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Research Article/Araştırma Makalesi

The Examination of the Relationship Between Bitcoin (BTC) Trading Volume in Türkiye and Google Trends Data on Bitcoin Searches in Google Search Engine

Türkiye'de Bitcoin (Btc) Ticaret Hacmi ile Google Arama Motorundaki Bitcoin aramalarına ilişkin Google Trends Verileri Arasındaki İlişkinin İncelenmesi

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Abstract

Bitcoin and cryptocurrencies have recently rekindled discussions in financial circles, both due to their technologies and price movements. The increasing inclination of investors who seek returns and embrace risk towards cryptocurrency markets is evident, driven by sudden price fluctuations. The potential of cryptocurrencies to serve as alternatives to traditional investment instruments continues to be debated within the financial framework. Researchers are persistently exploring financial instruments associated with the price fluctuations of Bitcoin and cryptocurrencies. This study investigates the interest in Bitcoin in Türkiye within the scope of Bitcoin trading volume and the "Bitcoin" search results on Google Trends. Bitcoin trade volume of BTCTurk and Paribu, two cryptocurrency exchanges operating in Türkiye, and Bitcoin search data on Google were included in the study. In this context, the long-term relationship between Bitcoin trading volume and Google Trends results is examined using the Engle-Granger cointegration test, and the existence of causality is explored through the Toda-Yamamoto causality test. According to the findings of the study, a cointegration relationship among the variables is identified. It is revealed that there is no bidirectional causality between Bitcoin trading volume and Google Trends search results. However, it is established that Google Trends is the cause of Bitcoin trading volume.

Jel Codes: *C32, G11, G12, G41*
Keywords: *Bitcoin (BTC), Cryptocurrencies, Bitcoin Trade Volume, Google Trends, Engle-Granger Cointegration Test, Toda-Yamamoto Causality Test*

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Öz

Bitcoin ve kripto paralar son dönemde hem teknolojileri hem de fiyat hareketleri ile finans çevrelerinde yeniden tartışılmaya başlanmıştır. Ani fiyat hareketleri sebebiyle getiri elde etmek isteyen aynı zamanda riski seven yatırımcıların, gün geçtikçe kripto paralara olan yönelimleri artmaktadır. Kripto paraların geleneksel yatırım araçlarına alternatif olma konusu da finansal çerçevede tartışılmaya devam etmektedir. Bununla birlikte araştırmacılar, Bitcoin ve kripto paraların fiyat değişimleri ile ilişkili olan finansal enstrümanları bulma yönünde incelemelerini sürdürmektedirler. Bu çalışma ile Türkiye'de Bitcoin'e olan ilgi, Bitcoin ticaret hacmi ile Google Trends'deki "Bitcoin" arama sonuçları kapsamında araştırılmıştır. Çalışmaya, Türkiye'de faaliyet gösteren kripto para borsalarından BTCTurk ve Paribu'ya ait Bitcoin ticaret hacim ve Google'da yapılan Bitcoin arama verileri dahil edilmiştir. Bu çerçevede, Engle-Granger eşbütünleşme testi kullanılarak Bitcoin ticaret hacmi ile Google Trends sonuçları arasındaki uzun dönem ilişki incelenmiş, Toda Yamamoto nedensellik testi kapsamında da nedensellik ilişkisinin var olup olmadığı araştırılmıştır. Çalışma bulgularına göre, seriler arasında eşbütünleşme ilişkisi elde edilmiş olup, Bitcoin ticaret hacmi ve Google Trends arama sonuçları arasında çift yönlü nedensellik ilişkisinin olmadığı, ancak Google Trends'in Bitcoin ticaret hacminin nedeni olduğu ortaya çıkarılmıştır.

Jel Kodları: *C32, G11, G12, G41*

Anahtar Kelimeler: *Bitcoin (BTC), Bitcoin Ticaret Hacmi, Google Trends, Engle-Granger Eşbütünleşme Testi, Toda-Yamamoto Nedensellik Testi*

1. Introduction

Global financial system has lost significant trust, especially with the crisis in 2008, and as a result, currencies of developed countries have depreciated. Investors' interest in alternative assets after such crisis periods can be seen as an expected outcome in light of past experiences. Bitcoin, the first cryptocurrency, emerged as a thought based on a decentralized structure to replace physical currencies and provide an alternative to the financial economic system. As per numerous economic experts, establishing an alternative digital payment system might require a substantial duration. However, Bitcoin (BTC), unveiled by an undisclosed figure identified as Satoshi Nakamoto in 2008 through the release of the document “Bitcoin: A Peer-to-Peer Electronic Cash System”, stands out as the inaugural recognized virtual payment entity (Nakamoto, 2008).

Cryptocurrencies began to be heard globally as early as 2010; however, their recognition and proliferation in Türkiye began around 2017. With the peak of Bitcoin prices in 2017, numerous news stories emerged both in traditional and social media, attracting the attention of investors. Cryptocurrency markets have experienced significant growth in Türkiye, particularly in recent years. With the rapid popularity of cryptocurrencies, many individuals have started to prefer them as investment instruments. In Türkiye, there are numerous cryptocurrency exchanges for buying and selling cryptocurrencies. Among these exchanges, the oldest and most popular ones are BTCTurk and Paribu platforms, with research indicating the continued operation of approximately 10 cryptocurrency exchanges. However, in recent times, cryptocurrency markets in Türkiye have faced certain regulations. According to the regulation published in the Official Gazette by the Central Bank of the Republic of Türkiye (CBRT) on April 16, 2021, with regulation number 31456, the direct or indirect use of cryptocurrencies in payments and the provision of services by payment and electronic money institutions in this field have been prohibited (TCMB, 2021). Despite the ban on the use of cryptocurrencies in payments, trading of cryptocurrencies as an investment instrument continues. Investors can trade on domestic and foreign cryptocurrency exchanges that facilitate the buying and selling of cryptocurrencies and acquire cryptocurrencies traded on cryptocurrency exchanges. The number of cryptocurrency investors continues to rise in Türkiye, as it does in many other countries. In 2018, according to an international study conducted by the International Netherlands Group (ING) regarding consumers' cryptocurrency ownership, Türkiye ranked first among 15 countries (Best, 2018).

