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Article

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The Relationship between Bitcoin and Nasdaq, U.S. Dollar Index and Commodities

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ABSTRACT

This paper investigates the long-run interaction between Bitcoin and Nasdaq, U.S. Dollar Index and commodities by applying weekly data from a January 1, 2017 until May 21, 2023. This study uses FMOLS, DOLS and CCR methods to examine the long-run association between the variables. The results reveal a positive and significant relationship between Bitcoin and Nasdaq, as well as a similar positive association between Bitcoin and Oil prices. Notably, the U.S. Dollar Index exhibits a negative and significant impact on Bitcoin. However, results show that Gold does not have significant impact on Bitcoin. Finally, the results show that there are significant Granger causality from Nasdaq, oil and gold to Bitcoin.

Keywords: Bitcoin, Nasdaq, U.S. Dollar Index, Gold, Oil, Cointegration
JEL Classifications: G12, G15

1. INTRODUCTION

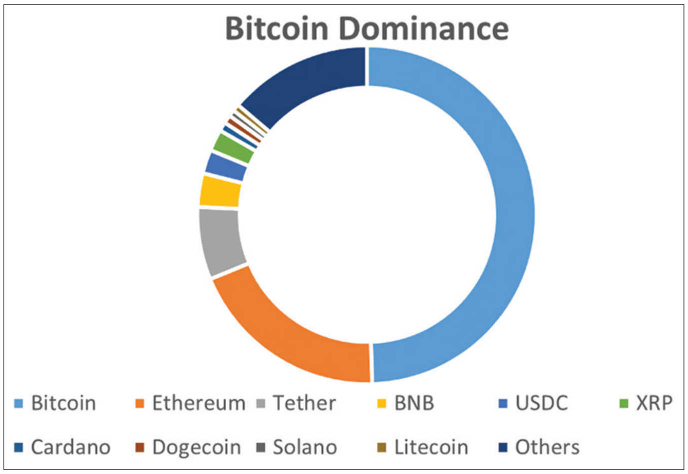
The development of money reflects the ever-changing demands of human cultures as well as technological improvements. In early days when there was no barter system but people were still exchanging items directly for other material gain that met an individual's need. Through the advent of physical media such as gold and metal coins significantly boosted a person's absolute knowledge to trade with various commodities. Paper cash dealt with the needs of climbing economic situations, while the transition from metal products to plastic cards advertised fast purchases. Electronic cash was developed throughout the electronic period, enabling smooth and quick purchases. Even so, the decentralized nature of Bitcoin, which is based upon blockchain innovation, is posing a difficulty for well-established financial establishments presently.

Over the last few years, the number of cryptocurrencies has increased exponentially. At the time of July 09, 2023, there are approximately 26,258 cryptocurrencies in the world. As the first and most popular cryptocurrency, Bitcoin is dominating the cryptocurrency world (Figure 1).

Bitcoin is a purely peer-to-peer version of electronic cash would allow online payments to be sent directly from one party to another without going through a financial institution (Nakamoto, 2008). BTC operates as a decentralized electronic system, facilitating anonymous transactions through peer-to-peer networking and algorithms, without the need for financial intermediaries such as central banks or government financial agencies (Weber, 2016). Despite its significance, BTC presents challenges in terms of valuation, similar to historical speculative assets such as Tulip Mania and the South Sea bubble, which experienced super-exponential growth reflecting human greedy behavior and the difficulty of objectively valuing assets.

The statistics around cryptocurrencies illustrate how revolutionary it will be if correctly utilized. According to studies, just 11% of

Figure 1: Major cryptoassets by percentage of total market capitalization



Source: https://coinmarketcap.com

bitcoins obtained are presently used for payments, indicating a considerable untapped potential for their use in transaction facilitation. Moreover 57% of the public has >50% of their wide range purchased cryptocurrencies, suggesting an increasing count on their worth plus prospective for long-lasting revenues. Cryptocurrencies are not just speculative properties; according to Binance, 39% of individuals purchase plus maintain them acknowledging their worth as a shop of wide range. While the whole market price of all cryptocurrencies has to do with 5% of the globe's cash there is still lots of area for advancement and also combination right into the worldwide economic system.

The current authorization of Bitcoin as a legal tender in El Salvador in addition to the limited amount of simply 21 million bitcoins that might ever before be generated emphasize the cryptocurrency' climbing reputation and also shortage worth. Moreover, the decrease in crypto criminal activity from $4.5 billion in 2017 to $1.9 billion in 2020 shows development towards developing a much safer community.

