IJEFI

International Journal of Economics and Financial Issues

ISSN: 2146-4138

available at http: www.econjournals.com

International Journal of Economics and Financial Issues, 2025, 15(4), 363-377.

Exploring External Influences on Cryptocurrency Prices: Using A Multi-Analytical Approach

Zaheda Daruwala*

Associate Professor, Department of Accounting and Finance, College of Business, City University Ajman, Ajman, United Arab Emirates. *Email: z.daruwala@cu.ac.ae

Received: 21 January 2025 **Accepted:** 24 May 2025 **DOI:** https://doi.org/10.32479/ijefi.19455

ABSTRACT

Cryptocurrencies have experienced exponential growth within the last decade, with market capitalization hovering above the one-trillion-dollar mark since 2022. One area of concern for current and potential crypto users and investors is their unprecedented price volatility. As cryptos become interlinked with the regulated financial system, questions emerge regarding the possibility of linkages of their prices to the external environments. Financial and macroeconomic factors of inflation, economic growth, interest rates, currency exchange rates, equity market returns, corporate bond yields, gold and oil prices are examined against the cryptocurrency returns. This study encompasses a multi-analytical approach, firstly with the empirical tests of Spearman's correlational analysis to discover the most pertinent relationships, followed by the PCA analysis to reduce redundancy. The predictive regression model of the Granger Causality test, a vector autoregression (VAR) time series forecasting method, is applied to examine whether the highly effective factors Granger cause the crypto price movements. The Machine Learning Random Forest Regression is also applied where a nuanced understanding of the external factors affecting cryptos prices is gained. The findings of this study pertain to more recent times when the pandemic crisis has subsided and stable economies are in place. The results examined four major cryptos of Bitcoin, Binance Coin, Ripple and Tether, where most behaviours suggest that users and investors are willing to take on riskier assets during periods of economic growth, a strong equity market complements crypto demands and gold and oil are good substitutes for cryptos. Tether, a stablecoin, was the least impacted by external factors and behaved similarly to a fiat currency. This investigation into external factors will empower cryptocurrency users and investors with valuable insights into the crypto price mechanisms, enabling them to refine their investing and portfolio diversification strategies.

Keywords: Cryptocurrency, Stock Markets, Gold Prices, Oil Prices, GDP, Exchange Rates, Granger Causality, ML Random Forest Regression
JEL Classifications: G10; G19, G40

1. INTRODUCTION

Cryptocurrencies, as virtual and digitally existing currencies, have the potential to revolutionize the payment mechanism not regulated by government authorities. The first cryptocurrency was Bitcoin (BTC), released in early 2009, a brainchild of Satoshi Nakamoto (Panda et al., 2023) and currently one of the most widely discussed topics in the global financial arena, popularized as 'DeFi' or decentralized finance. They are designed to work as a medium of exchange through a network of computers backed by a distributed ledger technology of blockchain to validate the transactions, ensuring transparency in financial transactions (Grinberg, 2012). They have the potential to shift financial power away from the central banks and financial institutions and an alternative to traditional banking (Sichinava, 2019). This entails a new way of accessing finance, reducing transaction costs and offering cheaper options than traditional financial services (Gomber et al., 2017). Cryptocurrencies are the instruments that facilitate DeFi and are expected to grow as their usage for borrowing, lending and trading increases by the day. Investments by private venture companies have seen an increase in the use of cryptos, for example, US cryptocurrency markets supported investments of

This Journal is licensed under a Creative Commons Attribution 4.0 International License

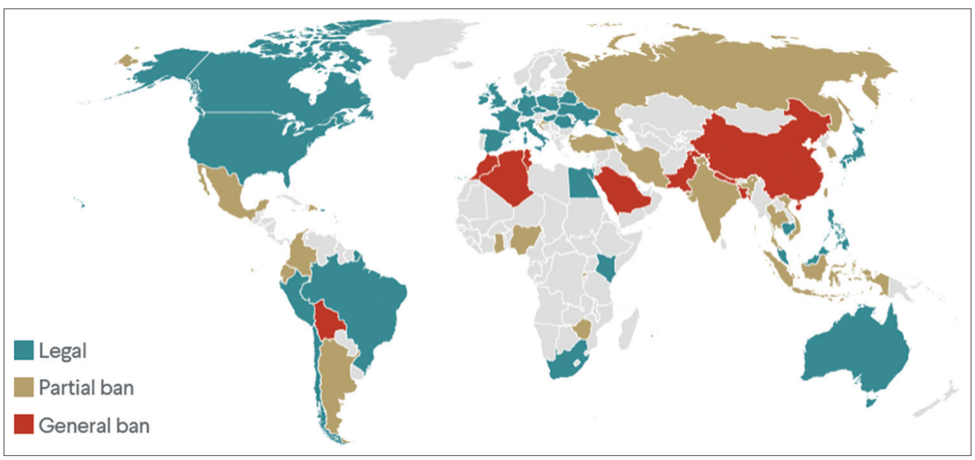
USD 6.1 billion in 2021 (Grand View Research, 2022). Emerging markets experiencing devaluation of local currencies have seen a rise in demand for crypto-based transactions.

Critics argue that cryptocurrencies enable criminals and terrorist organizations to pursue their harmful motives under disguise and escape the watch of the regulatory bodies (Gonzálvez-Gallego and Pérez, 2021). Others emphasize that the benefits and growth in the use of cryptos cannot be undermined, and the advantage gained by unlawful entities can be countered by intelligence-led, predictive policing and governance policies across borders (Irwin and Turner, 2018). Technological developments in Artificial Intelligence (AI) will aid in nurturing the use of cryptocurrencies by using machine learning to identify illicit transactions and other activities like illegal mining, thereby enhancing its security and privacy (Hassani et al., 2018). The world has experienced varying levels of adoption of cryptocurrencies, with some governments embracing cryptocurrencies and others totally banning their use. Figure 1 below shows the acceptance levels of cryptos worldwide as of September 2023.

As the world experiences growth in applicability and acceptance of cryptos for payments, transactional, and trading purposes (Fang et al., 2022; Kyriazis, 2019) and also as an investment vehicle and medium of exchange (Baur et al., 2018), one of the major concerns is the volatility in their prices. The past decade has witnessed significant fluctuations in the prices of major cryptocurrencies. Bitcoin (BTC) prices rose exponentially in November 2021 and reached highs of $63,000, an increase of 1200% in a short period of 9 months, only to dip in November 2022 to a low of $16,700. A big price jump was again observed in March 2024 as it exceeded the $73,000 mark, with the news of the approval of Bitcoin ETFs. BTC saw an exponential jump on November 23, 2024, when it reached $100,000, with analysts deeming this to be a bubble (Raynor de Best, 2024). Other cryptocurrencies like Stellar (XLM), Polkadot (DOT), and NEAR Protocol (NEAR) have surged 45.9%, 33.2% and 13.7%, respectively, in 1 day, November 24, 2024. Elon Musk's Dogecoin (DOGE), Cardano (ADA) and others also experienced a surge on that day (MacDonald, 2024). The crypto market volatility is shown in Figure 2 below.

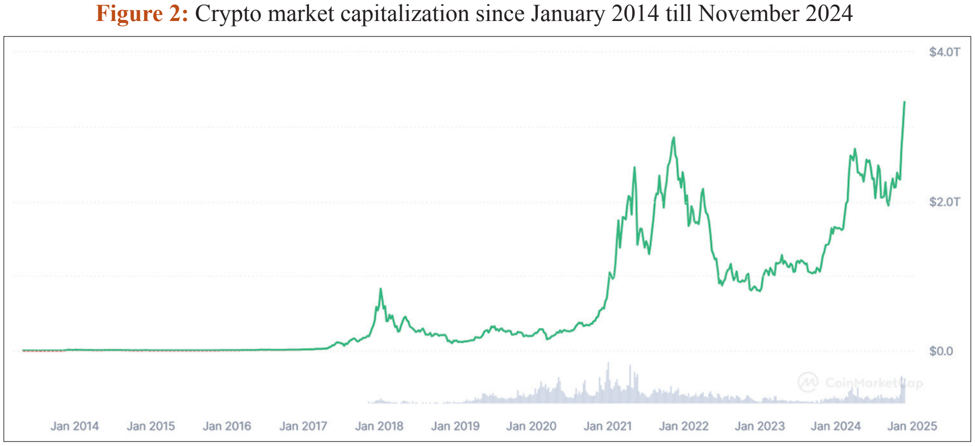
Analysts and investors encounter difficulty in identifying the fair value of cryptos where traditional valuation methods seem unsuccessful in their application to cryptos (Hu et al., 2019). The US courts have experienced increased disputes regarding cryptos, and one of the challenges they face is quantifying damages due to their unpredictability and volatility in prices and lack of robustness of valuation techniques (Chan et al., 2023). Cheah and Fry (2015) suggest that BTC price fluctuations do not permit a constant fundamental value. Cryptocurrencies differ from stocks because

Figure 1: Regulation of cryptocurrencies as of September 2023, selected governments



Source: Atlantic Council

Figure 2: Crypto market capitalization since January 2014 till November 2024



Source: Coinmarketcap.com 2024

they do not pay dividends and have no associated cash flows. Unlike tangible assets such as gold and commodities, they lack industrial usage. Prices have seen fluctuations when governments announce positive news relevant to cryptos or when markets hear negative news like the bankruptcy of a crypto exchange (Zhang et al., 2021). In March 2021, when Tesla announced that it would accept BTC as payment for their electric cars, BTC prices went up; later, when the payments were stalled, BTC prices fell. Some authors believe that high returns of cryptocurrencies are related to their high volatility, and investors could gain higher profits by holding cryptocurrencies during periods of a slowdown in other asset classes (Almeida et al., 2022).

