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Analysis of the Causal Relationship between Bitcoin and Hard Currency

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Abstract. Bitcoin is one of the most popular and highest-volume Cryptocurrency transactions in the world. Bitcoin is not only used as a payment instrument but also as an investment medium across countries. The openness of trade and integration of financial systems between countries will affect the demand and supply of the world's strong currencies (hard currencies) such as the Dollar, Pound sterling, Euro, Yen, and Yuan. The purpose of this study is to test the two-way causal relationship between Bitcoin and hard currency. This research uses a descriptive quantitative approach. The analysis method was used to determine the relationship between variables through the Johansen cointegration test, causality test with Engel Granger test, and Vector Error Correction Models (VECM). The results of this study indicate that Bitcoin has a long-term equilibrium relationship with the Dollar, Pound sterling, Euro, Yen, and Yuan currencies. However, there is no causality or feedback relationship between Bitcoin and hard currency and vice versa.

Keywords: Bitcoin, Hard Currency, Causality

1. Introduction

A new phenomenon in payment transactions is the use of crypto-based virtual currencies in financial transactions, which is currently very popular (Pieters and Vivanco 2017). The commonly used term for these currencies is Cryptocurrency. Currently, there are 4,146 types of cryptocurrencies with a total market capitalization of $771.83 billion and a transaction volume of $161.77 billion. (Coinmarket, Cryptocurrency Market Capitalization, 2021).

A new phenomenon in payment transactions is the use of crypto-based virtual currencies in financial transactions, which is currently very popular (Pieters and Vivanco, 2017). The commonly used term for these currencies is Cryptocurrency. Currently, there are 4,146 types of cryptocurrencies with a total market capitalization of $771.83 billion and a transaction volume of $161.77 billion (Coinmarket, Cryptocurrency Market Capitalization, 2021).

The use of cryptocurrencies is increasingly favored due to the benefits it provides in terms of low transaction costs, transaction speed, and transaction. (European Banking Authority 2014). Transaction costs using cryptocurrencies are less than 1%, whereas traditional online payments range from 2-4%. Transaction speed is instantaneous with transaction services available at all times. The significantly high returns on Bitcoin investments are a major attraction that boosts the popularity of cryptocurrencies (Phillip, Chan, and Peiris 2019). Bitcoin returns are higher than gold and other foreign currencies in terms of the US Dollar

(Dwyer 2015). As it develops, more and more sellers accept Bitcoin payments for the purpose of purchasing goods and services, both within legal corridors and beyond their boundaries. (Böhme et al. 2015).

The popularity of Bitcoin has increased rapidly in the past ten years since its introduction by Satoshi Nakamoto through the creation of cryptocurrency software in 2009. Bitcoin's development is based on the supply and demand of its users, but it does not continue to be produced despite high demand. The determination of Bitcoin's value is categorized into external and internal factors. The main internal factor that directly impacts the price level is based on the demand and supply of the cryptocurrency. External factors include monetary policies, regulations, stock markets, and gold prices (Poyser, 2017). When the demand for Bitcoin increases, the price of a Bitcoin will also rise, and the opposite is true when there is an increase in the supply of Bitcoin.

Hard currency is a term used for the currencies of economically strong countries that are widely accepted worldwide as a form of payment for goods and services. The supporting criteria state that hard currency originates from countries with stable political and economic conditions. Several currencies fall into this category due to their widespread use in global trade, including the United States Dollar, the Euro, the Japanese Yen, the British Pound, the Swiss Franc, and the Canadian Dollar.

Bitcoin is one of the most widely used cryptocurrencies in the world compared to other types of cryptocurrencies. Its usage popularity is higher, with its market capitalization dominating 49% of the total global cryptocurrency market. The value and position of Bitcoin being ranked first demonstrate its market dominance in the cryptocurrency world. Bitcoin transactions have an impact on the financial and monetary systems of a country due to financial integration, trade, and interconnectivity among regions.

The use of Bitcoin currency in economic transactions is believed to impact the monetary aggregates of a country. This is a consequence of economic, financial, and trade integration among nations. Paresh, Seema, and Iwam Paresh (2019) found strong evidence that Bitcoin price growth affects the monetary aggregates in Indonesia, leading to inflation growth, currency appreciation, and a decrease in the velocity of money.

The connection and role of Bitcoin in relation to a country's currency can be explained by referring to the theory of exchange rates. Gustav Cassel (1924) explained in the Purchasing Power Parity theory that the exchange rate between two countries depends on the relative purchasing power of their respective currencies. The forces of supply and demand for a currency determine its value. Edwards (1988) introduced the theory of real exchange rate behavior to analyze aspects that influence exchange rates in the long term, such as external trade patterns, the level and composition of government consumption, import tariffs, and capital flows.

Based on the description above, this research aims to examine and analyze whether there is a causal relationship between Bitcoin and Hard Currency (Dollar, Euro, Pounds, Yuan, and Yen). The focus of this research is on the Vector Error Correction Model (VECM) to analyze the causal relationship between Bitcoin and Hard Currency. Then, it will analyze based on the model structure to observe the relationship of each variable in the short and long run. Furthermore, it will provide forecasting and structural analysis based on the forecast.

