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A Study of the relationship between financial and commodity markets using time series regression

Seyed Hojat Hejazi
PhD student, Department of Economics, Aras International University, Tehran University Campus, Aras, Iran
Shhejazi60@gmail.com

Ebrahim Abbasi
Professor, Department of Management, Faculty of Social Sciences and economics, Alzahra University, Tehran, Iran
(Corresponding Author)
abbasiebrahim2000@alzahra.ac.ir

Zoleikha Morsali Arzanagh
Department of Management and Accounting, Islamic Azad University, Karaj Branch, Karaj, Iran.
Zmorsali@iau.ir

Yazdan Gudarzi Farahani
Assistant Professor, Faculty of Economic and Administrative Sciences, University of Qom, Qom, Iran
y.gudarzi@qom.ac.ir

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ABSTRACT

The relationship between financial markets such as exchange rates, Bitcoin, oil, and gold, as items considered by investors for portfolio management, especially in situations of exogenous shocks, has always been a complex issue, and the relationship between them and determining the causality of the transmission of fluctuations between them (receiving and transmitting fluctuations) may vary in each country and in different time periods. This study examines the relationship between financial and commodity market. For this reason, we used the Bitcoin (BTC) price, Gold, USD, and oil prices. Time series model to cover data from 2020 to 2024. In this study, first, the unit root test was performed on the variables. Then, time series and GARCH model were identified in order to have a relationship between the variables. Finally, using the time series model, the relationship between the variables was estimated. The results obtained from this study indicate the variables of us dollar and oil price and gold price had positive effects on the Bitcoin price.

Keywords: Bitcoin, Gold Price, Exchange rate, GARCH, Time series regression.

1. Introduction

Given the increasing connection between asset and financial markets, diversification of the investment portfolio is very important. Accordingly, investors are constantly replacing assets and diversifying the asset portfolio to hedge risk. Knowing how and the extent of spillovers between different assets over time, especially during periods of economic recession, can be helpful for investors in designing investment portfolios and hedging strategies (Mehrani et al, 2019). Investors can target assets that have negative correlation or the lowest spillovers with each other. Risk-averse investors seek to invest in assets that have strong spillovers over other assets. There is a strong relationship between fluctuations in the foreign exchange, stock, gold, and oil markets. Currency fluctuations lead to changes in the cash flows of companies listed on the stock exchange and also lead to an increase in cost prices and inflation in the economy. With increasing inflation, there is a possibility that the price of oil and other assets will also increase. Exchange rate fluctuations have a direct impact on the competitiveness of international companies listed on the stock exchange, which can lead to changes in their market value (Sandoval & Franca, 2012; Bouri et al., 2017). The price movements of Bitcoin (BTC) since its launch in 2009 have raised the question of whether BTC exhibits safe-haven properties as an alternative to stocks (Wang et al., 2019; Shahzad et al., 2019). BTC is seen as a safe haven for several reasons, including its independence from monetary policies in a country, its role in accumulating value, and its limited relationship with traditional assets The term cryptocurrency is used to refer to digital currencies or assets based on blockchain technology. With the rapid development of this technology, cryptocurrencies have received massive publicity in the financial markets because some argue that they can be considered a new category of investment assets. Today, the cryptocurrency market has become one of the fastest-growing markets in the world regarding trading volume and market cap (Delfabbro et al., 2021). Compared to traditional asset markets, cryptocurrency is an emerging market with a large market cap (Qiao et al., 2020).

Changes in asset values may accelerate capital flows between countries and subsequently change exchange rates (Pavlova and Rigoben, 2007). Similarly, adjustments in stock prices not only cause capital movements between countries, which affect exchange rates, but also affect hedging strategies across assets (Spencer et al., 2018). Also, as a firm’s stock price increases, its equity value increases, and assuming that the price of new equipment remains constant in the short run, investment becomes more attractive. This in turn leads to increased investment. Therefore, investment is a function of stock prices. An increase in stock prices increases the real demand for financial assets by households, and since these assets are considered part of an individual’s wealth, they affect household consumption. The increase in wealth from this location is less risky, and therefore households are driven to hold more non-cash assets. Therefore, spending on durable goods, including housing, increases, which will lead to an increase in stock prices, consumption, and investment (Mehrani et al, 2019; Vacha & Barunik, 2012; Dyhrberg, 2016a, 2016b; Bouri et al., 2017a; Kang et al., 2019; Goodell & Goutte, 2021).

