Research Article

Comparative Evaluation of Share Values of Five Magnificent Technology Companies with Bitcoin and Gold Prices

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Abstract: Especially new generation investors may prefer to use stocks of popular companies that use advanced technologies and cryptocurrencies as investment instruments. Gold, one of the classical investment instruments, still maintains its place among the commodity assets in the portfolios of investors around the world. These asset groups were evaluated in this study. As the first group investment tool, decacorn and hectocorn technology companies called the new generation the magnificent five; Company stock returns of Apple, Microsoft, Amazon, Alphabet, Nvidia Corporation and Tesla were analyzed. In addition, as the second financial asset, cryptocurrencies, which are used as investment instruments as well as being used in daily life with the evolution of technology, and Bitcoin (BTC), which remains popular among these cryptocurrencies, were the subject of the study. Finally, the study evaluated gold mines, one of the world's oldest valuable investment instruments, compared with other financial assets. The study examined the magnificent five stocks, BTC and gold ounce prices between the periods of 2020:01 and 2023:12, using mutual cointegration, vector error correction (VEC) and Granger causality analyses. Findings of the study; Short-term shocks caused by variables in BTC stabilise after about a month. In this process, as NVDA shares increase, BTC value decreases, and as gold value increases, BTC value increases.

Anahtar Kelimeler: Magnificent five, BTC, Gold, Cointegration, Granger causality analysis
Jel Kodları: F30, G15, O14

Muhteşem Beşli Teknoloji Şirketlerinin Hisse Değerleri ile Bitcoin ve Altın Fiyatlarının Karşılaştırmalı Değerlendirmesi

Öz: Özellikle yeni nesil yatırımcılar, ileri teknolojilerin kullanıldığı popüler şirketlerin hisse senetleri ile kripto paraları yatırım aracı olarak kullanmayı tercih edebilmektedirler. Klasik yatırım araçlarından olan altında hâlâ dünya genelinde yatırımcıların portföylerinde yer alan emtia varlıklar arasında yerini korumaktadır. Bu çalışmada bu varlık grupları değerlendirilmiştir. İlk grup yatırım aracı olarak; yeni nesil muhteşem beşli olarak adlandırılan decacorn ve hectocorn teknoloji şirketleri; Apple, Microsoft, Amazon, Alphabet, Nvidia Corporation ve Tesla şirket hisse değeri getirileri analiz edilmiştir. Ayrıca ikinci finansal varlık olarak çalışmada, günümüzde teknolojinin evrimi ile birlikte gündelik hayatta kullanılmanın yanı sıra yatırım aracı olarak da değerlendirilen kripto paralar ve bu kripto paralar arasında popülerliğini koruyan Bitcoin (BTC) çalışmaya konu edilmiştir. Çalışmada son olarak dünyanın en eski kıymetli yatırım araçlarından olan altın madeni diğer finansal varlıklarla karşılaştırmalı değerlendirilmiştir. Çalışma, 2020:01 ile 2023:12 dönemleri arasında muhteşem beşli hisse senetleri, BTC ve altın ons fiyatı karşılıklı olarak eşbütünleşme, vektör hata düzeltmeli (VEC) ve Granger nedensellik analizlerinden yararlanılarak incelenmiştir. Çalışmanın bulguları; değişkenlerin BTC'de meydana getirdiği kısa dönemli şoklar yaklaşık bir ay sonra dengeye gelmektedir. Bu süreçte NVDA hisseleri artış gösterdikçe BTC değeri düşmekte, altın değeri arttıkça BTC değeri de artmaktadır.

Keywords: Muhteşem beşli, BTC, Altın, Eşbütünleşme, Granger nedensellik analizi
Jel Codes: F30, G15, O14

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1. Introduction

As can be traced in the history of finance, the East India Company, the South Sea Company, the Mississippi Company and the Dot.com companies of the XVII century. Investing in tulips was considered profitable and popular in the Netherlands in the 19th century and investing in such company stocks and/or assets attracted the attention of investors for sociological and psychological reasons other than making profits. In the past, investors sometimes made their investment choices in line with the investment choices made by aristocrats and prominent people in society to be close to situations and trends that could provide them with prestige. Nowadays, as technology is developing rapidly, investment preferences are also changing and behavioural finance theories continue to be realized (Keskin, 2024, p. 296-299).

Due to the increasing cross-border movements of commodities, services, technology and capital in global markets, financial and commodity markets have become more integrated, and this has caused prices in the markets to move together (Pandey & Vipul, 2017, p. 426). In a world that is constantly changing with technology, markets are also developing and changing very rapidly. XX. The internet, which was invented at the beginning of the century and has been widely available to people since the early 1990s, is a dynamic element with a sectoral dimension. It has attracted a lot of attention from internet-based companies and has taken its place among the most invested areas of all time. Now in our lives; New expressions such as investing in unicorn, decacorn and hectocorn[1] companies have started to appear. New-generation investment preferences include companies that use and produce high technology. These companies are Apple (AAPL), Amazon (AMZN), Alphabet (GOOG/GOOGL), Nvidia Corporation (NVDA) and Tesla (TSLA). The so-called "Magnificent Five" companies are among the five largest companies in the technology industry by their value. The interest in these US-based multinational technology companies is not limited to the products they produce, but their publicly traded stocks are also attractive investment instruments for investors. The stocks of the technology companies called the Magnificent Five, are listed in the Nasdaq100 and S&P 500 index on the National Association of Securities Dealers Automated Quotations (Nasdaq) stock exchange.

In addition to the stocks of high-tech companies, BTC cryptocurrency, which has taken its place in human history as a product of technology, has become an asset that attracts attention all over the world with blockchain technology and has taken its place among the interesting investment instruments of this century, not only as a medium of exchange but also as an investment tool.

