Investigating the Market Linkages between Cryptocurrencies and Conventional Assets

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Abstract

Many investors include cryptocurrencies as potential investment tools in their portfolios. Previous studies have mostly analyzed Bitcoin regarding its hedge and safe haven features. Although the cryptocurrency market has expanded far beyond Bitcoin, few studies have examined the interaction among all other cryptocurrencies and conventional financial assets. For this purpose, as the dependent variable, we included the cryptocurrency index to represent the cryptocurrency market, whereas international stocks, bonds, United States (US) dollars, gold, and commodities as independent variables in the analysis. The interactions among the variables were analyzed using the Granger causality tests. The analysis results revealed a two-way causality relationship between the cryptocurrency market and the bond markets, indicating that the cryptocurrency index can be used to predict bond prices and vice versa.

Keywords: Cryptocurrency, Conventional Assets, Market Linkages, Granger Causality

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I. Introduction

Contrary to the 2008 crisis, the effects of the article titled "Bitcoin: A Peer-to-Peer Electronic Cash System," which was published during the 2008 Global Financial Crisis, continue (Nakamoto, 2008). Since its first appearance in January 2009, The debate whether Bitcoin is the currency of the future, a new investment tool, or a fraud product continues. Created by a person or group named using the pseudonym "Satoshi Nakamoto" and based on blockchain technology, Bitcoin takes its power from the decentralized structure. Since its launch in 2009, the value of Bitcoin has grown to over $750 billion (Coinmarketcap, 2022).

Although Bitcoin initially emerged as a medium of exchange and an alternative to cash payments, it has taken different forms over time. Although this development has not become widespread globally, many countries and companies accept Bitcoin as a payment method that can be used to purchase goods and services. As of December 2017, the Chicago Mercantile Exchange (CME) and the Chicago Options Exchange (CBOE) started to carry out futures transactions with Bitcoin and the Bitcoin mutual fund was created in the New York Stock Exchange (NYSE) market which paved the way for it to be accepted as an investment tool as well. Even though the country's economic share in the world is small, El Salvador's acceptance of Bitcoin as a legal payment method as of September 2021 has also contributed to the perception that Bitcoin could be an alternative to fiat currencies. Parallel to these developments, the number of studies examining the Bitcoin economy and its pricing dynamics (Branvold et al., 2015; Cheah and Fry, 2015; Ciaian et al., 2016; Balcılar et al., 2017; Urquhart, 2017), hedging capability (Dyhrberg, 2016; Briere et al., 2015; Bouri et al., 2017), volatility factors (Bouri et al., 2018; Katsiampa, 2017), and contamination risks (Huynh, 2019) has emerged rapidly.

The emphasis on Bitcoin in institutional regulations and academic research is primarily due to Bitcoin being the pioneer of cryptocurrencies and having the highest market capitalization value. However, Bitcoin does not reflect the entire crypto universe. Today the number of crypto assets (cryptocurrencies and tokens) has reached over nineteen thousand, and the market value of these assets has exceeded 1.5 trillion dollars (Coinmarketcap, 2022). On the other hand, Bitcoin makes up only 42% of the crypto market. Existing literature mainly focuses on Bitcoin, and studies have been shaped in this direction. Although some studies in the literature have addressed different cryptocurrencies other than Bitcoin, the cryptocurrencies included in the studies are limited to popular crypto-assets such as Ethereum, Litecoin, Ripple, and Stellar (Corbet et al., 2018a, 2018b; Bouri et al., 2019; Liu and Tsyvinski, 2021). Therefore, it is crucial to examine the interaction of the crypto-asset market with conventional financial assets, which has reached such a significant market value,

