Balkans JETSS (2022) 1: 1-14
DOI: https://doi.org/10.31410/Balkans.JETSS.2022.5.1.1-14

*Original Scientific Article*

# SPILLOVER AND QUANTITATIVE LINK BETWEEN CRYPTOCURRENCY SHOCKS AND STOCK RETURNS: NEW EVIDENCE FROM G7 COUNTRIES

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Received: April 24, 2022 / Revised: May 19, 2022 / Accepted: June 21, 2022


**Abstract:** *The objective of this article is to analyze the co-movements in the G7 stock markets, such as DJ index, S&P500 (representing the USA stock market), FTSE 100 (United Kingdom), S&P/TSX (Canada), DAX 30 (Germany), CAC 40 (France), Nikkei 225 (Japan), Italy Ds market (Italy) and the cryptocurrencies Bitcoin (BTC), Litecoin (LTC), Ethereum (ETH) and Crypto 10, during the period of February of 2018 to November of 2021. The results show that the cryptocurrencies BTC, ETH, and LTC increase the co-movements between their pairs, while the Crypto 10 index reduces the number of shocks when compared with the sub-period before COVID-19. Regarding the stock markets, DJ index kept the same level of shocks, whereas the Nikkei 225 decreased. For Germany (DAX), EUA (S&P500), Canada (S&P/TSX), United Kingdom (FTSE 100), France (CAC40), and Italy (Italy Ds Market) markets the results show an increase in movements during the global pandemic period. It is then possible to conclude the existence of evidence regarding synchronization and high co-movements, the results put at risk the implementation of efficient portfolio diversification strategies. These conclusions also open space for the market regulators to take steps to ensure better information on the dynamics of the international financial markets.*

**Keywords:** *Cryptocurrencies; G7 market; Co-movements; Portfolio diversification.*

**JEL Classification E44 · D53 · G15**

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## 1. INTRODUCTION

The effects of the global pandemic of 2020 (COVID-19) have been affecting negatively the economy on a global scale, originating very significant impacts on the financial market across the world, causing significant losses to the investors in a short period of time. In line with all the negative effects, it seems inevitable that the stock market, economic growth, and exchange rates had also been affected in the same way (Dias et al., 2021c; Vasco et al., 2021; Zebende et al., 2022).

During the last decade, the globalization phenomenon has shown that the correlation between international financial markets has increased, namely among developed markets. According to Dias, Alexandre, and Heliodoro (2020a), Dias, Pardal, Teixeira, and Machová (2020c) the synchronizations between the international stock market can be strongly affected during the crisis and quiet periods, which can make difficult the portfolio diversification.

Financial instability is a very important social factor, considering that a financial or a scholarly crash crisis can affect, directly or indirectly, the level of the economic well-being of a country's citizens. If a given financial market is strongly linked to another, then the financial stability of the first will depend, in some part, on the financial stability of the second. For this reason, a narrow or strong link between markets increases the vulnerability to external shocks and, in consequence, influences the economic conditions and the well-being levels of the countries (Dias et al., 2020a; Dias et al., 2020b; Dias et al., 2021a, 2021b; Dias and Carvalho, 2021; Pardal et al., 2021; Vasco et al., 2021).

Considering the above, and accordingly to the authors Silva et al. (2020), Zebende et al. (2022) understanding the degree of linkages and correlations of the assets markets, as well as evaluating the co-movements degree can help the investors to diversify their asset portfolio and consequently reduce their risk exposure, as well as leverage their earnings, since the diagnosis of the degree of the integration will allow the identification of whether the assets have similar returns, if they are assets belonging to integrated markets, or if, due to their exposure to different sources of risk, they have differentiated returns and, therefore, constitute assets that are part of the segmented market.

This article will analyze the co-movements between the G7 stock market, such as DJ index, S&P500 (representing the USA stock market), FTSE 100 (United Kingdom), S&P/TSX (Canada), DAX 30 (Germany), CAC 40 (France), Nikkei 225 (Japan), Italy Ds market (Italy) and the cryptocurrencies Bitcoin (BTC), Litecoin (LTC), Ethereum (ETH) and Crypto 10. The results mostly show that the co-movements between capital markets and the cryptocurrencies increased, which may jeopardize the implementation of an efficient portfolio diversification strategy.

This investigation adds contributions to the literature, namely the global pandemic 2020 accentuated the co-movements between the G7 financial markets, and the cryptocurrencies Bitcoin (BTC), Litecoin (LTC), Ethereum (ETH), and Crypto 10. Authors Aslam et al. (2020) and Nguyen (2021) have focused their research on the impact of the pandemic crisis on the existent correlation between stock markets and the cryptocurrencies, although, they haven't provided robust evidence.

In terms of structure, this article is organized into 5 sections. In addition to the current introduction, Section 2 presents a State-of-the-Art analysis of the article on international financial markets co-movements, section 3 describes the methodology and section 4 contains the data and results. Section 5 presents the general conclusions of the paper.

## 2. LITERATURE REVIEW

The study of the connection between the cryptocurrencies with the stock market indexes exists, on the one hand, because of the evidence that digital currencies are completely segmented relative to traditional assets and there is, on the other hand, opposing evidence has been showing that the cryptocurrency market is not totally isolated.

