OIL PRICES AND THEIR LONG-TERM RELATIONSHIP WITH MACROECONOMIC AND FINANCIAL INDICATORS

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DOI: 10.51558/2303-680X.2023.21.1.3

Abstract

The objective of this paper is to find out whether there is a long-term relationship or in other words cointegration, between the prices of oil futures and the following factors: the consumer price index (CPI), the exchange rate of the USD to the EUR, the prices of gold, and the price of Bitcoin. This research was conducted using monthly data, extracted from both Refinitiv and Yahoo Finance, in the period 2014-2022. In order to find the cointegrating relationship between the above mentioned variables, the Johansen test was used, after which, the Vector Error Correction Model (VECM) system was composed to formulate a set of equations that explain all the variables. The results of this research show that only one cointegrating relationship exists between the previously mentioned variables. Namely, in a state of long-term equilibrium, only the prices of gold have a statistically significant effect on oil prices.

Keywords: Bitcoin, gold, oil prices, cointegration, VECM

JEL: C01, C12, G10, C22, C51, C58

1. Introduction

The subject of this paper is to establish whether there is a potential long-term relationship between oil prices and various macroeconomic and financial factors, namely: the consumer price index (CPI), the exchange rate of the USD to the EUR, the prices of gold, and the price of Bitcoin. Moreover, a cointegration analysis was conducted including the above-mentioned variables in the period from 2014 to 2022, in order to detect if there was an existing long-term relationship and its magnitude. In this period there was high volatility in the movement of oil prices caused by: complex supply and demand dynamics, the unforeseen Covid-19 pandemic, as well as the uncertainty regarding the unstable geopolitical situation in Eastern Europe, where Russia, as one of the largest oil exporters is situated. The paper attempted to forecast the long-term relationship between the previously established variables and their fluctuation in times of economic ambiguity.

Gold and oil are two of the most traded commodities, thus they play a significant role in shaping the world's economy. Historically speaking, the first established relationship between these two commodities was discovered in the Middle East, where oil suppliers demanded payment in gold. In 1933, the first concession for oil was granted in Saudi Arabia, making it exclusively exchangeable for gold. Conversely, as time went on and a myriad of historical events happened, the markets for gold and oil experienced growth. As a result, nowadays the relationship between these two commodities is not based solely on their primary function as a medium of exchange, but they rather encompass numerous other components.

The immense fluctuations in oil prices have a significant effect on the world economy, subsequently changing the microeconomic and macroeconomic dynamics. The surging prices of oil lead to inflation, *i.e.*, higher prices of goods and services that arise from oil derivatives. This results in reduced economic growth, driven by a higher cost of production, along with a lower demand for goods and services.

Inflation caused by oil crises may influence the prices of gold, which is used as a hedging instrument in unpredictable economic times. Additionally, petroleum exporting countries use the revenues from this export to purchase gold, an asset that falls into the category of official reserve assets in their national accounts. Since 1975, all OPEC nations agreed to price their oil supplies exclusively in U.S. Dollars and to hold their oil proceeds in U.S. government debt securities. Consequently, the instability of the

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dollar may force the prices of oil and gold to move in the same direction. In addition to that, there is an ongoing dispute whether cryptocurrencies, such as Bitcoin, may be considered "modern gold" by investors.

The objective of this paper is to assist financial analysts in the process of predicting the future price movement of the variables mentioned above. Furthermore, this research is paramount, especially in a highly volatile and uncertain environment caused by the current oil crisis. At the same time, it also enables us to challenge the previously determined relationship between various aspects of the economic and financial world.

2. Literature review

There are numerous papers that showed empirical evidence that supports the long-term cointegrating relationship between the prices of oil and the prices of gold. Shimakova (2011) proved a strong connection between these two variables, both graphically and algebraically. Furthermore, using the Johansen test, she also showed a strong cointegrating relation between the abovementioned variables. By forming a Vector Error Correction Model (VECM) it was also confirmed that in spite of the fluctuations in the markets of these two commodities, their time series were in long-term equilibrium. In the paper co-authored by Phoong, Ismail, and Sek (2013), the Markov Switching Vector Error Correction Model (MS-VECM) was used in order to investigate the effects of oil prices and gold prices on the movement of Malaysia, Singapore, Thailand, and Indonesia stock market indices. Furthermore, the variables were proved to have cointegrating relations and the MS-VECM was applied to examine the economic relationship model. The results suggested that oil and gold prices significantly impacted stock market returns for the four selected Asian countries, and their effects varied depending on the state of the economy. An additional study by Sampurna, Wahyudi, and Mawardi (2017), analyzed the relationship between gold and crude oil prices by using the Augmented Dickey-Fuller test (ADF), Johansen cointegration analysis, and the Granger causality test. The study found evidence of cointegration between the two commodities and the Granger causality test results showed a significant relationship between gold prices and crude oil prices but not vice versa.

Moreover, inflation is the main link that usually explains the relationship between the gold and the crude oil market. Notably, the rise in prices of oil leads to higher price levels, thus bringing up the prices of gold as well (Hunt 2006; Hooker 2002). Aside from inflation, exports are an alternative channel that links the prices of oil and the prices of gold. One study by Gangopadhyay, Jangir, and Sensarma (2016), used an error correction approach to forecast the price of gold. The study found evidence of a long-run relationship between the price of gold and inflation, exchange rates, and the stock market indices. The error correction model was found to be a suitable tool for forecasting the price of gold, as it captures the dynamic relationship between the price of gold and other macroeconomic variables. Additionally, gold is a part of the official reserve assets controlled by monetary authorities of many different countries, including petroleum exporting countries. Consequently, if the prices of oil rise, petroleum exporting countries will obtain higher oil revenues, and this may have implications for the prices of gold. Provided that gold is a significant part of the portfolio of assets in the national accounts of these countries, in this case, the rise in the prices of oil will lead to a rise in the prices of gold (Melvin & Sultan, 1990).

A paper by Singh and Sharma (2018), investigated the long-term relationship and causal linkages among the US dollar, oil prices, gold prices, and the Sensex stock market index in India during the global financial crisis of 2008-2009. The paper utilized Johansen's cointegration technique, VECM, Vector Auto Regression (VAR), the VEC Granger Causality/Block Exogeneity Wald Test and Granger Causality, and Variance Decomposition to examine the interdependence of these variables. The results indicated that there were long-term relationships among the variables, and the Granger causality test results showed that there was one-way causality from the USD and Sensex to crude oil, and from gold and Sensex to the USD. According to the research conducted by the European Central Bank

(2014), a negative causality was found between the prices of oil and the exchange rate in two different scenarios. An increase in the price of oil by 10% led to a depreciation of the effective exchange rate of the US dollar by 0.28%, while a weakening of the US dollar by 1% caused the price of oil to rise by 0.73%. Furthermore, although the estimate of the relationship between exchange rates and oil prices was statistically significant, with variance decomposition it was concluded that the economic relevance of exchange rate movements in explaining overall oil price fluctuations was limited.

A paper by Jareño *et al*. (2021) found a positive long-term relationship between the returns of a group of various cryptocurrencies, which includes Bitcoin, and changes in the prices of oil in the period after the Covid-19 crisis. The research results were obtained using the Nonlinear Auto-Regressive Distributed Lag Model (NARDL). Adebola *et al*., (2019) analyzed the relationship between cryptocurrencies and gold prices and found there was evidence of mean reversion in gold prices and in some of the cryptocurrencies; however, cointegration was only found in a few cases with a very small degree of cointegration in the long run relationship. Wang, Xue, and Liu (2016) performed a cointegration analysis and VECM to illustrate the relationship between Bitcoin prices and variables including oil prices, the stock price index, and the daily trading volume of Bitcoin. The empirical research demonstrated a short-term dynamic relationship between Bitcoin prices and the stock price index while oil price and Bitcoin trading volume have little influence. In the long run, oil prices and the stock price index had a negative effect on Bitcoin prices, while the daily trading volume had a positive effect. Nghiem, Long, and Quynh (2021) implemented the Granger causality test between gold and cryptocurrencies and found out that an increase in gold prices had the tendency to lead to a rise in cryptocurrency prices, while the influence of cryptocurrency price changes on gold prices did not go in the same direction. According to this test, they concluded that cryptocurrencies may not be a perfect substitution for gold as an inflation hedge. Moreover, Kakinuma (2021) tested the return and volatility spillover effects among the Southeast Asian stock markets, Bitcoin, and gold in the periods before and during the COVID-19 pandemic. The results showed that Bitcoin and gold were interdependent during the pandemic and the contagion effect was inevitable. Additionally, the study suggested that gold assets were less risky than Bitcoin, especially in times of crisis. In another study by Caferra and Vidal-Tomás (2021), the performance of cryptocurrencies and stock markets was investigated during the COVID-19 pandemic using the Markov Switching Autoregressive Model. Initially, the findings of their research indicated the presence of financial contagion, as there was a significant decline in both cryptocurrencies and stock prices. In contrast with stock prices, cryptocurrencies had a faster recovery during the COVID-19 pandemic. There was evidence of causal regression between gold, exchange rate and Bitcoin prices. Shariati (2022) suggested analyzing the empirical relation between both assets via a Cointegration regression method.

