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Proceedings of the 5th International Conference on Economics and Social Sciences (2022), ISSN 2704-6524, pp. 797-806

The 5th International Conference on Economics and Social Sciences
Fostering recovery through metaverse business modelling
June 16-17, 2022
Bucharest University of Economic Studies, Romania

Cryptocurrencies in the Digital Era. Composite Index-Based Analysis for the Top Ten Virtual Currencies Traded

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DOI: 10.2478/9788367405072-075

Abstract

Virtual currencies represent a new alternative to payment that ensure secure financial transactions within a decentralized system. The basis of cryptocurrencies is represented by the innovative and revolutionary Blockchain technology or the DLT (Distributed Ledger Technology), which in recent years has captured the attention of researchers and practitioners. This paper aims to conduct a relevant analysis of the cryptocurrency market, considering the top ten digital currencies in terms of market capitalization. At the same time, we took into account the launching year of the selected virtual currencies, having as a benchmark the year 2017 in order to ensure a data set as comprehensive as possible. The authors' contribution is brought about by the construction of a composite index to synthesize the performance of the studied cryptocurrencies, the index being designed using the returns and traded volumes associated with each cryptocurrency. The correlations between the indicators will be studied, along with the exploration of the Granger causality between the variables. The paper is structured as follows: In the first part, there is a brief introduction in the sphere of the studied problem, later being presented the current state of knowledge in the field. The study continues with the statement of the purpose and hypotheses of the research, with the presentation of the research methods used, and with the illustration of the main results of the research. The study is completed by the main conclusions drawn and the bibliographical references.

Keywords: cryptocurrency market, Blockchain, composite index, Granger causality, correlation analysis.

JEL Classification: C22, C87, E59, G29.

1. Introduction

Digital currencies are a new type of currency, their foundation being represented by Blockchain technology. Both cryptocurrencies and Blockchain technology are an extremely interesting and attractive topic for both investors and the scientific and

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academic communities. The first virtual currency launched is the famous Bitcoin, which benefits from the Blockchain infrastructure and design. At the same time, Bitcoin is the most popular digital currency and is considered the leader of the cryptocurrency market. The inventor of Bitcoin is considered to be a certain Satoshi Nakamoto (2008), seen either as an individual or as a group of people who collaborated in order to lay the foundations of this digital currency. Although its popularity has grown exponentially in recent years, and its applications in various fields have multiplied rapidly, Blockchain technology is still a novelty for most people. Many researchers already believe that Blockchain technology could soon become part of our daily routine, comparing it to paradigms and technological innovations that have changed our lives: the Internet, computers, the emergence of cars and aircrafts, and so on (Gupta, 2017; Richards, 2019). Thus, Blockchain technology is perceived as a radical innovation with high beneficial potential for many industries and ensures the efficiency of the security, costs, or processing speed of various transactions. Areas in which this technology has already been successfully implemented include management, supply chains, health, insurance, or even government projects and public institutions.

The emergence of Blockchain technology has brought together the focus and research of groups working in distinct but interdependent fields, referring here to mathematicians, computer scientists or cryptographers. Obtaining cryptocurrencies is ensured by performing a process known as mining. Initially, this procedure could be performed using simple desktops or computer processing units (Connolly, Kick, 2015), but later, more powerful tools were needed to produce virtual currencies, such as Application Specific Integrated Circuit (ASIC).

2. Problem Statement

Interest in the cryptocurrency market has intensified in recent years with the expansion of this sector. The market capitalization of the traded currencies reached in April 2022 approximately 1.8 trillion USD dollars. A large number of scientific papers are focusing on research and development methods to ensure a better understanding over the dynamics of the digital currency market.

Bitcoin is the most popular electronic payment alternative that does not require the involvement of a third party in conducting transactions. Using specific cryptographic tools, the fully decentralized payment system associated with Bitcoin ensures that the problem of double spending is avoided. The operability of cryptocurrencies is based on the innovative Blockchain technology. This technology is actually a distributed ledger, and within it all transactions are recorded in chronological order and ensure the execution of transactions without the involvement of financial intermediaries (Aalborg et al., 2019).

Regarding Bitcoin, there are distinct visions. On the one hand, it is seen as an extremely safe and profitable asset, with some researchers even calling it "digital gold". On the other hand, Bitcoin is seen as a speculative bubble or even a Ponzi scheme. Many research papers are focused on forecasting the prices of digital currencies using time series analysis (Phillips, Gorse, 2018; Bartolucci et al., 2019;).

