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Yazar/Author

Gönül ÇİFÇİ *

Makale Adı/Article Name

Triangle of Cryptocurrency, Stock, and Gold Markets

Kripto Para, Pay ve Altın Piyasaları Üçgeni

ABSTRACT

This study aims to understand the relationship among cryptocurrency, stock, and gold markets. Cointegration, structured VAR, and causality tests were used with daily datasets from 11/09/2017 to 11/17/2023. A cryptocurrency basket is accepted as the cryptocurrency market for this study. The stock markets have a one-way relationship both with the gold and cryptocurrency markets in the short-run. All markets have effects on other markets' price variances, as well. The price shocks of the markets to each other are not so essential for the prices. However, their own price shocks impact their prices for a few days. The stock market has asymmetric relationships with the gold and cryptocurrency markets. A 1.00 % rise in stock price causes declines in the gold and cryptocurrency prices by 2.35% and 2.42%, respectively. If the gold market or stock market is ignored, a 1.00% rise in gold prices causes a 0.69% rise in cryptocurrency prices, or a 1.00% rise in stock prices raises the cryptocurrency prices by 4.03%.

Keywords: Cryptocurrency, Stock Market, Gold Market, Hedging, Portfolio Management

ÖZ

Bu çalışma, kripto para, hisse senedi ve altın piyasaları arasındaki ilişkiyi anlamayı amaçlamaktadır. 09/11/2017-17/11/2023 tarihleri arasındaki günlük veri seti ile eşbütünleşme, yapılandırılmış VAR ve nedensellik testleri kullanılmıştır. Bu çalışma için kripto para piyasası olarak bir kripto para sepeti kabul edilmiştir. Pay piyasalarının kısa vadede hem altın piyasası hem de kripto para piyasası ile tek yönlü ilişkisi vardır. Tüm piyasaların diğer piyasaların fiyat varyansları üzerinde de etkileri vardır. Piyasaların birbirlerine olan fiyat şokları fiyatlar için o kadar da önemli değildir. Ancak, kendi fiyat şokları ilgili değişkenin fiyatlarını birkaç gün etkiler. Borsa, altın piyasası ve kripto para piyasası ile asimetrik bir ilişkiye sahiptir. Pay fiyatında %1.00' lik bir artış, altın ve kripto para fiyatlarında sırasıyla %2,35 ve %2,42 oranında düşüşe neden olur. Altın veya borsa göz ardı edilirse, altın fiyatlarındaki %1,00' lik artış, kripto para fiyatlarında %0.69'luk bir düşüşe neden olur veya hisse senedi fiyatlarındaki %1,00' lik artış, kripto para fiyatlarını %4, 03 oranında düşürür.

Anahtar Kelimeler: Kripto Para, Pay Piyasası, Altın Piyasası, Riskten Kaçınma, Portföy Yönetimi

* Dr. Arş. Gör., Adıyaman Universitesi, İİBF, İşletme Bölümü, cifcigonul@gmail.com

Introduction

Cryptocurrencies (CCs) have continued their popularity since their first appearance with Bitcoin. Besides being new kinds of currencies, CCs are new investment classes. They established a new kind of financial market (Corbet et al., 2018). Despite CCs having risky structures and being blamed for money laundering and speculations, they are popular investment tools, especially in frontier and emerging markets. Moreover, they are accepted as new gold. Structural or functional similarities should exist to speak about the likeness of two things. According to Klein et al. (2018), CCs and gold have different structures; therefore, CCs cannot be new gold. There is no common sense if CCs' functions are the same as gold's. Maybe, the most important functions of gold markets (GMs) for stock markets (SMs) are their hedging and risk diversifying abilities. The SM and GM have an asymmetric relation which impacts prices and volatility of SMs both in the short (Yamaka, 2024) and long-run (Özer et al., 2011). That is a good chance for portfolio management because asymmetric movements of financial instruments provide risk elimination and hedging opportunities. Those functions make GMs safe havens of financial markets. At the same time, Velip et al. (2023) concluded that GMs' hedging abilities are not stable. The GMs could hedge the SMs' risks during early periods of the Russia-Ukraine war and diversify the shocks in the long-run on the three European markets (French, German, and Italian markets). Also, domination of a sector may impact that relation according to Chen and Wang (2019). If a sector has high-yield volatility, the hedging possibility would decrease, whereas it increases in low-yield volatility sectors. Based on those results, the GM & SM nexus is not stable and an alternative financial instrument & market seem necessary to avoid market risks. CCs might be used for that purpose, but different voices arise about the functions of CCs.

Most previous studies, such as Stensås et al. (2019), Şenol et al. (2022), Öğet (2023), and Ha (2023), have reported various interactions of SMs and CCs. Gambarelli et al. (2023) reasoned those conflicting conclusions with possible effects of using a single CC instead of a CC portfolio, besides micro-structures of financial markets and macroeconomic factors. A CC portfolio would be better for hedging and risk diversification compared to a single CC. All previous studies focused on a single CC. There is a gap in how a CC portfolio and SM are related to each other. Another gap is about the relationship of the GM and the CC portfolio. That possible relationship hasn't been investigated by existing studies. This study aims to fill those two gaps. Also, the SM and GM relationship is examined on the Borsa Istanbul (BIST). The reason behind focusing on Turkish markets is the high interest of the country in the CCs. According to Statista (2024) reports, Nigeria and Türkiye are at the top of countries where the CCs had been most traded (or owned) in Worldwide between years of 2019 and 2023. Investors' risk perceptions are able to impact the investments in the CCs in Türkiye (Çifçi, 2025). The main motivation of the investors of CCs is high future expectations to gain (Garda and Şahin, 2025). The Turkish investors are also likely to invest in gold markets and, as a macroeconomic factor, the gold price is an influential factor in Turkish markets (Gemici et al., 2023).