Baur et al. (2018) analyzed the statistical properties of the BTC cryptocurrency and present evidence pointing out that this cryptocurrency will not be correlated with certain traditional assets, such as stocks, bonds, and commodities, either in periods of stability or normal times or in periods of financial turbulence (stress in the international financial market).

Ji et al. (2018) examined the degree of the integration between BTC and traditional assets during the period from July 19th of 2021 to January 31st of 2017, they applied the VAR model by opting for the Johansen cointegration test. The authors show low correlations with the global financial system, however, there are indications that the integration process of the BTC may fluctuate with different time scales.

Bouri et al. (2018) by applying the VAR-GARCH model analyzed the links between the BTC and the financial markets, during the period between July 19th of 2010, and October 31st of 2017. The authors concluded that the BTC is integrated with some financial assets, such as commodities.

Umar et al. (2020) used the dynamic asymmetric conditional correlation and wavelet coherence approaches studied the integration between the cryptocurrencies (BTC, ETH, Ripple, Bitcoin cash e Ethereum Operating System) and the stock market of NYSE, NASDAQ, Shanghai Stock Exchange, Nikkei 225 e NYSE Euronext. The authors highlight that the analyzed cryptocurrencies show significant levels of integration with the analyzed stock markets.

Gil-Alana et al. (2020) by applying cointegration models analyzed the bidirectional links between the six largest cryptocurrencies, including the BTC, ETH, LTC, and six stock markets, from May 7th of 2015 and October 5th of 2018. Their results show that there is no relevant evidence to support the existence of cointegration among the six crypto-currencies and stock market indexes.

Nguyen (2021) applied the VAR-GARCH to test the impact of the stock markets in BTC during the time period between January 1st of 2016 and January 1st of 2021, during the period marked by the occurrence of the COVID-19 pandemic. The results provide evidence that during high uncertainty the stock markets and cryptocurrencies are more correlated.

Karim et al. (2022) analyzed the integration between the cryptocurrencies such as BTC, ETH, LTC, XRP, and Stellar, during the global pandemic of 2020 (April 17th of 2019, and September 15th of 2020). The authors highlight that the cryptocurrencies are segmented rather than integrated suggesting that these assets offer a broad opportunity for portfolio diversification.

## 3. METHODOLOGY

### 3.1. Data

The analysis of the causality relationships will be based on the daily stock market prices of the G7 member countries, namely the USA, Germany, France, UK, Italy, Japan, and Canada, as well as the quotes for the cryptocurrencies BTC, ETH, LTC and the Crypto 10 Index. The quotes comprise the time-lapse from February 2018 to November 2021, to provide a bigger robust to the investigation the sample was split into two sub-periods: from February 2018 to December 2019, which we call the pre-pandemic period; while the second subperiod, the global pandemic, has the time between January 2020 to November 2021. In order to provide reliable data for the research, it was decided to pull the time series from the Thomson Reuters platform (DataStream).

**Table 1.** The name of countries and their indexes used in this paper

| **Country** | **Index** |
|---|---|
| United States of America | DOW JONES COMPOSITE 65 STOCK |
| | S&P 500 |
| Germany | DAX 30 |
| France | CAC 40 |
| UK | FTSE 100 |
| Italy | Italy Ds Market |
| Japan | NIKKEI 225 AVERAGE |
| Canada | S&P/TSX COMPOSITE INDEX |
| Global | USD TO BITCOIN |
| Global | USD TO ETHEREUM |
| Global | USD TO LITECOIN |
| Global | CRYPTO MARKET INDEX 10 |

**Source:** Own elaboration

### 3.2. Methodology

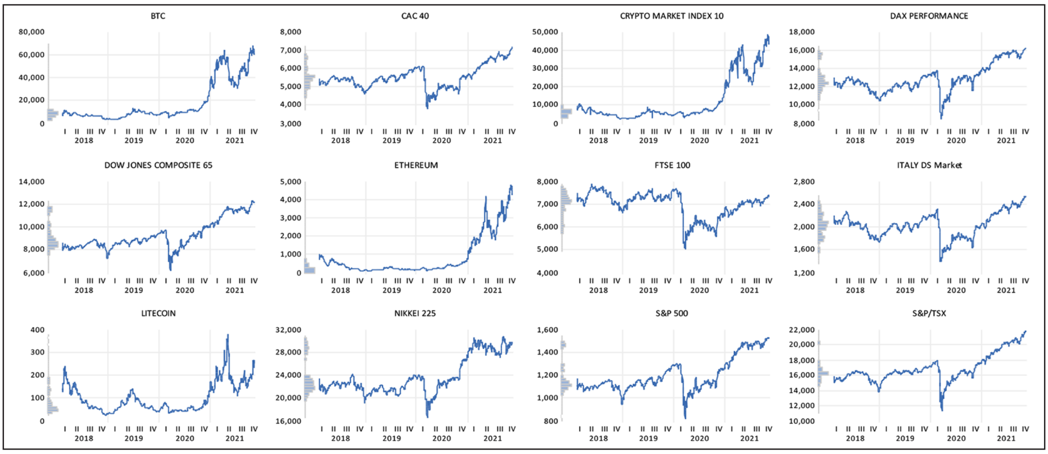
The following section will present the methodology and the tests to be used to answer the two research questions. The methodological process of this article was carried out in several steps. In the first stage, the sample was characterized by applying a set of descriptive statistical methods. Complementarily, in order to analyze the data distribution of the twelve time series and test the normality assumption, the Jarque and Bera (1980) test was applied. In a second step, to validate the stationarity of the times series, the panel unit root tests of Hadri (2000), Breitung (2000), and Levin, Lin, and Chu (2002) were applied. Finally, to answer the research question, we chose the VAR Granger Causality/Block Exogeneity Wald Tests model. This model allowed the detection of causal relations between data series, in the short term, as well as the movements existing in the dynamics of these relations.