Gold, which has been defined as a haven in all periods and is a classic investment tool with its universal demand, has been used in trade and as a reserve tool in many cultures throughout history since ancient times, due to its attractiveness and scarcity of supply. During the Gold Monetary System period, it formed the basis of the international monetary system. In later periods, gold was preferred as an investment instrument because it was accepted all over the world and was seen as a sheltered haven for safe investments, being away from economic risks related to state policies. Its historical performance has confirmed gold as one of the safe investments. However, in the new hyperreality era and digital world, the gold mine is an important commodity in diversifying investment portfolios, although its rate among investor preferences has decreased.

In the literature review conducted within the scope of this study, it was seen that; although there are studies on commodities, stock markets and cryptocurrencies from multiple perspectives, there are no studies that make a comparative evaluation of the new-generation companies called the magnificent five, the new generation cryptocurrencies and gold, one of the classic investment instruments. In this context, in this study, it was

[1] Ventures with a value over 1 billion US dollars are called unicorns, startups with a value over 10 billion US dollars are called decacorns, and startups with a value over 100 billion US dollars are called hectocorn ventures.

deemed worth examining the comparative effect of new generation companies, which are products of information technologies, and BTC, which is the first of the cryptocurrencies and has the highest market value, due to the demand for gold from past to present and its use as an investment tool in the financial system. In this context, after the introduction, which constitutes the first part of the article, the theoretical framework and literature studies are evaluated in the second part. In the third section, the study analysis and empirical findings are summarized. Finally, the section containing the results and recommendations is organized.

2. Conceptual Framework

2.1. The Magnificent Five Companies

As the world's largest technology companies transform our living standards with innovative products and innovative business models, they continue to be among the world's most valuable companies on a global scale. As studies on artificial intelligence in technology continue to increase, artificial intelligence and jeep etc. are in the markets. Interest in the shares of companies specializing in high-tech fields, such as, is increasing. A centre of attraction for investors; it can be seen from the stock market data that the interest in the shares of the technology companies called the magnificent five, including Apple, Amazon, Alphabet, Nvidia Corporation and Tesla, has increased.

Apple was founded by Steve Jobs, Steve Wozniak and Ronald Wayne on April 1, 1976, and is headquartered in Cupertino; is a multinational company that designs, develops and sells consumer electronics, computer software and personal computers (US Apple Store, 2024). Amazon was founded by Jeff Bezos on July 5, 1994. It was founded in Bellevue, Washington. While the company was first an online marketplace selling books, over time it has become an American multinational technology company focusing on e-commerce, cloud computing, digital streaming[2] and artificial intelligence (Lotz, 2018). Alphabet is a multinational conglomerate founded in 2015 to bring Google and other Google-owned companies under one roof. It is a technology company headquartered in Mountain View, California. Within the company, there are Google, Calico, GV, CapitalG, X Development, Google Fiber, Google Nest, Deep Mind, Intrinsic, Isomorphic Labs, Verily, Waymo and Wing. Nvidia is a technology company based in Santa Clara, California, founded in 1993 by Jen Hsun Huang, Chris Malachowsky and Curtis Priem. Company operates in the gaming, game consoles, professional visualization, data centers and automotive sectors. Tesla is a company based in Austin, Texas, USA, which produces electric luxury cars, automotive components and renewable energy storage systems, founded in 2003 by Martin Eberhard, Elon Musk, Marc Tarpenning, JB Straubel and Ian Wright. It is publicly traded on the Nasdaq stock exchange, like the other six companies mentioned. is an open technology company.

2.2. Bitcoin (BTC)

Cryptocurrencies are one of the innovations the 21st century has brought to human life. The first cryptocurrency used was Bitcoin. BTC is a non-physical virtual currency. This money name comes from Bit (0,1) and Coin. This virtual money used electronically does not get its power from a financial institution or a state. The BTC production amount is limited to 21 million and was determined during the money programming. Using BTC requires the existence of blockchain technology. The basis behind the rapid spread of BTC in the world is blockchain technology. Satoshi Nakamoto is the creative father of the technology that allows BTC to become widespread and the safe use of money. There is a common opinion that this name does not actually belong to a person but is a pseudonym. Nakamoto developed a theory on multiple spending with the article he wrote in 2008 (Köylü & Köylü, 2017, p. 360-367). BTC, the first cryptocurrency, entered human life with the article titled "Peer-to-peer electronic cash payment system" (Keskin, 2018, p. 815).

[2] It is the gathering of organizations engaged in business in different business lines under a well-known trade name.

Today, cryptocurrency is a new alternative medium of exchange. Contrary to the classical understanding of money as a medium of exchange, the digital economy has begun to attract the attention of investors. Although BTC does not have a market, it can be easily speculated from time to time, and is a commodity with many risks, it is in the portfolios of investors looking for new investment products to obtain high returns. BTC is at the forefront of investment and exchange tools in modern markets.

2.3. Gold and XAUUSD

Throughout history, civilizations have been fascinated by the allure of gold, resulting in a universal demand for gold. Demand combined with scarcity of supply makes gold valuable. In addition, gold has been evaluated in the markets as an investment and reserve instrument due to its features such as being easy to shape, not corroding for long periods, and being conductive. It has become more popular, especially in uncertain periods such as war, environmental disasters, political depressions and economic crises.

Gold has been a safe haven for investors during times of economic and political instability. Today's investors may choose to hold some of their assets in gold while diversifying their portfolios. Gold markets are deep and highly liquid markets. Gold can be used as an investment instrument, as bullion and currency, or as gold-based exchange traded funds.