This study provides a comprehensive empirical analysis of the interactions of the markets. The assumptions of this study point to positive co-movement of the CCs & GM and asymmetric relationships of the SM with the GM and CCs. The empirical evidences showed there are some cointegration and causality relationships between the markets. An indirect effect exists between the CCs & GM prices and direct effects between the CCs & SM and the SM & GM prices. Each market causes volatility in the prices of the other two markets. However, those effects are limited and disperse in a few days. The most important factor over a market price is its own shocks. Those shocks cause positive effects on the markets except the SM.

Based on the literature review, this study is the first article that investigates the market relations with a CC portfolio, clarifies the relationships of those three markets for the prices, and points to an alternative investment strategy. This study will be able to inspire future studies because it provides deep insights into the market relations. The results explain how price shocks can impact the other markets, how prices would change, and which market can be used for hedging and risk diversification. Portfolio managers can create optimum portfolios by following those results. Thus, the results of this study are important for the investors and portfolio managers, as well.

The following part of this study starts with 1.1 which is the literature review subsection. Section II is methodology. In that section, data, sample, and econometric model are explained. Section III is the analysis which stands for data analysis and the econometric tests' results. Section IV is the discussion section. The discussion section summarizes results and their contributions to previous studies. Section V is the conclusions.

1. Literature Review

The existing studies have concentrated hedging and diversifying abilities of CCs and have come to conditional results. The financial markets' micro-structures, macroeconomic factors, or time duration may impact the hedging and/or diversifying ability of CCs. Klein et al. (2018) and Gambarelli et al. (2023) concluded that Bitcoin and the markets have a negative relationship in the short-run. Therefore, Bitcoin is a safe haven for the markets, but that conclusion is not common for all CCs. Junior et al. (2020) found that most of the CCs can be used for hedging of price risk of gold, vice versa. However, Ethereum can't be used for hedging. Stensås et al. (2019) mentioned that Bitcoin is an effective risk diversifier in the developed markets, regional indexes and regional commodities, but those effects are less in most of the developing markets. Telek and Şit (2020) found that Bitcoin and gold prices positively cointegrate in Turkish markets. A 1% rise in gold price causes a 15% rise in Bitcoin price. However, that relation is not stable. The market conditions and shocks may affect CCs' connections with SMs and GMs.

SMs and CCs have a mutual relationship. Koy et al. (2021) explained how SMs cause volatility over CCs and Şenol et al. (2022) showed that the effect reached the top level during Covid-19 pandemic. The S&P 500, Etherium, and Bitcoin spread volatility to Shanghai, BIST, DAX, Litecoin, and Ripple.

The market shocks of gold differentiate Bitcoin while they move together and asymmetrically react to market shocks in normal times (Klein et al., 2018). The relationship of CC markets, GMs, and SMs can be attractive for investors during uncertain periods due to the opportunity of portfolio diversification and hedging (Junior et al., 2020; Öget, 2023). González et al. (2021) found that CCs could be used to hedge GMs' risks because they have an asymmetric and intense relationship with gold returns both for the short and long-run during the Covid-19 pandemic. CCs have an asymmetric cointegration and causality relationship with gold returns during the pandemic. The causality test concluded no any causality from CC to GMs, from GMs to both CC and SMs, and from SM to CC markets. However, Caferra and Vidal-Tomás (2021) mentioned that Covid-19 caused panic in markets for a short-period. Meanwhile that market shock, the intensity of the cointegration relationship of CCs, SMs, and GMs helped the SMs for fast recovery. Almost all markets have different connections with the CCs; the SMs lead their relationship with CCs. According to Öget (2023), the US markets (such as the S&P 500 index) are the more powerful and positive markets for Bitcoin compared to the Eurozone and Asian markets. On the other hand, Sami and Abdallah (2021) showed that SM-returns inversely move with CC-returns in MENA countries. Gökalp (2022) demonstrated a positive spillover effect of Bitcoin, Ethereum, and Ripple to BIST indexes (BIST 30, BIST 100, and XBANK). That difference may be explained by the highly volatile nature of Bitcoin and market liquidity (Stensås et al., 2019), negative and positive shocks (Koy et al., 2021; Wang et al., 2022), or uncertainty of the market. Öget (2023) showed how the relation changes with the pandemic. SPX and DAX indexes used to negatively affect the Bitcoin return volatility before the pandemic, but DAX's effect disappeared with the appearance of Covid-19 effects on the markets. Interestingly, CAC 40, FTSE MIB, NIKKEI 225, and TSX Composite indexes started to impact the return volatility of Bitcoin with the pandemic. The CCs can explain the volatility of the SMs with the impact of Covid-19 is the most severe at the beginning of 2020 (Ha, 2023). The cointegration of Bitcoin and Ethereum with market indexes (FTSE BIVA Real Time Index, IDX Composite, KOSPI, and BIST100) continued in the pandemic period. However, only the IDX and KOSPI indexes move positively together with Bitcoin and Ethereum, respectively. Also, Covid-19 causes positive bi-directional causalities between FTSE and two CCs and BIST and Ethereum. The one-way positive causalities are from Bitcoin to IDX and BIST 100 indexes and from Ethereum to the KOSPI index (Toprak and Kubar, 2023).

