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Are COVID-19-Related Economic Supports One of the Drivers of Surge in Bitcoin Market? Evidence from Linear and Non-Linear Causality Tests

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Abstract: The aim of this study was to investigate the causal relations between COVID-19 economic supports and Bitcoin markets. For this purpose, we first determined the degree of the integration of variables by implementing Fourier Augmented Dickey–Fuller unit root tests. Then, we carried out both linear (Bootstrap Toda–Yamamoto) and non-linear (Fractional Frequency Flexible Fourier form Toda–Yamamoto) causality tests to consider the nonlinearities in variables, to determine if the effects of multiple structural breaks were temporary or permanent, and to evaluate the unidirectional causality running from COVID-19-related economic supports and the price, volatility, and trading volume of Bitcoin. Our study included 158 countries, and we used daily data over the period from 1 January 2020 and 10 March 2022. The findings of this study provide evidence of unidirectional causalities running from COVID-19-related economic supports to the price, volatility, and trading volume of Bitcoin in most of the countries in the sample. The application of non-linear causality tests helped us obtain more evidence about these causalities. Some of these causalities were found to be permanent, and some of them were found to be temporary. The results of the study indicate that COVID-19-related economic supports can be considered a major driver of the surge in the Bitcoin market during the pandemic.

Keywords: COVID-19 economic supports; Bitcoin; Fourier unit root test; bootstrap Toda–Yamamoto causality test; Fractional Frequency Flexible Fourier form Toda–Yamamoto causality test

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1. Introduction

Human history will remember the COVID-19 pandemic, which started in 2019 in China and immediately spread to the rest of world. First of all, it is a global pandemic that has cost as many human lives as some of the deadliest world wars. Secondly, by creating contagious effects and raising economic uncertainty, it has caused disruptions and discontinuities in the global economy. Accordingly, we have seen serious slowdown in many economies and significant decreases in the activities of many sectors [1]. Thirdly, it has contributed to changes in the perception of governments' position towards governing health policies and their implementation. Fourthly, to avoid the spread of the pandemic, almost all countries across the globe have adapted similar measures, mostly aiming to limit the movement of people, such as stay-at-home orders, mandatory quarantines, social distancing, school and workplace closings, travel bans, and even complete curfews. Fifthly, the pandemic has become the one of the main drivers of deepening existing inequalities across and within countries, which has the potential to increase social, political, and economic tensions. Lastly, to compensate for the loss of workers and companies, governments have provided stimulus packages that we believe have had significant consequences on the economies, markets, household asset allocation, investment and portfolio decisions, and choices on saving and consumption.

Even though COVID-19 has caused many adverse effects on economies and markets, particularly financial markets, its effect on cryptocurrencies has mostly been positive across all regions [2,3]. In other words, it is fair to say that the pandemic has created a positive demand shock in cryptocurrency markets. As a result, there have been price surges, increasing the trade volume and volatilities of cryptocurrencies during the pandemic. Accordingly, the main goal of our study was to investigate the impact of COVID-19-related economic supports on Bitcoin. Our main hypothesis was that there are unidirectional causalities running from COVID-19-related economic supports to the return, volatility, and volume of Bitcoin. Therefore, we assumed that the bubbles we witnessed in cryptocurrency in general and specifically the Bitcoin market partly resulted from the increase in the COVID-19-related economic supports. Based on this hypothesis, we tried to provide answers to three following research questions. First, is there a unidirectional causality running from COVID-19-related economic supports to the return, volatility and volume of Bitcoin during the pandemic? Second, is there a region- and/or country-specific difference in this causal relationship? Third, is this causal relationship permanent or temporary? Answering these research questions will contribute to the literature in many respects. First of all, even though the impacts of COVID-19 on cryptocurrencies have been extensively studied in the literature, such as [4–11], no study, as far as we know, has examined the impacts of COVID-19 on the return, volatility and volume of Bitcoin. Secondly, in order to examine the causal relations between COVID-19-related economic supports and the return, volatility, and volume of Bitcoin, we implemented linear methods and methods that considered non-linearities in the studied data. Thirdly, we provide evidence regarding whether the observed causal relations were temporary or permanent. Fourthly, we provide evidence about whether the effects of these supports differed across regions and countries. Finally, we provide evidence regarding whether these supports can be considered one of the main drivers of the surges in the price, trading volume, and volatility of Bitcoin that we witnessed during the pandemic.

The basic findings of study can be summarized as follows. First of all, we found a unidirectional causality running from COVID-19-related economic supports to the return, volatility, and trading volume of Bitcoin in more than half of the countries in the sample. Though we found significant causal relations between the return of Bitcoin and economic supports in 70 countries, we also found evidence of causal relationships between the volatility and trading volume of Bitcoin and economic supports in 75 and 87 countries, respectively. These results imply that individuals did use these economic supports to invest in Bitcoin, thus leading to increases in the trading volume of Bitcoin. Secondly, this evidence was found to hold for both developed and underdeveloped countries, even though the size of economic supports was shown to differ depending on the country's developmental level. Lastly and may be the most importantly, all established causalities were found to be permanent, which also explains why the Bitcoin outperformed traditional assets.

The rest of the paper is organized as follows. Section 2 presents an overview of the developments in COVID-19-related economic supports and the Bitcoin market during the pandemic. Section 3 summarizes the related literature and presents the theoretical background. Section 4 discusses the data. Section 5 explains the methods used in the study. Section 6 discusses the results, and Section 7 concludes.

2. COVID-19-Related Economic Supports and Bitcoin Market during Pandemic

To decrease the adverse effects of the pandemic, especially to reduce the size of the supply and demand shocks caused by the pandemic, many countries started to support their economies with different degrees of fiscal stimulus and other monetary measures.

Within this framework, governments provided income supports to almost all employees. For businesses, in addition to direct supports, certain amounts of reimbursement for utility payments (gas, water and electricity) were provided, and loan and tax payments were partially or fully deferred. Direct support was also provided at certain rates/amounts for business closures due to restrictions. Figure 1 displays the ratio of COVID-19-related economic supports to the GDP of nations in 2020.

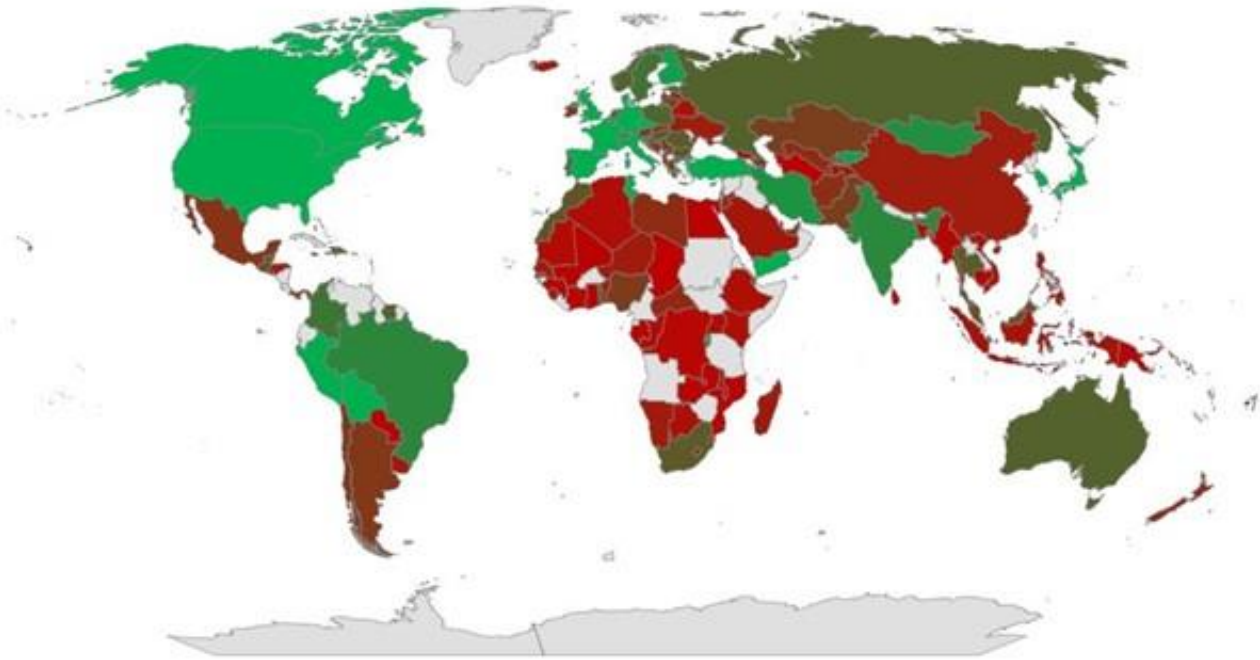

Figure 1. The ratio of COVID-19-related economic supports to GDP (%). Source: Authors' calculations based on IMF Database of Fiscal Policy Responses to COVID-19. https://www.imf.org/en/Topics/imf-and-covid19/Fiscal-Policies-Database-in-Response-to-COVID-19 (accessed on 1 October 2022).

As shown in Figure 1, there were significant differences in the amount of COVID-19-related economic supports across regions and countries. Developed nations provided more COVID-19-related economic supports than less developed nations.

To measure the responses of each government to the pandemic, the authors of [12] developed an index called the Oxford COVID-19 Government Response Tracker (OxCGRT). The main purpose of developing this index was not to provide an indicator that allows for the evaluation of the effectiveness of each government's response policies but to show whether a government response have grown weaker or stronger during the pandemic. The OxCGRT includes four policy indices. These are the overall government response index, the containment and health index, the stringency index, and the economic support index, each taking a value between 0 and 100 calculated by using all ordinal indicators of response policies. The economic support index provides information regarding how income assistance and debt relief policies are used. Figures 2 and 3 display the income supports and debt or contract relief implemented during the COVID-19 pandemic, respectively.

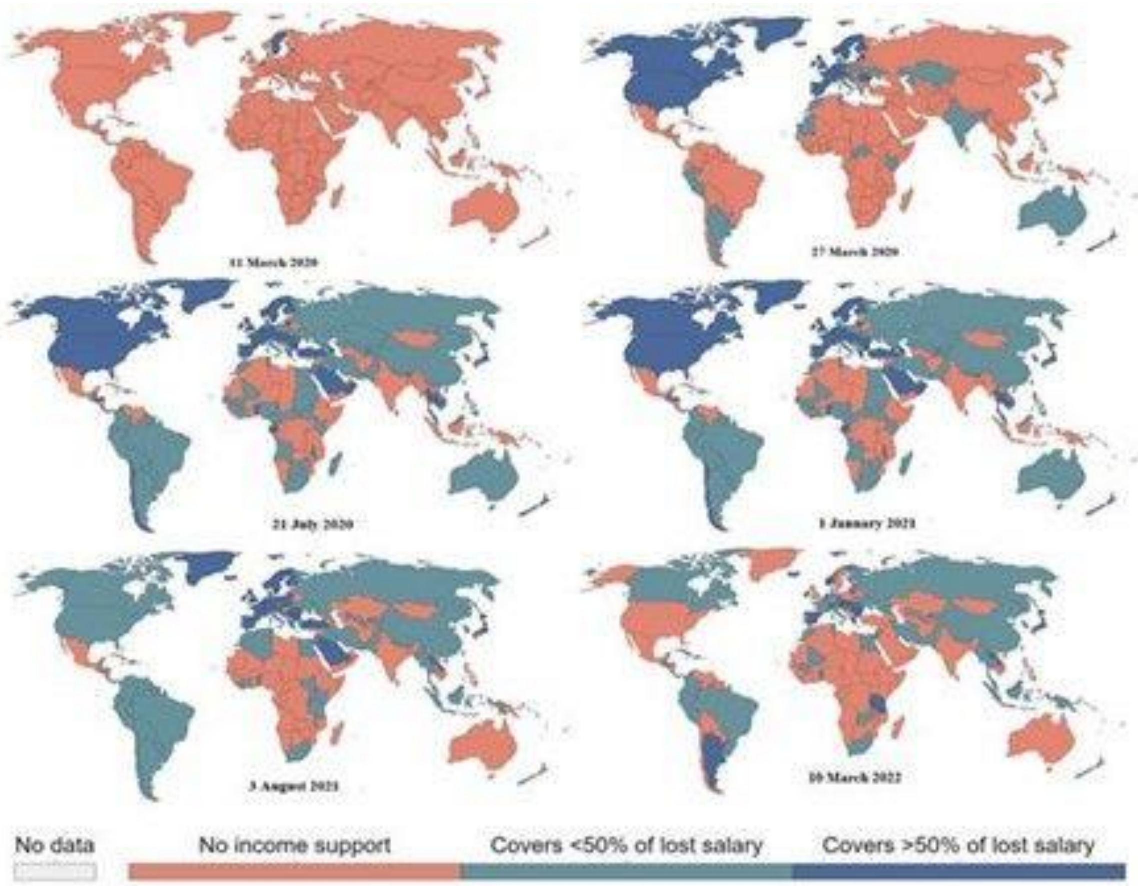

Figure 2. Income support during the COVID-19 pandemic. Source: Authors' calculations based on the OxCGRT. https://ourworldindata.org/covid-income-support-debt-relief (accessed on 15 April 2022).

As can be seen from Figures 2 and 3, there have been significant changes in the type and size of economic supports provided by different countries during the pandemic period, depending on factors such as economic development, and regional differences over time.

Cryptocurrencies have attracted the attention of many investors, researchers and policymakers since the creation of Bitcoin, the first digital currency. Compared with traditional currencies, digital currencies are based on cryptographic technologies and do not require any intermediary institutions such as banks for transactions. In other words, cryptocurrencies cannot be controlled by any government or central bank, and they are also not linked to the real economy. Although cryptocurrencies were initially thought of as digital cash [13], they are actually used more as a speculative investment tool [14,15]. In addition to their speculative features, studies conducted before and during COVID-19 have shown that cryptocurrencies have a safe-haven feature and that portfolio risk can be reduced with investments in these assets [16–18]. In addition, cryptocurrencies are considered excellent diversifiers during periods of high uncertainty and are seen as ideal investment alternatives to reduce risks during periods of financial instability [17,19].

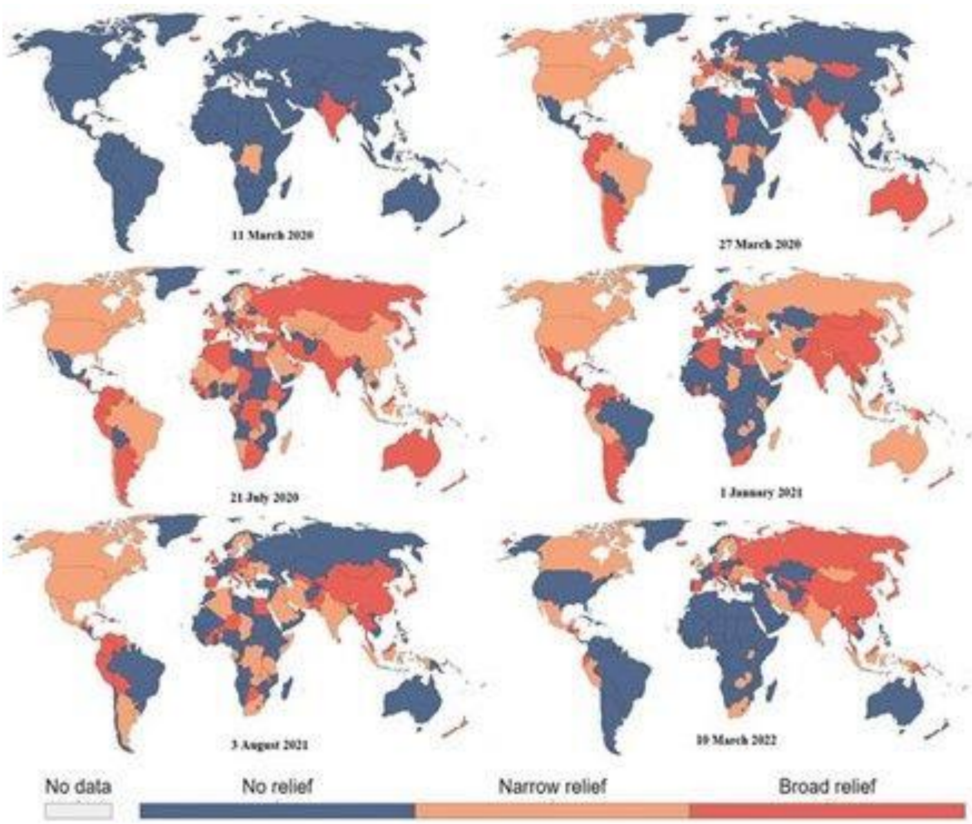

Figure 3. Debt or contract relief during the COVID-19 pandemic. Source: Authors' calculations based on the OxCGRT. https://ourworldindata.org/covid-income-support-debt-relief (accessed on 15 April 2022).

The market capitalization of crypto-assets has significantly grown between major price fluctuations. As can be seen in Figure 4, both the total cryptocurrency market capitalization and daily trading volume significantly increased with the monetary expansion that developed during the pandemic period.

Figure 4. Total cryptocurrency market capitalization and 24th Volume. Source: https://coinmarketcap.com/charts/ (accessed on 20 April 2022).

In early May 2021, the market capitalization of crypto-assets almost tripled to $2.5 trillion, followed by a 40 percent drop in May 2021 amid scrutiny and growing concerns over the crypto ecosystem. Since then, the market capitalization of crypto-assets has recovered to over $2 trillion [20]. On the other hand, as can be seen in Table 1, the share of major crypto-assets as a percentage of the total market capitalization has shown significant changes over time, as the demand for crypto-assets increased as a result of the rise in COVID-19-related economic supports along with other stimulus packages implemented worldwide during the pandemic. Therefore, it is extremely important to understand whether the pandemic-related economic supports are one of the main drivers of surges in the Bitcoin market.