With the large number of exchanges increasing by the day and high volumes in crypto trade, derivatives and EFTs entering the market, cryptocurrencies are viewed as investment vehicles to diversify portfolios along with their transactional uses. Therefore, the author pursues the examination of the external environment in which cryptos exist, including the macroeconomic environment and other traditional assets that the cryptos compete with. Studies exist in literature that have focused on the comparison of BTC price returns to stock indices (Ciaian et al., 2016) and investigations of the effect of oil prices on cryptocurrencies (Heikal et al., 2022; Yin et al., 2021) among others. The author endeavors to encompass significant macroeconomic factors like inflation, economic growth, interest and currency exchange rates, along with other financial assets like corporate bond yields, stock market returns, and commodity prices of gold and oil. There underlies a possibility that the multifaceted interplay of macroeconomic and financial factors could influence cryptos and the aim is to establish whether there exists such a connection.

The rest of this study is organized as follows. Section 2 describes the rise of cryptocurrencies and reviews the literature on price fluctuations in the cryptocurrency markets. Section 3 discusses the research objectives and hypotheses formulated. Section 4 describes the sample data and multi-faceted empirical methods applied, including Spearman's correlation analysis of the crypto returns to the selected macro external variables, followed by the Principal Component Analysis (PCA) that identifies the most relevant factors. These are then empirically tested through the Granger causality test to identify the predictor variables that Granger causes price movements in cryptos. The machine learning Random Forest Regression analysis further complements the study, adding insights into the highly complex relationships that previous methods could have omitted. Section 5 describes the findings of the empirical results with interpretations, followed by Section 6, which summarizes the concluding points with implications on crypto buying and investment decisions with direction for future research.

2. LITERATURE REVIEW

2.1. Growth of the Cryptocurrency Market

The cryptocurrency market experienced its debut with the emergence of the first of its type, Bitcoin (BTC), in January 2009, followed by Namecoin (NMC) in April 2011, then came Litecoin (LTC) and Swiftcoin (SWFTC). Ethereum (ETH) entered the market in 2015, growing to be the second-largest in market capitalization. Numerous cryptocurrencies, under altcoins, stablecoins, non-fungible tokens, and various memes, have entered the market in recent years, where a few survive the test of time, and some remain in the market for a short time, later becoming inactive. Elbahrawy et al. (2017) conducted a market investigation of cryptocurrencies between 2013 and 2017 and found 1469 cryptocurrencies existed during this period, and by the end of the period, only around 600 were active. In 2021, Gandal et al. (2021) found that 44% of the publicly traded coins were abandoned, some temporarily, from which 71% were later resurrected, and 18% failed permanently. At the end of 2024, approximately 10,000 active cryptocurrencies were registered at coinmarketcap.com[1]. Table 1 shows the top ten cryptocurrencies that hold almost 86% of the total market capitalization, where the top two, namely BTC and ETH, have almost 67% of the market share.

Over the past decade, cryptocurrencies have gained significant traction as investment assets and tools for facilitating transactions. There has been an increase of almost 190% between 2018 and 2020 in the global user base of cryptocurrencies. Figure 3 depicts the

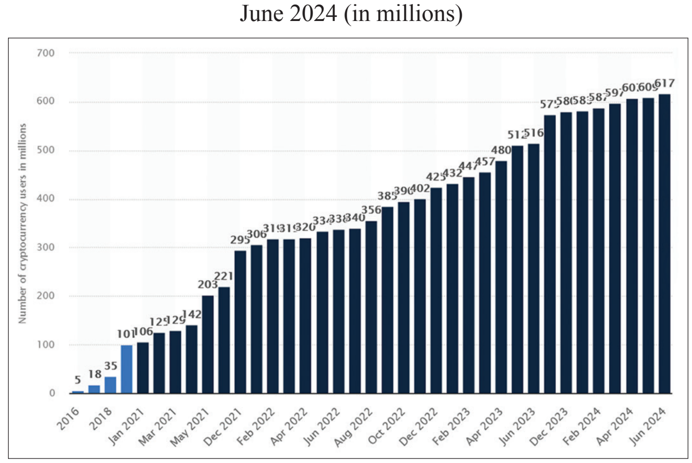
1 To know the latest updates visit https://coinmarketcap.com/

Table 1: Top ten cryptocurrencies as of December 2024

Rank	Name (Symbol)	Market Cap	Market Share (%)	Price (USD)
1	Bitcoin (BTC)	1,885,295,147,739	55.04	95262.31
2	Ethereum (ETH)	431,407,213,516	12.59	3581.86
3	Ripple (XRP)	141,861,691,653	4.14	2.49
4	Tether USDt (USDT)	134,691,560,747	3.93	1.00
5	Solana (SOL)	106,426,475,721	3.11	223.94
6	Binance Coin (BNB)	92,137,496,926	2.69	639.80
7	Dogecoin (DOGE)	59,795,712,706	1.75	0.41
8	Cardano (ADA)	42,075,042,847	1.23	1.20
9	USD Coin (USDC)	39,889,124,562	1.16	1.00
10	TRON (TRX)	20,512,245,797	0.60	0.24

Source: https://www.slickcharts.com/currency

Figure 3: Number of identity-verified crypto asset users from 2016 to June 2024 (in millions)



Source: Statista 2024

growth in user base from 2016 to 2024, by Statista, who gathered calculations from various sources, including trading platforms and on-chain wallets. In 2021, interest in cryptocurrency surged as major corporations, including Tesla and Mastercard, expressed their support for digital currencies (Philip and Pandey, 2024). By 2022, regions such as Africa, Asia, and South America emerged as leaders in cryptocurrency ownership, with BTC being one of the most commonly held digital assets (Evans and Oni, 2022). The number of users is estimated to reach more than 800 million, compared to the current number of 600 million, very soon, as per assessments by Statista.com, which reported in June 2024 that revenue from cryptocurrencies is expected to reach US$56.7 billion by the end of 2024.

2.2. Price Fluctuations and Volatility

Academia has seen an increase in studies related to cryptocurrencies since 2017 where research in this field, particularly within business and finance, has been systematically categorized by Corbet et al. (2019) and Manimuthu et al. (2019). They highlighted four primary themes: (1) the speculative bubbles in cryptocurrency prices, (2) the efficiency of these digital assets, (3) their role in portfolio diversification, and (4) challenges related to regulation and cybercrime. Building on this framework, Jalal et al. (2021) identified similar focal areas, emphasizing (1) determinants of cryptocurrency returns, (2) asset efficiency, (3) diversification benefits alongside investor herding behavior, and (4) the regulatory and governance dynamics associated with cryptocurrencies.

This study focuses on the area of crypto returns and their price fluctuations, as the historical price trends of cryptocurrencies reveal significant volatility, with frequent and pronounced fluctuations observed since their inception. In 2013, Forbes called BTC the year's best investment; in 2014, it was declared the worst investment by Bloomberg. The price variations in the last 5 years of the top three cryptos, BTC, ETH, and XRP, are shown in Figures 4-6, where jumps and falls in prices are seen at great levels. Cryptocurrencies present opportunities for substantial wealth creation and entail significant risks for investors. Given the nascent nature of the crypto market and its intricate financial instruments, the factors driving price movements remain ambiguous. Additionally, investors often lack comprehensive knowledge and trust in these assets compared to traditional financial instruments (Steinmetz et al., 2021).

The literature on crypto pricing dynamics can be divided into two primary categories. The *first* explores correlations or spillover

Figure 4: Bitcoin (BTC) prices (last 5 years)

Source: https://finance.yahoo.com

Figure 5: Ethereum (ETH) prices (last 5 years)

Source: https://finance.yahoo.com

Figure 6: Ripple (XRP) prices (last 5 years)

Source: https://finance.yahoo.com

effects on cryptocurrency prices from traditional investment markets, such as equity indices, oil prices, commodity markets, and currencies. The *second* scrutinizes the co-movement among different cryptocurrencies based on the notion that cryptos fundamentally differ from other asset classes and that the principles applicable to other asset classes do not apply (Baur et al., 2018). Studies in this area highlighted that crypto price fluctuations are based on their popularity rather than their demand and supply, as in traditional currencies (Goczek and Skliarov, 2019; Cheah and Fry, 2015). Bouri et al. (2019) uncovered that a lack of financial literacy among inexperienced investors would make them imitate others, displaying irrational behaviors and leading to price bubbles. Frehen et al. (2013) concluded that technological advances lead to price bubbles in cryptos. Phillip et al. (2018) investigated the interdependencies among cryptocurrencies and found similarities in price movements based on similar crypto characteristics like their market capitalization. Sensoy et al. (2021) identified that cryptos reveal clustering structures with BTC, LTC and ETH serving as connection hubs linking many other similar ones in their price and return volatility behaviors. Daruwala (2024) used a multi-analytical approach to detect two major crypto clusters where Binance Coin (BNB) and Ripple (XRP) dominated in one cluster, and Tether (USDT) was the leader in the other cluster. This study focuses on the first category, aiming to expand the understanding of the possibility of external macroeconomic and financial environment influencing cryptocurrency prices.

2.3. Price Fluctuations with Macroeconomic and Financial Factors

Previous studies have established that traditional assets like equity investments, bonds, and gold exhibit certain relationships with macroeconomic and financial variables (Huy et al., 2021; Bhuiyan and Chowdhury, 2020; Campbell et al., 2020; Singh and Kaur, 2020). Studies have suggested that cryptos are high-risk investments compared to traditional asset classes and perform well under positive economic conditions, as investors' risk-taking tendencies would be elevated during growth periods (Pflueger et al., 2018). Others have highlighted the growth in crypto markets during and immediately after the COVID-19 pandemic (Sarkodie et al., 2022). Hence, we observe research showing cryptocurrencies behaving differently at different times. Some studies have revealed that higher expected inflation drives investors toward cryptocurrencies for inflation hedging (Cong et al., 2024; Krakower, 2023). During inflation, the purchasing power of traditional assets falls, and as crypto assets are independent of the monetary system, they are expected to retain their value. This could be seen during hyperinflationary times in Venezuela and Zimbabwe, where there was a significant rise in crypto asset purchases (Zohar, 2020).