Besides those results, Klein et al. (2018) showed Bitcoin's positive correlation with downward markets for the short-run, but its relationship with gold shows variety. Bitcoin reacts asymmetrically to the market shocks, like gold in normal times of SM. Price increases lead to an increase in volatility. However, during turmoil times in the markets, Bitcoin behaves completely different from Gold. Bitcoin moves together with SMs. Gambarelli et al. (2023) deduced that a CC portfolio is better than a single CC for hedging and diversification on the European SM (Eurostoxx 50 index) and GM. Bitcoin and Tether have an inverse nexus with the SM in bearish markets. Tether can be used for hedging and portfolio diversification in European markets. Bitcoin and Ethereum's correlations are so high with the SM. However, they have a negative return relationship in the short-run. Differently, CC portfolios and the market don't have any kind of relationship. The CC portfolios showed the highest diversification benefit. All of those results are valid for SMs of Germany, France, the Netherlands, Spain, and Italy, as well. The findings indicate that adding a single CC to a stock portfolio does not provide effective hedging during market downturns and can increase the risk of short-term joint losses. However, adding a mix of CCs to a stock portfolio might lead to some diversification benefits. Creating a portfolio which includes CCs is a better strategy for hedging in bearish markets. In the context of the GM and SM relationship, in panic periods like as economic crises, GM becomes more crucial (Öncü et al., 2015) due to hedging needs.

2. Methodology

A CC basket was created for the proxy of the CC market. That basket is composed of five CCs which are Bitcoin, Ethereum, Tether, BNB, and XRP. The trade volume shows that demand of markets for a financial instrument. A markets demand and maybe desire can be estimated with the trade volumes. Therefore, it is the only criteria for the CC selection. Tether and BNB are the youngest and Bitcoin is the oldest CC. That basket is the weighted average price of those five CCs. The weight was calculated as the ratio of each CC's trade volume to the total trade volume of all five CCs.

The BIST All Shares index was used as the proxy for SM. Mostly, the most liquid stock indexes were preferred to reflect the markets' conditions in existing studies. However, the BIST All

Shares can be better than other indexes to understand how the whole market reacts to or is connected with the other financial markets. Table 1 defines the variables and their data sources.

Table 1. Variables and Sources

Variable	**Definition**	**Data Frequency**	**Data Sources**
CC Price	Weighted average prices of Bitcoin, Ethereum,Tether, BNB, and XRP	Daily	yahoofinance.com
BISTAS Price	BIST All Shares price	Daily	investing.com
Gold Price	Gold price	Daily	borsaistanbul.com

Notes: *CC price* denotes for cryptocurrency basket prices, *BISTAS price* denotes Borsa Istanbul All Shares index prices, *Gold Price* is gold market prices.

The time span is from 11/09/2017 to 11/17/2023. The date range starts in 2017, based on the first traded date of the youngest CC in the basket. The dataset is in daily frequency and the CCs are traded every day of a year, whereas gold and stocks are traded from Monday to Friday in Türkiye. To reach common dates for all three variables, some observations were deleted from the dataset. Three observations were missed for the GM and the SM. The previous five trade days' arithmetic average was accepted as the day data for the missing observations. Also, BIST was shut down after the earthquake disaster between 02/09/2023 and 02/14/2023 in Türkiye. That week's data was omitted from the data set. After those processes, 1513 observations were gathered for analysis. Table 2 shows the descriptive statistics for the variables.

Table 2. Descriptive Statistics for Prices

	Gold Prices	**BISTAS Prices**	**CC Prices**
Observations	1513	1513	1513
Mean	600591.00	2432.10	6875.20
Median	451600.70	1464.60	6194.70
Maximum	1829278.00	9853.60	31507.00
Minimum	153525.40	847.70	1469.80
Std. Dev.	445155.80	2184.20	4085.70
Skewness	1.10	1.80	0.90
Kurtosis	3.20	5.30	3.70
Jarque-Bera	305.60	1160.30	217.40
Probability	0.00	0.00	0.00

Notes: *CC price* denotes for cryptocurrency basket prices, *BISTAS price* denotes Borsa Istanbul All Shares index prices, *Gold Price* is gold market prices.

Jarque-Bera probabilities are 0.00 for all variables, while all those variables don't show normal distributions. Skewness and Kurtosis results also support that result. The gold prices have the highest average (mean) with 600591, and the lowest average is in the stock prices with 2432.10. Similarly, the gold prices have the highest max. and min. values. Table 3 gives details about the variables' correlations.

Table 3. Correlations of Variables

	BISTAS Prices	**CC Prices**	**GM Prices**
BISTAS Prices	1.00		
CC Prices	0.33	1.00	
GM Prices	0.94*	0.43	1.00

Notes:* *shows high correlation under 95% significance level, CC price* denotes for cryptocurrency basket prices, *BISTAS price* denotes Borsa Istanbul All Shares index prices, *Gold Price* is gold prices.

According to Table 3, the correlations of the BIST All Shares Index (SM) & CC are 0.33 and CC & GM is 0.43. The only high correlation is between SM and GM with 0.94. Though multicollinearity doesn't affect the analysis, it was tested with the Variance Inflation Factor (VIF), and Table 4 shows the VIF results.

Table 4. Variance Inflation Factor Results

Variable	Coefficient Variance	Uncentered VIF	Centered VIF
C	0.02	344.87	NA
Gold Price	0.00	518.53	1.56
CC Price	0.00	290.18	1.56

Notes: Stock market is dependent and gold market and cryptocurrency market is independent variables in the model. *CC price* denotes for cryptocurrency basket prices, c is constant, Gold price is gold market prices, and VIF is variance inflation factor.

According to Table 4, centered VIF values of the variables are 1.56 (less than 5). The variables don't have multicollinearity problems. The high correlations of the variables don't affect the analysis. The moves of the variables may give a foresight into the characteristics of the variables. Figure 1 shows the price and return changes of the variables during the time span.