## 4. RESULTS

Figure 1 graphically represent the evolution, in levels, of the twelve financial markets during the period of February 2018 to November 2021, from that observation, it is possible to observe the pre-crisis period and the highly complex period marked by the pandemic crisis.

Regarding the cryptocurrencies' evolution, we can observe that at the time of the announcement of the COVID-19 pandemic there are no accentuated breaks in structure, however, the behavior of cryptocurrencies between the second and third quarters of 2021 shows that there are sharp breaks in structure.

In the behavior of the G7 stock markets at the beginning of the crisis, i.e. between the first and second quarter of 2020, oscillations can be observed that suggest the existence of structural breaks.

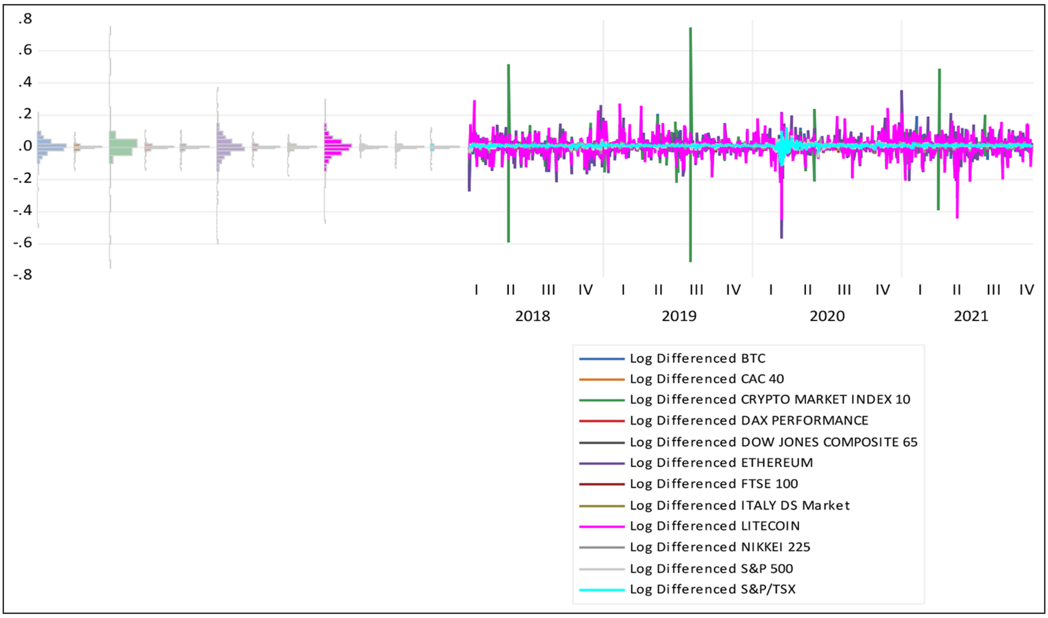



**Note:** Data worked by the author (software: Eviews12)

**Figure 1.** Evolution, in levels, of the financial market under analysis, for the period from 1st February of 2018 to 18th November of 2021

**Source:** Own elaboration

Figure 2 shows the evolution of the returns of the stock market indexes and cryptocurrencies under analysis.




**Note:** Data worked by the author (software: Eviews12)

**Figure 2.** Evolution of the returns, of the financial market under analysis, in the period from 1st of February 2018 to 18th November of 2021

**Source:** Own elaboration

Overall, it is possible to observe synchrony between all series and a generalized dispersion around the mean. However, in comparison with equity markets, the returns of the series representing the cryptocurrency markets show a greater dispersion from the mean. On the other hand, the existence of high volatility is felt especially in the first months of the year 2020. Complementarily, through the Kernel density, it can be seen that the cryptocurrency markets are more volatile when compared to the stock market under analysis.

Table 2 resumes the main descriptive statistics of the cryptocurrencies under analysis, as well as the results of the Jarque & Bera goodness of fit tests.

The descriptive statistics analysis from table 2 shows that the average daily returns of the cryptocurrencies under analysis register values close to zero, being LTC the digital currency with the lowest average daily return (0.0494), and BTC the digital currency with the highest average daily return over the sample period considered (0.1921). The standard deviation of Crypto 10 allows us to check the level of volatility, overall, of the cryptocurrency market stands at 6.6383%. The LTC and ETH have standard deviations very close to the index reference value.

On the other hand, BTC represents a standard deviation lower (4.7959%), which reveals that, during the considered period, it was the least volatile cryptocurrency. To all the cryptocurrencies, the asymmetry values are different from zero, presenting negative characteristics, with BTC, being the one with the most significant asymmetry levels (-1.228043). Additionally, when the kurtosis is analyzed values much higher than 3 are found. This evidence shows the rejection of the null hypothesis that postulates the normality of the data. To prove the evidence that the returns of the cryptocurrencies data series do not follow a normal distribution, the Jarque & Bera goodness of fit test was applied, which yielded values that lead to rejection of the null hypothesis in favor of the alternative.