Modern machine learning algorithms (Jing-Zhi, William, 2018) and artificial neural networks (Lahmiri, 2019) represent other innovative techniques used to explore the prices of virtual currencies.

Cryptocurrencies are characterized by extremely high volatility, which has been investigated with great interest by academics, who have repeatedly tried to identify the causes and determinants of this pronounced volatility (Katsiampa, 2017; Lahmiri, Bekiros, Salvi, 2018). There is strong evidence that issues such as global economic activity and trading volume significantly impact the evolution of cryptocurrency prices (Walther, Klein, Bouri, 2019; Bouri et al., 2019).

Uras and Ortu (2021) study Bitcoin price movements using machine learning techniques such as SVM, XGBoost or artificial neural networks such as CNN or LSTM. They also analyze whether the inclusion of technical indicators in the models, other than the classic macroeconomic variables, contributes to the improvement of the Bitcoin price prediction. Other aspects studied regarding cryptocurrencies include their fractal pattern (Stosic et al., 2019; Ferreira et al., 2020), but also the correlation between them (Drozdz et al., 2018; Watorek et al., 2020).

The study of the cryptocurrency market in the context of the COVID-19 pandemic has been a topic of great interest to the academic community, along with the financial contagion and the stability of financial markets (Zhang, Hu, Ji, 2020; Zaremba et al. 2020; Okorie, Lin, 2020; Lahmiri, Bekiros, 2020).

Bălă and Stancu (2021) study the evolution of the top five cryptocurrencies according to the market capitalization over the period 2017-2021. They analyze the existence of cointegration of digital asset prices and note that this is not present in the data set. The methodology used is that of the VECM and Granger causality testing. Their evidence indicates significant two-way influences between Bitcoin and Binance, Dogecoin and Binance, but also Bitcoin and Ethereum, and the fact that cryptocurrencies such as Ethereum or Dogecoin are more likely to be significantly affected by possible shocks to the cryptocurrency market. Another area explored with interest by researchers is that of the link between public opinion and the evolution of the cryptocurrency market. More specifically, a technique often used in this direction is the sentiment analysis.

The relationship between digital asset price dynamics and investor sentiment is studied by Smales (2022). The more pronounced the interest in certain digital assets, the higher the returns recorded by them. On the other hand, uncertainty regarding the crypto market negatively impacts the evolution of digital currencies. Shahzad, Anas and Bouri (2022) examine the correlation between Bitcoin and Dogecoin prices and the public sentiment expressed by Elon Musk on the Twitter platform regarding the cryptocurrency market. Their research reveals that the opinion of some public figures determines the appearance of bubbles in the price of digital assets.

3. Research Questions / Aims of the Research

This paper aims to conduct an analysis of the cryptocurrency market, considering the ten most important digital currencies from the perspective of market capitalization. On the one hand, a composite index was designed. The index has been obtained from the combination of two indicators regarded as relevant in the context of digital assets: the calculated returns of cryptocurrencies and, respectively, the traded volumes. For this purpose, we intended to observe how the evolution of cryptocurrencies would change, by simulating different values for the weights associated with the variables composing the proposed index. On the other hand, we proposed to evaluate the existence of causal relationships between the indices calculated for the considered cryptocurrencies.

4. Research Methods

In order to accomplish the research objectives presented in the previous section, this paper uses data on the top ten most significant digital currencies as of April 2022. The selection of these cryptocurrencies was based on two key elements, namely the market capitalization associated with each digital asset, but also the launching date of each cryptocurrency. In order to ensure a comprehensive data set, we decided to select and consider in this analysis data on cryptocurrencies launched after 2017. Data was collected using the Yahoo Finance database. The analysis was performed using EViews and RStudio and some processings were realised using the Python programming language. The considered cryptocurrencies are: Bitcoin (BTC), Ripple (XRP), Binance Coin (BNB), Ethereum (ETH), Cardano (ADA), Dogecoing (DOGE), Tether (USDT), Litecoin (LTC), Dash (DASH) and Monero (XMR). For each of these, we calculated the daily returns using the formula:

$$r_i = \frac{P_{t+1} - P_t}{P_t} * 100 \tag{1}$$

where:

r_i – represents the return of the cryptocurrency *i*;

P_{t+1} – represents the price of cryptocurrency i at the *t+1* moment;

P_t – represents the price of cryptocurrency *i* at the *t* moment;

Another indicator on which we collected data within this analysis is the traded volume. This indicator has been processed to summarize the growth rates of the traded volume.

