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The Impact of Cryptocurrency Markets on the Traditional Financial Markets of the USA, UK, and Germany

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Abstract

The acceleration of the globalization process and the structural changes in technology that emerged in the 2000s have affected financial markets. This interaction in the financial markets has made the emergence of new financial assets necessary. According to the ARDL boundary test results, there is no significant relationship between cryptocurrency markets and stock returns in both the long and short term for the UK financial markets. For the German financial markets, it has been determined that there is a significant and positive long-term relationship between the cryptocurrency market assets Bitcoin and Tether and stock market returns. In the short term, no significant relationship has been detected. For the long term in the U.S. financial markets, it has been determined that there is a significant and positive relationship between Bitcoin, a cryptocurrency market asset, and stock market returns, while there is no significant relationship between Ethereum and Tether with stock market returns. In the short term, no significant relationship has been detected. These findings offer significant implications for policymakers, investors, and market analysts.

Keywords: Cryptocurrencies, Bitcoin, Ethereum, Tether, Stock Returns, ARDL Bound Test.

JEL Classification: E44, G15, G38

Kripto Para Piyasasının ABD, İngiltere ve Almanya'nın Geleneksel Finansal Piyasaları Üzerindeki Etkisi

Öz

Küreselleşme sürecinin hızlanması ve 2000'li yıllarla birlikte ortaya çıkan teknolojideki yapısal değişimler, finansal piyasaları etkilemiştir. Finans piyasalarındaki bu etkileşimde yeni finansal varlıkların ortaya çıkmasını zorunlu hale getirmiştir. ARDL sınır testi sonuçlarına göre; İngiltere finansal piyasaları için hem uzun hem de kısa dönemde kripto para piyasaları ile borsa getirileri arasında anlamlı bir ilişki olmadığı tespit edilmiştir. Almanya finansal piyasaları için uzun dönemde kripto para piyasası varlıklarından Bitcoin ve Tether ile borsa getirileri arasında anlamlı ve pozitif yönlü bir ilişki olduğu tespit edilmiştir. Kısa vadede ise anlamlı herhangi bir ilişki tespit edilememiştir. ABD finansal piyasaları için uzun dönemde kripto para piyasası varlıklarından Bitcoin ile borsa getirileri arasında anlamlı ve pozitif yönlü bir ilişki olduğu, Ethereum ve Tether ile borsa getirileri arasında ise anlamlı bir ilişki olmadığı tespit edilmiştir. Kısa vadede ise anlamlı herhangi bir ilişki tespit edilememiştir. Bu bulgular, politika yapıcılar, yatırımcılar ve piyasa analistleri için önemli çıkarımlar sunmaktadır.

Anahtar Kelimeler: Kripto Paralar, Bitcoin, Ethereum, Tether, Borsa Getirileri, ARDL Sınır Testi.

JEL Sınıflandırması: E44, G15, G38

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1. Introduction

In the last decade, the financial world has witnessed an unprecedented transformation and continues to do so. Especially due to changes and developments in technology, the cryptocurrency revolution that began with the emergence of Bitcoin in 2009 not only created an alternative investment vehicle to traditional financial instruments but also started to question the fundamental dynamics of the global financial system. Cryptocurrencies with a market value of billions of dollars have a significant and sometimes unpredictable impact on modern financial markets. The speculative and complex nature of cryptocurrency markets is changing how investors behave in traditional markets, while also presenting new challenges for regulators and policymakers.

How do leading stock market indices like Deutscher Aktienindex (German Stock Index), Financial Times Stock Exchange, and Dow Jones Industrial Average get affected by the price movements of digital assets such as Bitcoin, Ethereum, and Tether? How do macroeconomic factors such as market sentiment, interest rates, inflation, and economic growth interact with this digital financial environment? This study aims to comprehensively analyze the effects of cryptocurrencies on traditional financial markets in order to answer these questions. The source of motivation for the study is generally uncertain, as the impact of cryptocurrencies on stock market returns is not clearly defined in the literature. The effects are complex and currently uncertain due to regional, methodological, and temporal differences. Therefore, more research and analyses that take into account various market conditions are needed to understand the impact of cryptocurrencies on traditional financial markets. As cryptocurrencies rapidly evolve and change, there are both opportunities and dangers. For this reason, understanding the investment strategies of cryptocurrencies and their impact on financial stability and market dynamics is crucial for shaping the financial structure of the future. The aim of this study is to demonstrate to investors, regulators, and academics the extensive effects of cryptocurrency markets on the traditional financial system.

The study stands out by examining in detail how cryptocurrencies are related to macroeconomic variables and the effects of these variables on financial markets in various economies (the USA, Germany, and the UK). For this reason, an important innovation that distinguishes this study from other studies in the literature is the analysis of both short- and long-term relationships using the ARDL bounds testing approach, as well as determining the effects of cryptocurrency volatilities on market sentiment and investor behaviors. To contribute to the existing literature on the effects of cryptocurrencies on financial markets in this field. The study only examined the top three cryptocurrencies by market capitalization to represent the cryptocurrency market and did not cover other altcoins. Again, the fact that the study only covers the period from April 2016 to June 2024 is another limitation. Because examining different time zones can lead to different results.

The aim of the study is to examine the relationship between the closing prices of leading stock indices in developed countries such as the United Kingdom, the United States, and Germany, and the value of the top three cryptocurrencies in the market. The data for the research consists of monthly data from April 2016 to June 2024. In the research, the reasons for preferring the USA, Germany, and the UK include that the USA is not only a significant market in cryptocurrency trading but also has the largest financial market in the world. Similarly, there are many major stock exchanges and financial institutions in the United States. Germany has been chosen as it is very important for evaluating the impact of cryptocurrencies on Europe's largest financial market and economy. The United Kingdom (England) has been preferred due to London's significant role as a global financial center for cryptocurrency trading and regulations.

The reason for selecting the dates April 2016 and June 2024 is as follows. Firstly, April 2016 is considered a period when the cryptocurrency markets began to mature and grow. This period marks a time when the popularity of major cryptocurrencies like Bitcoin and Ethereum, along with other altcoins, has started to rise. For this reason, the beginning of this period is very important to understand the development of cryptocurrency markets and their impact on traditional markets. The second aspect encompasses a period after 2016 during which many countries developed and implemented cryptocurrency regulations. Additionally, the comprehensive and reliable accessibility of cryptocurrency and traditional market data during these times makes it possible to analyze this data. Additionally, the periods after 2016 have been preferred due to the significant fluctuations witnessed in the cryptocurrency markets. It provides data for analyzing market behaviors due to the significant rise and subsequent rapid decline of cryptocurrencies at the end of 2017 and the beginning of 2018. Thirdly, the periods have been deliberately chosen because the shocks created by the COVID-19 pandemic in global markets in 2020 provided valuable opportunities to examine how both the cryptocurrency markets and traditional financial markets were affected.

The paper consists of five sections in line with the research purpose. The introduction section has been explained in the first chapter. The second section summarizes the current studies available in the literature. In the third section, the research method and dataset are explained in detail. In the fourth chapter, findings and interpretations related to these findings have been presented. In the fifth and final section, conclusions and evaluations have been made, and the study has been completed.

2. Theoretical Framework

2.1. The Concept of Cryptocurrency

Cryptocurrency refers to encrypted money, a term that combines the words crypto, currency, and money. Cryptocurrencies are referred to by this name because they are placed in virtual exchanges and wallets using a series of codes and similarly withdrawn from them (Eren et al., 2020: 1342). Cryptocurrencies are virtual currencies that are not tied to any central government or intermediary and can be used over the internet. Cryptocurrencies can be spent or accepted in the same way as real money (Çetinkaya, 2018: 13).

Cryptocurrency can be used for e-commerce in the virtual environment because it is seen as an alternative value. Cryptocurrencies, which can be expressed in forms such as virtual, digital, and e-money, are not subject to the policies, restrictions, regulations, and guarantees of central banks due to their characteristics as a global tool. The use of cryptocurrencies is rapidly increasing worldwide due to the fast changes and developments in technology (Eren et al., 2020: 1342). These currencies are attracting great interest from both individuals and legal entities. The reason for this is that it is neither monitored by public authorities nor are its costs very low (Dizkırıcı and Gökgöz, 2018: 93).

2.2. The Historical Development of Cryptocurrency

There are many different opinions regarding the emergence of cryptocurrencies. At the core of these views lies a decline in trust towards central banks and financial institutions as a result of the financial crises experienced (Eren et al., 2020: 1349). After the global crisis of 2008, the cryptocurrency Bitcoin was introduced for the first time in a paper titled "Bitcoin: A Peer-to-Peer Electronic Cash System," written by a person or group using the pseudonym Satoshi Nakamoto (Nakamoto, 2008).