Lately, we have all witnessed market disruption caused by the high volatility in the price of crude oil. More than ever policymakers are facing the problem of consistent predictions on the future values of commodities and assets as well exchange rates. The crucial importance that crude oil has for the real economy and even financial markets caused an increased interest to investigate the causality of the real oil price and the real exchange rate. Sahbaz *et al*. (2014) investigated the causality between crude oil prices and exchange rates in Romania using non-linear causality and frequency domain causality tests and found out that there was no causality between the variables. These results were not compatible with frequency domain causality results which showed the existence of causality from real exchange rate to real oil price. The existence of causality between two variables was also verified by Tasar (2017).

Our paper differs from the above-mentioned since we analyzed the period from October 2014 to May 2022, the period which captures the effects of the Covid 19 pandemic, as well as the period of the energy crisis due to war conflicts in Ukraine. Besides that, we also included CPI and exchange rate of the USD to the EUR. The background for this research lies in the fact that until now Bitcoin was treated as a hedge against inflation, and theoretically, it was expected that the Bitcoin market would get a boost as Russia's invasion on Ukraine had contributed to higher and more volatile crude oil prices. But the last few months showed that we must be very cautious since the increase in oil prices was followed by the rise of the interest rate by the Federal Reserve to cut inflation and the tightening of the monetary policy by the U.S. central bank (the Fed).

Table 1. *Unit root tests*

Tests	*P-Values*	*Oil*	*Usd*	*Gold*	*Cpi*	*Btc*
ADF test	Log	-1.881	-2.721	-0.598	2.016	-0.867
	t-stat (p-value)	(0.34)	(0.074)	(0.864)	(0.999)	(0.79)
	Differentiated	-9.007	-8.967	-8.404	-6.841	-7.89
	t-stat (p-value)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Phillips-Perron test	Log	-2.025	-1.672	-0.669	2.319	-0.914
	t-stat (p-value)	(0.28)	(0.089)	(0.848)	(0.999)	(0.779)
	Differentiated	-9.124	-8.963	-8.356	-4.965	-7.888
	t-stat (p-value)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
KPSS test	KPSS test statistic	5.702	2.854	1.078	1.234	1.140
	Differentiated	0.235	0.138	0.079	0.536	0.091

Source: Authors' calculations

In recent months, the price of Bitcoin has been falling in response to announcements from the Fed. All these events posed the question if Bitcoin is to become a secure means of payment, such as gold – that is, an asset whose price might benefit or keep its value when stock prices are falling.

3. Data description

This research was conducted using monthly data for the period from October 2014 to May 2022. This period was selected to provide the latest and most current data available, while the beginning of the time series was determined according to the first available information on Bitcoin trading in 2014. As a consequence of including CPI, the data frequency was monthly[1]. The data were taken from Refinitiv and Yahoo Finance, which are globally considered reliable sources.

The data were expressed in the following units: the prices of oil and Bitcoin were in the USD, gold was in the USD per ounce, and the exchange rate difference was expressed in the prices of the USD for one EUR. In addition, logarithmic values of the data were used from the abovementioned time series.

The ADF test was used to test the stationarity[2], which confirmed that the logarithmic variables were not stationary at the 5% significance level, but upon the first differentiating of the time series, they became stationary. In other words, all variables were integrated in the first order. Additionally, because of the size of the sample, we also conducted the Phillip-Perron test. The results of the test are showed in Table 1.

In order to check the robustness of the results, besides these two-unit root tests, we also conducted the Kwaitkowski-Philips-Schmid-Shinn test, which is a stationary test. The results are also presented in Table 1. We found that these results were consistent with the results of unit root tests, i.e., all the series were nonstationary, I ~ (1).

4. Methodology

The purpose of this paper is to investigate the long-term relationship between the prices of oil, the prices of gold, the price of the cryptocurrency Bitcoin, CPI, and the exchange rate of the USD to the EUR, i.e., to find out if there is a cointegration among them. For testing this long-term relationship, the Johansen test was used to find out the existence of cointegration among the variables, and afterwards a VECM model was made to compile a system of equations that describe the previously mentioned variables.

In order to determine the cointegrating relationship between the variables there were two options - either using the Engle-Granger model or the Johansen test. Engle and Granger (1987) introduced this model and formalized the cointegrating vectors approach and the biggest strength of this model lies in its simplicity. Despite its simplicity, this model has weaknesses, such as: it cannot examine whether there are cointegrating relationships between more than two variables, it encounters problems with small samples, no hypothesis testing can be conducted, and deciding which variable is dependent and which is independent is done arbitrarily (Brooks, 2014, p. 335). Johansen (1991) tried to overcome precisely these weaknesses of the Engle-Granger method, introducing the Johansen test. However, this method is not without shortcomings. Gonzalo and Lee (1998) in their research showed that the Engle-Granger method is more robust than Johansen's, indicating a higher probability of finding the so-called spurious cointegrating relationships when using the Johansen test.

For further explaining the variables, the VAR system was formed. McNeese (1986) showed in his research that more accurate forecasts are provided by VAR systems against different structural specifications. The drawback of the VAR system is that it is a theoretical model, *i.e.*, when creating the model, the links between the variables are formed solely mathematically without using the theoretical background. Another problem encountered when using the VAR system is the arbitrariness in determining the number of lags as well as the large number of parameters that are estimated. Pertaining to the arbitrariness in determining the lags, this paper used an information criterion, namely Schwartz's information criterion, while the problem of estimating a large number of parameters was attempted to be eliminated by enlarging the number of observations taken in the analysis (Brooks, 2014, p. 290).

In addition, both impulse response and variance decomposition were conducted in this paper. The impulse response actually examines how fast one variable reacts in the VAR system, relative to shocks from every other variable separately. The variance decomposition offers another method to explore the dynamics in VAR systems. It explains how much of the movement in a particular dependent variable is due to its shocks, as opposed to shocks from other variables. Most often in practice, the shocks of the time series are mostly explained by their own shocks in the variance, rather than by the same shocks of the other variables.

It must be noted that when calculating the impulse response and variance decomposition, the ordering of the variables is important. Often the ordering follows logically from the data set itself, but in certain cases, it may not. The answer to how the variables should be ordered, then, must be sought in the financial theory behind the model. According to Lutkepol (1991), the higher the correlation between the residuals in the system, the more important the ordering of the variables. In other words, in a system with uncorrelated residuals, the order does not matter.

5. Discussions of results

The results of the research show that among the above-mentioned variables, there was only one cointegrating relationship at a significance level of 5%. That is, in a state of long-term equilibrium, only the price of gold had a statistically significant effect on the price of oil. In the continuation of this paper, the results will be explained in more detail. Although the purpose of this paper is to examine and determine the long-term relationship between the previously mentioned variables, it is important to briefly consider the short-term relationship as well. Table 2 shows the output of the regression, having the oil as a dependent variable and using the variables in their logarithmic and differentiated form. From Table 2, it can be seen that only the USD and CPI variables were statistically significant, which means that only these variables had a short-term effect on the oil. To further comment on the results, it can be seen that the effect of CPI on Oil short term was far greater than the one from the USD/EUR exchange rate, considering the estimated coefficients, and they were both positive. There was a concern regarding the estimated coefficient of the CPI variable, but upon reviewing the dataset, it was deduced that the month-on-month changes of this index were small, thus yielding bigger numbers in this case. In order to get a better picture of the short-term effect of the variables, a stepwise regression was done, removing the insignificant variables. The results (Table 3) were more or less the same as before, with the p-values of the variables rising a bit, and the coefficient estimated for the CPI variables being lowered. When comparing the models, a couple of metrics can be observed. When considering the R^2, it is obvious that the linear regression will be better, but when this

Table 2. *Linear regression of the variables*

Variables	*Estimate*	*SE*	*tStat*	*pValue*
Intercept	-0.009	0.005	-1.727	0.088
D_USD	0.045	0.020	2.223	0.029
D_Gold	-1.098	0.820	-1.340	0.184
D_CPI	24.209	7.985	3.032	0.003
D_Btc	0.094	0.145	0.649	0.518

Source: Authors' calculations

Table 3. *Stepwise Regression*

Variables	*Estimate*	*SE*	*tStat*	*pValue*
Intercept	-0.008	0.005	-1.621	0.109
D_USD	0.040	0.020	2.040	0.044
D_CPI	21.762	7.838	2.776	0.007