2. Literature Review

The exchange rate refers to the exchange between two currencies, based on the relative value of one currency against another, both domestic and foreign currencies (Nopirin, 2014). The exchange rate is determined through the mechanism of the foreign exchange market, where they find relative equilibrium with each other due to supply and demand (Abimanyu, 2004). Changes in the exchange rate of a domestic currency against a foreign currency are influenced by several fundamental factors, technical factors, and market perceptions (Madura, 1993).

Currency exchange, known as "sharf" in Islamic law, is considered a permissible activity. Sharf refers to the exchange of domestic currency with foreign currency (Arifin, 2003). Transactions in Bitcoin are based on the concept of decentralized authority, using digital signatures for verification without the involvement of third parties (Nakamoto, 2008). The demand for Bitcoin is one of the internal factors that directly impact the unit price of Bitcoin itself. Related to its attractiveness (popularity), legality, and other macro-financial factors such as stock markets, gold prices, and interest rates, they are considered external factors that influence Bitcoin, both directly and indirectly (Poyser, 2017).

Atik et al. (2015) explored the relationship between Bitcoin and the exchange rate in Turkey during the period from 2009 to 2015. The interaction between the daily exchange rate of Bitcoin and the most commonly used cross exchange rate in the world was examined using cointegration analysis. The results of the analysis showed a one-way causality between Bitcoin and the Japanese yen, and also, the Japanese yen and Bitcoin had a lag effect on each other.

Empirical research on Bitcoin can be mapped as follows: Firstly, studies on the efficiency of the cryptocurrency market, specifically focusing on Bitcoin. These studies were conducted by Al-Yahyaee, Mensi, and Yoon (2018); Cheah et al. (2018); Almudhaf (2018) with findings indicating that Bitcoin is not efficient. Bitcoin does not correlate with various traditional assets such as stocks, bonds, and commodities (Baur, Hong, and Lee 2018). The price movement of Bitcoin is highly speculative, as found by Baek and Elbeck (2015); Konstantinos and Katsiampa (2020); Cheah and Fry (2015); Dyhrberg (2016) and emphasized by Baur et al. (2018) stating that Bitcoin is used as a speculative investment rather than as a currency or alternative medium of exchange. This evidence is further supported by findings that suggest the existence of cryptocurrency bubbles, as observed by Corbet, Lucey, and Yarovaya (2018) and Cheung, Adrian and Roca, Eduardo and Su (2013).

Secondly, research exploring the diversification benefits of Bitcoin shows that Bitcoin has a positive reaction to higher levels of uncertainty (Bouri et al. 2017), Furthermore Feng, Wang, and Zhang (2018); Dyhrberg (2016) and Śmiech and Papież (2017) explain that cryptocurrencies have the ability to serve as a great diversification option due to their safe-haven characteristics similar to gold and the US dollar.

Thirdly, research has attempted to predict the price or return rate of Bitcoin by examining economic uncertainty indices. Demir dan Vigne (2018) found that economic policy uncertainty can provide predictive power for Bitcoin returns with a positive influence. Balcilar dan Roubaud (2017) concluded that trading volume cannot be used to assist in predicting Bitcoin return volatility.

Fourthly, research has addressed the suitability of cryptocurrency as money from an Islamic perspective. Siswantoro, Handika, and Mita (2020) stated that the inadequacy of cryptocurrency as a medium of exchange, its volatility, and speculation are the main reasons for its prohibition in Islam, along with the belief that this currency will not thrive in Islamic countries. Meera (2018) explains that cryptocurrency involves transactions that resemble maysir (gambling) and gharar (uncertainty), making it inconsistent with Sharia principles.

Fifthly, research has addressed whether cryptocurrency can replace fiat currency. Nelson (2018) states that it is unlikely for digital currency to replace physical cash, thus posing minimal risk to monetary policy.

Table 1. Empirical Studies on Bitcoin Research

Title	Name	Method	Result
Analysis of relationships between Bitcoin and exchane rate, commodities and global indexes by asymmetric causality test	Mehmet Levent Erdas & Abdullah Emre Caglar (2018)	Uji Hatemi-J	There is a causal relationship from negative shocks to positive and positive to negative between Bitcoin and Gold, Brent Crude, US Dollar, and BIST 100 Index.
Het samenstellen van een efficiente markt portfolio met Bitcoins	V.Uiterwijk (2013)	Ordinary Least Squares	There is a long-term positive relationship between the Dow Jones Index, Euro Exchange Rate, and Oil Price.
Kripto Para : Bitcoin ve Doviz Kurlan Uzerine Etkilerl	Murat Atik, Yaşar Kose, Bülent Yilmaz, Fatih Saglam (2015)	Causality Granger, *Vector Autoregressive Model* (VAR), Johanssen Cointegration	There is a one-way causal relationship between the Japanese Yen to Bitcoin.
Hedging capabilities of bitcoin. Is it the virtual gold ?	Anne Haubo Dyhrberg (2015)	The asymmetric GARCH methodology	There is a short-term positive relationship between the value of the US dollar and Bitcoin.
Dependency Analysis between Bitcoin and Selected Global Currencies	Szetela, Mentel & Gędek. (2018)	Model ARMA dan GARCH	There is a negative relationship between Bitcoin and the exchange rates of other countries.
In search of the relationship between Bitcoin and selected exchange rates: Johansen test and granger causality test for the period 2013-2017	Icellioglu & Ozturk (2017)	*Johansen test and Granger causality test*	There is a long-term and short-term negative relationship between Bitcoin and the exchange rates of the US dollar, euro, pound, yen, and yuan.