Cryptocurrency is a decentralized digital currency that uses cryptography (encryption) (Gandal and Halaburda, 2014: 2). Cryptology is used in the processes of ensuring the reliability of transactions made with cryptocurrencies and in the formation process of money. The theoretical infrastructure of cryptocurrencies was first introduced by Wei Dai in 1998. The technical system that forms the infrastructure of today's existing cryptocurrencies was established by a person or group known as Satoshi Nakamoto, who is recognized as the founder of Bitcoin, which emerged in 2008 (Gültekin and Bulut, 2016: 83).

Bitcoin, known as the ancestor of cryptocurrencies, first emerged through a published article over the internet. The first transactions of Bitcoin date back to 2009. Since this year, a large number of cryptocurrencies have been created. In today's world, there are thousands of different cryptocurrencies available (Eren et al., 2020: 1349). Since the cryptocurrency market is dynamic, the number of cryptocurrencies listed on CoinMarketCap can constantly change. As of September 2024, the number of cryptocurrencies listed on CoinMarketCap has reached approximately 10,000.

2.3. Types of Cryptocurrencies

Cryptocurrencies can be bought and sold on many different exchanges using currencies like USD, EUR, and BTC. These funds can be in the form of parties consisting entirely of cryptocurrencies, as well as cryptocurrencies created with the currencies of governments (Eren et al. 2020: 1350). In today's financial world, there are over a thousand types of cryptocurrencies available. This section of the study includes the top three cryptocurrencies with the highest market value.

2.3.1. Bitcoin

Bitcoin, designed as an alternative to state-backed fiat currency, is a digital currency that was created in the midst of the 2008 global financial crisis. However, it is still not definitively known who or what created this. Satoshi Nakamoto is the name associated with the person or group that published the original Bitcoin white paper in 2008 and worked on the original Bitcoin software released in 2009 (Forbes, 2020). Bitcoin promises lower transaction fees compared to traditional online payment mechanisms and, unlike government-issued currencies, it is operated by a decentralized authority (Frankenfield, 2021).

Bitcoin is a combination of currencies that form the foundation of data mining in digital currency systems. The tool used to facilitate exchange transactions among users within this network system is called Bitcoin (Yumuşaker, 2019: 1012). Bitcoin is a type of cryptocurrency. There is no physical Bitcoin; there are only balances kept in a public ledger that everyone has transparent access to. All Bitcoin transactions are verified with an enormous amount of computing power. Bitcoins are not issued or supported by any bank or government. Despite not being a legal tender, Bitcoin has become very popular and triggered the launch of hundreds of other cryptocurrencies, commonly referred to as altcoins. Bitcoin is commonly abbreviated as "BTC." Launched in 2009, Bitcoin is the largest cryptocurrency in the world by market capitalization. Bitcoin is created, distributed, exchanged, and stored using a decentralized ledger system known as the blockchain. (Frankenfield, 2021).

Bitcoin is widely used in countries with a high level of development, such as the USA, Japan, Canada, Germany, France, and the UK. The first Bitcoin ATM was launched in Canada. After Canada, Bitcoin ATMs have been established in Japan and Ireland. In Türkiye, there is a Bitcoin ATM at Istanbul Atatürk Airport (Deniz, 2020:26).

2.3.2. Ethereum

Although Bitcoin is the first among cryptocurrencies and has sufficient features for transfer transactions, it is not suitable for all areas. When Bitcoin is attempted to be made suitable for all areas, it has to bear extra costs. To prevent such issues, a number of special protocols have been established, and mechanisms have been introduced that can provide solutions to potential new problems, with the most well-known being Ethereum (Eren et al., 2020: 1353).

The founder of Ethereum is Vitalik Buterin. Vitalik Buterin first introduced Ethereum at the North American Bitcoin Conference (Atam, 2020). The center of the Ethereum cryptocurrency is Switzerland. It was developed by the Ethereum Foundation (Yumuşaker, 2019: 1016). Ethereum is a blockchain-based cryptocurrency that enables software developers to create decentralized applications, free from interruptions, censorship, fraud, and third-party interference (Deniz, 2020: 30). From the outside, Ethereum may seem like an "altcoin," but compared to other altcoins, it actually encompasses a system with much more innovation. The Ethereum platform, created based on the logic of Bitcoin's Blockchain, has enabled the development of decentralized software protocols on this operating system using its own special programming language, Turing-Complete. Thanks to these protocols, it has become possible to create thousands of altcoins or tokens using accepted smart contracts on a single Blockchain with the same main operating system. Today, many companies and startups have created their own cryptocurrencies through Ethereum and have made them available as tokens (Atam, 2020).

2.3.3. Tether

Tether is the first cryptocurrency known as a stablecoin. Tether is based on fiat currency and combines traditional currencies with cryptocurrencies. This cryptocurrency was launched in 2015 by Tether Limited Company, which is based in Hong Kong. Tether operates on a blockchain system based on the ERC-20 protocol. Tether is abbreviated as USDT. The value of Tether, the virtual version of the US dollar, is always traded this way because it is pegged at 1 USDT = 1 $ (Deniz, 2020: 40).

3. Literature Review

Although studies in the literature generally conclude that there is a negative relationship between the cryptocurrency market and stock indices, there are also studies that find a positive relationship and/or no relationship at all. Among the studies that concluded there is a positive relationship between the cryptocurrency market and stock indices, Toudas et al. (2024) examined the relationship between Bitcoin cryptocurrency prices, gold, and the Dow Jones stock index. As a result of the study, they concluded that there is a statistically significant and positive relationship between the Dow Jones stock index and Bitcoin. In their study, Mgadmi et al. (2023) investigated the interconnectedness of stock indices and cryptocurrencies during the Russia-Ukraine war by utilizing data from February 24, 2022, to April 12, 2023. As a result of the study, they concluded that in the long term, the American, Canadian, French, and Ukrainian stock indices have a positive and significant impact on Bitcoin. In their 2023 study, Tosin-Amos examined the stock market's reaction to cryptocurrency investments in the U.S. stock market by utilizing monthly data covering the period from February 2016 to February 2022, employing ARDL simulation techniques. As a result of the study, they concluded that cryptocurrencies positively affect the US stock market, and that investing in Bitcoin and Ethereum is a good predictor of the stock market. In their study, Akkaya and Küçükpınar (2023) utilized daily stock returns from January 12, 2018, to December 31, 2022, focusing on developed countries such as the United States, Germany, and Japan, as well as emerging countries including Turkey, China, and India. They analyzed volatility and volatility spillovers using GARCH and EGARCH models. The study concluded that an asymmetric effect, or leverage effect, is valid in the Borsa İstanbul 100 index. Additionally, they noted volatility spillovers from the DAX (Germany) and NIFTY (India) indices to the Borsa İstanbul 100 index. In his study, Demir (2022) examined the relationship between Bitcoin and the Borsa İstanbul (BIST) index using monthly data from January 2015 to December 2022 through cointegration analysis. As a result of the study, there is a positive relationship between Bitcoin and the BIST index in both the short and long term. In their study, Thaker and Mand (2021) examined the relationship between Bitcoin and the stock exchanges of Japan, Korea, Singapore, the Philippines, and Hong Kong. As a result of the study, they concluded that there is a positive relationship between Bitcoin and the Philippine stock market. In his study, Hung (2021) examined the reciprocal relationships between Bitcoin prices and the stock exchanges of Central and Eastern Europe (Hungary, Czech Republic, Poland, Romania, and Croatia). As a result of the study, there is a positive relationship between Bitcoin prices and the indices of Central and Eastern European stock exchanges. In his study, Akkaya (2021) the GARCH method was employed to examine the symmetries and asymmetries in Bitcoin prices and the expected leverage effect, utilizing daily Bitcoin prices from December 11, 2017, to March 31, 2021. The findings shovs the EUR/USD exchange rate, GOLD price, USD 10-year bond yield, US Dollar Index, and VIX significantly impacted BTC volatility, while the NASDAQ and NIKKEI indices, as well as oil prices, did not have a significant effect on BTC volatility.

In studies concluding that there is a negative relationship between the cryptocurrency market and stock indices, Thaker and Mand (2021) examined the relationship between Bitcoin and the stock exchanges of Japan, Korea, Singapore, the Philippines, and Hong Kong. They concluded that there is a negative relationship between Bitcoin and the stock exchanges of Japan, Korea, and Hong Kong. Korkmazgöz et al. (2022) examined the short and long-term relationship between the Borsa Istanbul 100 price index, the Borsa Istanbul Financial price index, and the Borsa Istanbul Technology price index with Bitcoin using the ARDL bounds testing approach. There is a long-term relationship between the price of Bitcoin and the Borsa Istanbul Financial Index, and that the direction of this relationship is negative. Çıkrıkçı and Özyeşil (2019) analyzed the interaction between Bitcoin and the stock exchanges of Türkiye and nine different Southeast Asian countries, utilizing data from February 22, 2012 to August 15, 2018. There is a negative relationship between Bitcoin return rates and the stock market returns of the countries examined. Tiwari et al. (2019) examined the relationship between six cryptocurrencies and the S&P 500 index market using the E-GARCH model. The volatilities reacted more to negative shocks than to positive shocks in both markets. Georgoula et al. (2015) examined the relationship between Bitcoin prices and the S&P 500 index. There is a negative relationship between Bitcoin prices and the S&P 500 index.