Source: Authors' calculations

Table 4. *Comparison of the models*

Short-Term	*R^2*	*Adj R^2*	*Log-Likelihood*	*AIC*	*BIC*
Linear Regression	0.145	0.105	177.782	-345.563	-333.009
Stepwise Regression	0.121	0.101	176.550	-347.099	-339.567

Source: Authors' calculations

Table 8. *Normalized cointegration coefficients (standard error in parentheses)*

Normalized cointegrating coefficients (standard error in parentheses)				
_OIL 1.000000	_USD -2.241253 (1.48023)	_GOLD 1.838699 (0.38457)	_CPI -5.465838 (3.60450)	_BITCOIN -0.075961 (0.08537)
P-Values	0.1335	0.00	0.1329	0.3759

Source: Authors' calculations

coefficient is adjusted, it is still greater, hinting towards a better model. This is also supported by the log-likelihood of the models. However, the information criteria (Akaike Information Criterion - AIC and Schwarz Information Criterion or Bayesian - BIC) both agree that the stepwise regression better fits the data, so if the short-term effects are considered, it should be those in the stepwise regression (showed in Table 4). As stated above, the Johansen test was used in order to determine the cointegrating relationship between the variables. In the beginning, we implemented the AIC to decide what type of the Johansen test to form. The reasoning behind choosing the AIC for constructing the Johansen test was simple and pragmatic. The choice was between the AIC and the BIC. Table 5 in the Appendix shows that the BIC gave a model with zero cointegrating relations, whereas the AIC showed one. So, for practical reasons the AIC was used in order to further examine the one cointegrating relation found. According to the results presented in Table 5 in the Appendix we decided that it was best to include a linear deterministic trend with intercept into the cointegration[3].

Furthermore, the opinion prevails in academic literature of using trace test statistics in order to determine the number of cointegrating relationships, instead of using the maximum eigenvalue test. In compliance with this, the trace test statistic was used and the results relating to the number of cointegrating relations between the variables are given in Table 6 in the Appendix. Based on the results presented in Table 6 in the Appendix, we concluded that there was only one cointegrating relationship between the variables. In Table 7 in the Appendix, the cointegrating rank test which uses eigenvalues is shown, but the results were merely similar.

Further on, in Table 8 the equation of cointegration is represented, normalized for the prices of oil. To be more precise, the coefficients are given in the first row of Table 8 and they show the effect that the time series of the variables had on the prices of oil in a state of long-term equilibrium, while the standard deviations are given in the brackets, accordingly. Normalizing the equation for the prices of oil and doing algebraic transformation resulted in the coefficients having an opposite meaning[4]. The results illustrate that in a long-term state of equilibrium, if the price of gold rises by 1 USD per ounce, the price of oil would fall by 1.84 USD. When it comes to the other variables, all of them did not have a statistically significant effect on the prices of oil, because the coefficients in front of their variables were statistically insignificant[5]. In the Johansen test, the coefficients in front of the error correction term, or the so-called adjustment coefficients, indicated how long it took for a variable to reach its state of long-term equilibrium. In Table 9 these adjustment coefficients are shown for each of the abovementioned variables. Considering the adjustment coefficients shown in Table 9 and their t-statistic, on the one hand, both the price of Bitcoin and CPI were statistically insignificant.[5] This indicates that both variables showed weak exogeneity in the system. On the other hand, the adjustment coefficient for the other two variables, i.e., the prices of gold and the USD/EUR exchange rate, were both statistically significant. Comparing these two coefficients, the coefficient in front of the error correction term for the prices of gold

Table 9. *Adjustment coefficients (standard error in parentheses)*

Adjustment coefficients (standard error in parentheses)		*P-values*
D(_OIL)	0.007745 (0.11060)	0.061
D(_USD)	0.033220 (0.01592)	0.000
D(_GOLD)	-0.118623 (0.02416)	0.000
D(_CPI)	0.000528 (0.00143)	0.000
D(_BITCOIN)	-0.316315 (0.16657)	0.061

Source: Authors' calculations

was bigger than the one for the USD/EUR exchange rate, which indicates that the prices of gold got to the abovementioned state of long-term equilibrium faster than the USD/EUR exchange rate.

5.1 Vector Error Correction Model (VECM)

After the cointegration, a VAR model was created with the inclusion of the error correction term, making it VECM. In order to determine the number of lags used in the system, the information criterion was utilized. This time, instead of using the AIC, the BIC was used. The reasoning behind this decision lies in the number of coefficients that had to be estimated. If the AIC is followed, it always prefers larger models, which in our case when the sample contained only 92 observations made it difficult to accurately estimate all the coefficients, i.e. it made the estimates unreliable. According to the BIC, one period lag was added to the VECM system. Table 10 in the Appendix represents the information criterion that determines the number of time lags to include in VECM. Below, the equations from the VECM system are represented in a matrix form which makes them easier to read. Additionally, all the variables in the VECM system are in their first differential., where O - prices of oil, G - prices of gold, U - exchange rate of the USD

$$\begin{bmatrix} Ot \\ Gt \\ Ut \\ BTCt \\ It \end{bmatrix} = \begin{bmatrix} C1 \\ C2 \\ C3 \\ C4 \\ C5 \end{bmatrix} + \begin{bmatrix} A1*O(t-1) \\ A2*G(t-1) \\ A3*U(t-1) \\ A4*B(t-1) \\ A5*I(t-1) \end{bmatrix} + \begin{bmatrix} B1 & D1 & E1 & F1 & K1 \\ B2 & D2 & E2 & F2 & K2 \\ B3 & D3 & E3 & F3 & K3 \\ B4 & D4 & E4 & F4 & K4 \\ B5 & D5 & E5 & F5 & K5 \end{bmatrix} \begin{bmatrix} \Delta O(t-1) \\ \Delta G(t-1) \\ \Delta U(t-1) \\ \Delta BTC(t-1) \\ \Delta I(t-1) \end{bmatrix}$$

Figure 1. *Matrix representation of the VECM system*
Source: Authors' compilation

to the EUR, BTC - price of Bitcoin, I - CPI index. Moreover, B, E, D, and K are the slope coefficients, A the adjustment coefficient, C the intercept and t-time period. The resulting values from the system equations shown above are presented in Table 11. Examining the residuals of VECM, we first tested for autocorrelation. Figure 2 in the Appendix shows the ACF and PACF graph for the residuals of each variable, resulting in no significant autocorrelation and partial autocorrelation regarding the previous 20 lags. Furthermore, a Portmanteau Test for autocorrelation (Table 12 in the Appendix) with 12 lags was conducted, including one year lag. The results from this test also supported our previous claim of non-existent autocorrelation in the residuals of our model. Secondly, contesting the normality assumption of the residuals, the Jarque-Berra test was performed for the residuals of each variable in the system, and in addition, a combined F-test was also performed. Table 13 in the Appendix shows the results from both tests. From Table 13 in the Appendix, it is evident that two out of five variables were not normally distributed at the significance level of 5%; those two being the residuals from oil and CPI. At a closer look at the p-values, it can be seen that for the CPI variable it was a close call for non-normality which was not the case for the oil variable. Nonetheless, the non-normality of the oil combined with the one from CPI was enough to result in the F-test p-value of 0, thus rejecting the combined null hypothesis that residuals combined were all normally distributed. Despite this, by further analyzing this phenomenon in our residuals, we can look at their histograms (Figure 3 in the Appendix). Looking at these histograms, it is apparent that they resemble a normal distribution. Considering that our sample size only had 92 observations, it can be concluded that with the increase of the sample size, the effect of the Central Limit Theorem would take place and the distributions of the residuals would converge towards a normal distribution.

