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# BITCOIN AS AN INVESTMENT VEHICLE: THE ASYMMETRIC RELATIONSHIPS BETWEEN BITCOIN AND GLOBAL TECHNOLOGY INDEXES

# BİR YATIRIM ARACI OLARAK BİTCOİN: BİTCOİN İLE GLOBAL TEKNOLOJİ ENDEKSLERİ ARASINDA ASİMETRİK NEDENSELLİK İLİŞKİLERİ

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## Abstract

The concept of blockchain and cryptocurrencies is one of the most popular concepts of recent years. Cryptocurrencies were first introduces with Bitcoin in 2008 and now they have an increasing variety and popularity. Recent developments in technology firms have brought into question whether there is a relationship between Bitcoin and technology indexes. To this end, this study investigates the causality relationship between Bitcoin and technology indexes using monthly data between the years 2016 and 2021 in G7 and E7 countries. To test the causality relationship between the variables, the Hatemi-J (2012) asymmetric causality test was used. Hatemi-J (2012) test reveals that the relationship between bitcoin and technology indexes becomes different for G7 and E7 countries. The results suggest that developed countries affect bitcoin prices while developing countries are affected by Bitcoin prices. The conclusion is that findings point out the existence of an asymmetric relationship between the series for G7 and E7 countries.

***Keywords: Cryptocurrencies, Bitcoin, Technology Equities, Asymmetric Causality Test.***

## Öz

Blok zincir ve kripto paralar son yılların en popüler konuları arasındadır. İlk olarak 2008 yılında Bitcoin (BTC) ile tanıtılan kripto paralar günümüzde artan bir çeşitliliğe ve popülariteye sahiptir. Teknoloji sektöründeki güncel gelişmeler ise teknoloji endeksleri ile kripto paralar arasındaki ilişkilerin varlığına dair soruları akla getirmiştir. Bu amaçla bu çalışmada G7 ve E7 ülkelerinin teknoloji endeksleri ile Bitcoin arasındaki nedensellik ilişkileri 2016 ve 2021 yıllarına ait aylık veri seti kullanılarak araştırılmıştır. Değişkenler arasındaki nedensellik ilişkisinin araştırılmasında Hatemi-J (2012) testi kullanılmıştır. Hatemi-J (2012) testinden elden edilen sonuçlar Bitcoin ve teknoloji endeksleri arasındaki ilişkinin G7 ve E7 ülkeleri açısından farklılık gösterdiğini ortaya koymuştur. Buna göre gelişmiş ülkelerin endeksleri Bitcoin fiyatlarını etkilerken gelişmekte olan ülkelerin endeksleri Bitcoin fiyatlarından etkilenmektedir. Sonuç olarak bulgular G7 ve E7 ülkeleri için asimetrik ilişkinin varlığına işaret etmektedir.

***Anahtar Kelimeler: Kripto Paralar, Bitcoin, Teknoloji Hisseleri, Asimetrik Nedensellik Testi.***

## GENİŞLETİLMİŞ ÖZET

### Çalışmanın Amacı

Bu çalışmanın amacı borsalarda işlem gören teknoloji şirketlerinin hisseleri ile Bitcoin arasında asimetrik nedensellik ilişkilerinin varlığının araştırılmasıdır. Bu amaçla gelişmiş ülkeleri temsilen G7 ülkelerinin ve gelişmekte olan ülkeleri temsilen E7 ülkelerinin borsalarındaki teknoloji endeksleri ile Bitcoin'in Ocak 2016 ile Şubat 2021 dönemine ait aylık veri seti incelenmiştir.

### Araştırma Soruları

Gerek teknoloji firmalarının blok zincir ve kripto paralara doğrudan yatırımları, gerekse kripto paralara yönelik spekülatif talep, pek çok varlık grubuna karşı güvenli liman, riskten korunma ve çeşitlendirme aracı olarak görülen Bitcoin'in teknoloji hisseleri ile etkileşiminin yüksek olabileceği yönünde kuşkular doğurmuştur. Kripto paralar ile teknoloji sektörü arasındaki bağlantıyı ampirik olarak araştıran Umar, Trabelsi ve Alqahtani (2021), her ikisinin de arkasındaki gücün teknolojik inovasyon olmasından dolayı ikisinin de benzer piyasa dinamiklerine konu olabileceğini düşünerek aralarında bir bağlantının olabileceğini ileri sürmüşlerdir.

### Literatür Araştırması

Bitcoin ile belirli sektörler arasındaki doğrudan ilişkileri ele alan çalışmalar oldukça azdır. Bu çalışmalardan birinde Corbet, Lucey ve Yarovaya (2021), Bitcoin madenciliğinin gerektirdiği yüksek enerji kullanımından yola çıkarak, bu yeni finansal ürünlerin, özellikle de madenciliğinin en yüksek olduğu bölgelerde, enerji ve elektrik piyasaları üzerindeki etkilerini incelemişlerdir. DCC-GARCH analizinden elde edilen bulgular Bitcoin getirileri ile hem Çin hem de Rusya elektrik şirketlerinin fiyat volatiliteleri arasında güçlü pozitif ilişkilere işaret etmiştir. Damianov ve Elsayed (2020) ise 10 sanayi sektörü arasındaki dinamik koşullu korelasyonları araştırdıkları çalışmalarında ADCC-GARCH modeli ile Diebold ve Yılmaz'ın (2012) yayılma modelini kullanmışlardır. Bitcoin ile sanayi sektörlerinin aralarındaki koşullu korelasyonlar negatif olmakla birlikte istatistiksel olarak anlamlı bir sonuç elde edilmemiş olması, Bitcoin'in portföylerinin varyansını düşürmek isteyen yatırımcılar için sınırlı bir kullanımı olduğu ve güvenli liman ya da riskten koruma değil, yalnızca çeşitlendirme olanağı sağlayabileceği şeklinde yorumlanmıştır. Umar vd. (2021) çalışmalarında gelişmiş ve gelişmekte olan 12 ülkenin teknoloji endeksleri ile kripto paralar arasındaki ilişkiyi araştırmışlardır. Granger nedensellik testi sonuçlarına göre kripto para endekslerinden (CRIX) Türkiye ve Japonya teknoloji sektörlerine doğru %5 anlamlılık düzeyinde nedensellik tespit edilmiştir. Dolayısıyla CRIX bu iki ülkenin teknoloji endekslerini tahmin etmede kullanılabileceği şeklinde yorumlanmıştır. Hiçbir teknoloji endeksinden CRIX'e doğru nedensellik ise bulunamamıştır.

**Yöntem**

Verilerin analizinde Phillips ve Perron (1988) ve DF-GLS (1996) birim kök testleri için EViews paket programı, Zivot ve Andrews (1992), Lee ve Strazicich (2013) kırılmalı birim kök testleri ve Hatemi-J (2012) asimetrik nedensellik testi içinse Gauss 21 paket programları kullanılmıştır.