Although Bitcoin operates independently from traditional financial systems, its impact on established markets and assets is garnering increasing scrutiny. The Chicago Mercantile Exchange Group and the Chicago Board Options Exchange established futures contracts utilizing Bitcoin as the underlying asset in December 2017. Through this step, Bitcoin moved from the financial fringes to the mainstream by joining crude oil and gold in futures trading. This event gives Bitcoin respectability and makes it tough to dismiss as an investment alternative. Consequently, researches done in this field increased significiantly with growing interest toward Bitcoin.

Understanding the connection between Bitcoin and traditional financial indicators holds significant importance for various stakeholders. The Nasdaq, renowned as one of the world's primary stock exchanges, symbolizes the triumph of technology-oriented companies and serves as a gauge of market sentiment toward innovation and growth. Conversely, the US Dollar Index (DXY) tracks the value of the US dollar against a basket of major currencies and provides insights into global currency market trends. Furthermore, gold and oil, deemed essential commodities, are influenced by multiple factors including economic patterns, geopolitical events, and supply-demand dynamics. These commodities hold significance as safe-haven assets or alternative investments with their values mirroring market sentiment and risk perceptions. We would like to investigate interconnection and possible interdependence. This investigation will facilitate investors and researchers acquiring a proper understanding of the size, behavior, and position of Bitcoin within the larger financial ecosystem.

Previous publications have solely dealt with the financial aspects of Bitcoin, its price, and its classification as a financial asset. This paper provides a number of special facets that separate it from previous research studies on the connection between Bitcoin and financial indicators. First of all, a limited number of papers have appropriately taken into consideration the NASDAQ index as a crucial variable in checking out the characteristics of Bitcoin. The NASDAQ index, which stands for technology-oriented firms, provides insights right into the view of technology financiers. Given that Bitcoin is a technological item, the incorporation of NASDAQ as a variable gives a better scale of view compared to depending exclusively on the S&P 500 or DJIA (Dow Jones Industrial Average). Second of all, this study thinks about the effect of the extraordinary COVID-19 situation that unraveled in 2020. While previous research studies have actually discussed the connection between Bitcoin and financial indicators, the variety of documents that have specifically examined this connection within the context of the COVID-19 situation remains minimal. Last but not least, this research study exceeds previous research studies by integrating the shocks as well as occasions that have actually taken place in the cryptocurrency globe throughout the duration of 2022–2023. Especially, this paper considers occasions such as the collapse of Do Kwon/Terra on May 2022 and the failing of SBF/FTX as well as Three Arrows Capital's bankruptcy. Furthermore, this data interval takes into account the prospective influence of a worldwide economic crisis plus interest rate rises from the Federal Reserve. In addition to these, only a few authors have used the dollar index in their research. By taking into consideration these current and impactful occasions, this paper provides an understanding of just how shocks within the cryptocurrency environment can influence the connection between Bitcoin and the chosen economic indicators.

The rest of this paper is structured as follows: in section 2, relevant academic works are shown; in section 3, our methods and data specifications are briefly presented; in section 4, the results are provided; and in the final section, conclusions and recommendations are outlined. The study's findings and discussions are intended to be a valuable resource for future empirical, econometric, and theoretical research.

2. LITERATURE REVIEW

Bitcoin (BTC) has received a lot of interest in the academic literature, with several research looking into different facets of this cryptocurrency. Dwyer (2015) delivers an influential paper demonstrating that BTC has higher average monthly volatility than gold or a group of international currencies. Urquhart (2016), Nadarajah and Chu (2017), and Bariviera (2017) all corroborate this result by demonstrating BTC's inefficient returns.

The volatility of BTC has been extensively researched. In investigating BTC volatility, Katsiampa (2017) underlines the necessity of adding both short-run and long-run components of conditional variance, finding that the ARCGARCH model is the best fit. However, Charles and Darné (2019) contradict this conclusion, claiming a lack of clear evidence for the BTC volatility model. Furthermore, Conrad et al. (2018) investigate the determinants of long-term Bitcoin volatility and discover that it differs dramatically from those of other asset classes, such as gold. In their respective research, Bariviera (2017) and Nadarajah and Chu (2017) confirm the inefficiency of BTC. Guesmi et al. (2019), on the other hand, underline BTC's hedging potential and diversification benefits when examining coupled dynamics with other financial assets.

