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Market Integration between Bitcoin, Crude-Oil and Gold: Evidence from ARDL and JOHANSEN Models

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Abstract:

Purpose: *This study investigates the long-term and short-term relationships between Bitcoin, gold, and crude oil, with the aim of assessing their interaction dynamics and diversification properties within financial markets.*
Design/Methodology/Approach: *The analysis relies on the Auto Regressive Distributed Lag (ARDL) approach proposed by Pesaran et al. (2001) to examine both short-run and long-run relationships among the variables. A Vector Error Correction Model (VECM) is employed to capture long-term adjustments toward equilibrium. In addition, multivariate cointegration is tested using the Johansen (1988) methodology. The empirical investigation is conducted using high-frequency (intraday) Bitcoin data alongside gold and oil prices.*
Findings: *The results reveal the existence of distinct risk dynamics between Bitcoin and gold, suggesting that they behave differently across investment horizons while remaining complementary assets. In the short run, Bitcoin offers higher profit opportunities, whereas gold serves as a safe and stable long-term investment. The findings further indicate the absence of a significant relationship between Bitcoin and crude oil, highlighting their independence in terms of price movements.*
PracticalImplications: *These results provide valuable insights for investors and portfolio managers seeking to enhance diversification strategies by combining digital assets with traditional commodities. The complementary nature of Bitcoin and gold can help improve portfolio risk management across different time horizons.*
Originality/Value: *This study contributes to the growing literature on cryptocurrencies by offering empirical evidence on the dynamic linkages between Bitcoin, gold, and oil using both ARDL and Johansen cointegration frameworks. The use of high-frequency data strengthens the robustness of the findings and provides a deeper understanding of short-term and long-term investment behaviour.*

Keywords: *Cointegration, ARDL, Johansen test, Bitcoin, Gold, Crude Oil.*

JELClassification: *C32, G11, G15, Q43.*

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1. Introduction

Financial technology has come a long way in the last decade, including the emergence of digital currencies that are digitally or exclusively electronically delivered and not in physical form.These digital currencies fulfill his three purposes of money: medium of exchange, store of value, and unit of account. It was first made available by Bitcoin, Inc. (Gans and Halaburda, 2015). This is related to the idea of cryptocurrencies.

A cryptocurrency is a type of digital or virtual currency protected by cryptography. Moreover, it is not constrained by states, fiat currencies, monetary authorities, or national borders (Maese *et al.,* 2016). Since 2008, Bitcoin has been the first and most famous cryptocurrency in existence. Over the past decade, the price of Bitcoin has risen dramatically, benefiting many investors. Its technical and legal aspects first caught the attention of researchers.

The question of whether Bitcoin can function as money and whether it would be more appropriate to classify it as a commodity (similar to gold) or a fiat currency comparable to the dollar has been the subject of recent research (Selgin 2015; Dyhrberg 2016; Baur *et al.,* 2018).

Moreover, research has been done on the tradeability, liquidity, and efficiency characteristics of cryptocurrencies (Wei 2018; Kyriazis and Prassa, 2019; Fischer *et al.,* 2019). Bitcoin offers considerable benefits for diversification despite its high volatility,according to (Das *et al.,* 2020), and there is minimal correlation between it and conventional assets and alternative investments Because to the significant ramifications for investors, academics, and policymakers, the relation ship between Bitcoin and commodities (such as gold and crude oil) has recently drawn an intrig uing stream of study (Dutta *et al.,* 2020; Shahzad *et al.,* 2020).

Gold, which is traded all over the world, is often seen as a safe haven. What's interesting is that it generally moves independently of the US dollar, making it a fairly handy hedging tool. In many ways, particularly due to its decentralization and scarcity, Bitcoin, unlike gold, is a highly decentralized digital currency with a rather limited intrinsic value.

It is often presented as an innovative means of payment, but also as a highly speculative investment. Crude oil, on the other hand, remains a major strategic resource, a true engine for industry. These two assets – gold and oil – were chosen for this study due to their vastly different profiles. Gold primarily serves as a point of comparison, as many researcher. like Dyhrberg (2016), rightly describe bitcoin as "digital gold" or "new gold."

Crude oil was chosen as the second element of comparison because it is extracted similarly to bitcoin and is also classified as a commodity (Bouri *et al.,* 2018; Klein *et* *al.,* 2018). Most previous empirical studies on the global financial integration of markets have used cointegration techniques developed by Gregory and Hansen (1996) as well as Engle and Granger (1987).

The ARDL (Autoregressive Distributed Lags) method proposed by Pesaran et al. (2001) is also very attractive, flexible, and adaptive, notably because it allows for the integration of different time lags for the variables. This approach is used to analyze long-term relationships between stock markets. Its ability to account for sufficient lags allows for a better understanding of the data generation process.