When the studies on Bitcoin, especially in the post-2019 period, are examined, it is seen that these studies mainly focus on volatility. As crypto assets started to be traded in mutual funds in 2017, the interest in cryptocurrencies increased globally, prompting investors to invest in these new financial assets. However, the hacking of Coincheck and the massive attack on Coinrail caused the price increase in cryptocurrencies to no longer be sustained, resulting in severe losses in the crypto market in 2018. Then, in mid-2020, there was another rise in crypto assets, and the market started to decline again after the historical peaks in 2021. When the price movements of crypto assets in the past five years are examined, high volatility in the market can be observed. This extreme volatility in the crypto-asset market has attracted the attention of many researchers. While the results of some studies highlight the dangers of investing in crypto assets due to their high price volatility (Chkili, 2021; Ghorbel and Jeribi, 2021; Szetela et al., 2021; Demir et al., 2020; Omane-Adjepong et al., 2019), other studies have shown that Bitcoin and some cryptocurrencies can be effective diversifiers in portfolios for hedging due to their weak correlation with stocks (Shahzad et al., 2020; Kliberet al., 2019; Mokni et al., 2020; Bouri et al., 2017; Stensås et al., 2019). Current studies also indicate that, similar to commodities, Bitcoin can be a safe haven and a good diversifier against shocks in the face of economic and geopolitical uncertainties (Selmi et al., 2018; Wang et al., 2019; Wu et al., 2019; Urquhart and Zhang, 2019; Al-Yahyaee et al., 2019; Gronwald, 2019; Shahzad et al., 2020; Su et al., 2020; Li et al., 2021) although there are studies contradictory to this determination (Klein et al., 2018; Al Mamun et al., 2020; Das et al., 2020).

Existing studies have considered Bitcoin as a potential investment tool, similar to conventional investment tools. Although there is no complete consensus in the studies, it is stated that Bitcoin is both a good diversifier and an investment tool that reduces risks. Although Bitcoin prices have been mainly discussed and included in the analysis, the fact that the crypto asset market has reached significant levels in terms of both volume and number of assets has reduced the representation power of Bitcoin in the crypto market. In addition, although there is well-established literature examining Bitcoin's hedge and haven features, there is no detailed study investigating the interaction of crypto assets with conventional investment instruments in general. Identifying other investment instruments related to cryptocurrencies is important to protect investors from risk and help them make the right investment decisions. Therefore, it is essential to comprehensively evaluate cryptocurrencies' potential risks and advantages as well as revealing their link with conventional investment instruments.

This article attempts to bridge this gap by exploring the interaction between cryptocurrencies and conventional investment instruments. Uncovering this link will be helpful for portfolio management and hedging decisions and provide new perspectives on global finance. For this purpose, different than the existing studies, the cryptocurrency index representing all cryptocurrencies was used rather than only Bitcoin to represent the crypto market. The causal relationship was examined between the cryptocurrency index and international stocks, bonds, the US dollar (index), gold, and commodities. In this context, the study's main contribution to the literature is that it is one of the first to explore the relationship between the cryptocurrency index and conventional investment instruments. The remainder of the article is organized as follows. Chapter 2 describes the Data and Methodology, Chapter 3 discusses the Empirical Analysis, Chapter 4 is about Findings and Discussion and Chapter 5 includes Conclusion and Further Research Directions.

II. Data and Methodology

The data set used in this research consist of S&P Cryptocurrency Broad Digital Market Index, MSCI ACWI Index, US Dollar Index, S&P GSCI Commodity Index, PIMCO Global Bond Opportunities Fund, and gold ounce price variables. The data were obtained from the Eikon Thomson Reuters database at a daily frequency within the period of 28.02.2017-18.01.2022. Existing studies in the literature investigating the relationship among Bitcoin and key asset classes in the global financial system were taken into account in the selection of these financial assets (Baur et al., 2017; Bouri et al., 2017; Umar et al., 2021; Zhang and He, 2021).

To examine international stock markets, unlike some studies in the literature, a global stock index was taken into account (Munyas and Atasoy, 2021; Li et al., 2021; Ünvan, 2021; Wang et al., 2021). Due to the interest of investors in crypto assets, especially in emerging markets and economies, as well as developed countries, the trading volume has, in some cases, become comparable to the trading volumes in local stock markets (International Monetary Fund, 2021). This situation strengthens the possibility of any investor to have cryptocurrency in his portfolio along with the stocks traded in his local stock market. Previous studies have emphasized that Bitcoin and some cryptocurrencies are effective diversifiers in hedging portfolios for investors. Therefore, determining the relationship between global stock markets and cryptocurrencies is vital for investors and policymakers.