The literature has also paid attention to the link between Bitcoin and equities markets during times of uncertainty. The COVID-19 pandemic, on the other hand, acted as a stimulus for further research into this connection. Quantile regression analysis found that during moments of high uncertainty, such as the COVID-19 crisis, the returns of the S&P 500 had a considerable influence on BTC returns (Nguyen, 2022). Furthermore, stock market shocks affected BTC volatility throughout these years (Nguyen, 2022). This shows that during periods of great uncertainty, there is a stronger link between the stock market and BTC.

Several research have looked at BTC's possible hedging qualities. Dyhrberg (2016) analyzed the hedging capabilities of Bitcoin, the US dollar, and the UK stock market, concluding that Bitcoin has hedging capacities comparable to gold. Bouri et al. (2017a) used a quantile regression technique to explore the link between gold, global uncertainty, and BTC and suggested that BTC can act as a hedge against global uncertainty in short investment horizons and during bull market regimes. However, Bouri et al. (2017b) later discovered very minimal evidence of BTC's hedging and safe haven features. BTC's association with major foreign stock market indexes has also been studied. Garcia-Jorcano and Benito (2020) examined the connection using copula models, demonstrating BTC's hedging qualities under normal market conditions. Similarly, Urquhart and Zhang (2019) contended that BTC can serve as an intraday hedge for currencies such as CHF, EUR, and GBP.

Several research have focused on BTC's function in investing portfolios. Platanakis and Urquhart (2020) warn against the hazards of incorporating cryptocurrencies into investing portfolios, highlighting the significance of including these risks into decision-making. Briere et al. (2015), on the other hand, revealed that BTC can boost the performance of diverse portfolios, showing its potential as a valued asset class. Furthermore, the launch of BTC futures contracts in December 2017 represented a key milestone for the cryptocurrency, increasing its accessibility and respectability in the financial sector (Mensi et al., 2019).

Bouri et al. (2017a) and Bouri et al. (2017b) investigated the link between BTC and stock indices, demonstrating a weak and fluctuating association impacted by structural fractures. According to Bouoiyour et al. (2016) and Kristoufek (2015), this poor relationship is due to the lack of common price factors between BTC and equities markets. BTC's potential diversification benefits among Islamic managers have also been investigated. According to Lim and Masih (2017), there is a negative connection between Bitcoin and Shari'ah stock indexes, implying that Bitcoin may provide diversification advantages for Islamic investing portfolios.

The market dynamics of BTC have also been investigated. Urquhart (2017), for example, discovered considerable clustering in BTC prices, indicating the prevalence of speculative activity. Shen et al. (2019) discovered a substantial link between BTC trading volume and the quantity of tweets, implying that social media mood influences BTC market activity. These studies help us comprehend BTC's price dynamics and the elements that influence its market behavior.

Several studies have been conducted to investigate the link between Bitcoin, gold, and conventional currencies such as the US dollar. According to Dyhrberg (2016), Bitcoin may be a beneficial instrument for risk management, particularly for risk-averse investors anticipating negative market shocks. According to Baur et al. (2018), Bitcoin has different return, volatility, and correlation characteristics when compared to gold and the US dollar, suggesting its distinct nature as an asset. In terms of hedging capabilities, Dyhrberg (2016) contends that Bitcoin may be used as a hedge against equities in the Financial Times Stock Exchange Index, however Walther et al. (2017) contend that Bitcoin lacks unique gold qualities beyond asymmetric response in variance. Kyriazis (2020), on the other hand, thinks that Bitcoin can be an effective hedging asset in portfolios that incorporate gold.

The link between Bitcoin and gold prices has also been researched. Zwick and Syed (2019) discover a non-linear link between Bitcoin and gold prices, implying that the two assets have complex dynamics. According to Bouoiyour, and Selmi (2019), gold might operate as a diversifier for digital asset investors, underlining the possible complementarity between the two. Furthermore, research into the safe-haven features of Bitcoin and gold reveals intriguing results. While Su et al. (2020) contend that gold's capacity to avoid dangers remains, Kayral et al. (2023) contend that both Bitcoin and gold are safe-haven assets, with gold demonstrating greater hedging efficiency. Kumar (2020) agrees, claiming that both Bitcoin and gold demonstrate the safe-haven feature overall. Furthermore, Gkillas and Longin (2019) discover that Bitcoin and gold give diversification benefits during volatile periods, with the two assets having a low extreme correlation, indicating their possible usage together to safeguard equities portfolios.