Although different units of measurement are used in different parts of the world to express the weight of gold, international gold prices are expressed in ounces. There are different types of ounce units. However, the most common uses are avoirdupois ounce and troy ounce. In common international gold price usage, it is expressed in troy ounces. 1 troy ounce is equivalent to 31.103476 grams. The troy ounce unit got its name because it was first used in the town of Troy, France. Due to its practical use in daily life, it is expressed only in ounces. The currencies in which gold prices are priced internationally also vary, but the benchmark price is expressed in US Dollars ($) per ounce. (Köylü & Yücel, 2022, p. 602-603). XAUUSD also shows the value of gold in $. XAU/USD shows how much 1 troy ounce of gold is worth. XAU represents the symbol of gold in global markets. AU is the symbol for gold on the periodic table. In global markets, all financial assets are listed with three letters, and the letter AU is prefixed with the letter X. The symbol showing that gold is indexed to the US dollar was created by using XAU and USD together.

In addition to being used as a reserve, investment and exchange tool, as it has throughout human history, gold maintains its place in investors' portfolios in local and international markets. Investments in gold are generally made to protect against the effects of long-term inflation increases, political risks, crises and to benefit from price fluctuations in the short term (Dirk & McDermott, 2010). Therefore, gold prices have always been closely followed and have taken their place among investment assets.

3. Literature Review

It is possible to evaluate the literature research in three parts. Firstly, studies on the share values of the magnificent five companies were examined, in the second part, studies on BTC, and in the third and last part, studies on gold were examined.

3.1. Examples of Work with The Magnificent Five Companies and Company Values

Since the oldest of the companies known as the Magnificent Five is Amazon, with a founding date of 1994, it is XXI in the studies in the literature. It dates back to the century. Studies on the companies within the group, but not as a group of the Magnificent Five, are available in the literature. Some of these studies are as follows:

In their research, Meador & Gluck (2010) examined stock prices of AAPL, GOOG, AMZN, MSFT, Yahoo, Hershey's, Nike and Under Armor companies in 2010 by using mathematical algorithms by examining tweets about stocks. As a result, a very weak connection was found between Twitter and stock trading algorithms and the reasons for this result were discussed in the study. Vu et al. (2012) in their study; AAPL, GOOG, MSFT and AMZN prepared a model for the comparative relationship between stock prices and consumer sentiment (positive/negative) using the Decision Tree classification of stock prices within 41 market days via Twitter messages. model; AAPL was 75% successful in predicting GOOG daily bullish and bearish changes. Smailović et al. (2012) used Granger analysis on Apple financial tweets to predict future movements of Apple stock prices in 2011 in their research. The study concluded that the rise or fall in the closing price of Apple shares can be predicted two days before the change occurs. Mao et al. (2012) used Twitter, an online social media tool, and tweet messages about stocks such as Apple Inc. and GOOG, between February 16 and May 10, 2012, in their study. The relationship between tweets and stock values was tested with the linear regression analysis method. As a result of the study, it was stated that the number of daily tweets was related to stock market indicators at all levels.

Liu et al. (2019) in their study, AAPL, MSFT and Samsung Electronics Co., Ltd. were included in group I in 2012. While determining the share price values of companies from the news published by Thomson Reuters, II. The group includes GOOG, Boeing Company and Walmart Inc. They created the news about the news from news reports published on CNN. In the study, time series harmony was achieved between 2011-2012 financial news and company trade data. It is stated that the research offers a new method that integrates the knowledge graph embedding technique into stock market forecasting.

In the study of De Almeida (2020), in the period 2000-2018; he examined the performance of Facebook, Apple, Amazon, Alphabet, Netflix and Google companies with the Moving Average Convergence Divergence and the Relative Strength Index, and all applied methods overlapped with market activity in the sample. Raju et al. (2020) have research on which Apple, Microsoft, Intel, IBM and daily stock prices were predicted by using Recursive Neural Networks RNN and Long-Short Term Memory (LSTM) in the period 2012-2018, and it was concluded that LSTM is a more effective method. In their study, Bouktif et al. (2020) predicted the share prices of ten companies listed in Nasdaq-100, including Google, Yahoo, Amazon, Apple, Alibaba, Tesla, Microsoft, IBM, Facebook and Bitcoin, based on investor sentiment with information obtained from Twitter messages in the 2008-2018 period. Stock market prediction was made using causality analysis, algorithmic feature selection and machine learning techniques, and the performance of the model predicted share price movements with 60% accuracy. Ekapure et al. (2021) in their study, Amazon, Apple, Google and Microsoft. They have applied machine/deep learning-based analysis to predict stock value trends. It has been found that the model created by including the years 2014-2019 is powerful in predicting the direction of stock movement.

Wang et al. (2022) in their study, using daily data between July 2011 and September 2021, examined the correlations between AMZN, AAPL, GOOG, Goldman Sachs and IBM stock values traded in the S&P 500 with gray correlation wavelet analysis and found evidence of the co-movement of stocks. However, in his study, Chen (2022) comparatively evaluated Apple and Tesla stock risks between 2017 and 2022 using the CAPM model and suggested that Apple stocks should be preferred for risk-averse investors in the examined period.

Li et al. (2023) used AAPL, GOOG, MSFT and AMZN stock price data to predict future stock prices between 2012-2023. The study reported that the LSTM model was able to determine the increases and decreases in stock price movements and reached the potential to make reasonably accurate predictions. In her study, Guo (2024) examined investor preferences based on the analysis of risk, profitability and market rate for Tesla, Tencent, Microsoft and Apple in the 2022-2023 periods with ratio analysis. Growth rate investors' options are Tesla, Microsoft and Apple, while cash flow investors, it was concluded that they preferred Tesla, Tencent and Microsoft, and index investors and momentum investors chose Microsoft and Apple.

The common features of the studies selected from the literature are studies on the determination of future prices of technology companies and the effects of social media on prices. This research includes a comparative analysis of the value of Bitcoin, another technology product, and gold, one of the classical investment instruments.

3.2. Working Examples on BTC and Markets

Since the topic of BTC and its prices and comparison with financial assets is current and the dependent variable has been analyzed in different studies with different analysis methods and its relationship with different independent variables, selected examples from various studies are presented in Table 1.