In studies indicating that there is no relationship between the cryptocurrency market and stock indices, Döger Toprak and Kubar (2023) examined the long and short-term relationship between BTC and ETH, selected from the most popular cryptocurrencies, and chosen stock indices, based on the Covid-19 pandemic period. According to the findings of the Fourier cointegration test, it has been determined that there is a long-term cointegration relationship between cryptocurrencies and stock indices during the pandemic period. According to the findings of the Hatemi-J asymmetric causality test, there is no causal relationship between the positive and negative shocks of BTC and the South Korean stock index, and the positive and negative shocks of ETH and the Indonesian stock index. Gil-Alana et al. (2020) examined the stochastic properties of six major cryptocurrencies and their fractional integration relationships with six stock market indices using fractional integration techniques. There is no cointegration relationship between cryptocurrencies and stock indices. Kılıç and Çütcü (2018) examined the relationship between Bitcoin prices and the Borsa Istanbul index using cointegration and causality tests. As a result of the study, they concluded that there is no long-term relationship between Bitcoin prices and the Borsa

Istanbul index. Kanat and Öget (2018) conducted a cointegration analysis to determine the relationship between stock indices of Türkiye and G7 countries and the price of Bitcoin. They concluded that there is no relationship between Bitcoin and the mentioned exchanges. Dirican and Canöz (2017) utilized data from May 24, 2013 to November 5, 2017 to examine whether Bitcoin has an impact on stock indices using the ARDL bounds testing method. There is no long-term relationship between Bitcoin prices and both the US and Chinese stock indices. Baek and Elbeck (2015) utilized data from July 2010 to February 2014 to examine whether Bitcoin prices had any effect on the S&P 500 index through regression analysis. As a result of the study, they concluded that changes in Bitcoin prices have no effect on the S&P 500 index.

Based on the general arguments of the literature and theoretical framework, the following hypotheses can be formulated:

H_1: Bitcoin has a significant impact on the stock market return index.

H_2: Ethereum has a significant impact on the stock market return index.

H_3: Tether has a significant impact on the stock market return index.

4. Data Set and Method

4.1. Data Set

The study examines the relationship between cryptocurrency markets (Bitcoin, Ethereum, and Tether) and traditional financial markets (stock return indices) for the economies of the USA, Germany, and the UK. The reason for the preference of these three cryptocurrencies is that, as of September 30, 2024, they are the top three cryptocurrencies with the highest market value. The purpose of the study is based on utilizing monthly data from the period of April 2016 to June 2024. Closing prices have been used for cryptocurrency market assets and stock return index data. The data related to the variables included in the study has been obtained from https://www.investing.com/.

The natural logarithms of variables have been taken for analysis. Again, interest rates, GDP, and the market sentiment index, which are thought to be directly and indirectly related to these variables, have been identified as control variables, and the natural logarithm of the market sentiment index has been taken for analysis. The explanations of the variables used in the examination of the relationships between the cryptocurrency market and traditional financial markets are provided below. The leading stock indices of the countries included in the research scope among these variables are:

The Dow Jones Index (DJI) (Dow Jones Industrial Average): The Dow Jones Index (DJI) is one of the most well-known and widely used stock market indices in the world. The Dow Jones Index includes the 30 largest and most influential companies in the United States. These companies are selected from different industries and represent economic diversity. The DJI is considered an important indicator reflecting the overall performance of the U.S. economy. Investors closely monitor the DJI to understand economic policies, market trends, and overall economic health.

DAX (GDAXI) (German Stock Index): DAX measures the performance of the 40 largest German companies traded on the Frankfurt Stock Exchange. The companies included in the index are generally the strongest and most recognized firms in Germany. The DAX is considered an important indicator reflecting the overall performance of the German economy.

FTSE 100 (FTSE) (Financial Times Stock Exchange 100 Index): The FTSE 100 measures the performance of the 100 largest companies listed on the London Stock Exchange. Companies included in the index are generally the largest and most recognized firms in the United Kingdom. The FTSE 100 is considered an important indicator reflecting the overall performance of the UK economy. The index provides information about the health of the UK economy, the performance of the business sector, and the overall sentiment of investors.

Variables representing the cryptocurrency market:

Bitcoin (BTC): Bitcoin (BTC) is a decentralized digital currency built on blockchain technology. It was created in 2009 by an unknown person or group using the pseudonym Satoshi Nakamoto. Bitcoin has played a pioneering role in the world of digital currencies and has demonstrated the potential of blockchain technology. It continues to be a major point of interest for both investors and technology enthusiasts. In the study, the natural logarithm was taken and used with the LBTC code.

Ethereum (ETH): Ethereum (ETH) was developed by Vitalik Buterin in 2015 as a platform for decentralized applications (dApps) and smart contracts. Unlike Bitcoin, Ethereum is used not only for digital currency transfers but also for programmable transactions and applications. The native cryptocurrency used for transactions and smart contracts on the Ethereum network is Ether. (ETH). In the study, the natural logarithm was taken and used with the LETH code.

Tether (USDT): Tether is a cryptocurrency known as a stablecoin, which is pegged to the value of the US dollar. Launched in 2014, Tether is one of the most popular examples of stablecoins and is widely used in the cryptocurrency market. Tether is used as a preferred tool in cryptocurrency trading and transfers due to its price stability, wide acceptance, and high liquidity. In the study, the natural logarithm was taken and used with the LUSDT code.

Macroeconomic indicators considered as control variables:

Interest Rate: As an interest indicator, the monthly deposit interest rates of each country have been used. In the study, the code IR has been used to represent the interest rate.

Gross Domestic Product Growth Rate: The GDP calculated on a quarterly basis (i.e., every three months) has been converted into monthly periods using a weighted average method for the purposes of this study. In the study, the code GDP has been used to represent the Gross Domestic Product ratio.

Inflation Rate: It represents the consumer price index and has been referred to as CPI in the study.

Volatility Index: The VIX, officially known as the Chicago Board Options Exchange Volatility Index (CBOE Volatility Index), is based on the Standard & Poor's 500 (S&P500) index and represents the estimated 30-day volatility of the S&P500. Introduced by the CBOE, it measures volatility risk in the futures market. The VIX captures investor fears related to market stability (Kurtkaya and Özçelik (2024). High VIX values indicate high volatility and investor fear, while low values reflect confidence and market stability (UNLU Blog). In the study, the LVIX code has been used to represent the market sentiment index.

4.2. Research Methodology

4.2.1. ADF (Augmented Dickey-Fuller) and PP (Phillips-Perron) Unit Root Tests

If the mean, variance, and autocorrelation of a series remain constant over time, it indicates that the series does not contain a unit root; if they change over time, this suggests that the series does contain a unit root. Unit root tests help determine whether a series is stationary, thereby assisting in accurate modeling and forecasting. When a series is not stationary, one may encounter a spurious regression situation. To escape this situation and achieve accurate and effective results, the series needs to be stationary. In the study, the widely used Augmented Dickey-Fuller (ADF) (Dickey and Fuller, 1979) and Phillips-Perron (PP) (Perron, 1989) panel unit root tests have been applied. The Extended Augmented Dickey-Fuller (ADF) Test is the adaptation of the time series ADF test for panel data sets. This test applies ADF tests for individual time series and combines the results. The Panel ADF test uses the regression model given in equation 1 for each cross-section.

$$\Delta_{yt} = \alpha + \beta t + \gamma y_{t-1} + \delta_1 \Delta_{yt-1} + \delta_2 \Delta_{yt-2} + \dots + \delta_p \Delta_{yt-p} + \varepsilon_t \qquad (1)$$

In equation 1, the difference operator represents the time trend t. It shows the value of the series in the previous period. The coefficients of the delay terms, and represent the error term. The hypotheses of the Extended Augmented Dickey-Fuller (ADF) Test are as follows.

Null hypothesis (H_0): The series contains a unit root, meaning it is non-stationary. Alternative hypothesis (H_1): The series does not contain a unit root, meaning it is stationary.

The Phillips-Perron (PP) test, similar to the ADF unit root test, checks whether a series contains a unit root, but it employs a different approach to account for autocorrelation and heteroskedasticity in the error terms. The Phillips-Perron (PP) test is based on the regression model given in equation 2.

$$y_t = \alpha + \beta t + \gamma y_{t-1} + \varepsilon_t \qquad (2)$$

The hypotheses of the Phillips-Perron (PP) Test are:

The null hypothesis (H_0): Indicates that the series contains a unit root, meaning it is not stationary.

Alternative hypothesis (H_1): It indicates that the series does not contain a unit root, meaning it is stationary.