Several noteworthy observations arise from studies on the interaction between Bitcoin and the stock market. According to Wang et al. (2019), the S&P 500 and Dow Jones indexes have a favorable influence on Bitcoin, indicating a positive association between the cryptocurrency and the stock market. Maghyereh and Abdoh (2021) discover that the co-movement between Bitcoin and the US stock market is positive at particular frequencies and time periods, indicating that the two may be interdependent. Furthermore, Bouri et al. (2022) demonstrate how the co-movement of US equities and Bitcoin alters with time and frequency, demonstrating the dynamic nature of their interaction.

Dirican and Canoz (2017) employed the ARDL boundary test approach to find a cointegration relationship between Bitcoin prices and the NASDAQ index, revealing hidden links underneath apparent discrepancies. Jareño et al. (2020) used a non-linear ARDL technique to discover a positive relationship between Bitcoin and gold price returns, which was reflected in the correlation coefficients. This emphasizes their possible common characteristics as alternative investments amid market volatility. On a separate approach, Attarzadeh and Balcilar (2022) used the TVP-VAR technique to uncover a significant disparity between Bitcoin and oil. Their research demonstrates Bitcoin's different reactions to market fluctuations when compared to traditional commodities such as oil.

Furthermore, Erdas and Caglar (2018) find that variations in Bitcoin prices appear to impact investors' judgments about the S&P 500 Index, implying a causal link. Furthermore, Кузьмінська et al. (2021) argue that growing trust in Bitcoin by major corporations may lead to increased demand and pricing for the cryptocurrency, thereby influencing stock market dynamics. Akinci and Li (2018) investigate the Granger causality linkages between Bitcoin and stock market indexes, discovering substantial relationships for Japan, Russia, South Korea, Sweden, and the United States. Finally, Chu et al. (2021) argue that Bitcoin can act as a safe haven against Asian stock markets during bad markets, demonstrating its potential diversification advantages. These data point to a complicated and varied link between Bitcoin and the stock market, with variable degrees of interconnectedness, causation, and diversification potential.

Several research papers look at the link between Bitcoin, oil prices, and the Dow Jones Industrial Average. According to Li and Tao (2023), oil prices lead the US market at both low and high frequencies, implying that they have an impact on the Dow Jones Industrial Average. Su et al. (2020) argue that Bitcoin may be used to offset the risks associated with rising oil prices, meaning that Bitcoin might play a role in energy investing. Kaabia et al. (2020) show that a spike in Bitcoin prices has a major impact on the oil market and oil-exporting countries. According to Ma (2022), Bitcoin may be used as a hedge against shocks in the worldwide crude oil market, particularly during geopolitical crises. According to Das et al. (2020), Bitcoin is not better to other assets for hedging oil-related concerns. According to Bani-Khalaf and Taspinar (2023), a major increase in crude oil prices causes a considerable change in the co-movement of crypto assets. Al-Yahyaee et al. (2019) examine the volatility forecasting and diversification advantages of Bitcoin and oil, concluding that BTC and gold offer diversification benefits to oil and the S&P GSCI index. Finally, Yin et al. (2021) show that oil market shocks have both negative and positive effects on cryptocurrency long-term volatility, implying that severe oil market shocks may improve the appeal of cryptocurrencies as a safe haven from sovereign risk. These studies show the complex link between Bitcoin, oil prices, and the stock market, emphasizing the potential for dependency, hedging capabilities, and diversification advantages.

In this study, we extend the previously mentioned literature by discovering the long-run and short-run relationship between BTC and other variables. Furthermore, this paper also takes into accound U.S Dollar Index and covid crisis which make it different from previous studies.

3. DATA AND METHODOLOGY

3.1. Data

We use weekly series data from January 01, 2017 until May 21, 2023, the series are collected in USD. For variables that are in logarithmic form, we wrote L before variable names. The details of variables used are shown in the Table 1.

This paper adopts multiple techniques to investigate the relationship between BTC and other variables. The approached methodology follows the FMOLS,DOLS and CCR methods. Granger Causality test has also done in order to study relationship between variables.