In the present study, the co-movements of BTC, gold, oil, and USD will first be analyzed using the GARCH method. Then, the time-frequency structure of the correlation and co-movements between BTC prices and other financial assets and indicators will be discussed. The innovation of this study lies in the use of time series regression to provide information on the relations between BTC and gold, foreign exchange, and oil markets.

The main goal of this study is to examine BTC's movement and volatility spillovers with respect to traditional investment instruments and international financial indicators in Iran. The reason for taking the variables in Iran is to explore the movements in the last few years and to obtain helpful results for local decision-makers and policymakers. In addition, it ensures that inferences are made to represent developing countries with similar economic, financial, and social structures internationally. To this purpose, employing a time series and GARCH model, the current study evaluates the co-movement between Bitcoin, gold, USD, and oil.

The remainder of this paper is organized as follows. Section 2 describes the theoretical foundations, followed by a review of relevant studies in Section 3. Section 4 estimates and analyzes the research model, and finally, Section 5 gives some concluding remarks.

2. Literature Review

Changes in stock prices affect the exchange rate through two channels: wealth and expectations of individuals. A decrease in stock prices reduces the wealth of investors who have invested in the stock market. As investors' income decreases, their demand for money decreases due to a decrease in purchasing power. A decrease in the demand for money means a decrease in interest rates and capital outflows. As the demand for foreign currency increases, the exchange rate increases. In this way, a negative effect of stock prices on the exchange rate is conceivable. On the other hand, a boom in the stock market makes the stock market attractive to investors. Foreign investors transfer their capital to a country with a booming stock market when the stock market is booming. By transferring capital into the country, the supply of foreign currency increases and the exchange rate decreases. According to this analysis, there is a negative relationship between stock prices and the exchange rate. Domestic investors also invest in parallel markets and, as soon as there is a recession in one market, they migrate to other financial and asset markets to compensate for risk. With the booming capital market, capital flows to this market and people are forced to convert foreign currency into domestic currency to exit the foreign exchange market, which in turn increases the supply of foreign currency and decreases the price of the currency. In the field of gold, the price of gold and coins is a suitable measure to explain the pressures caused by inflation, such that during inflationary periods, increased currency fluctuations and political instability, the price of coins increases, and in such circumstances, people keep coins in their asset portfolios to maintain the value of liquidity. Different asset markets may face weak or strong fluctuations over time, and through the connections between them, there is the possibility of transferring fluctuations and risk spillover. In general, changes in asset returns cause changes in investors' motivation and the transfer of liquidity to other competing and parallel markets to maintain the value of cash. On the other hand, examining how to transfer risk between different assets as an efficient economic tool to achieve employment and production targets has always been a concern of policymakers. Accordingly, misrecognition of the interrelationship of markets can lead to the adoption of wrong investment and economic policies.

Bouri et al. (2017). Klein et al. (2018) and Smales (2018) find no consistent evidence that BTC acts as a haven for global assets, while Selmi et al. argue that it acts as a protection, safe haven, and diversifier. However, this feature seems sensitive to the different market conditions of BTC and Gold, and it depends on whether the oil price is in a down, regular, or upside regime. Kurka (2019) found that the relationship between BTC and other assets depends on price shocks. In addition, Matkovskyy and Jalan (2019) found that risk-averse investors in times of crisis tend to move away from BTC with the view that it is riskier than financial markets. Baek and Elbeck (2015) argue that BTC is merely a speculative commodity rather than a currency.

The view that gold can be considered a safe-haven asset is widely accepted, especially in depressed market environments (Beckmann et al., 2015). The traditional safe-haven feature of gold emerges in short intervals, especially in crisis periods (Bredin et al., 2015). For example, Gözde and Ünalmış (2014) found that gold is a safe haven for domestic and foreign investors, especially when the stock market shows more severe declines. Bulut and Rizvanoghlu (2020) emphasize that while gold is generally considered a hedging tool, it is a strong safe haven in only nine countries in their sample. BTC, the most popular and valuable of existing cryptocurrencies, has limited stock and short-term elasticity of supply (Dwyer, 2015). BTC is also called synthetic commodity money due to its scarcity and lack of fiat money (Selgin, 2015). BTC and gold have many similar features, such as being apolitical, safe-haven, and inflation-free (Shahzad et al., 2022).

