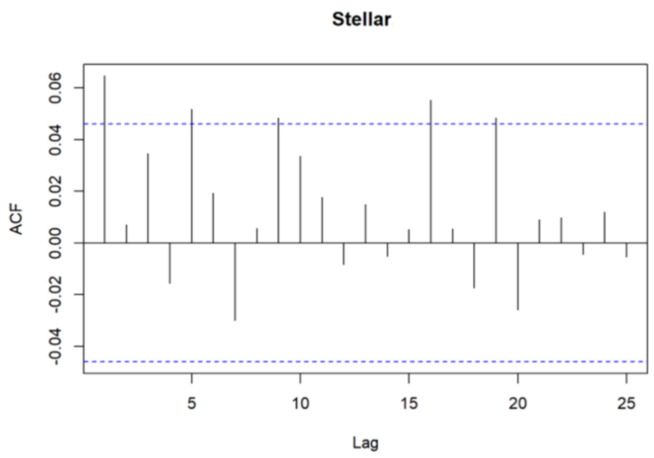

Ethereum
ACF
0.06
0.04
0.02
0.00
-0.02
-0.04
5
10
15
20
25
Lag

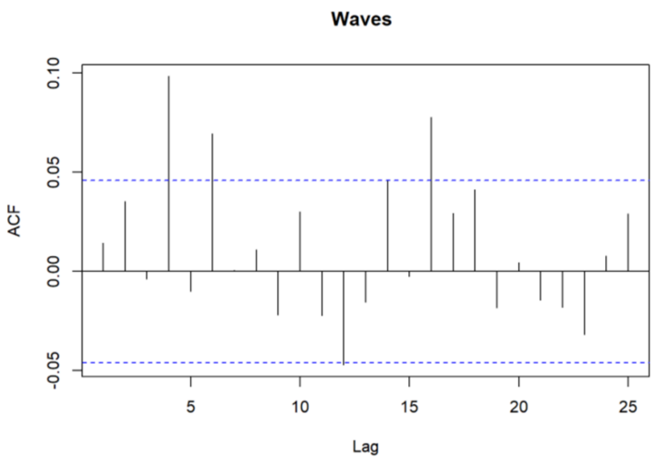

Litecoin
ACF
0.06
0.04
0.02
0.00
-0.04
5
10
15
20
25
Lag


Monero
ACF
0.10
0.05
0.00
-0.05
5
10
15
20
25
Lag


Nem
ACF
0.05
0.00
-0.05
5
10
15
20
25
Lag


Ripple
ACF
0.08
0.04
0.00
-0.04
5
10
15
20
25
Lag





Notes

[1] Consulted on https://pt.investing.com/crypto/currencies on January 10th, 2021.

[2]The blockchain is a public ledger that stores all transactions since the creation of BTC (Prybila *et al.*, 2020).

[3]The mining algorithm translates into a process that keeps the BTC network stable and secure by adding newly validated blocks to the blockchain (Duong *et al.*, 2020).

[4]Global: Another Cryptocurrency Causes Ripples. Stratfor Geopolitical Diary, Dec 2017. http://search.ebscohost.com/login.aspx?direct=true&db=bth&AN=127187235&site=eds-live, consulted on March 19, 2021.

[5]Distinct currencies refer to the fact that a user can transfer, for example, dollars through XRP, and the recipient receives the value in euros.

[6] These are digital assets that can be used within a set of interdependent relationships within a specific project. While tokens utilize the blockchain of other currencies, cryptocurrencies have their own blockchain.

[7] It consists of a messaging system that informs banks where to send the money. It also includes a service that assists banks in settling transactions.

[8] Value consulted on the website https://pt.investing.com/crypto/ on March 13th, 2021.
[9] It is named as such due to its structure.
[10] As of October 27th, 2021, the website https://coinmarketcap.com/ listed a total of 13,242 virtual currencies.
[11] The cost value was obtained from the website https://pt.investing.com/crypto/currencies, accessed on April 17th, 2021 at 11:39 AM. The cryptocurrencies are highly volatile and due to their high number of transactions, the cost value is constantly changing. The USD used is the US dollar.
[12] 1 T = one billion of US dollars.
[13] The cost and market capitalization values of the cryptocurrencies Dash, Waves, Monero, and Nem were extracted on August 14th, 2021, at 16:24.
[14] 1 B = one thousand million US dollars.
[15] Skewness is the degree of deviation that a distribution exhibits from its axis of symmetry. If this deviation occurs on the left side, it is negative skewness, and if the deviation occurs on the right side, it is positive skewness.
[16] Kurtosis is a measure of dispersion that characterizes the "flattening" of the curve of the distribution function.
[17]Information consulted on https://www.moneytimes.com on October 5th, 2021, at 17:40.
[18] Dash Text is a Venezuelan platform that enables cryptocurrency transactions based on SMS. In other words, this application eliminates the need for users to have more sophisticated mobile phones with internet access to carry out their cryptocurrency transactions. With this application, users can transact, receive, and check the available balance of their business wallet via SMS.