Interest rates are a key determinant of market liquidity. When central banks reduce interest rates, borrowing costs decrease, making loans attractive and spurring demand for riskier assets. In such an environment, cryptocurrencies become more appealing. Simultaneously, lower interest rates reduce the yield from bonds, reducing their appeal and steering investors to riskier investments as traditional investment options become less attractive (Aharon et al., 2021). Similarly, exchange rate fluctuations, particularly involving major currencies like the EUR/USD rates, have been shown to impact cryptocurrency prices. Higher expected volatility in exchange rates can spur speculative trading in cryptocurrencies, and movements in the exchange rate may influence broader investor sentiment, which can affect cryptocurrency markets. Almansour et al. (2023) highlighted a similar scenario during the pandemic crisis in 2019-2020, using the TVP-VAR model to analyze twelve cryptocurrencies and eight foreign exchange rates.

The interconnectedness between cryptocurrencies and traditional financial markets has been a key focus of scholarly work. The extensive body of research entails the interaction of factors like stock market indices, such as the S&P500 and FTSE100, US Treasury bond yields, exchange rates, inflation rates, and commodity prices of items like gold and oil to be key influencers of investment decisions, that would mist over the cryptocurrency markets as well. Selmi et al. (2018) have examined the interactions of BTC prices with gold and oil prices and concluded that both BTC and gold exhibit characteristics of a safe haven investment vehicle in times of political and economic uncertainty. This was further enhanced by using geopolitical risk indicators by Selmi et al. (2022). Dyhrberg (2016) envisaged early on the hedging capabilities of BTC against the equity markets and the US dollar in the short term. The same was confirmed by Bouri et al. (2017), who also added that BTC can be effectively used as a safe haven against stocks, bonds, oil, and gold investments. Corbet et al. (2018) and Baur et al. (2018) revealed that cryptocurrencies' returns are unrelated to traditional assets and provide an opportunity for investors to diversify their portfolios. A study by Basher and Sadorsky (2022) revealed that 10-year bond yields were most important for predicting BTC prices as compared to inflation. As most studies focused on BTC, Zhang et al. (2018) expanded their study to include eight other cryptocurrencies by creating a weighted average cryptocurrency composite index that was persistently cross-correlated with the Dow Jones Industrial Average.

In light of the comprehensive body of literature concerning the macroeconomic and financial factors impacting crypto prices, the author feels it is quite pertinent to delve further into this space to explore crypto connections that exist with the external factors and examine to what extent they influence the prices and whether any prominent factors exist. The theme underpinning this study is that crypto assets will soon become entrenched in our financial transactions and investments. The study is important due to the underlying dynamics of the complex nature of crypto assets characterized by tremendous volatility and unpredictability supplemented by the growing demand by individuals, companies, and investors presenting them with challenges in their decision-making process. This study augments extant literature and differs from the others, where most have focused their empirical investigation on BTC prices as a sample of cryptocurrency. In contrast, the author builds from previous research that identified crypto clusters with those dominating influence over others within their groups and uses them as sample cryptos for the study, whose results could be extrapolated to other smaller cryptos. Considering a more holistic view, crypto markets are not immune to the external environment in which they exist. The author asserts the need to scrutinize the interplay of multi-factor external elements with the aim of deciphering their impacts on crypto price movements. The next section describes the research objectives and hypotheses of the study, followed by the research data and methodology.

3. RESEARCH OBJECTIVES AND HYPOTHESES

This study aims to offer a perspective on the cryptocurrency price relationships with macroeconomic and financial factors to examine the most influential ones on different types of cryptocurrencies. Although cryptocurrencies are decentralized and not directly tied to traditional financial systems, they are still influenced by broader economic factors shaping investment decisions. Understanding the connection of these external factors could aid in forecasting crypto price movements. Current studies are dispersed with fragmented considerations, with some examining the macroeconomic variables like inflation, interest rates, and exchange rates, while others evaluate the stock and commodity prices. *Firstly*, this study includes all these factors to understand their connections comprehensively. Furthermore, the existing body of knowledge has mostly examined the impact of external factors on the prices of BTC and some other top cryptocurrencies. *Secondly*, this study aims to encapsulate major cryptocurrencies by incorporating those cryptos that influence the price movements of others within the crypto clusters, where the findings of this study encompass a larger number of cryptocurrencies rather than centering on only BTC. *Thirdly*, the focus is on more recent times, the period after the pandemic, taking into consideration the recent macroeconomic outcomes and the change in people's behaviours toward crypto markets as a means of a more efficient prediction of the times ahead.

The research was meticulously crafted to encapsulate both macroeconomic and financial variables that could impact crypto prices. The factors under consideration include inflation rates, economic growth rates, monetary policy interest rates, currency exchange rates, equity market returns, corporate bond yields, gold prices, and oil prices. Empirical methods are used to test the following hypotheses and research questions: (H_1) How do inflation rates, economic growth, interest rates, currency exchange rates, equity market returns, corporate bond yields, gold, and oil prices correlate with the returns of BTC, BNB, XRP, and USDT? (H_2) Do the identified key macroeconomic and financial factors Granger cause the price movements of BTC, BNB, XRP, and USDT? (H_3) What is their predictive power in forecasting crypto prices? (H_4) What insights can be drawn regarding the interrelationships between macroeconomic and financial variables and cryptocurrency prices?

4. DATA AND RESEARCH METHODOLOGY

To examine the multifarious macroeconomic and financial factors affecting price movements of cryptocurrencies, the research methodology employed by the author is multi-analytical and scrutinizes the variables using multiple approaches to decipher the factors that are most influential on crypto prices.

4.1. Sample Selection and Data Variables

The author employs the purposive sampling technique in determining the cryptocurrency sample that consists of the daily closing prices data from January 1, 2022 to June 30, 2023, for the four cryptocurrencies of Bitcoin (BTC), Binance Coin (BNB), Ripple (XRP) and Tether (USDT) that include 546 observations for each of the four cryptocurrencies with a total of 2,184 observations. The data source is CoinMarketCap (https://coinmarketcap.com). This source was preferred as it consolidates data from multiple cryptocurrency exchanges and is most popular for crypto price information. Additionally, it employs data cleaning and verification algorithms to ensure data integrity, making it more reliable than data from any single exchange. These specific four cryptocurrencies are selected based on the previous study by the author (Daruwala, 2024), where crypto interconnections were examined and grouped into clusters based on the strength of their price correlations. Additionally, BNB and XRP were empirically tested to Granger cause price movements in other cryptos within one cluster and USDT in another cluster. BTC was proven to be highly correlated with others in trading volumes, and previous studies have evidenced connectivity in crypto returns and trading volumes (Fousekis and Tzaferi, 2021; Zhang et al., 2018). These formed the dependent variables of the study. The macroeconomic and financial variables of the study were selected to amalgamate the impacts of the broader external environment in which cryptos operate. The eight factors included in the study are inflation, economic growth, interest rates, currency exchange rates, equity market returns, corporate bond yields, gold and oil prices as shown in Table 2.

Cong et al. (2024) and Blau et al. (2021) evidenced that cryptocurrencies are adopted for inflation hedging. However, research on the relationship of inflation with cryptocurrencies has yielded mixed results. In contrast, Matkovskyy and Jalan (2019) found that BTC was not a good hedge against the devaluing US dollar. More recent studies reported that BTC, ETH, and LTC proved to be hedging instruments against inflation, post-COVID-19 times (Sakurai and Kurosaki, 2023), and this study aims to augment the research in this aspect. US monthly consumer price index (CPI) data has been taken from the FRED Economic database[2] that has been interpolated to daily data for the period from January 2022 to June 2023. The second macroeconomic variable of the study is economic growth measured by the quarterly GDP per capita data of the US from the FRED Economic database[3]. Bhimani et al. (2022) found a positive relationship between the GDP and the adoption of cryptocurrencies across 137 countries, and this study deems it relevant to investigate the impact of GDP as a variable with long-term implications for the period.

Central banks do not directly control cryptocurrencies, but they do manage interest rates, and it is believed that when interest rates are lowered, the demand for cryptos increases, pushing their prices upwards. Kusumastuty et al. (2019) examined this relationship using the variance decomposition method, which resulted in a significant long-term relationship but did not find strong evidence in the short term. The data for this third macroeconomic variable was collected from the FRED economic database, which is the federal fund's effective daily rates[4] for the study period. When a fiat currency loses value, investors seek alternative stores of value and vice versa (Bouri et al., 2017). Fang et al. (2022) concluded that BTC was seen to be a hedge against devalued fiat currencies. To investigate this relationship between this fourth macroeconomic variable of exchange rates and crypto prices, the USD/EUR spot exchange daily rates are taken from the FRED Economic database.

As investors look to diversify their portfolios, the comparative options include equity and bond securities and commodities like gold and oil. Corbet et al. (2018) explored the relationships between traditional assets and cryptocurrencies and found that their returns are not correlated in the short run. Kurka (2019) employed the volatility spillover framework by Diebold and Yilmaz (2009), which suggested unconditional connectedness to be weak, whereas conditional analysis during periods of shocks revealed a strong negative connection with traditional assets. To conduct a consolidated study, the author includes the returns on traditional assets to examine whether there is any connection with crypto buying decisions. Literature has identified studies that examined connections with traditional asset types with mixed results (Dyhrberg, 2016; Selmi et al., 2018; Bouri et al., 2017; Corbet et al., 2018; Baur et al., 2018; Zhang et al., 2018; Basher and Sadorsky, 2022). S&P 500 daily returns data[5] are selected as representative of the equity market returns as they are indicative of the large-cap US equity market. The ICE BofA US Corporate Index daily yields are used to examine crypto connections with bonds. This index monitors the performance of investment-grade BBB-rated corporate debt securities, denominated in US dollars, that are publicly issued in the US domestic market.[6] The commodities selected for the study are gold and oil. The daily gold prices are taken from Investing.com, which is based on gold futures contracts traded on the Chicago Mercantile Exchange (COMEX). The West

Table 2: Variables of the study

Name/ code	Description	Source
BTC	Daily returns on Bitcoin	https://coinmarketcap.com
BNB	Daily returns on Binance Coin	https://coinmarketcap.com
XRP	Daily returns on ripple	https://coinmarketcap.com
USDT	Daily returns on tether	https://coinmarketcap.com
INF	Consumer price index (CPI) US as a measure of inflation	U.S. Bureau of labor statistics
GDP	Gross domestic product per capita US as a measure of economic growth	U.S. Bureau of labor statistics
INT	Federal funds effective rate (US) as a measure of interest rates	Board of governors of the federal reserve system (US)
EXC	US dollar to Euro Spot exchange rate as a measure of currency exchange rates	Board of governors of the federal reserve system (US)
SNP	S&P 500 daily closing prices as a measure of equity market returns	S&P 500
CBON	ICE BofA Corporate Index Effective yield	Ice Data Indices, LLC
GOLD	Daily gold Futures prices	COMEX exchange
OIL	West texas intermediate (WTI), Cushing, Oklahoma, Dollars per Barrel	U.S. Energy information administration

2 FRED Economic Database at https://fred.stlouisfed.org/series/CPIAUCNS December 31, 2024.

3 Gross domestic product per capita, Dollars, Quarterly, Seasonally Adjusted Annual Rate from the U.S. Bureau of Economic Analysis, Gross domestic product per capita [A939RC0Q052SBEA], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/A939RC0Q052SBEA, December 31, 2024.

