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Investigating the Impact of the Dollar Index and Gold Return Rate on Bitcoin Price: Non-linear and Asymmetric Analysis

Masoud Mohammadi [1] **MohammadReza Farzin**[2]
Shamseddin Hosseini [3] **Teymour Mohammadi**[4]

[1] Faculty of Management and Economics, Islamic Azad University Science and Research Branch, Tehran, Iran.
[2] Faculty of management, Allameh Tabataba'i University, Tehran, Iran, Corresponding Author, Email: b_farzin@yahoo.com.
[3] Faculty of Economics, Allameh Tabataba'i University, Tehran, Iran.
[4] Faculty of Economics, Allameh Tabataba'i University, Tehran, Iran.

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Abstract:
Over the past few years, Bitcoin's price has fluctuated significantly, making it a hot topic in finance research. Numerous studies have been conducted to determine whether Bitcoin is a reliable currency. This study aims to investigate how the Dollar Index and Gold Return Rate affect Bitcoin's price, using a non-linear approach with the NARDL method. The findings show that the Gold Return Rate (G) and Dollar Index Return Rate significantly negatively impact Bitcoin's return. Additionally, based on non-linear and asymmetric tests, the assumption of symmetry in the results for all variables, except nominal interest rate and commodity index return, is rejected. This indicates that the impact of the Gold Return Rate, nominal interest rate, fluctuations in the US stock market, and oil price return is asymmetric. These results confirm the non-linear nature of these relationships. They also demonstrate that Bitcoin's return has been able to protect itself to a certain degree against the US dollar or some other investments.

1. Introduction

In recent years, researchers across various fields have emphasized investigating and analyzing interconnections between markets. The complex landscape of financial and economic markets, along with their close relationships, has created a vital need for predicting future financial and economic scenarios. Financial researchers aim to discover and analyze these intermarket relationships to

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achieve effective and forward-looking goals within the financial and economic systems (Fernando et al., 2017).

In recent years, the cryptocurrency market has experienced significant growth, resulting in a wider and more diverse array of cryptocurrencies. These digital currencies have integrated themselves into the realm of investment assets, distinguished by their reliance on blockchain technology, decentralized governance, and their exclusive existence within the confines of the internet. They are acknowledged for their intrinsic value, capacity for conversion into alternative cryptocurrencies, traditional monetary units, and commodities. Additionally, they possess the capability to retain value over time and function as a standardized unit of measurement (Hoffman, 2017). Research in the domain of cryptocurrencies has experienced notable expansion, driven by the growing significance of foundational cryptocurrencies (Wang & Vergne, 2017; Klein et al., 2018; Pagano and Sedunov, 2019; Jareno et al., 2020). Additionally, a considerable volume of empirical literature suggests that foundational cryptocurrencies serve as a safe haven during global financial crises (Selmi et al., 2018; Klein et al., 2018; Beneki et al., 2019).

Since Nakamoto introduced the concept of Bitcoin in 2008, the popularity of cryptocurrencies has been steadily increasing. Cryptocurrencies offer several advantages, including innovative technology, a highly secure architecture, functional efficiency, and investment opportunities, which appeal to computer scientists, risk-taking investors, and traditional investors alike. The total market capitalization of cryptocurrencies reached its peak at 831 billion dollars in January 2018 (Hardle et al., 2018).

Gold has historically been held as the primary reserve in central banks and is considered the most desirable asset. Its value has been preserved during economic crises, leading to a perception of its enduring value (Heybati et al., 2017).

In financial markets, losses in an asset, a set of assets, or a country can trigger an increase in risk for other assets or countries (Branger et al., 2009). Das et al. (2019) observe that the correlation between gold returns and Bitcoin prices has fluctuated across different periods, exhibiting high volatility over the past decade. Notably, during the previous year, the correlation between Bitcoin and gold reached approximately 0.93, primarily influenced by the global COVID-19 pandemic and the growing interest in digital currencies as a safe haven asset alongside gold (Chevapatrakul and Mascia, 2020).

The USD index has also played a determinant role in the price fluctuations of Bitcoin. Certain researchers regard any correlation between the USD index and prominent currencies such as the pound and franc with Bitcoin as negative, considering the presence of correlation in specific studies to be transient rather than consistent (Yermak, 2013). Conversely, some others assert that the relationship between the USD index and Bitcoin prices has grown more substantial and robust in recent years, emphasizing that it should not be overlooked. They acknowledge that when the USD index reverses and starts to rise, the potential for stabilizing Bitcoin's price increases (Jareno et al., 2020).