3. Research Method

Research on the causal analysis of Bitcoin on Hard Currency exchange rates was conducted using a quantitative descriptive method. The currency sample used includes Bitcoin, as well as the hard currencies: US Dollar, Pound Sterling, Euro, Yen, and Yuan. The data used in this study are weekly Time Series secondary data covering the period from July 2013 to December 2019, with a total of 76 observations. The analysis employed the Vector Error Correction Model (VECM) model.

The Vector Error Correction Model (VECM) is an econometric model used to identify long-term relationships between variables (Gujarati, 2004). This model can also be used to estimate the response of variables to certain changes and predict how variables will react to future changes. The following are the steps involved in data analysis using VECM:

3.1 Stasionarity Test

The VECM model assumes that the tested variables have the same stationary characteristics. Stationarity tests determine whether the tested variables significantly change over time. The unit root test is used to test the stationarity of data using the Augmented Dickey-Fuller (ADF) test with the following equation formula:

$$\Delta Y_t = Y + \delta t + \rho Y_{t-1} + \sum_{j=1}^{k} \phi_j \, \Delta Y_{t-j} + e_t \tag{1}$$

With $\Delta Y_t = Y_t - Y_{t-1}$ dan $\rho = \alpha - 1$

At the significance level (1 - α) 100%, if the ADF test statistic is greater than the test critical values and the p-value is less than α (5%), then the data is stationary. However, if the opposite is true, it indicates the presence of a Unit Root in the data. Therefore, it is necessary to proceed with taking the first difference in the data.

3.2 Optimal Lag Selection Test

The Optimal Lag Selection Test in the VECM model is a method to determine the optimal number of lags to be used in the VECM model. This method utilizes statistics to determine the number of lags that will provide the most accurate model. Testing the number of lags involves criteria such as the Akaike Information Criterion (AIC), Schwarz Information Criterion (SIC), and Hanna-Quinn Information Criterion (HQC). The minimum values of these criteria are used to determine the length of the lags.

Akaike Information Criterion (AIC)

$$AIC(p) = \log \det \left(\hat{\sum}_u (p)\right) + \frac{2pk^2}{T} \tag{2}$$

Schwarz InformationCriterion (SIC)

$$SC(p) = \log \det \left(\hat{\sum}_u (p)\right) + \frac{\log(T)\, pk^2}{T} \tag{3}$$

Hannan-Quinn Information Criterion (HQ)

$$(HQ) = -2 \left[\frac{1}{T}\right] + 2k\log \left[\frac{\log(T)}{T}\right] \tag{4}$$

3.3 Cointegration Test

The cointegration test is conducted to examine the extent of long-term equilibrium relationships between variables. The cointegration testing is performed using the Angle-Granger method and the Johansen cointegration test based on the Vector Autoregressions (VAR) approach. The following is the equation for the VAR (p) model:

$$y_t = A_t y_{t-1} + \cdots + A_p y_{t-p} + Bx_t + \varepsilon_t \tag{5}$$

The variable y_t is a vector with k non-stationary variables of order I(1), x_t is a vector with *d* deterministic variables, and, ε_t is the error vector. The VAR (p) equation can also be written as follows:

$$\Delta y_t = \Pi y_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \Delta y_{t-1} + Bx_t + \varepsilon_t \tag{6}$$

Where :

$$\Pi = \sum_{i=1}^{p} A_i - \mathrm{I}, \quad \Gamma_i = -\sum_{J=i+1}^{p} A_i. \tag{7}$$

3.4 Granger Causality test

The Granger Causality test in the VECM model is a method used to test whether a specific variable statistically influences another variable. The Granger Causality test measures the relationship between two variables using historical data. Through this test, it is determined whether one or more variables significantly affect another variable in the VECM model. The equation for Granger causality is as follows:

$$F_{uji} = \frac{(RSS_R - RSS_{UR})/p}{RSS_R/(n-k)} \tag{8}$$

Where RSS_R is the restricted residual sum of squares, RSS_{UR} is the unrestricted residual sum of squares, p is the lag length, and n is the number of observations.

3.5 Goodness of Fit

In the VECM model, the Model Fit Test is used to assess whether the VECM model is suitable for describing the relationship between different variables. This test is useful in identifying assumptions that are not met by the model and measuring the extent to which the VECM model can explain the available data. The equation for the model fit test is as follows:

$$Q_h = T \sum_{j=1}^{h} tr\left(\hat{C}_j' \hat{C}_0^{-1} \hat{C}_j \hat{C}_0^{-1}\right), \tag{9}$$

Or

$$Q_h^* = T^2 \sum_{j=1}^{h} \frac{1}{T-j} tr\left(\hat{C}_j' \hat{C}_0^{-1} \hat{C}_j \hat{C}_0^{-1}\right), \tag{10}$$

Where $\hat{C}_i = \frac{1}{T} \sum_{t=i+1}^{T}$ ût ût $-$ i. This test statistic follows a distribution $x^2_{k^2(h-n^*))}$. Where n^* represents the number of coefficients, excluding the constant term, estimated in the VAR (p) model.

This test statistic follows a distribution X, where T represents the number of coefficients, excluding the constant term, estimated in the VAR (p) model.