Commodities are one of the important asset classes in the global financial system and are used as investment vehicles. Cryptocurrency mining plays a vital role in the survival of crypto assets. For mining activities to continue, energy (hence commodities) is required and thus represents the primary input (Ji et al., 2018; Li and Wang, 2017). In addition, metals (aluminum, nickel, etc.) are used extensively in producing hardware used in cryptocurrency mining. Therefore, the relationship between crypto-assets and commodities is not limited to portfolio diversification and hedging. Because of this reason, since this relationship of commodities with crypto assets is frequently used in current studies, the commodity index is included in the data set (Rehman and Kang, 2021; Lin and An, 2021; Erdaş and Çağlar, 2018; Hayes, 2018).

In recent years, it has been thought that Bitcoin and some stable coins (Tether, USD coin, Binance USD, etc.) can be alternatives to the main currencies that have global validity, such as the US dollar. Some cryptocurrencies (Bitcoin, Ethereum, Solana, chainlink, etc.) have created ecosystems and an alternative economy to the current economic system (Bouri et al., 2017). Therefore, if some investors lose confidence in economies or significant currencies, they may turn to Bitcoin and cryptocurrencies. Because of this feature, Bitcoin is sometimes called as the digital gold (Popper, 2015). In this context, Dyhrberg (2015) stated that Bitcoin could protect United Kingdom (UK) stocks and the US dollar. Therefore, the focus is on the US Dollar Index, which is at the center of today's financial system (Palazzi et al., 2021; Yu et al., 2021; Bekiros et al., 2021; Duan et al., 2021).

Gold is a good portfolio diversifier and an effective hedging investment tool in environments where global risks increase. Some studies define Bitcoin as the digital gold in terms of its features and compare it with the investment characteristics of gold. Therefore, gold prices are included in the analysis separately from the commodity index (Taskinsoy, 2021; Le et al., 2021; Selmi et al., 2022; Baur and Hoang, 2021; Zhu et al., 2017).

Bonds are assets that investors frequently use for portfolio diversification and risk reduction. It is important to examine the relationship between these assets issued by the sovereign authorities and cryptocurrencies, a new asset class independent of the sovereign authorities so that investors can make the right investment decisions (Elsayde et al., 2022; Briere et al., 2015; Huang et al., 2021). For this purpose, the bond index representing the global bond market is also included in the data set.

Dickey and Fuller (1979) Test

In this section, Dickey and Fuller's (1979) unit root test is briefly mentioned because of examining the stationarity of the variables examined first. Afterward, cointegration and Granger causality tests are included. In the test introduced by Dickey and Fuller (1979), the presence of a unit root is determined in the series. The existence of the unit root in the formation processes of the time series is tested under the null hypothesis.

$$Y_t = \rho Y_{t-1} + \varepsilon_t \tag{1}$$

Since the test statistic $\left(\tau = \frac{\hat{\rho}-1}{se(\hat{\rho})}\right)$ calculated under the first-order autoregressive process H_0 hypothesis $(H_0: \rho = 1)$ does not fit the standard t-distribution, it is decided by comparing it with the τ table. If the test statistic is less than the critical value, the H_0 hypothesis is rejected. The H_0 hypothesis states that the studied series are stationary and do not contain a unit root. In this test, the least squares estimators lose their efficiency in case of autocorrelation between the error terms. Therefore, it is recommended to use the Extended Dickey-Fuller test (ADF) in this case.

$$\Delta Y_t = \rho Y_{t-1} + \sum_{i=1}^{k} \beta_i \Delta Y_{t-i}\, \varepsilon_t \tag{2}$$

The decision stage proceeds in the ADF test as in the DF test. Various information criteria are used to determine the optimum number of delays to be included in the equation (Dickey and Fuller, 1979).