4.2.2. ARDL Bound Test Approach

The existence of the cointegration relationship between variables is tested using various cointegration tests. Among these, classical cointegration tests examine the relationship between variables that are integrated of the same order. However, this situation poses a constraint when considering cointegration tests. The Autoregressive Distributed Lag (ARDL) bounds testing approach proposed by Pesaran et al. (2001) allows for the examination of the cointegration relationship between variables of different integration orders as well as between variables that are integrated of the same order. Another advantage of this test is that the lags of both the dependent variable and the independent variable are included in the model. Another advantage is that it allows for the utilization of an unrestricted error correction model. This test allows for both short-term and long-term predictions to be made (Pesaran et al., 2001). This method yields healthier results even in small sample situations (Oğul, 2022). The general model of the ARDL boundary test approach is given as follows in equation 3.

$$Y_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i Y_{t-i} + \sum_{j=0}^{q} \beta_j X_{t-j} + \varepsilon_t \quad (3)$$

In this equation, Y_t represents the value of the dependent variable at time t, α_0 is the constant term, α_i are the coefficients of the lagged values of the dependent variable, X_{t-j} are the lagged values of the independent variables, β_j are the coefficients of the lagged values of the independent variables, ε_t is the error term, and p and q indicate the lengths of the lags.

The boundary testing approach of the ARDL model is used to test for long-term relationships (cointegration). The hypotheses of this test are as follows.

H_0: There is no cointegration (there is no long-term relationship).

H_1: There is co-integration (there is a long-term relationship).

The equation of the model is given as the equality in one-fourth.

$$\Delta Y_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i \Delta Y_{t-i} + \sum_{j=0}^{q} \beta_j \Delta X_{t-j} + \gamma_1 Y_{t-1} + \gamma_2 X_{t-1} + \varepsilon_t \quad (4)$$

In this formula, Δ represents the difference operator (stabilization through first differences), while Y_{t-1} and X_{t-1} denote the lagged values of the dependent and independent variables, respectively. γ_1 and $\gamma_2$indicate the long-term relationship coefficients

The ARDL bounds testing approach tests for the presence of cointegration using the F-statistic. The calculated F-statistic is compared against specific critical values.

a) If the F-statistic is greater than the upper limit, H_0 is rejected and it is assumed that there is cointegration.

b) If the F-statistic is less than the lower limit, H_0 is accepted and it is assumed that there is no cointegration.

c) Between the critical values of the F-statistic, the result is uncertain and further research is needed.

5. Results

Descriptive statistics for all recorded variables are presented in Table 1.

Table 1. Descriptive Statistics

United States of America (USA)								
	LSM	**LBTC**	**LETH**	**LUSDT**	**IR**	**CPI**	**GDP**	**LVIX**
Average	2.3253	2.2160	1.7566	-7.0821	1.8765	.28484	.87575	1.0437
Median	2.3229	2.2284	1.8107	-7.6011	1.35	.2	.86666	1.0225
Maximum	2.3600	2.4136	2.1329	-2.8426	5.33	1.3	11.6	1.3813
Minimum	2.2808	1.8092	.73209	-9.2103	.05	-.8	-9.333	.81197
St. Deviation	.02143	.15640	.36016	1.8256	1.8004	.30114	2.6936	.11993
Skewness	-.3720	-.9941	-1.4714	.77117	.86225	.40307	.23945	.41402
Kurtosis	2.1853	3.2169	4.4225	2.5635	2.4453	5.6107	14.187	.25859
Jarque-Bera	5.021	16.5	44.07	6.531	13.54	30.8	517.2	3.535
P-value	.0812	.00026	.00027	.0382	.0011	.00021	.00005	.1707
Number of Observations	99	99	99	61	99	99	99	99
Germany								
	LSM	**LBTC**	**LETH**	**LUSDT**	**IR**	**CPI**	**GDP**	**LVIX**
Average	2.2502	2.3229	1.7566	-7.0821	.83080	.27474	.31010	1.0437
Median	2.3229	2.2284	1.8107	-7.6011	0	.3	.36666	1.0225
Maximum	2.2849	2.4136	2.1329	-2.8426	4.5	4	3.7666	1.3813
Minimum	2.2167	1.8092	.73209	-9.2103	0	-.8	-3.6	.81197
St. Deviation	.01601	.15640	.36016	1.8256	1.6106	.59886	1.0565	.11993
Skewness	.18819	-.9941	-1.4714	.77117	1.5683	2.3086	-.5346	.41402
Kurtosis	2.3873	3.2169	4.4225	2.5635	3.6662	16.959	9.5429	.25859
Jarque-Bera	2.133	16.5	44.07	6.531	42.42	891.8	181.3	3.535
P-value	.3442	.00026	.00027	.0382	.00062	.00002	.00043	.1707
Number of Observations	99	99	99	61	99	99	99	99

Table 1. Continued

United Kingdom (UK)								
	LSM	**LBTC**	**LETH**	**LUSDT**	**IR**	**CPI**	**GDP**	**LVIX**
Average	2.1830	2.3229	1.7566	-7.0821	1.1161	3.4767	.12828	1.0437
Median	2.1853	2.2284	1.8107	-7.6011	.25	2.4	.1	1.0225
Maximum	2.1995	2.4136	2.1329	-2.8426	5	11.1	5.6	1.3813
Minimum	2.1548	1.8092	.73209	-9.2103	0	2	-6.766	.81197
St. Deviation	.00914	.15640	.36016	1.8256	1.7599	3.0577	1.6109	.11993
Skewness	-1.141	-.9941	-1.4714	.77117	1.4542	1.2223	-1.124	.41402
Kurtosis	4.0175	3.2169	4.4225	2.5635	3.3973	3.2474	14.627	.25859
Jarque-Bera	25.79	16.5	44.07	6.531	35.55	24.91	578.5	3.535
P-value	.00025	.00026	.00027	.0382	.00019	.00039	.00002	.1707
Number of Observations	99	99	99	61	99	99	99	99

Table 1 provides descriptive statistics for all variables. When examining the values given for the US economy in the table, the variable with the highest standard deviation is GDP (2.6936), while the variable with the lowest standard deviation is LSM (.02143). The GDP variable shows large fluctuations, while the LSM variable exhibits lower fluctuations. The variable with the lowest average (-7.0821) and the highest standard deviation (1.8256) among the variables representing the cryptocurrency market is the LUSDT variable. This situation indicates that the variable shows significant fluctuations. When examining the skewness values, LSM, LBTC, and LEHT are negatively skewed, while the other variables are positively skewed. When examining the kurtosis values, only the kurtosis value of the LVIX variable falls between the values of +1.96 and -1.96 (.25859) as mentioned in the literature, indicating that it is not skewed. In contrast, the kurtosis values of the other variables exceed the threshold values indicated in the literature, suggesting that they are skewed. When examining the results of the Jarque-Bera test, which tests whether the series follows a normal distribution, only the LSM and LVIX variables show a normal distribution since their probability values are greater than the critical value of 0.05. Since the p-values of the other variables, except for LSM and LVIX, are smaller than the critical value of 0.05, it can be said that these variables do not exhibit a normal distribution.

For the German economy in the table, the variable with the highest standard deviation is LUSDT (1.8256), while the variable with the lowest standard deviation is LSM (0.01601). The LUSDT variable exhibits large fluctuations, while the LSM variable shows lower fluctuations. It is observed that the variable with the lowest average (-7.0821) and the highest standard deviation (1.8256) among the variables representing the cryptocurrency market is the LUSDT variable. This situation indicates that the variable shows significant fluctuations. LBTC, LEHT, and GDP are negatively skewed, while the other variables are positively skewed. For examining the kurtosis values, it only the kurtosis value of the LVIX variable falls between the values of +1.96 and -1.96 (.25859) as mentioned in the literature, indicating that it is not skewed. In contrast, the kurtosis values of the other variables exceed the threshold values indicated in the literature, suggesting that they are skewed. For the

Jarque-Bera test, which tests whether the series follows a normal distribution, only the LSM and LVIX variables show a normal distribution since their probability values are greater than the critical value of 0.05. Since the p-values of the other variables, except for LSM and LVIX, are smaller than the critical value of 0.05, it can be said that these variables do not exhibit a normal distribution.

For the UK economy in the table, the variable with the highest standard deviation is CPI (3.0577), while the variable with the lowest standard deviation is LSM (0.00914). The CPI variable shows large fluctuations, while the LSM variable exhibits lower fluctuations. For the skewness values, LSM, LBTC, LEHT, and GDP are negatively skewed, while the other variables are positively skewed. For the kurtosis values, only the kurtosis value of the LVIX variable falls between the values of +1.96 and -1.96 (.25859) as mentioned in the literature, indicating that it is not skewed. In contrast, the kurtosis values of the other variables exceed the threshold values indicated in the literature, suggesting that they are skewed. When examining the results of the Jarque-Bera test, which tests whether the series follows a normal distribution, it can be stated that only the LVIX variable shows a normal distribution, as its p-value is greater than the critical value of 0.05. Since the p-values of the other variables, except for the LVIX variable, are less than the critical value of 0.05, it can be said that these variables do not exhibit a normal distribution.

5.1. Unit Root Test Results

The presence of a unit root in the series has been examined using the commonly used ADF (Augmented Dickey-Fuller) and PP (Phillips-Perron) unit root tests in the literature, and the results are presented in Table 2.