Thus, it can be applied to stationary time series at level I(0), integrated of order one I(1), or even fractionally integrated (Pesaran *et al.,* 2001). The ARDL method also provides unbiased estimates and precise t-statistics, even in the presence of some endogeneity of the regressors (Harris and Sollis, 2003; Jalil and Ma, 2008).

The choice of an appropriate lag indeed reduces the correlation of residuals, thereby mitigating the endogeneity problem (Ali *et al.,* 2016). Thanks to error correction modeling (ECM), it allows short-term adjustments to be linked to long-term equilibrium, and this thru a linear transformation that preserves information on long-horizon dynamics (Ali *et al.,* 2017).

The method also allows for the distinction between dependent and independent variables and the use of dummy variables to correct for outliers (Marques *et al.,* 2017; 2019). Finally, unlike other procedures, the ARDL framework only requires a single equation in reduced form (Bayer and Hanck, 2013), which makes its interpretation and implementation particularly simple (Rahman and Kashem, 2017). The ARDL approach is also more reliable on small samples than the Johansen and Juselius cointegration method (Haug, 2002).

According to Halicioglu (2007), it has two major advantages: the possibility of testing hypotheses on long-term coefficients, and the simultaneous estimation of short-term and long-term effects – which the Engle-Granger method does not allow. That being said, the Johansen cointegration test also retains significant advantages.

This test is designed for multivariate systems and may become an industry standard for determining cointegration. This paper systematically contributes to the extension of these strategies.

A vector error correction model (VECM) is used to compute the size of potential long-term relationships. Recent empirical studies have shown that this approach helps achieve desired results leading to reliable results. Also, select the Johansen cointegration test (Johansen, 1988).

The cointegration hypothesis is the reduced rank hypothesis of the matrix of regression coefficients derived from the two equations. The trace test and maximum eigenvalue test are provided as two likelihood ratio tests. By combining these two approaches, co-movement can be studied from short-term and long-term perspectives.

However, other studies distinguish between short-term and long-term correlations between Bitcoin and other assets (Ciaian *et al.,* 2018; Gozbasi *et al.,* 2021; AKKAYA, 2022; Deniz, 2020). Gold price movements can also be compared using comparable comparisons (Selmi *et al.,* 2018) and (Shahzad *et al.,* 2020). However, important information can be extracted from intraday data that is difficult to distinguish from daily closing prices.

Market information, such as intraday movements and market microstructures, is rich in high-frequency data. Check out Bitcoin's intraday dynamics in Eross *et al.* (2019). Using intraday data, the authors note that Bitcoin returns increased as trading volumes decreased and volatility decreased (Mensi *et al.,* 2019).

Intraday Data Analysis High-frequency data provides more information, but stocks and other traditional financial instruments do not experience as much volatility as Bitcoin returns. Weekly data collection helps reduce potential disruption from breaking changes.

The rest of this essay is structured as shown below. Section 2 provides a historical background and literature review of traditional assets and the Bitcoin market. We describe the data and methods used in Section 3 of this article. Section 4 presents descriptive statistics, key findings in connected networks, time-varying analysis, and robustness studies. Work will be completed in Section 5.

2. Literature Review

In recent decades, there seems to have been a closer relationship between the financial markets, especially the cryptocurrency market. Researchers (Bouri *et al.,* 2017; Das, Le Roux, Jana,and Dutta, 2020; Demir, Gozgor, Lau and Vigne, 2018) found that Bitcoin improves the performance of a diverse portfolio. Furthermore, Dutta, Choi, Somani, and Butala, (2020) suggest that correlations between Bitcoin, gold, and oil can be viewed as safe havens, leading to exploitation of certain diversification advantages.

Discovered Despite the extensive literature on Bitcoin and gold, research has been conducted on Bitcoin and oil or the relationship between Bitcoin, gold and oil. Several empirical studies have examined Bitcoin, gold and oil price volatility using a variety of models, including the Johansen model, the ARDL cointegration model, and others that focus on cointegration.

This study addresses the issue of investing in the cryptocurrency market. Since the pioneering work of Engle and Granger (1987), cointegration has emerged as a useful technique for analyzing common patterns in multivariate time series.

Cointegration has become an essential technique for analyzing the long-term and short-term dynamics of time series. Since the foundational work of Engle and Granger in 1987, this approach allows for the modeling of stable relationships between multiple variables while capturing their temporary adjustments.

Let's take the example of Bouoiyour and Selmi (2015), who used the ARDL model to examine the links between several economic variables, both in the short and long term. That said, one should not necessarily expect all variables to maintain lasting relationships.