Table 1. Major cryptocurrencies by percentage of total market capitalization.

	Bitcoin	Ethereum	Tether	XRP
11 March 2020	64.19%	4.10%	0.12%	0.20%
27 March 2020	65.04%	4.27%	0.12%	0.38%
21 July 2020	64.64%	1.12%	0.13%	0.47%
1 January 2021	68.63%	4.10%	0.12%	0.20%
3 August 2021	45.98%	2.12%	1.64%	1.76%
10 March 2022	41.98%	2.09%	0.85%	2.73%

Source: https://coinmarketcap.com/charts/ (accessed on 20 April 2022).

3. Literature Review and Theoretical Background

The pandemic era has significantly impacted financial markets. Investors have suffered significant losses in a short period of time due to the sharp rise in country risk premiums, and volatility has tremendously increased. Since the World Health Organization (WHO) declared the coronavirus epidemic to be a worldwide pandemic on 11 March 2020, several nations have enacted tight quarantine regulations, which have significantly reduced economic activity. According to [21], markets behaved erratically throughout the pandemic era and there was a tremendous deal of uncertainty. The authors of [22] believed that all sources of financing are affected by financial risk uncertainties. Cryptocurrencies, as an investment tool, also went through a period of extreme volatility during the pandemic. For instance, Bitcoin was only worth $8562 per coin on 1 March 2020, and on 7 March 2021, it reached a high of $51,207. In a special issue on the effects of COVID-19 on CCs, the authors of [23] reported on a significant increase in Bitcoin, particularly during the COVID-19 pandemic. For comparison, there are approximately 16,600 CCs, and the market capitalization of all CCs reached over $2.18 trillion in the middle of December 2021. At the time this report was written, Bitcoin accounted for around 40.9% of the overall market for CC ($781.4 billion), with Ethereum (ETH), the second-largest player, accounting for 18.9% ($360.5 billion). The value of Bitcoin's whole market fell by more than $500 billion as its price fell from $51,207 on 7 March 2021 to $29,807 on 19 July 2021 (the one-year low) [24]. The authors of [4] calculated the largest Lyapunov exponents and the approximate entropy in an effort to assess the stability and sequential regularity found in the values of 45 cryptocurrencies and 16 stock markets before and after the COVID-19 pandemic. To examine any discrepancies between before and during the COVID-19 outbreak, as well as between cryptocurrency and stock markets, several reliable statistical tests were used. The researchers came to the conclusion that during the pandemic period, these markets' regularity and stability underwent major changes. The pandemic was discovered to have a greater impact on cryptocurrency swings than on global stock markets. In particular, compared with stocks, cryptocurrency markets throughout the pandemic era showed greater unpredictability and irregularity. Consequently, cryptocurrency markets are more volatile and riskier [4]. Focusing on herd biases, the authors of [8] analyzed the dynamics of Bitcoin and investor reaction during the COVID-19 period. As a result, the primary goal of this research was to investigate the degree of efficiency using multifractal analysis in order to identify herd behavior and develop the most accurate forecasts and plans. According to empirical findings from the generalized Hurst exponent GHE calculations, Bitcoin was multifractal prior to the pandemic and became less fractal during the pandemic. After the pandemic, Bitcoin was shown to be more efficient using an efficiency index (MLM). The authors demonstrated that this pandemic had lessened herd bias based on the Hausdorff topology [8]. By using a causality analysis, the authors of [25] investigated the effect of the coronavirus pandemic and recognition on Bitcoin with precious metal prices. Depending on the factors used and the time period considered, the study's findings indicated that the rising rates of COVID-19 infection have had significant impacts on the values of Bitcoin, gold, platinum, and palladium. It may be claimed that the coronavirus process is raising the market for precious metals, which are generally low-risk and viewed as a safe haven by risk-averse investors. Additionally, it could be claimed that throughout the pandemic, investors searching for alternate investment options have resorted to Bitcoin [25]. Furthermore, the COVID-19 pandemic's impact on Bitcoin's market value, realized value, network value, and transaction signals was evaluated in [10] as a proxy for global economic uncertainty and market signal shock. The authors' empirical investigation showed that Bitcoin and other cryptocurrencies follow nonstationary processes, indicating that their mean market prices fluctuate over time. In contrast, COVID-19 health outcomes were found to follow a weakly dependent pattern, suggesting a potential for long-term reproduction effects that might lead to an increase in reported cases and fatalities. As verified COVID-19 cases and fatalities increased by 3.77% and 3.65% daily, they also noticed mean daily increases in the market prices of Ethereum, Bitcoin, Litecoin, and Bitcoin Cash of 0.58%, 0.44%, 0.36%, and 0.15%, respectively. An N-shaped association with the COVID-19 pandemic was revealed by the structural analysis of the different cryptocurrencies [10].

As one of its strategies to combat the COVID-19 pandemic, the US government directly distributed economic impact payments (EIPs) to households in April 2020. Although the Bitcoin (BTC) market may not have immediately soared due to the $2 trillion economic stimulus plan enacted by the US Congress on March 26, investors may have begun to notice slight, incremental gains starting in 2020 [26]. Additionally, as the news broke, Bitcoin surged after more than six weeks of calm, rising 2.5% in less than a day and momentarily crossing the $9400 mark in Europe [27]. These stimulus checks were described in [9] as a wealth shock for households, and their impact on retail Bitcoin trading was examined. The typical economic impact payment (EIP) amount of $1200 was the cause of the large spike in Bitcoin purchase trades. Similar gains in trade have been observed for other nations that have issued stimulus payments. The US dollar–Bitcoin trading pair was expected to be significantly impacted by the EIPs, with an increase in purchase volume of 3.8 percent and a price increase of 0.6 percent. In addition, it was discovered that demand for Bitcoin was far less price-sensitive than that for equities. The authors offered a list of demographic traits that increased a person's resistance to COVID-19 economic shock. People who are more interested in Bitcoin tend to be single, educated, and proficient with computers [9,28]. The cryptocurrency market saw a bullish recovery on 5 March after a modest dip. This corresponded with the announcement that Biden's package had been approved. Charts of the Bitcoin market showed that the news greatly boosted the value of cryptocurrencies [29]. Since the passage of the stimulus package, Ethereum (ETH) has seen a price increase of over 28%, whereas Bitcoin has only had a small 3% gain [30,31]. The authors of [32] believed that the one combination of factors might result in increased demand for cryptocurrencies in the event of a pandemic. Cryptocurrencies may be exchanged from anywhere in the world, which somewhat reduces the possibility of liquidity problems if local governments prohibit trading as part of a lockdown. As a result, cryptocurrencies stand out as more desirable than competing options. Investors may also want to move their money into the decentralized crypto market if they are concerned that a crisis may prompt central banks or other government actors to intervene in the market [11]. In other words, because cryptocurrencies run automatically rather than under the control of a single institution, they can help investors reduce some political risk, making them more desirable [32]. In [5], Guzman et al. looked into how COVID-19 lockdowns affected the volume of Bitcoin trade. They discovered that investors were active participants during the COVID-19 pandemic phase and traded more Bitcoins on days with limited mobility related to lockdown mandates using data from Apple mobility patterns and numerous time-series econometric models. After adjusting for stock and gold returns, the VIX index, and the degree of interest and mood toward Bitcoin (as shown by the frequency of Google searches and the tone of Tweets about the cryptocurrency), these results were still found to be solid. These findings imply that when individual investors have enough spare time, they engage in cryptocurrency trading as a hobby and enjoy watching the Bitcoin market [5]. Furthermore, their findings have significant ramifications for investor herding behavior, overconfidence, and noisy trading hazards, which can result in bubbles and excessive trading volume in cryptocurrency markets [5]. Another study [6] investigated the impact of verified cases and cumulative fatalities of COVID-19 on Bitcoin prices. The study included daily data collected from 20 January 2020, to 30 April 2020, during COVID-19's initial global outbreak. In order to determine the direction and whether the association between Bitcoin prices and COVID-19 was long or short term, this study used the enhanced Dickey–Fuller test, the co-integration test, and the vector error correction model. According to the study's findings, the short-term relationship between Bitcoin prices and COVID-19 is unfavorable and substantial [6,7]. Additionally, a one-way association between Bitcoin prices and overall mortality was seen. Due to cashless transactions, unbanked people, and less dangerous virus spreading, investors' and the general public's psychological conditions have had beneficial impacts on Bitcoin pricing over the long run. Decentralization and the simplicity of Bitcoin payments comprise the second factor contributing to the good psychological relationship. The results of this study provide decision makers with pertinent data about the volatility of Bitcoin price and how it affects people's psychological states in relation to COVID-19 [6].

This brief review of the literature shows that there is a gap in the existing literature about the impact of pandemic-related supports on the Bitcoin market. For this reason, our study was aimed to fill this gap by providing evidence about the causal effects of pandemic-related economic supports on the return, volatility and trading volume of Bitcoin.

4. Data Used in the Study

Recently, many studies have investigated the impact of COVID-19 on different financial markets and assets. As in [33–40], this study used the OxCGRT developed in [12] to investigate the responses of governments to the COVID-19 pandemic in terms of economic supports.

As we mentioned above, the OxCGRT provides information about the polices implemented by countries as a response to the pandemic. The index is calculated by using many different country-specific indicators (https://github.com/OxCGRT/covid-policy-tracker/blob/master/documentation/index_methodology.md, https://github.com/OxCGRT/covid-policy-tracker/blob/master/documentation/codebook.md#economic-policies, accessed on 15 April 2022) such as school closures, travel restrictions, and vaccination policies. Even though the OxCGRT calculates and publishes four indexes about the pandemic, we only used the economic support index in reference to income support and debt/contract relief for households [12] in our study. The index includes 180 countries around the world and starts from 1 January 2020; however, we included 158 countries and excluded 32 countries for two reasons. First, some countries provided the same amount of economic support for the entire sample period. Second, some countries only provided economic supports for a short period of time. Another important point about our sample is that sample size differed across the countries because the starting and ending dates of economic supports were not the same among all countries (see Table A1 in Appendix A for detailed information on the country-specific sample size).

In this study, we classified the considered countries according to the World Bank classification as low-income, lower-middle-income, upper-middle-income, and high-income countries. As is seen in Table 2, Low-income countries were in the Sub-Saharan Africa region; lower-middle-income and high-income countries were in the East Asia and Pacific, Europe and Central Asia, Latin America and the Caribbean, the Middle East and North Africa, South Asia, and Sub-Saharan Africa regions; there was no upper-middle-income country in the South Asia region.

Table 2. Country classifications (the Refinitiv code for the economic support index of the relevant country and the country abbreviation are shown in parentheses).

1. Low income: **a. Sub-Saharan Africa:** Burkina Faso (UVXCGES-BFA), Burundi (BNXCGES-BDI), Central African Republic (CEXCGES-CAF) Chad (CDXCGES-TCD), the Democratic Republic of the Congo (ZAXCGES-COD), Gambia (GMXCGES-GMB), Guinea (GEXCGES-GIN), Madagascar (MDXCGES-MDG), Malawi (MIXCGES-MWI), Mali (MLXCGES-MLI), Niger (NRXCGES-NER), Rwanda (RWXCGES-RWA), South Sudan (UDXCGES-SSD), Sudan (Country) (SNXCGES-SDN), Togo (TOXCGES-TGO), and Uganda (UGXCGES-UGA).
2. Lower-middle income **a. East Asia and Pacific**: Cambodia (KHXCGES-KHM), Indonesia (IDXCGES-IDN), LAO People's Democratic Republic (LAXCGES-LAO), Mongolia (MGXCGES-MNG), Myanmar (BUXCGES-MMR), Papua New Guinea (PGXCGES-PNG), the Philippines (PHXCGES-PHL), Solomon Islands (SLXCGES-SLB), Timor-Leste (TIXCGES-TLS), Vanuatu (VUXCGES-VUT), and Vietnam (VIXCGES-VNM). **b. Europe and Central Asia**: Kyrgyzstan (KYXCGES-KGZ), Tajikistan (TJXCGES-TJK), Ukraine (URXCGES-UKR), and Uzbekistan (UZXCGES-UZB). **c. Latin America and the Caribbean**: Belize (BZXCGES-BLZ), Bolivia (BVXCGES-BOL), El Salvador (ELXCGES-SLV), Haiti (HAXCGES-HTI), Honduras (HOXCGES-HND), and Nicaragua (NIXCGES-NIC). **d. The Middle East and North Africa**: Algeria (AAXCGES-DZA), Egypt (EYXCGES-EGY), Iran (IAXCGES-IRN), Morocco (MCXCGES-MAR), Tunisia (TUXCGES-TUN) **e. South Asia**: Bangladesh (BSXCGES-BGD), Bhutan (BTXCGES-BTN), India (INXCGES-IND), Nepal (NPXCGES-NPL), Pakistan (PKXCGES-PAK), and Sri Lanka (LKXCGES-LKA). **f. Sub-Saharan Africa**: Angola (AOXCGES-AGO), Benin (BEXCGES-BEN), Cameroon (CAXCGES-CMR), Cape Verde (CVXCGES-CPV), Eritrea (ENXCGES-ERI), Eswatini (SZXCGES-SWZ), Ivory Coast (IVXCGES-CIV), Kenya (KNXCGES-KEN), Lesotho (LSXCGES-LSO), Mauritania (MRXCGES-MRT), the Democratic Republic of the Congo (COXCGES-COG), Senegal (SGXCGES-SEN), Tanzania (TNXCGES-TZA), Zambia (ZMXCGES-ZMB), and Zimbabwe (ZIXCGES-ZWE).
3. Upper-middle income **a. East Asia and Pacific**: China (Mainland) (CHXCGES-CHN), Fiji (FJXCGES-FJI), Malaysia (MYXCGES-MYS), and Thailand (THXCGES-THA). **b. Europe and Central Asia**: Albania (ALXCGES-ALB), Azerbaijan (AJXCGES-AZE), Bosnia and Herzegovina (BPXCGES-BIH), Bulgaria (BLXCGES-BGR), Georgia (GGXCGES-GEO), Kazakhstan (KZXCGES-KAZ), Romania (RMXCGES-ROU), Russia (RSXCGES-RUS), Serbia (SBXCGES-SRB), Turkey (TKXCGES-TUR), and Turkmenistan (TMXCGES-TKM). **c. Latin America and the Caribbean**: Argentina (AGXCGES-ARG), Brazil (BRXCGES-BRA), Colombia (CBXCGES-COL), Costa Rica (CRXCGES-CRI), Cuba (CUXCGES-CUB), the Dominican Republic (DRXCGES-DOM), Guatemala (GWXCGES-GTM), Guyana (GYXCGES-GUY), Mexico (MXXCGES-MEX), Panama (PAXCGES-PAN), Paraguay (PYXCGES-PRY), Peru (PEXCGES-PER), Suriname (SUXCGES-SUR), and Venezuela (VEXCGES-VEN). **d. The Middle East and North Africa**: Iraq (IQXCGES-IRQ), Jordan (JOXCGES-JOR), and Lebanon (LBXCGES-LBN). **e. Sub-Saharan Africa**: Botswana (BOXCGES-BWA), Gabon (GAXCGES-GAB), Mauritius (MUXCGES-MUS), Namibia (WAXCGES-NAM), and South Africa (SAXCGES-ZAF).
4. High income **a. East Asia and Pacific**: Australia (AUXCGES-AUS), Brunei Darussalam (BIXCGES-BRN), Guam (GUXCGES-GUM), Hong Kong (HKXCGES-HKG), Japan (JPXCGES-JPN), Macao (MOXCGES-MAC), New Zealand (NZXCGES-NZL), Singapore (SPXCGES-SGP), and Taiwan (TWXCGES-TWN). **b. Europe and Central Asia**: Andorra (ADXCGES-AND), Austria (OEXCGES-AUT), Belgium (BGXCGES-BEL), Croatia (CTXCGES-HRV), the Czech Republic (CZXCGES-CZE), Denmark (DKXCGES-DNK), Estonia (EOXCGES-EST), the Faroe Islands (FAXCGES-FRO), Finland (FNXCGES-FIN), France (FRXCGES-FRA), Germany (BDXCGES-DEU), Greece (GRXCGES-GRC), Greenland (GLXCGES-GRL), Hungary (HNXCGES-HUN), Iceland (ICXCGES-ISL), Ireland (IRXCGES-IRL), Italy (ITXCGES-ITA), Latvia (LVXCGES-LVA), Lithuania (LNXCGES-LTU), Luxembourg (LXXCGES-LUX), Monaco (MTXCGES-MCO), the Netherlands (NLXCGES-NLD), Poland (POXCGES-POL), San Marino (SFXCGES-SMR), Slovenia (SJXCGES-SVN), Slovakia (SXXCGES-SVK), Spain (ESXCGES-ESP), Sweden (SDXCGES-SWE), Switzerland (SWXCGES-CHE), and the United Kingdom (UKXCGES-GBR). **c. Latin America and the Caribbean**: Aruba (AEXCGES-ABW), the Bahamas (BHXCGES-BHS), Barbados (BBXCGES-BRB), Chile (CLXCGES-CHL), Puerto Rico (PRXCGES-PRI), Trinidad and Tobago (TTXCGES-TTO), Uruguay (UYXCGES-URY), and the Virgin Islands (U.S.) (VGXCGES-VIR). **d. The Middle East and North Africa**: Bahrain (BAXCGES-BHR), Israel (ISXCGES-ISR), Kuwait (KWXCGES-KWT), Oman (OMXCGES-OMN), Qatar (QAXCGES-QAT), and the United Arab Emirates (UAXCGES-ARE). **e. North America**: Bermuda (BMXCGES-BMU), Canada (CNXCGES-CAN), and the United States (USXCGES-USA). **f. Sub-Saharan Africa**: Seychelles (SEXCGES-SYC).