Figure 2 reflects the evolution of Bitcoin, Nasdaq, DXY, Gold and Oil prices between the years 2017 and 2023. As seen in Figure 1, the price of Bitcoin series has an increasing trend with high volatility and the price of one Bitcoin (BTC/USD) reached a new all-time high in 2021, the Nasdaq has been frequently uptrend by years but the level of oil price is more balanced, and decreases in oil price are felt most heavily during COVID-19 period. The descriptive statistics of the variables are presented in Table 2.

Table 1: Definition of variables

Variable type	Variable name	Definition/measurement	Source of data
Dependent	Bitcoin (BTC)	BTC/USD bitfinex historical data	www.investing.com/crypto/bitcoin/btc-usd-historical-data
Independent	NASDAQ100 (NASDAQ)	Nasdaq 100 historical data	www.investing.com/indices/nq-100-historical-data
Independent	Dollar index (DXY)	US dollar index historical data	www.investing.com/indices/usdollar-historical-data
Independent	Gold (GOLD)	Gold futures historical data, USD per troy ounce	www.investing.com/commodities/gold-historical-data
Independent	Oil price (OPRC)	Crude oil WTI futures historical data, USD per barrel	www.investing.com/commodities/crude-oil-historical-data
Control	D1	Dummy variable for 2020 crisis	-

BTC: Bitcoin

Figure 2: Logarithmic graphs of variables

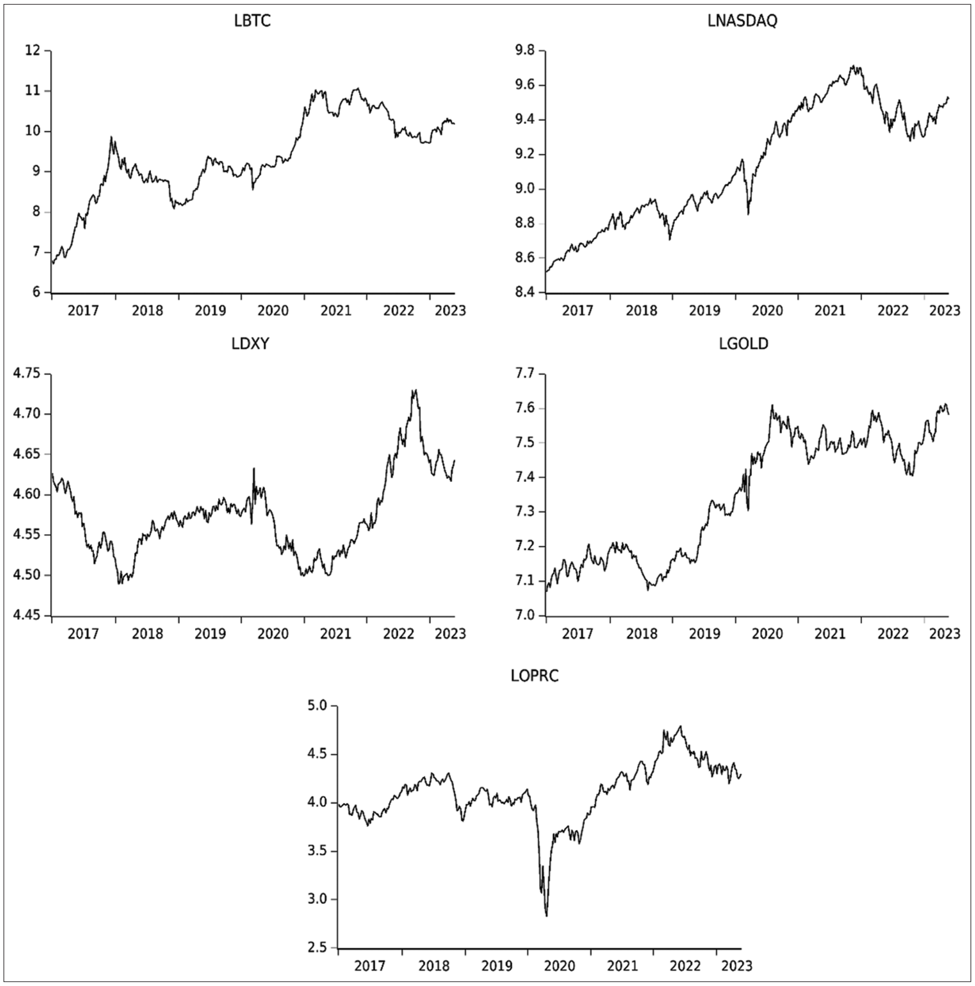


Table 2: Descriptive statistics of variables

Descriptive Metrics	BTC	Nasdaq	DXY	Gold	Oil
Mean	18,091.09	9835.336	97.04165	1577.336	63.37671
Median	10,277.50	8899.525	96.55500	1643.050	61.33500
Maximum	64,398.00	16,573.34	113.3100	2024.800	120.6000
Minimum	820.0000	5007.080	89.07000	1174.800	16.94000
SD	16,325.96	3285.829	4.955664	269.3436	18.67249
Observations	334	334	334	334	334