4 The Federal Open Market Committee (FOMC) meets eight times a year to determine the federal funds target rate. The federal funds rate is the central interest rate in the U.S. financial market. It influences other interest rates such as the prime rate, which is the rate banks charge their customers with higher credit ratings. Additionally, the federal funds rate indirectly influences longer-term interest rates such as mortgages, loans, and savings, all of which are very important to consumer wealth and confidence.

5 The index includes 500 leading companies in leading industries of the U.S. economy, which are publicly held on either the NYSE or NASDAQ, and covers 75% of U.S. equities. S&P Dow Jones Indices LLC, S&P 500 [SP500], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/SP500, January 1, 2025.

6 Ice Data Indices, LLC, ICE BofA BBB US Corporate Index Effective Yield [BAMLC0A4CBBBEY], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/BAMLC0A4CBBBEY, January 1, 2025.

Texas Intermediate (WTI) daily crude oil prices in dollars per barrel are sourced[7].

4.2. Empirical Methodology

The study employs multiple analytical methods to examine the connections of cryptocurrency price movements with the eight macroeconomic and financial variables. A quantitative data-driven approach is used to ensure objectivity and robustness in identifying correlations, causations and patterns between the price returns of the four cryptocurrencies, BTC, BNB, XRP and USDT and the eight macroeconomic and financial variables of inflation rates (INF), economic growth (GDP), interest rates (INT), USD/EUR exchange rates (EXC), S&P 500 returns (SNP), corporate bond yields (CBON), gold prices (GOLD) and oil prices (OIL). The four cryptocurrencies are representative of the other cryptos and previous studies have identified them as key price influencers within their respective clusters. All data was interpolated to daily values where monthly data was available for inflation and GDP to generate time series data. To confirm the robustness of the data for this test, Augmented Dicker-Fully (ADF) test is performed to confirm the stationarity of the time series where the null hypothesis was rejected with a $P < 0.05$ and data was transformed to log returns to manage heteroscedasticity problems for all the four cryptos returns and the required independent variables of the study. The daily price returns of each of the four cryptocurrencies *(rn)* is calculated as:

$$R_{i,t} = ln(P_{i,t}) \div ln(P_{i,t}-1) \tag{1}$$

Where Bitcoin ($i = 1$), Binance Coin ($i = 2$), Ripple ($i = 3$), Tether ($i = 4$). And where $P_{i,t}$ is the daily closing price of cryptocurrency i on day t.

Firstly, the statistical tests of Spearman's correlational analysis are performed to examine the correlation coefficients between each of the four sample cryptocurrencies of BTC, BNB, XRP and USDT with the eight macroeconomic and financial variables of INF, GDP, INT, EXC, SNP, CBON, GOLD and OIL. This method is most suitable for the study as the macroeconomic variables are monotonic and not linear, and the normality assumptions are not required.

$$r = 1 - 6 \sum_{n(n^2-1)} d_i^2 \tag{2}$$

where □ represents Spearman's rank correlation coefficient, □ is the number of data pairs, and □ is the square of the difference in the ranks of the two variables for each data pair. Iterations are performed and x and y pairs are replaced by $INF_{i,t}$, $GDP_{i,t}$, $INT_{i,t}$, $EXC_{i,t}$ $SNP_{i,t}$, $CBON_{i,t}$, $GOLD_{i,t}$ *and* $OIL_{i,t}$ where $i = 1\text{-}4$ for the four cryptocurrencies for t number of days.

Secondly, the factor analysis technique of Principal Component Analysis (PCA) is employed, which is a highly effective method for reducing the dimensionality of the factors that tend to be correlated, given their nature and interconnections in the macro environment. Spearman's correlation method is employed in this analysis where the PCA equation is expressed as:

$$Z = XW \tag{3}$$

Where Z is the transformed data, X is the original matrix centered by the mean, W is the Matrix of eigenvectors (principal component loadings)

Thirdly, the empirical test of Granger Causality is performed with the crypto returns and the four factors identified by the PCA to test whether any of these factors Granger causes cryptocurrency price movements. The Granger causality test is most suitable in this case for two reasons: That the study applies time series data, and secondly, as cryptocurrencies are special assets without any physical backing and are considered mostly inefficient in their pricing mechanisms (Vidal-Tomas et al., 2019). This test does not establish causation but rather examines whether past values of one variable (X) provide statistically significant information about the future values of another variable (Y) beyond what is contained in the past values of Y itself. It demonstrates how past values of one variable can cause a change in the other, which is relevant for cryptos that are exploited by speculative investors (Corbet et al., 2019). The bivariate model is as follows:

$$Y_t = □_0 + □_1 Y_{t-1} + □_2 Y_{t-2} + + □_m Y_{t-m} + □□ \tag{4}$$

$$Y_t = □_0 + □_1 Y_{t-1} + □_2 Y_{t-2} + + □_m Y_{t-m} + b_p X_{t-p} + b_q X_{t-q} + □_□ \tag{5}$$

where $□_0$, $□_1$, $□_2$ are model coefficients and $t\text{-}m$ is the model lag. X and Y are the two variables in the model where the lagged values of X are tested against the Y values.

Fourthly, the study augments the empirical tests by applying the multiple nonlinear regression model using machine learning with Random Forest Regression analysis, where the macroeconomic and financial variables identified by the PCA are the independent variables to determine the causation of the four crypto prices. The added test complements the Granger Causality test and brings robustness to the examination of those factors that influence the crypto prices. This method provides added insights to the factors as Random Forest can model complex, non-linear dependencies where each tree captures complex patterns and interactions between features. This ensemble of bootstrapped decision trees works well for irregular relationships such as that with cryptocurrencies. This model follows the general formula as described.

$$\hat{Y} = 1\sum_{m}^{m=1} f_m(X) \tag{6}$$

Where:

(□) be the prediction from the m-th decision tree

□ be the total number of trees.

□ be the input features.

$\hat{Y}$ be the final predicted value.

7 U.S. Energy Information Administration, Crude Oil Prices: West Texas Intermediate (WTI) - Cushing, Oklahoma [DCOILWTICO], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/DCOILWTICO, January 1, 2025.

Each decision tree $f_m(\cdot)$ makes a separate prediction, and the final $\hat{Y}$ is the average of all tree predictions.

This multi-analytical approach offers a comprehensive examination of the external factors as price determinants for the four cryptocurrencies that dominate other cryptos within their clusters.

5. EMPIRICAL RESULTS AND INTERPRETATIONS

5.1. Descriptive Statistics

The descriptive analysis of the study's quantitative variables is described in Tables 3 and 4. The analysis of the four cryptocurrency returns in Table 3 reveals that Ripple (XRP) had the highest returns during the study period at 22.6%, followed by Bitcoin (BTC) at 13.6%, with Binance Coin (BNB) closely behind at 13.1%, whereas Tether (USDT) recorded its highest return of only 5%. A similar pattern was observed in the range of the returns, where XRP had the broadest range of 44.3%, while USDT had the narrowest of 8.5%. XRP, BNB, and BTC exhibited significantly higher volatilities compared to USDT. The mean returns of all cryptos were negative, wherein USDT displayed the least negative mean. This suggests that the least volatile crypto generated the lowest average negative return.

Table 3: Descriptive statistics of cryptocurrency returns

Statistic	Returns BTC	Returns USDT	Returns BNB	Returns XRP
Nbr. of observations	548	548	548	548
Minimum	−17.405	−0.393	−20.537	−21.703
Maximum	13.576	0.462	13.059	22.624
Range	30.982	0.854	33.596	44.326
1st Quartile	−1.395	−0.007	−1.517	−2.112
Median	−0.098	0.000	−0.008	0.021
3rd Quartile	1.370	0.008	1.484	1.738
Mean	−0.0836	−0.0001	−0.1351	−0.1026
Standard deviation (n)	3.109	0.039	3.452	4.078
Variation coefficient (n)	−37.172	−476.672	−25.560	−39.761
Skewness (Pearson)	−0.436	0.811	−0.901	0.192
Kurtosis (Pearson)	4.842	68.884	5.131	6.159
Standard error of the variance	0.586	0.000	0.722	1.007

Table 4 displays the descriptive statistics of the macroeconomic and financial variables of the study. The interest rates revealed the largest range and highest standard deviation, followed by exchange rates, and the inflation range was 1.68%. and the USD/EUR rate was observed to be the most stable with the least standard deviation. The economy experienced an upward inflation and interest rate trend during this period. The highest oil prices were almost double than the lowest during the period. All the external variables showed a kurtosis of <3, indicating that the dataset is less extreme in terms of variability or outlier presence and homogeneity.

5.2. Correlational Analysis

Spearman's correlational analysis is conducted to examine the correlations between BTC, BNB, XRP, and USDT returns with the eight external variables. Spearman's correlation coefficient (Spearman *r*) is used to measure the strength and direction of the association between the variables. This method is the most suitable correlation measure applicable to the study variables as the macroeconomic variables are complex and do not confirm the assumptions of linearity and normality. The daily change in returns ($R_{i,t}$) of the sample four cryptocurrencies, BTC, BNB, XRP and USDT, are examined against the eight external variables of INF, GDP, INT, EXC, SNP, CBON, GOLD and OIL and the empirical results are shown in Tables 5 and 6.