Source: For country classification: World Bank; for abbreviations: Thomson Reuters Refinitiv database.

In the study, we only focused on the surge in the Bitcoin market for two reasons. First, as shown in Table 1, Bitcoin's total market capitalization is far greater than that of other cryptocurrencies. Secondly, Bitcoin outperforms conventional markets in terms of its return. Lastly, Bitcoin is the leading cryptocurrency in the market. We extracted all data used in the study from Thomson Reuters Refinitiv database.

5. Methods Used in the Study

The econometric framework that we used in this study consisted of three steps. In the first step of the analysis, we determined the degree of the integration variables by using the traditional augmented Dickey–Fuller (ADF) and Fourier ADF (FADF) tests. In the second step, we derived the volatility series of Bitcoin by using the GARCH (1,1) model, which is the preferred GARCH model for this purpose [41,42]. After determining the maximum degree of the integration of variables and deriving the volatility series of Bitcoin, we applied linear and non-linear causality tests. Since GARCH modelling has been widely covered in the literature, we do not provide any information about it.

5.1. Unit Root Tests

To determine the degree of the integration of variables, we implemented two different unit root tests: linear unit root tests of the traditional ADF test and non-linear unit root tests of the Fourier FADF unit root test developed by [43] based on the methodology of [44]. There is a clear advantage of using these tests over traditional unit root tests. According to [44], when any researcher uses this test, the researcher will be able to easily consider not only the unattended nonlinearity but also the unidentified multiple structural breaks of a model.

Thus, to implement this test, in the first stage of this procedure, we had to decide whether the series under consideration were linear or non-linear. In the second stage of the test, we carried out either the traditional ADF test or the FADF test depending on the outcome of the first stage of tests. In the both stages of the FADF test, we used the following test equation.

$$\Delta y_t = d(t) + c_0 + \rho y_{t-1} + \gamma_1 sin\left(\frac{2\pi kt}{T}\right) + \gamma_2 cos\left(\frac{2\pi kt}{T}\right) + \sum_{i=1}^{l} c_i \Delta y_{t-i} + u_t \quad (1)$$

where γ_1 and γ_2 are a parameter for the Fourier approximation and a measure of the height and width of the frequency component, respectively; k represents the selected frequency for the estimation of Fourier series; n is the number of frequencies; t is the trend term; T represents the number of observations; l is the lag length, which is determined with the AIC; and π = 3.1416. In the first stage, we tested the joint significance of the trigonometric terms. In other words, we tested the null hypothesis of $H_0: \ \gamma_1 = \gamma_2 = 0$ by using the F-test given in Equation (2).

$$F = \frac{(SSR_0 - SSR_1(k))/q}{SSR_1(k)/(T-r)} \quad (2)$$

where $SSR_1(k)$ stands for the sum of squared of residuals, q represents the number of restrictions, SSR_0 denotes the SSRs when Equation (1) is estimated without the trigonometric terms, and r represents the number of regressors in the regression. To determine the outcome of the test, we compared the calculated F-statistics value with the table critical value provided by [44] (p. 197). If the calculated F-statistics value is greater than the table critical value, one should reject the null $H_0: \ \gamma_1 = \gamma_2 = 0$. The rejection of a null hypothesis implies that one should continue with FADF tests to determine the degree of the integration of variables. Otherwise, the ADF test should continue.

To carry out the FADF unit root test, we again tested the null hypothesis of $H_0: \ p = 0$ based on Equation (1). The outcomes of tests can be interpreted as follows:

i. If we rejected the null hypothesis in both the FADF and the F-test (in stage 1), then we could conclude that we had a non-linear stationary series with multiple structural breaks.
ii. If the FADF test failed to reject the null hypothesis but the F-test rejected the null hypothesis of linearity, then the variable could be considered a non-stationary process around the multiple structural breaks.
iii. If both tests failed to reject the null hypothesis, then we had linear nonstationary variable.

An important issue regarding the implementation of these tests is the way that we determined the value of k. Enders and Lee (2012) used only two values for k, 1 and 2. The authors of [45] preferred to use fractional values of 0.1, ... ,2. Finally, the authors of [43] increased the interval to 5. One final important issue regarding this test is that we could determine whether the breaks in the data had either permanent or temporary effects. If the optimal frequency turned out to be factional, the breaks could be concluded to have permanent effects. Otherwise, the effects could be classified as transitory. The goal of using these unit root tests was to determine the maximum degree of the integration of variables so that we could augment the causality test equations by using this maximum degree of integration following the Toda–Yamamoto model.

5.2. Causality Tests

After determining the time series properties of variables, we carried out the Bootstrap Toda–Yamamoto (BTY) linear causality test and the Fractional Frequency Flexible Fourier form Toda–Yamamoto (FFFFTY) non-linear causality test. One of the major drawbacks of well-known causality tests is that they fail to consider the existence of structural breaks in variables. We know that these breaks always have the potential to affect the outcome of causality tests. To overcome this failure of traditional causality tests, there have been two attempts to develop causality tests that consider the structural breaks in visuality testing. The first of these attempts was in [46], and the other one was in [47]. What is common to both attempts is that they used Fourier functions to consider structural breaks. Indeed, both tests were developed based on the Granger and Toda–Yamamoto causality tests. Both approaches use integer frequency values. The only difference between two is that the former uses integer frequency values for k such as 1 and 2 while the latter uses integer frequency values for k such as 1, 2,..., 5. Developing these approaches solved problems of traditional causality tests related to unknown numbers of structural breaks and their dates of occurrence. Still, these attempts did not address the question of whether these causal relations are permanent or temporary, since according to [48], the use of the integer frequencies only allows one to determine that the influence of structural breaks is temporary. Accordingly, the study of [49] showed that the use of fractional frequencies allows for the determination of whether breaks have permanents effects. For this purpose, the authors developed the FFFFTY test, which uses the lag-augmented VAR (LAVAR) model with a Fourier function that extends the VAR model with maximum integration levels of the variables. Because of the structure of the VAR model and the methodology the authors adapted, there was no need to pre-filter the data.

$$Y_t = \beta_0 + \beta_1 sin\left(\frac{2\pi kt}{T}\right) + \beta_2 cos\left(\frac{2\pi kt}{T}\right) + \sum_{i=1}^{l+d_{max}} \theta_i Y_{t-i} + \sum_{i=1}^{l+d_{max}} \delta_i X_{t-i} + u_t \quad (3)$$

$$X_t = \alpha_0 + \alpha_1 sin\left(\frac{2\pi kt}{T}\right) + \alpha_2 cos\left(\frac{2\pi kt}{T}\right) + \sum_{i=1}^{l+d_{max}} \varphi_i X_{t-i} + \sum_{i=1}^{l+d_{max}} \lambda_i Y_{t-i} + v_t \quad (4)$$

To test the idea that X does not cause Y based on Equation (3), we tested the null hypothesis of $\delta_l = 0,\ \forall_i = 1,\ \ldots,\ l$ by using the Wald statistic based on a χ2 distribution. To obtain the critical values of the test, we needed to conduct bootstrap simulations.

We also applied another Toda–Yamamoto (TY)-based causality test known as the Bootstrap Toda–Yamamoto test developed by [50]. This test can also be applied to variables that may have different degrees of integration and also does not require any pre-filtering. One of main contributions of these tests is that they modify statistics. According to [50], the Wald test developed by TY cannot have a chi-squared distribution if there is heteroscedasticity in the test equation. Thus, the researchers developed MWALD statistics based on bootstrapping. The null hypothesis of this test can also be used to express the non-existence of causal relations between two variables.

6. Discussion of Empirical Results

In this section, we first examine the results of the unit root tests and then discuss the results of the causality tests.

6.1. The Results of Unit Root Tests

As we explained in the previous section, to determine the maximum degree of the integration of variables, we used the FADF and ADF tests. These tests were applied to COVID-19-related economic supports and the return, volatility and trading volume of Bitcoin. Table 3 displays the results of these tests.

According to the FADF tests results shown in Table 3, the F-test was significant in the economic support series of 12 countries (Bulgaria, Bolivia, Guinea, Hungary, Lesotho, Monaco, Paraguay, Senegal, Eswatini, Turkmenistan, Uruguay, and the United States), which implied that we should use the FADF test to determine the maximum degree of the integration of variables. The results of these tests indicated that the maximum degree of the integration of the economic support series of these countries was 1. Since the F-tests for the remaining 146 countries were not statistically significant, we used the traditional ADF tests to determine maximum degree of the integration of economic support series, and the results of these tests showed that the economic support series of 78 countries were stationary and 68 countries had unit roots. Because the F-tests that we applied to the return, volatility and trading volume of the Bitcoin series were not significant, we carried out traditional ADF tests to determine the maximum degree of the integration of these series. The results of the tests indicated that they were all level-stationary, implying that we should use only one additional lag in the test equations for 68 countries.

6.2. The Results of Causality Tests

Table 4 shows the results of the FFFFTY causality tests between economic supports and Bitcoin return.

Table 3. Results of FADF and ADF unit root tests [a].

	Freq.	Min. SSR	F Test Stat.	Opt. Lag	FADF Test Stat.	ADF		Freq.	Min. SSR	F Test Stat.	Opt. Lag	FADF Test Stat.	ADF
BTC_R	3.6	1.093	4.481	4	−11.29	−23.75 *	**KAZ**	1	88.56	4.575	1	−4.239	−3.000 **
BTC_V	1.9	<0.01	3.298	5	−5.869	−4.968 *	**KEN**	5	23.43	3.306	0	−2.585	−2.391
BTC_TV	0.5	75.56	4.773	9	−4.656	−8.879	**KGZ**	1.0	5.731	4.414	11	−4.407	−3.434 **
ABW	4.7	20.75	2.086	9	−2.222	−1.779	**KHM**	0.9	1.163	4.517	1	−2.831	−0.902
AGO	3.8	20.69	3.119	1	−2.236	−2.054	**KWT**	3.7	3.571	2.152	15	−4.475	−3.841 *
ALB	3.0	1.665	2.764	18	−3.988	−3.702 *	**LAO**	0.9	39.32	2.590	14	−3.984	−3.274 **
AND	1.3	1.708	2.968	0	−2.216	−2.231	**LBN**	2.4	1.390	2.084	5	−2.337	−3.058 **
ARE	0.1	24.93	1.501	0	−3.051	−2.908 **	**LKA**	0.1	28.74	5.950	14	−4.907	−3.535 *
ARG	0.7	22.54	1.414	2	−3.132	−2.758	**LSO**	1.0	24.88	**6.267** ***	1	−3.072	-
AUS	0.1	2.060	5.850	9	−2.490	−4.188 *	**LTU**	3.2	2.487	2.854	15	−2.320	−3.835 *
AUT	0.6	0.253	2.355	3	−2.431	−8.860 *	**LUX**	0.8	3.144	3.595	1	−2.833	−1.252
AZE	1.1	72.50	5.035	1	−3.838	−2.372	**LVA**	2.3	35.51	2.998	2	−2.205	−1.932
BDI	3.4	50.50	2.446	0	−2.691	−2.560	**MAC**	5.0	33.17	1.611	0	−3.196	−3.038 **
BEL	3.2	1.462	3.695	17	−3.707	−3.840 *	**MAR**	5.0	23.97	3.755	0	−2.019	−1.927
BEN	4.8	41.66	1.107	0	−4.001	−3.880 *	**MCO**	0.1	0.739	**6.167** ***	4	−2.839	-
BFA	1.7	30.74	3.285	1	−2.727	−1.890	**MDG**	0.9	20.53	2.913	10	−3.141	−2.197
BGD	2.5	30.76	1.842	0	−2.130	−2.073	**MEX**	0.1	1.178	2.341	1	−2.662	−1.806
BGR	0.9	1.100	**6.299** ***	10	−3.534	-	**MLI**	0.9	24.99	5.607	1	−3.122	−1.522
BHR	0.3	3.100	5.975	12	−3.002	−1.680	**MMR**	0.1	22.90	2.119	14	−2.618	−1.403
BHS	1.3	26.23	3.910	1	−2.756	−1.675	**MNG**	1.0	28.61	4.636	15	−3.962	−3.200 **
BIH	2.2	31.73	1.960	0	−1.661	−1.643	**MRT**	1.0	49.41	5.434	10	−3.368	−2.160
BLZ	1.1	30.63	2.614	11	−3.897	−3.226 *	**MUS**	3.4	2.430	3.148	1	−3.424	−2.821 ***
BMU	1.1	4.781	3.919	1	−2.820	−1.496	**MWI**	1.5	47.08	3.364	5	−3.552	−3.230 **
BOL	1.4	27.36	**9.206** **	10	−4.639	-	**MYS**	1.5	0.168	1.723	16	−5.424	−5.774 *
BRA	4.2	17.82	2.850	1	−2.220	−2.072	**NAM**	0.9	39.43	4.972	5	−2.889	−1.852
BRB	3.5	1.057	5.418	1	−2.514	−1.570	**NER**	2.8	30.32	2.624	1	−2.055	−1.828
BRN	0.8	1.420	4.140	2	−2.763	−10.28 *	**NIC**	0.7	19.25	4.060	7	−2.683	−1.476
BTN	4.9	0.551	3.287	0	−3.235	−2.961 **	**NLD**	0.4	0.942	3.220	10	−2.523	−2.673 ***
BWA	0.7	99.63	3.449	1	−3.630	−2.620 ***	**NPL**	0.8	5.151	4.166	6	−3.635	−2.424

Table 3. *Cont.*

	Freq.	Min. SSR	F Test Stat.	Opt. Lag	FADF Test Stat.	ADF		Freq.	Min. SSR	F Test Stat.	Opt. Lag	FADF Test Stat.	ADF
CAF	1.0	31.04	4.959	8	−2.780	−1.647	**NZL**	0.1	1.562	4.529	5	−2.777	−0.936
CAN	0.4	0.496	2.812	2	−2.262	−1.506	**OMN**	4.8	3.005	1.304	16	−2.208	−2.998
CHE	2.1	26.18	1.555	13	−3.992	−3.576 *	**PAK**	2.4	1.816	2.489	12	−2.841	−3.164 **
CHL	0.1	2.925	6.154	6	−2.931	−1.838	**PAN**	0.8	1.214	4.612	1	−2.748	−0.636
CHN	0.1	1.415	0.982	0	−3.375	−3.506 *	**PER**	0.1	1.419	2.616	17	−2.713	−4.610 *
CIV	2.2	48.63	2.831	10	−3.354	−3.745 *	**PHL**	1.4	31.09	2.712	0	−2.434	−2.321
CMR	0.6	0.153	3.109	1	−2.566	−1.270	**PNG**	2.7	26.18	2.572	1	−2.185	−1.848
COD	1.4	62.63	5.316	1	−3.757	−2.134	**POL**	0.7	2.113	3.310	5	−2.400	−4.174 *
COG	1.9	79.99	2.969	1	−3.672	−3.038 **	**PRI**	0.1	1.332	5.210	1	−2.830	−0.657
COL	0.1	1.691	2.224	15	3.015	1.478	**PRY**	0.7	4.424	**6.560** ***	1	−3.965	-
CPV	0.7	22.81	1.173	0	−2.365	−2.336	**QAT**	1.3	1.243	4.648	1	−3.926	−2.660 ***
CRI	0.8	0.925	4.591	14	−2.850	−1.438	**ROU**	0.4	1.161	3.690	6	−3.181	−4.298 *
CUB	4.3	0.256	1.148	17	−3.822	−3.554 *	**RUS**	1.1	4.301	5.981	9	−3.654	−1.843
CZE	2.7	2.613	4.889	13	−2.456	−2.758 ***	**RWA**	5.0	0.048	1.128	0	−3.428	−3.397 **
DEU	0.1	4.478	5.609	12	−2.871	−1.613	**SDN**	0.1	18.21	2.105	9	−3.598	−3.443 **
DMA	0.4	2.088	3.254	1	−2.964	−1.629	**SEN**	1.0	32.76	**6.448** ***	1	−3.240	-
DNK	0.8	1.471	5.762	1	−3.361	−1.695	**SGP**	0.1	1.194	0.415	18	−7.067	−6.205 *
DOM	0.9	16.26	1.632	0	−2.872	−2.711 ***	**SLB**	2.6	24.32	3.153	1	−2.575	−2.040
DZA	1.5	1.387	3.364	5	−3.133	−2.824 ***	**SLV**	0.8	2.105	3.669	9	−2.528	−1.863
EGY	3.9	0.143	1.472	15	−3.572	−4.437 *	**SMR**	3.6	0.162	1.106	0	−2.108	−2.063
ERI	0.7	0.464	3.869	1	−2.603	−0.596	**SRB**	0.1	0.513	3.481	1	−2.895	−2.080
ESP	0.1	0.369	5.186	18	−7.362	−11.86 *	**SSD**	1.3	40.31	4.270	1	−3.366	−2.008
EST	3.0	1.888	4.659	9	−2.726	−2.381	**SUR**	0.7	2.600	4.555	10	−3.031	−1.555
FIN	0.1	0.321	4.792	1	−2.971	−1.748	**SVK**	1.2	0.313	4.197	8	−2.870	−6.449 *
FJI	0.1	0.467	0.425	1	−2.962	−4.425 *	**SVN**	3.9	1.576	4.807	7	−3.656	−3.565 *
FRA	0.1	0.714	2.200	0	−1.234	−1.044	**SWE**	2.3	2.096	4.186	1	−2.710	−1.825
FRO	0.9	1.175	4.532	1	−2.833	−0.882	**SWZ**	1.0	1.233	**6.691** ***	1	−3.395	-
GAB	0.9	55.71	3.093	11	−3.589	−3.116 **	**SYC**	1.1	54.29	4.071	5	−2.883	−2.143
GBR	0.1	2.599	3.713	3	−2.508	−1.430	**TCD**	1.4	26.39	2.460	0	−2.753	−2.611
GEO	1.3	28.94	4.606	10	−3.397	−2.594 ***	**TGO**	0.8	41.36	2.726	12	−4.247	−4.310 *
GIN	1.0	28.79	**6.255** ***	1	−3.240	-	**THA**	3.6	5.367	2.220	18	−3.088	−2.988 *
GMB	0.9	15.74	5.972	1	−3.130	−1.232	**TJK**	5.0	68.23	3.821	0	−2.873	−2.581 ***
GRC	0.1	1.808	0.307	5	−1.858	−7.616 *	**TKM**	1.4	39.72	**7.356** **	6	−3.808	-
GRL	2.7	25.70	2.832	1	−2.371	−1.977	**TLS**	1.3	22.37	4.325	14	−3.568	−2.368
GTM	2.8	0.273	4.765	1	−2.767	−2.126	**TTO**	2.4	19.27	3.246	1	−2.116	−1.760
GUM	1.1	54.70	4.343	1	−3.761	−2.513	**TUN**	4.9	33.68	1.688	0	−3.820	−3.569 *
GUY	0.9	0.797	2.456	1	−2.645	−1.594	**TUR**	1.2	34.31	1.563	0	−2.759	−2.656 ***
HKG	0.4	0.081	2.948	1	−2.603	−1.374	**TWN**	2.3	3.004	3.596	1	−1.919	−1.344
HND	0.3	32.21	3.083	9	−4.668 *	−3.949	**TZA**	3.6	1.065	2.469	1	−3.367	−2.946 **
HRV	0.8	0.723	4.960	11	−2.742	−1.219	**UGA**	2.1	46.49	2.543	1	−2.511	−2.066
HTI	1.0	25.07	3.414	13	−3.776	−2.811 ***	**UKR**	2.1	4.695	2.731	14	−4.146	−5.296 *
HUN	2.4	3.206	**8.053** **	1	−3.057	-	**URY**	0.6	28.13	**7.988** **	8	−4.293	-
IDN	0.1	0.162	0.839	0	−1.787	−1.880	**USA**	0.1	2.336	**7.462** **	3	−3.308	-
IND	0.8	25.36	1.453	0	−3.126	−2.973 **	**UZB**	1.1	28.64	2.633	13	−4.201	−3.519 *
IRL	1.3	1.786	0.842	6	−3.421	−9.135 *	**VEN**	0.8	0.161	4.499	1	−2.841	−0.810
IRN	5.0	29.61	1.885	0	−2.950	−2.827 ***	**VIR**	3.6	21.24	1.969	0	−1.828	−1.795
IRQ	0.8	0.081	4.155	1	−2.768	−1.019	**VNM**	1.1	21.20	1.439	0	−2.100	−2.062
ISL	1.4	0.463	5.870	9	−3.091	−6.309 *	**VUT**	0.1	1.311	0.907	0	−2.089	−2.202
ISR	0.3	0.911	2.350	16	−2.612	−6.591 *	**ZAF**	1.1	3.704	3.924	1	−4.387	−3.485 *
ITA	5.0	0.235	1.369	8	−3.353	−4.795 *	**ZMB**	1.5	20.51	4.291	1	−2.935	−1.608
JOR	0.6	2.684	1.790	8	−3.109	−2.428	**ZWE**	1.1	24.89	5.585	1	−3.077	−1.426
JPN	2.9	0.939	2.089	5	−3.900	−3.711 *							