Table 2. ADF and PP Unit Root Test Results

	USA				Germany				UK			
	ADF Test		Phillips-Perron Test		ADF Test		Phillips-Perron Test		ADF Test		Phillips-Perron Test	
Variables	Stationary	Stationary and Trending	Stationary	Stationary and Trending	Stationary	Stationary and Trending	Stationary	Stationary and Trending	Stationary	Stationary and Trending	Stationary	Stationary and Trending
LSM	-1.453 (0.5566)	-3.326 (0.0621)	-1.383 (0.5906)	-3.218 (0.0809)	-1.396 (0.5843)	-2.850 (0.1793)	-1.316 (0.6220)	-2.325 (0.4199)	-2.257 (0.1863)	-2.355 (0.4039)	-2.269 (0.1823)	-2.380 (0.3901)
LBTC	-2.149 (0.2253)	-2.126 (0.5317)	-2.079 (0.2529)	-2.325 (0.4199)	-8.504 (0.0000)	-8.566 (0.0000)	-2.079 (0.2529)	-2.325 (0.4199)	-2.149 (0.2253)	-2.126 (0.5317)	-2.079 (0.2529)	-2.325 (0.4199)
LETH	-2.068 (0.2575)	-1.954 (0.6265)	-2.044 (0.2675)	-2.209 (0.2209)	-8.565 (0.0000)	-8.585 (0.0000)	-2.044 (0.2675)	-2.209 (0.2209)	-2.068 (0.2575)	-1.954 (0.6265)	-2.044 (0.2675)	-2.209 (0.2209)
LUSDT	-9.708 (0.0000)	-10.005 (0.0000)	-9.739 (0.0000)	-10.098 (0.0000)	-	-	-9.739 (0.0000)	-10.098 (0.0000)	-9.708 (0.0000)	-10.005 (0.0000)	-	-
IR	0.465 (0.9838)	-0.473 (0.9845)	-0.034 (0.9556)	-0.816 (0.9643)	1.790 (0.9983)	-0.513 (0.9829)	0.882 (0.9929)	-0.828 (0.9633)	2.145 (0.9988)	-0.372 (0.9877)	1.173 (0.9958)	-0.679 (0.9745)
GDP	-5.215 (0.000)	-5.189 (0.0001)	-5.238 (0.0000)	-5.213 (0.0001)	-5.403 (0.0000)	-5.384 (0.0000)	-5.508 (0.0000)	-5.489 (0.0000)	-5.804 (0.0000)	-5.774 (0.0000)	-5.673 (0.0000)	-5.641 (0.0000)
CPI	-5.721 (0.0000)	-5.906 (0.0000)	-5.669 (0.0000)	-5.860 (0.0000)	-8.407 (0.0000)	-8.492 (0.0000)	-8.331 (0.0000)	-8.416 (0.0000)	-1.053 (0.7335)	-0.140 (0.9925)	-1.282 (0.6372)	-0.706 (0.9728)
LVIX	-3.455 (0.0092)	-3.540 (0.0353)	-3.267 (0.0164)	-3.383 (0.0537)	-3.455 (0.0092)	-3.540 (0.0353)	-3.267 (0.0164)	-3.383 (0.0537)	-3.455 (0.0092)	-3.540 (0.0353)	-3.267 (0.0164)	-3.383 (0.0537)
Δ (LSM)	-8.790 (0.0000)	-11.067 (0.0000)	-11.320 (0.0000)	-11.293 (0.0000)	-10.694 (0.0000)	-10.644 (0.0000)	-10.716 (0.0000)	-10.666 (0.0000)	-10.191 (0.0000)	-10.138 (0.0000)	-10.211 (0.0000)	-10.155 (0.0000)
Δ (LBTC)	-8.442 (0.0000)	-8.509 (0.000)	-8.504 (0.0000)	-8.566 (0.0000)	-8.442 (0.0000)	-8.509 (0.000)	-8.504 (0.0000)	-8.566 (0.0000)	-8.442 (0.0000)	-8.509 (0.000)	-8.504 (0.0000)	-8.566 (0.0000)
Δ (LETH)	-8.467 (0.0000)	-8.491 (0.0000)	-8.565 (0.0000)	-8.585 (0.0000)	-8.467 (0.0000)	-8.491 (0.0000)	-8.565 (0.0000)	-8.585 (0.0000)	-8.467 (0.0000)	-8.491 (0.0000)	-8.565 (0.0000)	-8.585 (0.0000)
Δ (LUSDT)	-	-	-	-	-	-	-	-	-	-	-	-
Δ (IR)	-7.694 (0.0000)	-7.785 (0.0000)	-7.901 (0.0000)	-7.992 (0.0000)	-6.921 (0.0000)	-7.367 (0.0000)	-7.236 (0.0000)	-7.711 (0.0000)	-6.701 (0.0000)	-7.263 (0.0000)	-6.920 (0.000)	-7.526 (0.0000)

Table 2. Continued

Δ (GDP)	-	-	-	-	-	-	-	-	-	-	-	-
Δ (CPI)	-	-	-	-	-	-	-	-	-7.553 (0.0000)	-7.688 (0.0000)	-7.731 (0.0000)	-7.860 (0.0000)
Δ (VIX)	-13.033 (0.0000)	-12.992 (0.0000)	-13.478 (0.0000)	-13.455 (0.0000)	-13.033 (0.0000)	-12.992 (0.0000)	-13.478 (0.0000)	-13.455 (0.0000)	-13.033 (0.0000)	-12.992 (0.0000)	-13.478 (0.0000)	-13.455 (0.0000)
Critique is valuable %1	-3.514	-4.042	-3.511	-4.042	-3.514	-4.042	-3.511	-4.042	-3.514	-4.042	-3.511	-4.042
Critique is valuable %5	-2.892	-3.451	-2.891	-3.451	-2.892	-3.451	-2.891	-3.451	-2.892	-3.451	-2.891	-3.451
Critique is valuable %10	-2.581	-3.151	-2.580	-3.151	-2.581	-3.151	-2.580	-3.151	-2.581	-3.151	-2.580	-3.151

Note: The Δ expression represents the first differences, while L indicates the logarithmic values. Critical values for ADF and PP have been obtained by MacKinnon (1996). The values in parentheses are the one-tailed (p) probability values from MacKinnon (1996).

Table 2 presents the results of the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) panel unit root tests, for both stationary and trend-stationary models. For the USA, Germany, and the UK, both the ADF and PP unit root tests indicate that Tether (LUSDT), Gross Domestic Product (GDP), and the market sentiment index (LVIX) are stationary at level, while other variables achieve stationarity when first differences are taken. However, while the inflation rate (CPI) remains stationary at level for both the US and Germany in both tests, it appears that for the UK, after taking first differences, it meets the stationarity condition, indicating that it is not stationary at level. In Table 2, the results of the ADF and PP unit root tests for the USA and Germany indicate that the LUSDT, GDP, CPI, and VIX indices do not contain a unit root, meaning they are stationary at level, while the other variables do contain a unit root, indicating they are non-stationary. The results of the ADF and PP unit root tests for England indicate that the LUSDT, GDP, and VIX indices do not contain a unit root, meaning they are stationary at level, while the other variables do contain a unit root, indicating they are non-stationary. Since some of the variables are stationary at level and others become stationary after taking their first differences, the cointegration relationship among them can be examined using the ARDL bounds test.

5.2. Results of the ARDL Bound Test

In the second step, the existence of a cointegration relationship between the series was determined according to the F statistic, and the test results are presented in Table 3. The F statistic calculated for the model is compared with the significance levels asymptotically derived by Pesaran et al. (2001). If the F statistic value is greater than the critical upper limit, it can be said that there is a cointegration relationship; if the F statistic value is less than the critical lower limit, it can be concluded that there is no cointegration relationship. If the F-statistic is between the critical threshold values, the result is inconclusive. In this case, according to Banerjee et al. (1998) the significance of the error correction term is examined to determine the cointegration relationship.

Table 3. F Statistical Test Results

Country	Variables	F-Statistics	Critical Values
USA	(LSM LBTC, LEHT, LUSDT, IR, CPI, GDP, LVIX)	-3.770	%1 %5 %10
Germany	(LSM LBTC, LEHT, LUSDT, IR, CPI, GDP, LVIX)	-4.298	(-3.614) (-2.944) (-2.606)
UK	(LSM LBTC, LEHT, LUSDT, IR, CPI, GDP, LVIX)	-4.174	

Table 3 presents the F statistic value for the three countries included, along with the critical values that will be compared to this value. There is a long-term cointegration relationship among the variables, as the F statistic value for the three countries is greater than the upper limit of the critical value. After identifying the long-term cointegration relationship among the variables, it is necessary to determine the appropriate lag length for the ARDL bounds test. According to the Akaike Information Criterion (AIC), the ARDL (2, 2, 2, 2, 2, 2, 2, 2) model specification has been adopted and is presented in Table 4.