At times, cryptocurrencies with significantly increasing trading volumes may also experience considerable volatility in their prices during these periods. Several factors can contribute to the price volatility of cryptocurrencies, including investor demand and supply, regulations, speculations, and positive or negative news related to cryptocurrencies. Despite the increasing market volume of cryptocurrencies over time, it can be stated that they are still not fully accepted in financial circles. Criticisms directed at cryptocurrencies include their decentralized nature, high potential for speculative investors, and their potential use in money laundering (Çütcü & Kılıç, 2018). Despite criticisms and regulations, interest in cryptocurrencies continues to grow every day. Furthermore, due to the extreme volatility of Bitcoin and cryptocurrencies, their relationships with other financial instruments, including stock indices, exchange rates, and commodity prices, remain a topic of interest in the literature.

In the decision-making process for purchasing preferences, investors nowadays seek information from online data. Therefore, reasons for demand for a financial product are not only related to financial results but also to the frequency of searches for that product on internet search engines. One of the most popular search engines, Google, compiles regional, national, and global trends on a server called "Google Trends" and provides users with data in various fields. Google offers researchers and companies in the marketing sector the statistics of searches made on Google related to a word, person, or currency with the Google Trends application, presenting the frequency of searches as an index value (Samirkas, 2020).

One of the terms searched on Google and subject to researchers is Bitcoin. Research in the literature explores the correlation between variations in Bitcoin values and the frequency of Google searches for the term "Bitcoin". However, no study addressing the relationship between Bitcoin trading volume and Bitcoin searches on Google has been encountered during the relevant period. With Bitcoin gaining renewed interest, the main motivation of the study has been to reveal the relationship between Bitcoin transaction volume and Google Trends search results. The research is anticipated to add value to the existing literature by investigating the correlation between Bitcoin transaction volume and Google Trends search outcomes through time series analyses.

In the study, following the introduction, a literature review is presented, followed by evaluations pertaining to the literature in the final section. Subsequent sections provide a conceptual framework on Google Trends, Bitcoin, and Bitcoin trading volume topics. Then, the methodology and dataset of the research are introduced based on the collected data, and the research findings are presented. Following the determination of the stationary levels of variables, findings obtained through Engle-Granger cointegration analysis and Toda-Yamamoto causality analysis within the VAR model framework are included. The study concludes with the conclusion and evaluation section.

2. Literature Review

Recent years have witnessed numerous studies on Bitcoin and other cryptocurrencies. Upon reviewing the literature on Bitcoin and Google searches, it becomes evident that these studies predominantly center around exploring the correlation between Google searches and Bitcoin prices. No study directly utilizing Bitcoin trading volume and Google search data variables has been encountered. Therefore, the literature related to studies based on Bitcoin and Google searches has been comprehensively reviewed. In this context, when looking at the studies conducted based on this framework:

Kristoufek (2013) conducted an analysis of the correlation between Bitcoin prices and Google Trends search results, along with the frequency of visits to the Bitcoin page on Wikipedia. Kristoufek pointed out a dynamic relationship between Bitcoin prices and searches on both search engines. Additionally, the study suggested a bidirectional causality relationship between Bitcoin prices and results obtained from search engines. Matta et al. (2015) attempted to predict Bitcoin returns using social media and web searches. They used Google Trends searches to analyze the popularity of Bitcoin. According to their analysis, cross-correlation tests revealed a significant relationship between Google Trends data and Bitcoin prices. Dulupçu et al. (2017) contended that the upward movements in Bitcoin prices were not solely linked to its intrinsic value but also associated with its popularity. In their study, they utilized a VAR model-based variance decomposition analysis and Granger causality test, incorporating Google Trends search results. The findings indicated a robust connection between Bitcoin's price and popularity, leading to the conclusion that the causality direction was from popularity to Bitcoin prices. Thus, they stated that the increasing awareness of Bitcoin also increased its price. Philippas et al. (2019) attempted to determine if Bitcoin prices react to jumps in Twitter and Google Trends search results. Using a two-process diffusion model, they concluded that these media networks had only a partial effect on Bitcoin prices. They also suggested that during periods of high uncertainty, their impact was more significant and that, in some cases, they served as sources of information demand. Smuts (2019) constructed a long short-term memory recurrent neural network for forecasting the trajectory of cryptocurrency prices, utilizing data from Google Trends and Telegram. The findings indicated that Telegram data served as a more effective predictor of Bitcoin price direction compared to Google Trends. Yıldırım (2020) found cointegration between Bitcoin prices and Google search counts based on ARDL boundary test results. Furthermore, the Granger causality test results revealed a one-way relationship between Bitcoin prices and the volume of Google searches. In a study conducted amidst the Covid-19 pandemic, Raza et al. (2022) explored the connection between Google Trends search outcomes and the prices of Bitcoin along with five distinct altcoins. The results indicated that Google Trends search outcomes served as a Granger cause for Bitcoin prices.

Upon reviewing the literature, it is evident that both internationally and nationally conducted studies have primarily focused on examining the relationships between Bitcoin prices and Google Trends search results. The results of all examined studies consistently indicate an association between Bitcoin prices and Google Trends search results. However, no study addressing Bitcoin trading volume and Google Trends variables on both national and international scales has been identified in the literature.