Bitcoin, the most innovative digital currency created in 2008, has successfully captured significant attention from a large portion of the world despite experiencing periods of growth and decline. From 2011 to 2013, in just 3 years, Bitcoin's price increased a hundred thousandfold, reaching over $1,000 in November 2013. Following the collapse of one of the largest Bitcoin companies, Mt. Gox, a period of recession began, and the market lost trust in Bitcoin. Since 2016, Bitcoin's price has significantly changed, shifting from $360 to $766.62. During the coronavirus period, despite temporary declines, it reached historically high prices of around $69,000. These observations give rise to numerous valuable questions that warrant investigation. For instance, what factors influence Bitcoin's price? What is the relationship between Bitcoin and other economic indicators? Does a connection exist between Bitcoin's price and the performance of gold, the oil market, the U.S. stock market index, and more? All these questions remain unanswered. In this study, considering the importance of these inquiries that play a pivotal role in fundamental and technical analysis, particularly in decision-making within the digital currency market, the study could prove highly beneficial and practical.

Recent evaluations of time series behavior in recent years have showcased remarkable progress in the field of time series forecasting. Linear frameworks such as autoregressive integrated moving average (ARIMA) and vector autoregression (VAR), which have long served as the cornerstone of econometric modeling, relying on independently and identically distributed (IID) innovations, have given way to models that delve into the non-stationary and nonlinear characteristics of many economic and financial time series. This is due to the fact that relationships between variables are not strictly linear or symmetric. While advanced linear models have yielded appropriate predictions for short- and medium-term intervals, market analyses have revealed that the behavior of financial variables often adheres to a nonlinear and occasionally asymmetric pattern. Given this, the objective of this study is to explore the impact of the USD index and the gold return rate on Bitcoin prices using a nonlinear approach through the NARDL method.

Literature Review

What is digital money?

Digital money is a type of payment that exists solely in electronic form. Unlike physical currencies, like paper bills or coins, digital money cannot be physically held or touched. Instead, it is computed and transferred through online systems. Digital money can also represent stable currencies such as the US Dollar or Euro.

Transactions made with digital money are processed through technologies such as credit cards, online exchanges, and smartphones.

Sometimes, you can turn digital money into physical cash by using ATMs. Today, digital money comes in the form of digital cash held in online bank accounts within the community (Beneki et al., 2019). You can send or receive this digital cash from others, and use it for online transactions. Conceptually and functionally, digital money is similar to physical cash as it can be used as a unit of account and a means of exchange for daily transactions, but it is not physical. If you withdraw dollars from an ATM, they are no longer considered digital money since they become physical. Digital money differs from physical cash because it improves the process of financial transactions. For example, digital financial rails can make cross-border currency transfers easier and faster compared to standard currency. This form of money also simplifies the implementation of monetary policies for central banks.

Many forms of digital money use encryption to prevent tampering and censorship, making them independent of government or private control. This advantage has caused many governments to prioritize digital money. Since 2017, Sweden's central bank has been testing digital money as the country moves towards a cashless society. China has already piloted its Digital Currency Electronic Payment (DC/EP) and plans to launch it soon. In October 2020, the Bahamian Sand Dollar became another example of a national digital currency. According to a February 2021 survey by the International Monetary Fund (IMF), around 111 member countries are currently researching or planning to introduce digital money shortly.

Several systems currently conduct their transactions using digital forms of money. For example, credit card systems allow users to purchase goods and services on credit. Wire transfer systems enable the movement of physical cash across borders. Such transactions can be expensive and time-consuming due to the utilization of different processing systems. The SWIFT system, a network of payment systems composed of banks and financial institutions worldwide, is an example of such infrastructure. For every transfer made through the SWIFT network, there are associated fees. SWIFT member institutions also operate under a set of regulations, each tailored to a different financial domain.

Furthermore, these systems are designed based on the promise of future payments and ensure a time delay for each transaction. For instance, credit card settlements occur on different dates, and users can request refunds for transactions (Chiah & Free, 2015).

The primary objective of digital currency is to eliminate the hassle and costs associated with transactions by utilizing Distributed Ledger Technology (DLT). In a DLT system, multiple nodes or shared ledgers are interconnected to form a collective network that oversees transactions. This network can also extend to other areas, reducing the time required to complete transactions.