Table 4. ARDL (2, 2, 2, 2, 2, 2, 2, 2) Bounds Test Results (UK)

Variable	Coefficient	Std. Error	t-Statistic	p-value
LSM (L1)	0.4045593	0.2186482	1.85	0.101
LSM (L2)	0.108837	0.2254596	0.48	0.642
LBTC (L1)	0.0702933	0.0511425	1.37	0.207
LBTC (L2)	-0.0339511	0.0507252	-0.67	0.522
LEHT (L1)	-0.0089177	0.0297902	-0.30	0.772
LEHT (L2)	0.0584965	0.0320834	1.82	0.106
LUSDT (L1)	-0.001428	0.0008709	-1.64	0.140
LUSDT (L2)	-0.0011876	0.0008825	-1.35	0.215
IR (L1)	0.0245796	0.0123521	1.99	0.082
IR (L2)	-0.0093516	0.0068837	-1.36	0.211
CPI (L1)	-0.001112	0.0014646	-0.76	0.469
CPI (L2)	0.0024311	0.001756	1.38	0.204
GDP (L1)	-0.002195	0.0006132	-3.58	0.007
GDP (L2)	-0.000478	0.000372	-1.28	0.235
LVIX (L1)	0.010739	0.0150703	0.71	0.496
LVIX (L2)	0.003944	0.0110625	0.36	0.731
Cons	1.066966	0.4589079	2.33	0.049
R^2 = 0.8898			Adjusted R^2 = 0.8603	
S. S. E.= 0.00101037			F (23, 8) = 33.59 (0.000)	
LM Test= 2.258 (0.1329)			AIC=-302.5217	
Jargu-e Bera= 2.673 (0.2627)			Ramsey= 0.28 (0.8372)	

According to the ARDL boundary test presented in Table 4, when diagnostic tests are examined the model generally fits well, there is no significant autocorrelation or specification error, and the error terms are normally distributed. These results indicate that the ARDL (2, 2, 2, 2, 2, 2, 2, 2) model is appropriate and valid. After obtaining findings regarding the robustness of the model through diagnostic tests, the next step has been to interpret the ARDL bounds test coefficients for short-term and long-term relationships. Table 5 presents the long-term coefficient test and results of the ARDL model for the UK economy.

Table 5. Results of the Long-Term Coefficient Test of the ARDL Model (UK)

Variable	Coefficient	Std. Error	t-Statistic	p-value
LSM= f (LBTC LEHT LUSDT IR GDP CPI VIX)				
Bitcoin (LBTC)	-.003534	.0771618	-0.005	0.965
Ethereum (LETH)	-.0000512	.0301254	-0.00	0.999
Tether (LUSDT)	-.0045726	.0034023	-1.34	0.216
Interest Rate (IR)	-.0063149	.0020521	-3.077	0.005***
GDP (GDP)	-.0041544	.0016475	-2.52	0.036**
Inflation Rate (CPI)	.0006094	.0014988	0.41	0.695
Market Sentiment (LVIX)	-0,027563	.0117164	-2.35	0.047**

***, ** indicate significance at the 1% and 5% levels respectively.

According to Table 5, long-term effects of cryptocurrency markets on the FTSE 100 (FTSE) index are negative, but not statistically significant. Based on this result, the H_1, H_2, and H_3 hypotheses are not supported. There is a statistically significant and negative relationship between the interest rate and the FTSE 100 (FTSE) index at a 1% significance level among macroeconomic variables. 1% increase in the interest rate causes approximately a 0.063% decrease in the FTSE 100 (FTSE) index. Similarly, there is a statistically significant and negative relationship between GDP and the FTSE 100 (FTSE) index at a 5% significance level. 1% increase in GDP leads to an approximate 0.042% decrease in the FTSE 100 (FTSE) index. There is a positive but statistically insignificant relationship between the inflation rate and the FTSE 100 (FTSE) index among macro variables. There is a statistically significant and negative relationship between the market sentiment index and the FTSE 100 (FTSE) index at a 5% significance level. 1% increase in the VIX can be said to cause an approximate 0.028% decrease in the FTSE 100 (FTSE) index. The next step of predicting the short-term relationship was undertaken, and the results are presented in Table 6.

Table 6. Results of the Short-Term Coefficient Test of the ARDL Model (UK)

Variable	Coefficient	Std. Error	t-Statistic	p-value
LBTC (D1)	0.0394778	0.0371669	1.06	0.295
LETH (D1)	0.0278815	0.0140647	1.98	0.055
LUSDT (D1)	0.0003379	0.0005223	0.65	0.522
IR (D1)	0.0019125	0.0045986	0.42	0.680
LGDP (D1)	-0.0004421	0.000268	-1.65	0.108
CPI (D1)	0.0012021	0.0010562	1.14	0.263
LVIX (D1)	-0.0255468	0.0082558	-3.09	0.004
Ecm (-1)	-0.149805	0.0629897	-2.38	0.023
Cons	-0.3271242	0.1373697	2.37	0.023
R^2 = 0.4824			Adjusted R^2 = 0.3674	
S. S. E.= 00049155			F (8, 36) = 4.19 (0.0013)	
LM Test= 0.286 (0.5931)			AIC=-368.4034	
Jargu-e Bera= 2.673 (0.2627)				

According to Table 6, the model is generally significant and explains 48.24% of the variance of the dependent variable, LSM, through the independent variables. The overall significance test of the model (F-test) indicates that the independent variables in the model collectively explain the dependent variable in a significant manner. The Prob > F (0.0013) indicates the significance level of the model, and since the p-value is less than 0.05, it can be said that the model is significant. Among the short-term variables, only the change in the VIX index (LVIX) has a significant effect. The short-term effects of the other variables are not significant. Since the error correction term is negative and significant ($p < 0.05$), this indicates that the model has returned to long-term equilibrium and that short-term deviations have been corrected.

For the German economy, the model specification ARDL (1, 2, 0, 1, 0, 1, 1, 0) has been adopted according to the Akaike Information Criterion (AIC) and is presented in Table 7.

Table 7. ARDL (1, 2, 0, 1, 0, 1, 1, 0) Bounds Test Results (Germany)

Variable	Coefficient	Std. Error	t-Statistic	p-value
LSM (L1)	0.4316077	0.0793046	5.44	0.000
LBTC (L1)	0.1139274	0.0375526	3.03	0.007
LBTC (L2)	-0.0910773	0.0341124	-2.67	0.016
LEHT	-0.0119855	0.0120623	-0.99	0.334
LUSDT (L1)	-0.0012327	0.0006999	-1.76	0.095
IR	0.0002305	0.000486	0.47	0.641
CPI (L1)	0.0026055	0.0011336	2.30	0.034
GDP (L1)	0.0010742	0.0005886	1.83	0.085
LVIX	-0.0392135	0.006387	-6.14	0.000
Cons	1.204493	0.1720827	7.00	0.000
R^2 = 0.9792			Adjusted R^2 = 0.9642	
S. S. E.= .0009085			F (13, 18) = 65.22 (0.000)	
LM Test= 2.103 (0.1471)			AIC= -289.8938	
Jargu-e Bera= 3.057 (0.2169)			Ramsey= 0.07 (0.9755)	

The model generally fits well, there is no significant autocorrelation or specification error and the error terms are normally distributed. These results indicate that the ARDL (1, 2, 0, 1, 0, 1, 1, 0) model is appropriate and valid. After obtaining findings regarding the robustness of the model through diagnostic tests, the next step has been to interpret the ARDL bounds test coefficients for short-term and long-term relationships. Table 8 presents the long-term coefficient test and results of the ARDL model for the German economy.

Table 8. Results of the Long-Term Coefficient Test of the ARDL Model (Germany)

Variable	Coefficient	Std. Error	t-Statistic	p-value
LSM= f(LBTC LEHT LUSDT IR GDP CPI VIX)				
Bitcoin (LBTC)	-0.0997815	0.0510178	-1.96	0.066*
Ethereum (LETH)	-0.0210867	0.0215131	-0.98	0.340
Tether (LUSDT)	-0.0029087	0.0015313	-1.90	0.074*
Interest Rate (IR)	0.0004056	0.0008252	0.49	0.629
GDP(GDP)	-0.0000722	0.0014871	-0.05	0.962
Inflation Rate (CPI)	0.0055726	0.0025348	2.20	0.041**
Market Sentiment (LVIX)	-0.0689902	0.0148416	-4.65	0.000***

***, **, * indicate significance at the 1%, 5% and 10% levels, respectively.

The long-term effect of LBTC and LUSDT from the cryptocurrency markets on the DAX (GDAXI) index is negative and statistically significant at the 10% significance level. 1% increase in LBTC can be said to cause an approximately 0.998% decrease in the DAX (GDAXI) index. Similarly, a 1% increase in LUSDT can be said to cause an approximately 0.0029% decrease in the DAX (GDAXI) index. Based on these results, H_1 and H_3 hypotheses are not supported, while H_2 hypothesis is supported. The long-term effect of the LETH variable on the DAX (GDAXI) index is negative, but it is not statistically significant. There is a positive but statistically insignificant relationship between the interest rate and the DAX (GDAXI) index among macroeconomic variables. Similarly, the long-term effect of the GDP variable on the DAX (GDAXI) index is negative, but it is not statistically significant. There is a statistically significant and positive relationship between the inflation rate and the DAX (GDAXI) index at a 5% significance level. 1% increase in interest rates leads to an approximate 0.0056% increase in the DAX (GDAXI) index. It is observed that there is a statistically significant and negative relationship at the 1% significance level between the market sentiment index and the DAX (GDAXI) index. 1% increase in the VIX can be said to cause an approximately 0.069% decrease in the DAX (GDAXI) index. The next step of predicting the short-term relationship has been undertaken, and the results are presented in Table 9.