Once these two indicators were pre-processed, we proposed designing an index to summarize the evolution of the ten most popular digital currencies. We thus continued with the construction of a composite index, its form being represented below:

$$Crypto\_Index_{i,t} = \alpha_i * r_{i,t} + \beta_i * V_{i,t} \tag{2}$$

where:

$Crypto\_Index_{i,t}$ – represents the index associated with the cryptocurrency i at the time (time period) *t*;

α_i – represents the weight associated with $r_{i,t}$ in constructing the composite index;

β_i – represents the weight associated with $V_{i,t}$ in constructing the composite index;

$r_{i,t}$ – represents the return of the cryptocurrency *i* at the time *t*;

$V_{i,t}$ – represents the traded volume, expressed as growth rate, associated with the cryptocurrency *i*, at the time *t*.

The values representing the weights α_i and β_i can be established both using the observed data series but also using specific simulation techniques.

Furthermore, the correlation between the ten cryptocurrencies will be evaluated using the Pearson correlation coefficient. The intensity and direction of the linear relationship between two quantitative indicators are assessed using the correlation coefficient. The value of the correlation coefficient is situated in the [-1,1] range where values close to -1 indicate strong, negative correlations, while values close to 1 correspond to strong, positive correlations between variables. The absence of correlation is highlighted by values close to 0 of the correlation coefficient.

The Pearson correlation coefficient used to assess the relationship between variables is further highlighted:

$$corr = \frac{\sum_{i=1}^{n}(x_i-\bar{x})(y_i-\bar{y})}{\sqrt{\left[\sum_{i=1}^{n}(x_i-\bar{x})^2\right][\sum_{i=1}^{n}(y_i-\bar{y})^2]}} \quad (3)$$

where:
x_i – represents the *i*-th value of variable *x*;
$\bar{x}$ – represents the mean of variable *x*;
y_i – represents the *i*-th value of variable *y*;
$\bar{y}$ – represents the mean of variable *y*.

The test proposed by Granger (1969) will also be used to assess the causality between the analyzed variables, in this case, the composite indices associated with the selected digital currencies. Given the two variables X and Y, it will be determined whether X is a Granger cause of Y if the values of the variable Y can be explained based on the past values of Y and whether lagged values of the variable X can improve the prediction of the variable Y.

The associated mathematical model uses bivariate regressions of the form:

$$y_t = \alpha_0 + \alpha_1 y_{t-1} + \cdots + \alpha_l y_{t-1} + \beta_1 x_{t-1} + \cdots + \beta_l x_{-1} + \varepsilon_t \quad (4)$$

$$x_t = \alpha_0 + \alpha_1 x_{t-1} + \cdots + \alpha_l x_{t-1} + \beta_1 y_{t-1} + \cdots + \beta_l y_{-1} + u_t \quad (5)$$

considering all possible pairs (x, y).

Given the following hypothesis:

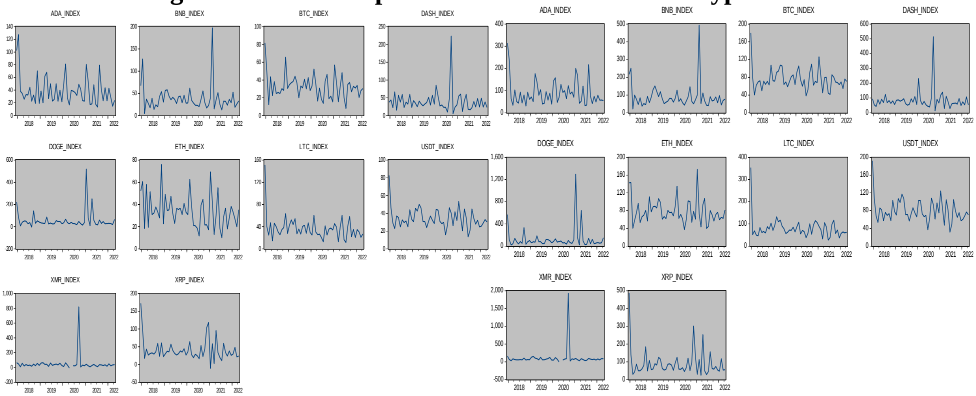
$$H_0: \beta_1 = \beta_2 = \cdots = \beta_l = 0 \quad (6)$$

the *F*-statistical indicator is calculated for each equation. The null hypothesis is that *x* is not a Granger cause of the variable *y* in the first regression model, while *y* is not a Granger cause of the variable *x*.