3. Google Trends

Google Trends is a publicly accessible website owned by Google Inc., allowing us to access information about searches made on the Google search engine. It provides anonymized, categorized, and aggregated access to data on real search queries submitted to Google, enabling us to examine which topics are popular globally or in any specific city (Google Trends Data FAQ, 2023).

Google Trends offers two types of data: real-time data covering the past seven days related to search terms and non-real-time data that can go as far back as 2004, up to 72 hours before your current search. For the purpose of comparing search popularity, Google Trends offers a

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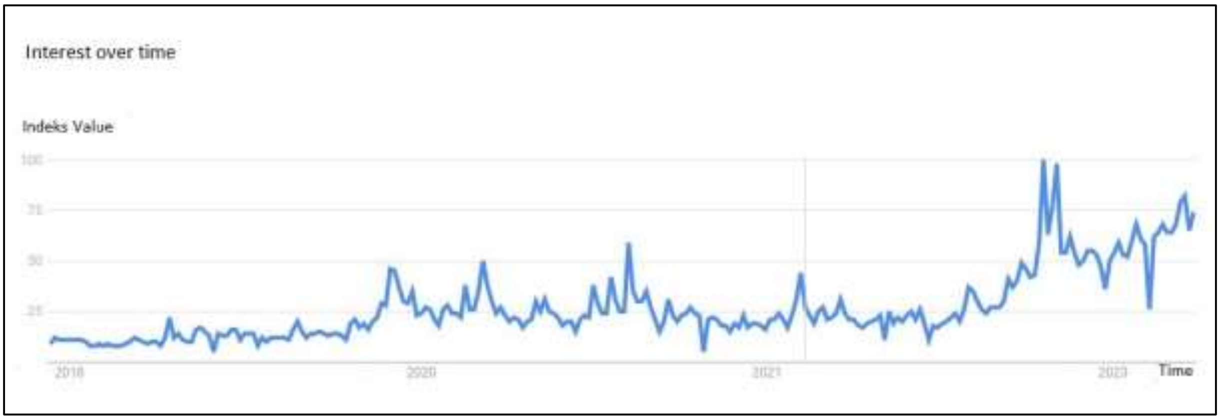
relative search volume index, which is scaled between 0 and 100 for each data point. This index is derived by dividing the total searches for the specified geography and time period by the search term being represented (Google Trends Data FAQ, 2023).

As a platform, Google Trends allows users to explore search volume data and charts for a specified keyword starting from the year 2004 or within a custom date range. Various filter options are available when conducting queries, including:

- Specified date range
- Preferred country for the search
- Selection of search category (e.g., automotive, real estate)
- Platform choice for the query.

In the operational system of Google Trends, data is standardized by dividing each data point by the total number of searches in its country and time range to simplify comparisons between concepts. The standardized data reaches a value between 0 and 100. The results obtained through Google Trends, reflecting online search interest, have become a new data source in many academic studies. Studies utilizing Google Trends data can be observed in various fields, from economics to the healthcare sector (Ayan, 2020).

Figure 1: The Result of the "BIST 100" Search Query on Google Trends



Source: https://trends.google.com/trends/ (Access Date: 12.09.2023)

The search query conducted with Google Trends is intended to be shown as an example in Figure 1. In the result graph, the index values obtained for the selected time period can be observed. Accordingly, the Google Trends search results for the Borsa Istanbul's BIST 100 index, covering the last 5 years in Türkiye, can be displayed as shown in Figure 1.

4. Bitcoin (BTC) and Bitcoin Trade Volume

For a more comprehensive understanding of the creation of Bitcoin, it is essential to grasp the global financial and economic crisis that originated in the United States in 2008. Starting in September 2008 in the United States, a crisis emerged that affected the entire world. At the core of this global crisis, referred to as the "mortgage crisis," were credit and real estate bubbles (Eğilmez, 2017). Subsequent to this crisis, which eroded public trust in governments and the economic-financial system, an unidentified individual named Satoshi Nakamoto released a paper titled "Bitcoin: A Peer-to-Peer Electronic Cash System". This article, considered by some as a manifesto, was released on November 1, 2008 (Çarkacıoğlu, 2016).

Bitcoin is a decentralized payment system with a peer-to-peer (P2P) structure, where the money supply is not regulated by any authority. The abbreviated code for Bitcoin is "BTC", and one BTC can be divided up to eight decimal places. The smallest unit of Bitcoin that can be divided is called a "Satoshi." Bitcoin is labeled as a cryptocurrency or digital currency because the system generates money and ensures payment security through cryptography. Therefore, Bitcoin operates without the need for a Central Bank, company, intermediary institution, or central authority; instead, it relies on cryptography (Çarkacıoğlu, 2016). In Nakamoto's created system, the trust issue that arises during money transfers through banks and intermediary institutions is eliminated, and no one is forced to trust anyone else. Transfers in Bitcoin are recorded in the global ledger called the Blockchain or, in Turkish, the Blockchain, by miners. The global ledger is a database where all transaction operations are recorded, and anyone using the Blockchain can see these operations. Consequently, users who join the system can download every transaction to their computers and transparently verify the accuracy of transactions (Baskak, 2018).