For this reason, BTC is also called digital gold (Popper, 2015; Rogojanu & Badea, 2014; Selmi et al., 2018). BTC also has advantages that differentiate it from gold, such as being independent of a country's politics and economy and relying on suitable algorithms and sophisticated protocols. Therefore, it is stated that BTC will not be affected by the co-movement and financialization of commodities such as gold. Such features make it meaningful to compare the safe haven features between BTC and gold. Gold and BTC are similar in terms of being a value protection tool and not being controlled by states. The fact that BTC can be used as a general payment method, such as cash or gold, due to its convertibility makes it attractive to investigations of hedge properties (Dyhrberg, 2016a; Bouri et al., 2017; Selmi et al., 2018; Li et al., 2022; Al-Nassar et al.., 2022). However, Wu (2021) investigated the relationship between BTC and traditional financial instruments regarding the asset quality and hedge effect of BTC and found that BTC has a unique risk-return feature and volatility clustering performance, and its high volatility persistence is similar to that of gold. At the same time, it was argued that while BTC exhibits a significant one-way spillover effect on other variables, BTC is much more affected by different market shocks than other markets are affected by BTC shocks. Therefore, BTC cannot be a safe haven.

Since crude oil occupies a dominant position in the global energy market (Zhang & Ji, 2019), the interaction of oil and BTC markets is another essential issue for policymakers and investors. This is because, according to the risk premium channel (Bruno & Shin, 2015), a crude oil shock can significantly affect investors' willingness to take the risk of BTC. Therefore, it is crucial to uncover the link between crude oil and BTC to more effectively assess the potential risks of cryptocurrencies and thus increase earnings (Li et al., 2022). Selmi et al. (2018) claim that BTC plays a diversifying role in hedging oil price changes and is seen as a private safe haven. However, this relationship is variable in different market conditions. Kurka (2019) points out that the unconditional link between cryptocurrency and crude oil can be ignored. However, recent studies have empirically confirmed the severe impact of financial shocks from extreme events (e.g., terrorist attacks, political events, and economic crises) on crude oil and BTC prices (Luo et al., 2020; Zhang et al., 2020; Li et al. ., 2022).

In particular, studies examine the relationship between BTC and strategic commodities such as gold and crude oil and suggest that BTC is a hybrid commodity that will be affected by crude oil prices (Bouri et al., 2018; Gkillas & Longin, 2019; Ji et al., 2018). Kwon (2020) examined whether BTC can be classified as a currency, commodity, or investment asset and found a similarity between BTC and USD. In addition, he discovered that the tail of the stock market return is associated with the risk premium in BTC's return. The bottom line shows that BTC is traded as an alternative to a medium of exchange and investment rather than a commodity. On the other hand, supply-demand factors dominate the price behavior in the BTC market (Ciaian et al., 2016). Thus, unlike standard currencies in circulation, BTC's liquidity and volatility are not influenced by a centralized system of financial institutions (e.g., central banks) or other major macroeconomic factors (Ciaian et al., 2016; Baur et al., 2018). Therefore, the price of BTC could potentially be separate from the economic and trade cycles that result from monetary policy and the central bank's money supply management (Kang et al., 2019). This latter feature suggests that BTC can serve as a dynamic diversification and hedging tool, thus managing market volatility risks (Feng et al., 2018; Kang et al., 2019). On the other hand, Baur et al. (2018) suggest that BTC's extreme returns and volatility are more like a highly speculative asset than gold or the USD.

3. Research Methodology

This study evaluates the relationship between Bitcoin, gold, USD, and oil in Iran. We used the time series method. The Generalized Autoregressive Conditional Heteroscedastic (GARCH) model is an extension of ARCH model. The Autoregressive Conditional Heteroscedastic (ARCH) model is a non-linear time series technique developed by Engle (1982) that is similar to AR (1) model where the variance of the current error term or innovation is a function of the lagged value of past error term, such that ARCH (1) follows:

$$h_t = b_0 + b_1 u_{t-1}^2 \quad \textbf{(1)}$$

The ARCH (1) model shows that the variance of innovation in a given period depends on the magnitudes of the squared errors of one lagged period. The ARCH (1) model can be extended to q lagged periods such that ARCH (q):

$$h_t = b_0 + \sum_{t=1}^{q} b_i u_{t-i}^2 \quad \textbf{(2)}$$

Where, $b_0 > 0$, $0 \le b_1 \le 1$.