Table 11. *Vector Error Correction Model (VECM)*

Vector Error Correction Model (VECM)					
Error Correction:	*D(OIL)*	*D(USD)*	*D(GOLD)*	*D(CPI)*	*D(BITCOIN)*
CointEq1	-0.03404 (0.0333) [-1.022]	0.02685 (0.0044) [6.0741]	-0.01940 (0.0084) [-2.310]	-0.00023 (0.0005) [-0.496]	-0.037805 (0.05280) [-0.71605]
D(OIL(-1))	0.12101 (0.1179) [1.0266]	-0.00407 (0.0156) [-0.260]	-0.04222 (0.0297) [-1.421]	0.00315 (0.0017) [1.9031]	0.301219 (0.18683) [1.61222]
D(USD(-1))	0.67284 (0.7463) [0.9015]	0.04889 (0.0990) [0.4937]	-0.37894 (0.1882) [-2.014]	-0.00120 (0.0105) [-0.114]	-0.695397 (1.18300) [-0.58783]
D(GOLD(-1))	0.41375 (0.4447) [0.9303]	0.04189 (0.0590) [0.7099]	-0.00559 (0.1121) [-0.050]	0.00917 (0.0063) [1.4658]	-0.639342 (0.70492) [-0.90697]
D(CPI(-1))	-3.97216 (7.2368) [-0.549]	-0.99488 (0.9602) [-1.036]	0.69839 (1.8247) [0.3827]	0.44389 (0.1018) [4.3608]	-13.30960 (-11.4709) [-1.16030]
D(BITCOIN(-1))	0.04984 (0.0721) [0.6909]	0.00212 (0.0096) [0.2215]	-0.02425 (0.0182) [-1.333]	-0.00138 (0.0010) [-1.359]	0.082552 (0.11433) [0.72205]
C	0.007492 (0.02100) [0.3568]	0.003485 (0.00279) [1.2510]	0.005721 (0.00529) [1.08056]	0.001193 (0.0003) [4.0392]	0.076013 (0.03328) [2.28402]
D(GOLD(-1))	0.41375 (0.4447) [0.9303]	0.04189 (0.0590) [0.7099]	-0.00559 (0.1121) [-0.050]	0.00917 (0.0063) [1.4658]	-0.639342 (0.70492) [-0.90697]
D(CPI(-1))	-3.97216 (7.2368) [-0.549]	-0.99488 (0.9602) [-1.036]	0.69839 (1.8247) [0.3827]	0.44389 (0.1018) [4.3608]	-13.30960 (-11.4709) [-1.16030]
D(BITCOIN(-1))	0.04984 (0.0721) [0.6909]	0.00212 (0.0096) [0.2215]	-0.02425 (0.0182) [-1.333]	-0.00138 (0.0010) [-1.359]	0.082552 (0.11433) [0.72205]
C	0.007492 (0.02100) [0.3568]	0.003485 (0.00279) [1.2510]	0.005721 (0.00529) [1.08056]	0.001193 (0.0003) [4.0392]	0.076013 (0.03328) [2.28402]
R-squared	0.050501	0.333222	0.132314	0.339317	0.089013
Adj. R-squared	-0.01814	0.285021	0.069589	0.291557	0.023159
Sum sq. resids	1.484560	0.026137	0.094385	0.000294	3.729888
S.E. equation	0.133740	0.017746	0.033722	0.001881	0.211987
F-statistic	0.735752	6.913189	2.109449	7.104595	1.351667
Log likelihood	57.00664	238.7851	181.0038	440.7686	15.54994

Source: Authors' calculations

5.2 Impulse response

In this paper, VECM was made up of time lags solely from endogenous variables. For this reason, the impulse response analysis was not just an analysis of the marginal effects that the shocks have, but rather of observing the complete dynamic of the model. The following of the exact dynamic in the VECM model was enabled by the impulse response function.

Figure 4 in the Appendix showcases the results from the conducted impulse response on every abovementioned variable in relation to the other variables in the system. Seeing that there were five variables in the system, 25 impulse responses existed in total, and they are showed graphically in a time frame that includes 12 periods[6].

According to the results, the innovation in the prices of oil had the utmost effect on the variable itself. This effect was instantaneous (happens in the first period) and it grew in the second period, after which it started to decline. It is the same effect the innovation in the gold prices had on the prices of oil. However, this effect did not occur instantaneously, but happened in the second period. The influences of the shocks in the other variables on the prices of oil had a trend of growing over time and eventually stabilizing. The effects differed in their magnitude and their value (positive or negative).

The impulse response varied for each variable. The usual trend was that the innovation in variables did not have an immediate effect on the other variables. The effects were either positive or negative but in some cases both. For example, the shocks in the prices of oil time series had a negative effect on the exchange rate time series in the first couple of periods, but then this effect became positive.

5.3 Variance decomposition

The variance decomposition was utilized in order to calculate the extent to which the shocks in some variables influenced the future estimated errors of the other variables. In other words, the sensitivity of the variables was examined as opposed to the change of the other variables. This is illustrated graphically in Figure 5 in the Appendix including a 12-period time frame. Moreover, the ordering was done by the criterion of Cholesky[7].

Regarding the variance decomposition of the prices of oil, it can be concluded that the prices of oil were not very sensitive to shocks from other variables. This can be deducted from the fact that the biggest part of the future estimated error in the prices of oil time series was due to the shocks of the time series itself.

As for the other variables, the opposite scenario took place. That is, the future estimated errors were mainly derived from the shocks that happened to the other variables. This effect on the abovementioned variables was not present in the first period but rather amplified as time went on, making all the variables (except for the prices of oil) more sensitive to each other and to the prices of oil. A more detailed description is given in Figure 5 in the Appendix.

6. Conclusions

This paper focused on finding a long-term relationship between the price of oil and the price of gold, the price of Bitcoin, the exchange rate of the USD to the EUR, and CPI. The period examined was 2014 to 2022, and the methods used were the Johansen test as well as VECM.

The results illustrated only one cointegrating relationship between the previously mentioned variables at a level of significance of 5%. At this level of significance, only the price of gold had a statistically significant effect on the price of oil, when both variables were in a state of long-term equilibrium. The reason for the cointegration between the two variables lies in their previously confirmed and inherent connection. On the contrary, cointegrating relations were not found between the prices of oil and the other above-mentioned variables. This may be due to the fact that there were other variables influencing the dynamics between the variables chosen in the model but were not included. Alternatively, these variables might influence each other, but with a certain time lag, as a consequence of the inefficiency of the markets. Research in the domain of commodity markets can make significant contributions that advance the field of study, and provide new insights and perspectives on existing research, thus enabling solutions to real-life problems. Nonetheless, the results from this research paper can be implemented in a variety of financial and economic analyses. Finding a long-term relationship between the prices of oil and the prices of gold serves as a helpful indicator in price forecasting. Even so, it can be helpful to note that there was no long-term relationship between variables. These findings are of great importance for policymakers to take strategies. On the other hand, the fact that the variables of interest were not related in the long run is of a great importance for investors to diversify their portfolio. Each contribution can help to advance the knowledge and understanding in this particular field.

A noticeable limitation this research faced was the number of observations used. This limitation was caused by the fact that Bitcoin appeared in 2014 so we did not have an opportunity to increase the time series. In future research, the results of this study can be improved by increasing the sample of data, or finding a different proxy for inflation in order to have the frequency higher than monthly. It would have been good to include the housing crisis period of 2008 in this paper, but the ever-growing influence of Bitcoin precluded such an expansion of the research.

Oil prices can be affected by a variety of factors, including supply and demand, geopolitical events, economic trends, and environmental regulations. Further research into understanding these factors that influence fluctuations in oil prices can facilitate more accurate predictions of future price movements. Additionally, geopolitical factors such as political instability, sanctions, and trade wars can have a noteworthy impact on oil prices. Future research could focus on exploring the relationship between geopolitical factors and commodity prices to provide insight into market trends and help investors make more informed decisions.

References

1. Adebola, S.S., Gil-Alana L.A. & Madigan, G. (2019) Gold Prices and the Cryptocurrencies: Evidence of Convergence and Cointegration. *Physica A: Statistical Mechanics and its Applications*. 523(C), pp. 1227-1236.
2. Beckmann J., Czudaj R. & Arora, V. (2020) The Relationship between Oil, Prices and Exchange Rates: Theory and Evidence. *Energy Economics*. 88(C), DOI: 10.1016/j.eneco.2020.104772
3. Brooks, C. (2014) *Introductory for Econometrics in Finance* 3rd edition, Cambridge: Cambridge University Press.
4. Caferra, R. & Vidal-Tomás, D. (2021) Who Raised from The Abyss? A Comparison Between Cryptocurrency and Stock Market Dynamics During The COVID-19 Pandemic. *Finance research letters*. 43(3), 101954.
5. Drachal, K. (2018), Exchange Rate and Oil Price Interactions in Selected SEE Countries. *Economies*. 6(2), pp. 31.
6. Engle, R. F. & Granger, C.W.J. (1987) Co-integration and Error Correction: Representation, Estimation, and Testing. *Econometrica: Journal of the Econometric Society*. 55(2), pp. 251-276.
7. Gangopadhyay, K., Jangir A. & Sensarma, R. (2016) Forecasting the Price of Gold: An Error Correction Approach. *IIMB Management Review*. 28(1), pp. 6-12.
8. Gonzalo, J. & Lee, T. H. (1998) Pitfalls in Testing for Long Run Relationships. *Journal of Econometrics*. 86 (1), pp. 129-154.
9. Jareño, F., González, M. D. L. O., López, R. & Ramos, A. R. (2021) Cryptocurrencies and Oil Price Shocks: A NARDL Analysis in the COVID-19 Pandemic. *Resources Policy*. 74, pp. 1-16
10. Johansen, S. (1991) Estimation and Hypothesis Testing of Cointegration Vectors in Gaussian Vector Autoregressive Models. *Econometrica: Journal of the Econometric Society*. 59(6), pp. 1551-1580.
11. Kakinuma, Y. (2022) Nexus between Southeast Asian Stock Markets, Bitcoin and Gold: Spillover Effect Before and During the COVID-19 Pandemic. *Journal of Asia Business Studies*. 16 (4), pp. 693-711.

