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Cryptocurrency Price Dynamics: Unveiling Bitcoin's Predictors

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Abstract
The advancement in technologies has changed the picture of today's economy. Cryptocurrency is the most trending currency nowadays. The form of cryptocurrency that is most commonly used in trading is Bitcoin. Since 2016, continuous fluctuations have been observed in the price of Bitcoin. The objective of the current study is to classify the strong predictor of Bitcoin's price fluctuations and the associations of all these variables with each other. The price of several variables is selected as independent variables, including oil, VIX index, and US dollars. The price values for all study variables are collected for one year daily. The study findings indicated that lag 2 in the VAR model is the optimum lag for the model using HQIC and SBIC criteria, so today's price depends on the previous two days' price of independent variables. The correlation results indicated that the previous two-day price of EURO predicts the BTC's today's price. A negative association is found between VIX and BTC. It is indicated that a 1 percent increase in the price of the VIX index will lead to the 60 decreases in BTC's today price. The study also showed that it is not the price of BTC that forecasts today's worth of BTC, but it is the prices of VIX, euro, and oil that can predict today's price of BTC.
Keyword: Cryptocurrency, Bitcoin, Oil price, VIX index

1. Introduction
The emergence of internet-based services and technologies transformed many facets of the economic and commercial sectors (Andrychowicz, 2015). Economic networks experience several modifications over time. Individuals now have confidence in internet platforms such as e-commerce. Historically, banknotes were utilized for the exchange of goods and services. Although paper money seems to have been a traditional way to conduct business, electronic cash has emerged as a much more desirable option (Deepika & Kaur, 2017; Ackah, 2023). Money is one of the most valuable commodities when it comes to trading products and services. Innovative technological advancements have given rise to novel kinds of currency. Throughout history, various forms of currency have emerged. Each form of currency possesses distinct advantages and disadvantages. The main objective is to examine the novel form of cryptocurrencies, sometimes referred to as digital money or cyber cash. Research indicates that Bitcoin is the most widely used cryptocurrency, despite the fact that there are numerous different varieties (Ben-Sasson et al., 2015; Adeel, 2019). It is considered the world's inaugural decentralized money, as it is not issued by a monetary institution and is exempt from governmental rules. It was initially launched in 2009.
Satoshi Nakamoto is the originator of Cryptocurrency (Andresen, 2014). The network operates on a peer-to-peer basis, facilitating direct payments between users without intermediaries. It consists of two terms: Bit and Coin. Bitcoin represents a remarkable cryptographic innovation that illustrates the capacity to create something distinctive in the digital domain (Clark et al., 2015). Cryptocurrency is a completely autonomous digital currency that utilizes cryptographic techniques. It possesses conventional monetary features as well, although it is unbacked by any sort of power. Bitcoin has become a widely used payment mechanism due to its many desirable qualities.
According to Andrychowicz et al. (2017), the ensuing are the key individualities of bitcoin expenses: Dues aren't needed for dealings. Outflows are inveterate in a small amount of phase, there is indeed a low danger of payment fraud due to the irreversibility of the transactions, and no identification is required. "Bitcoin is a wonderful cryptographic feat, and the potential to build something in the digital realm that can't be duplicated has huge value (General & General, 2016; Sorrell et al., 2016)."
Bitcoin may be obtained in three ways: mining new ones, purchasing them, and receiving them in return for products and services. The act of "mining" is the discovery of fresh Bitcoin. It is, in fact, a Bitcoin transaction confirmation service. This procedure is carried out on a desktop (Eyal & Sirer, 2014). Miners check Bitcoin transactions to ensure that they are legitimate. Individuals attempt to verify various transactions, not just one (Glaser, 2017; Nwezeaku, 2018). The 'blockchains' are comprised of these transactions grouped into boxes with a digital padlock. 'Miners' use software to locate the key to unlock the padlock. The box opens, and the transactions are validated after the computer has found it (Bissias et al., 2017; Sheikh & Ahmad, 2020). As a result, while Bitcoins are 'mined' by individuals, the program is the one that 'issues' them. When a new block is discovered during the mining process, the computer adds new Bitcoin transactions to the blockchain, and the miner receives a quMining is extremely costly (Eyal & Sirer, 2014; Mealli, 2021). As a result, an individual miner may occasionally join a mining pool. As a result, there is no need to construct mining farm because it is prohibitively expensive. All we need to do now is equip our pool with processing power (Ben-Sasson et al., 2015; Shahid & Ali, 2021; Iqbal & Shahzad, 2020; Serani, 2024). The mining proc costly, but it is also time demanding. So, before we start mining, we can compute the mining cost on the mining dashboard and decide whether to continue.

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Crude oil is considered one of the essential elements of energy in production. As Yoshino and pointsizadeh Hesary (2016) points out, one of the important contributors is oil to contributors is oil in the global economy. According to Lehmann (2019), oil has multiple benefits. Despite an increasing demand for those other renewable natural resources, including wind, water, nuclear, and solar electricity, crude oil plays an important part in macroeconomic movements. The oil price has fluctuated wildly—twice as much as other commodities (Dehn, 2001). Global oil price changes have been a topic of controversy and concern for several governments since the 1970s, comprising oil-exporting nations, where the government budget is based on oil income and where economic growth can be hurt directly or indirectly by these shocks, as well as oil-importing countries, where oil is utilized as a raw substantial for industrial and conveyance fuels (Shen et al., 2018; Roussel et al., 2021). A possible starting point might be Hamilton's seminal 1983 study on the issue, that found that the post-war era witnessed the U.S. industry influenced by external factors affecting oil prices. Cunado and Perez de Gracia (2003) established that fluctuations in the cost of oil extensively growth in the economy in various European countries, whereas Du et al (2010) demonstrated that worldwide oil price variations substantially impact China's economic development and inflation. There is also a debate on whether oil prices are external or internal. The oil price is influenced by distinct demand and supply shocks, rendering this variable non-exogenous (Kilian, 2009). There is a debate regarding the exogeneity or variation of oil prices. The oil price is influenced by distinct demand and supply disruptions. Therefore, this variable cannot be deemed exogenous (Kilian 2009).