[a] BTC_R, BTC_V, and BTC_TV denote the return, volatility, and trading volume of Bitcoin, respectively. Also *, **, *** indicate statistically significant results at 1%, 5% and 10% level of significance respectively.

Table 4. Fractional Frequency Flexible Fourier form Toda–Yamamoto causality tests between economic supports and Bitcoin return *.

	W-Statistics	Bootstrap Prob. Value	P	k		W-Statistics	Bootstrap Prob. Value	P	k
ABW_ES ≠ > BTC_R	0.040	0.822	1	2.8	KEN_ES ≠ > BTC_R	1.428	0.198	1	2.8
AGO_ES ≠ > BTC_R	0.065	0.720	1	2.4	KGZ_ES ≠ > BTC_R	2.061	0.147	1	2.8
ALB_ES ≠ > BTC_R	0.722	0.674	2	2.7	KHM_ES ≠ > BTC_R	1.104	0.229	1	0.7
AND_ES ≠ > BTC_R	0.765	0.344	1	2.8	KWT_ES ≠ > BTC_R	0.197	0.611	1	2.7
ARE_ES ≠ > BTC_R	0.145	0.665	1	2.0	LAO_ES ≠ > BTC_R	0.000	0.994	1	2.8
ARG_ES ≠ > BTC_R	0.498	0.429	1	2.4	LBN_ES ≠ > BTC_R	2.804	0.775	6	2.7
AUS_ES ≠ > BTC_R	22.17	**0.067**	10	**0.1**	LKA_ES ≠ > BTC_R	0.014	0.882	1	2.6
AUT_ES ≠ > BTC_R	3.581	0.428	4	2.8	LSO_ES ≠ > BTC_R	0.260	0.544	1	0.1
AZE_ES ≠ > BTC_R	0.061	0.804	1	2.5	LTU_ES ≠ > BTC_R	0.101	0.754	1	3.0
BDI_ES ≠ > BTC_R	0.117	0.725	1	1.9	LUX_ES ≠ > BTC_R	1.753	0.162	1	2.8
BEL_ES ≠ > BTC_R	0.159	0.638	1	3.0	LVA_ES ≠ > BTC_R	0.306	0.538	1	2.7
BEN_ES ≠ > BTC_R	2.329	0.113	1	2.5	MAC_ES ≠ > BTC_R	2.591	0.122	1	3.3
BFA_ES ≠ > BTC_R	0.299	0.573	1	1.2	MAR_ES ≠ > BTC_R	1.042	0.313	1	1.2
BGD_ES ≠ > BTC_R	0.305	0.540	1	2.5	MCO_ES ≠ > BTC_R	6.167	0.290	5	0.7
BGR_ES ≠ > BTC_R	9.175	0.482	10	0.7	MDG_ES ≠ > BTC_R	0.009	0.926	1	1.3
BHR_ES ≠ > BTC_R	0.043	0.809	1	2.1	MEX_ES ≠ > BTC_R	2.202	0.112	1	2.1
BHS_ES ≠ > BTC_R	0.055	0.784	1	1.7	MLI_ES ≠ > BTC_R	0.332	0.514	1	2.6
BIH_ES ≠ > BTC_R	0.057	0.761	1	2.7	MMR_ES ≠ > BTC_R	0.201	0.586	1	0.1
BZL_ES ≠ > BTC_R	4.346	**0.051**	1	**2.7**	MNG_ES ≠ > BTC_R	2.012	0.893	6	3.0

Table 4. *Cont.*

	W-Statistics	Bootstrap Prob. Value	P	k		W-Statistics	Bootstrap Prob. Value	P	k
BMU_ES ≠ > BTC_R	0.047	0.809	1	1.2	MRT_ES ≠ > BTC_R	0.486	0.442	1	1.2
BO_ES ≠ > BTC_R	1.177	0.226	1	1.4	MUS_ES ≠ > BTC_R	0.000	0.986	1	3.2
BRA_ES ≠ > BTC_R	0.726	0.354	1	2.8	MWI_ES ≠ > BTC_R	1.951	0.167	1	1.6
BRB_ES ≠ > BTC_R	0.004	0.930	1	2.3	MYS_ES ≠ > BTC_R	8.668	0.345	8	2.7
BRN_ES ≠ > BTC_R	2.802	0.353	3	0.7	**NAM_ES ≠ > BTC_R**	2.697	**0.092**	1	**0.7**
BTN_ES ≠ > BTC_R	0.155	0.652	1	3.2	NER_ES ≠ > BTC_R	0.057	0.770	1	2.9
BWA_ES ≠ > BTC_R	0.044	0.843	1	2.2	NIC_ES ≠ > BTC_R	7.345	0.497	8	0.7
CAF_ES ≠ > BTC_R	0.000	0.979	1	2.7	**NLD_ES ≠ > BTC_R**	16.103	**0.061**	8	**0.6**
CAN_ES ≠ > BTC_R	5.503	0.158	3	0.6	NPL_ES ≠ > BTC_R	1.217	0.258	1	0.7
CHE_ES ≠ > BTC_R	1.313	0.217	1	2.9	NZL_ES ≠ > BTC_R	0.767	0.364	1	0.1
CHL_ES ≠ > BTC_R	4.441	**0.037**	1	**0.1**	OMN_ES ≠ > BTC_R	1.356	0.225	1	1.5
CHN_ES ≠ > BTC_R	0.006	0.913	1	2.7	PAK_ES ≠ > BTC_R	5.831	0.547	7	2.5
CIV_ES ≠ > BTC_R	0.000	0.988	1	2.4	PAN_ES ≠ > BTC_R	0.020	0.820	1	2.6
CMR_ES ≠ > BTC_R	2.742	**0.097**	1	**0.3**	PER_ES ≠ > BTC_R	3.024	0.326	3	2.7
COD_ES ≠ > BTC_R	1.657	0.156	1	1.4	**PHL_ES ≠ > BTC_R**	4.968	**0.040**	1	**1.3**
COG_ES ≠ > BTC_R	0.162	0.663	1	1.9	**PNG_ES ≠ > BTC_R**	2.699	**0.092**	1	**2.8**
COL_ES ≠ > BTC_R	0.005	0.926	1	2.6	POL_ES ≠ > BTC_R	4.277	0.589	6	0.3
CPV_ES ≠ > BTC_R	0.257	0.589	1	2.3	PRI_ES ≠ > BTC_R	0.006	0.926	1	1.8
CRI_ES ≠ > BTC_R	17.08	0.299	15	0.7	PRY_ES ≠ > BTC_R	0.937	0.575	2	0.7
CUB_ES ≠ > BTC_R	1.547	0.900	5	2.5	**QAT_ES ≠ > BTC_R**	3.412	**0.070**	1	**3.0**
CZE_ES ≠ > BTC_R	0.380	0.523	1	2.7	ROU_ES ≠ > BTC_R	5.114	0.519	6	0.6
DEU_ES ≠ > BTC_R	2.175	0.133	1	0.1	RUS_ES ≠ > BTC_R	0.678	0.409	1	0.9
DMA_ES ≠ > BTC_R	0.969	0.301	1	0.6	RWA_ES ≠ > BTC_R	0.224	0.548	1	1.8
DNK_ES ≠ > BTC_R	0.368	0.489	1	0.7	**SDN_ES ≠ > BTC_R**	4.580	**0.045**	1	**1.6**
DOM_ES ≠ > BTC_R	2.281	0.115	1	1.8	SEN_ES ≠ > BTC_R	0.442	0.439	1	0.9
DZA_ES ≠ > BTC_R	8.435	**0.010**	1	**2.7**	SGP_ES ≠ > BTC_R	14.491	0.404	14	2.7
EGY_ES ≠ > BTC_R	0.114	0.732	1	2.8	SLB_ES ≠ > BTC_R	0.105	0.701	1	3.3
ERI_ES ≠ > BTC_R	0.010	0.870	1	0.7	SLV_ES ≠ > BTC_R	0.666	0.370	1	2.1
ESP_ES ≠ > BTC_R	9.368	0.541	11	2.8	SMR_ES ≠ > BTC_R	0.049	0.743	1	3.1
EST_ES ≠ > BTC_R	0.056	0.790	1	1.5	SRB_ES ≠ > BTC_R	0.000	0.990	1	2.3
FIN_ES ≠ > BTC_R	0.096	0.722	1	3.0	SSD_ES ≠ > BTC_R	0.052	0.785	1	2.6
FJI_ES ≠ > BTC_R	1.740	0.383	2	2.8	SUR_ES ≠ > BTC_R	0.125	0.694	1	0.6
FRA_ES ≠ > BTC_R	0.200	0.595	1	2.6	SVK_ES ≠ > BTC_R	11.860	0.237	9	2.6
FRO_ES ≠ > BTC_R	0.890	0.255	1	1.8	SVN_ES ≠ > BTC_R	0.000	0.987	1	2.5
GAB_ES ≠ > BTC_R	0.531	0.431	1	2.3	SWE_ES ≠ > BTC_R	0.127	0.934	2	2.3
GBR_ES ≠ > BTC_R	0.914	0.880	4	2.8	SWZ_ES ≠ > BTC_R	0.360	0.535	1	1.0
GEO_ES ≠ > BTC_R	3.281	**0.081**	1	**1.4**	SYSC_ES ≠ > BTC_R	1.050	0.284	1	2.5
GIN_ES ≠ > BTC_R	0.340	0.489	1	0.1	TCD_ES ≠ > BTC_R	0.432	0.465	1	2.6
GMB_ES ≠ > BTC_R	0.309	0.544	1	0.9	TGO_ES ≠ > BTC_R	0.298	0.538	1	2.8
GRC_ES ≠ > BTC_R	5.079	0.491	6	2.8	THA_ES ≠ > BTC_R	0.000	0.985	1	2.8
GRL_ES ≠ > BTC_R	0.325	0.525	1	2.6	TJK_ES ≠ > BTC_R	0.730	0.358	1	1.2
GTM_ES ≠ > BTC_R	1.373	0.247	1	2.7	TKM_ES ≠ > BTC_R	0.008	0.932	1	1.4
GUM_ES ≠ > BTC_R	1.519	0.213	1	1.0	TLS_ES ≠ > BTC_R	0.116	0.683	1	2.6
GUY_ES ≠ > BTC_R	0.731	0.399	1	2.8	TTO_ES ≠ > BTC_R	1.666	0.179	1	3.0
HKG_ES ≠ > BTC_R	0.326	0.471	1	3.2	TUN_ES ≠ > BTC_R	1.688	0.185	1	2.8
HND_ES ≠ > BTC_R	0.321	0.512	1	2.8	TUR_ES ≠ > BTC_R	0.093	0.720	1	1.7
HRV_ES ≠ > BTC_R	0.360	0.521	1	0.7	TWN_ES ≠ > BTC_R	3.045	0.359	3	2.7
HTI_ES ≠ > BTC_R	1.622	0.173	1	2.7	TZA_ES ≠ > BTC_R	0.868	0.334	1	3.5
HUN_ES ≠ > BTC_R	1.292	0.261	1	2.5	UGA_ES ≠ > BTC_R	0.086	0.785	1	2.7
IDN_ES ≠ > BTC_R	1.183	0.190	1	2.6	UKR_ES ≠ > BTC_R	0.957	0.295	1	2.7
IND_ES ≠ > BTC_R	0.006	0.933	1	3.2	URY_ES ≠ > BTC_R	4.393	0.466	5	0.6
IRL_ES ≠ > BTC_R	5.776	0.493	7	2.8	USA_ES ≠ > BTC_R	2.402	0.254	2	0.1
IRN_ES ≠ > BTC_R	4.409	**0.050**	1	**2.9**	UZB_ES ≠ > BTC_R	1.313	0.224	1	2.8
IRQ_ES ≠ > BTC_R	0.147	0.612	1	2.2	VEN_ES ≠ > BTC_R	0.750	0.309	1	2.3
ISL_ES ≠ > BTC_R	6.216	0.703	10	1.4	VIR_ES ≠ > BTC_R	0.586	0.420	1	2.1
ISR_ES ≠ > BTC_R	11.79	0.727	17	2.7	VNM_ES ≠ > BTC_R	0.234	0.578	1	1.7
ITA_ES ≠ > BTC_R	4.208	0.847	9	2.9	VUT_ES ≠ > BTC_R	0.021	0.855	1	3.8
JOR_ES ≠ > BTC_R	3.528	**0.059**	1	**2.8**	ZAF_ES ≠ > BTC_R	0.480	0.433	1	2.8
JPN_ES ≠ > BTC_R	0.060	0.797	1	2.8	ZMB_ES ≠ > BTC_R	0.804	0.353	1	2.8
KAZ_ES ≠ > BTC_R	0.065	0.779	1	1.5	ZWE_ES ≠ > BTC_R	0.144	0.657	1	1.0

* ES denotes economic supports; R denotes return.

The results of the causality tests showed that there was a permanent unidirectional causality running from economic supports to Bitcoin return for 14 countries (Australia, Belize, Chile, Cameroon, Algeria, Georgia, Iran, Iran, Jordan, Namibia, the Netherlands, the Philippines, Papua New Guinea, Qatar, and Sudan (country)). Table 5 includes the results of the FFFFTY causality tests between economic supports and Bitcoin volatility.

Table 5. Fractional Frequency Flexible Fourier form Toda–Yamamoto causality tests between economic supports and Bitcoin volatility *.