DLT, or distributed ledger technology, brings transparency to both authorities and stakeholders while enhancing the flexibility of financial networks by eliminating the requirement for a centralized database of records. Using DLT, every participant in the network has access to the same information, and any modifications made to the ledger are visible to all, ensuring complete transparency.

When it comes to digital money, a consensus algorithm is used to prevent double-spending. This is different from traditional systems where a central authority verifies transactions. In DLT, a decentralized consensus mechanism is used to validate and approve transactions, ensuring that double spending cannot occur.

DLT technology enables the development of decentralized digital currencies, including cryptocurrencies such as Bitcoin and Ethereum. These currencies function without a central authority and are distributed and issued collectively by network participants. DLT employs cryptographic methods and a unique identification system to confirm the individuality and authenticity of each digital currency unit.

Digital money aims to revolutionize the traditional financial system by using DLT. This offers faster, more cost-effective, and transparent transactions while maintaining security. It also eliminates the need for intermediaries and centralized control, as noted by Chevapatrakul and Mascia in 2020.

The rise of digital currencies, such as Bitcoin, has disrupted the traditional monetary system and sparked new ideas for policymakers, economists, and financial regulators. The development of these currencies has led to a reevaluation of the fundamental concept of money as a financial instrument. Bitcoin, for example, offers high liquidity, meaning that it can be easily exchanged for traditional currencies at any time.

One of the most well-known cryptocurrencies is Bitcoin, which has a dominant presence in terms of trading volume. Bitcoin and the US dollar share some similarities, as they both have limited or no intrinsic value and were originally used for exchanging goods and services. However, the main difference lies in the fact that the US dollar has the backing of a government that people trust, while Bitcoin is a non-governmental currency provided by the private sector. Consequently, the issuance, supervision, and control of these two assets are different, but comparing them can provide valuable insights into their monetary abilities.

Bitcoin has the potential to behave similarly to gold as a risk management tool against the dollar. However, this potential is dependent on the previous fluctuations of both Bitcoin and the dollar. Defining Bitcoin can be difficult, but analyzing its response to variables such as the dollar and gold can provide valuable insights. This type of cryptocurrency shares some key features with gold, such as global exchangeability and lack of government backing, while also possessing currency-like characteristics such as transaction intermediation. To diversify assets effectively, investors need sufficient information about the correlation between the assets in the asset basket. Therefore, this study examines the correlation between pairs of financial assets (gold and digital currencies) in order to investigate the relationship between the returns of these assets and the characteristics of the time series returns of the studied assets.

Among asset classes, Bitcoin has exhibited one of the most volatile trading trends. The first significant price increase of this cryptocurrency occurred in 2010, during which the value of one Bitcoin reached around $0.08. Since becoming available, this encrypted currency has experienced substantial fluctuations. The price changes of Bitcoin intermittently reflect investors' enthusiasm and dissatisfaction with holding it. Satoshi Nakamoto, the anonymous inventor of Bitcoin, designed it to be used as a tool for daily transactions and as a means to bypass traditional banking infrastructure after the financial collapse of 2008. Since then, this encrypted currency has gained attention as a medium of exchange and attracted traders who speculated on its price fluctuations. Additionally, it has evolved into a unique form of investment and a way to preserve value and hedge against inflation. Past price fluctuations have largely been driven by speculations from retail investors and traders betting on its increasing value. Despite Bitcoin's instability, it has now transformed into a tool for speculators seeking quick profits and has become a part of the mainstream economy (Das et al., 2019). The subsequent price trends of Bitcoin during the turbulent periods of 2015-2009 and 2020-2016 will be reviewed.

From 2009 to 2015

Bitcoin was initially introduced in 2009 with a value close to zero. Over time, it gradually increased to around $0.08 in 2010. However, in April 2011, Bitcoin went through a significant surge, reaching its peak of $32 in June of that year. This was an increase of approximately 3100% in just three months. Regrettably, the cryptocurrency market then suffered a severe recession, which led to Bitcoin's price dropping to $2 in November 2011.

Bitcoin experienced a significant price increase in 2012, rising from $0.84 in May to $15.2 in August. The following year, 2013, saw even more dramatic changes in Bitcoin's value. Starting the year at $13.40, the price skyrocketed to $220 by early April, only to drop to $70 a few weeks later. By October, it had climbed back up to $123, and by December, it reached an all-time high of $1,156 before crashing to $760 just three days later. In 2015, the price of Bitcoin fell to $315.