**Table 2.** Descriptive statistics, regarding the cryptocurrencies under analysis, for the period from 1st February 2018 to 18th November 2021

| | **Mean** | **Median** | **Max.** | **Min.** | **Std. Dev.** | **Skewness** | **Kurtosis** | **Jarque –Bera** | **Obs.** |
|---|---|---|---|---|---|---|---|---|---|
| BTC | 0.001921 | 0.002055 | 0.208085 | -0.493969 | 0.047959 | -1.228043 | 16.25200 | 7500.545 *** | 991 |
| CRYPTO 10 | 0.001545 | 0.000673 | 0.747271 | -0.715028 | 0.066383 | -0.128788 | 46.44371 | 77934.83 *** | 991 |
| ETH | 0.001450 | 0.001067 | 0.355149 | -0.575598 | 0.063070 | -0.855004 | 12.72397 | 4025.103 *** | 991 |
| LTC | 0.000494 | 0.000898 | 0.289690 | -0.457408 | 0.063079 | -0.623852 | 10.07312 | 2130.062 *** | 991 |

**Note:** Data worked by the author (software: Eviews12).
The asterisks *** represent the rejection of the null hypothesis at a significance level of 1%

**Source:** Own elaboration

Table 3 summarizes the main descriptive statistics of the stock market under analysis, as well as the results of the Jarque & Bera goodness of fit test.

The analysis of the descriptive statistics shows that most of the returns have positive daily averages very close to zero, except for the FTSE 100 stock market index. The DJ index is the index with, on average, the highest daily return (0.0343), as well as the most significant standard deviation (risk) (1.3685%), followed by the S&P 500 stock index (1.3513%). In comparative terms, the G7 stock markets are less volatile than the cryptocurrency market. Also, the stock markets show negative asymmetry values, with the Italian market presenting the sharpest asymmetry (-3.047814). In turn, the kurtosis analysis shows that for all the stock markets the values are greater than 3.

The results obtained indicate that the studied time series does not follow a normal distribution. To validate, the Jarque & Bera goodness of fit test was applied, which postulates the null hypothesis against the alternative. The values obtained, both for a significance level of 1% led to the rejection of the null hypothesis, which confirmed what had already been indicated, regarding the non-normal distribution of the time series for the G7 stock market indexes.

**Table 3.** Descriptive statistics for the stock market under analysis for the period from 1st February 2018 to 18th November 2021

| | Mean | Median | Max. | Min. | Std. Dev. | Skewness | Kurtosis | Jarque –Bera | Obs. |
|---|---|---|---|---|---|---|---|---|---|
| CAC40 | 0.000274 | 0.000915 | 0.080561 | -0.130983 | 0.012696 | -1.425271 | 20.98341 | 13689.38 *** | 991 |
| DAX 30 | 0.000225 | 0.000457 | 0.104143 | -0.130549 | 0.013066 | -1.016863 | 20.09637 | 12239.76 *** | 991 |
| DJ | 0.000343 | 0.000789 | 0.108264 | -0.130942 | 0.013685 | -0.995243 | 24.44722 | 19157.07 *** | 991 |
| FTSE100 | -2.72E-05 | 0.000345 | 0.086668 | -0.115124 | 0.011475 | -1.231606 | 19.99246 | 12173.24 *** | 991 |
| ITALY | 0.000141 | 0.000632 | 0.074081 | -0.174311 | 0.013112 | -3.047814 | 41.32004 | 62168.00 *** | 991 |
| NIKKEI 225 | 0.000233 | 0.000000 | 0.077314 | -0.062736 | 0.012148 | -0.162946 | 8.059633 | 1061.447 *** | 991 |
| S&P500 | 0.000257 | 0.000493 | 0.092341 | -0.123650 | 0.013513 | -1.067602 | 21.21429 | 13887.19 *** | 991 |
| S&P/TSX | 0.000314 | 0.000708 | 0.112945 | -0.131761 | 0.011704 | -2.109583 | 47.89022 | 83943.19 *** | 991 |

**Note:** Data worked by the author (software: Eviews12).
The asterisks *** represent the rejection of the null hypothesis at a significance level of 1%

**Source:** Own elaboration

In order to apply the econometric methods that will allow answering the research question, it was necessary to analyze the stationarity of the time series. To this end, Hadri (2000), Breitung (2000) and Levin, Lin, and Chu (2002) panel unit root tests were performed. The result of Breitung and LLC tests are respectively represented in Tables 4 and 5, suggesting for each of the tests the rejection of the null hypothesis, for the level of significance of 1%. In this sense, the null hypothesis of both tests that postulated the existence of a root (or inconstant variance) was rejected for the period of time under study.