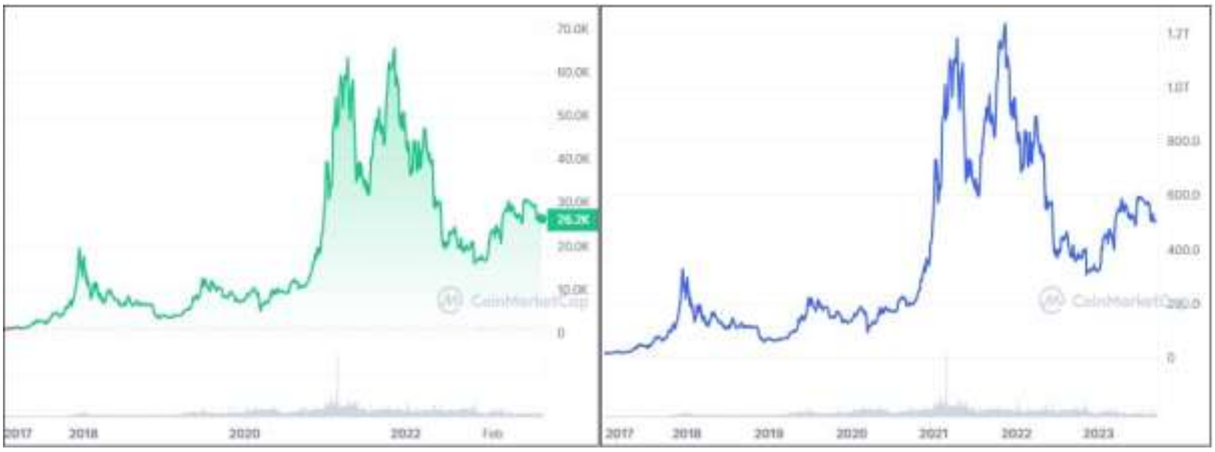
To evaluate whether Bitcoin serves an economic role as a currency, one can analyze its adherence to the functions of money, which include being a "medium of exchange, unit of account, and store of value." Bitcoin, not being issued by any country and lacking central bank printing, distinguishes itself from traditional currencies. The value of Bitcoin is directly proportional to the demand people show for it. Consequently, Bitcoin has been rapidly accepted by people in many countries and has started to be used in many buying, selling, and money transfer transactions. On the other hand, it is not possible to claim that Bitcoin has a widespread use in world economies compared to the use of central bank currencies. Bitcoin is still seen as a weak medium of exchange when compared to the currencies offered by states. Considering the abundance of goods and services in today's real markets, the integration of Bitcoin usage into all transactions in the economy is currently not feasible (İçellioğlu, Öztürk & Engin, 2017).

However, it can be argued that the use of Bitcoin in financial markets has increased in recent periods. The high volatility of Bitcoin prices has directed risk-taking investors to this area and increased the appetite of speculators for returns. In addition, high increases in Bitcoin trading volume can be observed parallel to the high volatility in Bitcoin prices. Investors attempting to achieve returns in the short term due to price changes have contributed both to the increase in trading volume and the volatility in prices (Kılıç & Çütcü, 2018).

Figure 2 illustrates the change in Bitcoin's price and trading volume from 2017 to 2023. The Bitcoin transaction volume graph moves in parallel with the graph of Bitcoin's price change. It can be observed that especially during the highest levels seen between 2017 and 2023, the transaction volume also reached the highest levels. It is observed that the total trading volume reached approximately 800 billion USD at around 19,000 USD, the highest value reached by

Bitcoin in December 2017, whereas at around 68,000 USD, the highest value reached in November 2021, the total trading volume rose to approximately 2.9 trillion USD.

Figure 2: Bitcoin Price and Trading Volume Change ($)



Source: https://coinmarketcap.com/currencies/bitcoin/ (Access Date: 13.09.2023)

5. Research DataSet and Methodology

The study aims to examine the relationship between Google Trends "Bitcoin" searches, representing the interest of cryptocurrency investors in Türkiye, and Bitcoin trading volume. In other words, it attempts to determine whether there are explanatory effects of Google searches and Bitcoin trading volume variables on each other. In the study, data from Paribu and BTCTurk, the cryptocurrency exchanges with the highest Bitcoin trading volumes operating in Türkiye, were utilized. Additionally, Google Trends data related to 'Bitcoin' search results on Google searches in Türkiye was included in the research. Nevertheless, a monthly dataset spanning from November 1, 2017, to August 31, 2023, encompassing 70 observations, was utilized to explore the cointegration and causality relationship between Bitcoin (BTC) trading volume and Google Trends search results. The reason for using monthly data is that Google Trends provides monthly data and searches consist of very few observations. This situation constitutes a small number in terms of determining the desired results. Google assigns a value of 100 to the period with the highest search volume within the specified date range and indexes other periods based on 100. Therefore, a value of 100 indicates that the searched term has the highest popularity, a value of 50 indicates half popularity for the searched term, and 0 implies insufficient data for the searched term. The choice of November 2017 is specifically due to the availability of Paribu exchange data through www.investing.com from that date onwards. At the outset, given the time series nature of both datasets, the level values of the datasets underwent Augmented Dickey Fuller (ADF) and Phillips-Perron (PP) stationarity tests, and non-stationary series were transformed into stationary ones. The cointegration relationship between the variables was examined through Engle-Granger cointegration analysis. To uncover the dynamic relationships between the series, causality analysis was performed using the VAR model, specifically employing the Toda-Yamamoto

(1995) causality test. Descriptive information about the datasets utilized in the study is presented in Table 1.