From 2016 to 2020

In 2016, the price of Bitcoin gradually increased to around $900. With continued price growth in 2017, the price of Bitcoin reached approximately $1,000. Following a brief downturn in the first two months, the price surged from $975 on March 25 to $2,089 in December. Mainstream investors, governments, economists, and scientists recognized the value of Bitcoin, prompting other entities to develop cryptocurrencies to compete with it. In June 2019, both the price and trading volume of Bitcoin surged, surpassing $10,000.

In 2020, the global economy experienced significant disruptions due to the COVID-19 pandemic. The price of Bitcoin started the year 2020 at $7,175. The pandemic-related shutdowns and ensuing government policies heightened investor concerns about the global economy, accelerating the growth of Bitcoin's price. On November 23, 2020, Bitcoin was traded at $18,353. By December 2020, the price of Bitcoin reached around $29,000, reflecting a 304% growth from the beginning of the year (Brandvold et al., 2015).

During the current period

In 2021, it took less than a month for Bitcoin to surpass its price record from 2020, breaking through $40,000 in January 2021. By April 2021, the price of Bitcoin reached its all-time high of over $60,000. Continuing its upward trajectory, on April 14, 2021, the price of Bitcoin surged past $64,000. However, by the summer of 2021, prices experienced a 50% decrease, dropping to $32,000. The fall was followed by another upward trend in the autumn, bringing prices up to $50,000, but a significant price drop brought it down to around $42,500.

On November 10, 2021, Bitcoin reached its highest level again, hitting $69,000. In early December 2021, Bitcoin plummeted to $46,583. The uncertainty about inflation, along with the emergence of a new variant of COVID-19, further contributed to heightened investor concerns, leading to increased price volatility for Bitcoin.

Empirical studies

There have been no specific studies conducted in Iran to explore the factors that affect the price of Bitcoin or the relationship between the dollar index and gold returns and Bitcoin. However, some research has been conducted to examine the correlation between different financial variables using various methods.

While there hasn't been much research on the relationship between Bitcoin's price and other financial variables in Iran, examining the correlation between various financial variables through different approaches can offer valuable insights into financial market dynamics and the interaction between economic indicators. Although these analyses don't specifically target Bitcoin, they contribute to a more comprehensive comprehension of financial markets and the complex connections between different economic indicators.

It is important to understand that the study of cryptocurrencies, such as Bitcoin, is constantly changing. With the increasing interest in digital currencies, there may be more academic research conducted both in Iran and around the world, exploring different aspects of the cryptocurrency market.

A study conducted in 2013 by Pazouki and his colleagues used wavelet transform to analyze the correlation between the dollar, oil price, gold price, and the Tehran Stock Exchange index between 2004 and 2010. The study revealed that the correlation between these factors varied over time, and significant correlations were observed during specific time intervals.

A study conducted by Falahi and Jahangiri in 2015 analyzed financial contagion in the currency, stock, and gold coin markets. They utilized the DCC-GARCH method and examined data from January 7, 2011, to June 31, 2014. Their research revealed that financial contagion was only present between the currency and gold coin markets.

A study on speculative bubbles in the Bitcoin digital currency market was conducted by Hatefi Majoomerd and a team in 2018. The study analyzed the period from August 2013 to January 2018 and used various frameworks such as SADF, RADF, and GSADF, and the recursive right-tailed unit root method. The study concluded that speculative bubbles were present during the examined periods, as determined by different methods.

A recent study by Salehifard (2019) examined the behavior of Bitcoin returns and risks compared to gold, currency, and stock markets from 2013 to 2018 using GJR-GARCH and Threshold GARCH models based on daily data. The findings revealed that although Bitcoin had significantly higher returns and risks compared to other investment opportunities such as currency, gold, and stock markets within the country, its behavior in terms of risk and return cannot be fully attributed to the related competitor markets. Furthermore, positive news had a more significant impact on Bitcoin transactions than negative news, unlike other assets. Lastly, Dyerberg's hypothesis (2016) suggesting Bitcoin to be an intermediate between gold and currency was not confirmed.

A study by Ali-Zadeh and Safarzadeh in 2019 looked into whether digital currencies had long-term memory in their price index between September 1, 2015, and September 1, 2018, using the AFRIMA approach. The study found that certain digital currencies, including DigiCoin, DogeCoin, EmerCoin, BitShares, MaidSafeCoin, XAYA, ReddCoin, Antioch, Vertcoin, and Ripple, displayed long-term memory in their price movements. However, Bitcoin, Sycoin, and Stellar were found to lack long-term memory and were therefore classified as market-efficient assets.