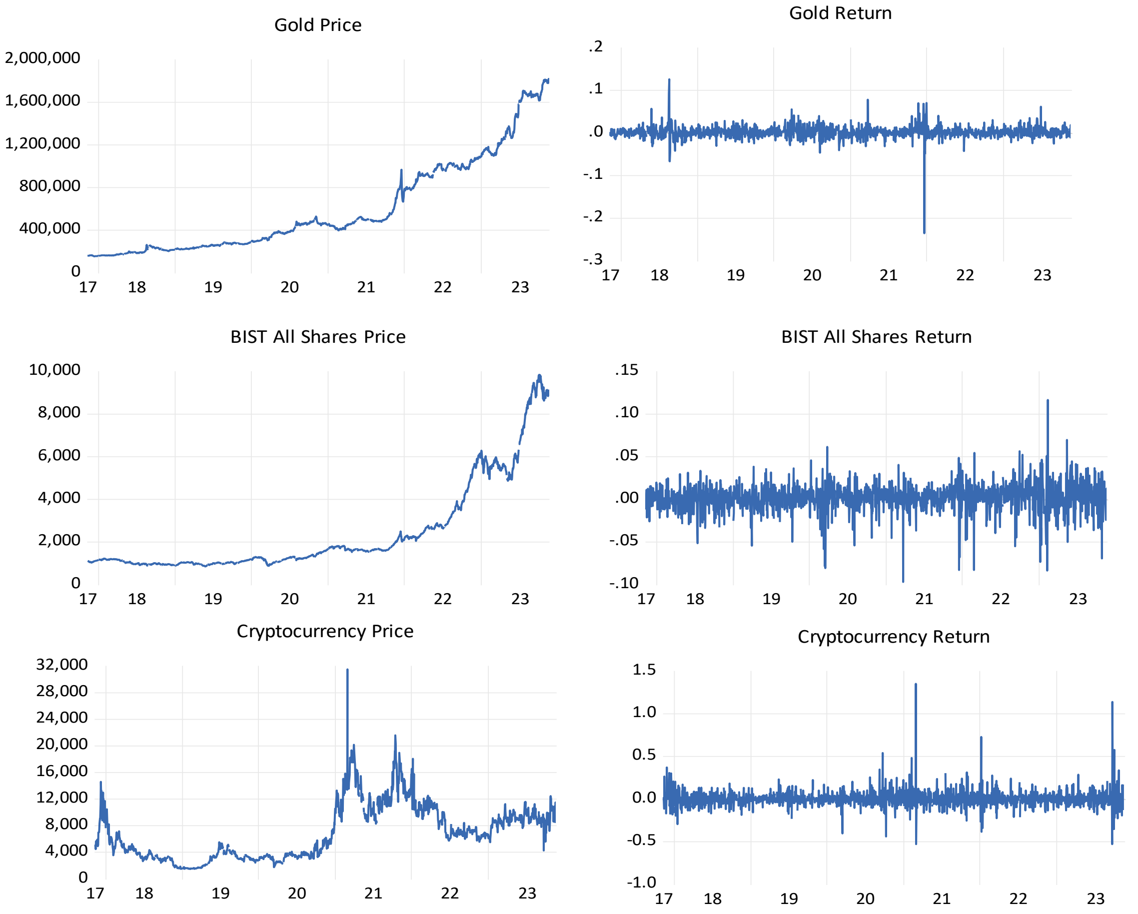

Figure 1. Price and Return Movements of the Variables

Source: The figures are generated by the author based on the dataset. The return calculated by $100*(P_t - P_{t-1})/ P_{t-1}$, where P_t is price on the day t and P_{t-1} is price on the day t-1 of the financial instrument.

Gold and stock prices have a non-linear rise and their movements look similar, but gold prices had been more dedicated uprising character. BIST All Shares prices bounced after 05/03/2023.

Compared to other trends, CC prices can be considered stable. In spite of CC prices having increased between years of 2017 and 2023, it is not as much as gold and stock prices. The CC prices have four peaks in that time span. The first is on 12/07/2017, the second and the most important is on 02/26/2021, the third is on 10/19/2021, and the fourth is on 01/07/2022. The CC prices reached 31,507 USD on 02/26/2021. The pandemic of Covid-19 was a good motivation for increasing prices in the markets. The returns of CC, stock, and gold move around zero. There are two important dates for GM investors. The investors could have 13% return on 08/14/2018, whereas they lost 24% on their investments on 12/22/2021. The CC and SM have volatile structures, but the SM is the most volatile series compared to the others. The investors of CC had high returns on 09/24/2020, 02/26/2021, 02/08/2021, 01/07/2022, and 09/22/2023 by 54%, 135%, 48%, 73%, and 114%, respectively. Also, there are some bad times of CC. For instance, the investors lost 53% of their returns on 03/01/2021 and 09/21/2023. The SM is the most volatile and it has a tendency to decrease the return.

3. Analysis

Based on existing studies, gold is known as a safe haven, which means investors can transfer their funds to GM if SM has some problems, vice versa. Therefore, the first assumption of this study is that the GM and CC markets should have an asymmetric connection with the SM. Similarly, an asymmetric connection is expected between the SM and CC market as the second assumption. The third assumption is the co-movement of the CC market and GM. GMs and CC markets may be an alternative to SMs. Depending on these three assumptions, the SM price would increase while gold and CC prices are decreasing, vice versa.

The expected relations for prices of the markets are represented in Figure 1 and formulated at eq.(1), eq.(2), and eq.(3), where SM_{pt} is the stock market price, GM_{pt} is the gold price, and CC_{pt} is the CCs basket price. x_{gt} is the gold price coefficient, x_{ct} is the CC price coefficient, and x_{st} is the stock price coefficient at time t in the equations.