Table 9. Results of the Short-Run Coefficient Test of the ARDL Model (Germany)

Variable	Coefficient	Std. Error	t-Statistic	p-value
LBTC (D1)	0.0362913	0.0373502	0.97	0.338
LETH (D1)	0.0139885	0.0141212	0.99	0.328
LUSDT (D1)	0.0000945	0.000552	0.17	0.865
IR (D1)	-0.0012756	0.0048884	-0.26	0.796
LGDP (D1)	-0.0005355	0.0006144	-0.87	0.389
CPI (D1)	0.0002249	0.0008143	0.28	0.28
LVIX (D1)	-0.0463658	0.0079672	-5.82	0.000
Ecm (-1)	-0.4014965	0.1365207	-2.94	0.006
Cons	0.000116	0.0006431	0.18	0.858
R^2 = 0.6258			Adjusted R^2 = 0.5427	
S. S. E.= .000512485			F (8, 36) = 7.53 (0.0000)	
LM Test= 0.004 (0.9508)			AIC= -366.5268	
Jargu-e Bera= 3.57 (0.2169)				

Model is generally significant and explains 62.58% of the variance of the dependent variable, LSM, through the independent variables. The overall significance test of the model (F-test) indicates that the independent variables in the model collectively explain the dependent variable in a significant manner. The Prob > F (0.0000) indicates the significance level of the model, and since the p-value is less than 0.05, it can be said that the model is significant. Among the short-term variables, only the change in the VIX index (LVIX) has a significant effect. The short-term effects of the other variables are not significant. Since the error correction term is negative and significant ($p < 0.05$), this indicates that the model has returned to long-term equilibrium and that short-term deviations have been corrected.

Table 10. ARDL (1,0,0,0,2,0,0,1) Bounds Test Results (USA)

Variable	Coefficient	Std. Error	t-Statistic	p-value
LSM (L1)	0.627399	0.1290389	4.86	0.000
LBTC	0.0833226	0.0239017	3.49	0.002
LEHT	-0.0146082	0.0069973	-2.09	0.050
LUSDT	-0.0004253	0.0004845	-0.88	0.391
IR (L1)	-0.0095088	0.0053431	-1.78	0.090

Table 10. Continued

IR (L2)	**0.0062693**	**0.0022004**	**2.85**	**0.010**
CPI	0.0039073	0.0022845	1.71	0.103
GDP	0.0003338	0.000162	2.06	0.053
LVIX (L1)	0.0173732	0.0090183	1.93	0.068
Cons	0.7170738	0.2694329	2.66	0.015
R^2 = 0.9837			Adjusted R^2 = 0.9747	
S. S. E.= .00009965			F (13, 20) = 109.43 (0.000)	
LM Test= 0.267 (0.6056)			AIC= -290.9335	
Jargu-e Bera= 3.812 (0.1487)			Ramsey= 1.11 (0.3733)	

For the US economy, according to the Akaike Information Criterion (AIC), the ARDL (1, 0, 0, 0, 2, 0 ,0, 1) model specification has been adopted and is presented in Table 10. The model generally fits well, there is no significant autocorrelation or specification error, and the error terms are normally distributed. These results indicate that the ARDL (1, 0, 0, 0, 2, 0, 0, 1) model is appropriate and valid.

Table 11. Results of the Long-Term Coefficient Test of the ARDL Model (USA)

Variable	Coefficient	Std. Error	t-Statistic	p-value
LSM= f(LBTC LEHT LUSDT IR GDP CPI VIX)				
Bitcoin (LBTC)	0.2236243	0.0570547	3.92	0.001***
Ethereum (LETH)	-0.039206	0.0237402	-1.65	0.114
Tether (LUSDT)	-0.0011413	0.0013467	-0.85	0.407
Interest Rate (IR)	0.0014183	0.0008354	1.70	0.105
GDP(GDP)	0.0008957	0.0004696	1.91	0.071*
Inflation Rate (CPI)	0.0104865	0.0057765	1.82	0.084*
Market Sentiment (LVIX)	-0.0398953	0.0160721	-2.48	0.022**

***, **, * indicate significance at the 1%, 5% and 10% levels, respectively.

Table 11 presents the long-term coefficient test and results of the ARDL model for the U.S. economy. The long-term effect of LBTC on the DOW JONES Index (DJI) in the cryptocurrency markets is positive and statistically significant at the 1% significance level. 1% increase in LBTC leads to an approximately 22% increase in the DOW JONES Index (DJI). Based on this result, the H_1 hypothesis is supported, but the H_2 and H_3 hypotheses are not supported. The long-term effect of LEHT and LUSDT on the DOW JONES Index (DJI) appears to be negative, but it is not statistically significant. It appears that there is a positive but statistically insignificant relationship between the interest rate and the DOW JONES Index (DJI) among macroeconomic variables. The long-term effect of the GDP variable on the DOW JONES Index (DJI) is positive and statistically significant at the 10% significance level. 1% increase in GDP can be said to cause an approximate 0.0009% increase in the DOW JONES Index (DJI). Similarly, the long-term effect of the IR variable on the DOW JONES Index (DJI) is positive and statistically significant at the 10% significance level. 1% increase in IR can be said to cause an approximate 0.010% increase in the DOW JONES Index (DJI). There is a statistically significant and negative relationship at the 5% significance level between the market sentiment index and the DOW JONES Index (DJI). 1% increase in the VIX can be said to cause an approximate 0.040% decrease in the DOW JONES Index (DJI).

Table 12. Results of the Short-Term Coefficient Test of the ARDL Model (USA)

Variable	Coefficient	Std. Error	t-Statistic	p-value
LBTC (D1)	.0534796	.0271335	1.97	0.056
LETH (D1)	.0003057	.0104112	0.03	0.977
LUSDT (D1)	-.0000949	.0004186	-0.23	0.822
IR (D1)	.0043794	.0016079	2.72	0.010
LGDP (D1)	-.0000993	.0001273	-0.78	0.440
CPI (D1)	.0015277	.002062	0.74	0.464
LVIX (D1)	-.0371533	.0056241	-6.61	0.000
Ecm (-1)	-.2548135	.1078115	2.36	0.024
Cons	.0003251	.0004258	0.76	0.450
R^2 = 0.7302			Adjusted R^2 = 0.6703	
S. S. E.= .00024294			F (8, 36) = 12.18 (0.0000)	
LM Test= 0.029 (0.8645)			AIC= -400.1159	
Jargu-e Bera= 3.812 (0.1487)				

The estimation results of the short-term relationship are presented in Table 12. The model is generally significant and explains 73.02% of the variance of the dependent variable, LSM, through the independent variables. The overall significance test of the model (F-test) indicates that the independent variables in the model collectively explain the dependent variable in a significant manner. The Prob > F (0.0000) indicates the significance level of the model, and since the p-value is less than 0.05, it can be said that the model is significant. Only the change in the VIX index (LVIX) has a significant effect. The short-term effects of the other variables are not significant. Since the error correction term is negative and significant ($p < 0.05$), this indicates that the model has returned to long-term equilibrium and that short-term deviations have been corrected. Table 13 shows whether the hypotheses are supported or not.

Table 13. Summary Table of Hypothesis Status

Country	Hypothesis	Status
USA	H_1: Bitcoin has a significant impact on the stock market return index.	Supported
	H_2: Ethereum has a significant impact on the stock market return index.	Not Supported
	H_3: Tether has a significant impact on the stock market return index.	Not Supported
UK	H_1: Bitcoin has a significant impact on the stock market return index.	Not Supported
	H_2: Ethereum has a significant impact on the stock market return index.	Not Supported
	H_3: Tether has a significant impact on the stock market return index.	Not Supported
Germany	H_1: Bitcoin has a significant impact on the stock market return index.	Supported
	H_2: Ethereum has a significant impact on the stock market return index.	Not Supported
	H_3: Tether has a significant impact on the stock market return index.	Supported

6. Conclusion and Discussion

The aim of this study is to analyze the effects of cryptocurrency markets, particularly major cryptocurrencies such as Bitcoin, Ethereum, and Tether, on traditional financial markets. For this purpose, monthly data for the period from April 2016 to June 2024 has been selected for the economies of the USA, Germany, and the UK. The ARDL boundary test has been utilized in the analysis of the data. When examining the short-term results of the ARDL test, the error correction term is negative and significant ($p < 0.05$), indicating that the models return to long-term equilibrium and that short-term deviations are corrected. All models meet the normality condition, that the explanatory power of the models is at a high level, and that there is no issue of autocorrelation. The limitations of the study include the inclusion of only the top three cryptocurrencies by market capitalization to represent the cryptocurrency market, while other altcoins were not included. Another limitation is that the study only covers a specific time period (April 2016-June 2024). Because examining different time zones can yield different results.