12. Le, T. H. & Chang, Y. (2012) Oil Price Shocks and Gold Returns. *International Economics.* 131(3), pp. 71-103.
13. Le, T.N., Le, H. L. & Pham, X. Q. (2021) Relationship between Gold and Cryptocurrencies: Evidence from the Granger Causality Tests. *Indian Journal of Economics and Business*. 20(4), pp. 71-103.
14. Lütkepohl, H. & Poskitt, D. S. (1991) Estimating Orthogonal Impulse Responses via Vector Autoregressive Models. *Econometric Theory*. 7(4), pp. 487-496.
15. McNees, S. K. (1986) Forecasting Accuracy of Alternative Techniques: A Comparison of US Macroeconomic Forecasts. *Journal of Business & Economic Statistics*. 49(1), pp. 5-15.
16. Phoong, S.W., Ismail, M.T. & Sek, S.K. (2013) A Markov Switching Vector Error Correction Model on Oil Price and Gold Price Effect on Stock Market Returns. *Information Management and Business Review*. 5(7), pp. 331-336.
17. Sahbaz, A. *et al*. (2014) Relationship Between Oil Prices and Exchange Rates: The Case of Romania. *Economic computation and economic cybernetics studies and research*. 48(2), pp. 245-256.
18. Sampurna, D.S., Wahyudi, S. & Mawardi, W. (2017) Cointegration and Causality among the Crude Oil Market and the Gold Market. *International Journal of Economic Research*. 14(17), pp. 155-165.
19. Schneider, D., Robays, I.V. & Fratzscher, M. (2014) Oil Prices, Exchange Rates and Asset Prices. Working Paper Series-European Central Bank. 1689.
20. Shariati, K. (2022, *The Influence of Gold Market on Bitcoin Prices: Is there a Correlation?* (master's thesis). Jönköping University, Småland, Sweden.
21. Šimáková, J. (2011) Analysis of the Relationship between Oil and Gold Prices. *Journal of Finance*. 51(1), pp. 651-662.
22. Sims, C. A. (1980) Macroeconomics and Reality. Econometrica: *Journal of the Econometric Society*. 48(1), pp. 1-48.
23. Singh, N.P. & Sharma, S. (2018) Cointegration and Causality among Dollar, Oil, Gold and Sensex across Global Financial Crisis. *The Journal of Business Perspective*. 22(4), pp. 365-376.
24. Su C.W., Qin, M., Tao, R., & Zhang, X. (2020) Is the Status of Gold Threatened by Bitcoin? *Economic Research-Ekonomska Istraživanja*. 33(1), pp. 420-437.
25. Wang, J., Xue, Y. & Liu, M. (2016) An Analysis of Bitcoin Price Based on VEC Model. 2016 International Conference on Economics and Management Innovations. Wuhan, Saturday 9th to Sunday 10th July 2016. pp.146–152.
26. Wang L., Ruan H., Hong, Y. & Luo K. (2023) Detecting the Hidden Asymmetric Relationship between Crude Oil and the US Dollar: A Novel Neural Granger Causality Method. *Research in International Business and Finance* - Elsevier. 64(C), https://www.sciencedirect.com/science/article/pii/S0275531923000259
27. Wong, W.S., Saerbeck, D. & Silva, D.D. (2018) Cryptocurrency: A New Investment Opportunity? An Investigation of the Hedging Capability of Cryptocurrencies and their Influence on Stock, Bond and Gold Portfolios. SSRN Electronic Journal. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3125737

[1] Higher frequency measured for CPI.
[2] Unit root test.
[3] The values of the information criterion are shown inTable 2.
[4] Due to transferring the prices of the oil variable from the left-hand side to the right-hand side.
[5] 5% significance level.
[6] Months.
[7] Cholesky ordering.

Appendix

Table 5. *Akaike information criterion for the Johansen test*

Akaike information criterion for the Johansen test					
Data Trend: Test Type: Trace: Max-Eig:	None No Intercept No Trend 1 1	None Intercept No Trend 2 1	Linear Intercept No Trend 1 1	Linear Intercept Trend 1 0	Quadratic Intercept Trend 1 0
*Critical values based on MacKinnon-Haug-Michelis (1999)					
Data Trend: Rank or No. of CEs	None Intercept No Trend	None Intercept No Trend	Linear Intercept No Trend	Linear Intercept Trend	Quadratic Intercept Trend
Log Likelihood by Rank (rows) and Model (columns)					
0	958.5104	958.5104	967.4312	967.4312	970.6868
1	977.2044	977.2044	985.0942	985.1219	988.3239
2	985.7034	989.6068	996.4481	997.8174	1000.281
3	992.2370	997.4901	1002.389	1009.094	1010.944
4	995.9285	1003.260	1006.183	1013.619	1015.352
5	996.1736	1006.870	1006.870	1015.394	1015.394
Akaike Information Criteria by Rank (rows) and Model (columns)					
0	-19.73587	-19.73587	-19.82601	-19.82601	-19.78590
1	-19.93573	-19.91275	-20.00217	-19.97981	-19.96147
2	-19.90123	-19.94498	-20.0333*	-20.01879	-20.00647
3	-19.82154	-19.87334	-19.93998	-20.02514	-20.02171
4	-19.67652	-19.75310	-19.79732	-19.87629	-19.89315
5	-19.45227	-19.58322	-19.58322	-19.66423	-19.66423
Schwarz Criteria by Rank (rows) and Model (columns)					
0	-16.90149*	-16.90149*	-16.84991	-16.84991	-16.66809
1	-16.81792	-16.76659	-16.74263	-16.69194	-16.56022
2	-16.49997	-16.48704	-16.49032	-16.41913	-16.32178
3	-16.13685	-16.10361	-16.11357	-16.11370	-16.05358
4	-15.70839	-15.67160	-15.68747	-15.65307	-15.64158
5	-15.20070	-15.18993	-15.18993	-15.12923	-15.12923

Source: Source: Authors' calculations

Table 6. *Unrestricted cointegration rank test (trace)*

Unrestricted cointegration rank test (trace)				
Hypothesized No. of CE(s)	*Eigenvalue*	*Trace Statistic*	*0.05 Critical Value*	*Prob.***
None *	0.333721	78.87733	69.81889	0.0079
At most 1	0.229726	43.55132	47.85613	0.1197
At most 2	0.127657	20.84351	29.79707	0.3675
At most 3	0.083532	8.961708	15.49471	0.3689
At most 4	0.015656	1.372832	3.841465	0.2413
Max-eigenvalue test indicates 1 cointegrating eqn(s) at the 0.05 level * denotes rejection of the hypothesis at the 0.05 level **MacKinnon-Haug-Michelis (1999) p-values				

Source: Authors' calculations

Table 7. *Cointegration rank test with eigenvalues*

Cointegration rank test with eigenvalues				
Hypothesized No. of CE(s)	*Eigenvalue*	*Max-Eigen Statistic*	*0.05 Critical Value*	*Prob.***
None *	0.333721	35.32602	33.87687	0.0334
At most 1	0.229726	22.70780	27.58434	0.1863
At most 2	0.127657	11.88181	21.13162	0.5594
At most 3	0.083532	7.588876	14.26460	0.4220
At most 4	0.015656	1.372832	3.841465	0.2413
Max-eigenvalue test indicates 1 cointegrating eqn(s) at the 0.05 level * denotes rejection of the hypothesis at the 0.05 level **MacKinnon-Haug-Michelis (1999) p-values				

Source: Authors' calculations

Table 10. *Information criterion for time lags for VECM*

Information criterion for time lags for VECM						
Lag	*LogL*	*LR*	*FPE*	*AIC*	*SC*	*HQ*
0	358.273	NA	1.53e-10	-8.4113	-8.26658	-8.35310
1	891.608	990.4795	8.49e-16	-20.514	-19.6463*	-20.1655*
2	918.460	46.6701*	8.2e-16*	-20.559*	-18.9670	-19.9188
3	940.334	35.41601	8.95e-16	-20.484	-18.1691	-19.5535
4	956.162	23.74160	1.15e-15	-20.266	-17.2272	-19.0443
5	978.704	31.12984	1.28e-15	-20.207	-16.4453	-18.6950
6	996.584	22.56273	1.64e-15	-20.038	-15.5523	-18.2346
7	1016.57	22.84191	2.07e-15	-19.918	-14.7095	-17.8244
8	1041.83	25.85741	2.41e-15	-19.924	-13.9921	-17.5397