A study conducted by Zhu et al. in 2017 analyzed the factors that influenced the price of Bitcoin between 2011 and 2016, using monthly data and the Vector Error Correction Model (VECM). The findings revealed that the US Dollar had the highest impact on Bitcoin's price among the variables examined. Surprisingly, the gold return had the least impact on Bitcoin's price compared to other variables.

A study was conducted by Huynh et al. in 2020 to examine how gold and platinum returns affect the expected return of Bitcoin. They used the Quantile Regression method and analyzed data from 2013 to 2018 on a daily basis. The study discovered that the returns of gold and platinum were significant explanatory factors for the changes in Bitcoin's return. The findings suggested that fluctuations in Bitcoin's return were influenced by the returns of gold and platinum, indicating that changes in the gold market may affect the Bitcoin market as well.

A study by Telli and Chen (2020) compared the behavior of Bitcoin and gold from 2015 to 2019 in terms of return and volatility. They collected daily data and used the Rolling Window Regression approach. The analysis revealed that Bitcoin's return series had significantly different multifractal properties compared to gold. Additionally, Bitcoin's return and volatility series showed continuous behavior and had higher multifractal degrees than gold. On the other hand, gold's return series had nonstationary behavior, while its volatility series had continuous behavior. Structural break tests identified that the gold time series had different regimes with distinct multifractal properties.

Liu et al's (2020) research focused on forecasting Bitcoin's price using Deep Learning and Support Vector Regression (SVR). The study analyzed daily data from 2014 to 2019. The results showed that Stacked Denoising Autoencoder (SDAE) model was more effective in predicting the direction and level of Bitcoin's price compared to other popular machine learning methods, such as neural networks and SVR. Common evaluation metrics were used to arrive at this conclusion.

In a 2020 study, Jareno et al explored the relationship between Bitcoin and gold returns using Quantile Regression and Non-linear AutoRegressive Distributed Lag (NARDL) methods. They analyzed daily data from 2010 to 2018 and found that the US stock market volatility index had the greatest impact on Bitcoin's price. Additionally, the study uncovered a non-linear and non-monotonic positive relationship between Bitcoin and gold returns during the examined period.

Research method and model

This study examines how the Dollar index and gold's return rate affect Bitcoin's price using the Non-linear AutoRegressive Distributed Lag (NARDL) approach. The model used in this research is structured as follows:

$$B_t = f(G,\ R,\ VIX,\ Oil, COM, DOL) \tag{1}$$

In the estimation section of the model using the NARDL approach, the research model is specified as follows:

$$\begin{aligned} B_t = {} & \beta_0 + \beta_1 G_t^+ + \beta_2 G_t^- + \beta_3 R_t^+ + \beta_4 R_t^- + \beta_5 VIX_t^+ + \beta_6 VIX_t^- \\ & + \beta_7 OIL_t^+ + \beta_8 OIL_t^- + \beta_9 COM_t^+ + \beta_{10} COM_t^- + \beta_{11} DOL_t^+ \\ & + \beta_{12} DOL_t^- + \mu_t \end{aligned}$$

When using the NARDL approach to estimate, the first step is to extract positive and negative shocks from the independent variables. For example, for the variable G (G+_P), positive shocks are defined as the cumulative sum of positive increments, which represent the positive components of the gold return rate, according to the definition by Granger and Yoon (2002). To calculate this, follow the steps below.

$$G_t^- = \sum_t^i \Delta G_t^- = \text{Max}\,(\Delta G, 0)$$

In this method, the model does not directly use the variables themselves. Rather, the Granger and Yoon (2002) framework is used to extract their positive and negative shocks, which are then integrated into the analysis. The concluding section will discuss the symmetric or asymmetric effects of the relationships being studied using the Wald test.

The nonlinear ARDL approach is a new method for identifying nonlinear and asymmetric connections between economic variables in both the short and long term. It was developed by Shin and colleagues (2011) and is an extension of the linear ARDL model. The nonlinear ARDL approach has several advantages over other cointegration techniques. It can be used regardless of whether the variables in the model are I(1) or I(0). In addition, it does not introduce short-term dynamics into the error correction term (Banerjee et al., 1993). Furthermore, it can be applied to models with a limited number of observations. While linear regression models provide a comprehensive and versatile framework and supply answers to various analytical needs, they may not always be suitable for all problems. Sometimes, it may be better to explain the relationship between the response and predictor variables using a known nonlinear function. This approach is useful when some of the explanatory variables are endogenous (Alam & Quazi, 2003).