The results reveal some very interesting findings, where the values in bold are where ρ is significantly different from 0, indicating that the empirical test determines a significant correlation between their populations. It is pertinent to observe the direction of the relationship as the first step in the analysis. INF is negatively correlated with returns of BTC, USDT and XRP, whereas it reveals a positive relationship with BNB. Previous studies have suggested that inflation enhances the demand for cryptos (Cong et al., 2024; Krakower, 2023) and the findings reveal here that this may not apply to all cryptos, as mixed results are derived and the *ρ coefficient* depicts a weak monotonic or a non-monotonic (U-shaped) relationship. Cong et al. (2024) investigated BTC and USDT, where their study emphasized emerging markets; in contrast, this study examines an economy with strong currencies like the dollar, suggesting that most cryptos do not confirm previous findings. Zohar (2020) examined hyperinflationary periods in Venezuela and Zimbabwe, which are special cases where

Table 4: Descriptive statistics of the external factor variables

Statistic	INF rates	GDP per Capita	INTR rates	EXC rates	SNP returns	CBON yields	GOLD prices	OIL prices
Nbr. of observations	548	548	548	548	548	548	548	548
Minimum	−0.307	74450.000	0.070	0.962	−4.420	2.350	1623.600	66.610
Maximum	1.374	81968.000	5.080	1.149	5.395	6.140	2055.700	123.640
Range	1.681	7518.000	5.010	0.187	9.815	3.790	432.100	57.030
1st Quartile	0.215	77421.000	0.830	1.035	−0.412	4.320	1775.350	76.780
Median	0.406	79355.000	3.080	1.068	0.000	5.060	1842.300	85.670
3rd Quartile	0.841	81197.000	4.570	1.091	0.341	5.433	1934.400	98.608
Mean	0.501	79097.688	2.706	1.063	−0.010	4.733	1847.328	88.247
Standard deviation (n)	0.471	2284.801	1.858	0.043	1.120	0.919	104.569	14.227
Variation coefficient (n)	0.940	0.029	0.686	0.041	−108.932	0.194	0.057	0.161
Skewness (Pearson)	0.265	−0.434	−0.169	−0.271	−0.127	−0.932	−0.160	0.565
Kurtosis (Pearson)	−0.776	−0.901	−1.544	−0.561	2.477	−0.020	−0.860	−0.756
Standard error of the variance	0.013	316235.887	0.209	0.000	0.076	0.051	662.404	12.261

Table 5: Correlation matrix (ρ Spearman)

Variables	Returns BTC	Returns USDT	Returns BNB	Returns XRP
Returns BTC	1	0.212	0.783	0.731*
Returns USDT	0.212	1	0.181	0.177
Returns BNB	0.783*	0.181	1	0.695
Returns XRP	0.731*	0.177	0.695	1
INF rates	−0.010	−0.011	0.016	−0.022
GDP per capita	0.067	−0.030	0.024	0.048
INTR rates	0.057	−0.040	0.014	0.046
EXC rates	0.040	−0.044	−0.007	−0.008
SNP returns	0.396*	0.145*	0.328*	0.312*
CBON yields	0.023	−0.015	0.002	0.032
Gold prices	0.036	−0.053	−0.003	−0.003
OIL prices	−0.050	0.055	0.010	−0.039

Note: *indicates ρ is significantly different from

Table 6: Coefficients of determination (R^2 Spearman)

Variables	Returns BTC	Returns USDT	Returns BNB	Returns XRP
INF rates	0.000	0.000	0.000	0.000
GDP per capita	0.004	0.001	0.001	0.002
INTR rates	0.003	0.002	0.000	0.002
EXC rates	0.002	0.002	0.000	0.000
SNP returns	0.157	0.021	0.107	0.097
CBON yields	0.001	0.000	0.000	0.001
Gold prices	0.001	0.003	0.000	0.000
OIL prices	0.003	0.003	0.000	0.002

fiat currencies lose value and individuals yearning to maintain the value of their wealth look for alternatives like cryptos, increasing their demand during hyperinflationary periods.

GDP was observed to have a positive correlation with BTC, BNB and XRP returns and a negative coefficient for USDT. The results align with the study on the economy of Indonesia by Jati et al. (2022) that investors in a growing economy are more willing to take on riskier assets in their portfolios. Corbet et al. (2020) found similar outcomes but only for BTC. The negative correlation with USDT suggests that stablecoins do not reflect behaviours similar to those of altcoins with respect to GDP. INTR rates exhibit positive relationships with BTC, BNB, and XRP and a negative relationship with USDT, a US dollar-backed stablecoin. EXC rates exhibited a positive relation only with BTC and negative for the others. It contradicts previous studies that posit that BTC is used as a hedge against traditional currency. The findings suggest that other studies that infer cryptocurrencies as a threat to the dollar (Pew, 2024), may not be such a pressing concern currently, as the results are statistically insignificant within the time period of the study.

The significant finding of this analysis is the positive correlation of all four cryptos with the SNP returns, which is statistically significant. This indicates that cryptos are not substitutes for equity markets but actually complement and mirror the equity markets. Higher equity returns motivate investors towards riskier assets. This contradicts studies by Corbet et al. (2018) and Baur et al. (2018), which found no relation between equity markets and cryptos. Notably, those studies were conducted before the pandemic crisis, and the findings of this more recent data suggest changes in investor behaviours post-COVID-19. BTC, BNB, and XRP exhibited higher correlation coefficients than USDT. The Spearman R^2 of BTC indicates that almost 16% of the variation in BTC returns could be explained by SNP returns monotonically, which, due to the complex nature of cryptos, is of evocative essence. CBOND yields indicate similar effects to that of interest rates, but with a high coefficient as corporate bonds carry a higher risk than treasury instruments, where BTC, BNB and XRP are positively correlated, except for USDT, this again does not consent with Bouri et al. (2017) and Selmi et al. (2018) that posit cryptos as safe havens against bonds. The results confirm previous suggestions that cryptos are safe havens against commodity investments like gold but not oil. GOLD prices revealed negative correlation coefficients with BNB, XRP and USDT, whereas BTC showed a positive relation.

The key highlight of the correlation analysis, clearly indicates a statistically positive correlation of all four cryptos to that of stock market returns. The second essential correlation is that with gold, suggesting that investors alternate cryptos with gold rather than equity securities and both these could be inferred as hedges against the US dollar. Among macroeconomic variables, GDP growth is observed to have a positive influence on cryptocurrency demand, while the USD/EUR exchange rate exhibits a negative relation with the BNB, XRP and USDT prices, indicating that a weaker dollar tends to shift buying behaviour in favour of these cryptocurrencies. An exception has been observed with BTC where interestingly a positive correlation is observed that contradicts previous studies that posit the BTC to be an alternative currency against the US dollar (Dyhrberg, 2016; Almansour et al., 2023).

5.3. Factor Analysis using Principal Component Analysis (PCA)

The study utilizes Principal Component Analysis (PCA), a powerful dimensionality reduction technique, to extract the study's most relevant factors. Some of the macroeconomic and financial factors tend to exhibit similar relationships with crypto returns and identifying them from the dataset would help retain the factors that can be further tested for Granger causality. The empirical results of the PCA analysis in Table 7, with the eigenvalues indicate that four factors contribute to almost 94% of the variability in results, and adding the fifth would add only 4% to the outcomes. The factor loadings in Table 8 confirm that GDP per capita, INTR rates, and CBON yields could explain 47.49% of the variance. An additional 27.17% of the variance contributors are from F2, the EXCH rates and GOLD prices, suggesting investors move to safer assets under economic uncertainty. F3 focuses on SNP returns independent of other macroeconomic variables and contributes 12.4% of the variance, and F4 reveals OIL prices, adding another 6.6% representing the commodity alternatives.

Table 9 shows the eigenvectors of the variables. PCA 1 (F1) shows high positive contributions from GDP per Capita (0.483), Interest Rates (0.489) and CBON Yields (0.459), where high economic growth leads to high interest rates that, in turn, bring about high bond yields. Hence, considering GDP per capita from this component can explain the other two factors. PCA 2 (F2) captures currency and gold as safe havens with EXC rates (0.603) and GOLD prices (0.634), whereas PCA 3 (F3) is entirely linked to SNP returns and PCA 4 (F4) reveals a commodity-driven alternative of OIL prices (0.486) as an important factor.