	W-Statistics	Bootstrap Prob. Value	p	k		W-Statistics	Bootstrap Prob. Value	p	k
ABW_ES ≠ > BTC_V	0.000	0.985	1	0.80	KEN_ES ≠ > BTC_V	1.189	0.251	1	0.80
AGO_ES ≠ > BTC_V	0.014	0.877	1	0.80	KGZ_ES ≠ > BTC_V	1.126	0.264	1	0.80
ABL_ES ≠ > BTC_V	0.503	0.757	2	2.70	KHM_ES ≠ > BTC_V	1.054	0.255	1	0.80
AND_ES ≠ > BTC_V	0.572	0.439	1	2.80	KWT_ES ≠ > BTC_V	0.224	0.595	1	0.80
ARE_ES ≠ > BTC_V	0.337	0.495	1	0.80	LAO_ES ≠ > BTC_V	0.053	0.802	1	0.80
ARG_ES ≠ > BTC_V	0.215	0.608	1	0.80	LBN_ES ≠ > BTC_V	2.375	0.825	6	2.70
AUS_ES ≠ > BTC_V	0.007	0.935	1	0.80	LKA_ES ≠ > BTC_V	0.035	0.850	1	0.80
AUT_ES ≠ > BTC_V	1.840	0.669	4	2.80	LSO_ES ≠ > BTC_V	0.151	0.630	1	0.80
AZE_ES ≠ > BTC_V	0.250	0.613	1	0.80	LTU_ES ≠ > BTC_V	0.011	0.911	1	0.80
BDI_ES ≠ > BTC_V	0.236	0.591	1	0.80	**LUX_ES ≠ > BTC_V**	3.708	**0.062**	1	**0.80**
BEL_ES ≠ > BTC_V	0.070	0.762	1	3.00	LVA_ES ≠ > BTC_V	0.690	0.420	1	0.80
BEN_ES ≠ > BTC_V	2.016	0.147	1	0.80	**MAC_ES ≠ > BTC_V**	2.615	**0.078**	1	**0.80**
BFA_ES ≠ > BTC_V	0.271	0.568	1	0.80	MAR_ES ≠ > BTC_V	0.715	0.339	1	0.80
BGD_ES ≠ > BTC_V	0.667	0.375	1	0.80	MCO_ES ≠ > BTC_V	5.708	0.293	5	0.70
BGR_ES ≠ > BTC_V	9.847	0.452	10	0.70	MDG_ES ≠ > BTC_V	0.001	0.983	1	0.80
BHR_ES ≠ > BTC_V	0.011	0.901	1	0.80	MEX_ES ≠ > BTC_V	1.364	0.228	1	2.10
BHS_ES ≠ > BTC_V	0.014	0.899	1	0.80	MLI_ES ≠ > BTC_V	0.097	0.720	1	0.80
BIH_ES ≠ > BTC_V	0.002	0.968	1	0.80	MMR_ES ≠ > BTC_V	0.136	0.649	1	0.80
BZL_ES ≠ > BTC_V	3.497	**0.070**	1	**0.80**	MNG_ES ≠ > BTC_V	0.012	0.908	1	0.80
BMU_ES ≠ > BTC_V	0.131	0.660	1	0.80	MRT_ES ≠ > BTC_V	0.936	0.323	1	0.80
BO_ES ≠ > BTC_V	1.450	0.200	1	0.80	MUS_ES ≠ > BTC_V	0.000	0.991	1	0.80
BRA_ES ≠ > BTC_V	0.919	0.305	1	0.80	MWI_ES ≠ > BTC_V	1.962	0.157	1	0.80
BRB_ES ≠ > BTC_V	0.003	0.947	1	2.30	MYS_ES ≠ > BTC_V	11.30	0.195	8	2.70
BRN_ES ≠ > BTC_V	2.522	0.383	3	0.70	NAM_ES ≠ > BTC_V	2.264	0.135	1	0.80
BTN_ES ≠ > BTC_V	0.165	0.665	1	3.20	NER_ES ≠ > BTC_V	0.002	0.958	1	0.80
BWA_ES ≠ > BTC_V	0.001	0.988	1	0.80	NIC_ES ≠ > BTC_V	1.142	0.281	1	0.80
CAF_ES ≠ > BTC_V	0.063	0.797	1	0.80	**NLD_ES ≠ > BTC_V**	14.96	**0.088**	8	**0.60**
CAN_ES ≠ > BTC_V	4.616	0.204	3	0.70	NPL_ES ≠ > BTC_V	0.907	0.339	1	0.80
CHE_ES ≠ > BTC_V	2.382	0.122	1	0.80	NZL_ES ≠ > BTC_V	0.471	0.434	1	0.10
CHL_ES ≠ > BTC_V	5.502	**0.029**	1	**0.80**	OMN_ES ≠ > BTC_V	1.579	0.198	1	0.80
CHN_ES ≠ > BTC_V	0.008	0.916	1	2.70	PAK_ES ≠ > BTC_V	5.649	0.551	7	2.60
CIV_ES ≠ > BTC_V	0.034	0.867	1	0.80	PAN_ES ≠ > BTC_V	0.038	0.782	1	2.50
CMR_ES ≠ > BTC_V	2.528	**0.088**	1	**0.30**	PER_ES ≠ > BTC_V	1.313	0.681	3	2.70
COD_ES ≠ > BTC_V	1.494	0.199	1	0.80	**PHL_ES ≠ > BTC_V**	4.739	**0.032**	1	**0.80**
COG_ES ≠ > BTC_V	0.268	0.582	1	0.80	PNG_ES ≠ > BTC_V	2.197	0.152	1	0.80
COL_ES ≠ > BTC_V	0.000	0.978	1	2.70	POL_ES ≠ > BTC_V	4.095	0.631	6	0.30
CPV_ES ≠ > BTC_V	0.662	0.369	1	0.80	PRI_ES ≠ > BTC_V	0.183	0.623	1	0.10
CRI_ES ≠ > BTC_V	15.35	0.402	15	0.70	PRY_ES ≠ > BTC_V	0.012	0.893	1	0.80
CUB_ES ≠ > BTC_V	1.349	0.920	5	2.50	**QAT_ES ≠ > BTC_V**	5.160	**0.032**	1	**3.00**
CZE_ES ≠ > BTC_V	2.068	0.150	1	0.80	ROU_ES ≠ > BTC_V	3.969	0.657	6	0.60
DEU_ES ≠ > BTC_V	2.006	0.133	1	0.80	RUS_ES ≠ > BTC_V	0.881	0.347	1	0.80
DMA_ES ≠ > BTC_V	0.990	0.255	1	0.80	RWA_ES ≠ > BTC_V	0.176	0.627	1	1.70
DNK_ES ≠ > BTC_V	0.404	0.451	1	0.80	SDN_ES ≠ > BTC_V	2.035	0.148	1	0.80
DOM_ES ≠ > BTC_V	2.543	**0.087**	1	**0.80**	SEN_ES ≠ > BTC_V	0.606	0.379	1	0.80
DZA_ES ≠ > BTC_V	7.236	**0.012**	1	**2.70**	SGP_ES ≠ > BTC_V	17.13	0.296	14	2.70
EGY_ES ≠ > BTC_V	0.150	0.693	1	2.80	SLB_ES ≠ > BTC_V	0.151	0.639	1	0.80
ERI_ES ≠ > BTC_V	0.035	0.812	1	0.70	SLV_ES ≠ > BTC_V	0.893	0.333	1	0.80
ESP_ES ≠ > BTC_V	7.374	0.705	11	2.70	SMR_ES ≠ > BTC_V	0.056	0.733	1	3.10
EST_ES ≠ > BTC_V	0.001	0.973	1	0.80	SRB_ES ≠ > BTC_V	0.000	0.990	1	2.30
FIN_ES ≠ > BTC_V	0.083	0.743	1	3.00	SSD_ES ≠ > BTC_V	0.316	0.532	1	0.80
FJI_ES ≠ > BTC_V	1.646	0.409	2	2.80	SUR_ES ≠ > BTC_V	0.018	0.895	1	0.80
FRA_ES ≠ > BTC_V	0.250	0.572	1	2.60	SVK_ES ≠ > BTC_V	10.396	0.341	9	2.60
FRO_ES ≠ > BTC_V	0.599	0.363	1	1.70	SVN_ES ≠ > BTC_V	0.002	0.963	1	2.50
GAB_ES ≠ > BTC_V	0.497	0.456	1	0.80	SWE_ES ≠ > BTC_V	0.304	0.569	1	0.80
GBR_ES ≠ > BTC_V	0.123	0.698	1	0.80	SWZ_ES ≠ > BTC_V	0.055	0.806	1	0.80
GEO_ES ≠ > BTC_V	2.493	**0.090**	1	**0.80**	SYC_ES ≠ > BTC_V	0.577	0.433	1	0.80
GIN_ES ≠ > BTC_V	0.598	0.383	1	0.80	TCD_ES ≠ > BTC_V	0.499	0.418	1	0.80
GMB_ES ≠ > BTC_V	0.054	0.805	1	0.80	TGO_ES ≠ > BTC_V	0.081	0.729	1	0.80
GRC_ES ≠ > BTC_V	3.857	0.623	6	2.70	THA_ES ≠ > BTC_V	0.016	0.865	1	0.80
GRL_ES ≠ > BTC_V	0.831	0.319	1	0.80	TJK_ES ≠ > BTC_V	0.487	0.448	1	0.80
GTM_ES ≠ > BTC_V	1.091	0.286	1	2.70	TKM_ES ≠ > BTC_V	0.128	0.721	1	0.80
GUM_ES ≠ > BTC_V	1.175	0.290	1	0.80	TLS_ES ≠ > BTC_V	0.106	0.729	1	0.80
GUY_ES ≠ > BTC_V	0.602	0.398	1	2.80	**TTO_ES ≠ > BTC_V**	3.536	**0.075**	1	**0.80**
HKG_ES ≠ > BTC_V	0.409	0.434	1	3.20	TUN_ES ≠ > BTC_V	0.757	0.295	1	0.80
HND_ES ≠ > BTC_V	0.469	0.429	1	0.80	TUR_ES ≠ > BTC_V	0.043	0.788	1	0.80
HRV_ES ≠ > BTC_V	0.330	0.500	1	0.70	TWN_ES ≠ > BTC_V	1.482	0.200	1	0.80
HTI_ES ≠ > BTC_V	0.764	0.337	1	0.80	TZA_ES ≠ > BTC_V	1.728	0.180	1	0.80
HUN_ES ≠ > BTC_V	0.977	0.305	1	0.80	UGA_ES ≠ > BTC_V	0.108	0.733	1	0.80
IDN_ES ≠ > BTC_V	1.390	0.168	1	2.60	UKR_ES ≠ > BTC_V	1.167	0.263	1	0.80
IND_ES ≠ > BTC_V	0.031	0.824	1	0.80	URY_ES ≠ > BTC_V	0.054	0.800	1	0.80
IRL_ES ≠ > BTC_V	3.513	0.766	7	2.80	USA_ES ≠ > BTC_V	1.725	0.172	1	0.80
IRN_ES ≠ > BTC_V	5.298	**0.043**	1	**0.80**	UZB_ES ≠ > BTC_V	1.464	0.219	1	0.80
IRQ_ES ≠ > BTC_V	0.001	0.948	1	0.70	VEN_ES ≠ > BTC_V	1.075	0.250	1	2.30
ISL_ES ≠ > BTC_V	4.126	0.886	10	1.30	VIR_ES ≠ > BTC_V	0.772	0.353	1	0.80
ISR_ES ≠ > BTC_V	12.03	0.715	17	2.70	VNM_ES ≠ > BTC_V	0.087	0.714	1	0.80
ITA_ES ≠ > BTC_V	4.431	0.790	9	2.80	VUT_ES ≠ > BTC_V	0.020	0.842	1	0.80
JOR_ES ≠ > BTC_V	3.383	**0.076**	1	**0.80**	ZAF_ES ≠ > BTC_V	0.590	0.414	1	0.80
JPN_ES ≠ > BTC_V	0.046	0.821	1	2.80	ZMB_ES ≠ > BTC_V	0.342	0.528	1	0.80
KAZ_ES ≠ > BTC_V	0.053	0.818	1	0.80	ZWE_ES ≠ > BTC_V	0.019	0.858	1	0.80

* ES denotes economic supports; V denotes volatility.

The results of these causality tests showed that there was a permanent unidirectional causality running from economic supports to Bitcoin volatility for 13 countries (Belize, Chile, Cameroon, the Dominican Republic, Algeria, Georgia, Iran, Jordan, Luxembourg, Macau, the Netherlands, the Philippines, and Trinidad and Tobago) and temporary causality for Qatar. Table 6 includes the results of the FFFFTY causality tests between economic supports and the trading volume of Bitcoin.

Table 6. Fractional Frequency Flexible Fourier form Toda–Yamamoto causality tests between economic supports and the trading volume of Bitcoin *.

	W-Statistics	Bootstrap Prob. Value	p	k		W-Statistics	Bootstrap Prob. Value	p	k
ABW_ES ≠ > BTC_TV	2.643	0.127	1	0.80	KEN_ES ≠ > BTC_TV	0.553	0.440	1	0.80
AGO_ES ≠ > BTC_TV	1.030	0.303	1	0.80	KGZ_ES ≠ > BTC_TV	0.827	0.355	1	0.60
ABL_ES ≠ > BTC_TV	2.940	0.208	2	0.40	**KHM_ES ≠ > BTC_TV**	4.692	**0.042**	1	**1.60**
AND_ES ≠ > BTC_TV	2.009	0.353	2	0.70	KWT_ES ≠ > BTC_TV	4.109	0.127	2	0.70
ANRE_ES ≠ > BTC_TV	0.108	0.701	1	0.80	LAO_ES ≠ > BTC_TV	0.272	0.562	1	0.80
ARG_ES ≠ > BTC_TV	1.067	0.268	1	0.80	LBN_ES ≠ > BTC_TV	3.190	0.777	6	0.60
AUS_ES ≠ > BTC_TV	7.078	0.654	10	0.10	LKA_ES ≠ > BTC_TV	0.217	0.615	1	0.80
AUT_ES ≠ > BTC_TV	11.39	**0.042**	4	**0.30**	LSO_ES ≠ > BTC_TV	0.000	0.979	1	0.80
AZE_ES ≠ > BTC_TV	0.306	0.594	1	0.80	LTU_ES ≠ > BTC_TV	0.559	0.422	1	0.10
BDI_ES ≠ > BTC_TV	0.057	0.815	1	0.80	LUX_ES ≠ > BTC_TV	0.083	0.771	1	2.90
BEL_ES ≠ > BTC_TV	0.031	0.841	1	0.10	**LVA_ES ≠ > BTC_TV**	2.674	**0.097**	1	**0.80**
BEN_ES ≠ > BTC_TV	0.750	0.341	1	0.80	**MAC_ES ≠ > BTC_TV**	3.137	**0.076**	1	**0.80**
BFA_ES ≠ > BTC_TV	0.034	0.817	1	0.80	MAR_ES ≠ > BTC_TV	0.066	0.783	1	0.80
BGD_ES ≠ > BTC_TV	0.001	0.963	1	0.80	MCO_ES ≠ > BTC_TV	1.714	0.869	5	0.60
BGR_ES ≠ > BTC_TV	5.494	0.825	10	0.70	MDG_ES ≠ > BTC_TV	0.401	0.535	1	0.80
BHR_ES ≠ > BTC_TV	1.227	0.248	1	0.10	MEX_ES ≠ > BTC_TV	1.198	0.226	1	1.00
BHS_ES ≠ > BTC_TV	0.150	0.663	1	0.80	MLI_ES ≠ > BTC_TV	0.048	0.830	1	0.80
BIH_ES ≠ > BTC_TV	3.125	**0.080**	1	**0.80**	MMR_ES ≠ > BTC_TV	0.531	0.425	1	0.80
BZL_ES ≠ > BTC_TV	0.577	0.420	1	0.80	MNG_ES ≠ > BTC_TV	0.004	0.952	1	0.80
BMU_ES ≠ > BTC_TV	0.266	0.575	1	0.10	MRT_ES ≠ > BTC_TV	1.235	0.260	1	0.80
BOL_ES ≠ > BTC_TV	0.707	0.375	1	0.80	MUS_ES ≠ > BTC_TV	1.208	0.265	1	0.10
BRA_ES ≠ > BTC_TV	2.435	**0.099**	1	**0.80**	MWI_ES ≠ > BTC_TV	1.000	0.316	1	0.80
BRB_ES ≠ > BTC_TV	0.628	0.722	2	0.30	MYS_ES ≠ > BTC_TV	6.914	0.460	8	0.70
BRN_ES ≠ > BTC_TV	5.147	0.168	3	1.00	**NAM_ES ≠ > BTC_TV**	2.955	**0.082**	1	**0.80**
BTN_ES ≠ > BTC_TV	0.183	0.664	1	0.70	NER_ES ≠ > BTC_TV	2.230	0.139	1	0.80
BWA_ES ≠ > BTC_TV	0.063	0.780	1	0.80	**NIC_ES ≠ > BTC_TV**	3.742	**0.055**	1	**0.80**
CAF_ES ≠ > BTC_TV	0.521	0.446	1	0.80	NLD_ES ≠ > BTC_TV	10.23	0.295	8	0.60
CAN_ES ≠ > BTC_TV	6.421	**0.098**	3	**3.00**	NPL_ES ≠ > BTC_TV	1.122	0.580	2	0.60
CHE_ES ≠ > BTC_TV	0.976	0.293	1	0.80	NZL_ES ≠ > BTC_TV	5.569	0.430	6	0.50
CHL_ES ≠ > BTC_TV	11.88	**0.037**	5	**0.10**	OMN_ES ≠ > BTC_TV	0.006	0.950	1	1.70
CHN_ES ≠ > BTC_TV	2.179	0.133	1	1.30	PAK_ES ≠ > BTC_TV	6.586	0.435	7	0.90
CIV_ES ≠ > BTC_TV	0.351	0.502	1	0.80	PAN_ES ≠ > BTC_TV	0.008	0.921	1	0.70
CMR_ES ≠ > BTC_TV	0.072	0.773	1	2.00	PER_ES ≠ > BTC_TV	2.326	0.492	3	0.40
COD_ES ≠ > BTC_TV	3.682	**0.059**	1	**0.80**	**PHL_ES ≠ > BTC_TV**	3.916	**0.049**	1	**0.80**
COG_ES ≠ > BTC_TV	0.271	0.599	1	0.80	PNG_ES ≠ > BTC_TV	1.741	0.163	1	0.80
COL_ES ≠ > BTC_TV	0.100	0.773	1	0.10	POL_ES ≠ > BTC_TV	2.130	0.877	6	0.40
CPV_ES ≠ > BTC_TV	0.021	0.882	1	0.80	**PRI_ES ≠ > BTC_TV**	2.909	**0.094**	1	**2.00**
CRI_ES ≠ > BTC_TV	33.24	**0.009**	15	**3.00**	PRY_ES ≠ > BTC_TV	0.293	0.852	2	0.10
CUB_ES ≠ > BTC_TV	2.579	0.756	5	0.70	**QAT_ES ≠ > BTC_TV**	5.401	**0.026**	1	**0.10**
CZE_ES ≠ > BTC_TV	1.941	0.357	2	0.10	ROU_ES ≠ > BTC_TV	2.485	0.859	6	0.60
DEU_ES ≠ > BTC_TV	0.834	0.641	2	0.10	RUS_ES ≠ > BTC_TV	0.307	0.862	2	0.70
DMA_ES ≠ > BTC_TV	1.446	0.209	1	1.90	RWA_ES ≠ > BTC_TV	2.058	0.311	2	1.60
DNK_ES ≠ > BTC_TV	1.517	0.181	1	1.60	SDN_ES ≠ > BTC_TV	0.511	0.440	1	0.80
DOM_ES ≠ > BTC_TV	1.362	0.231	1	0.80	SEN_ES ≠ > BTC_TV	0.793	0.328	1	0.80
DZA_ES ≠ > BTC_TV	4.379	**0.046**	1	**0.60**	SGP_ES ≠ > BTC_TV	20.17	0.174	14	1.00
EGY_ES ≠ > BTC_TV	0.182	0.659	1	0.70	SLB_ES ≠ > BTC_TV	1.585	0.203	1	0.80
ERI_ES ≠ > BTC_TV	0.064	0.798	1	1.40	SLV_ES ≠ > BTC_TV	0.613	0.398	1	0.10
ESP_ES ≠ > BTC_TV	8.671	0.629	11	0.90	SMR_ES ≠ > BTC_TV	0.185	0.635	1	1.40
EST_ES ≠ > BTC_TV	0.170	0.678	1	1.70	SRB_ES ≠ > BTC_TV	1.501	0.199	1	0.60
FIN_ES ≠ > BTC_TV	1.588	0.205	1	0.30	SSD_ES ≠ > BTC_TV	0.030	0.869	1	0.80
FJI_ES ≠ > BTC_TV	1.017	0.568	2	0.60	SUR_ES ≠ > BTC_TV	15.13	0.192	11	0.70
FRA_ES ≠ > BTC_TV	0.263	0.598	1	2.00	SVK_ES ≠ > BTC_TV	4.963	0.761	9	1.20
FRO_ES ≠ > BTC_TV	0.540	0.403	1	1.40	SVN_ES ≠ > BTC_TV	0.429	0.802	2	0.50
GAB_ES ≠ > BTC_TV	0.262	0.576	1	0.80	SWE_ES ≠ > BTC_TV	3.616	0.156	2	0.40
GBR_ES ≠ > BTC_TV	2.457	0.587	4	2.20	SWZ_ES ≠ > BTC_TV	0.000	0.981	1	1.40
GEO_ES ≠ > BTC_TV	0.023	0.879	1	0.80	SYSC_ES ≠ > BTC_TV	0.043	0.842	1	0.80
GIN_ES ≠ > BTC_TV	0.125	0.699	1	0.80	TCD_ES ≠ > BTC_TV	0.902	0.314	1	0.80
GMB_ES ≠ > BTC_TV	0.608	0.410	1	0.80	TGO_ES ≠ > BTC_TV	0.087	0.723	1	0.80
GRC_ES ≠ > BTC_TV	12.17	**0.082**	6	**1.30**	THA_ES ≠ > BTC_TV	1.435	0.458	2	0.60
GRL_ES ≠ > BTC_TV	3.737	**0.048**	1	**0.80**	**TJK_ES ≠ > BTC_TV**	2.653	**0.093**	1	**0.80**