Regarding Bitcoin, Wang, Xue, and Liu (2016) demonstrated, using the Johansen test, that its price has a stable long-term relationship with stock indices, oil prices, and its own daily trading volume. On his part, Dyhrberg (2016) compared Bitcoin and gold as hedging assets, concluding that their risk reduction properties were similar.

Finally, Ciaian, Kancs, and Rajcaniova (2018) examined the interactions between 17 cryptocurrencies, including Bitcoin, during the period 2013-2016. In the model include oil prices, gold prices, stock indices, interest rates, and exchange rates. Results using the ARDL (Autoregressive Distributed Lag) model show that 15 of the 16 cryptocurrencies studied are vulnerable to short-term real shocks to Bitcoin's value.

Only 4 cryptocurrencies that can coexist with Bitcoin in the long term. Further investigation by Shahzad *et al.* (2019), Bouoiyour *et al.* (2019) and Panagiotidis *et al.* (2018) also showed a strong link between Bitcoin and gold. Klein *et al.* (2018), Symitsi and Chalvatsis (2019), and Panagiotidis *et al.* (2019) produced evidence that Bitcoin shares no properties with gold.

A comprehensive review of empirical data comparing the performance of Bitcoin and gold is provided by Kyriazis (2020). Not much research has been done on the relationship and spillovers between Bitcoin and Crude Oil or Bitcoin, Gold and Crude Oil, but there is a wealth of information on both Bitcoin and Gold.

Diverse portfolios alongside oil and gold. Gozbasi, Altinoz, and Sahin (2021) attempted to explain the relationship between risk-related variables and Bitcoin, gold, oil, S&P indices, and monthly data from 2010 to 2021. With this method, gold has no visible impact on Bitcoin in the short or long term, but rising oil prices have a negative impact on the price of Bitcoin and the stock market in the short term.

Gül *et al.* (2020) examined the impact of including cryptocurrencies (Bitcoin, Ethereum, Ripple) in portfolios of different assets, including oil. The paper argues that adding cryptocurrencies to portfolios can help investors reduce risk while increasing overall returns. Charfeddine, Benlagha, and Maouchi, (2020) used a 'copula' approach using the GARCH model to analyze two cryptocurrencies (Bitcoin and Ethereum) and three traditional assets (S&P 500, gold and oil) analyzed the relationship between how financial assets are linked exploring the links between 7 Cryptocurrencies, Gold and Oil (Deniz, 2020).

According to the VAR model, Johansen's cointegration test, and Granger's causality test, there was a short-term cointegration relationship between Bitcoin and gold.

Cryptocurrencies have grown in popularity in recent years, especially in light of the coronavirus (COVID-19) outbreak. These cryptocurrencies are seeing increased trading volumes and profits, but are viewed with suspicion by some prominent economists.

In a study by Kurt and Kula (2021), to examine the relationship between Bitcoin, Ethereum, and oil over the entire period from cointegration test and follow the work by Johansen (1988) as the basis for their analysis. The author provides an example of how Bitcoin and oil are unrelated.

Kumar, Kumar, and Singh, (2023)) investigated the causality among gold prices, crude oil prices, bitcoin and stock prices by using daily data from January 2014 to December 2021. The study also examines the data during the COVID-19 outbreak from January 2020 to December 2021, to estimate the long- and short-run causality, this study considers the nonlinear autoregressive distributed lag (NARDL) cointegration test.

The analysis found the existence of an asymmetric long-run cointegration among selected assets. During the COVID-19 period, the study notices the presence of an asymmetric long-term cointegration between selected assets except bitcoin.

Besides, findings revealed that negative price adjustments in gold lead to significant positive shocks in stock market. Ekrem Tufan, Bahattin Hamarat, and Aykut Yalvaç (2022) reviewed the causal relationships between Bitcoin, gold and oil prices. Research data covers the period from 2015 to July 2020. The question of whether or not research series are co-integrated was investigated with the Gregory and Hansen test.

The causality between series was examined with the Toda-Yamamoto causality test, which is based on the VAR (Vector Autoregression) model and examines causality in the serie independently of the unit root. As a result, we give evidence that the price series of Bitcoin and gold followed a parallel pattern while with oil not. Therefore, investors can add bitcoins to their portfolios to balance risk and return.

According to their research, Wang, Liu, Sbai, Sheng, Hu, and Tao (2024), used the Quantile Autoregressive Distributed Lag model to examine Bitcoin's price behavior across market conditions, focusing on the influence of Bitcoin's historical prices, news sentiment and market indicators like oil prices, gold and the S&P index. The authors also assess the stability of Bitcoin-inclusive hedging portfolios under different market conditions.