VIX is a 30-day forward-looking volatility index calculated from S&P 500 options (Kuepper & Scott, 2020), with the value of each choice indicating the industry's forecast of 1-month forward-looking volatility. The VIX aims to measure the magnitude of price fluctuations in the S&P 500, namely its volatility. Increased volatility correlates with more pronounced price fluctuations in the index, and conversely. Traders can trade VIX contracts, swaps, and ETFs to protect or gamble on volatility swings in the index and use the index to monitor volatility. In general, there are two ways to calculate volatility. The first way is based on actual volatility, which is calculated statistically based on prior prices over a given period. This method involves calculating statistical metrics, including mean, variance, and standard deviation, from historical pricing datasets. The VIX utilizes the second method, which involves deducing its value from indicated option prices. Options are derivative instruments whose value is contingent upon the probability that the present price will fluctuate adequately to attain a specified level, known as the strike amount or exercise price. Each day at the petrol station and the supermarket, the worth of money impacts you. Gas and food demand is inelastic (Ali et al., 2021; Eitches & Crain, 2016). Producers are aware that you must purchase petrol and food weekly. When prices rise, it's not always practical to postpone purchases. Any additional expenses incurred by producers will be passed on to the consumer. You'll pay the higher price for a while until you can modify your behaviours. An increase in foreign capital contributes to a robust capital account and elevated demand for dollars. Investors consistently pursue the most reliable or ‘secure’ returns.

The functioning of the business is critical when selecting whether to buy or sell dollars. A thriving economy will encourage business worldwide due to its perceived security and capacity to deliver a reasonable degree of profitability. In currency trading, when creating a position in the dollar, the trader must assess many factors that affect the dollar's value to identify a trend or direction.

As it is clear from the above discussion that fluctuation in oil price, VIX index, and U.S. dollar affects a country's economy a lot. Therefore, this study also wants to investigate the price fluctuations of the crypto market's fluctuations of various assets such as commodities and securities index to determine what tendencies cryptocurrencies demonstrate most. The independent variables in this study are oil price fluctuations, VIX index price fluctuations, and U.S. dollar fluctuations. The dependent variable of this study is Bitcoin price fluctuations. The objectives of this study is as follows: analyze the price fluctuations of Bitcoin in relation to the price fluctuations of oil, the VIX index, and the U.S. dollar, in comparison with the EURO over a specific period.

2. Literature Review

According to the pricing theory, the supply and demand link calculates the cost of any commodity or service. The most optimal market rate for an item or service, according to pricing theory, is when the profit earned from those who want it equals the purchaser's marginal expenses. The pricing theory, sometimes known as “price theory,” is a microeconomic concept that examines supply and demand to determine the best price point for a particular commodity or service. The goal is to achieve the balance in which the supply of products or services satisfies the demands of products or services. The theory is about the relationship between changes in market conditions and corresponding price changes (Mills, 1959).

The same market dynamics that drive the value of other products and services also affect the value of bitcoin. If there are more buyers than sellers, prices are likely to rise. When there are more buyers than sellers, the value tends to drop. The stock market, real estate, and most open markets are comparable. The maximum quantity of Bitcoin is capped at 21 million coins, with over 19 million coins having been mined to date. This idea is similar to outstanding stock in the share market (Aggarwal and Kumar, 2021; Shair et al., 2021). The order is activated at the point where buyer and seller meet at the common price. The final trading price represents the current bitcoin value. A website like CoinMarketCap or a public blockchain explorer that allows anybody to study each bitcoin transaction that has ever occurred may be used to obtain the most current bitcoin price (Aysan, 2021).

Scholars have studied Bitcoin price to deduce the elements that influence its worth. Macroeconomic and financial factors, attractiveness, and demand-supply fluctuations are the three groupings of these factors reported in the literature. Many research has focussed on only one of these categories, while others attempt to undertake a more comprehensive study by examining all of them. In the current study, the variables from Microeconomics will be studied to affect Bitcoin's price. The division of economics that focuses on the people's choices regarding the lack of resources and the relationship between these choices and the availability of products is called microeconomics (Education, 2015). This study will investigate the association between oil price fluctuations, VIX index price fluctuations, and U.S. dollar fluctuations.

The effects of Bitcoin (petroleum) and economic markets (equity, gold, and stock prices) on the value of the U.S. dollar were examined. Monthly data spanning from August 2010 to September 2016 was employed to analyze these relationships with a GJR-GARCH model. The results indicate that bitcoin, gold, and stock prices (DSJI) exert a negative and statistically significant influence on the performance of the U.S. dollar index. There is also proof that the market for bitcoin and its correlation with the value of the U.S. currency are unbalanced. The latter can be considered a secure haven for gold, stocks, and bitcoin (Antoniadis et al., 2018). A study was performed to ascertain the association between price swings in cryptocurrencies and the VIX, employing bivariate and multivariate wavelet methodologies (BTC). The consequences of three significant global factors—oil price volatility, geopolitical concerns, and US economic policy—are taken into account in order to achieve this. Wavelet Coherence (W.C.), Cross Wavelet Transform (CWT), Power Wavelet Coherence (PWC), and Multiple Wavelet Coherence (MWC) are approaches employed to achieve this. The BTC-VIX correlation varies over time and across both low and high frequency. Moreover, if the two variables change in the same direction, they are positively correlated. Still, if this movement is in the opposite direction, it can be said that they are negatively correlated. VIX news can anticipate bitcoin price returns at various frequencies. PWC and MWC studies reveal that OVX, EPU, and GPR variables have varying effects on the BTC-VIX nexus at different frequencies. Finally, investment horizons affect the relationships between BTC-uncertainty indexes (Al-Yahyaee 2019).