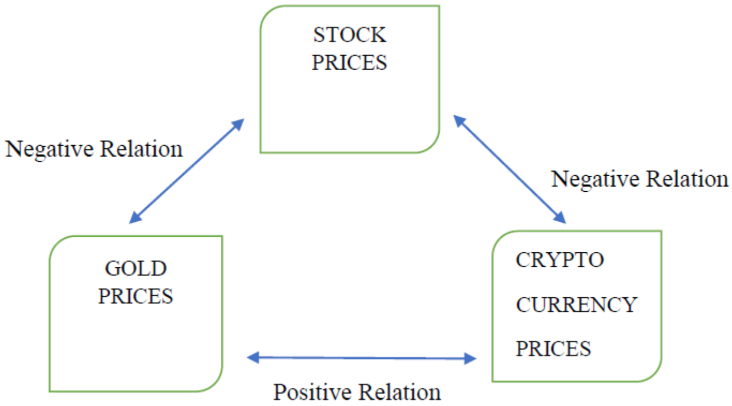

Figure 2. Relationships of the Markets

Notes: The figure was generated by the author.

$$SMpt = -xgt(GMpt) \quad \text{eq. (1)}$$

$$GMpt = xct(CCpt) \quad \text{eq. (2)}$$

$$CCpt = -xst(SMpt) \quad \text{eq. (3)}$$

The data was converted to natural log. before the tests.The effects of information in financial markets can impact the markets for the following few days. Therefore, the lags are generally between 2 to 5 days in finance and economic studies. However, to decide the optimum lag for this study was a VAR model was run. Table 5 represents the lag length selection results.

Table 5. Lag Length Selection

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-2861.78	NA	0.00	3.79	3.80	3.80
1	9679.23	25015.59	0.00	-12.80	-12.76	-12.79
2	9749.45	139.78	0.00	-12.88	-12.81*	-12.86
3	9778.00	56.73*	0.00*	-12.91*	-12.81	-12.87*

Notes: * indicates lag order selected by the criterion. LR: sequential modified LR test statistic (each test at 5% level). FPE is final prediction error, AIC is Akaike information criterion, SC is Schwarz information criterion, and HQ is Hannan-Quinn information criterion.

LR, FPE, AIC, and HQ selected lag as 3, and SC selected 2. Due to the domination of the lag selection, the lag length is accepted as 3 for this study. To understand the structure of the dataset and as the first part of the structural vector autoregression (SVAR), the series were examined for unit root with Augmented Dickey-Fuller (ADF, 1979) and Phillips-Perron (PP, 1988) unit root tests. The unit-root test results are in Table 6.

Table 6. Unit Root Tests

		ADF TEST					PP TEST	
		t-Stat.	**Prob.***	**1% level CV**	**5% level CV**	**10% level CV**	**t-Stat.**	**Prob.***
GOLD	*Level&Intercept*	0.31	0.98	-3.43	-2.86	-2.57	0.41	0.98
	Level&Trend and Intercept	-2.9	0.16	-3.96	-3.41	-3.13	-2.68	0.25
	First Difference & Intercept	-24.05	0.00*	-3.43	-2.86	-2.57	-33.14	0.00*
BISTAS	*Level&Intercept*	2.16	0.99	-3.43	-2.86	-2.57	2.07	0.99
	Level&Trend and Intercept	-1.2	0.91	-3.96	-3.41	-3.13	-1.22	0.9
	First Difference&Intercept	-38.42	0.00*	-3.43	-2.86	-2.57	-38.44	0.00*
CRYPTO CURRENCY	*Level&Intercept*	-1.79	0.39	-3.43	-2.86	-2.57	-2.1	0.24
	Level&Trend and Intercept	-2.6	0.28	-3.96	-3.41	-3.13	-2.99	0.14
	First Difference&Intercept	-36.41	0.00*	-3.43	-2.86	-2.57	-52.79	0.00*

Notes: * indicates the stationary. *CV* is critical value, *ADF* is Augmented Dickey-Fuller unit root test, *PP* is Phillips-Perron unit root test. Gold shows gold market prices, BISTAS shows stock market prices. It was estimated with Borsa Istanbul All Share Index value, Cryptocurrency is crytocurrency basket price.

Three different versions of the series were tested for the stationary. All series are stationary on the first difference and intercept model. The first difference and intercept model of the series can be used for the SVAR test. All variables are stationary at the same model (at I(1)), which points to the possibility of cointegration relations (Çetin and Sezen, 2018: 145). The residuals were also tested for normality, autocorrelation, homoskedasticity, and stationary. The test results are in Table 7.

Table 7. Test Results for Residuals

Normality Test Results			
	Value	**Adj. Value**	**Prob.**
Lilliefors (D)	0.08	-	0.00*
Cramer-von Mises (W2)	3.43	3.43	0.00*
Watson (U2)	3.26	3.26	0.00*
Anderson-Darling (A2)	19.93	19.94	0.00*
Unit Root Test Results			
		t-Stat.	**Prob.**
Augmented Dickey-Fuller		-38.39	0.00*
Autocorrelation Test Results			
	Value	**Adj. Value**	**Prob.**
Breusch-Pagan-Godfrey LM Test	3	1.29	0.28
Homoskedasticity Test Results			
	df	**F-stat.**	**Prob.**
Breusch-Pagan-Godfrey Test	2	4.20	0.02*
White Test	5	5.38	0.00*

Notes: * denotes significance at 95% level. df is degree of freedom. The null hypothesis of Breusch-Pagan-Godfrey and White test is homoskedasticity.

The distribution of the residuals was tested with four different normality tests. According to those tests, the residuals show a normal distribution (prob ≤ 0.05). The ADF (1979) unit root test revealed that the residuals are stationary at trend. There is no autocorrelation (prob≥ 0.05) depending on the Breusch-Pagan-Godfrey LM (1980) test. However, White and Breusch-Pagan-Godfrey (1979) homoskedasticity tests showed the residuals have a heteroskedasticity problem (prob ≤ 0.05). The tests were run with White- adjusted (robust) standard errors to eliminate the bad effects of the heteroskedasticity problem.