This study indicated that oil prices have minimal impacts on Bitcoin, whereas gold is a stabilizing asset in bear markets, with the S&P index influencing short-term fluctuations.

At the same time, Bitcoin's volatility varies with market conditions, proving more efficient as a hedging tool in bear and stable markets than in bull ones.
Mehmet Levent Erdas and Gamze Gocmen Yagcilar (2024) investigated the interaction between Bitcoin, Brent oil, global indexes, and gold using current cointegration and causality tests. The results of cointegration tests indicate that there is a cointegration relationship between variables.

3. Methodological Approach

3.1 Research Design and Foundations

To empirically study the interactions between selected variables, we consider two econometric methods. In fact, to address long-term connections, we first use his ARDL technique for cointegration in Pesaran *et al.* (2001). Next, we examine Johansen's cointegration method. A combination of these methods allows separation of long-term and short-term synkinesis.

3.1.1 ARDL approach to cointegration

The ARDL approach proposed by Pesaran *et al.* (2001) significantly improves the properties of the estimates produced, regardless of whether these variables are stationary or not, thus allowing long-term A very valuable tool for analyzing relationships. In contrast to traditional cointegration methods, the ARDL approach allows variable lag lengths to be varied. The ARDL method also has the advantage of being applicable to small sample sizes. Next, the following his ARDL model (p, p1, p2, , pn) is used as a basis for studying cointegration between stock markets

$$\Delta \mathrm{L}Y_t = \alpha + \beta_t + \sum_{i=1}^{p} a_i \, \Delta LY_{t-i} + \sum_{k=1}^{n} \sum_{i=0}^{Pk} b_{ki} \Delta \mathrm{L}X_{k,t-1} + \lambda \mathrm{L}Y_{t-1} + \sum_{k=1}^{n} \lambda_k \mathrm{L}X_{k,t-1} + \mu_t \quad (1)$$

where n is the number of explanatory variables and ΔLY and ΔLXk are the natural logarithmic changes of the variables Y and Xk (k = 1, 2, ... n). The short-term coefficients are a_i and b_{ki} and the long-term coefficient is k. Optimal delay lengths ($\hat{p}$, $\hat{p}1$, $\hat{p}2$, ..., $\hat{p}n$) can be identified.

Below is the analytical formulation of the null hypothesis that there is no cointegration between the variables. According to Fisher's test for joint significance of the lag variables, H0 = 1 = 2 = n = 0, which is true. The asymptotic distribution of the test statistic is non-standard under the null hypothesis, leading to the determination of two sets of critical values for the variables I(0) and I(1).

In this situation, regardless of whether the variable is I(0) or I(1), the null hypothesis of non-cointegration is rejected if the observed value of the test statistic is greater than the upper bound I(1). On the other hand, whether the variables are I(0) or I(1), if the computed test statistic does not exceed the lower critical constraint I(1), we conclude that there is no cointegration between the variables.

Regardless of whether the variable is I(0) or I, the test is inconclusive if the empirical test statistic is between the lower bound and the upper bound I(1).

Use the following ARDL (p, $p1$, $p2$, pn) to estimate the long-term coefficients of variables for which the null hypothesis of lack of cointegration is rejected:

$$(L,P)Y_t = \alpha_0 + \sum_{i=1}^{n} \beta_i\,(L,P_i)X_{it} + \gamma' \upsilon_t + \varepsilon_t$$

Where

$$(L,P) = 1 - \Phi_1 L - \Phi_2 L^2 - \cdots - \Phi_P L^P$$

And

$$\beta(L,P_i) = \beta_{i0} + \beta_{i1}L + \beta_{i2}L^2 + \cdots + \beta_{ip}L^{pi} \; (i = 1,2,\ldots,n)$$

The dependent variable is called Yt, the explanatory variable is Xit, the vector of deterministic variables is υt, and the error term is t. Long-term coefficients can be calculated by choosing the correct ARDL model (p, p^1, p^2, p^n). This is represented by the following formula:

$$\mu_i = \frac{\beta_{i0}+\beta_{i1}+\beta_{i2}+\cdots+\beta_{ip_i}}{1-\Phi_1-\Phi_2-\cdots-\Phi_{\hat{p}}} \quad ; i = 1,2,\ldots,n \qquad (3)$$

To show the cointegration between the variables, we estimate the following error correction model.

$$\Delta Y_t = -(1-\Phi_1-\Phi_2-\cdots\Phi_{\hat{p}})ECM_{t-1} + \sum_{i=1}^{n} \beta_{i0}\,\Delta X_{it} + \gamma'\Delta\upsilon_t - \sum_{j-1}^{\hat{p}-1} \phi * \Delta Y_{t-j} - n \sum_{j-1}^{\hat{p}-1} \beta *_{ij}\,\Delta X_{i,-j} + \varepsilon_t \qquad (4)$$