**Sonuç ve Değerlendirme**

Elde edilen sonuçlara göre gerek gelişmiş gerekse gelişmekte olan ülkelerin teknoloji endeksleri ile Bitcoin fiyatı arasında bir ilinti olduğu anlaşılmaktadır. Söz konusu ilinti asimetrik bir nedensellik ilişkisi olup, negatif şoklar karşısında daha güçlü görülmektedir. Nedenselliğin yönü genel olarak bu çalışmada alınan tüm G7 ülkelerinin teknoloji endekslerinden Bitcoin'e doğru ve Bitcoin'den E7 ülkelerine doğrudur. G7 ülkeleri arasında yalnızca Almanya (pozitif) ve Kanada (negatif) Bitcoin'den gelen şoklardan etkilenmektedir. Almanya ve Kanada arasındaki bu farkın, ilkinin daha çok blok zincir teknolojisinin geliştirilmesine ya da kullanılmasına yönelik yatırımlar gerçekleştirmesine rağmen ikincisinde doğrudan kripto para yatırımlarının ağırlık kazanmasıyla ilişkili olduğu düşünülmektedir. E7 ülkelerinde ise Çin yalnızca negatif şoklardan, Türkiye ve Hindistan ise hem pozitif hem de negatif şoklardan etkilenmektedir.

## 1. INTRODUCTION

On February 8, 2021; Elon MUSK announced that the company he owns, Tesla bought a Bitcoin equivalent to 1,5 billion dollars and they will accept Bitcoin as an instrument of payment soon. Then, Bitcoin increased 19,56%, which is the highest daily increase since December 7, 2017; and reached the highest value of all times. The share values of the several companies which invested in Bitcoin increased considerably in the same day. Then attentions drawn to the relationship between technology companies and blockchain, cryptocurrencies, and especially Bitcoin.

In 2008, several technology companies were established in order to provide services through blockchain technology after an anonymous programmer, Satoshi Nakamoto, introduced the revolutionary Bitcoin and the blockchain technology behind it. Blockchain has a wide field of utilization even though it is generally mentioned with cryptocurrencies. It enables the types of operations from several fields such as supply chain, logistics, energy, health, finance, public management to be more reliable and faster along with its advanced technology infrastructure it provides. Blockchain technology brings innovations related to funding provision types of businesses. Several newly founded technology companies get finance through initial coin offering which is generally based on selling a crypto asset (which is named as “token” or “coin”) produced on behalf of them against Bitcoin or Ethereum (for detailed information, see BTC Turk). Today, legal infrastructures for the businesses to issue security token offering for their debts and to supply equities in several developed countries including USA and Germany. Several businesses from different sectors increased their capital and indicated their intentions about it in this way.

However, it is presumed that the motivation which leads the companies to invest in cryptocurrencies and the unavoidable rise of cryptocurrencies has the same dynamic behind them: Speculative earning potential! For example, after the camera manufacturer, Eastman Kodak, introduced the image rights management and protection platform, which is secured by blockchain, a great increase in the value was recorded in its stocks (Corbet et al., 2020). It was also determined that there are numerous companies which mentioned their good intentions related to this technology speculatively in their public and official announcements and that their stock values increased considerably in short term and provided positive abnormal returns in addition to the companies which invested in blockchain actually in several countries (Cheng, De Franco, Jiang and Lin, 2019; Cahill, Baur, Liu and Yang, 2020). Besides, several companies changed their names and they included “blockchain”, “cryptocurrency” or similar expressions associated with them in their names. It was also determined that stock values of those companies in short term, this increase is permanent for a specific period (Jain and Jain, 2019; Akyıldırım et al. 2020) and that the correlations with the currencies of the countries where they are registered decreased and the correlations with the cryptocurrencies increased (Akyıldırım et al., 2020).

The foregoing issues suggest that the blockchain is not perceived as a technological infrastructure and cryptocurrencies are not perceived as an instrument for change. For example; Ciaian et al. (2016) did not detect any kind of finding indicating that the macroeconomic indicators affect the Bitcoin prices in contrast with the conventional currencies; and they determined that the speculative behaviors and supply & demand basis of the investors specify the prices. Baur, Hong and Lee (2019), who focused on the objects of the utilization of Bitcoin in the economy, suggested that Bitcoin may be considered as a speculative investment instrument, one-third of Bitcoin is kept by the investors and just a little part of it is used as a payment instrument. Pelster et al. (2019) increased the motivations of the cryptocurrency investors. It was founded that the first entities investing in cryptocurrency increased their risks related to the share market; thus, a part of the cryptocurrency demand is caused by the investors seeking risk. Hui et al. (2020) and Kwon (2020) suggested that Bitcoin is demanded as an instrument of investment in addition to the fact that it is a store of value and instrument of change. Lee, Li and Zheng (2020) concluded that the speculative actions, as well as the expectations of the investors interested in technology, are determinant by focusing on the dynamics of the formation of the prices of Bitcoin. Grobys and Juntilla (2021) determined that there are behavioral mechanisms similar to the share market behind the behaviors of the investors in the virtual money markets. Its volatility against the increasing transaction volume and dollar (Üzer, 2017) verifies the determinations suggested by the relevant researches.

The direct investments in the blockchain and cryptocurrency of the technology companies and the speculative demand on the cryptocurrency caused suspicions suggesting that Bitcoin, which is considered as a security blanket, protection against any kind of risk or instrument of diversification against several assets may have high interaction with the stocks related to technology. Umar et al. (2021); who empirically analyzed the connection between cryptocurrencies and the technology industry; suggested that they could be the subject of similar market dynamics since the power behind both is technological innovation. Thus, this study aims to investigate the existence of asymmetric casualty relationships between the shares of the publicly traded technology companies and Bitcoin. Therefore, the Hatemi-J (2012) asymmetric casualty test was applied to the technology indices of the G7 countries representing the developed countries and the E7 countries representing the developing countries and the monthly data of Bitcoin for the period between January 2016 and February 2021. The findings reveal that E7 countries are affected by the price of Bitcoin while G7 countries affect the price of Bitcoin in general. The results of this study are expected to provide investors with a unique perspective within the context of international portfolio diversification. It is thought that this study contributes to the literature in terms of examining the causal relationships between technology indices and the crypto market, taking into account possible asymmetries. Additionally, the differentiation of the causality relationship between technology indices and Bitcoin according to G7 and E7 country groups is among the original findings of the study.

The structure of the paper is as follows: After the Introduction, Section 2 provides a brief literature review on the relationship between Bitcoin and stock markets. Sources of the data employed as well as the methodology are presented in Section 3. Section 4 reveals the empirical results. In the last chapter, all findings are interpreted within the frame of the literature and policy recommendations are proposed.