SD: Standard deviation, BTC: Bitcoin

Table 2 reports the results of the descriptive statistics for all variables. When Table 2 is analyzed based on the January 01, 2017–May 21, 2023 periods, it can be observed that the average price of 1 Bitcoin is about $18091, and Bitcoin ranges between $820 and $64398. The maximum values of the Nasdaq, Oil, US dollar index, and Gold are 16573.34, 120.6, 113.31, and 2024.8, respectively. Furthermore, the minimum values of the Nasdaq, Oil, US dollar index, and Gold are 5007.08, 16.94, 89.07, and 1174.8, respectively.

Table 3: Correlation matrix

Variables	BTC	Nasdaq	DXY	Gold	Oil
Bitcoin	1,00	0,89	−0,11	0,68	0,50
Nasdaq	0,89	1,00	0,07	0,89	0,49
DXY	−0,11	0,07	1,00	0,17	0,39
Gold	0,68	0,89	0,17	1,00	0,32
Oil	0,50	0,49	0,39	0,32	1,00

BTC: Bitcoin

Correlation matrix of variables is presented in Table 3. According to the table, Bitcoin is higly correlated with Nasdaq and gold. The correlation between gold and Nasdaq is also significiant.

3.2. Methodology

The study employs the Fully Modified Ordinary Lears Squares (FMOLS) approach develped by Phillips and Hansen (1990), as well as the Dynamic Ordinary Least Squares (DOLS) estimator produced by Stock and Watson (1993) and Canonical Cointegrating Regressions (CCR) method by Park (1992). These strategies allow for asymptotic efficiency by accounting for the serial correlation effect as well as the test for endogeneity that results from the presence of a cointegrating connection.

Table 4: Unit root test results

Variables	The ADF test				The PP test		The KPSS test	
	Level	k	First difference	k	Level	First difference	Level	Firstdifference
Intercept								
Lbtc	−2.424	0	−18.286***	0	−2.407	−18.337***	1.619***	0.228
Lnasdaq	−1.439	0	−19.456***	0	−1.433	−19.627***	1.975***	0.153
Ldxy	−1.561	0	−20.604***	0	−1.573	−20.461***	0.541**	0.228
Lgold	−1.228	0	−20.064***	0	−1.132	−20.257***	1.931***	0.069
Loprc	−2.107	1	−15.696***	0	−2.075	−15.631***	0.698**	0.051
Trend and intercept								
Lbtc	−2.122	0	−18.391***	0	−2.230	−18.409***	0.139*	0.077
Lnasdaq	−1.842	0	−19.460***	0	−1.706	−19.674***	0.240***	0.078
Ldxy	−2.304	0	−20.671***	0	−2.299	−20.532***	0.214**	0.071
Lgold	−2.324	0	−20.035***	0	−2.229	−20.226***	0.227***	0.061
Loprc	−2.416	1	−15.672***	0	−2.410	−15.617***	0.259***	0.047

***, ** and * indicate rejection of the null hypotheses at the 1%, 5% and 10% significance levels respectively. ADF, PP and KPSS denote the Augmented Dickey-Fuller, Phillips-Perron (Phillips (1988) and Kwiatkowski-Phillips-Schmidt-Shin tests respectively. Maximum lag order is set to 16 and optimal lag order (k) is selected based on Schwarz criterion in the ADF test. The critical values are taken from MacKinnon (1996) and Kwiatkowski-Phillips-Schmidt-Shin (1992) for the ADF, PP and KPSS tests respectively. Estimation period: 01.01.2017–05.21.2023

Table 5: Cointegration test results: Fully modified ordinary lears squares, dynamic ordinary least squares and canonical cointegrating regression

Cointegration Approaches	Engle-Granger test		Phillips-Ouliaris test	
	Tau-statistic	Z-statistic	Tau-statistic	Z-statistic
FMOLS	−4.017854*	−28.71154*	−4.026750*	−28.75819*
DOLS	−4.017854*	−28.71154*	−4.026750*	−28.75819*
CCR	−4.017854*	−28.71154*	−4.026750*	−28.75819*

*Denotes significance level of 10%. Null hypothesis is there is no cointegration. FMOLS: Fully modified ordinary lears squares, DOLS: Dynamic ordinary least squares, CCR: Canonical cointegrating regression

Note that the FMOLS, DOLS, and CCR can only be used when the cointegration criteria among the I(1) variables is met. As a result, the long-run elasticities in this article will be computed using FMOLS, DOLS, and CCR.