Source: Authors' calculations

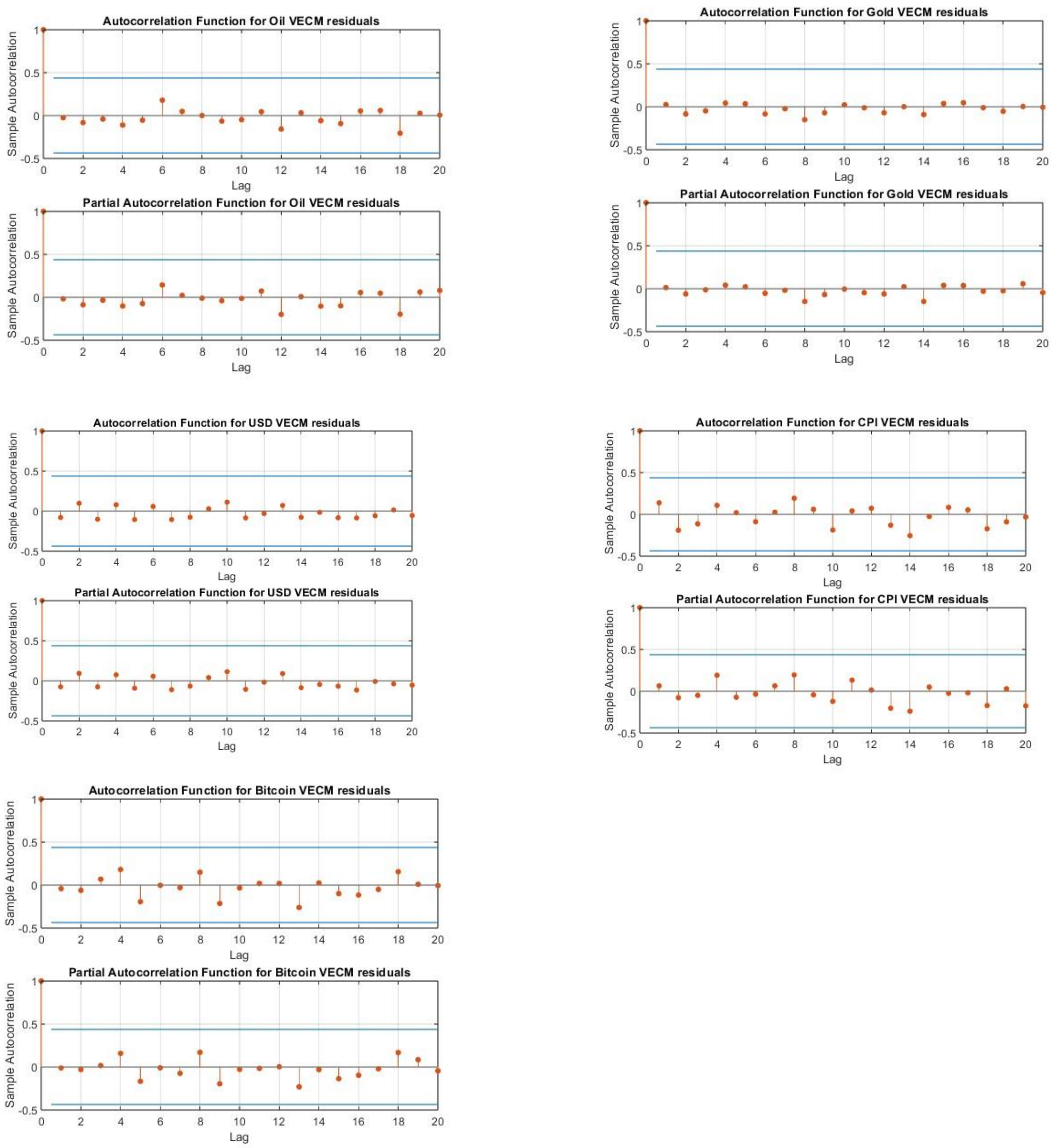


Figure 2. *ACF and PACF graphs*

Source: Authors' calculations

Table 12. *VEC Residual Portmanteau Tests for Autocorrelations*

Null Hypothesis: No residual autocorrelations up to lag h
Date: 04/28/23 Time: 16:22
Sample: 2014M10 2022M05
Included observations: 90

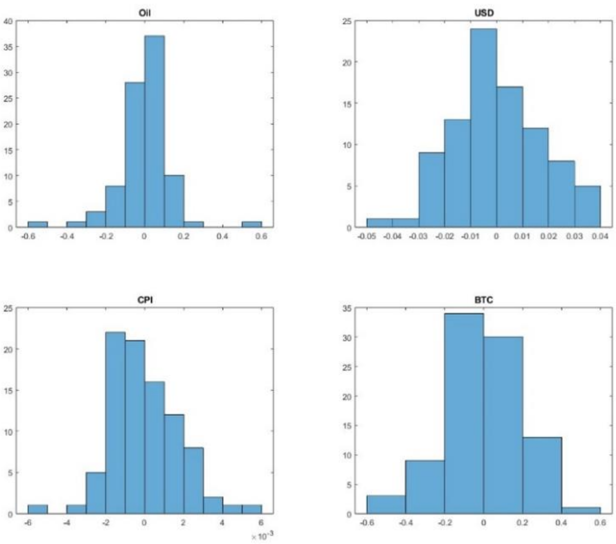
Lags	Q-Stat	Prob.*	Adj Q-Stat	Prob.*	df
1	6.129018	---	6.197883	---	---
2	29.53242	0.9636	30.13318	0.9564	45
3	55.78380	0.8919	57.28978	0.8621	70
4	80.91328	0.8481	83.58807	0.7924	95
5	107.0828	0.7945	111.2970	0.7029	120
6	124.4311	0.8908	129.8844	0.8108	145
7	137.3733	0.9686	143.9182	0.9275	170
8	157.1961	0.9783	165.6749	0.9373	195
9	182.3527	0.9697	193.6267	0.8996	220
10	204.1050	0.9733	218.0979	0.8911	245
11	230.1582	0.9623	247.7789	0.8302	270
12	252.8754	0.9638	273.9911	0.8048	295

*Test is valid only for lags larger than the VAR lag order.
df is degrees of freedom for (approximate) chi-square distribution after adjustment for VEC estimation (Bruggemann *et al.* 2005)
Source: Authors' calculations

Table 13. *Jaque-Berra Test*

	Oil	Usd	Gold	Cpi	Btc	Combined F-Test
P-Value	0.00	0.50	0.47	0.05	0.49	0.00
Is it Normally dist (1=no)	1.00	0.00	0.00	1.00	0.00	1.00