Using weekly data from 2010 to 2018, researchers looked at the factors that impact the values of the most popular five cryptocurrencies: Bitcoin, Ethereum, Dash, Litecoin, and Monero. The research uses the ARDL approach and reports on several findings. Firstly, multiple factors are considered both long and short-term determinants of the cryptocurrency's price, including the amount of trading activity, movements of an asset, and variation in trading price at a specific time. The other determinant of the price of cryptocurrencies that goes to the long term is consumers' demand, and it is a long-term process. This suggests that the creation (perception) of the appeal of cryptocurrencies is influenced by the passage of time. To put it another way, it moves slowly inside the market.

Moreover, cryptocurrencies are positively affected by the VIX index, but their impacts are long-term. But these impacts vary from positive to negative, and at the current level, the index lacks importance, except for bitcoin. The bitcoin has a -0.20 estimation rate with a 10% probability value (Sovbetov, 2018, pp.1-27).

By evaluating the price time series over three years, research was done to expose the efficacy of the standard autoregressive integrative moving average (ARIMA) model in making predictions value of bitcoin. On the one hand, empirical investigations show that this basic approach is effective in sub-periods where the time-series behavior is nearly unaltered, especially when employed for short-term prediction, such as 1-day forecasting. Whenever investigators try to train the ARIMA model for three years, during which the bitcoin price has undergone a variety of behaviors, or when they try to use it for long-term prediction, they find that it adds significant prediction mistakes. The ARIMA model, in particular, seems unable to capture price spikes, such as those seen towards the end of 2017. Then, more characteristics should be retrieved and combined with the price for a more appropriate price forecast. They looked into bitcoin price prediction further using an ARIMA model trained on a huge dataset, and a narrow test window of the bitcoin price with length *w*as input. The interplay of prediction accuracy (p,q,d) and window size w is investigated in this work (Azari, 2019).

Using an impartial quantile volatility estimator, this paper explores the excess volatility in Bitcoin prices. This study uses bootstrap, multi-horizon, sub-sampling, and rolling-window techniques to capture Bitcoin price movements are virtually efficient, according to academics. Although Bitcoin prices have experienced significant volatility and shown evidence of excess volatility in the past, this has been reducing over time. After accounting for outliers, it was also discovered that the Bitcoin market is becoming more mature. Overall, Bitcoin prices indicate that efficiency is improving while volatility is reducing. Results have ramifications for investors and policymakers when making investment decisions (Kayal & Balasubramanian, 2021).

Because Bitcoin is a one-of-a-kind asset still in its infancy, its future is often seen as unclear. Even though it's been around for a decade, it's still a Wild West territory in several ways, with future restrictions unpredictable. While it's feasible that bitcoin's value would rise over $100,000, it's also possible that it may go below $0. Government action is expected to have the greatest influence on bitcoin's price. Regulatory authorities in the United States may enact new rules or regulations that significantly restrict bitcoin, if not outright ban it. When it comes to federal authorities, the ones to keep an eye on regarding cryptocurrency regulation are the FTC, the CFTC, and the SEC. Because bitcoin is still unregulated, it lacks the same legal and privacy safeguards as funds and securities denominated in U.S. dollars (Jones, 2021).

As concluded from the above discussion, previous studies showed a correlation between oil price, VIX index price, U.S. dollar price, and bitcoin price. And the price of bitcoin is continuously the fluctuations. Therefore, this study wants to explore the factors that are the best predictor of bitcoin price fluctuations.

3. Methodology

This research is about to investigate the impact of multiple factors on Bitcoin's price fluctuations. These factors are related to microeconomics: oil price, VIX index, and U.S. dollar. The study focuses on the association among the price fluctuations of oil, VIX index, U.S. dollar, and Bitcoin to determine which factors are closely related to each other's especially associations of all the factors with the price of Bitcoin. The study has independent and dependent variables, and independent variables included oil price, VIX index price, and U.S. dollar price. The dependent variable is the price of Bitcoin.

The research design refers to a researcher's approach to answering the research question. It is the combination of multiple strategies to collect, analyse and present data according to the needs of the research question (Suter, 2012, pp.342-386). The quantifiable investigation strategy is used in this work because the data is figures, e.g., prices of Bitcoin, VIX index, U.S. dollar, and oil. The research method used to collect and analyze numerical data or figures is called quantitative research. It is used to interpret numerical data to find averages and analyze patterns. Based on the analysis of numerical data, predictions are made and determine cause and effect relationships (Bhandari, 202 p. 2019).

The data is collected for all study variables (oil prices, U.S. dollar prices, VIX index prices, and Bitcoin prices). The prices of all variables from Jan. 1, 2020, to Dec. 31, 2021. Prices are recorded daily and used in the study. The data about price fluctuations of study variables are collected from two websites, Yahoo and Finance.

This study uses following econometric model to identify the impact of the price of oil, U.S. dollar, and VIX in a specific period.

$$bitcoin = \beta_0 + \beta_1(vix) + \beta_2(crudeoil) + \beta_3(eurusd) + \varepsilon_0$$

The inferential analysis is more specifically used to test the study's hypothesis. VAR model will be used for regression of a target variable, and the Engle-Granger test investigates correlation among study variables.