Table 1. Table of Literature on BTC

Author	Subject	Data Set Period	Method	Result
Yermack (2013)	While the actual use of Bitcoin as a currency in the USA has been questioned, its relationship with currencies has been examined.	2010-2013	Correlation test	The degree of correlation between Bitcoin and gold, which are the major currencies such as the US dollar, Euro, Swiss Franc and Japanese Yen, is very low.
Glaser et al. (2014)	BTC is an asset on the Mt Gox Bitcoin Exchange It has been discussed whether it is a currency or not.	2011-2013	GARCH model	Bitcoin users use BTC as a currency It was concluded that it was evaluated not as a unit but as an asset for speculative purposes.
Kristoufek (2015)	Determination of market drivers that are effective in determining the price of BTC in China.	2011-2014	Wavelet Coherence Analysis	In determining the price of BTC No market driver can be effective, BTC is a different asset from other investment instruments that are open to speculative features. conclusion has been reached.
Dyhrberg (2015)	BTC hedge in Great Britain The debate about whether it is an instrument or not.	2010-2015	GARCH model	Bitcoin has similar hedging properties as gold instruments, In addition, it acts as a hedging tool for the FTSE 100 index. It was concluded that it can be used as.
Bouoiyour et al. (2015)	BTC in China.	China 2010-2014	Granger Causality analysis	E-commerce transactions and the price of BTC. There is a causal relationship between investor attractiveness.
Carpenter (2016)	Portfolio diversification with BTC.	BTC 2012-2016	The Capital Asset pricing Model (CAPM)	BTC should be included in a certain weight in the portfolio In case the risk incurred is less than the return obtained remains. This situation was characterized by bubble formation and The sudden incident in 2013 Volatility movement has been associated with this situation.
Koçoğlu et al. (2016)	Relationship between BTC exchange and Bitfinex, Bitstamp, Mt.Gox, Okcoin, Kraken, Anx and Coinfloor exchanges.	2014-2015	Johansen Cointegration Granger Causation analysis	BTC has no causal relationship with any exchange.
Eswara (2017)	BTC to Rupee, Pound and Yuan rates The relationship between.	India 2017	GARCH	BTC-Rupee and Dollar positive between exchange rates and negative between sterling and yuan. It was concluded that there was a correlation.
Jin Lim & Masih (2017)	The relationship between the stock index created according to Islamic sharia principles and Bitcoin.	2013-2017	M-GARCH-DCC, Continuous Wavelet Transforms (CWT), and Maximum Overlap Discrete	Share created according to Islamic qualifications The relationship between the stock index and BTC is quite low. As a result, they concluded that BTC can be used as a diversification tool for portfolios created in this index.

			Wavelet Transform (MODWT)	
Moro & Kajtazi (2017)	The impact of BTC in China on the portfolio.	China 2010-2012	Mathematical Analysis	BTC has a very low correlation with traditional investment instruments.
Bağcı & Köylü (2018)	Relationship between gold prices and BTC prices.	2010-2018	Time Series Analysis.	There is interaction between variables.
Şahin (2018)	BTC price prediction.	2012-2018	Artificial Neural Networks Autoregressive Integrated Moving Average (ARIMA)	Between 10.01.2018 and 18.01.2018, the direction and values of the prices predicted by the Artificial Neural Networks model gave more successful results than the ARIMA model.
Philippasa et al. (2019)	Relationship of BTC price with Twitter and Google Trends information.	2016-2018	Granger Causality	BTC prices are partly driven by social networks and media, and investors' emotions. It was concluded that they act with appetite.
Millera et al. (2019)	An automated price model analysis for the BTC currency.	February 2018-March 2018	Spline Non-parametric regression	The results of trading strategies based on working methods are significantly promising and can be used as a reference.
Guizani & Nafti (2019)	To identify the main determinants of BTC price.	2011-2018	VECM, Causality test	There is a one-way causality relationship from negative shocks in BTC price to negative shocks in transaction volume and from positive shocks in transaction volume to positive shocks in prices.
Mittal et al. (2019)	To determine the correlation between BTC price and Twitter and Google search patterns.	2014-2019	Linear Regression, Polynomial Regression, Neural Network and Long Short Term Memory based analysis	There is a significant correlation between Google trends and Tweet volume data with the BTC price.
Kahraman et al. (2019)	BTC, Ethereum and Ripple volatility structure.	2016-2018	ARCH GARCH	The volatility effect of shocks on BTC and Ethereum is permanent and positive The volatility effect of shocks on Ripple is temporary and the volatility is short-term.
Su & Li (2020)	BTC, Ethereum and Ripple volatility structure.	2013-2019	Mathematical analysis	BTC sentiment spread varies over time and market events. However, the net sentiment volatility of gold and oil comes from the buyer. It has been concluded that buyers prefer these assets during periods of net volatility in gold and BTC.
Ahn & Kim (2020)	Investor sentiment disagreement and bitcoin price fluctuations.	2017-2018	Textual sentiment analysis	The sensitivity of investors causes high volatility in BTC prices.
Ali & Shatabda (2020)	Bitcoin price prediction.	2014-2020	Linear Regression model	The linear regression model price prediction accuracy is 96.97%.
Aggarwal et al. (2020)	Bitcoin's price prediction.	2012-2018	Machine learning algorithm	It can predict BTC prices five steps ahead.
Kalyvas et al. (2020)	Bitcoin's price risk.	2011-2018	Mathematical analysis	There is a weak correlation between BTC price crash risk and market sentiment. Investors can use BTC as a hedging tool during periods of high economic uncertainty.
Vo et al. (2021)	Bitcoin price movements.	2010-2020	Time series analysis	It has been concluded that BTC is no longer a speculative trading instrument but an independent investment instrument sensitive to macroeconomic factors.
Cabarcos et al. (2021)	Relationship between BTC, S&P 500, VIX index and investor sentiment.	2016-2019	GARCH EGARCH	In stable periods, S&P 500 and VIX volatilities affect BTC volatility.
Chen (2021)	Factors affecting Bitcoin volatility.	2009-2019	Co-integration VAR ADRL	In the short term, the BTC price is affected by current events and financial expectations. Blockchain technology has a small impact on the BTC price. But different Using econometric analysis gives different results in the short term.
Chkili (2021)	Identifying the volatility dynamics of Bitcoin price.	2013-2020	FIGARCH model	FIGARCH model is better than any other model at modelling BTC price volatility