$\sum i{=}1$

Where

$$ECM_t = \sum_{i=1}^{n} \hat{\mu}_i X_{it} - \hat{\eta}' \upsilon_t$$

The short-term coefficients are $\phi *j$ and $\beta *ij$, and the long-term coefficients of the deterministic variables are represented by the vector η̂

3.1.2 Johansen's cointegration procedure

The second method uses the multivariate cointegration approach of Johansen, (1988). This is because the analysis includes more than one variable, so there can be multiple long-term relationships between them. The methodology of Johansen, (1988) is based on autoregressive vector models (VAR). This allows both estimation and verification of equilibrium relationships between nonstationary series. He showed that the cointegration hypothesis can be formulated as the reduced rank hypothesis of the matrix of regression coefficients estimated from two equations.

$$Y_t = C + \sum_{I=1}^{P} \Phi_i Y_{t-i} + \varepsilon_t$$

where Yt is a (kx1) vector of variables integrated of order one,I(1) , and εt is a (kx1) vector of error terms. In order (P-1) error correction form, this method can be re-parameterized as follows

$$\Delta Y_t = C + \sum_{i=1}^{p+1} \Theta_i \Delta Y_{t-i} + \Pi Y_{t-1} + \varepsilon_t \tag{6}$$

where

$\Theta i = \sum_{j=i+1}^{P} (-\Phi j)$, i = 1,2,…, P-1

And $\Pi = \sum_{i=1}^{P} \Phi i - I$

We can write the matrix as Π = αβ'. where the (kx1) matrix of fit coefficients using (r,k) and β' is the (kx1) matrix of coefficients of r cointegration vectors. Long-term relationships are represented by linear combinations. Johansen's approach involves determining the rank of the matrix. For r = 0, there is no cointegration between the variables in this situation. If 1≤ r ≤ k− 1, there are r long-lived connections.

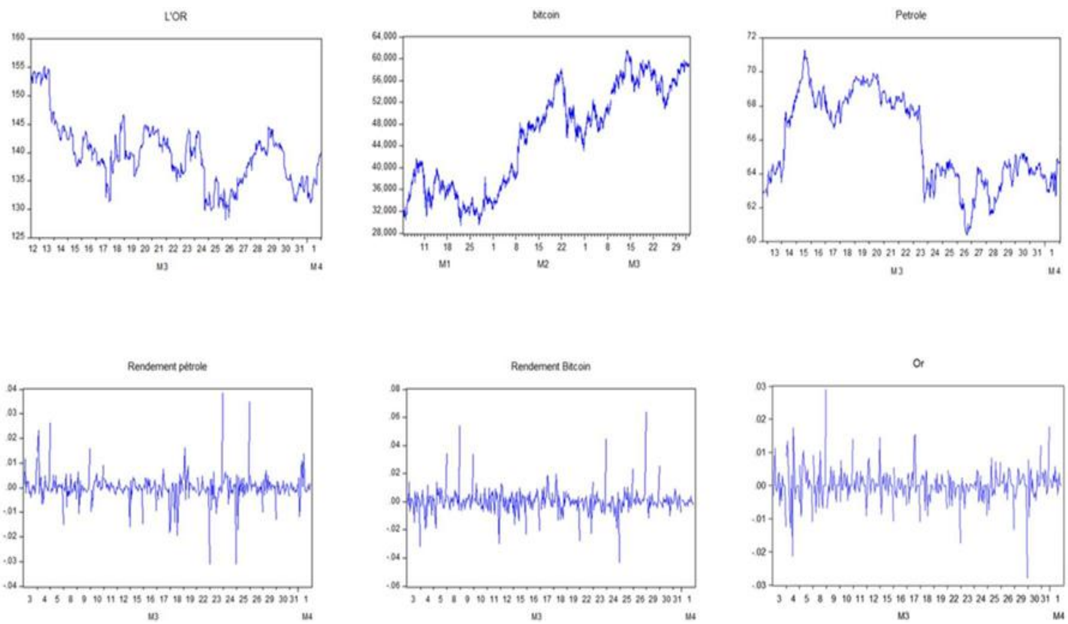
Since all variables are integrated to order 0, I(0), there is no cointegration when r = k. Determine the number of cointegration vectors r using the maximum eigenvalue test and the trace test. The main advantage of the Johansen test is the ability to generate cointegration vectors and perform hypothesis testing directly on the price series itself without the need for continuous stationarity checks.