**Table 4.** Breitung tests for the 12 financial markets under analysis for the period from 1st February 2018 to 18th November 2021

| Method | | | Statistic | Prob.*** |
|---|---|---|---|---|
| Breitung | | | -42.3883 | 0.0000 |
| | *Coefficient* | *t-Stat* | *SE Reg.* | *Obs.* |
| Pooled | -0.49086 | -42.388 | 0.012 | 11828 |

**Note:** Data worked by the author (software: Eviews12).
*** Probability is assumed to be asymptotically normal

**Source:** Own elaboration

**Table 5.** Levin, Lin and Chu tests for the 12 financial markets under analysis for the period from 1st February 2018 to 18th November 2021

| Method | | | | Statistic | | Prob.** |
|---|---|---|---|---|---|---|
| Levin, Lin & Chu t* | | | | -86.9478 | | 0.0000 |
| | *Coefficient* | *t-Stat* | *SE Reg* | *mu** | *sig** | *Obs.* |
| Pooled | -1.02128 | -75.540 | 1.004 | -0.500 | 0.707 | 11840 |

**Note:** Data worked by the author (software: Eviews12).
*** Probability is assumed to be asymptotically normal

**Source:** Own elaboration

Additionally, and to validate the previously obtained evidence, the Hadri tests were applied, which statistical result is presented in Table 6. The result leads to the non-rejection of the null hypothesis, for the level of significance of 1%, meeting what was pointed out earlier, that is that all panel time series is stationary.

**Table 6.** Hadri tests for the 12 financial markets under analysis for the period from 1st February 2018 to 18th November 2021

| Method | Statistic | Prob.** |
|---|---|---|
| Hadri Z-stat | -1.60286 | 0.9455 |
| Heteroscedastic Consistent Z-stat | -2.28213 | 0.9888 |

**Note:** Data worked by the author (software: Eviews12).
*** Probability is assumed to be asymptotically normal

**Source:** Own elaboration

To determine the causality relationship between pairs of the markets under analysis, the VAR model was used. Given the temporal partition into two periods, namely pre-COVID, and COVID, two models were estimated.

**Table 7.** Selection criteria for the number of lags of the VAR model, concerning the period 01/02/2018 to 31/12/2019 (pre-COVID 19)

| Lag | LogL | LR | FPE | AIC | SC | HQ |
|---|---|---|---|---|---|---|
| 0 | 18557.99 | NA | 1.85e-48 | -75.85271 | -75.74983* | -75.81230 |
| 1 | 18835.24 | 539.7558 | 1.07e-48* | -76.39769* | -75.06025 | -75.87238* |
| 2 | 18954.08 | 225.5317 | 1.19e-48 | -76.29479 | -73.72279 | -75.28459 |
| 3 | 19076.24 | 225.8384 | 1.31e-48 | -76.20548 | -72.39892 | -74.71038 |
| 4 | 19169.10 | 167.1087 | 1.62e-48 | -75.99631 | -70.95519 | -74.01631 |
| 5 | 19261.73 | 162.1439 | 2.01e-48 | -75.78620 | -69.51051 | -73.32130 |
| 6 | 19346.97 | 145.0331 | 2.59e-48 | -75.54588 | -68.03563 | -72.59608 |
| 7 | 19450.90 | 171.7332 | 3.10e-48 | -75.38200 | -66.63720 | -71.94731 |
| 8 | 19554.62 | 166.2847 | 3.73e-48 | -75.21724 | -65.23788 | -71.29765 |
| 9 | 19670.76 | 180.5110 | 4.30e-48 | -75.10331 | -63.88939 | -70.69882 |
| 10 | 19798.57 | **192.3754*** | 4.75e-48 | -75.03712 | -62.58863 | -70.14773 |

**Note:** Data worked by the author (software: Eviews12). The asterisk * indicates the optimal number of lags selected by each criterion. LR: Modified LR test statistic (5% test). AIC: Akaike's information criterion. FPE: Final Error Prediction. SC: Schwarz information criterion. HG: Hannan-Quinn information criterion

**Source:** Own elaboration

The first step in estimating VAR model is to determine the optimal number of lags. To determine the number of lags of the VAR model for the pre-COVID period, the criteria used are present in Table 7. Based on the results obtained, the LR criterion was selected, which suggests a model with 10 lags.

Table 8 shows that for the number of lags equal to ten, the null hypothesis is true, rejecting the possibility of autocorrelation of the residuals, thus ensuring the robustness and validity of the estimated model for the first time period under the analysis.

**Table 8.** VAR residual serial correlation LM tests,
concerning the period 01/02/2018 to 31/12/2019 (pre-COVID 19)

| Lag | LRE* stat | df | Prob. | Rao F-stat | df | Prob. |
|---|---|---|---|---|---|---|
| 1 | 144.9419 | 144 | 0.4623 | 1.006844 | (144, 2971.8) | 0.4629 |
| 2 | 111.3522 | 144 | 0.9799 | 0.769224 | (144, 2971.8) | 0.9800 |
| 3 | 132.7994 | 144 | 0.7384 | 0.920643 | (144, 2971.8) | 0.7389 |
| 4 | 136.7018 | 144 | 0.6547 | 0.948310 | (144, 2971.8) | 0.6553 |
| 5 | 139.5785 | 144 | 0.5886 | 0.968727 | (144, 2971.8) | 0.5892 |
| 6 | 99.07841 | 144 | 0.9984 | 0.683050 | (144, 2971.8) | 0.9984 |
| 7 | 148.4463 | 144 | 0.3826 | 1.031786 | (144, 2971.8) | 0.3833 |
| 8 | 136.9253 | 144 | 0.6497 | 0.949895 | (144, 2971.8) | 0.6502 |
| 9 | 151.8925 | 144 | 0.3100 | 1.056343 | (144, 2971.8) | 0.3105 |
| 10 | 119.4495 | 144 | 0.9330 | 0.826267 | (144, 2971.8) | 0.9331 |
| 11 | 146.9320 | 144 | 0.4165 | 1.021006 | (144, 2971.8) | 0.4171 |

**Note:** Data worked by the author (software: Eviews12)

**Source:** Own elaboration

To determine the optimal number of lags for the estimation of the VAR model for the COVID-19 period, it was used the criteria present in Table 9. Based on the LR criteria, the results point to a model that considers 10 lags.