3.6 Forecasting and Structural Analysis

Forecasting and Structural Analysis are the same models in the VAR model. The analysis methods used include impulse response analysis and variance decomposition. Mean Absolute Percentage Error (MAPE) is used as a criterion to validate the accuracy of the model used in generating forecasts. The equation for the MAPE model is as follows:

$$MAPE = \frac{\sum_{t=1}^{n} \frac{\hat{Y}_t - Y_t}{Y_t}}{n} \times 100\% \tag{12}$$

and *Mean Square Error* (MSE):

$$MSE = \frac{1}{n} \sum_{i=1}^{n} \left(Y_T - \hat{Y}_t\right) \tag{13}$$

Where n represents the number of data. The smaller the values of MAPE and MSE, the more accurate the forecasting results.

4. Result and Discussion

Based on the predefined sample criteria for the research, with Bitcoin as the independent variable and the exchange rates of the Dollar, Pound Sterling, Euro, Yen, and Yuan as the dependent variables, the following data can be obtained as the sample :

Table 1. Result of ADF (Augmented Dickey-Fuller) Test at Level

Variable	Probability ADF - Fisher Chi-square	Information
Bitcoin	0.0212	Stasioner
Dollar	0.4713	Tidak Stasioner
Euro	0.4493	Tidak Stasioner
Pounds	0.6942	Tidak Stasioner
Yen	0.2633	Tidak Stasioner
Yuan	0.1443	Tidak Stasioner

Source: Data processing results, 2021.

The results of the stationarity test at the level indicate that only one variable, Bitcoin, passes the test, while the other variables do not pass the level test using the ADF Fisher chi-square method. This is indicated by the probability values being less than 0.05. The next step is to perform the stationarity test at the first difference level.

Table 2. Result of ADF (Augmented Dickey-Fuller) Test on First Difference

Variable	Probability ADF - Fisher Chi-square	Information
Bitcoin	0.0000	Stasioner
Dollar	0.0000	Stasioner
Euro	0.0000	Stasioner
Pounds	0.0000	Stasioner
Yen	0.0000	Stasioner
Yuan	0.0000	Stasioner

Source: Data processing results, 2021.

The results of stationarity testing at the first difference level using the ADF Fisher Chi-Square method indicate that all variables pass the test with probability values less than 0.05.

The lag length is determined to identify the relationship between past variables and the current variable. The optimal lag length can be seen in the table below:

Table 3. Optimal Lag Test Results

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-494.0712	NA	0.052827	14.08651	14.27773	14.16255
1	-85.90995	735.8400	1.48e-06*	3.603097	4.941584*	4.135371*
2	-52.86210	53.99367*	1.65e-06	3.686256	6.172017	4.674765
3	-26.37670	38.79552	2.28e-06	3.954273	7.587308	5.399016
4	6.400274	42.47157	2.78e-06	4.045063	8.825372	5.946040
5	33.83978	30.91776	4.27e-06	4.286203	10.21379	6.643416
6	82.84321	46.93285	4.01e-06	3.919910	10.99477	6.733357
7	142.5904	47.12457	3.31e-06	3.250974	11.47311	6.520655
8	211.6588	42.80297	2.73e-06	2.319469*	11.68888	6.045385

Source: Data processing results, 2021.

Based on the optimal lag length of all variables determined by the criteria of Likelihood Ratio (LR), Final Prediction Error (FPE), Akaike Information Criterion (AIC), Schwartz Information Criterion (SIC), and Hannan-Quinn Information Criterion (HQ) within the interval scale of lag 0 to 8, it indicates that the variables are present at lag 1.

4.1 Cointragation Test

The Johansen cointegration test was conducted to examine the long-term relationship among the variables under study. The results of the Johansen cointegration test at a 5% significance level are presented in the following table:

Table. 4 Johansen Cointegration Test based on Trace Statistic

Variable	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.
Bitcoin Dollar	0.240890	24.23676	15.49471	0.0019
Bitcoin Euro	0.259937	26.92068	15.49471	0.0006
Bitcoin Pounds	0.924876	52.33885	15.49471	0.0000
Bitcoin Yen	0.312248	33.35556	15.49471	0.0000
Bitcoin Yuan	0.281660	29.78276	15.49471	0.0002

Source: Data processing results, 2021.

Table. 5. Result of Johansen Cointegration Test based on Rank Test (Maximum Eigenvalue)

Variable	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.
Bitcoin Dollar	0.240890	20.94626	14.26460	0.0038
Bitcoin Euro	0.259937	22.87752	14.26460	0.0017
Bitcoin Pounds	0.356659	33.52211	14.26460	0.0000
Bitcoin Yen	0.312248	28.44889	14.26460	0.0002
Bitcoin Yuan	0.281660	25.14174	14.26460	0.0007

Source: Data processing results, 2021.

Based on the test results, indicates that Bitcoin has a long-term relationship (long-run equilibrium) with the currencies of the Dollar, Pound Sterling, Euro, Yen, and Yuan.