Table 7: PCA eigenvalues

Description	F1	F2	F3	F4	F5	F6	F7	F8
Eigenvalue	3.799	2.174	0.992	0.531	0.321	0.096	0.072	0.015
Variability (%)	47.490	27.171	12.405	6.633	4.014	1.194	0.899	0.194
Cumulative (%)	47.490	74.662	87.067	93.700	97.714	98.908	99.806	100.000

Table 8: PCA factor loadings

Factors	F1	F2	F3	F4	F5	F6	F7	F8
INF rates	−0.685	0.470	0.008	0.444	0.325	−0.083	−0.016	0.001
GDP per capita	0.941	0.237	−0.007	0.158	−0.090	−0.061	−0.122	−0.081
INTR rates	0.953	0.230	−0.014	0.127	−0.063	−0.068	−0.076	0.094
EXC rates	−0.297	0.889	−0.046	−0.272	0.084	0.150	−0.123	0.006
SNP returns	0.066	0.104	0.992	−0.033	0.009	−0.001	0.005	0.000
CBON yields	0.895	−0.214	0.005	0.258	0.190	0.215	0.057	−0.002
Gold prices	0.053	0.934	−0.038	0.160	−0.272	0.020	0.150	−0.005
OIL prices	−0.800	−0.350	0.070	0.354	−0.294	0.105	−0.101	0.011

Table 9: PCA eigenvectors

Factors	F1	F2	F3	F4	F5	F6	F7	F8
INF rates	−0.352	0.319	0.008	0.609	0.573	−0.269	−0.060	0.005
GDP per capita	0.483	0.161	−0.007	0.217	−0.158	−0.196	−0.455	−0.651
INTR rates	0.489	0.156	−0.014	0.174	−0.111	−0.220	−0.284	0.752
EXC rates	−0.152	0.603	−0.046	−0.374	0.148	0.487	−0.458	0.050
SNP returns	0.034	0.070	0.996	−0.046	0.016	−0.005	0.019	0.000
CBON yields	0.459	−0.145	0.005	0.354	0.335	0.696	0.212	−0.017
Gold prices	0.027	0.634	−0.038	0.220	−0.481	0.064	0.558	−0.042
OIL prices	−0.410	−0.237	0.070	0.486	−0.519	0.340	−0.377	0.085

5.4. Granger Causality Test

The PCA analysis reveals the five most pertinent external factors sifting through the eight factors and now the study delves deeper into these conspicuous connections to explore whether the five factors highlighted by the PCA analysis Granger cause the price movements in the cryptocurrencies. The factors that are considered for further testing among the macroeconomic variables would be economic growth and USD/EUR exchange rate. Alternative investment instruments are stock markets, gold and oil from the commodities. The variables applied in the Granger Causality test include GDP per capita, GOLD prices, EXCH rates, SNP returns, and OIL prices. The Granger test helps determine whether these external factors have a causal impact on cryptocurrency demand. This test is well-suited for cryptocurrencies that demonstrate speculative tendencies (Bouri et al., 2019; Cheah and Fry, 2015; Goczek and Skliarov, 2019). The time series data is employed to perform a vector autoregression (VAR) forecasting technique using lags of the five predictor variables to examine whether a causal relationship exists with the four crypto returns. As the crypto markets are highly volatile and susceptible to quick changes, for SNP returns, GOLD prices, EXCH rates and OIL prices 1- and 2-day lag tests are iterated. As these are alternative investment instruments for cryptocurrencies and expect quick contagion spread from these instruments to the crypto markets (Bouri et al., 2019; Jalal et al., 2021). Lags of two and four days are iterated for the macroeconomic variable of GDP per capita, expecting this economic outcomes data to take some more time to permeate crypto decisions. The ADF test was conducted on all datasets that confirmed stationarity before selecting the lag order. Iterative tests were conducted by replacing the X values with $R_{i,t}$ returns of BTC, USDT, BNB and XRP against Y values of the five predictor variables with *m* symmetric lags in the empirical model. Table 10 shows the P-values resulting from the Granger Causality Test. The factors with significant thresholds of <10% have been considered for analysis rather than the conventional 5%, due to the speculative nature of the cryptos, where considering a more relaxed threshold could divulge potential relationships for further investigation (Wasserstein and Lazar, 2016). Secondly, the nature of the study is exploratory, entailing macroeconomic variables, where a larger threshold is suggestive in identifying connections rather than confirming definitive effects (Lescaroux and Mignon, 2008). The results uncover varying outcomes for the four different cryptocurrencies. BTC returns are shown to be Granger-caused by the three external factors of GDP per capita, SNP returns and OIL prices. Economic growth has a delayed effect as compared to the other two external factors, where f-statistics reveal a stronger impact with a lag of 1 rather than 2. Granger causality is observed for only one factor, OIL prices, with USDT returns. BNB returns suggest a connection with the GDP per capita and the USD/EUR exchange rates, with a longer lag. XRP returns are Granger caused by EXCH rates and OIL prices.

To summarize the results, the study reveals that the most prominent external factor to Granger cause crypto movements is the OIL prices, where for three out of the four cryptos the outcomes were statistically significant. The second is the GDP per capita and the EXCH rates where two crypto returns were observed to be Granger-caused, and the third factor is SNP returns. However, the f-statistics reveal that the strength of OIL prices and SNP returns is higher for BTC returns than others.

Figure 7: Variable importance for (a) BTC, (b) USDT, (c) BNB, (d) XRP

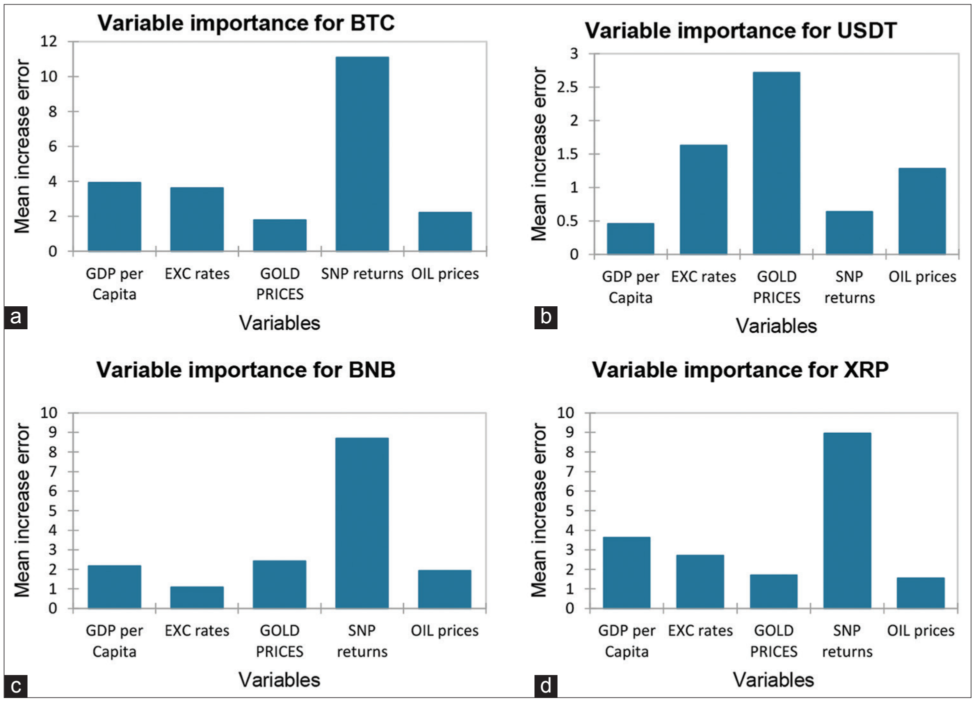


Table 10: P-values Granger causality test X values of BTC, USDT, BNB and XRP

Y-value Factor	Df	X-value BTC		X-value USDT		X-value BNB		X-value XRP	
		F	Pr (>F)	F	Pr (>F)	F	Pr (>F)	F	Pr (>F)
GDP per capita	−2	1.902	0.150	0.020	0.980	0.651	0.522	0.909	0.404
GDP per capita	−4	3.207*	0.013	0.046	0.996	2.123*	0.077*	1.019	0.397
EXCH rates	−1	0.037	0.848	0.024	0.878	1.464	0.227	0.412	0.521
EXCH rates	−2	0.839	0.433	1.661	0.191	3.024*	0.049*	3.719*	0.025*
GOLD prices	−1	0.455	0.500	0.401	0.527	0.698	0.404	0.016	0.900
GOLD prices	−2	1.968	0.141	0.440	0.644	1.249	0.288	0.371	0.690
SNP returns	−1	4.736*	0.030*	1.385	0.240	0.245	0.621	0.994	0.319
SNP returns	−2	2.431*	0.089*	0.982	0.375	0.140	0.870	0.645	0.525
OIL prices	−1	5.692*	0.017*	0.050	0.823	0.819	0.366	2.939*	0.087*
OIL prices	−2	3.873*	0.021*	2.821*	0.060*	0.426	0.653	1.935	0.145

Note: *indicates statistically significant ρ values

Table 11: Random forest regression: Variable importance (mean increase error)

Variables	BTC	USDT	BNB	XRP
	Variable importance	Variable importance	Variable importance	Variable importance
GDP per Capita	**3.913**	0.456	**2.167**	**3.613**
EXC rates	3.621	**1.629**	1.084	2.699
Gold prices	1.788	**2.717**	2.419	1.691
SNP returns	**11.088**	0.635	**8.699**	**8.942**
OIL prices	2.211	1.279	1.920	1.545
OOB sample	8.677	0.002	11.060	15.487

5.5. Machine Learning Random Forest Regression Analysis

Incorporating non-linear regression into the empirical analysis enhances the study's ability to capture complex associations, and the author utilizes machine learning to assess the existence and strength of nonlinear relationships between the five external factors and crypto returns identified through the PCA. The Machine Learning Random Forest Regression technique is applied to the dataset, which is an ensemble learning method combining multiple decision trees to enhance prediction accuracy and reduce overfitting. The four crypto returns of BTC_t, $USDT_t$, BNB_t and XRP_t were regressed against the five macro variables of *GDP_t per capita, EXC_t rates, $GOLD_t$ prices, SNP_t returns and OIL_t prices.* The bootstrapping of random subsets of different sizes and decision trees varying in number was iterated via machine learning to the training data set. The subset size of 50 with decision trees of 150 provided stabilization of the OOB score, resulting in a more robust and stable model. Table 11 represents the variable importance in a Random Forest model, measured by Mean Increase in Error, indicating how much the model's predictive accuracy decreases when that specific variable is removed or permuted. Figure 7 is the graphical representation of the variable importance for each of the four cryptos.

For BTC, the SNP returns with a coefficient of 11.088 is the most important variable, and removing or altering it would significantly reduce model performance, and the second most important variable is economic growth represented by GDP per capita. BNB and XRP mimic BTC with SNP returns as the most important variable with the largest mean increase in error at 8.699 and 8.942, respectively.

USDT stands apart from the other three cryptocurrencies, showing SNP returns and GDP per capita as the least important variables and GOLD (2.717) as the most important, followed by EXC rates (1.629). It is interesting to observe that BTC, BNB and XRP returns are highly influenced firstly by SNP returns and secondly by GDP per capita. USDT reveals a different behaviour to external factors, where SNP returns and GDP per capita are the least important, and GOLD prices and EXC rates are the most important among the five external factors. Further, it is noteworthy to observe that for USDT, the model's predictions are highly accurate with a low MSE for the OOB sample of 0.002.