Table (1) presenting the research variables and their sources:

variable	description	source
G	Gold return	FRED*
OIL	Oil price return	FRED*
VIX	VIX index (Volatility index in the US market)	FRED*
R	Changes in the nominal interest rate of the US	FRED*
BIT	Bitcoin price return	FRED*
COM	Commodity price index	FRED*
DOL	US Dollar Index	FRED*

*Federal Reserve Economic Data

Results and Findings

Stationarity Test

In order to prevent inaccurate results in our regression analysis, we checked to ensure that the time series variables used in this study were stationary. To do this, we conducted the Augmented Dickey-Fuller unit root test (ADF) on the variables being investigated and determined their cumulative degrees. Table (2) and Table (3) show the results of the ADF unit root test for both the level and first difference of the variables.

Table (2): Augmented Dickey-Fuller (ADF) Unit Root Test Results (Level)

Variable	Test Statistic	*p-value*	Stationarity
BIT	–0/444	0/77	Non-stationary
G	–1/77	0/99	Non-stationary
R	–1/99	0/33	Non-stationary
VIX	–5/22	0/00	stationary
OIL	–1/99	0/88	Non-stationary
COM	–4/11	0/000	stationary
DOL	–0/66	0/22	Non-stationary

Source: Research results

When conducting stationary tests, the null hypothesis assumes the presence of a unit root, which suggests that the time series being analyzed is not stationary. In other words, the null hypothesis implies that the time series is non-stationary. If the null hypothesis is rejected, it means that the alternative hypothesis is accepted, indicating stationarity. In Table (2), the null hypothesis of stationarity was rejected for all research variables, except for the Dow Jones Index (VIX) and Commodity Price Index (COM), which suggests that these variables are non-stationary. Table (3) shows the results of the unit root tests for the first difference of non-stationary variables.

Table (3): Results of Unit Root Tests for Variables using the ADF Method (First Difference)

Variable	Test Statistic	*p-value*	Stationarity
BIT	–0/444	0/00	stationary
G	–4/66	0/00	stationary
R	–6/11	0/00	stationary
OIL	–5/66	0/00	stationary
DOL	–6/44	0/00	stationary

Source: Research results

After analyzing Table (3), it was determined that the null hypothesis of the unit root test for the first-order difference of non-stationary variables was rejected. This means that the aforementioned variables (1) are integrated and have been made stationary by first differencing. In order to estimate an error correction model, it is necessary to establish and estimate the long-run cointegration or relationship between the variables of interest. Since the time series used in the analysis contains both I(0) and I(1) variables, the Autoregressive Distributed Lag (ARDL) approach with extensive interruptions can be used. Additionally, for non-stationary data of order one, the nonlinear ARDL method can also be applied. The following section will present the results of the NARDL approach.

The results of the NARDL regression

In order to determine the effects of influential factors on price returns, we need to analyze the asymmetric impact they have on the exchange rate. To calculate positive and negative shocks, we follow the definition provided by Granger and Yoon (2002) and extract the positive parts of variable X to obtain positive shocks (X+_P). This is done by calculating the cumulative sum of positive parts of the variable X using the following formula:

$$X_t^+ = \sum_{T+n}^{T} \Delta X_t^+ = \text{Max } (\Delta LX, 0)$$

To calculate the negative shocks of the exchange rate, the method proposed by Granger and Yoon (2002) is utilized. The negative shocks for each variable (X-_P) are obtained as the cumulative sum of the negative parts of the variable X. The calculation is performed as follows:

$$X_t^- = \sum_{T+n}^{T} \Delta X_t^- = \text{Min } (\Delta X, 0)$$

Based on the information provided, we have calculated that the most effective number of lags for the model is 1. To estimate the model, we will be using the OLS (Ordinary Least Squares) method. We have computed the test statistic value for the test to be 35.6. As all the variables in the model are either I(0) or I(1), the test statistic does not follow a normal distribution.

To determine the significance of the test statistic, we have compared it with the critical values provided by Pesaran, Shin, and Smith (2001) at a 95% confidence level. The upper and lower critical values are respectively 3.83 and -3.92 for the test statistic. Since the test statistic value falls outside this range, it falls into the critical region. Therefore, the test result is statistically significant at the 95% confidence level.