3.1. VAR Model

This study used Var Model for identifying the best predictor that can affect the price fluctuations of Bitcoin. A statistical model called vector autoregression (VAR) describes the connection between several quantities about their changes over a specific period. VAR is a stochastic process model. It generates an autoregressive model for a single variable through multivariate time series. The Var models are most commonly used in natural sciences and economics. In Var models, every variable has an equation that models its progression through time. An equation has multiple components, including past values of the target variable, the past value of other variables, and the error term. The Var model does not require the force that affects the target variables. It just required a list of variables that affect that specific variable or phenomena so that it can make a hypothesis about their relationship.

The fields of economics and finance use this model because of the functions it performs. It provides a framework to achieve the specific goals of that field, including analyzing policy, drawing inferences from a structure, making predictions and describing data (Stock & Waston, 2001, pp.101-115.). These models have a long history of analyzing various time series (Quenouille, 1957). They are generally simple to work within theory and practice since they are linear models. The models were recommended by Sim (1980, pp.1-48.) for analysis in the field of economics rather than the simultaneous equations model, and they got popular. The lengthier observation time series availability highlighted necessity models focused on the variables' dynamic structure. VAR models are simple to use for predicting and may be applied to economic analysis. Disentangling the relationships among the variables in a VAR model is often done using frequency response analyses or error correction model decomposition.

3.2. Engle-Granger

To determine the association between all of the study factors, the Engle Graner test is utilized. The Engle-Granger test is employed to achieve the goal of the study, which is to examine the nature and extent of correlations among the study's variables. The Engle-Granger analysis is a sort of cointegration analysis that measures the degree of association between two or more-time series. A British economist named Paul Newbold and Granger published the concept of fictional regression in 1987, with the original proposal coming from Nobel laureates Robert Engle and Clive Granger. When many non-stationary series are cointegrated, they are unable to deviate from equilibrium over time, which is what cointegration tests reveal. The main purpose of these tests is to check the association of variables with expected value over a specific period and determine how they are different in this association.

This test was employed when royalties were formulated based on static regression analysis. Subsequently, an analysis was conducted to ascertain the existence of a unit root. The primary objective of this examination is to examine the interrelationship among research variables, particularly those represented as time series. This test used the Dickey and Fuller test to achieve its goals and used the other tests. It describes the relationship among variables that's values are continually changing. It can describe the relationship among more or more variables but has a drawback when the number of variables is more than two. The drawback is that it describes multiple relationships among them as the model depends on only one equation, so that it can be the other drawback. Some tests are used to overcome these flaws, including Johansen's and Phillips-Outliers. In this study, the STATA is used to run all the analysis.

4. Results and Discussion

In this analysis daily data set has been used for all four variables first one is a bitcoin second one is Euro to USD exchange rate the third variable is VIX index and the last variable is crude oil prices. A total of 397 observations are has been taken. The data is taken from 10 January 2020 to 31st December 2021. The mean value of a difference in BTC price is 83.76, the minimum value is negative 7554.0 39 and the maximum value is 4326.047 (see Table 1). The first difference is Euro to USD exchange rate mean value is zero minimum negative 0.3 and the maximum is 0.016. The next variable of analysis is VIX index whose mean value is negative 0.15, the minimum value is negative 17.64 and the maximum value is 21.57. The first difference in oil prices is also has been included in the analysis whose average value is 0.236, its minimum value is -6.58 and the maximum value is 46.69.

Table 1: Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
dbtc	397	83.766	1445.07	-7554.039	4326.047
deur	397	0	.005	-.03	.016
dvix	397	-.15	2.69	-17.64	21.57
doil	397	.236	2.71	-6.58	46.69

Table 2: Linear regression

BTC	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
VIX	362.774	65.244	5.56	0.00	234.588	490.96	***
Crudeoil	989.257	38.578	25.64	0.00	913.462	1065.051	***
EURUSD	84372.186	12498.715	6.75	0.00	59815.713	108928.66	***
Constant	-130788.41	14787.452	-8.84	0.00	-159841.61	-101735.21	***
Mean dependent var		29262.001		SD dependent var		19690.016	
R-squared		0.712		Number of obs		504	
F-test		411.485		Prob > F		0.000	
Akaike crit. (AIC)		10777.364		Bayesian crit. (BIC)		10794.254	

**** p<.01, ** p<.05, * p<.1*

In this linear regression table 2, bitcoin taken as dependent variable and VIX, Crude oil and euro/usd taken independent variable. These regression analysis confirms that this model is giving highly significant results with R-Sq 71 percent explaining the variation in dependent variable by independent variable. The coefficient of vix is explaining that when vix index will increase by one percent the bitcoin will increase by 362.77 percent. When prices of crude oil will increase by one percent the bitcoin value will increase by 989.25 percent. When euro/usd price will increase by one percent the bitcoin value will increase by 84372.18 percent. All of these values are highly significant as their p-values are less than 0.05 so these are significant at 99% percent. From the above regression analysis, we can conclude that euro/usd is the best predictor for bitcoin as its coefficient is highest and positively effecting the bitcoin.

$$bitcoin = -130788.41 + 362.774(vix) + 989.257(crudeoil) + 84372.186(eurusd) + \varepsilon_0$$

The table 3 shows that four variables—DBTC, DOil, DVix, and DEur/Usd—have stationary time series data according to the Augmented Dickey-Fuller (ADF) test. If a time series has a unit root, it is non-stationary and its statistical features (such mean and variance) fluctuate over time. The ADF test determines this. The test results for DBTC (-19.009), DOil (-34.681), DVix (-20.173), and DEur/Usd (-13.574) are all significantly negative. These values are substantially lower than the 1%, 5%, and 10% significance levels' critical values of -3.457, -2.878, and -2.570. This shows that all four variables reject the null hypothesis (which assumes a unit root), showing that time series data is stationary. Additionally, all MacKinnon p-values are 0.000, strongly rejecting the null hypothesis. Thus, these variables' data does not show non-stationary behaviour like trends or cycles, so they can be used for further research or forecasting with confidence that their statistical features will remain constant.