The generalized ARCH (GARCH) model is a parsimonious representation of ARCH model developed by Bollerslev (1986). In GARCH model, the error variance takes the form of an ARMA model in which the conditional variance is also a function of its own lag along with squared of lagged error terms. The GARCH model is a parsimonious model as here the unconditional autocorrelation function of the past squared error term can decay slowly, the ARCH does not possess this property and the decay is too rapid. The most commonly used model of GARCH is GARCH (1, 1) model, where,

$$h_t = \varphi + \theta_1 h_{t-1} + b_1 u_{t-1}^2 \quad \textbf{(3)}$$

The GARCH (1, 1) model can be extended to a GARCH (p, q) model where p= lagged terms of the conditional variance (h) and q= lagged terms of the squared error (u^2). Such that,

$$h_t = \varphi + \sum_{k=1}^{p} \theta_k h_{t-k} + \sum_{i=1}^{q} b_i u_{t-i}^2 \quad \textbf{(4)}$$

For stationarity, $b_1 + \theta_1 < 1$. The GARCH model describes how volatility changes with the past shocks (u_{t-1}^2) and the momentum within the system via h_{t-1}.

In our study we have used the GARCH-in-mean effect model in order to see the effect of conditional variance on the conditional mean of the output series in addition of analyzing the dynamics of volatility. The GARCH-in-mean effect model is specified below:

$$\Delta y_t = \beta_0 + \beta_1 \Delta y_{t-1} + \delta \sigma_{y,t}^2 + u_{y,t} \quad \textbf{(5)}$$

$$\sigma_{y,t}^2 = \alpha + \theta \sigma_{y,t-1}^2 + \gamma u_{y,t-1}^2 + \varphi \Delta x_t \quad \textbf{(6)}$$

Equation (5) models the dynamics of output growth series as AR (1) process with GARCH-in-mean effect (δ) to capture the effect of output volatility on growth rate of output. The conditional variance of the error term ($u_{y,t}$) is modeled as GARCH (1, 1) process in equation (6) to capture the both the ARCH effect (γ) and GARCH effect (θ) of output growth series. The model also includes a control variable,Δx_t which represents growth rate of remittances at time t to measure the effect of remittances on output volatility. The error term is allowed to follow normal Gaussian distribution. For application of GARCH model, the error term must have ARCH effect or so to say the variance of the error term must not be constant. This study examines the movement of daily BTC (BTC) price, spot Gold price, USD, and Brent Crude Oil futures in terms of USD from 12/31/2020 to 05/31/2024. The logarithmic values of the variables were used in the analysis.

Table 1 presents the summary statistics of the BTC and the other related variables. The numbers in the table are statistics calculated over logarithmic values. In the whole period the mean daily logarithmic price of BTC is 12.29. Skewness, Kurtosis, Jarque-Bera, and Probability values indicate that the data are typically not normally distributed. Other statistics that can be used in the context of the structure of the data set in the table are mean, median, maximum, minimum, and standard deviation statistics. For example, standard deviation *(sd)* can evaluate every variable's volatility. BTC and oil series are skewed to the left because the skewness value is negative, while other variables are skewed to the right.

Table 1. Descriptive Statistics

	LNBTC	LNGOLD	LNUSD	LNOIL
Mean	12.78	6.69	2.22	4.15
Median	12.59	6.21	2.15	4.25
Maximum	13.16	6.84	2.79	4.78
Minimum	10.37	5.57	1.64	2.85
Std. Dev.	0.23	0.36	0.34	0.42
Skewness	-0.53	0.62	0.82	-0.37
Kurtosis	1.62	2.39	2.45	2.54
Jarque-Bera	74.59	45.12	83.61	17.79
Probability	0.00	0.00	0.00	0.00

***Source**: Research finding*

4. Model Estimation

According to the econometric literature, before any estimation and in order to prevent the emergence of false regressions, the variables must be stationary. If the model's variables are static, estimates will not be subject to the issue of false regression. Using the ADF test, the variables were examined regarding stationarity. The null hypothesis in these tests is that there is a unit root. The summary of test results is shown in Table 2. According to the results, all variables are within 5% points of the y-intercept.