Table (4): Results of Asymmetric Cointegration Test

F-test	**٪90 Level**		**٪55 Level**	
	I(1)	I(0)	I(1)	I(0)
6/35	3/22	. /55	4/11	2/66

Source: Research results

Based on the information provided in the table above, it has been determined that there is a long-term relationship among the variables, as the calculated test statistic exceeds the critical values. To further estimate this relationship, the Unrestricted Error Correction Model (UECM) approach has been applied. The UECM model has allowed for the computation of the long-term coefficients between the variables.

Table (5): Results of Long-term Coefficients Estimation

Variable	Coefficient	t-statistic	Significance Level
G+	. -0/6666	-2/00	Significant at 95% level
G-	-0/666	-1/77	Significant at 95% level
OIL+	0/7777	1/88	Significant at 95% level
OIL-	0/7777	1/99	Not significant
VIX+	-0/888	-1/55	Significant at 95% level
VIX-	0/333	-2/77	Significant at 95% level
R+	-0/5555	-1/99	Significant at 95% level
R-	0/5555	2/33	Significant at 95% level
COM+	0/888	2/11	Significant at 95% level
COM-	-0/4444	-1/33	Significant at 95% level
DOL+	-0/2222	-1/77	Significant at 95% level
DOL-	-0/6666	-1/33	Significant at 95% level

Source: Research results

Once cointegration is confirmed and the long-term coefficients of the model are estimated, the Error Correction Model (ECM) can be determined. ECM models link short-term fluctuations of variables to their long-term equilibrium values. The objective of these models is to determine the influential forces in the short run and the rate of convergence towards the long-term equilibrium.

The ECM coefficient determines how much the short-term fluctuations in Bitcoin returns are adjusted towards the long-term balance in each period. This coefficient shows how many periods it takes for Bitcoin returns to go back to their long-term pattern after a sudden change.

Table (6) the results of estimating the Error Correction Coefficients

Variable	Coefficient	t-statistic	results
Ecm(-1)	-0/999	**-2/99**	**significant**
R^2=0/33		**F= (28/37 (0/000)**	

Source: Research results

Based on the data presented in the table above, it appears that whenever there is a sudden impact on Bitcoin returns, it takes around 5 periods for the effects of the shock to subside and for the returns to revert back to their usual long-term trend. Essentially, this means that any temporary fluctuations in Bitcoin returns tend to balance out over a span of roughly 5 periods, ultimately returning to their expected equilibrium state.

Table (7): Results of the Wald Test for Nonlinearity

Variable	Probability of Wald statistics
Gold Returns (G)	0/333
Oil Price (OIL)	0/000
Dow Jones Index Returns (VIX)	0/000
Nominal Interest Rate (R)	0/777
Commodity Returns (COM)	0/555
Dollar Index Returns (DOL)	0/111

Source: Research results

According to Table 7, the Wald test results show that there is a lack of symmetry in the long-term relationships of various variables. The test indicates that, at a 95% confidence level, the assumption of equal positive shock coefficients for all variables, except for nominal interest rates and commodity index returns, has been rejected. This means that the impact of gold returns, nominal interest rates, fluctuations in the U.S. stock market returns, and oil price returns is non-linear and asymmetric.

Interpretation of findings:

The NARDL approach's coefficient estimation results reveal that the USD index had a significant negative impact on Bitcoin returns. These effects were found to be nonlinear and asymmetric based on the Wald test results. Likewise, the nonlinear approach's coefficient estimation results show that gold returns had a significant negative impact on Bitcoin returns. The Wald test results in the NARDL approach also discovered these effects to be nonlinear and asymmetric.

Based on the results, it appears that Bitcoin can be a good hedge against the US dollar and some other investments, especially during times of higher returns. However, the study also found that there is a strong correlation between the gold market and Bitcoin, and that gold returns can have a negative impact on Bitcoin returns. This impact seems to be more significant when gold prices are high, which could potentially limit the returns of Bitcoin.

The objective of the research was to analyze Bitcoin as an asset rather than a conventional currency. The findings from the non-linear and asymmetric approach propose that Bitcoin's profits could be affected by economic indicators and significant asset prices included in the model. This implies that the price of Bitcoin is not exclusively determined by its own supply and demand, but is also impacted by external factors.

The findings have important implications for policymakers, financial market participants, and traders in global forex and digital asset markets. The decrease in Bitcoin prices can be partly explained by the decline in gold prices since 2013. However, Bitcoin and gold prices have different tendencies. While they show similar trends in the short term, they exhibit different patterns in the long run. Currently, Bitcoin can be seen as a hedging asset against gold.