Table 3: Augmented Dickey Fuller Test

ADF FOR		Test statistics	1% critical value	5% critical value	10% critical value	MacKinnon approximate p-value for	Stationarity level
DBTC	Z(T)	-19.009	-3.457	-2.878	-2.570	0.000	Stationary (1)
DOil	Z(T)	-34.681	-3.457	-2.878	-2.570	0.000	Stationary (1)
DVix	Z(T)	-20.173	-3.457	-2.878	-2.570	0.000	Stationary (1)
DEur/Usd	Z(T)	-13.574	-3.457	-2.878	-2.570	0.000	Stationary (1)

To forecast today's price using the VAR (Vector Autoregressive) model, one must choose an ideal lag length, which dictates the number of periods' prices (or returns) that are utilized (see Table 4). If the model employs a single lag, for instance, the current price is dependent on the price of the previous day. The current price is dependent on the prices of the previous two days if two lags are selected, and similarly for subsequent days. Multiple criteria are employed to determine the optimal lag length for the annualized returns of Bitcoin, VIX, EURUSD, and crude oil prices. These criteria include log-likelihood, likelihood ratio test, final prediction error, Akaike Information Criterion, Hannan-Quinn Information Criterion, and Schwarz Bayesian Information Criterion. Using FPE and AIC, we can compare the prediction abilities of various models and determine which one strikes the optimal balance between simplicity and accuracy. Finding the ideal lag length is crucial because if you use too many lags, the model will become too complex and less effective, and if you use too few, it will miss important information. This analysis focusses on three key criteria: Akaike, Schwarz, and Hannah-Quinn. Since all of these tests reach their highest values at lag 4, it appears that this model's sweet spot is at this point. In particular, lag 4 is further supported as the best choice by the highest value of 17.5272 provided by the AIC criterion. The appropriate latency for each test is indicated by the stars in the fourth row of the table. The HQIC and SBIC criteria have determined that lag 1 is the ideal latency for Bitcoin, VIX, EURUSD, and Crude Oil. By "constant" we mean the exogenous variable, which is defined as the average value of the dependent variable in the absence of independent variables; this variable is decided externally to the model. The disparity among the annualised returns of the logarithmic prices for Bitcoin, VIX, EURUSD, and Crude Oil constitutes the endogenous variable. The optimal latency for this model is lag 1, as determined by the log-likelihood ratio test and several information criteria.

Table 4: Lag length Selection order criteria

Sample: 10 Jan, 2020 - 17 Dec, 2021, but with gaps. Number of observations = 86								
Lags	LL	LR	Df	p	FPE	AIC	HQIC	SBIC
0	-1408.44				2.2e+09	32.8474	32.8933	32.9615
1	-742	1332.9	16	0.000	584.027	17.7209	17.9506*	18.2917*
2	-719.808	44.385	16	0.000	506.991	17.5769	17.9904	18.6043
3	-703.883	31.85	16	0.010	511.066	17.5787	18.1759	19.0627
4	-685.671	36.424*	16	0.003	491.182*	17.5272*	18.3082	19.4679
Endogenous: VIX BTC Crudeoil EURUSD								
Exogenous: constant								

After the optimal lag for equations 1 and 2 has been determined, the coefficient matrix that was derived from the VAR model is displayed in Table 5. According to Equation 1, the dependent variable is the first difference in the price of Bitcoin, and the second lag of the log return on investment price demonstrates a strong link with the first difference in the price of Bitcoin. The p-value for this link is lower than the 5% significance level, and the coefficient for this relationship is -0.1296, which is also statistically significant. The return on the price of Bitcoin from two days ago can be used to make a prediction about the price of Bitcoin today. An rise of one percent in the two-day lagged return on the logarithm of price will result in a decrease of 0.1296% in the current price, which is an effect that is noteworthy from a statistical point of view.

Subsequently, inside the same equation, the second lag of the log return on price demonstrates a substantial connection with the first difference of Euro price. This correlation is described by a coefficient of 51629.52 and a p-value that falls within the 5% threshold. In light of this, it appears that the return on the Euro price from two days ago can be employed to make a prediction on the price of Bitcoin today. There is an extremely significant correlation between the two variables, as evidenced by the fact that a one percent increase in the two-day lagged return on the logarithm of the Euro price will result in a 58,720.85% fall in the price of Bitcoin today. A coefficient of -11.702 indicates that there is a considerable connection between the second lag of the log return on price and the first difference in the price of the VIX Index. Also, this connection is significant. Given that the p-value for this link is more than the standard threshold of 5%, it may be concluded that the effect is statistically insignificant. Due to the fact that a 1% increase in the lagged return would only result in a 0.06064% decrease in the price of Bitcoin, the two-day lag in the return of the VIX Index does not have a significant impact on the price of Bitcoin today.