**Table 9.** Selection criteria for the number of lags of the VAR model,
for the period 01/01/2020 to 18/11/2021 (COVID-19)

| Lag | LogL | LR | FPE | AIC | SC | HQ |
|---|---|---|---|---|---|---|
| 0 | 16871.16 | NA | 6.75e-46 | -69.95501 | -69.85100* | -69.91413 |
| 1 | 17223.14 | 684.9695 | 2.85e-46 | -70.81799 | -69.46579 | -70.28656* |
| 2 | 17417.45 | 368.4664 | 2.31e-46 | -71.02675 | -68.42637 | -70.00478 |
| 3 | 17572.17 | 285.6906 | 2.22e-46 | -71.07124 | -67.22268 | -69.55872 |
| 4 | 17721.25 | 267.8445 | 2.18e-46* | -71.09231* | -65.99557 | -69.08924 |
| 5 | 17846.84 | 219.3954 | 2.37e-46 | -71.01593 | -64.67100 | -68.52231 |
| 6 | 17954.16 | 182.1269 | 2.80e-46 | -70.86372 | -63.27061 | -67.87955 |
| 7 | 18065.56 | 183.5139 | 3.26e-46 | -70.72846 | -61.88717 | -67.25375 |
| 8 | 18163.38 | 156.2715 | 4.03e-46 | -70.53685 | -60.44737 | -66.57159 |
| 9 | 18299.57 | 210.7815 | 4.29e-46 | -70.50444 | -59.16678 | -66.04863 |
| 10 | 18441.14 | **212.0673*** | 4.49e-46 | -70.49437 | -57.90853 | -65.54802 |

**Note:** Data worked by the author (software: Eviews12). The asterisk * indicates the optimal number of lags selected by each criterion. LR: Modified LR test statistic (5% test). AIC: Akaike's information criterion. FPE: Final Error Prediction. SC: Schwarz information criterion. HG: Hannan-Quinn information criterion

**Source:** Own elaboration

In Table 10 it is possible to observe the results of the tests, which for the number of lags equal to 10, leads to not rejecting the null hypothesis, which postulates the non-existence of autocorrelation of the residuals. Thus, ruling out the autocorrelation hypothesis, and determining the model with a number of lags equal to 10 ensures that it has a robust and valid estimation for the second time period under analysis.

**Table 10.** VAR Residual Serial Correlation LM Tests, for the period 01/01/2020 to 18/11/2021 (COVID-19)

| Lag | LRE* stat | df | Prob. | Rao F-stat | df | Prob. |
|---|---|---|---|---|---|---|
| 1 | 141.3930 | 144 | 0.5459 | 0.981605 | (144, 2911.8) | 0.5465 |
| 2 | 145.0986 | 144 | 0.4586 | 1.007962 | (144, 2911.8) | 0.4593 |
| 3 | 151.3530 | 144 | 0.3209 | 1.052521 | (144, 2911.8) | 0.3215 |
| 4 | 177.8826 | 144 | 0.0289 | 1.242575 | (144, 2911.8) | 0.0290 |
| 5 | 150.8133 | 144 | 0.3320 | 1.048673 | (144, 2911.8) | 0.3326 |
| 6 | 168.5635 | 144 | 0.0791 | 1.175622 | (144, 2911.8) | 0.0794 |
| 7 | 150.4202 | 144 | 0.3402 | 1.045870 | (144, 2911.8) | 0.3408 |
| 8 | 159.2765 | 144 | 0.1816 | 1.109107 | (144, 2911.8) | 0.1821 |
| 9 | 143.1611 | 144 | 0.5041 | 0.994177 | (144, 2911.8) | 0.5047 |
| 10 | 154.8281 | 144 | 0.2541 | 1.077320 | (144, 2911.8) | 0.2546 |
| 11 | 140.3547 | 144 | 0.5703 | 0.974226 | (144, 2911.8) | 0.5710 |

**Note:** Data worked by the author (software: Eviews12)

**Source:** Own elaboration

In Table 11, it is possible to observe the results regarding the VAR Granger Causality tests for the period pre-COVID-19. The DJ stock market index and Nikkei 225 have the higher co-movements number, causing, in the Grangerian way, 6 of their pairs (out of 11 possible). Followed by the LTC, the Crypto 10, the S&P 500 and the S&P/TSX, which, in the Granger way, 5 of their pairs (out of 11 possible). The FTSE 100, CAC 40 and the Italian stock market index caused in the Granger way, 4 markets (out of 11 possible). DAX 30 caused in the grangerian sence, 3 pairs (out of 11 possible). And BTC and ETH just caused in the grangerian sence 1 financial market (out of 11 possible).

In turn, Table 12 shows the results obtained in the VAR Granger Causality tests for COVID-19 period. The Italian stock market presented all the 11 possible causal relationships with the financial markets under analysis. Followed by BTC and ETH which caused 8 of the financial markets (out of 11 possible). The LTC, S&P/TSX, FTSE 100 and CAC 40 caused 7 (out of 11 possible) and the two North American indexes, DJ and S&P 500, presented 6 causal relations. Next were the DAX 30 index and Nikkei 225 caused, in the Granger sense, 5 financial markets (out of 11 possible) and finally, the Crypto 10 index, which only caused, in the Granger sense, 4 financial markets (out of 11 possible). Overall, in the period marked by the pandemic outbreak, among the pairs of financial markets analyzed, it was possible to identify 22 bidirectional causal relationships (see table 12).