SVAR has three sections; a cointegration test, impulse-response function analysis, and variance decomposition test. The first step is searching for cointegration of the variables. There is at least one cointegration relation should be between the markets based on the existing studies. Johansen-Juselius (1990) cointegration test reveals long-term relationships among the variables, which is more than two. The Johansen test uses max. likelihood strategy and that makes it possible to estimate all cointegrating vectors. It tested the m-1 cointegrating vectors for m variables in stationary series (Dwyer, 2015; Çetin and Sezen, 2018). Therefore, Johansen-Juselius (1990) cointegration test can define the long-term relationships of CC market, SM, and GM with two cointegrating vectors for this study. Table 8 shows the Johansen cointegration test results.

Table 8. Johansen Cointegration Test Results and Cointegrating Equatio

Numbers of Cointegration Equations	Eigenvalue	Max-Eigen Stat.	5% CV	Trace Stat.	5% CV
None	0.27	468.28	22.30	1109.52	35.19
At most 1	0.22	365.11	15.89	641.24	20.26
At most 2	0.17	276.13	9.17	276.13	9.17

Cointegrating Equations

Equation 1

BISTAS Prices	Gold Prices	CC Prices	Constant	Model
1.00	-2.35**	-2.42**	0.00	SM = -2.35GM - 2.42CC
	(0.46)	(0.11)	(0.00)	

Equation 2

BISTAS Prices	Gold Prices	CC Prices	Constant	Model
a. 1.00	0.00	-4.03**	0.00	SM = 4.03CC

		(0.17)	(0.00)	
b. 0.00	1.00	-0.69**	0.00	GM = 0.69CC
		(0.03)	(0.00)	

Notes:* denotes cointegration relation at 5% level. CV is critical value. Equation 1 shows unnormalized coefficients and Equation 2 shows normalized coefficients for cointegration model. The parenteses show standart errors. ** denotes 20% significance level for t-stat. Gold shows gold market prices, BISTAS shows stock market prices. It was estimated with Borsa Istanbul All Share Index value, Cryptocurrency is crytocurrency basket price.

Johansen cointegration test defines two different t-statistics as the trace test and the max. eigenvalue test for cointegration. The trace test is a joint test that testimony the null hypothesis of no cointegration. The max. eigenvalue tests the null hypothesis that the number of cointegrating vectors is equal to r against the alternative of r +1 cointegrating vectors and the significantly non-zero eigenvalue means a significant cointegrating vector (Maggiora and Skerman, 2009). The results, which are shown in Table 8, indicate that there are two cointegrating vectors. The variables have cointegration relationships, while they move together in the long-run. The test also gives two cointegrated equations with normalized and unnormalized coefficients. Equation 1 shows unnormalized coefficients. According to Equation 1, the SM price has inverse relationships both with gold and CC prices. A 1% rise of SM prices causes changes in gold prices by -2.35% and in CC prices by -2.42%. GM and CC prices will increase while SM prices are declining. Equation 2 shows coefficients for two normalized models, which are a and b. The normalized coeffients show elasticities, as well (Sevüktekin and Çınar, 2017). In model a, the SM was normalized and the cointegration model was estimated with CC prices. If the gold price doesn't impact the stock price, only the SM and CC market has a cointegration and a 1% increase in stock prices raises the CC prices by 4.03%. If GM is normalized, which is represented at model b, only GM and CC prices show cointegration and 1% increase in GM prices causes a 0.69% rise in CC prices. Although these results indicate all variables have elasticities, compared to the effect of stock prices by 4.03%, gold prices' effects on CC prices are slightly lower with 0.69%.

3.1. Impulse-Response Function Analysis

Impulse-response function measures endogenous variables' reactions to a one-unit random shock in the error term. It shows how far and in which direction endogenous variables move because of shocks (Sevüktekin and Çınar, 2017). The possible nine different impulse-response models were computed with the Cholesky method for the markets. Figure 3 shows the markets' reactions to gold prices.

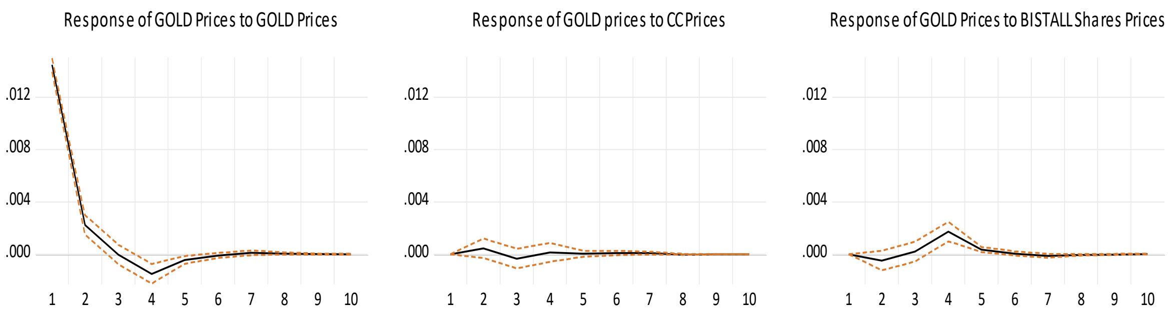

Figure 3- Impulse-Response Function Analysis- Gold Prices

Notes: CC is the cryptocurrency market, BIST All Shares is a stock market, and gold prices is gold market.