4.2 Portmanteau Test

Table. 6 Result of Portmanteau Test

Lags	Q-Stat	Prob.*	Adj Q-Stat	Prob.*	df
1	7.814613	---	7.917437	---	---
2	41.33336	---	42.33002	---	---
3	77.07225	0.0001	79.51778	0.0000	36
4	110.9163	0.0022	115.2163	0.0009	72
5	137.7501	0.0282	143.9136	0.0119	108
6	171.1442	0.0609	180.1297	0.0221	144
7	199.8091	0.1485	211.6610	0.0532	180
8	220.9243	0.3947	235.2245	0.1760	216
9	265.6588	0.2652	285.8796	0.0700	252
10	306.9124	0.2121	333.2905	0.0341	288
11	349.0626	0.1620	382.4657	0.0140	324
12	379.2061	0.2333	418.1742	0.0185	360
13	418.3189	0.2112	465.2318	0.0093	396
14	448.5853	0.2810	502.2241	0.0109	432
15	482.3292	0.3137	544.1318	0.0085	468
16	517.7353	0.3265	588.8248	0.0053	504
17	545.0691	0.4309	623.9031	0.0071	540
18	581.5108	0.4280	671.4627	0.0036	576
19	611.4103	0.4991	711.1568	0.0033	612
20	638.4869	0.5976	747.7340	0.0039	648

Source: Data processing results, 2021.

From the p-value values for the Q-statistic, it is obtained that the null hypothesis of the model is not rejected because most of the lag values have p-values greater than the coefficient standard of 0.05, indicating that there is no autocorrelation and the model meets the criteria for the model fitness test.

4.3 Causality Granger Test

The Granger causality test aims to examine the influence of past values of one variable on the current condition of another variable. The significance level for the Engel Granger causality test is set at 0.1 (10%) with the determination of lag length for the Bitcoin exchange rate variable on the exchange rates of the Dollar, Pound Sterling, Euro, Yen, and Yuan adjusted to the previously conducted optimal lag test, which is lag 1. The following are the results indicated by the Engel-Granger causality test:

Table 7. Result of Causality Granger Test

Null Hypothesis:	Obs	F-Statistic	Prob.
D(DOLLAR) does not Granger Cause D(BITCOIN)	76	1.32379	0.2726
D(BITCOIN) does not Granger Cause D(DOLLAR)		0.89877	0.4117
D(EURO) does not Granger Cause D(BITCOIN)	76	0.54269	0.5836
D(BITCOIN) does not Granger Cause D(EURO)		0.71303	0.4936
D(POUNDS) does not Granger Cause D(BITCOIN)	76	0.06918	0.9332
D(BITCOIN) does not Granger Cause D(POUNDS)		0.10470	0.9007
D(YEN) does not Granger Cause D(BITCOIN)	76	0.06432	0.9378
D(BITCOIN) does not Granger Cause D(YEN)		1.15872	0.3198
D(YUAN) does not Granger Cause D(BITCOIN)	76	0.88239	0.4183
D(BITCOIN) does not Granger Cause D(YUAN)		0.00814	0.9919
D(EURO) does not Granger Cause D(DOLLAR)	76	0.70900	0.4956
D(DOLLAR) does not Granger Cause D(EURO)		1.37781	0.2588
D(POUNDS) does not Granger Cause D(DOLLAR)	76	0.56862	0.5689
D(DOLLAR) does not Granger Cause D(POUNDS)		1.13043	0.3286
D(YEN) does not Granger Cause D(DOLLAR)	76	1.72513	0.1855
D(DOLLAR) does not Granger Cause D(YEN)		0.04534	0.9557
D(YUAN) does not Granger Cause D(DOLLAR)	76	0.46929	0.6274
D(DOLLAR) does not Granger Cause D(YUAN)		0.26288	0.7696
D(POUNDS) does not Granger Cause D(EURO)	76	0.21890	0.8039
D(EURO) does not Granger Cause D(POUNDS)		0.28862	0.7502
D(YEN) does not Granger Cause D(EURO)	76	0.97315	0.3829
D(EURO) does not Granger Cause D(YEN)		0.27530	0.7601
D(YUAN) does not Granger Cause D(EURO)	76	0.35103	0.7052
D(EURO) does not Granger Cause D(YUAN)		0.15706	0.8549
D(YEN) does not Granger Cause D(POUNDS)	76	2.73315	0.0719
D(POUNDS) does not Granger Cause D(YEN)		3.34737	0.0408
D(YUAN) does not Granger Cause D(POUNDS)	76	0.32059	0.7268
D(POUNDS) does not Granger Cause D(YUAN)		0.04439	0.9566
D(YUAN) does not Granger Cause D(YEN)	76	0.61667	0.5426
D(YEN) does not Granger Cause D(YUAN)		1.33560	0.2695

Source: Data processing results, 2021.

Based on the obtained results, variables that have causality relationships are those with probability values less than the alpha level of 0.05, leading to the rejection of the null hypothesis (Ho). This indicates that one variable influences another variable. The Granger causality test results show that the Pound has a statistically significant influence on the Yen (0.04), accepting the null hypothesis. However, the Yen does not have a significant influence on the Pound (0.07), leading to the rejection of the null hypothesis. Therefore, it can be concluded that there is a unidirectional causality between the Pound and the Yen, but not vice versa. As for the other variables, there is no evidence of bidirectional/causal relationships.