The Random Forest Regression results confirm the Granger Causality test results for BTC where SNP returns and GDP per capita reveal an important connection. For the BNB and XRP, the results of Granger causality do not reveal causality with SNP returns. However, GDP per capita is showing moderate importance from the regression outcomes, which support the Granger tests. A combined assessment of both tests uncovers that Granger causation is most likely with GDP per capita, EXC rates and OIL prices for most of the cryptos, whereas the Regression analysis shows that SNP returns and GDP per capita are the most important factors for most of the cryptos.

6. CONCLUSION

6.1. Summary of the Findings

The cryptocurrency market has seen strong growth in 2024, with the mining of cryptos growing at a rate of 30-40% (Stepanova et al., 2024). Bitcoin reached an overall high of USD 73,000 in March 2024, fueled by the issue of spot Bitcoin EFTs that increased investor confidence (Wu, 2024). Cryptocurrencies like DOGE, PEPE, XRP and others have also seen enormous gains (Forbes, 2024). As this market grows with the integration of artificial intelligence and governments around the world working towards improving regulations, a major concern regarding investment in cryptocurrencies is seen in their instability of prices (Blackstone, 2025). This concern is addressed in this study by investigating the connections between cryptocurrency prices and external factors. The study aims to offer guidance to investors and users of cryptos to make better decisions considering the influence of the macroeconomic and financial environment by answering the questions raised through the hypotheses of this study.

- (H_1) How do inflation rates, economic growth, interest rates, currency exchange rates, equity market returns, corporate bond yields, gold, and oil prices correlate with the returns of BTC, BNB, XRP, and USDT? Spearman's correlation analysis *(ρ)* reveals interesting connections with the eight external factors. INF is observed to be negatively related to most cryptos except BNB. Previous studies have suggested that inflationary pressures on currency shift demand towards cryptocurrencies as alternative modes of maintaining the value of wealth (Cong et al., 2024; Krakower, 2023), but this study reveals contradictory outcomes. Although this may be suggestive in the case of hyperinflationary times and under crisis situations (Zohar, 2020), the findings do not indicate that they apply in developed economies and during stable times. GDP per capita is seen to be positively correlated with most cryptos except USDT, a stablecoin backed by the US dollar. This suggests that investors are willing to take on more risk during growth in economies, which is supported by previous studies (Pflueger et al., 2018). INTR rates and CBOND yields reveal positive relations with all cryptos except USDT (stablecoin) and contradicts previous studies that infer that cryptos could be safe havens against CBONDs (Bouri et al., 2017; Selmi et al., 2018). EXC rates revealed mixed relations with the cryptos, BNB, XRP, and USDT, which were negatively related, confirming previous studies that cryptos are alternatives to fiat currencies. However, BTC did not show similar behaviour and cannot be considered a threat to the dollar. The key highlight is seen in the statistically positive correlation of all four cryptos to that of stock market returns. As GOLD and OIL commodity investments are considered to be safe havens for investors, the correlation with these suggests that investors alternate cryptos with commodities rather than equity securities.
- (H_2) Do the identified key financial and macroeconomic factors Granger-cause the price movements of BTC, BNB, XRP, and USDT? The PCA eigenvalues and the factor loadings revealed GDP per capita, GOLD prices, EXCH rates, SNP returns, and OIL prices as significant external factors. Granger causality test with lags of 1,2, and 4, depending on the variable characteristics, was applied and revealed varying outcomes for each of the four cryptos. GDP per capita, SNP returns and OIL prices revealed strength in causing a change in the BTC prices. BNB prices were Granger-caused by GDP per capita and EXCH rates, XRP by EXC rates and OIL prices. USDT was the least impacted by external factors and the only factor of importance was the OIL prices. The most statistically significant impact was that of SNP returns on BTC prices.
- (H_3) What is their predictive power in forecasting? The study uses a multi-analytical approach to investigate the strengths of the Granger causality findings and further investigate the connections. The machine learning Random Forest Regression analysis was applied as a complementary technique. The variable importance for BTC results is similar to the Granger causality test, where SNP returns and GDP per capita are identified as most important. The regression also revealed that SNP returns are of prime importance to BNP and XRP. For USDT, commodity prices play an important role and GOLD prices are found to be more important than OIL.
- (H_4) What insights can be drawn regarding the interrelationships between financial and macroeconomic variables and cryptocurrency prices? This question seeks to answer the added value of combining multiple analytical methods of correlation analysis, Granger causality and machine learning regression in understanding the complex relationships of external factors affecting different types of cryptocurrencies. External factors can be divided into two major groups, one pertaining to the economic factors and the other the alternative investment instruments, including commodities. The key findings of the study are, firstly, under stable economic conditions, investors and users are more willing to take on riskier investments of cryptocurrencies when there is economic growth. Secondly, the findings suggest that strong

and bullish equity markets tend to encourage investors to invest in riskier options like cryptocurrencies. The results do not indicate a substitution effect between equity markets and cryptocurrencies, rather a complementary behaviour between them. Thirdly, commodities like gold and oil are observed to be safe havens against cryptocurrencies and are important only second to equity markets.

6.2. Scope and Recommendations

The study highlights the complexity of the relationships of different types of cryptocurrencies with various external factors. As the literature posits, the increase in the applicability and growth of newer cryptocurrencies in the times ahead is irreversible. The results empower investors desirous of including riskier assets like cryptocurrencies in their portfolios to make better-informed decisions by examining the macroeconomic environment and the impact it is suggested to have on their near future prices. The sample of cryptocurrencies taken for the study are the major players in the market, and they also have been evidenced by other studies to represent other smaller cryptocurrencies that exhibit similar behaviours, thereby enabling the application of these results to a wider range of cryptos. The complexity of the factors opens doors for future research in different economies to compare the results between developed and developing economies. This study shall provide a platform for further investigation into the long-term implications of external factors on crypto prices. The findings of this study offer newer perspectives on the dynamics of external factors and alternative investments with crypto markets, providing a wider understanding of the highly volatile and novel crypto vehicles. The machine learning approach applied to the training dataset can be applied to expanded datasets for future predictive research.

REFERENCES

Aharon, D.Y., Umar, Z., Vo, X.V. (2021), Dynamic spillovers between the term structure of interest rates, bitcoin, and safe-haven currencies. Financial Innovation, 7(1), 59.

Almansour, B.Y., Uddin, M.M., Elkrghli, S., Almansour, A.Y. (2023), The dynamic connectedness between cryptocurrencies and foreign exchange rates: Evidence by TVP-VAR approach. Industrial Engineering and Management Systems, 22(3), 349-362.

Almeida, D., Dionísio, A., Vieira, I., Ferreira, P. (2022), Uncertainty and risk in the cryptocurrency market. Journal of Risk and Financial Management, 15(11), 532.

Basher, S.A., Sadorsky, P. (2022), Forecasting Bitcoin price direction with random forests: How important are interest rates, inflation, and market volatility? Machine Learning with Applications, 9, 100355.

Baur, D.G., Hong, K., Lee, A.D. (2018), Bitcoin: Medium of exchange or speculative assets? Journal of International Financial Markets, Institutions and Money, 54, 177-189.

Bhimani, A., Hausken, K., Arif, S. (2022), Do national development factors affect cryptocurrency adoption? Technological Forecasting and Social Change, 181, 121739.

Bhuiyan, E.M., Chowdhury, M. (2020), Macroeconomic variables and stock market indices: Asymmetric dynamics in the US and Canada. The Quarterly Review of Economics and Finance, 77, 62-74.

Blackstone, T (2025), 2024 Cryptocurrency Adoption and Sentiment Report. Available from: https://www.security.org/digital-security/cryptocurrency-annual-consumer-report/2024/#concerns [Last accessed on 2025 Feb 02].

Blau, B.M., Griffith, T.G., Whitby, R.J. (2021), Inflation and bitcoin: A descriptive time-series analysis. Economics Letters, 203, 109848.

Bouri, E., Gupta, R., Roubaud, D. (2019), Herding behaviour in cryptocurrencies. Finance Research Letters, 29, 216-221.

Bouri, E., Gupta, R., Tiwari, A.K., Roubaud, D. (2017), Does Bitcoin hedge global uncertainty? Evidence from wavelet-based quantile-in-quantile regressions. Finance Research Letters, 23, 87-95.

Campbell, J.Y., Pflueger, C., Viceira, L.M. (2020), Macroeconomic drivers of bond and equity risks. Journal of Political Economy, 128(8), 3148-3185.

Chan, E., Tang, N., Taylor, E. (2023), Crypto disputes: The valuation challenge. Dispute Resolution International, 17(1), 21.

Cheah, E.T., Fry, J. (2015), Speculative bubbles in bitcoin markets? An empirical investigation into the fundamental value of bitcoin. Economics Letters, 130, 32-36.

Ciaian, P., Rajcaniova, M., Kancs, D. (2016), The economics of BitCoin price formation. Applied Economics, 48(19), 1799-1815.

Cong, L.W., Ghosh, P., Li, J., Ruan, Q. (2024), Inflation Expectation and Cryptocurrency Investment (No. w32945). United States: National Bureau of Economic Research.

Corbet, S., Larkin, C., Lucey, B.M., Meegan, A., Yarovaya, L. (2020), The impact of macroeconomic news on Bitcoin returns. The European Journal of Finance, 26(14), 1396-1416.

Corbet, S., Lucey, B., Urquhart, A., Yarovaya, L. (2019), Cryptocurrencies as a financial asset: A systematic analysis. International Review of Financial Analysis, 62, 182-199 .

Corbet, S., Meegan, A., Larkin, C., Lucey, B., Yarovaya, L. (2018), Exploring the dynamic relationships between cryptocurrencies and other financial assets. Economics Letters, 165, 28-34.

Daruwala, Z. (2024), Deciphering crypto interconnections using a multi-analytical approach. International Journal of Applied Economics, Finance and Accounting, 19(1), 149-175.

Diebold, F.X., Yilmaz, K. (2009), Measuring financial asset return and volatility spillovers, with application to global equity markets. The Economic Journal, 119(534), 158-171.