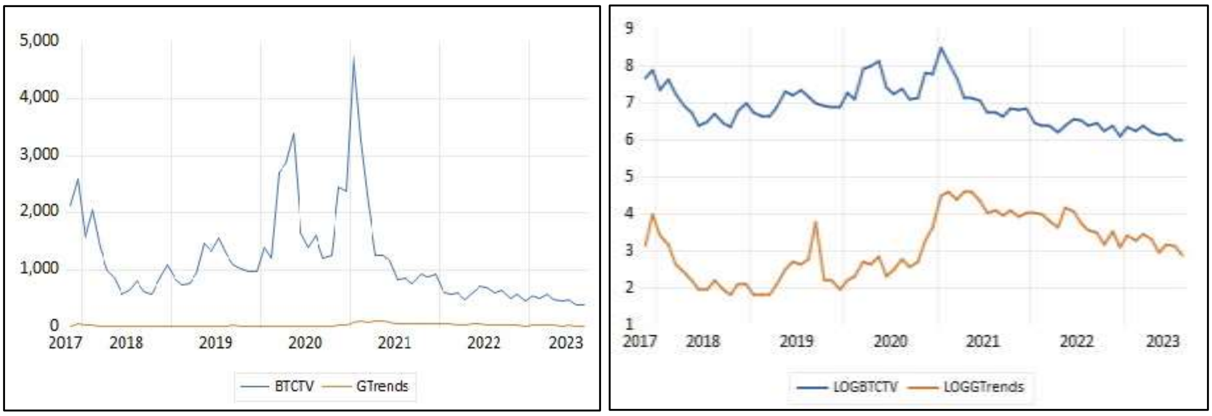
The causal relationship between Bitcoin trading volume and Google Trends search result data is examined in the study using the Toda-Yamamoto (1995) test. The Toda-Yamamoto (1995) causality test is based on the Vector Autoregressive (VAR) model, which uses the level values of variables. The superiority of the method over the Granger (1969) causality test, which is frequently used in the literature to detect causality between variables, lies in its analysis not being affected by the presence of unit roots and cointegration relationships in the series. In other words, the Toda-Yamamoto (1995) causality test has valid statistical tests and inferences for Granger causality in level VAR values, regardless of whether the series related to variables are integrated or cointegrated (Elian & Suliman, 2015).

Table 1: Descriptive Information about the Dataset

BTCTV	Bitcoin Trade Volume	The data for the Paribu and BTCTurk cryptocurrency exchanges, with the highest Bitcoin trading volume in Türkiye, was compiled as monthly data between 01.11.2017 and 31.08.2023. The dataset was obtained from the http://www.investing.com website.
GTRENDS	Google Trends	Google search results for the term 'Bitcoin' in Türkiye between 01.11.2017 and 31.08.2023 were obtained from https://trends.google.com/trends/.

Logarithmic series, especially in cases of long-term and high variability, provides more reliable results when compared to the historical values of the data. Hence, the natural logarithm of the time series associated with the included variables in the study has been computed. This approach aims to minimize measurement differences between the series (Özçelik & Göksu, 2020). The left panel of Figure 3 depicts the views of the variables before taking the logarithms, while the right panel displays the views of the variables after the logarithmic transformation. Accordingly, it can be observed that the variables, after being transformed by taking the logarithms, exhibit a closer proximity to each other compared to their original states before the logarithmic transformation.

Figure 3: The Graphs Depicting the Data Before and After Logarithmic Transformation



5.1. Engle-Granger Cointegration Test

In the study, the cointegration relationship between the variables BTCTV and GTRENDS has been analyzed using the Engle-Granger Cointegration Test. The aim of the study, which investigates the relationship between Bitcoin trading volume and Google Trends search results, is to identify long-term relationships using the Engle-Granger Cointegration Test, which is commonly used in the literature.

The Engle-Granger Cointegration Test is a two-step method. Prior to conducting this test, it is imperative to ensure that the variables are integrated of order one, denoted as I(1). Once the stationarity of the variables is confirmed, the first step involves estimating a regression model using the level values of the series through Ordinary Least Squares (OLS) method. This estimation of the regression model yields residuals associated with the error terms. In the second step, the stationarity of the residuals obtained from the regression equation is tested. Stationarity testing is conducted using unit root tests. If the residuals are stationary at the level, denoted as I(0), it is concluded that there exists a cointegrating relationship among the variables. However, if the variables are not stationary at the level, it is not possible to infer the presence of a cointegrating relationship.

If a long-term relationship exists between variables, a Vector Error Correction Model (VECM) should be applied. Even if equilibrium is achieved among the variables in the long run, there may still be some imbalances in the short run. Therefore, VECM is used to ensure equilibrium among the variables in the short term (Aygün, 2022). The residuals obtained from the OLS estimation can be observed. Finally, the residuals of the error terms are tested for unit roots.

5.2. Toda-Yamamoto Causality Test

In the investigation, the Toda-Yamamoto Causality Test was employed to scrutinize the causal relationship between the variables BTCTV and GTRENDS. The analysis aimed to discern both the direction and existence of causality pertaining to Bitcoin trading volume and Google Trends search results. The application of the Toda-Yamamoto (1995) test, a widely utilized method in econometric analyses, was instrumental in examining the causal nexus between the variables.

In contrast to the Granger causality test, the Toda-Yamamoto examination does not necessitate the variables to exhibit cointegration. In the Toda-Yamamoto test, the crucial aspect is the accurate calculation of the model and the maximum order of integration (Kızılgöl & Erbaykal, 2008). As per Toda-Yamamoto (1995), in cases where the series are non-stationary, it is feasible to estimate a VAR model for the series and subsequently apply the Wald test. For the Toda-Yamamoto causality test, a VAR model of [k+(dmax)] order is estimated, and the Wald test is applied. The correct determination of the system's lag length (k) and the integration degrees of the series (dmax) is crucial for the test to be conducted accurately. The method's significant feature is that it does not require preliminary tests used to identify unit roots and cointegration properties. This reduces the risk associated with the incorrect determination of the method's usage and the integration degrees of the series (Kılıç & Çütcü, 2018).

6. Research Findings

In order to apply econometric analysis in the study, the EViews 12 software package was utilized. The descriptive statistics obtained during the application are presented in Table 2.