4.4 Vector Error Correction Model (VECM)

Table 8. Result of Short-Term VECM Estimation

Variable	Coefesien	Statistic
CointEq1	-0.005933	-0.69928
D(BITCOIN(-1)	-0.610745	-6.13477
D(BITCOIN(-2)	-0.549112	-6.02767
D(DOLLAR(-1)	-5.72E-06	-0.06167
D(DOLLAR(-2)	-3.17E-05	-0.40457
D(EURO(-1)	2.44E-05	0.33796
D(EURO(-2)	7.86E-05	1.15704
D(POUNDS(-1)	1.01E-05	0.22768
D(POUNDS(-2)	8.60E-06	0.19820
D(YEN(-1)	0.000102	1.74215
D(YEN(-2)	7.86E-05	1.44334
D(YUAN(-1)	1.22E-05	0.18836
D(YUAN(-2)	7.42E-05	1.17152
C	3.40E-05	0.43257

Source: Data processing results, 2021.

Based on the above results, in the short run, there are two significant variables at the significance level of 0.05, along with one error correction variable. The three significant variables at the 0.05 level are Bitcoin at lag 1 and Bitcoin at lag 2. The presence of a significant error correction parameter indicates the existence of an adjustment mechanism from the short run to the long run, with an estimated magnitude of -0.005 percent.

The short-term estimation results show that the Bitcoin variable at lag 1 has a negative impact with a coefficient of (-0.61). This means that a 1 percent increase in the previous year will decrease the demand for Bitcoin by 0.61 percent in the current year. On the other hand, the Bitcoin variable at lag 2 also has a negative impact with a coefficient of (-0.54), indicating that a 1 percent increase in the demand for Bitcoin two years ago will decrease the demand for Bitcoin by 0.54 percent in the current year.

Table 9. Short-Term VECM Estimation Result

Variable	Coefesien	Statistic
Dollar	-0.012374	-5.87676
Euro	-0.005488	-2.00141
Pounds	-0.003405	-1.97605
Yen	-0.000673	-0.29367
Yuan	0.001343	0.64320

Source: Data processing results, 2021.

The currency Dollar has a negative impact on Bitcoin, specifically -0.012374 percent. This means that an appreciation in the value of the Dollar will lead to a depreciation of Bitcoin by 0.012 percent, and vice versa. The same applies to the currencies Euro, Pound, and Yen, which also have a negative influence on Bitcoin. However, the currency Yuan has a positive impact on Bitcoin with a coefficient of 0.001343. This implies that an appreciation in the value of the Yuan will cause Bitcoin to rise by 0.0013 percent.

Based on the findings of this research, it can support several previous studies. One of these studies is conducted by Jamal Bouoiyour and Refk Selmi (2015), which found a long-run negative relationship between the exchange rate of Bitcoin and trading transactions in the

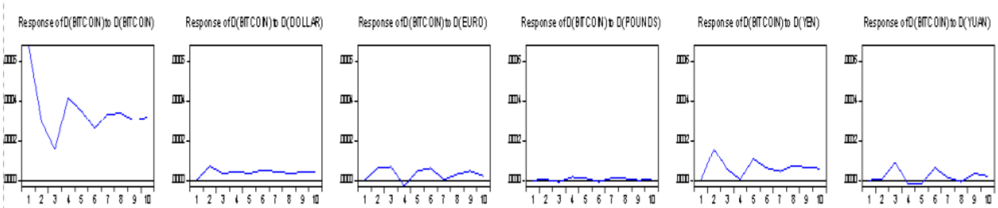
Shanghai stock market and the hash rate. The method used to strengthen this research is the ARDL Bounds Testing approach. Another study by Atik et al. (2015) indicates that there is a one-way causality between the exchange rate of Bitcoin and the Japanese Yen.

The one-way relationship between the Japanese Yen and Bitcoin has been studied using various methods such as Granger Causality, Vector Autoregressive Model (VAR), and Johansen Cointegration. Icellioglu and Ozturk (2017) examined the long-run and short-run relationships between the US Dollar, Euro, Pound Sterling, Japanese Yen, Chinese Yuan, and Bitcoin using Johansen cointegration test and Engel-Granger causality test. They found negative long-run and short-run relationships between Bitcoin and the mentioned currencies. Another study conducted by Szetela et al. (2018) identified the relationships between Bitcoin and 66 major currencies, including the US Dollar, Euro, Pound Sterling, Chinese Yuan, and Polish Zloty. They applied the ARMA and GARCH models to analyze the mean and conditional variations. The GARCH model helped identify dependencies in explaining the conditional differences between Bitcoin and the mentioned currencies.

Meanwhile, the ARMA analysis results indicate no significant relationship between Bitcoin and other dependent variables, which are other currencies. This further clarifies that the existing relationship is negative. Jin and Masih (2017) explain in their study that Bitcoin is a form of digital currency that circulates without the support of a central bank or monitoring authority. Therefore, there is skepticism regarding the status of Bitcoin as a legitimate means of payment. However, due to the increasing popularity and perceived significance of Bitcoin, researchers have explored the possibility of using Bitcoin as an optimization portfolio strategy for Islamic fund managers. Three recent and relevant methodologies were employed: M-GARCH-DCC, Continuous Wavelet Transforms (CWT), and Maximum Overlap Discrete Wavelet Transform (MODWT). The results indicate that the Bitcoin stock index and the low Shariah index are negatively correlated, suggesting that Shariah stock investors can benefit from diversifying with Bitcoin and that the fundamentals of such cryptocurrencies can be further investigated for the benefit of the Islamic capital market.