Table 6. *Cont.*

	W-Statistics	Bootstrap Prob. Value	p	k		W-Statistics	Bootstrap Prob. Value	p	k
GTM_ES ≠ > BTC_TV	6.098	**0.058**	2	**0.60**	TKM_ES ≠ > BTC_TV	1.121	0.286	1	0.80
GUM_ES ≠ > BTC_TV	0.222	0.619	1	0.80	TLS_ES ≠ > BTC_TV	1.058	0.285	1	0.80
GUY_ES ≠ > BTC_TV	0.747	0.373	1	1.70	**TTO_ES ≠ > BTC_TV**	6.902	**0.013**	1	**0.80**
HKG_ES ≠ > BTC_TV	0.475	0.425	1	0.40	TUN_ES ≠ > BTC_TV	0.035	0.827	1	0.80
HND_ES ≠ > BTC_TV	0.654	0.372	1	0.80	TUR_ES ≠ > BTC_TV	0.162	0.663	1	0.80
HRV_ES ≠ > BTC_TV	0.004	0.953	1	0.10	TWN_ES ≠ > BTC_TV	1.362	0.217	1	0.10
HTI_ES ≠ > BTC_TV	0.045	0.809	1	0.80	TZA_ES ≠ > BTC_TV	2.027	0.161	1	4.90
HUN_ES ≠ > BTC_TV	0.694	0.672	2	0.30	UGA_ES ≠ > BTC_TV	0.094	0.732	1	0.80
IDN_ES ≠ > BTC_TV	2.312	0.120	1	1.40	UKR_ES ≠ > BTC_TV	1.857	0.385	2	0.10
IND_ES ≠ > BTC_TV	0.065	0.756	1	0.80	URY_ES ≠ > BTC_TV	0.221	0.612	1	0.80
IRL_ES ≠ > BTC_TV	9.798	0.252	7	0.70	USA_ES ≠ > BTC_TV	0.940	0.571	2	0.10
IRN_ES ≠ > BTC_TV	5.225	**0.027**	1	**0.80**	UZB_ES ≠ > BTC_TV	0.089	0.737	1	0.80
IRQ_ES ≠ > BTC_TV	0.172	0.648	1	1.30	VEN_ES ≠ > BTC_TV	0.117	0.685	1	1.60
ISL_ES ≠ > BTC_TV	20.63	**0.069**	10	**0.40**	**VIR_ES ≠ > BTC_TV**	3.434	**0.058**	1	**0.80**
ISR_ES ≠ > BTC_TV	22.76	0.171	17	0.30	VNM_ES ≠ > BTC_TV	0.387	0.460	1	0.80
ITA_ES ≠ > BTC_TV	12.36	0.203	9	1.00	VUT_ES ≠ > BTC_TV	0.013	0.921	1	0.10
JOR_ES ≠ > BTC_TV	8.189	**0.013**	1	**1.70**	ZAF_ES ≠ > BTC_TV	1.119	0.273	1	0.90
JPN_ES ≠ > BTC_TV	3.777	**0.052**	1	**0.70**	ZMB_ES ≠ > BTC_TV	0.060	0.765	1	0.80
KAZ_ES ≠ > BTC_TV	1.936	0.159	1	0.80	ZWE_ES ≠ > BTC_TV	0.005	0.930	1	0.80

* ES denotes economic supports; TV denotes trading volume.

The results of these causality tests showed that there was a unidirectional causality running from economic supports to the trading volume of Bitcoin for 26 countries (Austria, Bosnia and Herzegovina, Brazil, Canada, Chile, the Democratic Republic of the Congo, Costa Rica, Algeria, Greece, Greenland, Guatemala, Iran, Iceland, Jordan, Japan, Cambodia, Latvia, Macau, Namibia, Nicaragua, the Philippines, Puerto Rico, Qatar, Tajikistan, Trinidad and Tobago, and Virgin Islands (U.S.)). Out of these 26 countries, the established causalities were permanent in 23 countries and transitory for Costa Rica, Canada, and Puerto Rico. Table 7 displays the results of the BTY causality tests between economic supports and Bitcoin return.

Table 7. Bootstrap Toda–Yamamoto causality tests between economic supports and Bitcoin return *.

	Estimated Test Value (MWALD)	Bootstrap Critical Values				Estimated Test Value (MWALD)	Bootstrap Critical Values		
		1%	5%	10%			1%	5%	10%
ES ≠ > ABW_R	0.011	8.154	4.338	3.016	**ES ≠ > KGZ_R**	15.09	17.61	12.84	11.08
ES ≠ > AGO_R	0.057	9.804	4.513	2.612	**ES ≠ > KHM_R**	3.143	10.96	4.450	2.899
ES ≠ > ALB_R	1.854	6.687	4.275	3.036	**ES ≠ > KWT_R**	15.34	18.64	13.16	11.10
ES ≠ > AND_R	0.417	7.607	3.839	2.515	**ES ≠ > LAO_R**	15.29	18.68	12.75	10.68
ES ≠ > ARE_R	0.591	7.088	4.012	2.819	**ES ≠ > LBN_R**	15.64	18.52	13.59	11.37
ES ≠ > ARG_R	0.267	7.725	4.092	2.788	**ES ≠ > LKA_R**	15.21	19.63	14.28	11.45
ES ≠ > AUT_R	5.437	6.926	3.689	2.715	**ES ≠ > LSO_R**	3.222	8.639	3.824	2.319
ES ≠ > AZE_R	0.200	7.509	4.111	2.840	**ES ≠ > LTU_R**	15.09	20.29	13.33	10.85
ES ≠ > BDI_R	0.153	6.388	3.563	2.459	ES ≠ > LUX_R	3.679	21.80	14.22	11.81
ES ≠ > BEL_R	2.321	7.429	4.336	2.952	ES ≠ > LVA_R	3.661	18.53	13.44	10.96
ES ≠ > BEN_R	0.013	7.101	4.530	3.062	**ES ≠ > MAC_R**	15.73	19.49	13.94	11.28
ES ≠ > BFA_R	0.064	6.557	4.014	2.715	ES ≠ > MAR_R	3.757	20.15	13.82	11.52
ES ≠ > BGD_R	0.642	7.232	3.751	2.702	ES ≠ > MCO_R	3.792	20.37	14.32	11.17
ES ≠ > BGR_R	1.008	10.74	6.391	5.048	**ES ≠ > MDG_R**	3.214	9.419	4.184	2.638
ES ≠ > BHR_R	< 0.001	8.448	3.834	2.408	ES ≠ > MEX_R	2.775	9.359	4.760	2.956
ES ≠ > BHS_R	< 0.001	8.792	4.338	2.852	ES ≠ > MLI_R	3.775	18.29	13.91	11.62
ES ≠ > BIH_R	< 0.001	7.393	3.633	2.432	ES ≠ > MMR_R	4.060	19.47	13.80	11.16
ES ≠ > BMU_R	0.018	9.002	4.709	3.248	**ES ≠ > MNG_R**	15.08	16.84	12.97	10.78
ES ≠ > BOL_R	14.71	18.66	13.11	10.58	ES ≠ > MRT_R	2.677	8.549	4.471	3.175
ES ≠ > BRA_R	3.793	21.58	14.16	11.26	**ES ≠ > MUS_R**	16.02	17.83	13.21	10.86
ES ≠ > BRB_R	3.775	18.29	13.91	11.62	ES ≠ > MWI_R	2.730	7.483	4.095	2.885
ES ≠ > BRN_R	0.001	6.811	3.925	2.752	**ES ≠ > MYS_R**	15.34	18.64	13.16	11.10
ES ≠ > BTN_R	15.56	19.32	13.86	11.24	ES ≠ > NER_R	4.167	20.96	14.07	10.84
ES ≠ > BWA_R	15.94	18.13	12.99	10.95	**ES ≠ > NIC_R**	3.235	9.331	3.714	2.433
ES ≠ > CAF_R	3.708	19.52	14.40	11.58	ES ≠ > NPL_R	3.662	20.78	13.85	11.07
ES ≠ > CAN_R	3.792	20.37	14.32	11.17	ES ≠ > NZL_R	3.793	21.58	14.16	11.26
ES ≠ > CHE_R	3.784	17.74	13.51	11.27	**ES ≠ > OMN_R**	4.298	7.045	4.590	3.098
ES ≠ > CHN_R	15.51	20.27	13.52	11.09	**ES ≠ > PAK_R**	15.60	20.35	12.70	10.93
ES ≠ > CIV_R	3.719	19.61	13.72	11.01	ES ≠ > PAN_R	4.096	20.31	13.97	10.94
ES ≠ > COD_R	3.939	19.64	14.08	11.14	**ES ≠ > PER_R**	15.19	18.74	13.62	11.10
ES ≠ > COG_R	2.674	5.856	3.617	2.484	**ES ≠ > POL_R**	15.08	16.84	12.97	10.78
ES ≠ > CO_R	4.045	21.19	14.08	11.83	ES ≠ > PRI_R	2.768	9.587	4.846	2.899
ES ≠ > CPV_R	3.729	21.25	14.33	11.78	ES ≠ > PRY_R	2.521	6.694	4.239	2.943
ES ≠ > CRI_R	3.770	18.76	13.67	11.36	**ES ≠ > ROU_R**	14.95	18.14	13.43	11.13
ES ≠ > CUB_R	15.60	20.35	12.70	10.93	ES ≠ > RUS_R	3.775	18.29	13.91	11.62
ES ≠ > CZE_R	15.62	19.84	13.40	11.28	ES ≠ > RWA_R	2.769	6.508	3.992	2.891
ES ≠ > DEU_R	3.792	20.37	14.32	11.17	ES ≠ > SEN_R	0.950	8.798	4.150	2.449
ES ≠ > DMA_R	3.176	10.72	4.739	2.894	**ES ≠ > SGP_R**	15.34	18.64	13.16	11.10
ES ≠ > DNK_R	6.630	19.15	13.45	10.88	ES ≠ > SBL_R	0.470	10.88	4.657	2.977
ES ≠ > DOM_R	2.542	6.475	3.908	2.775	ES ≠ > SLV_R	3.998	18.62	12.77	10.86
ES ≠ > EGY_R	14.95	18.14	13.43	11.13	ES ≠ > SMR_R	3.724	18.75	13.83	11.19
ES ≠ > ERI_R	3.261	8.578	4.353	2.478	ES ≠ > SRB_R	3.719	19.61	13.72	11.01
ES ≠ > ESP_R	15.09	20.29	13.33	10.85	ES ≠ > SSD_R	4.204	18.85	13.40	11.40
ES ≠ > EST_R	2.699	8.419	4.123	2.521	ES ≠ > SUR_R	0.859	9.697	4.008	2.709
ES ≠ > FIN_R	3.792	20.37	14.32	11.17	**ES ≠ > SVK_R**	15.08	16.84	12.97	10.78

Table 7. *Cont.*

	Estimated Test Value (MWALD)	Bootstrap Critical Values				Estimated Test Value (MWALD)	Bootstrap Critical Values		
		1%	5%	10%			1%	5%	10%
ES ≠ > FJI_R	15.09	17.61	12.84	11.08	**ES ≠ > SVN_R**	14.96	19.39	13.19	11.42
ES ≠ > FRA_R	3.792	20.37	14.32	11.17	ES ≠ > SWE_R	3.665	20.12	14.21	11.29
ES ≠ > FRO_R	3.928	17.67	13.41	11.21	**ES ≠ > SWZ_R**	2.708	9.194	3.903	2.537
ES ≠ > GAB_R	15.76	17.28	12.73	10.98	ES ≠ > SYC_R	4.035	19.80	13.97	11.43
ES ≠ > GBR_R	3.793	21.58	14.16	11.26	**ES ≠ > TCD_R**	14.82	19.43	13.64	11.48
ES ≠ > GIN_R	1.478	6.756	4.090	3.161	**ES ≠ > TGO_R**	15.34	18.64	13.16	11.10
ES ≠ > GMB_R	1.816	10.70	4.775	2.863	**ES ≠ > THA_R**	15.34	18.95	13.63	11.39
ES ≠ > GRC_R	15.08	16.84	12.97	10.78	ES ≠ > TJK_R	0.304	7.470	4.227	3.070
ES ≠ > GRL_R	4.196	17.02	12.91	10.68	ES ≠ > TKM_R	2.847	7.124	4.074	2.953
ES ≠ > GTM_R	4.066	19.64	14.43	12.08	ES ≠ > TLS_R	3.932	20.83	14.27	11.90
ES ≠ > GUM_R	4.175	17.96	13.50	11.22	ES ≠ > TTO_R	3.784	17.74	13.51	11.27
ES ≠ > GUY_R	3.691	19.68	13.71	11.24	**ES ≠ > TUN_R**	14.95	18.14	13.43	11.13
ES ≠ > HKG_R	3.809	20.70	14.44	11.04	ES ≠ > TUR_R	2.905	7.210	4.157	2.931
ES ≠ > HND_R	15.51	21.01	13.74	11.84	ES ≠ > TWN_R	3.670	19.05	13.62	10.92
ES ≠ > HRV_R	3.916	19.83	13.39	11.34	ES ≠ > TZA_R	0.447	6.076	4.169	2.968
ES ≠ > HTI_R	15.21	19.63	14.28	11.45	ES ≠ > UGA_R	3.757	20.15	13.82	11.52
ES ≠ > HUN_R	15.08	16.84	12.97	10.78	**ES ≠ > UKR_R**	15.62	19.84	13.40	11.28
ES ≠ > IDN_R	3.775	18.29	13.91	11.62	**ES ≠ > URY_R**	15.08	16.84	12.97	10.78
ES ≠ > IND_R	16.02	17.83	13.21	10.86	ES ≠ > USA_R	4.847	19.52	14.19	11.83
ES ≠ > IRL_R	15.19	18.74	13.62	11.10	**ES ≠ > UZB_R**	15.05	19.03	13.15	11.29
ES ≠ > IRQ_R	3.998	16.84	13.24	10.90	ES ≠ > VEN_R	4.204	18.85	13.40	11.40
ES ≠ > ISL_R	15.74	18.64	13.45	11.38	ES ≠ > VIR_R	4.049	19.24	13.21	11.17
ES ≠ > ISR_R	15.71	17.97	13.52	11.07	ES ≠ > VNM_R	3.930	19.48	14.05	11.32
ES ≠ > ITA_R	15.09	20.29	13.33	10.85	ES ≠ > VUT_R	1.849	10.83	4.34	2.554
ES ≠ > JPN_R	15.19	18.74	13.62	11.10	**ES ≠ > ZAF_R**	15.32	18.20	13.44	11.26
ES ≠ > KAZ_R	2.338	7.549	4.126	2.777	ES ≠ > ZMB_R	3.662	20.78	13.85	11.07
ES ≠ > KEN_R	3.967	19.86	13.73	10.75	ES ≠ > ZWE_R	4.167	20.96	14.07	10.84

* ES denotes economic supports; R denotes return.