## 2. LITERATURE REVIEW

It was observed that the investors increased their Bitcoin demands especially in the extreme periods (Kwon, 2020) because their return characteristics are different from other asset groups (Baur et al., 2018) and they are seen as a relatively isolated market (Corbet et al. 2018; Damianov and Elsayed, 2020; Bhuiyan et al. 2021). It has motivated the researches on whether Bitcoin provides a security blanket, hedging, or diversification opportunity against other markets. In one of the abovementioned studies, Bouri et al. (2017) analyzed the relationship between Bitcoin and several financial assets including stocks, bonds, currencies and commodities through the DCC-GARCH method. The findings revealed that Bitcoin's ability to protect against risk is weak; however, it enables diversification in many cases. Klein, Thu and Walter (2018) compared the general behavioral characteristics of Bitcoin with gold by approaching it from a perspective of an investment instrument. The findings obtained from the BEKK-GARCH method reveal that although the volatility dynamics of Bitcoin show some similarities with gold and silver, from the perspective of the portfolio, gold does not have the security blanket function, which is a prominent characteristic. Bitcoin yields have been found to react asymmetrically to market shocks. Selmi et al. (2018) provided strong evidence to confirm that Bitcoin and gold are useful in diversifying gains and mitigating downside risk in managing the risk of the oil portfolio in their studies which they applied the quantile regression approach. When oil prices move down, Bitcoin's characteristic of being a security blanket precludes gold. Al-Yahyee et al. (2019) tried to predict volatility and conditional correlation relationships between Bitcoin and the oil, gold and commodity markets through the DCC-GARCH method. The findings showed that Bitcoin can function as a hedging instrument against oil and as a diversification instrument against gold and commodities. Through the wavelet matching approach, Bhuiyan et al. (2021) suggested that there is no kind of relationship between Bitcoin and traditional asset classes and that it can offer diversification in such portfolios; however, there is a premise-residue relationship with gold. On the other hand; Zhang et al. (2021) determined the presence of downside risk spread between Bitcoin and four financial assets (shares, commodities, currencies and bonds) through the CAR-ARCHE model.

When those studies are evaluated together, it is understood that the protection characteristics of Bitcoin stand out against the risks arising from oil prices; however, it has more interaction with the gold market. On the other hand, it is observed that the relationship between Bitcoin and stock markets occupies a large place in the relevant literature. Zhang et al. (2018) showed that there is a cross-correlation between DJIA and the cryptocurrency composite index through DFA and DCCA models with multiple breaks and is permanent throughout the entire period. Through the Copula-ADCC-EGARCH model; Tiwari et al. (2019) suggested that the correlations of cryptocurrencies between the S&P 500 stock market are low so that the cryptocurrencies can function as assets which will protect against the risks of the share market. Bouri et al. (2020) determined that Bitcoin is superior to gold and commodities in terms of diversifying against different share markets through the wavelet matching approach and VAR model. Through the EXO-DCC model, Okorie (2020) suggested that Bitcoin and S&P 500 can be used for risk protection against each other. The time-varying correlation obtained from the studies Mokni et al. (2020) through the DCC-EGARCH model also suggested that Bitcoin can provide risk protection against US share market changes. Mariana et al. (2021) showed in their studies that they applied DCC-GARCH and corrected the DCC model that in the COVID-19 period, Bitcoin and Ethereum were negatively correlated with the returns of the S&P 500 index so that it could be a security blanket in the short term. Lopez-Cabarcos et al. (2021) suggested that Bitcoin can be used as a security blanket when the volatility of the share markets is high; however, when the stock markets are stable, Bitcoin is more attractive to speculative investors in their studies which they applied the GARCH and EGARCH model.

In one of the studies analyzing the effect of cryptocurrencies on portfolio performance, Platanakis and Urquhart (2020) showed that the portfolio's performance metrics measured by Sharp, Omega and Sortino ratios improved by adding Bitcoin to the stock-bond portfolio. In another study; Matkovsky et al. (2021) found that the performance of the portfolios created from the worst-performing stocks in the stock market increased significantly after the addition of the cryptocurrencies to portfolios, with the greatest benefit for companies with small market capitalization. There are also studies analyzing the relationships between cryptocurrencies and Islamic markets. Mensi et al. (2020) analyzed the co-mobility between Bitcoin and regional Islamic market indexes and Sukuk by applying the wavelet-based tests. It was concluded that the Islamic markets of the USA and Japan are more financially integrated with Bitcoin, so they do not allow portfolio diversification in the long term; however, Canada and IMXL Islamic stocks and Sukuk can be evaluated in the same portfolio as Bitcoin. Besides, it was observed that the possibility of diversification is stronger in short-term investments when they are compared to long-term investments. Rehman et al. (2020) concluded that the Islamic capital markets have the capacity to hedge when evaluated in the same portfolio as Bitcoin, the most effective diversification is achieved under bear market conditions and that the benefits of diversification remain moderate under normal market conditions through the ARFIMA-FIGARCH method. A group of researchers focused on analyzing the behavioral patterns of investors within the price formation mechanism of cryptocurrencies. Within this frame; Gurdgiev and O'Loughlin (2020) suggested that investor sentiment can predict the direction of the prices of cryptocurrencies in the period between January 1, 2017, and April 2, 2019. It directly indicates the presence of herd behavior and anchoring bias. Vidal-Tomas Ibanez and Farinos

(2019) applied CSSD and CSAD approaches. It was observed that excessive price movements can be explained rationally by asset pricing models in accordance with the CSSD model. On the other hand, when the CSAD method is applied, they found that the herd behavior occurs when the market turns down in the cryptocurrency market. Stavros and Vassilos (2019) showed that the herd behavior observed when applying the OLS method for the eight largest cryptocurrencies disappeared when more robust predictive methods such as quantile regression were applied. Studies analyzing the direct relationships between Bitcoin and specific industries are very few. In one of those studies; Corbet et al. (2021) analyzed the effects of those new financial products on the energy and electricity markets, especially in regions where mining is the highest, based on the high energy use required by the Bitcoin market. Findings of the DCC-GARCH analysis indicated the strong positive relationships between Bitcoin returns and price volatility of both Chinese and Russian power companies. Damianocv and Elsayed (2020), on the other hand, applied the ADCC-GARCH model and the diffusion model of Diebold and Yılmaz (2012) in their study of the dynamic conditional correlations between 10 industrial sectors. Although the conditional correlations between Bitcoin and industry sectors are negative, the fact that any kind of statistically significant result was not obtained was interpreted as that Bitcoin has limited use for the investors who desire to reduce the variance of their portfolios and can only provide diversification, not as a security blanket or risk protection instrument. Umar et al. (2021) analyzed the relationship between the technology indexes of 12 developed and developing countries and cryptocurrencies. Therefore, CRIX was interpreted as it can be applied to estimate the technology indexes of those two kinds of countries. Any kind of causality from any technology index to CRIX was not found. Erdas and Caglar (2018) studied the asymmetric relationship between Bitcoin and S&P 500 and BIST 100 indexes for the weekly data of the period between 2013 and 2018 by Hatemi-J (2012) test. The results indicate that there is only an asymmetric link between Bitcoin price and S&P 500 index. They suggest that the relationship between Bitcoin and S&P 500 index may depends on the technological developments and the investors in S&P 500 Index have closely followed the new technological developments in the market.