The Federal Reserve's interest rate policy has a significant impact on Bitcoin prices as an investment asset. This study has shown that different approaches can negatively affect Bitcoin prices. An increase in nominal interest rates (R) could have two negative effects on Bitcoin prices: an appreciation of the US dollar and a decrease in speculative investments. Firstly, higher interest rates benefit the US dollar as it attracts capital back to the US market, leading to a decrease in Bitcoin prices. Secondly, an increase in interest rates could reduce speculative investments. Bitcoin is currently a speculative asset, and a large outflow towards more stable and lower-risk investment areas could have a detrimental effect on Bitcoin prices.

While there are two assumptions at play, the connection between Bitcoin prices and the Federal Reserve's interest rate policy is still quite intricate and has various complexities to consider.

Conclusion and Recommendations:

This study examined how gold and USD index returns impact Bitcoin returns using a nonlinear approach. The results showed that gold returns (G), Dow Jones index returns (VIX), nominal interest rate (R), and USD index returns had a negative effect on Bitcoin returns, while commodity returns (COM) and oil price growth (OIL) had a positive effect. Additionally, the null hypothesis of symmetry for all variables, except nominal interest rate and commodity returns, was rejected based on nonlinearity and asymmetry tests and probability values. This means that the effects of gold returns, nominal interest rate, stock market volatility, and oil price returns were asymmetric. These nonlinear findings were confirmed.

The study has found that Bitcoin can act as a hedge against the US dollar and other investments in a significant way, which has important policy implications. This suggests that Bitcoin isn't only a credit currency and its price is influenced by other factors, like gold returns, dollar returns, and other financial and economic indicators. Like traditional financial markets, Bitcoin and digital currencies also experience fluctuations. However, Bitcoin has more significant ups and downs due to its recent introduction. Therefore, it is highly beneficial to understand the relationships between Bitcoin prices and variables like the US market interest rate, the dollar index, gold returns, oil market, and commodities for diversifying investment portfolios in global stock markets, forex, and digital currencies.

Investors and market participants can make better predictions about Bitcoin prices by understanding its relationships with variables like the US market interest rate, dollar index, gold returns, oil market, and commodities. By doing so, they can take advantage of opportunities to profit from market fluctuations through buying and selling. Additionally, Bitcoin can also be a good long-term investment due to its unpredictable supply and advantages over some national currencies. It is a global currency that is not tied to a central bank, making it easily transferable across borders and resistant to damage. However, as a new market, caution should be exercised as there is no mathematical way to accurately predict its future behavior. Therefore, buyers should be vigilant about this aspect.

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بررسی اثر شاخص دلار و نرخ بازدهی طلا بر قیمت بیت‌کوین: تحلیل غیر خطی و نامتقارن

چکیده:
بررسی عوامل موثر بر قیمت بیت‌کوین طی سال‌های اخیر با نوسانات گسترده در قیمت بیت‌کوین به یک بخش جذاب در سمت مطالعات مالی تبدیل شده است. بیشتر این مطالعات به دنبال این موضوع هستند که آیا بیت‌کوین یک ارز اعتباری است یا خیر. با توجه به این موضوع، هدف این پژوهش بررسی تاثیر شاخص دلار و نرخ بازدهی طلا بر قیمت بیت‌کوین با رویکردی غیرخطی با استفاده از روش NARDL بود. یافته‌های این مطالعه نشان داد که بازدهی طلا (G) و بازده شاخص دلار دارای اثر منفی و معنی‌داری بر بازدهی بیت‌کوین بوده‌اند. همچنین براساس آزمون‌های غیرخطی بودن و نامتقارن بودن ضرایب نیز با توجه به مقدار احتمال آماره محاسباتی، فرضیه صفر مبنی بر تقارن نتایج برای کلیه متغیرها بجز نرخ بهره اسمی و بازده شاخص کامودیتی‌ها رد شده است؛ به عبارتی دیگر، تاثیر متغیرهای بازدهی طلا، نرخ بهره اسمی، نوسانات بازده بازار سهام آمریکا و بازده قیمت نفت نامتقارن بوده است. این نتایج برای غیر خطی بودن نیز تائید شده است. این یافته‌ها نشان داده است که بازدهی بیت‌کوین تا حد زیادی توانسته است که در برابر دلار آمریکا یا برخی سرمایه‌گذاری‌های دیگر از خود محافظت کند.

کلمات کلیدی: شاخص دلار، نرخ بازده طلا، بیت کویین.