This methodology allowed us to answer the research question, namely if sharp shocks between markets could jeopardize the portfolio diversification hypothesis? In Table 11 it is possible to see that, in total, during the pre-COVID period, 49 co-movements (out of 132 possible), while in table 12 it is possible to see 81 co-movements (out of 132 possible) during the COVID-19. In comparative terms, it is possible to see a significant increase in the number of co-movements after the shock caused by the 2020 global crisis, triggered by the onset of the COVID-19 pandemic.

During the pre-COVID-19 period, BTC and ETH show no significant evidence of causality with respect to the stock markets, merely exhibiting causality, in the Grangerian sense, with the representative index of the 10 referenced digital currencies (Crypto 10). The LTC and the Crypto 10 market index show some causality relations with the G7 stock markets. Compared to the COVID-19 period, it is possible to see that all the digital currencies under analysis started to cause more markets, both at the cryptocurrency level and at the stock market index level.

**Table 11.** Granger causality/Block Exogeneity Wald Tests, of the financial markets under analysis, over the period from 02/02/2018 to 31/12/2019 (pre-COVID 19)

| | BTC | ETH | LTC | CRYPTO10 | DJ | DAX 30 | S&P500 | S&P/TSX | FTSE 100 | NIKKEI 225 | CAC 40 | ITALY |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| BTC | | 1.15998 | 1.25020 | **1.74228*** ** | 0.94838 | 0.92758 | 1.22608 | 0.96052 | 1.18408 | 0.92256 | 1.28180 | 1.32159 |
| ETH | 0.55950 | | 1.00762 | **7.71090*** ** | 0.85696 | 0.87424 | 0.93879 | 0.86292 | 1.09337 | 0.65299 | 0.75068 | 0.81883 |
| LTC | 0.76779 | 0.58324 | | **6.26701*** ** | 1.56101 | 1.16423 | **2.47545*** ** | **2.56234*** | 1.42022 | **2.65272*** ** | **1.67606*** | 1.04418 |
| CRYPTO10 | **1.74228*** | 1.49120 | 0.87318 | | 0.76503 | **2.49679*** ** | 1.52799 | **1.63169*** | 1.08042 | 0.69303 | **3.04104*** ** | **2.43933*** ** |
| DJ | 1.20687 | 1.40438 | 1.46439 | 0.59205 | | **2.17775** ** | **1.89890** ** | **2.40488*** ** | **2.12659** ** | **26.8483*** ** | **2.90409*** ** | 1.21391 |
| DAX | **1.99870** ** | 1.29832 | **2.63585*** ** | 1.25118 | 0.62454 | | 0.56335 | 1.19818 | 0.32145 | **11.6049*** | 0.45163 | 1.47253 |
| S&P500 | 1.14441 | 1.12784 | 1.33160 | 0.45567 | **2.03337** ** | 2.19308** | | **2.45111*** ** | **2.26270** ** | **30.5547*** ** | **2.86761*** ** | 1.08588 |
| S&P/TSX | **1.69048*** | **1.74197*** | 1.50786 | 1.37995 | 1.47715 | 1.45494 | **2.34621** ** | | 1.34327 | **10.6177*** ** | **2.14446** ** | 1.19116 |
| FTSE 100 | 1.56186 | 1.08342 | 0.94669 | 1.09371 | 0.68989 | 0.77623 | **3.97691*** ** | **2.23184** ** | | **6.53457*** ** | 0.87772 | **4.66367*** ** |
| NIKKEI 225 | 1.01592 | 1.17330 | 1.28352 | 0.66787 | **2.38234*** ** | **1.86545** ** | **1.71378*** ** | **3.31831*** ** | 1.50703 | | **1.89136** ** | **1.82883*** |
| CAC 40 | **1.93068** ** | **1.79852*** | **2.47719*** | 0.70986 | 0.73338 | 1.08908 | 0.56171 | 1.04154 | 0.71687 | **13.0584*** ** | | 0.87933 |
| ITALY | 1.31777 | 1.11763 | **2.17511** ** | 1.01834 | 1.13647 | 1.50913 | 0.87865 | **1.96687** ** | 1.51175 | **8.92464*** ** | **1.81099*** | |