## 3. DATA AND METHODOLOGY

In the study, it was analyzed whether there is a relationship between Bitcoin, which is the most commonly used among cryptocurrencies, and the technology indexes. In this study, which analyses how Bitcoin price changes affect the technology sector in developed and developing countries, the G7 countries indicating the seven most developed countries representing all developed countries and the E7 countries indicating the fastest developing countries representing all developing countries are analyzed. China (CHN), India (IND) and Turkey (TUR) represent E7 countries; Germany (DEU), France (FRA), England (GBR), Italy (ITA) and Canada (CAN) represent the G7 countries in the study. Other G7 and E7 countries were excluded from the analysis due to the inaccessibility of their data.

The data related to the variables were obtained from the investing.com and Bloomberg finance websites. All data are made logarithmic by obtaining the natural logarithm of those variables in the study. The data set consists of monthly data for the period between January 2016 and February 2021. Although it was first introduced in 2008, it was observed that the interest in digital currencies and blockchain has increased significantly since 2016. Since the beginning of 2016, many companies have changed their names with the names related to cryptocurrency and blockchain technology (Akyıldırım et al., 2020); and a significant part of the public disclosure announcements related to the blockchain made by companies took place after it (Cheng et al., 2019). The cryptocurrency market reached its highest market capitalization to date in January 2016 (Grobys and Juntilla, 2021). Bitcoin's market capitalization of $10.1 billion reached $79.7 billion in October 2017, and its price also reached from $616 to $4800 (Corbet et al., 2018). Additionally, the initial coin offerings/ICOs between 2014 and 2016 were $246 million, while it reached $5.6 billion in 2017 and $12.7 billion in 2018 (Cahill et al., 2020). In line with this fact, it was thought that the impact power of Bitcoin has increased since 2016 and the analysis period was started in 2016. In the analysis of the data; the EViews package program was applied for the Phillips and Perron (1988) unit root tests, Gauss 21 package program was applied for Zivot and Andrews (1992), Lee and Strazicich (2013) unit root test with breaks.

Before proceeding to causality analysis, unit root tests were conducted to reveal the characteristics of selected technology indexes and Bitcoin. For conducting the causality test, the variables must contain unit roots in their level values and their degree of integration must be the same. Based on this fact, classical and unit root tests with breaks were applied to determine whether the series are stationary or not. Additionally, the breaks occurring in the series were predicted through the unit root tests with breaks. Thus, it was analyzed whether the predicted breakpoints were similar between Bitcoin and technology indexes.

It was observed that the symmetrical causality tests such as Sims (1972), Hsiao (1981), Toda and Yamamoto (1995), Hacker and Hatemi (2006) are applied in most of the studies analyzing the causality relationships between variables. However, due to the possibility that those symmetrical tests will not distribute the errors normally, new critical values are created with the bootstrap method. The fact that positive and negative shocks to the variables cannot be separated in those tests reveals the weakness of the tests. However; in the presence of asymmetric data in financial markets and heterogeneous market participants, it can be indicated that the results obtained from symmetric causality tests may be misleading since participants do not provide similar responses to positive and negative shocks of the same size (Yılancı and Bozoklu, 2014). Granger and Yoon (2002) suggested for the first time that the relationship between positive and negative shocks may differ from the relationship between the variables (Özcan, 2015). On the other hand, Hatemi-J (2012) was based on the Granger and Yoon (2002) approach and developed it for the causality test. In the literature, when causality tests are applied to the financial time series, it is important to allow hidden relationships (Hatemi-J et al., 2014).

Therefore, the application of this method to financial series is really important in terms of obtaining strong results. From this point of view, the asymmetric causality test which entered the literature with Hatemi-J (2012) was applied to determine the causality relationship between the variables in the study. This is because, in the analysis conducted with the Granger causality test, the issue of reacting differently against the shocks which may be experienced in the financial markets cannot be taken into consideration. Therefore, Hatemi-J argued that the effect of shocks will not be the same on the market and shocks should be separated as positive and negative (Mert and Cağlar, 2019).

Hatemi-J (2012) asymmetric causality test is applied with the help of the following equations. The causality analysis between variables in the VAR models can be carried out in accordance with the cumulative sums approach. In other words, the causality analysis is performed within the VAR model (Hatemi-J, 2012: 449). It is assumed that there are two series as y1t and y2t in order to reveal the asymmetric causality relation between two integrated series (Hatemi-J, 2012).

$$y_{1t} = y_{1t-1} + \varepsilon_{1t} = y_{1,0} + \sum_{i=1}^{t} \varepsilon_{1i} \quad t = 1,2,.....,T \tag{1}$$

$$y_{2t} = y_{2t-1} + \varepsilon_{2t} = y_{2,0} + \sum_{i=1}^{t} \varepsilon_{2i} \quad t = 1,2,.....,T \tag{2}$$

Where, t=1,2,…T; y1,0 and y2,0 represent initial values of both random walk processes and the error terms ε1i and ε2i are determined as white noise residuals in both equations. In this regard, the positive and negative shocks are presented as follows, respectively (Hatemi-J, 2012).

$$\varepsilon_{1i}^{+} = \max\left(\varepsilon_{1i},0\right),\ \varepsilon_{2i}^{+} = \max\left(\varepsilon_{2i},0\right),\ \varepsilon_{1i}^{-} = \min\left(\varepsilon_{1i},0\right),\ \varepsilon_{2i}^{-} = \min\left(\varepsilon_{2i},0\right) \tag{3}$$

In this respect, residuals can be expressed as a sum of the positive and negative shocks as $\varepsilon_{1i} = \varepsilon_{1i}^{+} + \varepsilon_{1i}^{-}$, and $\varepsilon_{2i} = \varepsilon_{2i}^{+} + \varepsilon_{2i}^{-}$. With the information assumption, it is possible to express the equations for a y1,0 and y2,0 as follows:

$$y_{1t} = y_{1t-1} + \varepsilon_{1t} = y_{1,0} + \sum_{i=1}^{t} \varepsilon_{1i}^{+} + \sum_{i=1}^{t} \varepsilon_{1i}^{-} \tag{4}$$

And similarly;

$$y_{2t} = y_{2t-1} + \varepsilon_{2t} = y_{2,0} + \sum_{i=1}^{t} \varepsilon_{2i}^{+} + \sum_{i=1}^{t} \varepsilon_{2i}^{-} \tag{5}$$

With the equations (4) and (5), the positive and negative shocks which take part in each variable can be stated as an equation in cumulative form as follows:

$$y_{1t}^{+} = \sum_{i=1}^{t} \varepsilon_{1i}^{+},\ y_{1t}^{-} = \sum_{i=1}^{t} \varepsilon_{1i}^{-},\ y_{2t}^{+} = \sum_{i=1}^{t} \varepsilon_{2i}^{+},\ y_{2t}^{-} = \sum_{i=1}^{t} \varepsilon_{2i}^{-} \tag{6}$$

With the equation (6), it is accepted that the positive and negative shocks may have a permanent impact on other variables.