Source: Authors' calculations



Source: Authors' calculations

Figure 3. *Histogram of the residuals of the VEC*

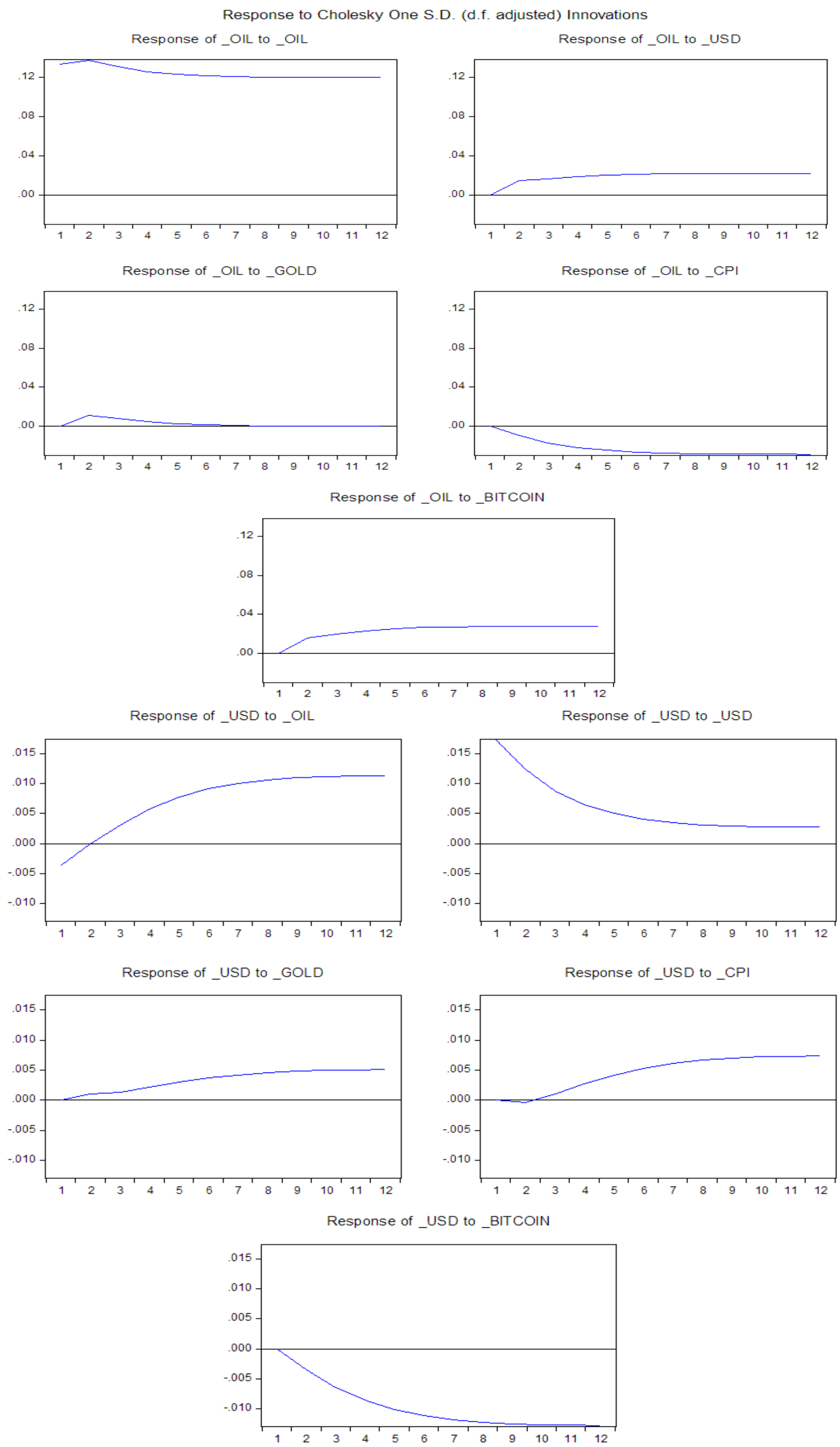


Figure 4. *Impulse response*
Source: Authors' calculations

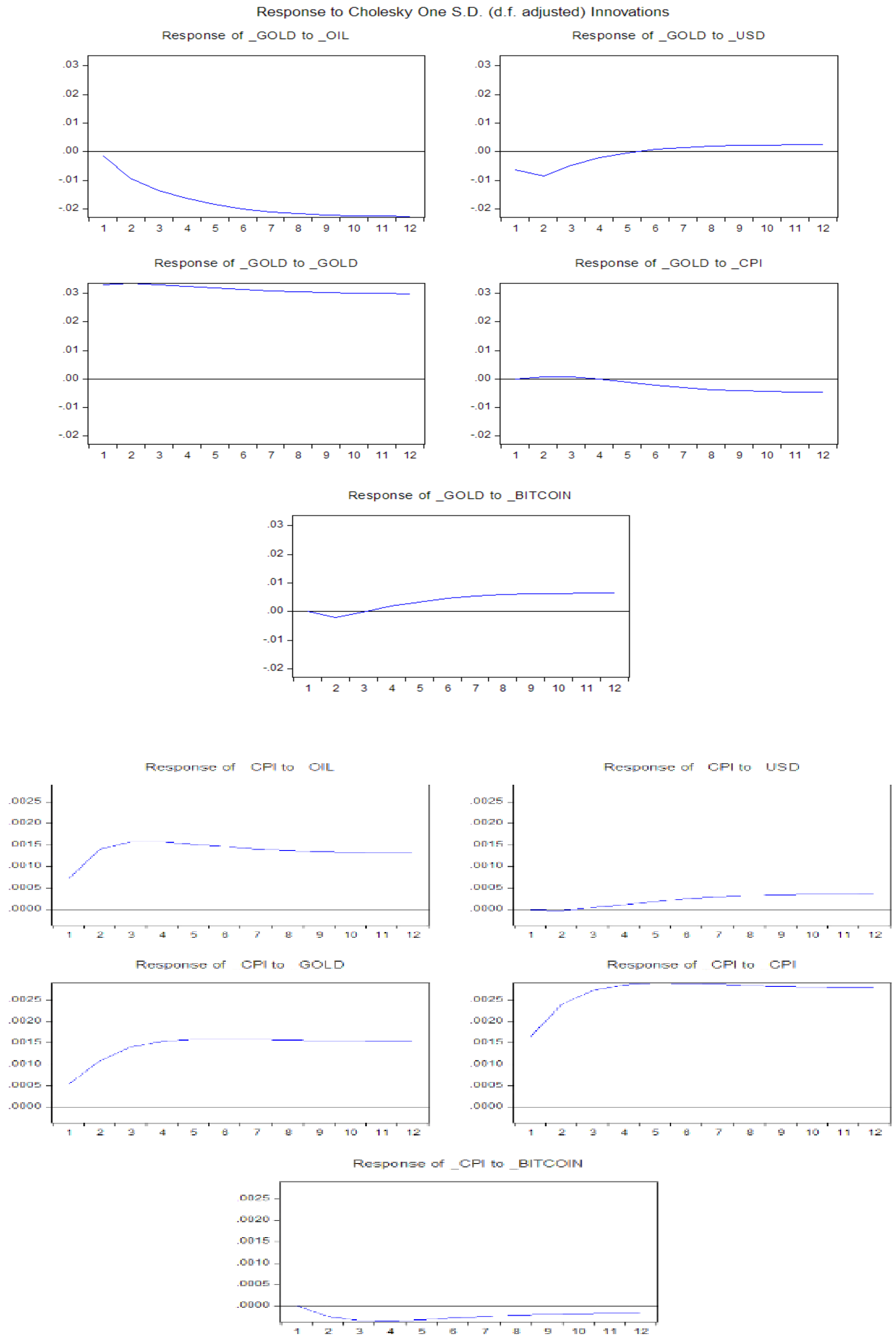


Figure 4. *Impulse response (continued)*
Source: Authors' calculations

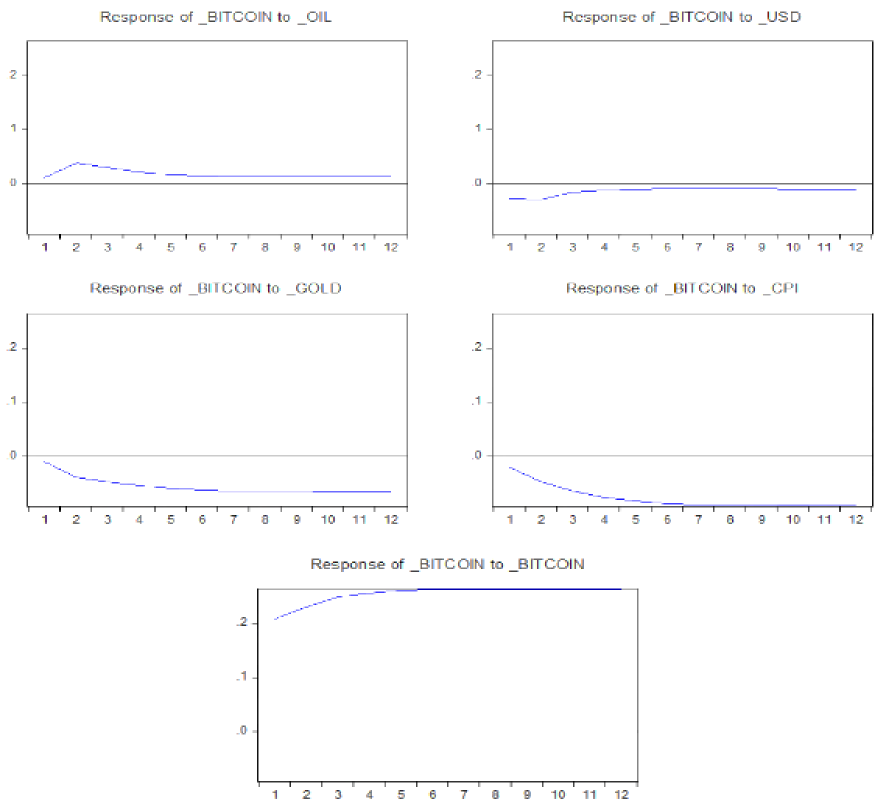


Figure 4. *Impulse response (continued)*