Table 5: Coefficient matrices

Equation	Parms	RMSE	R-sq	chi2	P>chi2	
Dbtc	9	1357.17	0.1034	21.67704	0.0056	
Deur	9	.005008	0.1266	27.25439	0.0006	
Dvix	9	3.03638	0.1207	25.81455	0.0011	
Doil	9	1.3371	0.0918	19.00932	0.0148	
	Coef.	Std. Err.	z	P>z	[95% Conf. Interval]	
Dbtc						
L1.	-.1296327	.0680508	-1.90	0.057	-.2630099	.0037444
L2.	.0771146	.0689526	1.12	0.263	-.05803	.2122591
Deur						
L1.	51629.52	21386.49	2.41	0.016	9712.78	93546.27
L2.	-58720.85	22274.13	-2.64	0.008	-102377.3	-15064.36
Dvix						
L1.	-11.70252	34.70659	-0.34	0.736	-79.72619	56.32115

L2.	60.64034	44.96314	1.35	0.177	-27.4858	148.7665
Doil						
L1.	-45.22136	70.29643	-0.64	0.520	-182.9998	92.55712
L2.	12.64265	27.03209	0.47	0.640	-40.33927	65.62457
_cons	123.7829	98.39661	1.26	0.208	-69.07092	316.6367
deur dbtc						
L1.	5.50e-07	2.51e-07	2.19	0.029	5.77e-08	1.04e-06
L2.	3.26e-08	2.54e-07	0.13	0.898	-4.66e-07	5.31e-07
Deur						
L1.	.1295594	.0789199	1.64	0.101	-.0251207	.2842395
L2.	.3159132	.0821954	3.84	0.000	.1548132	.4770133
Dvix						
L1.	-.000028	.0001281	-0.22	0.827	-.000279	.0002231
L2.	-.0001957	.0001659	-1.18	0.238	-.0005209	.0001295
Doil						
L1.	-.0000719	.0002594	-0.28	0.782	-.0005803	.0004365
L2.	-.0000102	.0000998	-0.10	0.918	-.0002058	.0001853
_cons	-.0004446	.0003631	-1.22	0.221	-.0011563	.0002671
dvix dbtc						
L1.	-.0000226	.0001522	-0.15	0.882	-.000321	.0002758
L2.	-.0001771	.0001543	-1.15	0.251	-.0004795	.0001252
Deur						
L1.	36.18794	47.84779	0.76	0.449	-57.59201	129.9679
L2.	100.2084	49.8337	2.01	0.044	2.536132	197.8807
Dvix						
L1.	-.2892339	.0776487	-3.72	0.000	-.4414226	-.1370452
L2.	-.1743235	.1005956	-1.73	0.083	-.3714873	.0228403
Doil						
L1.	-.158947	.1572736	-1.01	0.312	-.4671975	.1493035
L2.	.017958	.0604786	0.30	0.767	-.100578	.136494
_cons	-.2157362	.2201418	-0.98	0.327	-.6472063	.2157339
doil dbtc						
L1.	.0001153	.000067	1.72	0.086	-.0000161	.0002467
L2.	-.0000155	.0000679	-0.23	0.820	-.0001486	.0001177
Deur						
L1.	1.328005	21.07026	0.06	0.950	-39.96894	42.62495
L2.	-44.21315	21.94478	-2.01	0.044	-87.22412	-1.202178
dvix						
L1.	-.0676553	.0341934	-1.98	0.048	-.1346732	-.0006375
L2.	-.0137202	.0442983	-0.31	0.757	-.1005433	.0731028
doil						
L1.	-.099989	.069257	-1.44	0.149	-.2357303	.0357522
L2.	.0656384	.0266324	2.46	0.014	.0134399	.1178369
_cons	.0586439	.0969417	0.60	0.545	-.1313583	.2486461

There is a correlation between the second lag of the log return on price and the first difference in the price of crude oil, which is represented by a coefficient of -45.221. A correlation exists between the two. Despite this, the p-value for this link is greater than 5%, which indicates that the effect is not statistically significant. Although this discovery is not statistically significant, it would result in a 12.642% decrease in the price of Bitcoin today if there was a 1% increase in the two-day lagged return of the oil price logarithm. The two-day lagged returns for Bitcoin, the VIX, the Euro, and the price of crude oil all display noteworthy correlations with the first difference in Bitcoin prices. However, only the correlations between Bitcoin and Euro prices, the VIX to Bitcoin, and the crude oil to Bitcoin are statistically significant, with p-values that are less than 5%. Some of the noteworthy findings are a VIX value of -0.0676, a Euro value of 5.50, and a crude oil price of 0.00011; all of these results demonstrate a significant capacity for prediction.

Last but not least, the table 5 contains constant terms for every equation. Based on the absence of independent variables in the model, these constants represent the average value of the dependent variable, which includes the price of Bitcoin, the VIX Index, the Euro/USD exchange rate, and the price of crude oil. The constant term is always 0.000, which indicates that, eliminating the independent variables, the average variance in these variables is not significant. This is the case in every single instance.

Table 6 represent the stability of the results of VAR model confirms about stationarity of the model. When the VAR is not stable then the test and standard error of impulse response function will not be accurate. The results show that VAR stabilizes the model and that all values are within the unit circle; furthermore, it is statistically significant.

Table 6: VAR Stable: Eigenvalue stability condition

Eigenvalue	Modulus
.5835591	.583559
.510142	.510142
.1719919 + .2083868i	.270197
.1719919 - .2083868i	.270197
.2505058 + .06497622i	.258795
.2505058 - .06497622i	.258795
.191141 + .02364733i	.192598
.191141 - .02364733i	.192598
All the eigenvalues lie inside the unit circle.	
VAR satisfies stability condition.	