Table 2: Descriptive Statistics

Variables	LOGBTCTV	LOGGTRENDS	Variables	LOGBTCTV	LOGGTRENDS
Mean	6.9010	3.0887	Correlation	1.0000	0.0984
Median	6.8295	3.1354	Probability	----	0.4173
Maximum	8.4775	4.6051	Jarque-Bera	4.1875	3.9618
Minimum	5.9677	1.7917	Probability	0.1232	0.1379
Std. Dev.	0.5781	0.8305	Observations	70	70

According to Table 2, when examining the mean values of the variables on a logarithmic scale, the mean of the LOGBTCTV variable is 6.9010, while the mean of the LOGGTRENDS variable is 3.0887. Due to the Jarque-Bera probability values being greater than 0.05, it has been determined that both series exhibit a normal distribution. Additionally, when examining the standard deviation data in Table 2, it is observed that the GTRENDS data has a relatively higher degree of volatility compared to the BTCTV data. Examining the correlation coefficient, it can be concluded that there is a weak positive relationship between BTCTV and GTRENDS.

Financial time series should not exhibit autocorrelation. The Breusch-Godfrey Serial Correlation LM test can be used to determine whether autocorrelation exists in time series data. The results of the Breusch-Godfrey Serial Correlation LM Test are provided in Table 3.

Table 3: Breusch-Godfrey Serial Correlation LM Test

F-Statistic	2.2121	Prob. F(1.67)	0.1416
Obs*R-squared	2.2053	Prob. Chi-Square(1)	0.1375

As can be seen in Table 3, the probability value at the 5% significance level is greater than 0.05, indicating the absence of autocorrelation in the series. Furthermore, financial time series should not exhibit changing variance. To determine whether there is changing variance in the time series, the Breusch-Pagan-Godfrey Heteroscedasticity test is employed. The results of the Breusch-Pagan-Godfrey Heteroscedasticity test for the series are shown in Table 4.

Table 4: Breusch-Pagan-Godfrey Heteroscedasticity Test

F-Statistic	0.3571	Prob. F(1.68)	0.5521
Obs*R-squared	0.3656	Prob. Chi-Square(1)	0.5454
Scaled explained SS	0.1192	Prob. Chi-Square(1)	0.7298

As observed in Table 4, the probability value at the 5% significance level is greater than 0.05, indicating the absence of changing variance in the series.

6.1. Unit Root Test Results

The stationarity of Bitcoin trading volume and Google Trends search results variables within the specified time series was examined using the Augmented Dickey-Fuller (ADF) (1979) and Phillips-Perron (PP) (1988) unit root tests.

The Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) unit root tests and hypotheses were formulated as follows:

H_0: Time series variables contain a unit root and are non-stationary.

H_1: Time series variables do not contain a unit root and are stationary.

Table 5: Level ADF Unit Root Test Results

Variables	Constant		Constant and Trend	
	t- Statistic	Prob.	t- Statistic	Prob.
LOGBTCTV	-1.9521	0.3070	-2.2621	0.4483
LOGGTRENDS	-1.8489	0.3542	-2.2034	0.4800
	MacKinnon Critical Values			
	LOGBTCTV	LOGGTRENDS	LOGBTCTV	LOGGTRENDS
%1 level	-3.5285	-3.5285	-4.0966	-4.0966
%5 level	-2.9041	-2.9041	-3.4762	-3.4762
%10 level	-2.5895	-2.5895	-3.1656	-3.1656

In Table 5, it can be observed whether the variables LOGBTCTV and LOGGTRENDS contain unit roots in their level values according to the ADF test. Accordingly, it is revealed that both the LOGBTCTV and LOGGTRENDS variables contain unit roots in both the constant and constant and trend level values.

Table 6: Results of the First Difference ADF Unit Root Test

Variables	Constant		Constant and Trend	
	t- Statistic	Prob.	t-Statistic	Prob.
LOGBTCTV	-8.8590	0.0000	-8.7898	0.0000
LOGGTRENDS	-9.9709	0.0001	-9.9115	0.0000
	MacKinnon Critical Values			
	LOGBTCTV	LOGGTRENDS	LOGBTCTV	LOGGTRENDS
%1 level	-3.5300	-3.5300	-4.0987	-4.0987
%5 level	-2.9048	-2.9048	-3.4772	-3.4772
%10 level	-2.5899	-2.5899	-3.1661	-3.1661

In Table 6, it can be observed whether the variables LOGBTCTV and LOGGTRENDS contain unit roots in their first differences. Accordingly, it is revealed that neither the LOGBTCTV nor the LOGGTRENDS variables contain unit roots according to the ADF unit root test in both the constant and constant and trend level values.

Table 7: Results of the Level Phillips-Peron Unit Root Test

Variables	Constant		Constant and Trend	
	t- Statistic	Prob.	t- Statistic	Prob.
LOGBTCTV	-1.9521	0.3070	-2.2621	0.4483
LOGGTRENDS	-1.7883	0.3832	-2.1449	0.5119
	MacKinnon Critical Values			
	LOGBTCTV	LOGGTRENDS	LOGBTCTV	LOGGTRENDS

%1 level	-3.5285	-3.5285	-4.0966	-4.0966
%5 level	-2.9041	-2.9041	-3.4762	-3.4762
%10 level	-2.5895	-2.5895	-3.1656	-3.1656

In Table 7, it can be observed whether the variables LOGBTCTV and LOGGTRENDS contain unit roots in their level values according to the P-P test. Accordingly, it is revealed that both the LOGBTCTV and LOGGTRENDS variables contain unit roots in both the constant and constant and trend level values.