4. RESULTS

4.1. Unit Root Tests

To determine the methods to be applied to estimate long-term and short-term regression coefficients, identifying the variables' order of integration is needed. Table 4 tabulates ADF (Dickey (1981), PP and KPSS unit root test results with intercept, and with trend and intercept. Almost all unit root tests end with the same integration order for the variables. It is found that originally all variables are stationary at the first difference. Hence, it is concluded that our variables are I(1).

Because all variable are I(1), we can successfully apply FMOLS, DOLS and CCR methods to estimate whether there is long-run association between the variables of interest. The following section outline estimation outputs obtained from aforementioned cointegration tecnhiques.

4.2. Estimation Outputs

To obtain more reliable estimates regarding the long-run effects of variables on the Bitcoin price, FMOLS, DOLS, and CCR cointegration methods are applied together. At the first stage, we started with testing whether there is a cointegration relationship in the estimated model (Table 5). Both the Engle–Granger (Engle (1987) and the Phillips–Ouliaris (Phillips (1990))cointegration tests rejected the "no cointegration" hypothesis at 10% significance level. Hence, we could proceed to interpret the estimation outcomes (Table 6).

According to EngleGranger and PhillipsOuliaris Cointegration tests, Table 5 reports the results. Both tests produced the same taustatistic and zstatistic values for all cointegration equations estimated by employing FMOLS, DOLS and CCR. Against the null hypothesis of no cointegration, the null is rejected at 10% level of significance for all cases. Though the significance is relatively weak, we assume that the cointegration exists and weakness is due to not taking longer time path. Thus, we find evidence for the existence of longrun relationship in estimated cointegration equations. We can proceed to the interpretation of longrun coefficients.

Table 6 presents longrun coefficients in the equations estimated by using FMOLS, DOLS, and CCR cointegration methods respectively. Most of the estimated model coefficients are statistically significant at 5%, which also provided strong evidence to argue the role of variables on the Bitcoin price. However, results indicate no significant relationship between Gold and Bitcoin price. According to estimated models using FMOLS, DOLS and CCR, we should be 90% confident that U.S. Dollar index, oil price and NASDAQ-100 index significantly impact the Bitcoin price. Nasdaq and Oil price produce positive but U.S. Dollar index presents negative association. Theoretically, negative association is expected.

In the FMOLS model, a 1% increase in LOPRC increase Bitcoin by 0.779%, and a 1% increase in LNASDAQ increase Bitcoin by 2.299%, in average. On the contrary, a 1% increase of LDXY leads to a 2.865% decline in Bitcoin. Here, the coefficient of LGOLD are insignificant, which means that variable has no meaningful impact on Bitcoin.

In the DOLS model, a 1% increase in LNASDAQ, and LOPRC increase Bitcoin by 2.391%, and 0.686% in Bitcoin, in average. On the contrary, a 1% increase of LDXY leads to, on average, a 3.872% decline in Bitcoin. Here, the coefficient of LGOLD is insignificant again, which is similar to the FMOLS results.

Table 6: Long-run coefficients by fully modified ordinary lears squares, dynamic ordinary least squares and canonical cointegrating regression

Variable	Coefficient	SE	t-statistic	P
Panel A: Results from FMOLS				
LDXY	−4.103610	0.559470	−7.334812	0.0000***
LNASDAQ	2.299986	0.394785	5.825913	0.0000***
LGOLD	0.531979	0.714106	0.744958	0.4568
LOPRC	0.779715	0.190246	4.098463	0.0001***
D1	1.716106	0.564854	3.038139	0.0026***
Panel B: Results from DOLS				
LDXY	−3.871958	0.606652	−6.382507	0.0000***
LNASDAQ	2.390990	0.429332	5.569090	0.0000***
LGOLD	0.327495	0.781394	0.419116	0.6754
LOPRC	0.684991	0.205526	3.332874	0.0010***
D1	0.529845	0.688515	0.769548	0.4421
Panel C: Results from CCR				
LDXY	−4.144730	0.565113	−7.334344	0.0000***
LNASDAQ	2.275648	0.400269	5.685294	0.0000***
LGOLD	0.577446	0.724297	0.797251	0.4259
LOPRC	0.797852	0.191617	4.163787	0.0000***
D1	1.747425	0.575255	3.037655	0.0026***