			Markov switching model	shows performance.
Guégan & Renault (2021)	The relationship between investor sentiment on social media and BTC returns.	2017-2019	iStockTwits data analysis	There is a statistically significant relationship between investor sentiment and BTC returns at frequencies up to 15 minutes.
Ibrahim (2021)	Tweets interpretations for early market movement prediction of BTC cryptocurrency.	2020	Logistic Regression, Support Vector Naive Bayes model XGBoost Composite sensitivity model	With the XGBoost-composite sentiment model, a relationship between Twitter sentiment and future price fluctuations of BTC was determined.
Edgari et al. (2022)	The impact of tweets about BTC during COVID-19 on the BTC price.	2021-2021	XG-Boost VADER Sensitivity analysis	Twitter sentiment analysis BTC during COVID-19 It has been proven that it affects the price and using models with sentiment analysis performs well.
Nguyen (2022)	Bitcoin price relationship with S&P 500	2016-2021	Kantil regression VAR GARCH model	During periods of high uncertainty, the S&P 500 and BTC currency are more correlated.
Dumitrescu et al. (2023)	Market connection with Bitcoin Price volatilities	Bulgaria, Croatia, Czechia, Hungary, Norway, Poland, Romania, Sweden and Switzerland 2017–2022	Variance influence factor (VIF) Levin-Lin-Chu (LLC) test Im-Pesaran-Shin (IPS) test	Bitcoin's fluctuations have the potential to affect the functioning of monetary policy through the exchange rate channel. Investors can benefit from diversification by including the BTC currency in their portfolio.
Maleki et al. (2023)	Comparative analysis of BTC prices with other cryptocurrencies	2018-2019	Machine learning, Time series analysis Lasso Regression	It is possible to use Zcash cryptocurrency price information to predict the BTC price.
Conlon et al. (2024)	Volume and volatility relationship of Bitcoin futures and spot exchanges	2017–2021	Mathematical analysis	CME Bitcoin futures do not contribute to systemic risk in Bitcoin during the period examined.

As can be seen in the literature, while the early case studies with BTC were on the security of money, the effect of important people and events on the BTC price was analyzed in later studies. The impact of governments' economic policies, events or financial transactions on the BTC price was compared with classical investment instruments. In recent studies, there are studies aimed at predicting future BTC prices.

3.3. Studies on the investment value of gold

Many studies have been conducted from the past to the present regarding gold prices and financial markets. Table 2 gives examples of studies in chronological order.

Table 2. Examples of Studies Evaluating Gold Prices and Financial Assets

Author	Subject	Data Set Period	Method	Result
Gilmore et al. (2009)	The relationship between gold prices and stock market prices of gold mining enterprises.	USA 1996-2007	Cointegration Vector error correction model	A short-term unidirectional causality relationship was found between stocks and gold.
Dirk & McDermott (2010)	The role of gold in the global financial system.	G7 BRIDGE Australia Switzerland	Mathematical analysis	It has been concluded that gold is both a hedge and a safe haven for major European stock markets and the USA, but it is not safe for Australian, Canadian and Japanese markets.
Omag (2012)	The relationship between gold prices, interest rates, exchange rates, inflation and stock market index.	IMKB100 2002-2011	Regression analysis ANOVA Test	Gold prices are positively affected by the IMKB100 index.
Brooks & Prokopczuky (2013)	Stock market relationship with commodities including gold.	USA 1985-2010	Bayesian Markov Chain Monte Carlo model	It has been concluded that the return correlation between the commodity and the stock market index is low and the volatility between the commodity and the stock market is low.
Patel (2013)	Relationship between Nifty index and gold prices in India.	India 1991-2011	Augmented Dickey-Fuller unit root test, Johansen cointegration test and Granger causality test	Gold price is only related to the Nifty index. Hence, the gold price can be used to predict the return of Nifty.
Benli & Yıldız (2014)	Forecast of gold price.	Istanbul Gold Exchange 1996-2013	ARIMA Artificial neural networks	ARIMA model artificial neural networks in price prediction was found to be more successful than the model.
Gayathri & Dhanabhakyam (2014)	Relationship between gold price and basic index of Indian stock exchange NIFTY.	India NSE Nifty 2003-2013	Cointegration Causality test	It reveals a one-way causality relationship between the gold price and NSE's Nifty50 index.
Kothari & Gulati (2015)	Relationship between gold prices and Indian stock market index.	India SENSEX index 1979-2013	Granger causality test	There is a highly positive correlation between the gold price and the SENSEX index during the examined period.
Pandey & Vipul (2017)	Volatility spillover of commodities such as gold and crude oil into BRICS equity markets.	Brazil, Russia, India, China and South Africa 2000–2015	Kraft and Kroner (BEKK) Model GARCH	It has been determined that there is a spillover of volatility from gold and crude oil to the share markets of BRICS countries.
Çelik et al. 2018)	Emerging stock markets and valuables mine return relationship.	Indonesia, India, Brazil South Africa, and Türkiye 2015-2021	VAR EGARCH	Indonesia, India, Brazil from gold returns and had a positive impact on Turkish stock markets.
Tolu (2020)	The relationship between the London FTSE100 stock market index and gold prices.	London FTSE100 2010-2020	Cointegration Granger causality	It has been determined that there is no long-term cointegrated structure between the FTSE100 stock market index and gold prices, but there is a bidirectional causality relationship in the short term.
Kumar et al. (2023)	Relationship between gold and other commodity prices and the stock market.	India 1994-2019	The nonlinear autoregressive distributed lag model (NARDL)	The Indian stock market is not affected by gold prices.
Sinlapates & Chancharat (2024)	Returns and effects of gold prices on Southeast Asian stock markets.	Southeast Asia markets 2016-2023	Quantile regression model	In Singapore and Thailand, gold returns significantly and positively affect stock returns.