The number of independent portfolios resulting from different linear combinations of price time series is given by the cointegration order, or rank (r) for short, according to the Johansen criterion.

3.2 Data and Preliminary Analysis

Use high-frequency (intra-day) data for Bitcoin**,** Gold, and Crude Oil from 03/03/2021 to 04/01/2021. Make a price decision every half hour (30 minutes). The departure date and this frequency were chosen to avoid liquidity problems caused by periods of low activity on very short timeframes.

Figure 1. *Graphical representation of variables and returns*



Source: *Own study.*

Bitcoin chart (https: http://www.bitcoincharts.com) is used to collect intraday price information for cryptocurrencies. Crude oil data comes from the Pi Trading database, while gold data can be found at www.disktrading.com and www.kibot.com. Following a series of stages, the market exhibits behavioral trends during the study period, which indicates potential consolidation between markets.

A plot of the data makes some sense (Figure 1). The levels and returns of the three variables indicate market trends during the study period and may indicate potential cooperative consolidation links between them. Cryptocurrency prices are highly volatile.

The fact that Bitcoin yields fluctuate around 0 suggests that Bitcoin yields are changing over time. This is probably due to volatility. However, we have noticed that sustained volatility is moving away from zero. Moreover, compared to Bitcoin and oil, we often find gold trending in the opposite direction.

Numerous studies in the literature (Briere *et al.,* 2015; Dyhrberg, 2016; Bouri *et al.,* 2018) found that cryptocurrencies outperformed at the time of their emergence, despite negative correlations. It shows that it was a safe haven. The European Union is very interested in the growth of the European economy. Today, with its inclusion in various institutional portfolios or increased use in the real economy, this negative correlation tends to decrease and may even turn into a positive correlation.

Table 1. *Descriptive statistics and statistical propreties of series * and ** indicate the rejection of the null hypothesis of the associated tests at the 1% and 5% levels, respectively.*

Series	**Moyenne**	**Ecartype**	**Skew**	**Kurt**	**JB**
Bitcoin	55214.19	3203.073	-0.783439	2.583316	37.89756*
gold	136.4625	3.894932	0.170727	1.843217	20.97248*
oil	65.86841	2.507778	-0.083332	1.816057	20.60861*
Return	**Moyenne**	**Ecartype**	**Skew**	**Kurt**	**JB**
Bitcoin	0.000420	0.009330	1.383494	15.949	2520.789*
gold	0.000197	0.005148	-0.001854	10.05091	714.657*
oil	5.83E-05	0.006132	0.5344	15.496	2261.206*

Source: *Own study E-Views.*

Table 1 contains descriptive statistics of Bitcoin price relative to gold and oil prices, along with risk factors that account for all variables and the entire sample period.

These consist of mean, standard deviation, asymmetry, and kurtosis measures. The Jarque-Bera normality test statistic is denoted as JB. We can see that the average yield variables are all positive (Table 1). We found that crude oil has the lowest yield and Bitcoin has the highest yield.

These results show that Bitcoin variables have the highest costs and risks. The risk index shows that the variable with the highest standard deviation and the most volatility is the Bitcoin price. The kurtosis coefficient appears to be less than 3 for all variables. This indicates that the distribution is less flattened than the normal distribution. The normality hypothesis for the relevant variables was rejected by the significant results of the Jarque-Bera test.

Table 2. *Correlation Matrix*

Variables	gold	oil	bitcoin
1. gold	1		
2. oil	0.1631998	1	
3. bitcoin	0.6475708	-0.1681584	1
Returns	**gold**	**oil**	**bitcoin**
5. gold	1		
6. oil	0.309761325	1	
7. bitcoin	0.222217584	0.19755324	1

Source: *Own study EViews.*

Stationarity and non stationarity must be determined to perform the cointegration test. Stationarity is a desired assumption in most time series modeling and analysis because nonstationary data is unpredictable and should be changed to become stationary in most situations. According to Challis and Kitney (1991), a steady-state process is one whose mean, variance, and autocorrelation structure do not change over time.

The extended Dickey-Fuller test (ADF) (Dickey and Fuller, 1979) is effective The KPSS test divides the series into three components (deterministic part, random part, and white noise) and uses the null hypothesis of stationarity in the presence of error autocorrelation. For heteroscedastic errors, the Phillips Perron (PP) test (Johansen, 1988) is presented. Unit radical test results for ADF, PP, and KPSS tests, shown in Table 3, indicate that Bitcoin, Gold, and Oil consolidate in the order of 1 (the first difference is followed by a steady).