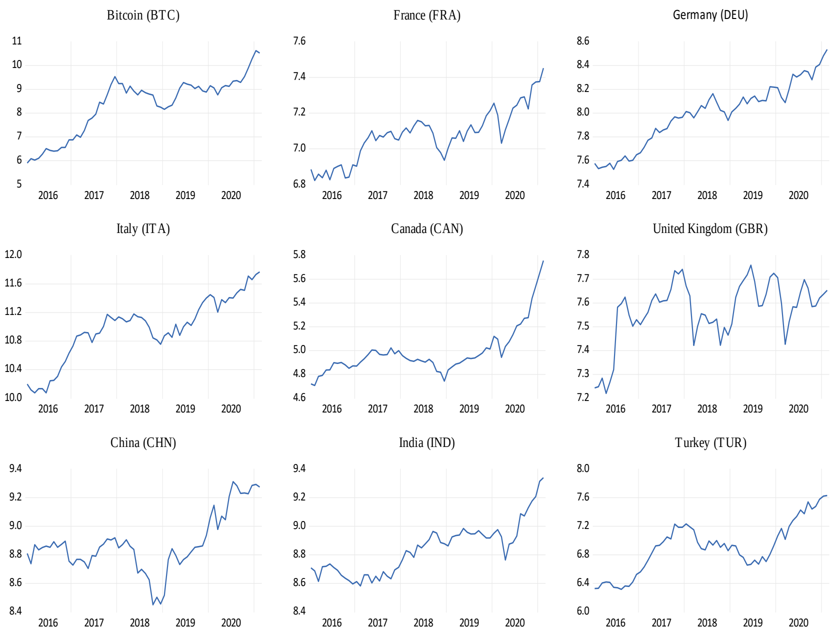
**Table 1.** Descriptive Statistics of the Variables

| Countries | Index | Period |
|---|---|---|
| Germany | DAX Technology | 01/2016-02/2021 |
| France | CAC Technology | 01/2016-02/2021 |
| Italy | FTSE Italia Technology | 01/2016-02/2021 |
| Canada | S&P/TSX Technology | 01/2016-02/2021 |
| United Kingdom | FTSE All Technology | 01/2016-02/2021 |
| China | FTSE China Technology | 01/2016-02/2021 |
| India | S&P BSE Tech Index | 01/2016-02/2021 |
| Turkey | BIST Technology | 01/2016-02/2021 |

**Source:** investing.com

Figure 1 illustrates the plots of Bitcoin and technology indexes over time in movements.

**Figure 1.** The Plot of the Data of Series




**Source:** own calculations

According to Figure 1, it is observed that the evolution of the Bitcoin and technology indexes monotonically exhibits a mixture of upward and downward trending. Figure 1 suggests that the price of the Bitcoin is markedly increasing except for 2018. According to figure 1, the price of Bitcoin started to decline in 2018 and it initiated a rapid upward movement. As shown in Figure 1, the price of Bitcoin history has been volatile. As can be observed from Figure 1, the presence of breaks in the series in the period discussed is remarkable. Moreover, it is observed in the graphics that any of the series is not in a distribution around a specific mean, therefore none of them is stationary.

## 4. RESULTS

In the section on empirical findings, the descriptive statistics of Bitcoin and technology indexes to be applied in the study were determined first. The mean, median, maximum, minimum values and the standard deviation values obtained as a result of the descriptive statistics test are presented in Table 2.

**Table 2.** Descriptive Statistics of the Series

| Variables | Mean | Median | Maximum | Minimum | Std. Dev. |
|---|---|---|---|---|---|
| BTC | 7404.834 | 6538.200 | 40969.00 | 365.5 | 7779.416 |
| FRA | 1196.934 | 1199.410 | 1723.490 | 919.0 | 178.3827 |
| DEU | 3052.729 | 3036.835 | 5084.770 | 1857.080 | 793.4242 |
| ITA | 63753.92 | 61552.12 | 129055.7 | 23784.77 | 25721.08 |
| CAN | 149.8708 | 139.0150 | 316.0 | 110.70 | 37.47470 |
| GBR | 1950.031 | 1974.830 | 2342.850 | 1367.110 | 234.7412 |
| CHN | 7326.966 | 6996.680 | 11074.73 | 4679.010 | 1580.927 |
| IND | 7022.725 | 7081.715 | 11380.96 | 5338.080 | 1343.878 |
| TUR | 1066.917 | 1019.575 | 2060.330 | 554.0 | 393.7651 |

**Source:** Own calculations

As can be observed in Table 2, considering the standard deviation between January 2016 and February 2021, the technology indexes with the greatest difference among the G7 and E7 countries are Italy and China, respectively. Similarly, Canada and Turkey have the technology indexes in which the lowest difference was observed among the G7 and E7 countries. It was observed that Italy and Canada have the highest and lowest technology indexes, respectively among the G7 countries; and China and Turkey have the highest and lowest technology indexes, respectively in terms of their mean values.

Before applying the Hatemi-J (2012) causality test, the results of the unit root test is analysed to reveal the characteristics of the series. Firstly, DF-GLS (1996) and PP (1988) unit root tests, which do not consider the breaks, were conducted. The results of the unit root tests in the level values and first differences of the series are presented in Table 3.

**Table 3.** The Results of DF-GLS and Phillips-Perron Test Statistic

| | **DF-GLS (1996) unit root test (Trend and Intercept Model)** | | | | | | |
|---|---|---|---|---|---|---|---|
| | **Level** | | | | **1st difference** | | |
| BTC | | -1.409802 | | | | -6.638492* | |
| FRA | | -2.391120 | | | | -7.086985* | |
| DEU | | -2.659643 | | | | -7.324919* | |
| ITA | | -1.706307 | | | | -7.848904* | |
| CAN | | 0.250767 | | | | -6.848526* | |
| GBR | | -2.331353 | | | | -6.807412* | |
| CHN | | -1.508225 | | | | -7.436964* | |
| IND | | -1.612680 | | | | -8.760847* | |
| TUR | | -1.274422 | | | | -8.262812* | |
| CV | %1 | %5 | %10 | CV | %1 | %5 | %10 |
| | -3.72 | -3.15 | -2.85 | | -3.732 | -3.158 | -2.86 |
| | **Phillips-Perron (1988) unit root test (Trend and Intercept Model)** | | | | | | |
| | **Level** | | | | **1st difference** | | |
| BTC | | 0.197400 | | | | -7.379234* | |
| FRA | | -2.302617 | | | | -8.090184* | |
| DEU | | -2.648490 | | | | -8.444535* | |
| ITA | | -1.867606 | | | | -8.600623* | |
| CAN | | 1.754094 | | | | -6.923812 * | |
| GBR | | -2.711318 | | | | -6.828949* | |
| CHN | | -1.501920 | | | | -7.724426* | |
| IND | | -1.774442 | | | | -8.666629* | |
| TUR | | -1.447927 | | | | -8.192749* | |
| CV | %1 | %5 | %10 | CV | %1 | %5 | %10 |
| | -4.11 | -3.48 | -3.17 | | -4.11 | -3.48 | -3.17 |

**Note:** CV indicates critical values. All variables become stationary when they are first differenced. The results of the unit root test for the ERS test were obtained by applying the Schwarz information criteria. For the spectral estimation method Bartlett Kernel was determined and for the Newey-West method Bandwidth options were used. *, **, and *** indicate significance at the 0.1, 0.05, and 0.01 levels, respectively.