As can be seen from the examples taken from studies on gold and stock markets, a common feature is a causal relationship between stock markets and gold prices. In this study, gold prices and their relationship with the technology companies that rank first in the indices and BTC prices were evaluated mutually. The absence of any study in this direction in the literature makes this study unique.

4. Empirical Analysis

4.1. Data and Method

In this study, the data between 2020:01 and 2023:12 was taken from Gold Spot US Dollar Once (XAUUSD) data, the publicly available online platform investing.com, which provides financial analysis and data sharing. It owns the most valuable technology stocks in the world, called the Magnificent Five; AAPL, AMZN, GOOG, NVDA and TSLA company share value was obtained from Nasdaq (2024) and BTC daily price data was obtained from BTC (BTC, 2024) official website.

In the study, the short and long-term relationships between gold and selected stocks in the Nasdaq index AAPL, AMZN, GOOG, NVDA, TSLA and BTC and the reason for BTC were examined. For the purpose of the study, cointegration and vector error corrected (VEC) Granger causality analyzes were used. Before the cointegration analyses, the normal distributions of the series were checked, and their single normal distributions were ensured by making logarithmic transformations.

Since the series must be stationary at the same level (integrated of the same degree) to perform the cointegration analysis, the Augmented Dickey-Fuller (ADF) (Dickey & Fuller, 1979) unit root test was applied, and it was observed that both variables contained unit roots at the level, but were stationary when their first differences were taken. In the unit root test, all three models without a constant term, with a constant term and with a constant term and trend were tested and reported in Table 4.

The Wald lag exclusion test (VEC Lag Exclusion Wald Tests) was used to determine the appropriate lag length in the cointegration analysis. Since the null hypothesis in the test is that "the relevant delay should be excluded", when $p>0.05$, the hypothesis is accepted and the relevant delays are excluded; When $p<0.05$, the null hypothesis is rejected and the relevant delay is accepted.

Since heteroscedasticity, autocorrelation and distribution with multiple norms must be ensured for the validity of the model test, the White test (White VEC Residual Heteroskedasticity) is used for the heteroscedasticity problem, LM test (VEC Residual Serial Correlation LM Test) is used for the autocorrelation problem and Cholesky (Lutkepohl) is used for the multiple normal distribution condition. Multiple normal distribution test was applied. The White test (White VEC Residual Heteroskedasticity), which performs the heteroscedasticity problem, tests the null hypothesis that "the series have common variance" and the hypothesis is accepted when $p>0.05$ for the chi-square test statistic. LM test (VEC Residual Serial Correlation LM Test) tests the null hypothesis of "there is no serial relationship/correlation" for each delay within the specified delay range, and the hypothesis is accepted when $p>0.05$ for the LM test value. Cholesky (Lutkepohl) decomposition, which is used in mathematics to separate the Hermit matrix, is used in statistics to solve normal equations in linear least squares problems. In the analysis evaluated using Jarque Berra's (1980) test statistics, the null hypothesis "residuals of the series show a normal distribution" is tested separately for each component, but when the Joint test result is $p>0.05$, it is understood that multiple normal distribution is achieved.

Johansen cointegration test was performed to determine the number of cointegration equations, and Trace and Max-Eigen test results were taken into account to determine the number of vectors. Johansen (1988) recommends trace tests and maximum eigenvalue tests to determine the number of cointegration vectors and emphasizes that these calculated test statistics should be compared with the obtained critical values or p values should be taken into account. In the tests, cointegration numbers are determined for models without a constant term, with a constant term, and with a constant term and trend, as well as testing the null hypothesis of "there is no cointegration". The null hypothesis is tested separately for Trace and Max-Eigen statistics and when the values of these tests exceed the critical values ($p < 0.05$), the hypothesis of no cointegration relationship is rejected.

Finally, in the study, the prediction model was tested by considering the linear vector error corrected (VECM) cointegration model. Since this study examines the relationship and effect of gold and selected stocks with BTC, the cointegration model in which only BTC is the dependent variable was evaluated, the causality test was evaluated and BTC was left as the dependent variable in the causality analysis. When BTC is the dependent variable in the test, the null hypothesis for each independent variable regarding which of the independent variables should be excluded from the model is "the relevant independent variable should be excluded". When the chi-square test statistic is $p<0.05$, the null hypothesis is rejected and it is understood that the relevant independent variable should remain in the model and is the cause of the dependent variable.

4.2. Empirical Findings

Table 3 shows the descriptive statistics of the series included in the model.

Table 3. Descriptive Statistics of the Series

Serial	Short form	Log	Min.	Maks.	Mean	SS	J-B(p)
Bitcoin	BTC	LNBTC	6412.5	61309.6	29244	14845	1.722(0.422)
Apple	APPLE	LNAPL	63.570	196.450	142.05	34.198	0.942(0.624)
Amazon	AMZN	LNAMZ	84.000	175.350	137.285	26.847	2.951(0.0228)
Gold	GOLD	LNGLD	1571.3	2062.6	1829.1	118.88	5.257(0.072)
Alphabet	GOOGL	LNGOG	61.060	139.07	99.659	25.153	3.540(0,170)
NVDIA	NVDA	LNNVD	1470.0	20300	4738.5	4538.75	4.641(0.098)
Tesla	TESLA	LNTES	34.930	381.59	214.09	86.348	2.571(0.276)

[a]: J-B after logarithmic transformation: Jarque-Bera

ADF unit root test was used to determine the stationarity of the logarithmically transformed series. Table 4 shows the unit root test results.