PP(1988) Test

In this test, which uses non-parametric statistical methods without adding the autocorrelation delayed values in the error term, new assumptions are added to the error term. With the addition of constant or constant and deterministic components (X_t) that express the trend, it expresses $\alpha = \rho - 1$.

$$\Delta Y_t = \alpha Y_{t-1} + X_t'\delta + \varepsilon_t \tag{3}$$

Test statistic obtained as a result of non-parametric corrections $\left(\hat{t}_\alpha = t_\alpha \left(\frac{\gamma_0}{f_0}\right)^{-1/2} - \frac{T(f_0-\gamma_0)(s_e(\hat{\alpha}))}{\alpha f_0^{1/2} s}\right)$ tests the existence of unit root ($H_0: \alpha = 0$) under the H_0 hypothesis by comparing it with Mackinnon critical values. The f_0 estimation can be made with the AR Spectral Density Estimation Method (Phillips & Perron, 1988).

Johansen Cointegration Test

Tests are divided into two to test whether there is a cointegration relationship between time series variables. First, we proceed over the residuals obtained from the cointegration regression equation. The second is testing based on vector autoregression. Johansen's cointegration method (1988) is based on vector autoregression and it is superior to residue-based tests (Baharumshah and Rashid, 1999) since it allows the estimation of more than one cointegrating vector and does not look for the weak externality condition of the variables. At the same time, all examined variables are accepted as endogenous and resistant to estimation deviations (Song and Witt, 2000; Önel, 2004). In order to use the Johansen cointegration test, the time series must be stationary at the first difference.

$$X_t = b_1 + b_2 Y_t + \mu_t \tag{4}$$

$$\mu_t = X_t - b_1 - b_2 Y_t \tag{5}$$

In the cointegration analysis, if two variables, such as X_t and Y_t, that are not stationary at level ($I(0)$) are stationary at any $I(d)$ point, their linear combination can be stationary (Gujarati, 2009:726).

Granger Causality Test

In the test in which the definition of *"If the prediction of variable Y is more successful when the past values of X are used than when the past values of X are not used, then X is the Granger cause of Y"* is tested, causality inference is made, not prediction. Therefore, the variables should be stationary beforehand. The causality test examines the direction of this relationship if there is a relationship between two variables (Granger, 1988:554).

$$Y_t = \sum_{j=1}^{m} c_j X_{t-j} + \sum_{j=1}^{m} d_j Y_{t-j} + \varepsilon_{1t} \tag{6}$$

$$X_t = \sum_{j=1}^{m} \alpha_j Y_{t-j} + \sum_{j=1}^{m} \beta_j X_{t-j} + \varepsilon_{2t} \tag{7}$$

Here, m represents the delay length and the error terms ε_{1t} and ε_{2t} are independent of each other (white noise). The causality relationship from X to Y in equation 6 and from Y to X in equation 7 is examined. In the Granger causality analysis, which is performed by determining the optimal lag length with the help of information criteria, the sum of the error squares of the models is obtained after the models are estimated. Afterward, the F-statistic developed by Wald is calculated. However, if there are more than two variables, it is possible to examine the extent of the relationship between them by applying the Blok Granger causality test. Employing the block Granger causality test, it is possible to examine whether a lagged variable is the Granger cause of other variables in the system.

III. Empirical Analysis

The analyses were carried out through the Eviews program. The definitions and abbreviations of the variables used in the analysis are provided in Table 1.

Table 1: Variable Definitions

Variables	Definition	Abbreviation
MSCI All	Country World Equity Index	LALL
Gold Price	Gold Price Per Ounce	LGOLD
S&P GSCI	GSCI Commodity Index	LCOMMODITY
S&P Cryptocurrency	Cryptocurrency Broad Digital Market Index	LCRYPTO
PIMCO	Global Bond Opportunities Fund	LBOND
US DOLLAR	US Dollar Index	LDOLLAR

Source: Authors' own compilation

Descriptive statistics of the variables with logarithmic transformation are provided in Table 2.

Table 2: Descriptive Statistics

Variables / Statistics	LALL	LGOLD	LCOMMODITY	LCRYPTO	LBOND	LDOLLAR
Mean	6.308787	7.306769	7.750423	6.806084	2.224338	4.553383
Median	6.255566	7.283771	7.795930	6.589655	2.226783	4.555297
Maximum	6.631823	7.626814	8.005596	8.734880	2.284421	4.632980
Minimum	5.950742	7.072558	7.130299	4.592490	2.065596	4.484019
Std. Dev.	0.154010	0.164948	0.168902	0.943528	0.036154	0.031734
Skewness	0.760636	0.243921	-1.259312	0.331338	-0.682822	-0.091366
Kurtosis	2.440374	1.441044	4.039260	2.698957	3.808145	2.157403

Source: Eviews Software Output

In order to investigate the cointegration relationship between the variables, unit root tests were applied and the stationarities of the variables were determined. The results are shown in Table 3.