According to the results of the DF-GLS and PP unit root tests, the null hypothesis defined as "the series is fixed, and the trend model has a unit root" cannot be rejected for any series in case of level. As a result of the unit root tests conducted on the level value of the series included in the analysis, it was determined that the data were not stationary, and as a result of the DF-GLS and PP tests performed on the first differences, it was concluded that the data were significant at the level of 1%. Therefore, according to the unit root test results without including the structural breaks, it is observed that the technology indexes selected to represent G7 and E7 countries present a random walk in the period under consideration.

The results of the unit root tests, which consider the regime shifts, in the level values and first differences of the series are reported in Table 4.

**Table 4.** The Results of Single Break Unit Root Test

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| | **Zivot and Andrews (1992) ADF Test** | | | | | | |
| | **Model A** | | **Breakpoint** | | **Model C** | | **Breakpoint** |
| BTC | -2.582 | | 06/2018 | | -2.372 | | 03/2018 |
| FRA | -4.206 | | 07/2018 | | -4.117 | | 07/2018 |
| DEU | -4.610 | | 08/2018 | | -4.547 | | 08/2018 |
| ITA | -3.724 | | 06/2018 | | -3.198 | | 06/2018 |
| CAN | -0.762 | | 05/2020 | | -3.243 | | 01/2020 |
| GBR | -4.980 | | 01/2018 | | -5.118 | | 11/2017 |
| CHN | -2.978 | | 11/2019 | | -4.817 | | 05/2018 |
| IND | -2.555 | | 05/2020 | | -3.995 | | 01/2020 |
| TUR | -2.876 | | 02/2018 | | -2.556 | | 02/2018 |
| CV | %1 | %5 | %10 | CV | %1 | %5 | %10 |
| | -5.34 | -4.80 | -4.58 | | -5.57 | -5.08 | -4.82 |
| | **Lee and Strazicich (2013) LM Test** | | | | | | |
| | **Model A** | | **Breakpoint** | | **Model C** | | **Breakpoint** |
| BTC | -1.427 | | 10/2018 | | -2.264 | | 04/2018 |
| FRA | -3.003 | | 09/2018 | | -3.123 | | 08/2018 |
| DEU | -3.369 | | 08/2018 | | -4.207 | | 08/2018 |
| ITA | -1.920 | | 09/2018 | | -2.424 | | 07/2018 |
| CAN | -1.461 | | 12/2019 | | -2.324 | | 03/2020 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| GBR | -3.171 | | 02/2018 | | -4.092 | | 02/2018 |
| CHN | -1.912 | | 05/2020 | | -3.531 | | 09/2018 |
| IND | -2.376 | | 04/2020 | | -2.673 | | 02/2020 |
| TUR | -1.833 | | 02/2020 | | -1.974 | | 02/2020 |
| **CV** | **%1** | **%5** | **%10** | **CV** | **%1** | **%5** | **%10** |
| | -4.239 | -3.566 | -3.211 | | -5.15 | -4.45 | -4.18 |

**Note:** CV indicates critical values. All variables become stationary when they are first differenced.Zivot-Andrews (1992) indicates the single break unit root test; Lee-Strazicich (2013) indicates the LM-type single break unit root test. The values in the Model A and C indicate the t-statistic. The model A indicated the break on the fixed model and the model C indicates the break on the fixed and trend models. The critical values related to the statistics of the test were taken from the study of Zivot and Andrews (1992).

According to the results presented in Table 3, the hypothesis including the presence of H0 unit root in accordance with A and C models in both tests was not rejected, i.e., there is unit root under structural breaks. As a result, when the test statistics are analyzed, it is observed that the test statistics for both models are under the critical value. Therefore, the basic hypothesis related to the relevant break dates and unit root with structural break is adopted according to both models at the significance level of 5%. The break dates were estimated as 2018 for G7 countries for Model A by the result of the Zivot and Andrews test except for Canada and as 2018 for Model C except for Canada and England. However, it is observed that the break dates differ in Model A and Model C by the results of the Zivot-Andrews test for E7 countries. By the results of the Lee and Strazicich test, it was estimated as 2018 for G7 countries except Canada and 2020 for E7 countries except for China. The estimated break date is 2018 for G7 countries and 2020 for E7 countries in general. Within this frame, it is possible to say that the breaks on the technology indexes are considered as an important indicator related to the events in the economy. The break date for Bitcoin is estimated as 2018 in accordance with the results of the Zivot and Andrews and Lee and Strazicich tests. As can be observed from the table, the break dates estimated for the technology indexes of Bitcoin and G7 countries are similar. Therefore, the close break dates can be interpreted as they indicate causality between Bitcoin and technology indexes. It is thought that the breaking dates of the G7 countries may be related to the trade wars between the USA and China in 2018. On the other hand, it is interpreted that the pandemic period is more effective on structural breaks in developing countries.

The causal relations which show mutual interactions between the Bitcoin and technology indexes are summarized in Table 5. Faced with positive and negative shocks, the reciprocal reactions of Bitcoin and technology indexes for G7 and E7 countries were analysed as Panel A1-A5 and Panel B1-B3, respectively.

In accordance with the results of the Hatemi-J asymmetric test (2012), when the causality from Bitcoin prices to technology indexes is considered, it is observed that there is a causality relationship from the positive shocks to the positive shocks of the DEU technology sector and that there is a causality relationship from the negative shocks of Bitcoin price to the negative shocks of the CAN technology sector. At this point, it is observed that among the companies included in the technology indexes in Germany (For example; SAP SE, Infineon Technologies AG, Deutsche Telekom AG are among the companies with the highest transaction volume in the DAX technology index, which are examples of companies that offer their users the opportunity to benefit from blockchain technology), there are businesses developing blockchain technology, whereas technology businesses in Canada (Mogo Inc., NexTech AR Solutions become prominent with their investments in Bitcoin. Galaxy Digital Holding bought two companies carrying out operations related to trading cryptocurrency in November 2020. HIVE Blockchain Technology, DMG Blockchain and Bitfarms are the companies carrying out operations related to mining Bitcoin and/or providing for cryptocurrency mining opportunities) stand out with Bitcoin investments. Therefore, Canadian companies increased their risks due to the high volatility of Bitcoin, while German companies accompanied the positive price movements in Bitcoin by strengthening their technology infrastructures and making their current products and systems faster and safer depending on the blockchain technology. On the other hand, in the case of positive shocks, any kind of causality relationship was not found from Bitcoin prices to the technology indexes of FRA, ITA and GBR. When the opposite direction of the relationship is taken into consideration, while a causality relationship cannot be found in positive shocks from technology to Bitcoin prices, it is observed that there is a causality in negative shocks. It was determined that there is a causality from negative shocks in all technology indexes to negative shocks in Bitcoin prices. Within the scope of the relevant relationship, it is understood that a decrease in the stocks in the technology sector in the G7 countries will pull the Bitcoin prices down. As technology companies of the developed countries heavily invested in cryptocurrencies and blockchain technology, Bitcoin investors are likely to refer to the performance of those companies in creating expectations. It is thought that the depreciation of technology stocks caused a decrease in reliability of the cryptocurrencies and a depreciation of Bitcoin, which gained prominence with its high volatility.