The results in Table 7 clearly show strong evidence of unidirectional causality running from economic supports to Bitcoin return in 56 countries. Table 8 displays the results of the BTY causality tests between economic supports and Bitcoin volatility.

Table 8. Bootstrap Toda–Yamamoto causality tests between economic supports and Bitcoin volatility *.

	Estimated Test Value (MWALD)	Bootstrap Critical Values				Estimated Test Value (MWALD)	Bootstrap Critical Values		
		1%	5%	10%			1%	5%	10%
ES ≠ > ABW_V	3.775	18.29	13.91	11.62	**ES ≠ > KGZ_V**	15.09	17.61	12.84	11.08
ES ≠ > AGO_V	0.509	10.61	4.578	2.595	**ES ≠ > KHM_V**	3.130	9.745	3.872	2.470
ES ≠ > ALB_V	15.27	20.37	13.75	11.30	**ES ≠ > KWT_V**	15.27	20.37	13.75	11.30
ES ≠ > AND_V	3.803	18.36	13.61	11.35	**ES ≠ > LAO_V**	15.29	18.68	12.75	10.68
ES ≠ > ARE_V	16.09	19.17	13.30	11.02	**ES ≠ > LBN_V**	15.64	18.52	13.59	11.37
ES ≠ > ARG_V	3.757	20.15	13.82	11.52	**ES ≠ > LKA_V**	15.21	19.63	14.28	11.45
ES ≠ > AUS_V	0.016	6.812	3.713	2.522	**ES ≠ > LSO_V**	3.222	8.639	3.824	2.319
ES ≠ > AUT_V	15.19	18.74	13.62	11.10	**ES ≠ > LTU_V**	15.09	20.29	13.33	10.85
ES ≠ > AZE_V	4.104	19.79	14.19	11.21	ES ≠ > LVA_V	3.661	18.53	13.44	10.96
ES ≠ > BDI_V	2.737	8.141	3.589	2.212	ES ≠ > MAR_V	3.757	20.15	13.82	11.52
ES ≠ > BEL_V	14.82	19.43	13.64	11.48	ES ≠ > MCO_V	3.792	20.37	14.32	11.17
ES ≠ > BEN_V	15.45	19.83	14.07	11.31	**ES ≠ > MDG_V**	3.214	9.419	4.184	2.638
ES ≠ > BFA_V	0.503	9.534	3.988	2.761	ES ≠ > MEX_V	2.775	9.359	4.760	2.956
ES ≠ > BGD_V	3.940	17.95	13.48	11.07	ES ≠ > MLI_V	3.775	18.29	13.91	11.62
ES ≠ > BGR_V	15.12	17.96	13.45	11.27	ES ≠ > MMR_V	4.06	19.47	13.80	11.16
ES ≠ > BHR_V	4.088	19.90	13.64	11.54	**ES ≠ > MNG_V**	15.08	16.84	12.97	10.78
ES ≠ > BHS_V	3.794	20.75	13.81	11.05	ES ≠ > MRT_V	2.677	8.549	4.471	3.175
ES ≠ > BIH_V	4.011	19.30	13.39	11.07	**ES ≠ > MUS_V**	16.02	17.83	13.21	10.86
ES ≠ > BMU_V	3.708	19.52	14.40	11.58	ES ≠ > MWI_V	2.730	7.483	4.095	2.885
ES ≠ > BOL_V	14.71	18.66	13.11	10.58	**ES ≠ > MYS_V**	15.34	18.64	13.16	11.10
ES ≠ > BRA_V	3.793	21.58	14.16	11.26	ES ≠ > NAM_V	4.167	20.96	14.07	10.84
ES ≠ > BRB_V	3.775	18.29	13.91	11.62	ES ≠ > NER_V	2.704	7.986	4.462	2.970
ES ≠ > BRN_V	0.001	6.811	3.925	2.752	**ES ≠ > NIC_V**	3.235	9.331	3.714	2.433
ES ≠ > BTN_V	15.56	19.32	13.86	11.24	ES ≠ > NPL_V	3.662	20.78	13.85	11.07
ES ≠ > BWA_V	15.94	18.13	12.99	10.95	ES ≠ > NZL_V	3.793	21.58	14.16	11.26
ES ≠ > CAF_V	3.708	19.52	14.40	11.58	**ES ≠ > OMN_V**	4.298	7.045	4.590	3.098
ES ≠ > CAN_V	3.792	20.37	14.32	11.17	**ES ≠ > PAK_V**	15.60	20.35	12.70	10.93
ES ≠ > CHE_V	3.784	17.74	13.51	11.27	ES ≠ > PAN_V	4.041	21.40	13.68	11.22
ES ≠ > CHN_V	2.772	9.735	4.389	2.924	**ES ≠ > PER_V**	15.19	18.74	13.62	11.10
ES ≠ > CIV_V	3.719	19.61	13.72	11.01	ES ≠ > PNG_V	3.775	18.29	13.91	11.62
ES ≠ > COD_V	3.939	19.64	14.08	11.14	**ES ≠ > POL_V**	15.08	16.84	12.97	10.78
ES ≠ > COG_V	2.674	5.856	3.617	2.484	ES ≠ > PRI_V	2.768	9.587	4.846	2.899
ES ≠ > CO_V	4.045	21.19	14.08	11.83	ES ≠ > PRY_V	2.521	6.694	4.239	2.943
ES ≠ > CPV_V	3.729	21.25	14.33	11.78	**ES ≠ > ROU_V**	14.95	18.14	13.43	11.13
ES ≠ > CRI_V	3.770	18.76	13.67	11.36	ES ≠ > RUS_V	3.775	18.29	13.91	11.62
ES ≠ > CUB_V	15.60	20.35	12.70	10.93	ES ≠ > RWA_V	2.769	6.508	3.992	2.891
ES ≠ > CZE_V	15.62	19.84	13.40	11.28	ES ≠ > SDN_V	2.847	7.124	4.074	2.953
ES ≠ > DEU_V	3.792	20.37	14.32	11.17	ES ≠ > SEN_V	0.950	8.798	4.150	2.449
ES ≠ > DMA_V	3.176	10.72	4.739	2.894	**ES ≠ > SGP_V**	15.34	18.64	13.16	11.10
ES ≠ > DNK_V	6.630	19.15	13.45	10.88	ES ≠ > SLB_V	0.470	10.88	4.657	2.977
ES ≠ > DOM_V	2.542	6.475	3.908	2.775	ES ≠ > SLV_V	3.998	18.62	12.77	10.86
ES ≠ > EGY_V	14.95	18.14	13.43	11.13	ES ≠ > SMR_V	3.724	18.75	13.83	11.19

Table 8. *Cont.*

	Estimated Test Value (MWALD)	Bootstrap Critical Values				Estimated Test Value (MWALD)	Bootstrap Critical Values		
		1%	5%	10%			1%	5%	10%
ES $\neq$ > ERI_V	3.261	8.578	4.353	2.478	ES $\neq$ > SRB_V	3.719	19.61	13.72	11.01
ES $\neq$ > ESP_V	15.09	20.29	13.33	10.85	ES $\neq$ > SSD_V	4.204	18.85	13.40	11.40
ES $\neq$ > EST_V	2.699	8.419	4.123	2.521	ES $\neq$ > SUR_V	0.859	9.697	4.008	2.709
ES $\neq$ > FIN_V	3.792	20.37	14.32	11.17	**ES $\neq$ > SVK_V**	15.08	16.84	12.97	10.78
ES $\neq$ > FJI_V	15.09	17.61	12.84	11.08	**ES $\neq$ > SVN_V**	14.96	19.39	13.19	11.42
ES $\neq$ > FRA_V	3.792	20.37	14.32	11.17	ES $\neq$ > SWE_V	3.665	20.12	14.21	11.29
ES $\neq$ > FRO_V	3.928	17.67	13.41	11.21	**ES $\neq$ > SWZ_V**	2.708	9.194	3.903	2.537
ES $\neq$ > GAB_V	15.49	18.06	13.23	11.14	ES $\neq$ > SYC_V	4.035	19.80	13.97	11.43
ES $\neq$ > GBR_V	3.793	21.58	14.16	11.26	**ES $\neq$ > TCD_V**	14.82	19.43	13.64	11.48
ES $\neq$ > GIN_V	3.082	8.874	4.644	2.858	**ES $\neq$ > TGO_V**	15.34	18.64	13.16	11.10
ES $\neq$ > GMB_V	1.872	9.483	3.577	2.271	**ES $\neq$ > THA_V**	15.34	19.03	13.75	11.49
ES $\neq$ > GRC_V	15.08	16.84	12.97	10.78	ES $\neq$ > TJK_V	0.304	7.470	4.227	3.070
ES $\neq$ > GR_V	4.196	17.02	12.91	10.68	ES $\neq$ > TKM_V	2.847	7.124	4.074	2.953
ES $\neq$ > GTM_V	4.066	19.64	14.43	12.08	ES $\neq$ > TLS_V	3.898	19.33	13.49	11.47
ES $\neq$ > GUM_V	4.175	17.96	13.50	11.22	**ES $\neq$ > TUN_V**	14.95	18.14	13.43	11.13
ES $\neq$ > GUY_V	3.691	19.68	13.71	11.24	ES $\neq$ > TUR_V	2.905	7.210	4.157	2.931
ES $\neq$ > HKG_V	3.809	20.70	14.44	11.04	ES $\neq$ > TWN_V	3.670	19.05	13.62	10.92
ES $\neq$ > HND_V	15.51	21.01	13.74	11.84	ES $\neq$ > TZA_V	0.447	6.076	4.169	2.968
ES $\neq$ > HRV_V	3.916	19.83	13.39	11.34	ES $\neq$ > UGA_V	3.757	20.15	13.82	11.52
ES $\neq$ > HTI_V	15.21	19.63	14.28	11.45	**ES $\neq$ > UKR_V**	15.62	19.84	13.40	11.28
ES $\neq$ > HUN_V	15.08	16.84	12.97	10.78	**ES $\neq$ > URY_V**	15.08	16.84	12.97	10.78
ES $\neq$ > IDN_V	3.775	18.29	13.91	11.62	ES $\neq$ > USA_V	4.847	19.52	14.19	11.83
ES $\neq$ > IND_V	16.02	17.83	13.21	10.86	**ES $\neq$ > UZB_V**	15.09	20.29	13.33	10.85
ES $\neq$ > IRL_V	15.19	18.74	13.62	11.10	ES $\neq$ > VEN_V	4.204	18.85	13.40	11.40
ES $\neq$ > IRQ_V	3.998	16.84	13.24	10.90	ES $\neq$ > VIR_V	4.049	19.24	13.21	11.17
ES $\neq$ > ISL_V	15.74	18.64	13.45	11.38	ES $\neq$ > VNM_V	3.930	19.48	14.05	11.32
ES $\neq$ > ISR_V	15.71	17.97	13.52	11.07	ES $\neq$ > VUT_V	1.849	10.83	4.337	2.554
ES $\neq$ > ITA_V	15.09	20.29	13.33	10.85	**ES $\neq$ > ZAF_V**	15.32	18.20	13.44	11.26
ES $\neq$ > JPN_V	15.19	18.74	13.62	11.10	ES $\neq$ > ZMB_V	3.662	20.78	13.85	11.07
ES $\neq$ > KAZ_V	2.338	7.549	4.126	2.777	ES $\neq$ > ZWE_V	4.167	20.96	14.07	10.84
ES $\neq$ > KEN_V	3.967	19.86	13.73	10.75					

* ES denotes economic supports; V denotes volatility.

According to results in Table 8, there was evidence of unidirectional causality running from economic supports to Bitcoin volatility in 61 countries. Table 9 presents the results of the BTY causality tests between economic supports and the trading volume of Bitcoin.

Table 9. Bootstrap Toda–Yamamoto causality tests between economic supports and the trading volume of Bitcoin *.

	Estimated Test Value (MWALD)	Bootstrap Critical Values				Estimated Test Value (MWALD)	Bootstrap Critical Values		
		1%	5%	10%			1%	5%	10%
ES $\neq$ > ABW_TV	3.775	18.29	13.91	11.62	**ES $\neq$ > KWT_TV**	15.34	18.64	13.16	11.10
ES $\neq$ > AGO_TV	0.509	10.61	4.578	2.595	**ES $\neq$ > LAO_TV**	15.29	18.68	12.75	10.68
ES $\neq$ > ALB_TV	15.27	20.37	13.75	11.30	**ES $\neq$ > LBN_TV**	15.64	18.52	13.59	11.37
ES $\neq$ > AND_TV	3.803	18.36	13.61	11.35	**ES $\neq$ > LKA_TV**	15.21	19.63	14.28	11.45
ES $\neq$ > ARE_TV	16.09	19.17	13.30	11.02	**ES $\neq$ > LSO_TV**	3.222	8.639	3.824	2.319
ES $\neq$ > ARG_TV	3.757	20.15	13.82	11.52	**ES $\neq$ > LTU_TV**	15.09	20.29	13.33	10.85
ES $\neq$ > AUS_TV	0.016	6.812	3.713	2.522	ES $\neq$ > LUX_TV	3.679	21.80	14.22	11.81
ES $\neq$ > AZE_TV	4.104	19.79	14.19	11.21	ES $\neq$ > MAR_TV	3.757	20.15	13.82	11.52
ES $\neq$ > BDI_TV	2.737	8.141	3.589	2.212	ES $\neq$ > MCO_TV	3.792	20.37	14.32	11.17
ES $\neq$ > BEL_TV	14.82	19.43	13.64	11.48	**ES $\neq$ > MDG_TV**	3.214	9.419	4.184	2.638
ES $\neq$ > BEN_TV	15.45	19.83	14.07	11.31	ES $\neq$ > MEX_TV	2.775	9.359	4.760	2.956
ES $\neq$ > BFA_TV	0.503	9.53	3.99	2.76	ES $\neq$ > MLI_TV	3.775	18.29	13.91	11.62
ES $\neq$ > BGD_TV	3.940	17.95	13.48	11.07	ES $\neq$ > MMR_TV	4.060	19.47	13.80	11.16
ES $\neq$ > BGR_TV	14.54	17.48	12.97	11.14	**ES $\neq$ > MNG_TV**	15.08	16.84	12.97	10.78
ES $\neq$ > BHR_TV	4.088	19.90	13.64	11.54	ES $\neq$ > MRT_TV	2.677	8.549	4.471	3.175
ES $\neq$ > BHS_TV	3.794	20.75	13.81	11.05	**ES $\neq$ > MUS_TV**	16.02	17.83	13.21	10.86
ES $\neq$ > BLZ_TV	15.19	18.74	13.62	11.10	ES $\neq$ > MWI_TV	2.730	7.483	4.095	2.885
ES $\neq$ > BMU_TV	3.708	19.52	14.40	11.58	**ES $\neq$ > MYS_TV**	15.34	18.64	13.16	11.10
ES $\neq$ > BOL_TV	14.71	18.66	13.11	10.58	ES $\neq$ > NER_TV	2.704	7.986	4.462	2.970
ES $\neq$ > BRB_TV	3.775	18.29	13.91	11.62	**ES $\neq$ > NLD_TV**	15.09	20.29	13.33	10.85
ES $\neq$ > BRN_TV	0.001	6.811	3.925	2.752	ES $\neq$ > NPL_TV	3.662	20.78	13.85	11.07
ES $\neq$ > BTN_TV	15.56	19.32	13.86	11.24	ES $\neq$ > NZL_TV	3.793	21.58	14.16	11.26
ES $\neq$ > BWA_TV	15.94	18.13	12.99	10.95	**ES $\neq$ > OMN_TV**	4.298	7.045	4.590	3.098
ES $\neq$ > CAF_TV	3.708	19.52	14.40	11.58	**ES $\neq$ > PAK_TV**	15.60	20.35	12.70	10.93
ES $\neq$ > CHE_TV	3.784	17.74	13.51	11.27	ES $\neq$ > PAN_TV	4.041	21.40	13.68	11.22
ES $\neq$ > CHN_TV	15.51	20.27	13.52	11.09	ES $\neq$ > PER_TV	15.19	18.74	13.62	11.10
ES $\neq$ > CIV_TV	3.719	19.61	13.72	11.01	ES $\neq$ > PNG_TV	3.775	18.29	13.91	11.62
ES $\neq$ > CMR_TV	0.465	11.24	4.074	2.869	**ES $\neq$ > POL_TV**	15.08	16.84	12.97	10.78
ES $\neq$ > COG_TV	2.674	5.856	3.617	2.484	ES $\neq$ > PRY_TV	2.521	6.694	4.239	2.943
ES $\neq$ > COL_TV	4.045	21.19	14.08	11.83	**ES $\neq$ > ROU_TV**	14.95	18.14	13.43	11.13
ES $\neq$ > CPV_TV	3.729	21.25	14.33	11.78	ES $\neq$ > RUS_TV	3.959	19.25	13.70	11.88
ES $\neq$ > CUB_TV	15.60	20.35	12.70	10.93	ES $\neq$ > RWA_TV	2.769	6.508	3.992	2.891
ES $\neq$ > CZE_TV	15.62	19.84	13.40	11.28	ES $\neq$ > SDN_TV	2.847	7.124	4.074	2.953
ES $\neq$ > DEU_TV	3.792	20.37	14.32	11.17	ES $\neq$ > SEN_TV	0.950	8.798	4.150	2.449
ES $\neq$ > DMA_TV	3.176	10.72	4.739	2.894	**ES $\neq$ > SGP_TV**	15.34	18.64	13.16	11.10
ES $\neq$ > DNK_TV	6.630	19.15	13.45	10.88	ES $\neq$ > SLB_TV	0.470	10.883	4.657	2.977
ES $\neq$ > DOM_TV	2.542	6.475	3.908	2.775	ES $\neq$ > SLV_TV	3.998	18.62	12.77	10.86
ES $\neq$ > EGY_TV	14.95	18.14	13.43	11.13	ES $\neq$ > SMR_TV	3.724	18.75	13.83	11.19
ES $\neq$ > ERI_TV	3.261	8.578	4.353	2.478	ES $\neq$ > SRB_TV	3.719	19.61	13.72	11.01
ES $\neq$ > ESP_TV	15.09	20.29	13.33	10.85	ES $\neq$ > SSD_TV	4.204	18.85	13.40	11.40
ES $\neq$ > EST_TV	2.699	8.419	4.123	2.521	ES $\neq$ > SUR_TV	0.859	9.697	4.008	2.709
ES $\neq$ > FIN_TV	3.792	20.37	14.32	11.17	**ES $\neq$ > SVK_TV**	15.08	16.84	12.97	10.78
ES $\neq$ > FJI_TV	15.09	17.61	12.84	11.08	**ES $\neq$ > SVN_TV**	14.96	19.39	13.19	11.42