Table 3. *ADF, PP and KPSS test*

Variables	Test	Niveau	1st difference
bitcoin	ADF	-1.604	-18.59*
	PP	-1.608	-18.59*
	KPSS	0.928	0.075
Gold	ADF	-18.58*	-12.88*
	PP	-18.58*	-345.341*
	KPSS	0.189	0.5
oil	ADF	-1.343	-11.103*
	PP	-1.610	-17.945*
	KPSS	1.277	0.151
Returns	**Test**	**Niveau**	**1st difference**
bitcoin	ADF	18.631*	-13.259*
	PP	-18.631	-191.359*
	KPSS	0.078	0.066
Gold	ADF	-19.442*	-12.802*

	PP KPSS	-19.561* 0.150	-289.311* 0.088
Oil	ADF PP KPSS	-11.216* -17.965* 0.145	-13.795* -147.713* 0.107

Source: *Own study EViews.*

4. Empirical Results

We initially examine all conceivable specifications since the long run connection directio among all equities are unknown in advance. Indeed, there are three models to estimate: All models consider the remaining indices to be explanatory factors. The cost of bitcoin is the dependent variable in model 1. The cost of gold is the dependent variable in model 2. The cost of oil is the dependent variable in model 3.

By examining the cointegration between two sets of variables, we then concentrate on the incorporation of bitcoin into each variable taken into account. Before doing the cointegration test for each model, we performed diagnostic tests to ensure that it was valid.

The Jarque- Bera normality test, the Ramsey RESET test for the correct functional form, the Breusch Godfrey LM test for order 12order autocorrelation, and the ARCH test for order 1 2- order autocorrelation were among these tests. We may use the limits test technique to test for cointegration between variables since the results agree with the evidence provided by the accurately specified models.

The ARDL test technique seeks to determine if the equation's variables show any long-term associations. The computation of the ARDL model is necessary for the cointegration test described in Pesaran *et al.* (2001). The crucial values will be compared to the test statistic that was produced, Fisher's F value. The outcomes of the multivariate models are shown in Table (4) along with the Fisher test value of the linked test for each model that uses each variable as a dependent variable.

Fisher F's statistical value in the first model was (15,446), surpassing the 10% upper limit; as a result, the null hypothesis is rejected and the alternative hypothesis of an integration connection is accepted. This explains how the variables are cointegrated. The second model's outcomes were identical (F=101.2). The results demonstrate that there is no variable overlap because the Fisher F statistical value for the third model (F=0.740) was below the lower bound.

Table 4. *F-statistic for cointegration for the multivariate setting*

Model 1	Model 2	Model 3
15.446	101.2	0.740

Notes: *The lower bound critical values are 2.63 (10%), 3.1(5%) and 4.13(1%), and the upper bound critical values are 3.35 (10%), 3.87(5%) et 5(1%) (see Pesaran et al., 2001))*
Source: *Own study EViews.*

Table 5. F-statistic for cointegration for the bivariate setting

Bitcoin/ gold	**Bitcoin/oil**
20.648	1.115

Notes: *The lower bound critical values are 2.63 (10%), 3.1(5%) and 4.13(1%), and the upper bound critical values are 3.35 (10%), 3.87(5%) et 5(1%) (see Pesaran et al., 2001))*
Source: *Own study EViews.*

According to Table 5, the Fisher F-statistic value is below the minimum cutoff and the cointegration relationship between Bitcoin and gold (F=20.648) exceeds the cap set, thus the relationship between Bitcoin and oil (F=1.115). There is no long-term cointegration relationship between them. % at 10 o'clock. Due to the short observation time (every 30 minutes from 03/03/2021 to 04/01/2021), cointegration links may not have occurred.

To check for cointegration between variables, we estimate an error-corrected model that serves as an additional test of the cointegration hypothesis. In the rare cases where the null hypothesis of no cointegration is rejected, we estimate an error-correction model of the variables to achieve this.

We also evaluate the coefficient signs and statistical significance of the error correction terms. Since the ECM coefficient represents the speed or slowness of returning to connection with its equilibrium trajectory, the data collected must be of negative sign and of statistically significant magnitude. Our theory is also based on Banerjee *et al.* (1998).

Table 6. *Estimates of the error correction terms for the multivariate setting*

Model 1	**Model 2**	**Model 3**
-0.0126*	-1.008*	-0.01

Notes: *The values in parentheses are the standard errors. * Indicates significance at 1% level.*
Source: *Own study EViews.*

Table 7. *Estimates of the error correction terms for the bivariate setting*

Bitcoin/ gold	**Bitcoin/oil**
-0.0186**	-0.00975

Notes: *The values in parentheses are the standard errors. ** indicates significance at 5% level.*
Source: *Own study EViews.*

The results in Tables 6 and 7 show that the long-term error correction coefficients are highly negative, supporting the cointegration of gold and Bitcoin in multivariate and bivariate frameworks. Statistical significance, negative sign, and a range of absolute values between 0 and 1 for adjustment coefficients perpetuate cointegration relationships between variables. This range of values also ensures the existence of an error correction mechanism. We can see that the CointEq(-1) coefficient for Model 1 is calculated as -0.0126.