Table 8: Results of the First Difference Phillips-Peron Unit Root Test

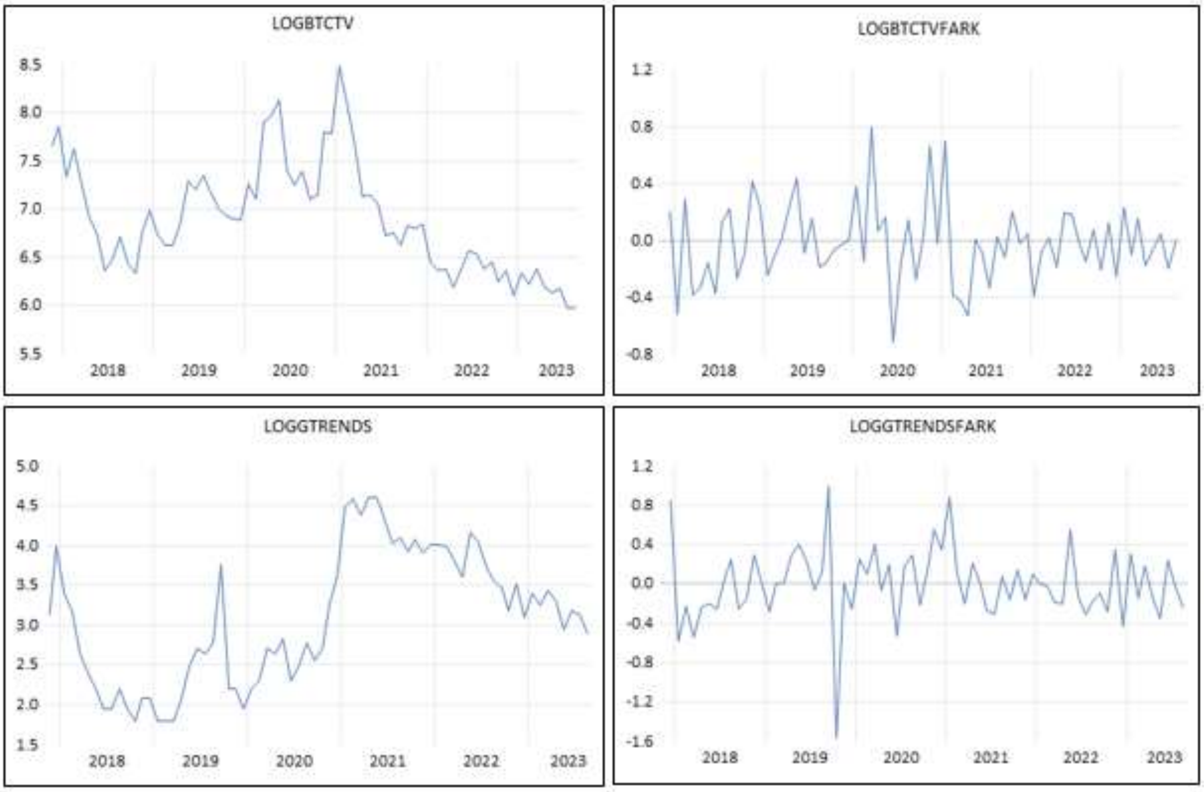
Variables	Constant		Constant and Trend	
	t- Statistic	Prob.	t- Statistic	Prob.
LOGBTCTV	-8.8364	0.0000	-8.7706	0.0000
LOGGTRENDS	-9.8184	0.0000	-9.7643	0.0000
MacKinnon Critical Values				
	LOGBTCTV	LOGGTRENDS	LOGBTCTV	LOGGTRENDS
%1 level	-3.5300	-3.5300	-4.0987	-4.0987
%5 level	-2.9048	-2.9048	-3.4772	-3.4772
%10 level	-2.5899	-2.5899	-3.1661	-3.1661

In Table 8, it can be observed whether the variables LOGBTCTV and LOGGTRENDS contain unit roots in their first differences according to the P-P unit root test. Accordingly, it is revealed that both the LOGBTCTV and LOGGTRENDS variables do not contain unit roots in both the constant and constant and trend level values according to the P-P unit root test.

As a result, stationarity tests have been applied to the level values of the time series BTCTV and GTRENDS on a logarithmic scale. In both the ADF and P-P unit root test results for the variables, it can be observed that neither the constant nor trend level values are stationary when compared with the MacKinnon critical values. Thus, it is evident that the series contain a unit root and are non-stationary. However, when the first difference of the series is taken, the probability value is less than 0.05, indicating that both stationary and trended values become stationary.

Figure 4 presents the graphical views of the non-stationary time series BTCTV and GTRENDS after taking their first differences.

Figure 4: Non-Stationary and Stationarized Series of Variables



The left panel of Figure 4 displays the graphical representation of the variables' values on a logarithmic scale before taking the differences. On the right panel, the values of the variables after taking their first differences can be observed graphically. The variables are coded as LOGBTCTVFARK and LOGGTRENDSFARK after taking their first differences. It can be observed that the variables exhibit a highly volatile structure before taking the differences. However, after taking the differences, the variables appear to be more stationary. Thus, it can be said that the results of the unit root tests are corroborated by the graphical representations.

6.2. Engle-Granger Cointegration Test Results

Having established that all LOGBTCTV and LOGGTRENDS variables are stationary both at the same level and in first differences, the Engle-Granger Cointegration Test was employed to analyze the long-term relationship between these two variables. The results of the cointegration test are presented in Table 9.

Table 9: Engle-Granger Cointegration Test Results

		t-Statistic	Prob.
Augmented Dickey-Fuller test statistic		-9.0348	0.0000
Test Critical Values;	1% level	-2.5994	
	5% level	-1.9456	
	10% level	-1.6136	

According to Table 9, the variables BTCTV and GTRENDS are cointegrated at a 1% significance level, reaching equilibrium in the long term.

6.3. Toda-Yamamoto Causality Test Results

Toda-Yamamoto (1995) causality analysis allows for testing causality between series regardless of whether they are stationary or cointegrated. Causality analysis was performed between the LOGBTCTV and LOGGTRENDS series using Toda-Yamamoto (1995) causality analysis, and determining the optimal lag length for the VAR model is necessary for the application of this analysis. In the ADF and PP unit root tests performed on the variables incorporated into the Toda-Yamamoto test, it was noted that all variables possessed a unit root at the level, and upon differencing, they attained stationarity at the 1st order. Consequently, the selection of dmax=1 was warranted.