Table 3: Unit Root Tests Results

Test	ADF (Constant & Trend)			PP (Constant & Trend)		
	%1	%5	%10	%1	%5	%10
Variable	-3.96	-3.41	-3.12	-3.96	-3.41	-3.12
LALL		-2.341543			-2.264662	
ΔLALL		-10.49584			-32.9560	
LGOLD		-2.136596			-2.051040	
ΔLGOLD		-34.58514			-43.9351	
LDOLLAR		-2.314348			2.239938	
ΔLDOLLAR		-34.29524			-38.2741	
LCOMMODITY		-1.154045			-1.169184	
ΔLCOMMODITY		-35.75003			-41.3134	
LBOND		-2.104944			-1.860241	
ΔLBOND		-19.43819			-53.0612	
LCRYPTO		-1.762923			-1.942369	
ΔLCRYPTO		-35.77465			-47.2059	

Note: The Schwarz information criterion for optimal delay length was used in the ADF test, and the Newey-West Bandwith criterion was used to determine the bandwidth for the PP test.

Source: Eviews Software Output

According to the unit root test results, the series was not stationary at level but became stationary when the first difference was taken. Since the series are stationary in the same order, their relationship is tested with the Johansen cointegration method. However, the cointegration method includes the vector autoregression model (VAR) approach, which shows that each variable in an econometric model developed by Sims (1980) is affected both by itself and the lagged values of other variables. Therefore, it is necessary to determine the optimal lag length for the unconstrained VAR model.

Table 4: Determining the Optimal Lag Length

Lag	LogL	LR	FPE	AIC	SC	HQ
0	8922.814	NA	2.75e-14	-14.19875	-14.17421	-14.18953
1	25541.77	33052.66	9.35e-26	-40.60472	-40.43299*	-40.54018
2	25643.54	201.4459	8.42e-26	-40.70946	-40.39053	-40.58959*
3	25692.58	96.58427	8.25e-26	-40.73022	-40.26408	-40.55502
4	25760.69	133.5115	7.84e-26	-40.78135	-40.16801	-40.55083

Source: Eviews Software Output

In the estimated var model, the optimal lag length was determined as 1 according to the Schwarz information criterion. As a result of testing the validity of the established VAR model, it has been determined that the residuals are normally distributed and have zero mean and constant variance *(N.i.i.d)*. The presence of cointegration vector among the variables have been examined by the Johansen cointegration test and the results are presented in Table 5.

Table 5: Johansen Cointegration Test Results

Cointegration Test by Trace Statistics				
Hypotheses	Eigenvalue	Trace Statistics	5% Critical Value	Probability
$r = 0$*	0.041466	134.6678	103.8473	0.0001
$r \leq 1$*	0.023464	81.26353	76.97277	0.0227
Cointegration Test According to Maximum Eigen Value Statistics				
Hypotheses	Eigenvalue	Maximum Eigenvalue Statistics	5% Critical Value	Probability
$r = 0$*	0.041466	53.40423	40.95680	0.0013
$r \leq 1$	0.023464	29.94140	34.80587	0.1699

Source: Eviews Software Output

$$LCRYPTO_t = \alpha_1 + \sum_{p=1}^{k} \beta_{1p} LBOND_{t-p} + \sum_{p=1}^{k} \beta_{2p} LCOMMODITY_{t-p} + \sum_{p=1}^{k} \beta_{3p} LDOLLAR_{t-p} + \sum_{p=1}^{k} \beta_{4p} LGOLD_{t-p} + \sum_{p=1}^{k} \beta_{5p} LALL_{t-p}$$

When Table 5 is examined, the Trace statistic and the Maximum Eigen Value test statistic values calculated from the Johansen cointegration test were more significant than the critical value at the 5% significance level. It has been seen that there is one cointegration vector according to the trace statistics and two according to the maximum eigenvalue statistics. Therefore, by looking at the results obtained with the Johansen cointegration test, it is possible to say that the examined series affect each other in the short term. As a result of detecting a cointegrated relationship between the variables in the short run, it was determined that causality analysis could be performed. The results of the block Granger causality analysis estimated by the unit root tests are provided in Table 6.