The ARDL boundary test long-term results indicate that Bitcoin, Ethereum, and Tether do not have significant effects on the traditional financial markets of the UK. This result is similar to the findings of existing literature; Döger Toprak and Kubar (2023), Gil-Alana et al., (2020), Kılıç and Çütcü (2018), Dirican and Canöz (2017), and Baek and Elbeck (2015). None of the hypotheses are supported for the UK economy. It is believed that the lack of impact of Bitcoin, Ethereum, and Tether on the traditional financial markets of the UK is due to market fragmentation, investor confidence and perception, market maturity, macroeconomic factors, speculation, and the influence of short-term movements. England's traditional financial markets are largely influenced by macroeconomic factors and global financial developments. Macroeconomic variables such as interest rates, GDP, and market sentiment indices have significant effects on the FTSE 100 (FTSE) index. The interest rate (IR) has a significant and negative effect on the FTSE 100 (FTSE) index. Accordingly, the interest rate negatively affects operating costs, thereby impacting company profitability and, consequently, stock prices. It is observed that the Gross Domestic Product (GDP) has a significant and negative impact on the FTSE 100 (FTSE) index. The declining GDP suggests that economic growth is slowing and that company revenues are falling, which negatively impacts stock prices. Once again, it is observed that the market sentiment index (VIX) has a significant and negative impact on the FTSE 100 (FTSE) index. The high levels of this VIX index reflect the increasing uncertainty and risk perception in the markets. According to this conclusion, it is believed that it has negatively affected the FTSE 100 (FTSE) index by causing investors to behave more cautiously and leading to an increase in stock sales. These findings are consistent with theoretical expectations and validate the effects of macroeconomic variables on financial markets. In particular, the negative effects of interest rates and the market sentiment index on the FTSE 100 (FTSE) index highlight the importance of market conditions on investor behavior. The negative effect of GDP demonstrates the impact of economic growth on financial markets.

Test results for the German economy, shows that in the long term, Bitcoin and Tether have significant effects on traditional financial markets. This has revealed that the volatility of cryptocurrency markets has a significant impact on traditional market returns. These effects are negative. This result is similar to the findings in the literature by Thaker and Mand (2021), Korkmazgöz et al. (2022), Çıkrıkçı and Özyeşil (2019), Tiwari et al. (2019), and Georgoula et al. (2015), indicating that cryptocurrencies are increasingly playing an important role in the traditional financial system. In particular, the impact of the price movements of Bitcoin and Tether on the DAX (GDAXI) illustrates how cryptocurrencies have changed investor behavior. Hovewer the German economy, hypotheses H_1 and H_3 are supported, while hypothesis H_2 is not supported. The effect of Ethereum on the DAX (GDAXI) index is negative, but it is not statistically significant. Similarly, the analysis results indicate that the inflation rate (CPI) and the market sentiment index have significant effects on the DAX (GDAXI) index. The impact of the inflation rate on the DAX (GDAXI) index is significant and positive. The increase in the inflation rate generally allows companies to raise the prices of their products and services. These price increases can boost companies' revenues and profit margins, which can drive stock prices up. Thus, increases in the inflation rate are believed to positively affect the stock prices of companies listed on the DAX (GDAXI) index. Similarly, during periods of high inflation, investors typically turn to investments that will increase nominal returns. Stocks are generally considered assets that provide returns above inflation. This situation leads to an increase in demand for stocks as inflation rises, and consequently, the DAX (GDAXI) index is expected to rise. It appears that the market sentiment index (VIX) has a significant and negative impact on the DAX (GDAXI) index. The high levels of this VIX index reflect the increasing uncertainty and risk perception in the markets. Investors are behaving more cautiously and that the increase in stock sales has negatively affected the DAX (GDAXI) index. These findings particularly highlight the importance of market conditions on investor behavior, especially the positive effects of the inflation rate on the DAX (GDAXI) index and the negative effects of the market sentiment index on the DAX (GDAXI) index.

Test results for the US economy, highlights that Bitcoin has a significant impact on traditional financial markets in the long run. This effect is statistically significant and positive. Bitcoin's volatility has a significant impact on traditional market returns. This result is consistent with the findings in the literature; it shows similarities with the studies of Toudas et al., (2024), Mgadmi et al., (2023), Tosin-Amos (2023), Demir (2022), Thaker and Mand (2021), and Hung (2021), indicating that cryptocurrencies are increasingly playing an important role in the traditional financial system. For the US economy, hypothesis H_1 is supported, but hypotheses H_2 and H^3 are not supported. The impact of Ethereum and Tether on the DOW JONES (DJI) index is negative, but it is not statistically significant. Bitcoin has a more significant impact on traditional markets, while the effects of Ethereum and Tether are more limited. These findings suggest that Bitcoin may be an important factor influencing risk perception in traditional markets, while the effects of other cryptocurrencies appear to be less pronounced. Similarly, the analysis results show that macroeconomic variables such as the inflation rate (CPI), GDP, and the market sentiment index have significant effects on the DOW JONES (DJI) index. The inflation rate and GDP have a significant and positive effect on the DOW JONES (DJI) index. The increase in the inflation rate generally allows companies to raise the prices of their products and services. These price increases can boost companies' revenues and profit margins, which can drive stock prices up. For this reason, increases in the inflation rate are believed to positively affect the stock prices of companies listed in the DOW JONES (DJI) index. Similarly, during periods of high inflation, investors typically turn to investments that will increase nominal returns. Stocks are generally considered assets that provide returns above inflation. This situation leads to an increase in demand for stocks as inflation rises, and consequently, the DAX (GDAXI) index is expected to rise. The significant and positive effect of GDP on the DOW JONES (DJI) index indicates that economic growth and the financial health of companies have a favorable reflection in the stock markets. High GDP growth usually increases companies' profits, which can lead to a rise in stock prices. Strong GDP growth provides investors with expectations of economic stability and growth. This situation may lead investors to take on more risk and increase their stock investments, which could consequently cause the DJIA to rise. Positive GDP growth creates an attractive market environment for international investors. Investors may prefer to invest in a growing economy, which can increase the value of indices like the DJIA. It appears that the market sentiment index (VIX) has a significant and negative impact on the DAX (GDAXI) index. The high levels of this VIX index reflect the increasing uncertainty and risk perception in the markets. Investors are behaving more cautiously and that the increase in stock sales has negatively affected the DAX (GDAXI) index. These findings particularly highlight the importance of market conditions on investor behavior, especially the positive effects of the inflation rate on the DAX (GDAXI) index and the negative effects of the market sentiment index on the DAX (GDAXI) index.

These findings provide significant insights for policymakers, investors, and market analysts. Overall, the limited impact of cryptocurrencies on traditional financial markets for the UK economy necessitates a careful consideration of these assets in investment strategies. Clarifying the regulatory frameworks for cryptocurrencies and increasing market maturity could make the impact of these assets on financial markets more evident. Similarly, it is important to develop regulatory frameworks and ensure financial stability, considering the significant impact of cryptocurrencies on traditional financial markets, especially for the economies of the USA and Germany. Raising investor awareness, increasing academic research, and developing risk management strategies will be beneficial. Monitoring interest rates, GDP, inflation, and the market sentiment index closely can help optimize investment decisions. In this regard, it is suggested that more conscious and strategic approaches be adopted in financial markets. As a result, considering the volatility of cryptocurrencies, financial regulators should impose stricter regulations on these markets. Investors should consider the high volatility of cryptocurrencies while diversifying their portfolios. In this way, both the stability of the markets can be ensured and the risks faced by investors can be minimized.

Future research should examine the effects of cryptocurrencies in different geographical regions. The long-term effects of cryptocurrencies on other financial asset classes should be investigated. Studies should examine the effects of cryptocurrencies comparatively across different countries and markets. This can reveal the regional differences in the effects of cryptocurrencies and allow for universal conclusions to be drawn. It should examine the effects of cryptocurrencies on different sectors and determine which sectors are more affected. This can help in developing more specific strategies on a sectoral basis. Future studies should examine the effects of cryptocurrencies on traditional financial markets during extraordinary periods such as economic crises and market collapses. This can reveal the role of cryptocurrencies during times of crisis and their potential protective functions.

Research and Publication Ethics Statement

In this study, which did not require ethics committee approval and/or legal/private permission, complied with research and publication ethics.

Researcher's Contribution Rate Statement

I am a single author of this paper. My contribution is 100%.

Researcher's Conflict of Interest Statement

There is no potential conflicts of interest in this study.

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