The responses of gold prices to CC and stock prices are around zero. All markets show different responses to gold prices. The most affected market from the gold price impulse is GM. However, the severity of the impulse declines roughly in one and a half days, and this decline continues until day 4. The GM negatively responds to the gold price shock between the 3th and 6th day. After the 4th day, the price effect increases again. It moved around zero at the 7th and disappeared after the 8th day. The CC markets' first reaction to the gold price shocks occurs on the 2th day, initially positive, and then becomes negative on the 3th day as the price declines. The effect of the gold price on the CC market disappears. Figure 4 shows the reactions to CC price shocks.

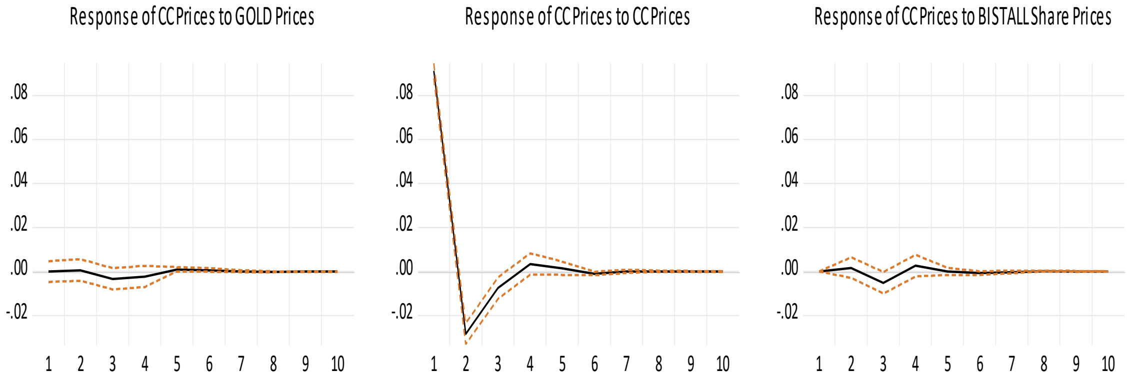

Figure 4- Impulse-Response Function Analysis- Cryptocurrency Prices

Notes: CC is the cryptocurrency market, BIST All Shares is a stock market, and gold prices is gold market.

The response of the GM to CC price shocks is almost zero. After the initial shock, the GM doesn't show any reactions until the third day. The reactions remain slightly below zero for two days and completely disappear by day 5th. Similar to the GM, the most severe impact of the CC price shocks is observed in the CC markets. The effect of the price shocks shows a downward trend from the beginning of the 2th day and drops below zero. The negative impact of the price shocks stays below zero for the second and third days. From the beginning of the 4th day to the 6th day, the markets show some reactions to the price shocks. Although it is not as effective as gold price shocks, the SM reactions to the CC price shocks show the same paths. The SM remains unreacted during the first two days. Its first reaction is negative until the fourth day. Those negative responses become positive for a short time, which passes between the 4th and 5th days.

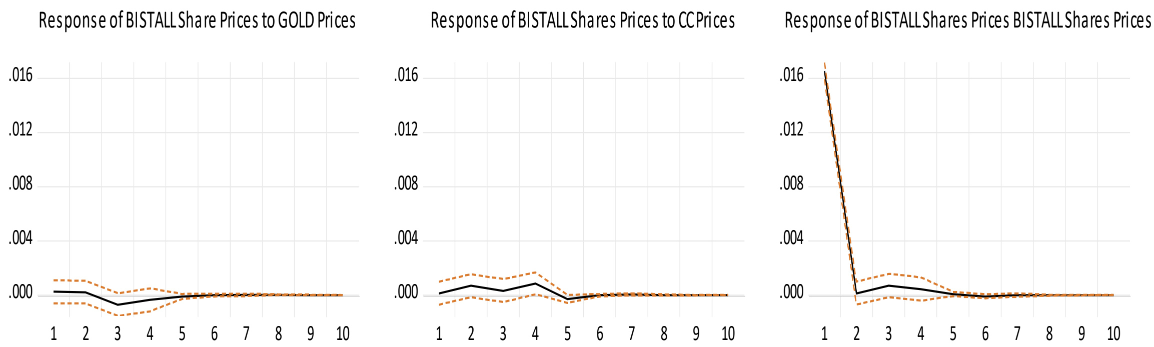

Figure 5- Impulse-Response Function Analysis- Cryptocurrency Prices

Notes: CC is the cryptocurrency market, BIST All Shares is a stock market, and gold prices is gold market.

Figure 5 shows markets' reactions to SM price shocks. The responses of the SM to GM shocks are slightly lower. The first real reaction of the SM is negative and observed at day 3th. However, it is around zero. Compared to the effect of GM on SM, the effect of SM on GM is strictly low. That implies a stronger effect of gold prices on stock prices. A shock of GM is more influential than a shock of SM for the markets' investors. The CC market responds to the impulses from SM with positive but unstable reactions during 5 days. The responses of SM by itself are strong from the beginning of the second day, similar to the other markets. The market's positive but less effects last until the 5th day when the effects vanish.

3.2. Variance Decomposition

Unlike the impulse-response factor, variance decomposition is the ratio of each variable's own shock's effect to other variables' shocks. It shows a share of the current period's error in the average error square in h periods later. The variance decomposition helps to discriminate endogenous and exogenous variables and to reveal the reasons for variance changes (Sevüktekin and Çınar, 2017:515). The variance decomposition results are represented in Table 9 for the variables.