Table 6: Block Granger Causality Analysis Results

Statistic Dependent Variable	*df*	X^2-Statistics	*p*-value
CRYPTO			
BOND	1	7.712696	0.0211*
COMMODITY	1	1.426198	0.4901
DOLLAR	1	3.929096	0.1402
GOLD	1	3.486197	0.1750
ALL	1	3.80257	0.2162
General	5	39.96452	0.0000*
ALL			
GOLD	1	0.282568	0.5950
DOLLAR	1	0.431831	0.5111
BOND	1	0.288643	0.5911
CRYPTO	1	4.565227	0.0326*
COMMODITY	1	0.163458	0.6860
General	5	10.40620	0.0645
GOLD			
ALL	1	2.992686	0.0836
DOLLAR	1	0.111073	0.7389
BOND	1	8.282855	0.0040*
CRYPTO	1	1.810546	0.1784
COMMODITY	1	2.588756	0.1076
General	5	18.82826	0.0021*
DOLLAR			
ALL	1	1.535483	0.2153
GOLD	1	4.142111	0.0418*
BOND	1	9.270013	0.0023*
CRYPTO	1	1.364380	0.2428
COMMODITY	1	5.992115	0.0144*
General	5	17.13345	0.0043
BOND			
ALL	1	11.83678	0.0006*
GOLD	1	0.043544	0.8347
DOLLAR	1	0.989600	0.3198
CRYPTO	1	16.93327	0.0000*
COMMODITY	1	0.389037	0.5328
General	5	26.11562	0.0001
COMMODITY			
ALL	1	4.690762	0.0303*
GOLD	1	5.819948	0.0158*
DOLLAR	1	0.974276	0.3236
BOND	1	12.71132	0.0004*
CRYPTO	1	0.170517	0.6797
General	5	17.82555	0.0032*

Note: *p<0.05

Source: Eviews Software Output

The VEC block causality test was performed as a result of determining the short-term cointegration relationship among the variables, All the results are provided in Table 6. Only the results of the trial of the crypto index and other dependent variables as the dependent variable are discussed for the research.

$$\Delta LCRYPTO_t = \alpha_1 + \sum_{p=1}^{k} \beta_{1p} \Delta LBOND_{t-p} + \sum_{p=1}^{k} \beta_{2p} \Delta LCOMMODITY_{t-p} + \sum_{p=1}^{k} \beta_{3p} \Delta LDOLLAR_{t-p} + \sum_{p=1}^{k} \beta_{4p} \Delta LGOLD_{t-p} + \sum_{p=1}^{k} \beta_{5p} \Delta LALL_{t-p} + \varepsilon_{1t}$$

Looking at the equation where the dependent variable is the crypto index, it is seen that there is a two-way causality from the bond to the crypto index and one-way causality to MSCI All World Index. In addition, when the independent variables are examined whether they are the cause of the crypto index in blocks (collectively), it is possible to state that bonds, commodities, MSCI All World Index, dollar, and gold are the Granger reasons for the crypto index.

IV. Findings and Discussion

The findings obtained while examining the relationship between the cryptocurrency market and conventional investment assets make it possible to draw general conclusions on the subject. First, the empirical results show a causal relationship between the conventional investment instruments (stock market, bond, commodity, gold, dollar) and the cryptocurrency market. This finding proves that cryptocurrencies are not entirely isolated from conventional investment instruments. This result parallels some studies in the literature (Kang et al., 2020; Briere et al., 2015). In existing studies, it is still debated whether cryptocurrencies are a new generation of financial instruments. While Zang and He (2021) argue that Bitcoin cannot be accepted as a new financial product, some studies support that Bitcoin and cryptocurrencies are alternative investment tools to conventional assets (Dynberg, 2016a; Dynberg, 2016b). Due to the fact that cryptocurrency markets interact with conventional asset markets and the movements in conventional investment instruments affect the cryptocurrency markets, findings of this research also support the idea that cryptocurrencies are an alternative investment tool for investors.