4.5 Forecasting and Structural Analysis

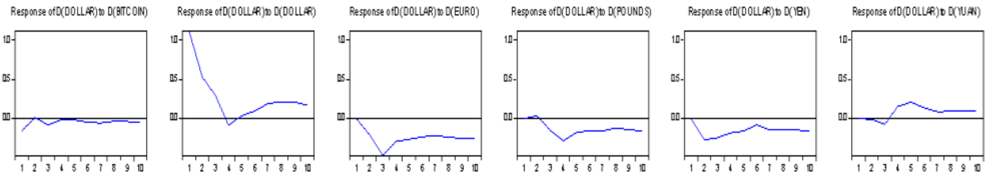
Analysis of Impulse Response Function (Bitcoin)



From the above figure, it can be explained that the response of Bitcoin to the dollar shock from the first period to the tenth period tends to fluctuate, but the IRF (Impulse Response Function) movement is positive. This is because the line is above the horizontal line throughout the first to tenth periods, and the highest peak is observed in the second period. On the other hand, the response of Bitcoin to the euro shock shows fluctuating patterns in each period, and the movement tends to be positive as the IRF line is above the horizontal line. However, in the fourth period, there is a negative response observed as it falls below the horizontal IRF line. Regarding the response of Bitcoin to the pounds shock, there is no significant movement observed from the first to the tenth period, and the IRF line tends to be above the horizontal line.

Slightly different from the response of Bitcoin to the yen shock, it shows a fluctuating pattern from the first to the tenth period. The IRF line is located above the horizontal line, indicating a positive movement. As for the response of Bitcoin to the yuan shock, it exhibits fluctuating patterns from the first to the tenth period. However, the movement of the IRF line tends to be positive as it is positioned above the horizontal line, except for the fourth period leading to the fifth period where it shows a negative response.

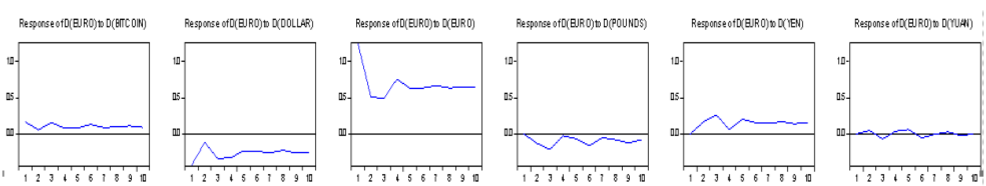
Analysis of Impulse Response Function (Dollar)



As seen in the above figure, the response of the dollar variable to the Bitcoin shock shows fluctuating patterns from the first to the tenth period. However, the movement is not too extreme or significant. The IRF line tends to be negative as it is located below the horizontal line. On the other hand, for the dollar variable responding to the euro shock, a similar pattern can be observed, but there is a significant decline in the first to the third period. The movement of the IRF line, which is below the horizontal line, indicates a negative response.

A similar pattern can be observed for the dollar variable responding to the pound shock, as it experiences relatively extreme movements from the first to the fourth period. However, there is a slight difference in the second period, where the IRF line is positive as it is located above the horizontal line, while the subsequent IRF lines tend to be negative as they are below the horizontal line. The dollar variable responding to the yen shock, shows fluctuating patterns from the first to the tenth period, and the IRF line tends to be below the horizontal line, indicating a negative response. As for the dollar variable responding to the yuan shock, it also exhibits fluctuating patterns. However, there is a slight difference. In the first to the third period, the IRF line is below the horizontal line, indicating a negative response. Whereas, from the fourth to the tenth period, the IRF line is above the horizontal line, indicating a positive response.

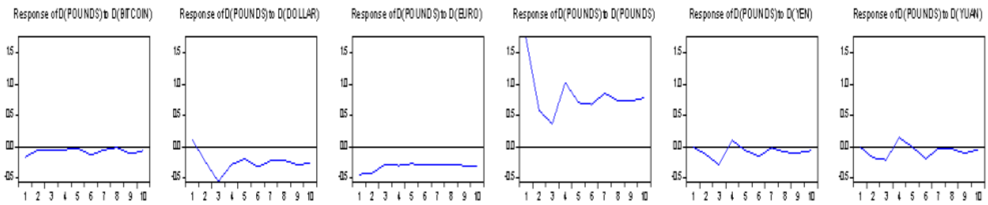
Analisys of Impulse Response Function (Euro)



The above graph shows that the euro variable responding to the bitcoin shock exhibits fluctuating patterns and stability from the first to the tenth period. However, the movement of the IRF line tends to be positive as it is located above the horizontal line. As for the euro variable responding to the dollar and pound shocks, it indicates fluctuating movements from the first to the tenth period. The positioning of the IRF lines below the horizontal line suggests negative movements.

The euro variable responding to the yen shock exhibits fluctuating movements from the first to the tenth period, with only the fifth to tenth periods showing a more stable pattern. The IRF line located above the horizontal line indicates positive movements. As for the euro variable responding to the yuan shock, there are fluctuating movements, but the IRF line behaves differently. In the first, second, fourth, fifth, and ninth periods, the IRF line is located above the horizontal line, indicating positive movements. However, in the third, sixth, ninth, and tenth periods, the IRF line is below the horizontal line, indicating negative movements.