**Table 5.** The Results of Hatemi-J (2012) Asymmetric Causality Test

| **Null Hypothesis** | **Test Value** | **Critical Bootstrap Value** | | | **Null Hypothesis** | **Test Value** | **Critical Bootstrap Value** | | |
|---|---|---|---|---|---|---|---|---|---|
| | | %1 | %5 | %10 | | | %1 | %5 | %10 |
| **G7 COUNTRIES** | | | | | | | | | |
| *Panel A1* | | | | | | | | | |
| $BTC^{+} \neq> FRA^{+}$ | 0.027 | 7.465 | 4.113 | 2.847 | $FRA^{+} \neq> BTC^{+}$ | 0.277 | 8.178 | 4.413 | 2.959 |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| $BTC^- \neq> FRA^-$ | 0.207 | 10.309 | 4.737 | 2.871 | $FRA^- \neq> BTC^-$ | 3.501*** | 9.362 | 4.268 | 2.785 |
| $BTC^+ \neq> FRA^-$ | 1.179 | 8.010 | 4.274 | 2.900 | $FRA^+ \neq> BTC^-$ | 0.331 | 7.569 | 4.059 | 2.853 |
| $BTC^- \neq> FRA^+$ | 0.399 | 8.250 | 4.256 | 2.859 | $FRA^- \neq> BTC^+$ | 0.163 | 7.695 | 4.261 | 2.932 |
| *Panel A2* | | | | | | | | | |
| $BTC^+ \neq> DEU^+$ | 3.873*** | 7.280 | 4.076 | 2.823 | $DEU^+ \neq> BTC^+$ | 0.202 | 7.290 | 4.181 | 2.867 |
| $BTC^- \neq> DEU^-$ | 1.959 | 10.511 | 4.964 | 3.186 | $DEU^- \neq> BTC^-$ | 3.088*** | 7.832 | 4.177 | 2.861 |
| $BTC^+ \neq> DEU^-$ | 1.402 | 7.798 | 4.135 | 2.893 | $DEU^+ \neq> BTC^-$ | 1.203 | 8.034 | 4.229 | 2.853 |
| $BTC^- \neq> DEU^+$ | 0.405 | 7.298 | 4.154 | 2.921 | $DEU^- \neq> BTC^+$ | 0.050 | 7.559 | 4.245 | 2.919 |
| *Panel A3* | | | | | | | | | |
| $BTC^+ \neq> ITA^+$ | 0.141 | 7.182 | 4.111 | 2.810 | $ITA^+ \neq> BTC^+$ | 1.262 | 8.778 | 4.726 | 3.260 |
| $BTC^- \neq> ITA^-$ | 0.626 | 9.563 | 4.237 | 2.683 | $ITA^- \neq> BTC^-$ | 2.886*** | 9.130 | 4.108 | 2.713 |
| $BTC^+ \neq> ITA^-$ | 2.391 | 7.845 | 4.139 | 2.825 | $ITA^+ \neq> BTC^-$ | 0.179 | 7.800 | 4.268 | 2.991 |
| $BTC^- \neq> ITA^+$ | 0.776 | 6.957 | 3.962 | 2.789 | $ITA^- \neq> BTC^+$ | 0.232 | 7.393 | 4.109 | 2.872 |
| *Panel A4* | | | | | | | | | |
| $BTC^+ \neq> CAN^+$ | 0.008 | 6.872 | 4.023 | 2.840 | $CAN^+ \neq> BTC^+$ | 0.140 | 6.928 | 4.042 | 2.796 |
| $BTC^- \neq> CAN^-$ | 6.236** | 10.259 | 4.371 | 2.611 | $CAN^- \neq> BTC^-$ | 3.201*** | 10.354 | 4.196 | 2.612 |
| $BTC^+ \neq> CAN^-$ | 2.275) | 7.191 | 4.108 | 2.865 | $CAN^+ \neq> BTC^-$ | 1.407 | 7.835 | 4.169 | 2.851 |
| $BTC^- \neq> CAN^+$ | 1.601 | 7.791 | 4.014 | 2.795 | $CAN^- \neq> BTC^+$ | 1.173 | 7.319 | 3.989 | 2.814 |
| *Panel A5* | | | | | | | | | |
| $BTC^+ \neq> GBR^+$ | 0.128 | 7.521 | 4.103 | 2.841 | $GBR^+ \neq> BTC^+$ | 0.885 | 7.537 | 4.129 | 2.840 |
| $BTC^- \neq> GBR^-$ | 0.002 | 9.246 | 4.352 | 2.795 | $GBR^- \neq> BTC^-$ | 4.167** | 9.442 | 4.146 | 2.633 |
| $BTC^+ \neq> GBR^-$ | 0.124 | 9.038 | 4.068 | 2.648 | $GBR^+ \neq> BTC^-$ | 1.646 | 7.463 | 4.242 | 2.918 |
| $BTC^- \neq> GBR^+$ | 0.316 | 10.682 | 4.438 | 2.758 | $GBR^- \neq> BTC^+$ | 1.100 | 7.607 | 3.988 | 2.864 |
| **E7 COUNTRIES** | | | | | | | | | |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| *Panel B1* | | | | | | | | | |
| $BTC^{+} \neq> CHN^{+}$ | 0.166 | 7.809 | 4.243 | 2.902 | $CHN^{+} \neq> BTC^{+}$ | 0.396 | 7.489 | 4.173 | 2.836 |
| $BTC^{-} \neq> CHN^{-}$ | 3.086*** | 9.216 | 4.231 | 2.755 | $CHN^{-} \neq> BTC^{-}$ | 1.835 | 9.486 | 4.108 | 2.696 |
| $BTC^{+} \neq> CHN^{-}$ | 1.305 | 8.472 | 4.227 | 2.830 | $CHN^{+} \neq> BTC^{-}$ | 1.899 | 7.832 | 4.219 | 2.908 |
| $BTC^{-} \neq> CHN^{+}$ | 0.018 | 10.112 | 4.732 | 2.888 | $CHN^{-} \neq> BTC^{+}$ | 0.042 | 7.773 | 4.065 | 2.867 |
| *Panel B2* | | | | | | | | | |
| $BTC^{+} \neq> IND^{+}$ | 6.783* | 7.126 | 4.040 | 2.800 | $IND^{+} \neq> BTC^{+}$ | 1.282 | 7.461 | 4.071 | 2.880 |
| $BTC^{-} \neq> IND^{-}$ | 5.582** | 11.706 | 4.477 | 2.639 | $IND^{-} \neq> BTC^{-}$ | 0.469 | 10.359 | 4.316 | 2.753 |
| $BTC^{+} \neq> IND^{-}$ | 0.011 | 9.244 | 4.541 | 3.003 | $IND^{+} \neq> BTC^{-}$ | 1.241 | 7.247 | 3.920 | 2.740 |
| $BTC^{-} \neq> IND^{+}$ | 2.683 | 8.272 | 4.080 | 2.747 | $IND^{-} \neq> BTC^{+}$ | 0.036 | 7.507 | 4.180 | 2.917 |
| *Panel B3* | | | | | | | | | |
| $BTC^{+} \neq> TUR^{+}$ | 3.683*** | 6.905 | 4.004 | 2.831 | $TUR^{+} \neq> BTC^{+}$ | 0.064 | 7.884 | 4.293 | 2.995 |
| $BTC^{-} \neq> TUR^{-}$ | 12.879* | 9.350 | 4.347 | 2.875 | $TUR^{-} \neq> BTC^{-}$ | 2.165 | 7.838 | 4.161 | 2.877 |
| $BTC^{+} \neq> TUR^{-}$ | 2.004 | 8.165 | 4.348 | 2.916 | $TUR^{+} \neq> BTC^{-}$ | 1.512 | 7.564 | 4.271 | 3.021 |
| $BTC^{-} \neq> TUR^{+}$ | 0.000 | 7.584 | 4.118 | 2.881 | $TUR^{-} \neq> BTC^{+}$ | 0.060 | 6.968 | 3.939 | 2.779 |