The results are seen in Table 1. In general, all series do not contain unit roots in their level values and are stationary in level. This study uses the GARCH analysis as a main method. With this analysis, the conditional correlations between the variables were determined. As a result of the *GARCH* analysis, we can say that the positive correlation between *BTC* prices and other variables is characteristic for the entire period. Next, we check for presence of ARCH effect in AR (1) model of growth series. There is ARCH effect in growth series as reported in table 3. Hence, we proceed for GARCH estimation using the numerical optimization algorithm Marquardt to calculate the maximum likelihood estimates of the parameters. Table 3 reported the estimated parameters of the model. Considering growth model as represented in equation 5, we find that output volatility (δ) does not influence output growth. This result corroborates with Cermeno et.al (2016), where they find no significant relationship exist between output volatility and output growth. For growth volatility model as represented in equation 6, all the parameters are statistically significant and the sum of ARCH and GARCH term is less than one ($\gamma + \theta < 1$) which implies that the GARCH process is stationary. The coefficient of remittances (φ) is positive and statistically significant. Again, diagnostic tests are conducted to select the model that best fits the data. There is no heteroscedasticity and auto-correlation in the residual of the model which indicates that the model is fit and appropriate.

Table 2. Results of the unit root test

Variables	ADF	
LNBTC	T-statistic	45.23
	P-value	0.00
LNGOLD	T-statistic	28.56
	P-value	0.00
LNUSD	T-statistic	31.69
	P-value	0.00
LNOIL	T-statistic	48.12
	P-value	0.00

***Source**: Research finding*

Table 3. GARCH estimation result

Variable	Coefficient	Standard error	Z-statistics	Prob.
Conditional mean				
Constant	0.33	0.08	4.11	0.000
AR(1)	0.96	0.31	3.56	0.000
δ	-0.03	0.11	-0.24	0.813
Conditional variance				
Constant	0.06	0.00	7.18	0.000
γ	0.37	0.14	2.45	0.015
θ	0.46	0.07	5.92	0.000
φ	1.23	0.14	7.75	0.000
Adjusted R^2	0.78			
Log Likelihood	-45.1807			

***Source**: Research finding*

Table 4 depicts the relationship between financial market. Regarding the DCC modeling, the estimated coefficients on gold, oil and dollar are all positive and statistically significant. These estimated coefficients sum to a value inferior to one, indicating that the asymmetric dynamic conditional correlations are mean reverting. The Shape parameter (mshape) equates the freedom degrees. In effect, the more the number of freedom degrees tends to approach infinity, the more the t distribution's shape tends towards the normal. The obtained results indicated a positive relationship between Bitcoin and the USD, Gold and Oil price in the model.

Table 4. Time series estimation result

	BTC	US Dollar	OIL	GOLD
mu	0.35	-0.26	0.01	0.07
ar1	0.32	-0.07	-0.15	-0.07
omega	0.30	1.56	0.02	0.02
alpha1	0.34	0.32	0.26	0.04
beta1	0.81	0.69	0.85	0.95
eta11	-0.14	-0.09	-0.21	-0.02
alpha1+ eta11	0.21	0.23	0.06	0.014
shape	2.34	2.29	2.58	6.62

***Source**: Research finding*

5. Finding

This study examines the relations between Bitcoin (BTC) prices and fluctuations with gold, USD, and oil. For this purpose, we used the time series regression and GARCH model from 2020 to 2024. The estimation results revealed the existence of a link between these variables. The results show that there is a positive relationship between Bitcoin and the USD, Gols price and Oil price in the model. As a result of GARCH analysis, co-movements and significant relations between Bitcoin, gold, USD, and oil were determined. The findings of this study show that the BTC market should be constantly monitored, given its ability to transfer volatility risk to strategic commodities (such as crude oil) and even safe havens (such as gold) that are often seen as hedging instruments. The results indicate that short-term co-movements of BTC and Gold, oil, and USD are challenging to predict. The results also reflect the behavior of assets that appeal to speculators and uninformed noise investors, which cause significant market fluctuations with their excessive transaction volumes during crisis periods that potentially affect the entire world economy and financial markets, such as the pandemic. Considering that before the pandemic, BTC was considered a relatively weak hedging tool or diversifier, the findings from this study become more remarkable. Additionally, policymakers should pay close attention to the tight interconnections between crude oil, especially during a crisis, if they want to implement optimal economic and energy policies to minimize the destabilizing effects of oil/BTC return shocks and avoid contagion risks. The results of this study also serve as a cautionary note for portfolio managers and investors who include BTC in their portfolios as a hedge against uncertainty. These results also show whether each asset/commodity can be used to manage and hedge the risk of the other asset/commodity due to the downward movement of the general market or sector.

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Data Availability

We encourage all authors to make their research data available.

Conflicts of Interest

The authors declare no conflict of interest.

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