Source: Authors' calculations

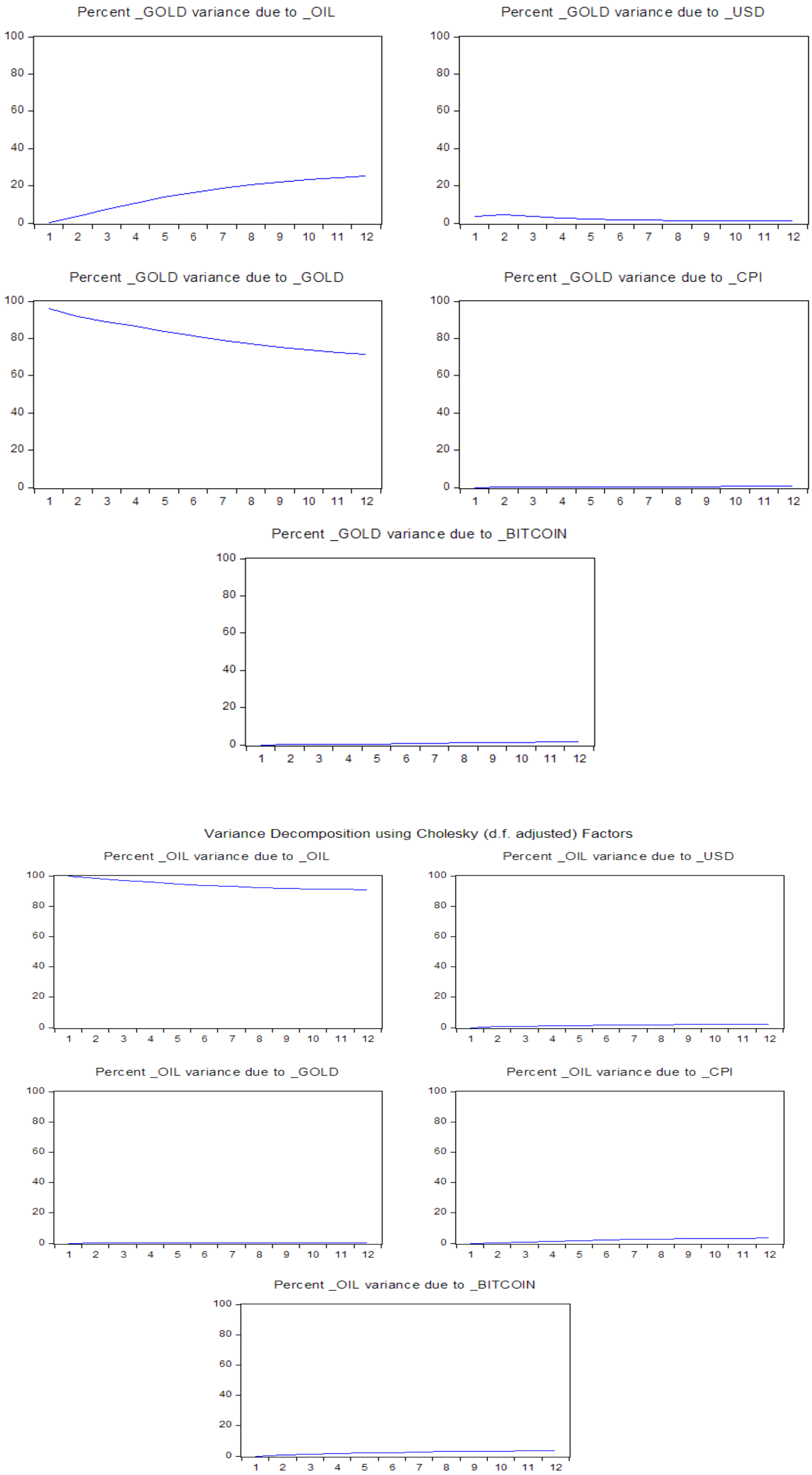


Figure 5. *Variance decomposition*

Source: Authors' calculations

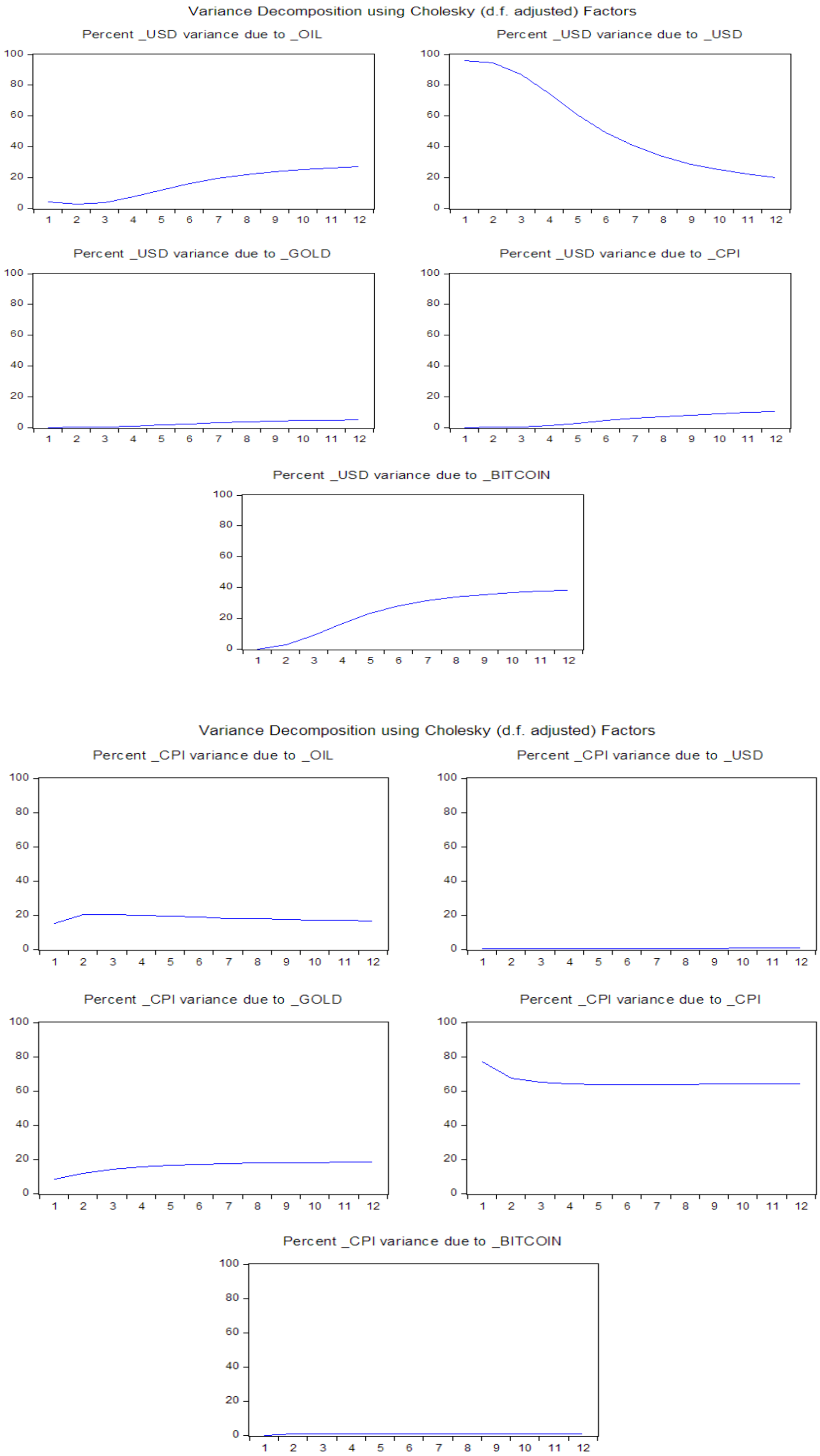


Figure 5. *Variance decomposition (continued)*

Source: Authors' calculations

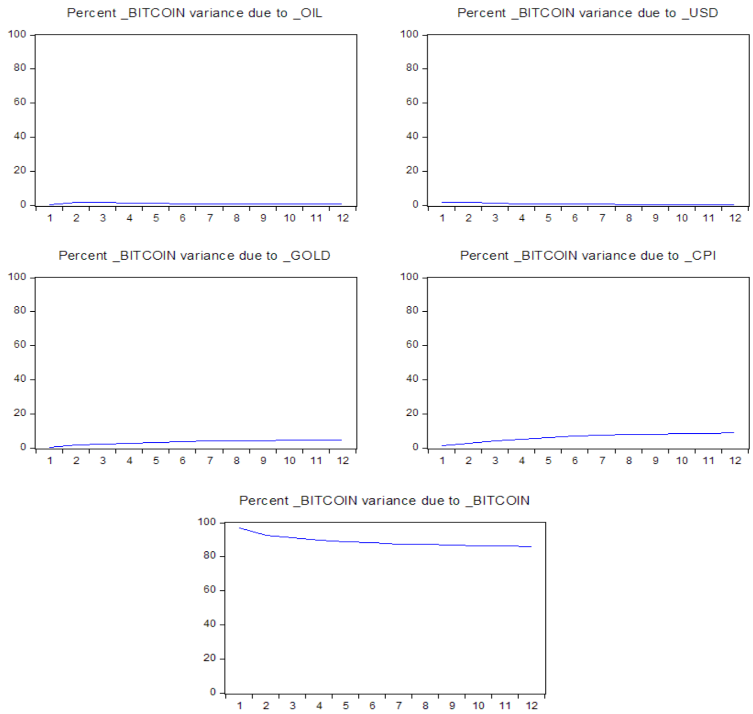


Figure 5. *Variance decomposition (continued)*

Source: Authors' calculations