**Notes:** *, ** and *** denote significance at the .01, .05, and .10, respectively. The denotation x ≠> y indicates the null hypothesis that variable x does not cause variable y. For example, BTC+ ≠> FRA- means that a positive shock in BTC does not cause negative shocks in the FRA. The optimal lags in VAR(p) model was determined based on Akaike Information Criteria (AIC) and Schwarz Information Criteria (SIC). Additional lags=1. The bootstrap p-values are, in each case, based on 10,000 replications. The consistency conditions (AR characteristic, autocorrelation, heteroscedasticity) necessary for the Hatemi-J test were provided in the analysis. The bootstrap p-values are, in each case, based on 10,000 replications.

In accordance with the results of the Hatemi-J (2012) asymmetric causality test in Table 5, any kind of causality relationship was found from technology indexes to Bitcoin in case of positive or negative shocks. When the other aspect of causality is analysed, it is observed that there is a causality from the negative shocks in Bitcoin prices to the negative shocks in the technology indexes of CHN, IND and TUR. Besides, it was also concluded that a positive shock on Bitcoin prices caused a positive shock on the technology indexed of IND and TUR. As a result, it is understood that the technology indexes of developing countries do not affect Bitcoin, but they are affected by Bitcoin prices. When it is compared with the technology sectors of G7 countries, the technology companies of E7 countries have a narrower range and more fragile against external shocks depending on the small market capitalization and on the fact that they are less developed in terms of technological infrastructure. It was concluded that Bitcoin prices can affect the investment decisions of the investors in the stock markets in long term within the frame of this relationship.

While the results in the Table 5 are evaluated together, it can be observed that there are asymmetric relationships between Bitcoin and global technology indexes for G7 and E7 countries. It seen that the asymmetric relationship between Bitcoin and technology indexes becomes different for G7 and E7. The results suggest that developed countries affect Bitcoin prices while developing countries are affected by Bitcoin price.

## 5. CONCLUSION AND POLICY RECOMMENDATION

Recently; innovations and changes in financial technologies are unavoidable with the advancements in technology, internet speed and range. Digital currencies (virtual currencies/cryptocurrencies) are tried to be strengthened their positions in the financial markets for a period more than ten years with the aim to be an alternative for the current currencies. The fact that it is adopted as a payment instrument by the companies, that the securities are transformed into digital investment instruments (tokenized stocks), that the crypto-financing instruments are developed (ICO and STO), that the companies carry out operations for mining cryptocurrencies or for buying them directly, and that several applications are increasing in number inevitably make the governments design their legal regulations by covering this new technology product. The fact that digital currencies gain prominence around the world was considered an important base of this study.

The results of the Hatemi-J (2012) asymmetric causality test provide important economic inferences. Accordingly, it is understood that there is a connection between the technology indexes of the developing countries and Bitcoin prices. The relevant connection is an asymmetrical relationship and is considered stronger against the negative shocks. The direction of causality is from the technology indexes of all G7 countries to Bitcoin and from Bitcoin to E7 countries in this study in general. Only Germany (positive) and Canada (negative) among G7 countries are affected by the shocks from Bitcoin. The difference between Germany and Canada is thought to be caused by the fact that the former's investments are generally related to the advancement and application of blockchain technology and the latter's investments are directly related to cryptocurrencies. Among the E7 countries, China is only affected by the negative shocks and Turkey and India are affected sometimes by the positive and sometimes by the negative shocks.

The fact that Bitcoin is sensitive to the negative shocks from the G7 countries indicates that it has a higher integration with the markets of those countries. The fact that the technology indexes of the developed countries lose their values results in a reaction similar to Bitcoin which is thought to be under the effect of the same dynamics. Different from the findings of Umar et al. (2021) suggesting that the cryptocurrencies have low integration with the global system from 2014 to 2018, different evidences related to the existence of the interaction in the period of 2016-2021 were obtained in this study.

The original side of this study is, to the best of our knowledge, that we presume it is the first research investigating the relationships between Bitcoin and global technology indexes via Hatemi-J (2012) asymmetric causality test. This paper attempts to explore the impacts of Bitcoin on the technology equities with the increase in its use as a decentralized payment vehicle and its treatment as an investment vehicle.

This study is important in terms of revealing the causal relationship between Bitcoin and developed and emerging technology indices asymmetrically. It is expected that the findings obtained from the study will provide insight for the investors in portfolio selection, on one hand, and guide the companies in shaping their technology-based investment strategies, on the other hand.

Policy implications of this research can be summarized as follows: i) Developing countries' technology sectors are the recipients of shocks, while Bitcoin is the transmitter. ii) Basing on the causality relationship revealed, it can be argued that keeping Bitcoin in portfolios of developing countries' technology stocks will not provide effective diversification. iii) Negative shocks arising in developed technology indices are delivered to Bitcoin prices. This result suggests that Bitcoin cannot be considered as a safe haven against technology stocks. iv) When the negative and positive shocks from Bitcoin to advanced technology indices are evaluated together, the following inferences can be made: if the increase in value of Bitcoin is depending on the technological developments, a positive response occurs in the indices with companies benefiting from blockchain. On the other hand, speculative negative shocks have a negative impact on companies which carry on business in crypto markets.

When all these results are evaluated together, it is revealed that the returns of technology indices interact with Bitcoin returns. From this interaction, it is ascertained that the indices separated positively are which includes the companies benefiting from the blockchain technology behind the cryptocurrencies, rather than the companies that consider them speculatively.

In this study, the relationship between bitcoin as cryptocurrencies and global technology indexes was examined. This paper has made certain contributions to the current literature, but several extensions are still possible, and it can reveal the suggestions by using different econometric analyses such as wavelet coherence analysis. However, the proliferation of the COVID-19 pandemic process caused changes in the fields of political, social, economic and cultural. Hence, in further study, it is recommended to consider the effects of the blockchain and cryptocurrencies such as pandemic for the studies to be conducted and investigated their impact on the cryptocurrency markets. The findings of this study are expected to offer insight into the financial policymakers and for future studies.

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