5. Findings

The following figure describes the evolution of the top ten cryptocurrencies, according to the constructed composite index. The two graphs show a comparison between the movement of the composite index, considering distinct weights for the two components of the index. Over the analysed time period, there have been significant fluctuations in the evolution of the ten cryptocurrencies considered, in terms of returns and trading volumes. Significant increases are associated with Binance (BNB_Index), Dash (DASH_Index), Dogecoin (DOGE_Index), and Monero (XMR_Index) in the fourth quarter of 2020. However, the four cryptocurrencies subsequently declined, both in terms of returns and traded volumes. The most popular cryptocurrencies, Bitcoin and Ethereum, also had an oscillating evolution, but according to the charts below, we did not notice significant shocks in terms of the value of the constructed composite index.

Figure 1. Index comparison for the ten selected cryptocurrencies



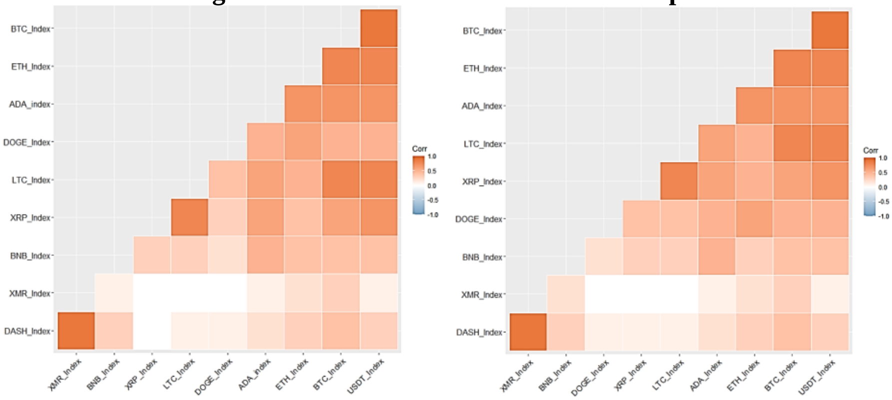
Source: Authors' processing using EViews and RStudio.

Comparing the two graphs, it is noticeable that if we take into account the weights associated with the components of the index, the differences regarding the index oscillation are almost insignificant, except for a few situations, namely: ETH_INDEX, LTC_INDEX, and USDT_INDEX. The difference between the index of these cryptocurrencies and the index associated with other digital currencies is that for Ethereum, Litecoin, and Tether, positive and significant correlations have been identified between traded volumes and their associated returns.

Through the simulations performed, on the whole spectrum of the analysis, the shift of proportion between the two indicators used in the construction of the composite index from 0.7 versus 0.3 (and vice versa) does not significantly change the value of the composite index.

At the same time, the correlation between the indices associated with the ten cryptocurrencies was analyzed. Charts built using correlation matrices indicate strong correlations between digital currencies, regardless of the weights associated with calculated returns and traded volumes in defining the composite index. The index associated with Bitcoin is strongly correlated with most indices, except Monero (XMR_Index). Weak correlations correspond to the calculated indices for Monero (XMR) and Ripple (XRP). One can note that the computed index for Monero is not significantly associated with the evolution of other cryptocurrencies.

Figure 2. Correlation between the ten computed indices



Source: Authors' processings using EViews and RStudio.

Stationarity was analyzed for the variables considered in the study. The use of the Augmented Dickey-Fuller stationarity test indicates the non-stationarity of the level time series, but all indicators become stationary after applying the first order differentiation procedure.

Table 1. ADF Stationarity test results

Variable	Prob.	Conclusion
ADA_INDEX	0.843	Non-stationarity
BNB_INDEX	0.273	Non-stationarity
BTC_INDEX	0.188	Non-stationarity
DASH_INDEX	0.973	Non-stationarity
DOGE_INDEX	0.472	Non-stationarity
ETH_INDEX	0.725	Non-stationarity
LTC_INDEX	0.678	Non-stationarity
USDT_INDEX	0.375	Non-stationarity
XMR_INDEX	0.524	Non-stationarity
XRP_INDEX	0.341	Non-stationarity

Source: Authors' processings using EViews and RStudio.