The stationarity and stability of the model are both confirmed by Figure 1, which also demonstrates that the residual is displaying an adequate estimated linear regression model. All daily observations are located close to the mean value, with the exception of a few that are considered to be outliers. The graph is dependent on residual and years of the data from January 1, 2020 to December 31, 2021.

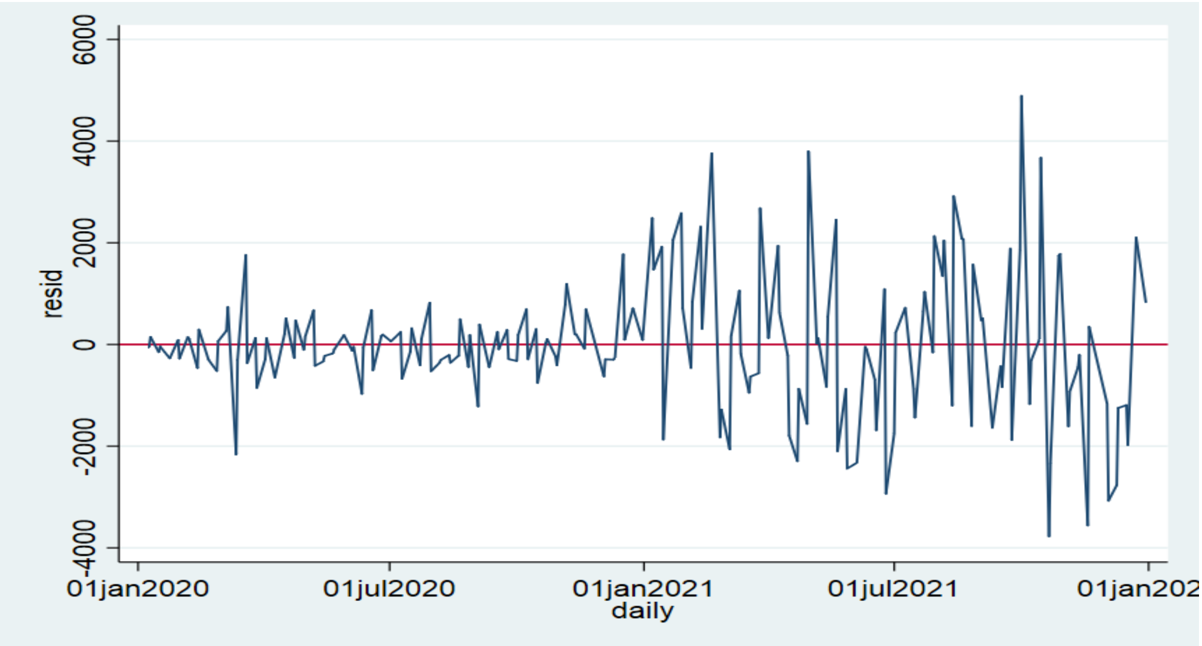

Figure 1: Residual line graph around the mean

Granger causality Wald tests determine if one time series can "cause" changes in another, as seen in Table 7. The test compares BTC, EUR, VIX Index, and Crude Oil prices. The equation including BTC (denoted "dbtc") shows that BTC considerably affects the Euro (EUR) price, since the chi-square value is 12.143 with a p-value of 0.002, which is below the 5% barrier. The causal relationship suggests that BTC prices can foretell EUR prices. BTC and VIX and BTC and Crude Oil have p-values of 0.361 and 0.765, respectively, considerably above 0.05, indicating no causal link. The combined equation ("ALL") indicates one causal association with a chi-square value of 13.736 and a p-value of 0.033, showing that one variable influences another.

The Euro (EUR) equation shows that the Euro affects BTC prices, with a chi-square value of 4.8218 and a p-value of 0.090, slightly beyond the 5% barrier. Euro and VIX or Crude Oil prices have no significant causal link, according to p-values of 0.496 and 0.950. The EUR combined equation shows no causal correlations (p-value 0.279). The p-value for the VIX Index equation is 0.517, indicating no causal association between VIX and BTC. However, with a chi-square value of 4.7885 and a p-value of 0.091, the VIX price may be influenced by the Euro price. VIX and Crude Oil have no causal association (p-value of 0.597), and the entire test shows no causal relationships (p-value of 0.250).

Finally, the Crude Oil equation shows no significant effect on BTC or the Euro, with p-values of 0.205 and 0.131. Crude Oil and the VIX Index exhibit a minimal causal relationship (chi-square = 3.9304, p=0.140). With a p-value of 0.044, the Crude Oil equation shows one significant causal relationship, showing another variable influences it. BTC affects Euro prices, but not VIX or Crude Oil prices. Crude Oil marginally affects VIX but not BTC or Euro.

Table 6: Granger causality Wald tests

Equation	Excluded	chi2	df	Prob > chi2	Results
Dbtc	deur	12.143	2	0.002	Btc does affect price of deur
Dbtc	dvix	2.0359	2	0.361	There is no causal relation
Dbtc	doil	.535	2	0.765	Btc does not affect price of oil
Dbtc	ALL	13.736	6	0.033	There is one causal relation
Deur	dbtc	4.8218	2	0.090	Eur does affect price of btc
Deur	dvix	1.4033	2	0.496	There is no causal relation
deur	doil	.10247	2	0.950	Eur does not affect price of oil
deur	ALL	7.4717	6	0.279	There is no causal relation
dvix	dbtc	1.3181	2	0.517	Btc does not affect price of eth
dvix	deur	4.7885	2	0.091	Vix index price is effected by eur price
dvix	doil	1.0315	2	0.597	vix does not affect price of oil
dvix	ALL	7.8452	6	0.250	There is no causal relation
Doil	dbtc	3.1661	2	0.205	oil does not affect price of btc
Doil	deur	4.061	2	0.131	There is no causal relation
Doil	dvix	3.9304	2	0.140	oil does not affect price of vix
Doil	ALL	12.911	6	0.044	There is one causal relation

The impulse response function shows how an exogenous shock affects the system equation. Impulse response function has four variables plus the response. Figure 2 classifies the initial BTC price difference as an impulse variable and the other three independent variables as reaction variables. This graph shows how a one-standard-deviation impulse affects the BTC pricing equation's initial difference. Since the initial spike, Bitcoin's price log of return swings dramatically, and the IRF between Bitcoin and the Euro, Crude Oil, and VIX index is larger Price predictions are consistent in figure 2 columns 2, 3, and 4.