Table 10: Determination of Optimal Lag Length in VAR Model Based on Information Criteria

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-134.5627	NA	0.244592	4.267586	4.335051	4.294164
1	-15.24792	227.4439*	0.006660*	0.663998*	0.866393*	0.743731*
2	-11.83887	6.285436	0.006788	0.682465	1.019790	0.815354
3	-9.792726	3.644699	0.007223	0.743523	1.215778	0.929568
4	-8.809879	1.689269	0.007953	0.837809	1.444995	1.077010
5	-6.049460	4.571943	0.008293	0.876546	1.618662	1.168903
6	-4.177380	2.983628	0.008904	0.943043	1.820089	1.288556

* indicates lag order selected by the criterion

As seen in Table 10, it is observed that the lag order for the degrees of freedom (k) is 1 according to all information criteria. Therefore, the lag length in the Toda-Yamamoto Causality Test will be considered as 1. In this context, a causality test was conducted based on the 2nd-degree VAR model, where k+d(max)=(1+1)=2.

Table 11: Toda-Yamamoto Causality Test Results

Hypotheses	Chi-Square	Prob.	Decision
GTRENDS→BTCTV	5.8506	0.0155	At the 5% significance level, there is a unidirectional Toda-Yamamoto causality relationship from Google Trends search results to Bitcoin trading volume.
BTCTV→GTRENDS	0.3551	0.5512	There is no unidirectional Toda-Yamamoto causality relationship from Bitcoin trading volume to Google Trends search results.

Derived from the data presented in Table 11, it is deduced that the integration degrees are 2, indicating a two-fold integration. Furthermore, a unidirectional causality relationship is identified from Google Trends search results to Bitcoin trading volume. Conversely, no causality relationship is observed from Bitcoin trading volume to Google Trends search results.

7. Conclusion

Bitcoin, a financial asset distinct from traditional investment instruments, has recently regained attention. Despite its current value being lower than its peak, Bitcoin maintains the highest trading volume among cryptocurrencies. Its increasing usability in international trade and payment systems positions Bitcoin and other cryptocurrencies as alternative investment tools for investors. Both in the years 2017 and 2021, sharp movements in Bitcoin prices have led to reaching all-time highs. Furthermore, it is observed that investor interest has begun to revive in recent times.

The correlation between Bitcoin and conventional financial assets and indices has consistently sparked curiosity. Due to its vulnerability to speculative fluctuations, Bitcoin is viewed as a high-risk investment instrument. The association between Bitcoin and other cryptocurrencies, as well as the analysis of Google Trends searches related to price changes, stands as a focal point of interest in both scholarly research and discussions within social media forums.

This study explores the long-term relationship between Bitcoin's trading volume, considered an indicator among cryptocurrencies, and Google Trends search results. The period from November 2017 to August 2023 is investigated. Initially, the study examines whether the data contain unit roots, followed by determining the stationarity of the first difference in the data. Afterwards, Engle-Granger cointegration analysis revealed cointegration between Bitcoin trading volume and Google Trends search results. Subsequently, Toda-Yamamoto Causality Analysis indicated that there is no bidirectional causal relationship between Bitcoin trading volume and Google Trends search results. Accordingly, it is evident that there is no unidirectional Toda-Yamamoto causality from Bitcoin trading volume to Google Trends search results. However, a unidirectional Toda-Yamamoto causality from Google Trends search results to Bitcoin trading volume was identified.

In light of these results, it can be argued that Google Trends search results are associated with Bitcoin trading volume in the long term, and therefore, it can be said that Turkish investors' interest in Bitcoin also increases during periods of increasing Bitcoin trading volume. Turkish cryptocurrency investors may be able to manage their investments more effectively by tracking both trends and Bitcoin trading volume in potential Bitcoin investments. Additionally, in the short term, it is observed that Google search results lead to changes in Bitcoin trading volume. Accordingly, it can be seen that when Turkish investors' interest in Bitcoin increases in trends, their interest in Bitcoin trading also increases. This situation is expected to lead to an increase in interest among investors in Türkiye due to global media trends resulting from the increase in trading volumes on international cryptocurrency exchanges. Bitcoin is frequently mentioned in broadcasts made both on TV and the internet, especially on social media platforms worldwide. Therefore, there is an increasing need for people to acquire information about Bitcoin. In short, as Bitcoin transaction volumes increase in global markets, people are more inclined to conduct further research on Bitcoin. In summary, it can be said that the conducted Bitcoin research contributes to increasing Bitcoin transaction volumes.

Under the literature review section, it was noted that no prior studies were encountered focusing on Bitcoin trading volume and Google Trends search result variables. However, studies associating Bitcoin price changes and Google Trends search result variables are present in the literature. The sentence "Volume is necessary for prices to increase," which is an old Wall Street proverb, signifies the significance of volume for prices (Lee & Rui, 2000). Therefore, when comparing the empirical findings with existing research, it can be observed that the study is supportive of Kristoufek (2013), Matta et al. (2015), Dulupçu et al. (2017), Smuts (2019), and Raza et al. (2022) studies.

The study is anticipated to augment the existing literature through the disclosed findings. Accordingly, the study is considered unique in its relationship between Bitcoin trading volume data and Google Trends search results. It is anticipated that researchers can obtain expansive results in future studies by employing different temporal data and methodologies to expand the literature.

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Etik Beyanı: Bu çalışmanın tüm hazırlanma süreçlerinde etik kurallara uyulduğunu yazar beyan eder. Aksi bir durumun tespiti halinde Fiscaoeconomia Dergisinin hiçbir sorumluluğu olmayıp, tüm sorumluluk çalışmanın yazarına aittir.

Ethical Approval: The author declare that ethical rules are followed in all preparation processes of this study. In the case of a contrary situation, Fiscaoeconomia has no responsibility, and all responsibility belongs to the study's author.