The Johansen cointegration procedure was applied in order to test the cointegration of the studied variables. The notion of cointegration refers to the existence of a long-term relationship between the considered indicators. According to the results presented in the table below, it is noted that there is a long-term association between the variables studied, as indicated by the existence of a cointegration equation.

Table 2. Johansen cointegration test results

Unrestricted Cointegration Rank Test (Trace)		
Hypothesized No. of CE(s)	**Eigenvalue**	**Prob.**
None	0.881	0.000
At most 1	0.728	0.000
At most 2	0.612	0.109
At most 3	0.523	0.218

Source: Authors' processings using EViews and RStudio.

To investigate the association between the variables in more detail manner, we used the Granger causality test. Based on this, one can note whether a variable is considered significant in predicting the evolution of other variables. In this case, we intend to observe which are the cryptocurrencies that influence the evolution of other digital assets, having as benchmark the calculated dynamics index.

Table 3. Results of Granger causality test

Null Hypothesis	Prob.
BTC_INDEX does not Granger cause BNB_Index	0.000
BNB_Index does not Granger cause BTC_INDEX	0.009
BTC_INDEX does not Granger cause DOGE_INDEX	0.000
DOGE_INDEX does not Granger cause BTC_INDEX	0.002
BTC_INDEX does not Granger cause ETH_Index	0.001
ETH_Index does not Granger cause BTC_INDEX	0.000
DASH_Index does not Granger cause XMR_Index	0.001
XMR_Index does not Granger cause DASH_Index	0.010
XRP_Index does not Granger cause LTC_Index	0.003
LTC_Index does not Granger cause XRP_Index	0.000

Source: Authors' processings using EViews and RStudio.

In the previous table, only the causal relationships identified as significant, or in other words, the situation of those cryptocurrencies that can explain the evolution of other digital assets, were exposed. We found the existence of bidirectional causal relationships between Bitcoin and Binance, Bitcoin and Dogecoin, Bitcoin and Ethereum, Dash and Monero, but also between Ripple and Litecoin. For example, the BTC_Index can be used to predict the BNB_Index.

6. Conclusions

Many companies, organizations and even industries, if we focus on a large scale, are impacted by the technological innovations represented by Blockchain and cryptocurrencies. Attracting the attention of both researchers and practitioners, these elements are intensively studied, the interest being focused on identifying how they will succeed in revolutionizing other products and services. Cryptocurrencies and underlying technology have already infiltrated many industries, including cloud services, real estate, healthcare, management, logistics, and retail. Given the growing popularity of these elements, this paper considered a study of the cryptocurrency market in terms of correlations between the main virtual currencies traded and the study of causality between them. Prior to the analysis, we proposed the construction of an index that summarizes the evolution of the main cryptocurrencies, through two measures, namely the calculated returns of the selected virtual currencies and their traded volume. The index was established using importance coefficients or weights associated with the two previously mentioned indicators, weights simulated or given based on the observed data. Giving distinct weights to the two indicators that compose the proposed index, we noticed that the evolution of the main digital assets does not change significantly, and any changes correspond only to cryptocurrencies for which there are correlations between returns and traded volumes. In addition, using the Pearson correlation coefficient, we noticed that the connections between the ten currencies considered are predominantly statistically significant and denote strong, positive correlations between the studied variables. Subsequently, evaluating Granger causality, we identified bidirectional causal relationships between Bitcoin and Binance cryptocurrencies, Bitcoin and Dogecoin, Bitcoin and Ethereum, Dash and Monero, and Ripple and Litecoin. This translates into the fact that past values regarding the price of these cryptocurrencies may prove useful in predicting the price of other cryptocurrencies. These records can be considered useful for investors interested in acquiring digital assets, as well as for the academic community focused on discovering mechanisms and tools that will better serve the understanding of the fundamentals of the cryptocurrency market. As a future research guideline, the inclusion of a volatility measure in the construction of the proposed composite index may be considered.

Acknowledgment

This paper was co-financed by The Bucharest University of Economic Studies during the PhD program.

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