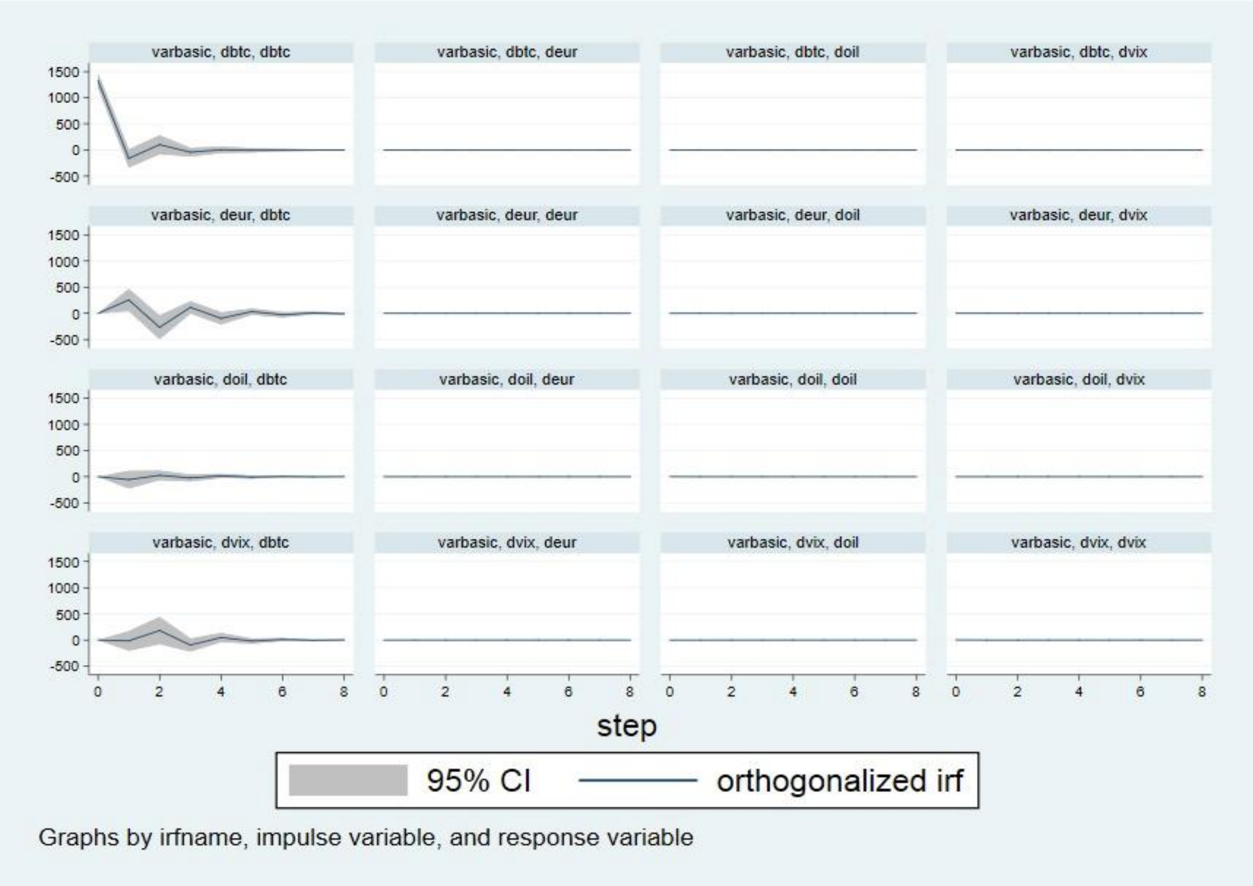

Figure 2 Impulse response function on dependent (BTC) and all independent variables

5. Conclusion

The primary aim of the study was to examine the price volatility of Bitcoin, the oil VIX index, and the exchange rate. This study also aims to examine the link among these four factors. These four aspects are the most volatile elements of the economy. These elements fluctuate swiftly, potentially altering the entire economic landscape. This study conducted a unit root test to assess the stationarity of the variables, confirming that all factors are stationary at the first difference. The VAR model has been utilized to examine the price fluctuations among the four variables. After applying VAR model, VARSTABLE test was performed to assess parameter stability. Engle Granger approach was utilized to check parameter causality.

Bitcoin to Euro and Euro to Bitcoin both have significant relationships. The next significant relationship is between viax index and Bitcoin significant impact on each other and lastly oil prices also significantly affected Bitcoin the effect the significant variables are used to detect fluctuations in the prices of Bitcoin. VAR stability test confirm the stability of the parameters Engle-Granger test confirms the causal relationship there exist causal relationship between the parameters. The figure is also confirming that the Bitcoin value prices are exactly around the mean. These result fulfil all the objectives and clearly confirms about price fluctuations and significant relationships among the variables.

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