Table 4. Unit Root Statistics of the Series

Serial	Model	Trend	Constant
LNBTC	At the level 1st difference	0.481 *-5.272****	-1.996 *-5.307****
LNAPL	At the level 1st difference	-1,573 *-6.022****	-1,218 *-6.286****
LNAMZ	At the level 1st difference	-1.102 *-8.015****	-2.065 *-7.974****
LNGLD	At the level 1st difference	-1.431 *-6.719****	-1.471 *-6.826****
LNGOG	At the level 1st difference	6.425 -2.168*	-0.767 *-8.270****
LNNVD	At the level 1st difference	1.031 *-6.969****	-0.808 *-7.082****
LNTES	At the level 1st difference	0.623 *-6.616****	-2.290 *-6.577****

*: Significant at 5% level **: Significant at 1% level

According to the ADF unit root test results in Table 4, it was determined that both variables were not stationary at the level of the models with and without a constant term and that the means of the variables [I(1)] were stationary at their first differences in the model with a constant term. Accordingly, cointegration will be sought in the relationship between the variables. Table 5 shows the results of the Wald lag exclusion test (VEC Lag Exclusion Wald Tests) performed to determine the appropriate lag length for the cointegration model.

Table 5. Delay Length Determination Results

Delay	Joint (p)
Dlag1	164.568 (0,000)
Dlag2	69.137 (0,030)
Dlag3	79.539 (0,004)

According to the Wald error-corrected delay length exclusion test results in Table 5, the hypothesis that the delay should be excluded was rejected for all three delays ($p<0.05$). Accordingly, the most suitable delay lengths are 1-3. delays.

Table 6 shows the results of heteroskedasticity, autocorrelation and multiple normal distribution in the vector error correction model (VECM) cointegration model.

Table 6. Descriptive Statistics of the Series

	Statistics	**p**	**Result**
heteroscedasticity (White VEC Residual Heteroskedasticity)	1196.287	0.334	There is no heteroscedasticity problem
Autocorrelation (VEC Residual Serial Correlation LM Test)	(1)46.85/ (2)55.01/ (3)43.99	0.561/ 0.257/ 0.676	There is no autocorrelation problem
Multiple normal distribution (VEC Residual Normality Test / Cholesky (Lutkepohl)	10.268	0.742	Residuals are normally distributed

The model showed no heteroscedasticity problem (X2=1196.29; $p>0.05$), no autocorrelation problem at all three lags (LM-Stat=46.85/55.01/43.99; $p>0.05$) and multiple. It was determined that the normal distribution condition was met (Joint J-B=10.27; $p>0.05$).

In Table 7, the Johansen cointegration test was performed to determine the number of cointegration equations, and Trace and Max-Eigen test results were taken into account to determine the number of vectors. Johansen (1988) recommends trace tests and maximum eigenvalue tests to determine the number of cointegration vectors and emphasizes that these calculated test statistics should be compared with the obtained critical values or p values should be taken into account. Table 7 shows the Trace and Max-Eigen test results for determining Johansen cointegration vector numbers and unconstrained cointegration ranking.

Table 7. Cointegration Vector Numbers and Orders Test Results

	- **No S** **No T**	**-** **Yes S** **No T**	**Linear** **Yes S** **No k**	**Linear** **Yes S** **Yes T**	**Quadratic** **Yes S** **Yes T**		
Trace	6	6	4	5	7		
Max-Eigen	3	4	3	3	3		
H_0 Hypothesis	**Eigenvalue**	**Trace**	**p**	**H_0 Result**	**MaxEigen**	**p**	**H_0 Result**
No cointegration	0.874	258.39	0.000	Rejection	91.470	0.000	Rejection
Up to 1	0.735	166.93	**0.000**	**Assent**	58.510	**0.000**	**Assent**
Up to 2	0.567	108.42	**0.000**	**Assent**	36.881	**0.028**	**Assent**
Up to 3	0.477	71.54	0.001	Assent	28.590	0.050	Rejection
Up to 4	0.386	42.95	0.006	Assent	21.470	0.065	Rejection
Up to 5	0.300	21.48	0.033	Assent	15.697	0.054	Rejection

S: Constant term, T: Trend

According to the Johansen cointegration test results, it was determined that the hypothesis of no cointegration was rejected ($p<0.05$) and there were at least two cointegration equations. Since the study searches for a linear relationship, a linear vector error corrected (VECM) cointegration model with constant terms and maximum third lags were taken into consideration. Vector error-corrected short- and long-term forecast results are given in Table 8. Since the relationship of other variables with BTC was examined in the research, a maximum of 1 cointegration relationship was taken into account and only the cointegration model in which the BTC variable was the dependent variable was evaluated.

Table 8. Short And Long-Term Forecast Results with Vector Error Correction

Forecast Period	**B**	**β**	**SH**	**t**
Long Term				
LNBTC(-1)	1.000			
LNNVD(-1)	-97.474	-1.750	16.495	-5.909**
LNAMZ(-1)	-2.235	-0.107	5.221	-0.427
LNGLD(-1)	10.270	0.984	1.833	5.600**
LNAPL(-1)	6.665	0.368	8.897	0.749
LNGOG(-1)	-18.079	-0.507	8.572	-2.109*
LNTES(-1)	-49.939	-0.346	52.796	-0.945
C	686.569			
Short Term[1]				
COINTEQ	***-0.2294***		***0.0729***	***-3.149****
D(LNBTC(-1))	0.6428	0.655	0.212	3.023**
D(LNNVD(-1))	-28.456	-0.638	9.937	-2.863**
D(LNNVD(-3))	-21.811	-0.511	8.256	-2.642**
D(LNGLD(-2))	3.5348	0.587	1.327	2.663**
R^2	0.697			
ΔR^2	0.380			
F	2.196*			

*: Significant at 5% level **: Significant at 1% level [1]: Only statistically significant ones are shown.