Dyhrberg, A.H. (2016), Hedging capabilities of bitcoin. Is it the virtual gold? Finance Research Letters, 16, 139-144.

ElBahrawy, A., Alessandretti, L., Kandler, A., Pastor-Satorras, R., Baronchelli, A. (2017), Evolutionary dynamics of the cryptocurrency market. Royal Society Open Science, 4(11), 170623.

Evans, O., Oni, O. (2022), Fintech, cryptocurrency and blockchain technology: Towards promoting a digital Africa. In: Digital Business in Africa: Social Media and Related Technologies. Cham: Springer International Publishing. p193-215.

Fang, F., Ventre, C., Basios, M., Kanthan, L., Martinez-Rego, D., Wu, F., Li, L. (2022), Cryptocurrency trading: A comprehensive survey. Financial Innovation, 8(1), 13.

Forbes. (2024), 'Bitcoin Wasn't Even the Best-Performing Cryptocurrency of 2024-Despite Breaching $100,000'. Available from: https://www.forbes.com/sites/tylerroush/2024/12/28/bitcoin-wasnt-even-the-best-performing-cryptocurrency-of-2024-despite-breaching-100000

Fousekis, P., Tzaferi, D. (2021), Returns and volume: Frequency connectedness in cryptocurrency markets. Economic Modelling, 95, 13-20.

Frehen, R.G., Goetzmann, W.N., Rouwenhorst, K.G. (2013), New evidence on the first financial bubble. Journal of Financial Economics, 108(3), 585-607.

Gandal, N., Hamrick, J.T., Moore, T., Vasek, M. (2021), The rise and fall of cryptocurrency coins and tokens. Decisions in Economics and Finance, 44(2), 981-1014.

Goczek, Ł., Skliarov, I. (2019), What drives the Bitcoin price? A factor augmented error correction mechanism investigation. Applied Economics, 51(59), 6393-6410.

Gomber, P., Koch, J.A., Siering, M. (2017), Digital finance and FinTech:

Current research and future research directions. Journal of Business Economics, 87, 537-580.
Gonzálvez-Gallego, N., Pérez-Cárceles, M.C. (2021), Cryptocurrencies and illicit practices: The role of governance. Economic Analysis and Policy, 72, 203-212.
Grand View Research. (2022) Cryptocurrency Market Size, Share and Trends Analysis Report By Component, By Hardware, By Software, By Process (Mining, Transaction), By Type, By End-use, By Region, And Segment Forecasts, 2023 - 2030. Report ID: GVR-4-68039-979-9. San Francisco: Grand View Research.
Grinberg, R. (2012), Bitcoin: An innovative alternative digital currency. Hastings Science and Technology Law Journal, 4, 159.
Hassani, H., Huang, X., Silva, E. (2018), Big-crypto: Big data blockchain and cryptocurrency. Big Data and Cognitive Computing, 2, 10-34.
Heikal, M., Saragih, M.M.S., Ilham, R.N., Khaddafi, M., Rusydi, R. (2022), Effect of World Oil Prices on Cryptocurrency Return. Journal of Accounting Research, Utility Finance and Digital Assets, 1(1), 61-68.
Hu, Y., Rachev, S.T., Fabozzi, F.J. (2019), Modelling Crypto Asset Price Dynamics, Optimal Crypto Portfolio, and Crypto Option Valuation. [arXiv Preprint].
Huy, D.T.N., Nhan, V.K., Bich, N.T.N., Hong, N.T.P., Chung, N.T., Huy, P.Q. (2021), Impacts of internal and external macroeconomic factors on firm stock price in an expansion econometric model-a case in Vietnam real estate industry. Data Science for Financial Econometrics. Germany: Springer Nature. p189-205.
Irwin, A.S., Turner, A.B. (2018), Illicit Bitcoin transactions: Challenges in getting to the who, what, when and where. Journal of Money Laundering Control, 21(3), 297-313.
Jalal, R.N.U.D., Alon, I., Paltrinieri, A. (2021), A bibliometric review of cryptocurrencies as a financial asset. Technology Analysis and Strategic Management, 37, 1-16.
Jati, W., Rachmawaty, R., Holiawati, H., Syatoto, I. (2022), Correlation of financial innovation, stock market, cryptocurrency on economic growth. Economics Development Analysis Journal, 11(3), 329-338.
Krakower, R.H. (2023), Exploring The Relationship Between Bitcoin and Inflation Expectations: An Empirical Analysis [Doctoral Dissertation, University of Pennsylvania].
Kurka, J. (2019), Do cryptocurrencies and traditional asset classes influence each other? Finance Research Letters, 31, 38-46.
Kusumastuty, C.A., Wulandari, D., Narmaditya, B.S., Kamaludin, M. (2019), Do monetary variables affect to cryptocurrency price? Lesson from Indonesia. Jurnal Ekonomi dan Studi Pembangunan, 11(2), 131-142.
Kyriazis, N.A. (2019), A survey on efficiency and profitable trading opportunities in cryptocurrency markets. Journal of Risk and Financial Management, 12(2), 67.
Lescaroux, F., Mignon, V. (2008), On the influence of oil prices on economic activity and other macroeconomic and financial variables. OPEC Energy Review, 32(4), 343-380.
MacDonald, C. (2024), Why Stellar, Polkadot and NEAR Protocol Were 3 Of the Biggest Crypto Winners This Weekend. The Motley Fool. Available from: https://finance.yahoo.com/news/why-stellar-polkadot-near-protocol-183910951.html
Manimuthu, A., Rejikumar, G., Marwaha, D. (2019), A literature review on Bitcoin: Transformation of crypto currency into a global phenomenon. IEEE Engineering Management Review, 47(1), 28-35 .
Matkovskyy, R., Jalan, A. (2019), From financial markets to Bitcoin markets: A fresh look at the contagion effect. Finance Research Letters, 31, 93-97.
Panda, S.K., Sathya, A.R., Das, S. (2023), Bitcoin: Beginning of the cryptocurrency era. In Recent Advances in Blockchain Technology: Real-World Applications. Cham: Springer International Publishing. p25-58.
Pew, D. (2024), A Digital Threat to Dollar Dominance, FPRI: Foreign Policy Research Institute. United States of America. Available from: https://coilink.org/20.500.12592/hx3fmn0/on/02/feb/2025. coi: 20.500.12592/hx3fmn0
Pflueger, C., Siriwardane, E., Sunderam, A. (2018), A Measure of RISK APPetite for the Macroeconomy (No. w24529). United States: National Bureau of Economic Research.
Philip, B., Pandey, P. (2024), Cryptocurrency fluctuations: Investigating a decade of top cryptocurrency fluctuations and influential factors. International Journal for Multidisciplinary Research (IJFMR), 6(3), 1-13.
Phillip, A., Chan, J.S., Peiris, S. (2018), A new look at cryptocurrencies. Economics Letters, 163, 6-9.
Raynor de Best. (2024), 'Bitcoin BTC/USD Price History up Until. Available from: https://www.statista.com/statistics/326707/bitcoin-price-index
Sakurai, Y., Kurosaki, T. (2023), Have cryptocurrencies become an inflation hedge after the reopening of the US economy? Research in International Business and Finance, 65, 101915.
Sarkodie, S.A., Ahmed, M.Y., Owusu, P.A. (2022), COVID-19 pandemic improves market signals of cryptocurrencies-evidence from Bitcoin, Bitcoin Cash, Ethereum, and Litecoin. Finance Research Letters, 44, 102049.
Selmi, R., Bouoiyour, J., Wohar, M.E. (2022), Digital Gold and geopolitics. Research in International Business and Finance, 59, 101512.
Selmi, R., Mensi, W., Hammoudeh, S., Bouoiyour, J. (2018), Is bitcoin a hedge, a safe haven or a diversifier for oil price movements? A comparison with gold. Energy Economics, 74, 787-801.
Sensoy, A., Silva, T.C., Corbet, S., Tabak, B.M. (2021), High-frequency return and volatility spillovers among cryptocurrencies. Applied Economics, 53(37), 4310-4328.
Sichinava, D. (2019), Cryptocurrency-a future medium of exchange. Economics and Business, 11(1), 55-69.
Singh, A., Kaur, N. (2020), Macroeconomic determinants of gold prices-a bounds testing approach. Indian Journal of Finance, 14, 21.
Steinmetz, F., Von Meduna, M., Ante, L., Fiedler, I. (2021), Ownership, uses and perceptions of cryptocurrency: Results from a population survey. Technological Forecasting and Social Change, 173, 121073.
Stepanova, D., Yousif, N.B.A., Karlibaeva, R., Mikhaylov, A. (2024), Current analysis of cryptocurrency mining industry. Journal of Infrastructure, Policy and Development, 8(7), 4803.
Vidal-Tomás, D., Ibáñez, A.M., Farinós, J.E. (2019), Herding in the cryptocurrency market: CSSD and CSAD approaches. Finance Research Letters, 30, 181-186.
Wasserstein, R.L., Lazar, N.A. (2016), The ASA statement on p-values: Context, process, and purpose. The American Statistician, 70(2), 129-133.
Wu, D. (2024), Bitcoin ETF: Opportunities and Risk. [arXiv Preprint].
Yin, L., Nie, J., Han, L. (2021), Understanding cryptocurrency volatility: The role of oil market shocks. International Review of Economics and Finance, 72, 233-253.
Zhang, W., Li, Y., Xiong, X., Wang, P. (2021), Downside risk and the cross-section of cryptocurrency returns. Journal of Banking and Finance, 133, 106246.
Zhang, W., Wang, P., Li, X., Shen, D. (2018), Multifractal detrended cross-correlation analysis of the return-volume relationship of bitcoin market. Complexity, 2018(1), 8691420.
Zhang, W., Wang, P., Li, X., Shen, D. (2018), The inefficiency of cryptocurrency and its cross-correlation with dow jones industrial average. Physica A: Statistical Mechanics and its Applications, 510, 658-670.
Zohar, N. (2020), The adoption of cryptocurrencies in hyperinflationary economies. Journal of Digital Banking, 5(3), 220-234.