**Source:** Own elaboration

**Table 12.** Granger causality/Block Exogeneity Wald Tests, of the financial markets under analysis, over the period from 01/01/2020 to 18/11/2021 (COVID-19)

| | BTC | ETH | LTC | CRYPTO10 | DJ | DAX | S&P500 | S&P/TSX | FTSE 100 | NIKKEI 225 | CAC 40 | ITALY |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| BTC | | **1.74065*** | 0.98380 | **9.06781*** ** | **4.87204*** ** | 1.47707 | **4.65791*** ** | **4.36851*** ** | **2.10458** ** | **4.33289*** ** | **2.09121** ** | 0.80608 |
| ETH | 1.38788 | | 1,34586 | **6,09309*** ** | **4,09635*** ** | **1,68664*** | **4,06131*** ** | **3,28679*** ** | **2,15063** ** | **3,22561*** ** | **1,90381** ** | 0,63946 |
| LTC | **1.70741*** | 1,36553 | | **4,88773*** ** | **2,58254*** ** | 1,06624 | **2,47545*** ** | **2,56234*** ** | **1,68916*** ** | **2,65272*** ** | 1,19979 | 0,65871 |
| CRYPTO10 | 0.56508 | 0,78438 | 1,14168 | | **2,41286*** ** | 0,53363 | **2,13168** ** | **2,03955** ** | 0,68567 | **2,45438*** ** | 0.71432 | 0,36877 |
| DJ | 1.21138 | 1,02147 | 0,96502 | 1,12171 | | **5,33727*** ** | **1,67572*** | **6,70095*** ** | **5,00562*** ** | **7,27309*** ** | **7,62371*** ** | 7,56227*** |
| DAX | 1.22879 | 1,41733 | 1,27945 | 1,14369 | **6,99476*** ** | | **6,58902*** ** | **5,16048*** ** | 1,59852 | **10,9128*** ** | 1,30123 | **2,86817*** ** |
| S&P500 | 1.12557 | 1,13674 | 0,88018 | 1,16307 | 1,24031 | **4,73401*** ** | | **4,92003*** ** | **4,72453*** ** | **7,23524*** ** | **7,08720*** ** | **7,36375*** ** |
| S&P/TSX | 0.94345 | 1,25526 | 0,78580 | 0,97445 | **7,85903*** ** | **3,97272*** ** | **6,67276*** ** | | **3,72907*** ** | **6,35176*** ** | **4,05811*** ** | **6,40451*** ** |
| FTSE 100 | 0.84497 | 0,91802 | 0,94669 | 1,26496 | **3,53071*** ** | **3,09420*** ** | **3,97691*** ** | **2,23184** ** | | **6,53457*** ** | **3,21321*** ** | **4,66367*** ** |
| NIKKEI 225 | 1.08304 | 0,95363 | 0,69160 | 0,78470 | **1,92144** ** | 1,53431 | **1,71378*** | **3,31831*** ** | 1,27817 | | **1,80432*** | **2,62510*** ** |
| CAC 40 | 1.32308 | 1,51220 | 1,56819 | 1,18166 | **7,49661*** ** | **1,95348** ** | **7,36394*** ** | **4,38587*** ** | **3,51775*** ** | **9,63043*** ** | | **1,99469** ** |
| ITALY | **3.15111*** ** | **2,78631*** ** | **2,41904*** ** | **2,42353*** | **10,5762*** ** | **6,04379*** ** | **11,2372*** ** | **9,93237*** ** | **6,33681*** ** | **11,1406*** ** | **5,85702*** ** | |

**Notes:** Data worked by the author (software: Eviews12). The markets in column “cause” the markets in row.
The asterisks ***,**,* indicate the significance of the statistics at 1%, 5% and 10%, respectively

**Source:** Own elaboration

The stock markets analyzed during the pre-COVID-19 period had some influences on the cryptocurrency markets, most notably the DAX index, S&P/TSX, CAC 40 and Italy DS Market. However, during the COVID-19 period, just the Italy DS Market kept some influence under the behavior of all digital currencies. Regarding the causality relations between the stock markets, in general, an increase after the occurrence of the shock is observed.

The results are in agreement, with what is evidenced by Jiang et al. (2017), who suggests an increase in the number of co-movements between the stock market under the occurrence of shocks created by the crisis. The results obtained for the cryptocurrencies are also in line with the evidence recently presented in Karim et al. (2022).

## 5. CONCLUSION

In this paper, we tested the co-movements between DJ index, S&P500 (representing the USA stock market), FTSE 100 (United Kingdom), S&P/TSX (Canada), DAX 30 (Germany), CAC 40 (France), Nikkei 225 (Japan), Italy Ds market (Italy) and the cryptocurrencies Bitcoin (BTC), Litecoin (LTC), Ethereum (ETH) and Crypto 10. In order to answer the objective, two research questions were formulated: i) The cryptocurrencies versus G7 stock markets tend towards integration during the period marked by the 2020 global crisis; and, ii) The sharped shocks between the markets could jeopardize portfolio diversification assumption.

The results related to the research question suggest that the cryptocurrencies BTC, ETH and LTC increased the co-movements between their pairs, while the Crypto 10 index decreased the shocks when compared to the pre-COVID subperiod. Regarding the stock market, it was found that the DJ index maintained the same level of shocks, while the Japanese index (Nikkei 225) decreased. The German market (DAX 39), EUA (S&P 500), Canada (S&P/TSX), UK (FTSE 100), France (CAC 40), and Italy (Italy Ds market) increased the co-movements during the global pandemic period.

The general conclusion to be retained and sustained in the results obtained through the tests carried out with econometric and mathematical models show that the current global pandemic of 2020 has a significant impact, for the most part, on the memory properties of the analyzed markets. This evidence is relevant for the individual and institutional investors seeking to diversify their investments to mitigate the risk to their portfolios that they are subject to in periods of extreme volatility in international financial markets.

Traditionally, investors seek safe havens for their investments in periods of crisis, with a preference for assets that do not show correlations with other assets or markets, the results obtained do not meet these requirements once the memory properties of the analyzed financial markets fluctuate in the same direction as the global economy.

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