This indicates that the relationship between the dependent variable Bitcoin and the other variables is about 1.26% from the shock- adapted long-term equilibrium. Additionally, when gold is the dependent variable, we find the coefficient for Model 2 (-1.008). The bivariate scenario results show the presence of a significant unfavorable long-term error correction factor (-0.0186) supporting the cointegration of Bitcoin and gold. Our results are consistent with those of (Deniz, 2020).

One of the first steps in the Johansen methodology is to identify the number of "p" lags at the model level using the AIC and SIC criteria. The symbol for r, the estimated order of integration, is given by the number of cointegration vectors under the null hypothesis.

Therefore, if the null hypothesis r = 0 is not rejected, we can conclude that the cointegration vector does not exist. Although the null hypothesis r = 1 cannot be rejected, the results show that the cointegration vector exists if r = 0 is rejected.

Table 8. *AIC and SC criteria*

	AIC	**SC**
0	39.58751	39.62144
1	32.18991*	32.32564*
2	32.23682	32.47435
3	32.25967	32.59899
4	32.30792	32.74904
5	32.35385	32.89677
6	32.3845	33.02921
7	32.42846	33.17497
8	32.47551	33.32382

Notes: **indicates significance at 1%level.*
Source: *Own study EViews.*

The results show the existence of a model of order 1 (VAR(1)). Then, to simplify the analysis, we take into account that there is no trend in the cointegration relationship. This choice can be economically justified by assuming no trends in the long-run equilibrium links between variables. The trace test results are shown in Table (9) below.

Table 9. *Johansen's cointegration test results*

Variables	**Rang**	**Trace**	Maximum eigenvalue	Probability
Bitcoin/gold	r=0	67.951	65.735	0.000*
	r≤0	2.216	2.216	0.136
Bitcoin/oil	r=0	5.159	3.047	0.943
	r≤0	2.111	2.111	0.146

Notes: **indicates significance at 1%level.*
Source: *Own study EViews*

The results of the Johansen test (Table 9) show that there is a significant long-term relationship between Bitcoin and gold (67.951) above the maximum trace value, rejecting the null hypothesis, co is the ARDL It provides an integration between Bitcoin and Oil that supports the cointegration metric found in testing. Our results are consistent with (Deniz, 2020) and (Kurt and Kula, 2021).

5. Conclusion

The interconnectedness of financial assets is important to investors as it can influence the diversification strategies they choose. The main purpose of this project was not to hijack the Bitcoin, gold and oil markets, but to connect frequencies. Long-term diversification potential among different assets is implied by the short-term effectiveness of data analysis on other assets. On the one hand, volatility may occur over time as a result of some shocks, which may affect investor expectations.

The study looked at correlations between the prices of crude oil, gold and Bitcoin. Ranks were examined using ADF, PP, and KPSS root tests, and each rank was evaluated using the I(1 ARDL test and error correction model used in the study (ECM).

According to the unit root test results, the variables were I(1) processes, requiring the use of error correction models. Cointegration results establish long- term relationships between dependent and independent variables, so some variables are shows that they change together over time Show variables.

The Johansen cointegration test is performed when data are shown to be integrated in the same order Second, the black information criterion (SIC) is used to determine the length of the offset. The trace and maximum test show that Bitcoin and gold are cointegrated. This review is more palatable and provides a strong framework for further research.

To prevent method misuse, estimation, and interpretation that can lead to model specification problems, we have led to the ARDL cointegration approach. It is important to check the requirements. It is the solution to the analysis of cointegrated vector series and one of the greatest discoveries of the 20th century. This finding reveals insights on the relationships between Bitcoin and both gold and oil. However, a further examination comparing the findings presented in this paper using different times and keywords would be useful.

A complete analysis should be performed to determine whether these findings are valid only for a certain time frame or can be broadly applied to all times. Investors should be aware that even though this paper makes every attempt to expand the coverage of the data, the ongoing evolution of the financial markets may be impacted by various factors that are beyond our control.

In recent years there has been an increased focus on digital marketplaces by institutional investors, individual investors, media outlets, and researchers. As such, we believe this research into the correlation between cryptocurrencies and their ability to reduce portfolio risk is important for investors looking for ways to expand their investment options.

Lastly, we recommend conducting comte research into how well the Bitcoin market functions in practice.

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