The fact that the error correction coefficient (COINTEQ) is negative (between 0 and -2) and significant shows that the variables are cointegrated, and the inverse of the coefficient (1/coefficient) gives information about how long it will take for shocks to occur in the short term to balance. In other words, it means that shocks experienced in the short term are balanced in the long term. When the test results in Table 8 were examined, it was determined that the error correction coefficient of the estimated model was negative and statistically significant (Cointeg=-0.229; t=-3.15; p<0.01). According to the cointegration coefficient, shocks occurring in the independent variables in the short term come to balance in the long term (after approximately 4 months) (1/0.2294=4.359). When long-term equations are examined, a 1% increase in the value of NVDA (LNNVD) leads to a decrease of approximately 1.75% in the value of BTC in the long term. A 1% increase in the value of Gold (LNGLD) leads to an increase of approximately 0.98% in the value of BTC in the long term. A 1% increase in the value of Alphabet (LNGOG) leads to a decrease of approximately 0.51% in the value of BTC in the long term.

When short-term relations are examined, the increase in BTC value leads to a positive change in BTC value with a period delay. The increase in NVDA value leads to a negative change in BTC value with a period delay. The increase in NVDA value leads to a negative change in BTC value with a three-period delay. The increase in gold value leads to a positive change in BTC value with a delay of two periods.

The results of the vector error corrected (VEC) Granger causality / Block Exogeneity Wald test used in the causality/externality relationship between variables are shown in Table 9. In test statistics, the null hypothesis (H_0) is "Variable X is not the cause of Y/should be excluded". In this case, when the p-value of the X2 statistic is less than 0.05 (p<0.05), it is understood that the independent variable is the cause of the dependent variable and can be included in the model.

Table 9. VEC Granger causality/block exogeneity Wald test results

	X^2	**sd**	**p**
When D(LNBTC) is the dependent variable:			
LNNVD(-1)	11.734	3	**0.008**
LNAMZ(-1)	4.639	3	0.200
LNGLD(-1)	8.776	3	**0.032**
LNAPL(-1)	4.404	3	0.221
LNGOG(-1)	2.251	3	0.522
LNTES(-1)	1.260	3	0.738
All	40.046	3	**0.002**

The tests in Table 9 support the findings in the cointegration analysis, and it is seen that the null hypothesis that the NVDA (LNNVD) and Gold (LNGLD) series "are not the cause of the external independent variable and dependent variable" is rejected at the 0.05 level. Therefore, it is consistent that both independent variables are included in the model, and NVDA and Gold variables are the reasons for the change in BTC values.

5. Discussion and Conclusion

With technological developments and their reflection on financial markets, cryptocurrencies have begun to be considered as a new investment instrument. BTC is the pioneer of cryptocurrencies, has the highest value and stands out with the blockchain technology it uses behind it. In addition, the relationship between technology infrastructures and products, which are among the new generation investment preferences, and AAPL, AMZN, GOOG, NVDA and TSLA company shares, called decacorn and hectocorn enterprises, and gold, one of the classical investment instruments, was analyzed.

In the study, the short and long-term relationships between BTC and the stocks of companies known as the magnificent five in the XAUUSD and Nasdaq index and the reason for BTC were examined. For the purpose of the study, cointegration and vector error corrected (VEC) Granger causality analyses were used. Before the cointegration analyses, the normal distributions of the series were checked, and their single normal distributions were ensured by making logarithmic transformations. In summary, as a result of the study; It has been observed that the short-term shocks caused by the independent variables included in the research in BTC stabilized after approximately 1 month. In this process, as NVDA shares increase, BTC value decreases, and BTC value increases as gold value increases. After about a month, the relationship stabilizes.

Although the analysis results of the study are desired to be compared with other studies in the literature, no comparative study has been found in the literature that compares BTC prices, XAUUSD, and the shared values of the companies referred to as the "Magnificent Five." Therefore, there is no direct comparison between the findings of these variables and other studies in the literature. However, the analysis result indicating no relationship between BTC and gold prices during the examined period in this study is similar to the findings of Moro & Kajtazi (2017). The results obtained through studies comparing gold prices and stock market indices support the research findings of Kumar et al. (2023) and Tolu (2020) for the long term.

A limitation of this study is that it evaluates the stock prices of only the five companies referred to as the "Magnificent Five." Additionally, the different responses of investment instruments such as technology stocks, BTC and gold to varying economic and political conditions are among the factors that influence the findings in the analysis of the study.

It is thought that this study makes a significant contribution to the field of finance by filling a gap in the literature in the context of being able to compare the stock values of technology companies, one of the new generation popular investment instruments, and BTC, another product of technology, and traditional asset prices. The future studies are expected to focus on increasing certainty by conducting more research on technology companies and cryptocurrencies.

The study demonstrates the economic and political implications, showing that technology stocks become attractive for long-term investors due to their innovation and growth potential, while also carrying risks such as high volatility and sensitivity to economic conditions. BTC offers high return potential, but it can expose investors to risks due to uncertainties. Gold, on the other hand, with its low volatility and safe-haven characteristics, can provide a safeguard for investors during periods of economic uncertainty.

Investors may consider investing in each of these assets in a balanced way to diversify their portfolios and minimize risks. Technology stocks, Bitcoin, and gold respond differently to various economic and political conditions, so establishing the right balance among these assets is crucial for long-term investment success. Especially when considering new generation investor trends, it is recommended to diversify the portfolio by investing in different technology companies, as well as traditional investment instruments and cryptocurrencies, to expand the range of investment options.

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