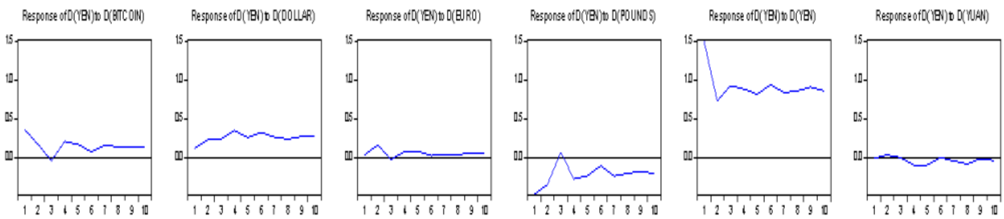
Analisys of Impulse Response Function (Pounds)



The graph above shows that the pounds variable responding to bitcoin and euro shocks tends to be stable, and the IRF line below the horizontal line indicates negative movements from the first to the tenth period. As for the pounds variable responding to the dollar shock, it exhibits more fluctuating movements. Only in the first period does it show a positive movement as the IRF line is located above the horizontal line. However, from the second to the tenth period, there are negative movements as the IRF line is below the horizontal line.

For the pounds variable responding to the yen shock, it exhibits similar and fluctuating movements. In the first, second, and fifth to tenth periods, there are negative movements as the IRF line is located below the horizontal line. However, in the fourth period, there is a positive movement as the IRF line is above the horizontal line.

Analisys of Impulse Response Function (Yen)



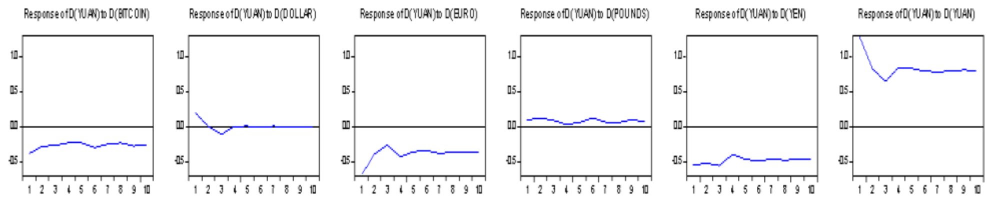
The above graph shows that the yen variable responding to the shock exhibits fluctuating movements from the first to the tenth period. However, looking at the IRF line, there is a positive movement as it is located above the horizontal line, despite experiencing a decline in the first to third periods.

As for the yen variable responding to the euro and dollar shocks, it also shows fluctuating to stable movements. However, the IRF lines indicate positive movements as they are located above the horizontal line, although there is a slight decline in the second to third periods for the yen variable responding to the euro shock.

The yen variable responding to the pound shock exhibits fluctuating movements from the first to the tenth period. There is a slight change in the movement from the first to the third period, resulting in a positive movement as the IRF line is located above the horizontal line. However, there is a subsequent decline from the third to the tenth period, with the IRF line located below the horizontal line, indicating a negative movement.

As for the yen variable responding to the yuan shock, it also shows fluctuating movements from the first to the tenth period. However, only in the first and second periods, the IRF line is located above the horizontal line, indicating a positive movement. In contrast, from the third to the tenth period, the IRF line is located below the horizontal line, indicating a negative movement.

Analisys of Impulse Response Function (Yuan)



The above graph shows similar movements for the yuan variable in response to the bitcoin, euro, and yen shocks. It exhibits fluctuating movements that eventually stabilize from the first to the tenth period. The positioning of the IRF line below the horizontal line indicates negative movements in response to all shock variables.

As for the yuan variable in response to the dollar shock, it also demonstrates fluctuating movements that eventually stabilize from the first to the tenth period. The positioning of the IRF line in the middle of the horizontal line from the fourth to the tenth period indicates the absence of shocks between the variables. However, there is a decline from the first to the third period, initially showing positive movements that transition to negative movements.

Regarding the yuan variable in response to the pounds shock, it exhibits fluctuating yet relatively stable movements from the first to the tenth period. The positioning of the IRF line above the horizontal line indicates positive movements.

5. Conclusion

The test results indicate that Bitcoin has cointegration or a long-term equilibrium relationship with the currencies of the Dollar, Pound, Euro, Yen, and Yuan. The variables that exhibit bidirectional causality are the Pound, which significantly influences the Yen, while the Yen does not significantly influence the Pound. There is a unidirectional causality between the Pound and Yen, but not the other way around. However, there is no bidirectional relationship or causality observed among the other variables. The currencies of the Dollar, Euro, Pound, and Yen have a negative impact on Bitcoin, while the Yuan has a positive impact on Bitcoin.

The exchange rate of Bitcoin is greatly influenced by the forces of demand and supply in the global market. The more liquid the Bitcoin market is, the easier its price can change. Market perception and sentiment towards hard currency can have a significant impact on its exchange rate, leading market participants to seek alternatives such as Bitcoin, which is more advantageous as a medium of exchange. Therefore, the role of the government becomes necessary in terms of supervision and policymaking regarding market participants' response to using Bitcoin and its relation to the exchange rate of fiat currencies. The government can implement policies to reduce volatility in the exchange rate by adopting stable economic and prudent monetary policies.

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