* , **and ***denote significance levels of 10%, 5% and 1%, respectively. FMOLS: Fully modified ordinary lears squares, DOLS: Dynamic ordinary least squares, CCR: Canonical cointegrating regression, SE: Standard error

Table 7: Results of granger causality tests

Null hypothesis	F-statistic	P
LBTC does not granger cause LNASDAQ	0.531	0.4671
LNASDAQ does not granger cause LBTC	4.661	0.0316**
LBTC does not granger cause LDXY	3.209	0.0741*
LDXY does not granger cause LBTC	0.834	0.3617
LBTC does not granger cause LGOLD	0.216	0.8060
LGOLD does not granger cause LBTC	3.624	0.0277**
LBTC does not granger cause LOPRC	5.161	0.0238**
LOPRC does not granger cause LBTC	3.104	0.0790**

***and **indicate rejection of the null hypotheses at the 1%, 5% and 10% significance levels respectively

CCR results also show a similar pattern with previous models. In the CCR model, in average, a 1% increase in LNASDAQ and LOPRC increase Bitcoin by 2.276% and 0.798% respevtively. On the contrary, a 1% increase of LDXY lead to, on average, 4.145% decline in Bitcoin.

Changes in LOPRC and LNASDAQ across several econometric models consistently show a positive relationship with Bitcoin, while LDXY continually indicates a negative impact. Regarding LGOLD, all models show that its coefficient is insgnificant, suggesting that it has no meaningful effect on Bitcoin.

4.3. Granger Causality

Examining the relationship between the series based on the estimation of the present and past values is called the Granger causality test (Granger (1969). At the 5% significance level, the results show that there are significant Granger causality from Nasdaq to Bitcoin and Gold to Bitcoin (Table 7). Also, there is Granger causality from Oil price to Bitcoin at the 10% level of significance.

5. CONCLUSION

This study analyses the long-run relationship between Bitcoin and Nasdaq, U.S. Dollar Index and Commodities. In this study, FMOLS, DOLS and CCR models are used to analyse the long-run relationship among the variables in the model.

Employing FMOLS, DOLS and CCR cointegration methods over a time-series dataset of the 2017-2023 period, current research findings present strong evidence for a long-term causal relationship between Nasdaq, Oil price and Bitcoin, in line with previous studies by Dirican and Canoz (2017) and Al-Yahyaee et al. (2019), but in contrast with study by Attarzadeh and Balcilar (2022). Nevertheless, this study reveals an reverse relationship between the U.S. Dollar index and Bitcoin for a long-term relationship, as we expected. On the contrary, results show that Gold does not have significant effect on Bitcoin, in line with previous studies by Erdas and Caglar (2018), but in contrast with studies by Jareño et al. (2020).

The robustness of our models is supported by statistically significant coefficients across most variables. Moreover, this interaction between Bitcoin and other variables is confirmed by the Granger causality. The causality tests show that there is significiant Granger causality to Bitcoin from Nasdaq, oil and gold.

This paper is relevant to a wide range of readers, including investors, traders, and speculators interested in learning more about the complex link between Bitcoin and major financial indicators. Portfolio managers can learn about prospective diversification methods and risk management measures. Furthermore, the study is a great resource for future academics interested in the changing dynamics of cryptocurrency markets and their interconnections with traditional financial institutions.

Future research should address certain limitations highlighted by this study. Firstly, investigating the potential expansion of countries recognizing Bitcoin as legal tender could provide deeper insights into the currency's global acceptance and influence on traditional financial systems. Secondly, considering the impact of the anticipated 2024 halving event on Bitcoin's dynamics and data utilization would enhance our understanding of its evolving narrative. Lastly, an exploration of the ramifications of the acceptance of Spot ETFs, like Blackrock's, could shed light on Bitcoin's role within the broader global financial ecosystem and its evolving connectivity. These potential directions could significantly contribute to a more comprehensive comprehension of Bitcoin's future trajectory and its integration into the global economy.

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