Table 9. *Cont.*

	Estimated Test Value (MWALD)	Bootstrap Critical Values				Estimated Test Value (MWALD)	Bootstrap Critical Values		
		1%	5%	10%			1%	5%	10%
ES ≠ > FRA_TV	3.792	20.37	14.32	11.17	ES ≠ > SWE_TV	3.665	20.12	14.21	11.29
ES ≠ > FRO_TV	3.928	17.67	13.41	11.21	**ES ≠ > SWZ_TV**	2.708	9.194	3.903	2.537
ES ≠ > GAB_TV	15.49	18.06	13.23	11.14	ES ≠ > SYC_TV	4.035	19.80	13.97	11.43
ES ≠ > GBR_TV	3.793	21.58	14.16	11.26	**ES ≠ > TCD_TV**	14.82	19.43	13.64	11.48
ES ≠ > GEO_TV	3.228	6.529	3.754	2.737	**ES ≠ > TGO_TV**	15.34	18.64	13.16	11.10
ES ≠ > GIN_TV	3.082	8.874	4.644	2.858	**ES ≠ > THA_TV**	15.34	18.95	13.63	11.39
ES ≠ > GMB_TV	1.816	10.70	4.775	2.863	ES ≠ > TKM_TV	0.304	7.165	4.154	2.901
ES ≠ > GUM_TV	4.175	17.96	13.50	11.22	ES ≠ > TLS_TV	3.932	20.07	14.04	11.81
ES ≠ > GUY_TV	3.691	19.68	13.71	11.24	**ES ≠ > TUN_TV**	14.95	18.77	13.51	11.11
ES ≠ > HKG_TV	3.809	20.70	14.44	11.04	**ES ≠ > TUR_TV**	2.905	6.518	3.756	2.711
ES ≠ > HND_TV	15.51	21.01	13.74	11.84	ES ≠ > TWN_TV	3.670	19.31	13.78	10.99
ES ≠ > HRV_TV	3.916	19.83	13.39	11.34	ES ≠ > TZA_TV	0.447	6.789	4.215	2.874
ES ≠ > HTI_TV	15.21	19.63	14.28	11.45	ES ≠ > UGA_TV	3.757	19.81	14.09	11.58
ES ≠ > HUN_TV	15.08	16.84	12.97	10.78	**ES ≠ > UKR_TV**	15.62	19.72	13.59	11.55
ES ≠ > IDN_TV	3.775	18.29	13.91	11.62	**ES ≠ > URY_TV**	15.08	18.02	13.66	11.22
ES ≠ > IND_TV	16.02	17.83	13.21	10.86	ES ≠ > USA_TV	4.847	19.52	14.19	11.83
ES ≠ > IRL_TV	15.19	18.74	13.62	11.10	**ES ≠ > UZB_TV**	15.05	19.03	13.15	11.29
ES ≠ > IRQ_TV	3.998	16.84	13.24	10.90	ES ≠ > VEN_TV	4.204	18.85	13.40	11.40
ES ≠ > ISR_TV	15.71	17.97	13.52	11.07	ES ≠ > VNM_TV	3.930	19.48	14.05	11.32
ES ≠ > ITA_TV	15.09	20.29	13.33	10.85	ES ≠ > VUT_TV	1.849	10.83	4.34	2.55
ES ≠ > KAZ_TV	2.338	7.549	4.126	2.777	**ES ≠ > ZAF_TV**	15.32	18.20	13.44	11.26
ES ≠ > KEN_TV	3.967	19.86	13.73	10.75	**ES ≠ > ZMB_TV**	15.12	17.96	13.45	11.27
ES ≠ > KGZ_TV	15.09	17.61	12.84	11.08	ES ≠ > ZWE_TV	4.167	20.96	14.07	10.84

* ES denotes economic supports; TV denotes trading volume.

The results in Table 9 clearly show that there was evidence of unidirectional causality running from economic supports to the trading volume of Bitcoin in 61 countries.

The results of both the FFFFTY and BTY causality tests provided some evidence of our main hypothesis predicting the causal relations between economic supports and the return, volatility, and trading volume of Bitcoin. Additionally, we found evidence to answer the first research question of "*Is there unidirectional causality running from COVID-19-related economic supports to the return, volatility, and trading volume of Bitcoin during the pandemic*?" for more than half of the countries in the sample. Regarding the return series, we found significant results in 70 countries in total. For volatility, we found significant casualties for 75 countries. Finally, for the trading volume of Bitcoin, we found significant results in 87 countries. It is interesting that most of the significant findings were found in the relations of these economic supports with the trading volume of Bitcoin. These results support the idea that the 2008 global crises caused a significant change in the average investors' attitude towards asset allocation and investment portfolio decisions. As a result, there has been strong demand for cryptocurrencies, particularly Bitcoin, after crises, and the pandemic has accelerated this strong demand for cryptocurrencies. It seems that instead of spending these economic supports, people are using them to invest in highly speculative but profitable assets to gain additional income to prepare themselves for upcoming big uncertainties and events that have potentially adverse effects. This implies some kind of Ricardian equivalence in the use of some lump sum economic supports.

Regarding the second research question of "*Are there region- and country-specific differences in this causal relationship*?", it is hard to claim that there have been region- and/or country-specific differences in terms of the effects of economic supports on the Bitcoin market. This conclusion shows that regardless of where people live, they generally show the same attitude towards the use this kind of economic support and generally behave cautiously.

Regarding the third research question of "*Is this causal relation permanent or temporary*?", the results mostly supported the view that they were permanent. This means even though the pandemic is almost under control and most countries have ceased providing economic supports, the effects of these economic supports on the Bitcoin market will not end soon. This results also showed that economic supports could be a major source of the speculation and bubbles we have witnessed during the pandemic.

7. Conclusions

In this study, we examined the causal effects of COVID-19-related economic supports on surges in the Bitcoin market by using recently developed linear and non-linear unit root and causality tests. Along with the results' implications for policy makers, market participants, regulators, and individual investors, an important conclusion of this paper is that use of non-linear methods provided enriched results. The results of the study also provide many insights regarding the effects of these economic supports on the return, volatility and trading volume of Bitcoin. First of all, the results of study reinforce the fact that there has been structural shift in the perception of individuals regarding the way they see this kind of lump sum support. Instead of using economic supports to compensate for the income losses that they suffer during unprecedented times such as global crises and pandemics, they prefer to invest into vast array of assets including speculative ones such as cryptocurrencies. As a result, we have witnessed a sharp surge in this kind of market (particularly the Bitcoin market) during the pandemic. This shift in individual perception and behavior can obviously cause surges in the price, return, volatility, and trading volume of this kind of asset. Therefore, the results of this study should be cautiously considered since they have significant implications for policy makers, market participants, and regulators. For policy makers and regulators, this kind of economic support could be interpreted as a "remedy worse than disease" policy, since these economic supports impact the Bitcoin market through structural changes in the behavior of individuals in almost all countries. It seems that individuals see this kind of support as a way of accumulating wealth and making quick money with one of the most speculative kinds of investments. Market participants have to understand that unprecedented events such as pandemics or global crises, as well as the polices implemented to decrease the adverse effects of these events, have the potential to increase uncertainty and speculation in financial markets. Thus, individual investors must consider the timing and circumstances of investing money into these kinds of assets. Lastly, central bankers should remember that there seems to be a broken line between the rising money supply caused by this kind of pandemic support and price levels since people are becoming more precautionary but also involving themselves in risky investment activities. As a final conclusion, we argue that the value and practicability of this paper's results can be increased by carrying out further research on the signs of the established causalities. This study can be extended by examining the presence of asymmetry in the effects of economic supports. Additionally, the study can be replicated by the using time-varying Granger causality test, as seen in [51] for the forecasting of Bitcoin price.

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Appendix A

Table A1. Beginning and ending dates of sample data for countries.

	Beginning	End	Ob.		Beginning	End	Ob.		Beginning	End	Ob.
ABW	4.01.2022	3.10.2022	507	GAB	4.03.2020	11.22.2021	427	NPL	30.03.2020	3.10.2022	509
AGO	4.09.2020	11.20.2020	162	GBR	17.03.2020	3.10.2022	518	NZL	17.03.2020	3.10.2022	518
ALB	3.19.2020	2.28.2022	508	GEO	24.04.2020	10.15.2021	386	OMN	24.03.2020	7.12.2021	340
AND	3.13.2020	3.10.2022	520	GIN	4.06.2020	5.24.2021	296	PAK	4.09.2020	3.10.2022	501
ARE	4.01.2020	11.12.2022	423	GMB	10.09.2020	8.09.2021	217	PAN	30.04.2020	3.10.2022	486

Table A1. *Cont.*

	Beginning	End	Ob.		Beginning	End	Ob.		Beginning	End	Ob.
ARG	3.23.2020	3.10.2022	514	GRC	18.03.2020	3.10.2022	517	PER	16.03.2020	3.10.2022	519
AUS	3.12.2020	3.30.2021	274	GRL	23.03.2020	11.23.2021	437	PHL	4.06.2020	4.05.2021	261
AUT	3.16.2020	3.10.2022	519	GTM	21.04.2020	3.10.2022	493	PNG	4.01.2020	3.10.2022	507
AZE	4.08.2020	3.10.2022	502	GUM	17.04.2020	1.03.2022	447	POL	18.03.2020	3.10.2022	517
BDI	10.02.2020	2.21.2022	362	GUY	26.03.2020	3.10.2022	511	PRI	16.03.2020	9.03.2021	385
BEL	3.06.2020	12.31.2021	476	HKG	26.02.2020	3.10.2022	532	PRY	31.03.2020	8.18.2021	362
BEN	6.10.2020	3.10.2022	457	HND	3.04.2020	3.10.2022	505	QAT	30.03.2020	3.10.2022	509
BFA	2.02.2021	8.20.2021	144	HRV	17.03.2020	1.03.2022	470	ROU	23.03.2020	3.10.2022	514
BGD	3.19.2020	1.03.2022	468	HTI	23.03.2020	2.04.2022	490	RUS	4.01.2020	3.10.2022	507
BGR	3.30.2020	3.10.2022	509	HUN	18.03.2020	3.10.2022	517	RWA	18.03.2020	8.31.2021	380
BHR	2.03.2020	12.31.2021	500	IDN	4.01.2020	3.10.2022	507	SDN	15.04.2020	6.14.2021	304
BHS	3.17.2020	9.16.2021	393	IND	3.02.2020	3.10.2022	529	SEN	4.01.2020	9.24.2021	388
BIH	3.02.2020	1.03.2020	481	IRL	16.03.2020	3.10.2022	519	SGP	4.01.2020	3.10.2022	507
BLZ	3.16.2020	3.10.2022	519	IRN	16.03.2020	3.10.2022	519	SLB	27.03.2020	12.29.2020	198
BMU	3.25.2020	3.10.2022	512	IRQ	18.05.2020	12.31.2021	425	SLV	19.03.2020	10.22.2021	417
BOL	3.31.2020	11.30.2021	436	ISL	3.10.2020	3.10.2022	523	SMR	3.02.2020	3.10.2022	529
BRA	3.17.2020	3.10.2022	518	ISR	3.09.2020	3.10.2022	524	SRB	31.03.2020	3.10.2022	508
BRB	4.01.2020	3.10.2022	507	ITA	17.03.2020	3.10.2022	518	SSD	28.04.2020	1.17.2022	450
BRN	30.03.2020	3.31.2021	263	JOR	18.03.2020	3.10.2022	517	SUR	18.05.2020	11.12.2021	390
BTN	4.10.2020	3.10.2022	500	JPN	16.03.2020	3.10.2022	519	SVK	18.03.2020	3.10.2022	517
BWA	31.03.2020	11.01.2021	415	KAZ	16.03.2020	7.30.2021	360	SVN	19.03.2020	3.10.2022	516
CAF	16.03.2020	3.01.2022	512	KEN	18.03.2020	2.22.2022	505	SWE	3.11.2020	3.10.2022	522
CAN	16.03.2020	3.10.2022	519	KGZ	26.03.2020	3.10.2022	511	SWZ	23.03.2020	7.09.2021	340
CHE	19.03.2020	3.10.2022	516	KHM	21.05.2020	7.05.2021	293	SYC	1.04.2020	2.14.2022	489
CHL	27.03.2020	8.27.2021	371	KWT	4.01.2020	3.10.2022	507	TCD	27.03.2020	1.21.2022	476
CHN	13.04.2020	3.10.2022	499	LAO	4.02.2020	3.10.2022	506	TGO	4.01.2020	3.10.2022	507
CIV	31.03.2020	3.10.2022	508	LBN	8.04.2020	3.10.2022	502	THA	4.01.2020	3.10.2022	507
CMR	1.06.2020	11.23.2020	126	LKA	24.04.2020	3.10.2022	490	TJK	5.05.2020	6.11.2021	289
COD	3.02.2020	12.21.2021	472	LSO	20.04.2020	5.24.2021	286	TKM	9.03.2020	11.02.2021	304
COG	31.03.2020	9.17.2021	384	LTU	17.03.2020	3.10.2022	518	TLS	30.03.2020	1.17.2022	471
COL	17.03.2020	1.31.2022	490	LUX	17.03.2020	2.28.2022	510	TTO	19.03.2020	3.10.2022	516
CPV	24.03.2020	3.10.2022	513	LVA	12.03.2020	3.10.2022	521	TUN	23.03.2020	3.10.2022	514
CRI	20.03.2020	3.10.2022	515	MAC	13.02.2020	3.10.2022	541	TUR	4.07.2020	8.11.2021	352
CUB	4.09.2020	3.10.2022	501	MAR	23.03.2020	3.10.2022	514	TWN	3.10.2020	3.10.2022	523
CZE	12.03.2020	3.10.2022	521	MCO	16.03.2020	3.10.2022	519	TZA	6.08.2021	3.10.2022	198
DEU	16.03.2020	3.10.2022	519	MDG	28.04.2020	5.24.2021	280	UGA	23.03.2020	3.10.2022	514
DMA	19.05.2020	5.13.2021	258	MEX	9.10.2020	3.10.2022	370	UKR	3.12.2020	3.10.2022	521
DNK	3.09.2020	9.06.2021	391	MLI	4.01.2020	3.10.2022	507	URY	18.03.2020	3.10.2022	517
DOM	27.03.2020	9.03.2021	376	MMR	28.04.2020	3.10.2022	488	USA	27.03.2020	10.01.2021	396
DZA	4.06.2020	2.04.2022	480	MNG	18.03.2020	3.10.2022	517	UZB	24.03.2020	3.10.2022	513
EGY	23.03.2020	3.10.2022	514	MRT	25.03.2020	7.02.2021	333	VEN	23.03.2020	12.10.2021	450
ERI	31.03.2020	4.02.2021	264	MUS	3.02.2020	3.10.2022	529	VIR	9.09.2020	3.10.2022	392
ESP	17.03.2020	3.10.2022	518	MWI	4.09.2020	8.10.2021	349	VNM	4.09.2020	10.15.2021	397
EST	3.02.2020	7.05.2021	351	MYS	4.01.2020	3.10.2022	507	VUT	4.08.2020	1.29.2021	213
FIN	16.03.2020	3.10.2022	519	NAM	26.03.2020	11.16.2021	429	ZAF	21.04.2020	3.10.2022	493
FJI	26.03.2020	3.10.2022	511	NER	15.04.2020	8.16.2021	349	ZMB	30.03.2020	3.10.2022	509
FRA	16.03.2020	3.10.2022	519	NIC	23.03.2021	3.10.2022	253	ZWE	4.08.2020	11.29.2021	429
FRO	16.03.2020	9.27.2021	401	NLD	17.03.2020	3.10.2022	518				

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