Secondly, our empirical results have determined a causal relationship between cryptocurrency markets and MSCI ACWI Index. The result obtained reveals the interaction between the cryptocurrency market and stock markets. In addition, these findings are compatible with existing studies in the literature (Vardar and Aydoğan, 2019; Mizerka et al., 2020; de Senna and Souza, 2022; Panagiotidis et al., 2019). In addition, various studies in the literature investigate the causal relationship between some cryptocurrencies and conventional stock markets. In a study conducted by Xunfa et al. (2020), a Granger causality relationship could not be determined among the 30 cryptocurrencies they included in the data set and the emerging stock markets. This relationship was also tested with Liang's causality analysis in the same study and a one-way relationship from the cryptocurrency market to the emerging stock markets was found in the short-term. Various studies in the literature examine the relationship between Bitcoin and conventional stock markets. In the study by Maghyereh and Abdoh (2021), a causal relationship between Bitcoin and MSCI ACWI Index was determined. In the study conducted by Unvan (2021), the causality relationship between Bitcoin and the stock markets of Japan, China, Turkey, and the USA was examined and a two-way causality relationship was determined only with the Turkish stock markets.

The study also revealed a bidirectional causality between the PIMCO Global Bond index and the cryptocurrency market. There are studies in the literature that support our findings (Nunes, 2017; Milunovich, 2018; Oktar & Salihoğlu, 2018; Vardar & Aydoğan, 2019). Since the bond markets are one of the leading indicators of the direction of the global conjuncture for investors, this finding might help to shape investors' investment strategies, especially during economic and political uncertainty times (Papadamou et al., 2021).

V. Conclusion and Further Research Directions

This article explored the relationship between the cryptocurrency market and conventional investment instruments. The scarce literature on the subject constitutes the motivation of this study. Research seeks to bridge this gap by exploring the interaction between the cryptocurrency market and conventional investment instruments. For this purpose, the Granger causality test was applied to explore the relationship among S&P Cryptocurrency Broad Digital Market Index, MSCI ACWI Index, US Dollar Index, S&P GSCI Commodity Index, PIMCO Global Bond Opportunities Fund, and gold ounce price variables at a daily frequency within the period 28.02.2017-18.01.2021. According to the results obtained, one-way Granger causality has been observed from all the variables that make up the data set to the cryptocurrency index. In addition, a one-way causality relationship has been determined between the MSCI ACWI Index and the cryptocurrency index. The most striking result of research analysis is the bidirectional causality between the PIMCO Global Bond Opportunities Fund, which represents the global bond market, and the S&P Cryptocurrency Broad Digital Market Index. The changes in the bond markets give investors important signals about the global economy's direction. Since bond markets are deep and calm by nature, it is possible to analyze sudden changes in global economic conditions through bond markets. Therefore, the bidirectional causality relationship between cryptocurrency markets and bond markets should be addressed in this direction.

The environment of uncertainty created by the recent Covid-19 pandemic has affected both the cryptocurrencies and the conventional markets. Especially in this period, the monetary support of governments to their citizens determined the direction of conventional assets and cryptocurrency markets. The governments' monetary expansion policies of 13 trillion dollars in the mentioned period enabled the market value of cryptocurrencies to reach approximately 3 trillion dollars (Nasdaq, 2022; Coinmarketcap, 2022). In the post-Covid period, the inflationary environment that is expected to be experienced on a global scale has increased investors' search for a safe haven. This situation has significantly affected the cryptocurrency market and conventional asset markets. With these expectations, exits from the cryptocurrency markets started, and the market value decreased to 1.3 trillion dollars (Coinmarketcap, 2022). Therefore, it would not be a mistake to comment that cryptocurrency markets have become an alternative market for investors, similar to conventional asset markets.

In future studies on this subject, while examining the relations between the cryptocurrency market and conventional asset markets, they can differentiate according to the level of development of countries and economic regions (BRICS, MENAT, European Union, etc.). In addition, new studies can focus on variables that measure global uncertainty. Further research can be conducted by using different statistical techniques since a significant relationship was found among the variables.

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