Table 9. Variance Decomposition

	GOLD PRICES				CC PRICES				BISTAS PRICES			
Period	**S.E.**	**Gold Price**	**CC Price**	**SM Price**	**S.E.**	**Gold Price**	**CC Price**	**SM Price**	**S.E.**	**Gold Price**	**CC Price**	**SM Price**
1	0.015	100.00	0.000	0.000	0.091	0.000	99.999	0.000	0.017	0.022	0.006	99.972
2	0.015	99.791	0.095	0.114	0.095	0.005	99.963	0.032	0.017	0.037	0.181	99.782
3	0.015	99.715	0.152	0.133	0.096	0.127	99.551	0.321	0.017	0.223	0.218	99.560
4	0.015	98.354	0.156	1.490	0.096	0.182	99.421	0.397	0.017	0.268	0.483	99.248
5	0.015	98.299	0.156	1.545	0.096	0.193	99.410	0.397	0.017	0.273	0.515	99.212
6	0.015	98.295	0.159	1.546	0.096	0.197	99.401	0.403	0.017	0.273	0.515	99.212
7	0.015	98.285	0.162	1.553	0.096	0.197	99.400	0.403	0.017	0.273	0.516	99.211
8	0.015	98.284	0.162	1.554	0.096	0.197	99.399	0.404	0.017	0.273	0.516	99.211
9	0.015	98.283	0.163	1.554	0.096	0.197	99.399	0.404	0.017	0.273	0.516	99.211
10	0.015	98.283	0.163	1.554	0.096	0.197	99.399	0.404	0.017	0.273	0.516	99.211

Notes: In the calculation of the variance decomposition, Cholesky method was prefferd. Cholesky Ordering is as like GOLD Price, CC Price, and SM Price. *CC* is basket price of cryptocurrencies, *SM* is Borsa Istanbul All Shares Index price, Gold price is gold market prices, and *S.E.* is standart error.

According to the test results, in period 1, 100% of changes in the standard deviation of gold prices come from itself. Similarly, 99.99% of changes in the standard deviation of CC prices stem from CC prices. However, that is slightly different in SMs. 99.972% of the standard deviation of SM prices can be explained by SM prices, 0.022% by gold prices, and 0.006% by CC prices.

The variables' effects on the other variables increase over the 10 period, though those effects seem small. The gold prices' effects on gold price variance change is 98.283%, on CC prices it is 0.197%, and it is 0.273% in SM prices at period 10. The SM prices are more effective for gold prices. 1.554% of the variance changes of gold prices is because of SM prices.The last test for the relationship of the variables is the Granger (1969) causality test. The causality test results are in Table 10.

Table 10. Granger Causality Test Results

Causality			$\chi 2$	df	Prob.
From CC	→	**to SM**	7.80	3	*0.05
		to GM	2.89	3	0.41
From GM	→	**to CC**	3.66	3	0.30

	to SM	3.92	3	0.27
From SM	to CC	4.66	3	0.20
	to GM	23.54	3	*0.00

Notes: * denotes causality. *df.* is degree of freedom. *CC* is basket price of cryptocurrencies, *SM* is Borsa Istanbul All Shares Index price, Gold price is gold market prices,

There are two causalities were detected. The first causality is from CC prices to SM prices (prob.$\leq$ 0.05). The CCs prices cause changes in the SM prices. This is a one-way short-run relationship. It means the SM prices are not causality for the CC prices. The second causality is from the SM prices to the GM prices. The SM prices impact or change the GM prices. There are no more causality relations between the variables.

4. Discussion

This study aims to reveal the relationship between stock, gold, and CC markets because this relationship can illuminate the markets about the possibility of hedging and risk diversification. The results explain how portfolio management can use those markets. Daily price data were collected for a time span from 11/09/2017 to 11/17/2023 and have 1513 observations for the analysis. Instead of a single CC, a CC basket was created, which is composed of the most traded CCs by following Gambarelli et al. (2023). The CCs are Bitcoin, Ethereum, Tether, BNB, and XRP in the basket.

The CC market is more stable compared to the other markets. The prices of CCs have four peaks in that time span. The first is on 12/07/2017, the second and highest is on 02/26/2021 (its price was 31,507 USD), the third is on 10/19/2021, and the fourth is on 01/07/2022. The gold and stock prices seem similar with an upward line. The price of SM reached its highest value on the 5th of March in 2023. Whereas volatility was high in all markets (SM was the most volatile market), the market prices had increased during the Covid-19 pandemic. The CC investors gained 54%, 135%, 48%, 73%, 114% high returns, respectively on 09/24/2020, 02/26/2021, 02/08/2021, 01/07/2022, 09/22/2023. However, they lost 53% on their returns on 03/01/2021 and 09/21/2023.

The variables aren't normally distributed according to the Jarque-Bera & Skewness and Kurtosis tests. Various macroeconomic factors may cause that result. There is also a heteroskedasticity problem (prob $\leq$ 0.05) in the residuals, but all of the variables are stationary at trend and there is no autocorrelation (prob $\geq$ 0.05).

The nexus of the SM, CCs market, and GM was examined with causality, cointegration, and the SVAR tests. The SVAR has two steps, like variance decomposition and impulse-response function tests. The results of those tests will be discussed in the context of short-run and long-run relationships. The causality, variance decomposition, and impulse-response function tests show short-run relationships.

The causality test demonstrated there are two causality relationships. The first causality is one-way causality from the CC market to the SM (prob.$\leq$ 0.05). CC prices impact SM prices, but SM prices don't impact CC prices. Caferra and Vidal-Tomás (2021), Toprak and Kubar (2023), and Gambarelli et al. (2023) mentioned a causality between Bitcoin and SM. However, there is no causality between the CC market and GM. Those results can be explained by Klein et al.(2018) results which deduced that CC and SM have a direct relationship, while CC and GM have a conditional relationship. Bitcoin and GM move together, and Bitcoin acts like gold. However, they don't have any connections during panic periods of the SMs. The Covid-19 caused a panic in many financial markets around the World. Therefore, the relationship between CC and GM may be impacted during that chaotic period, while CC affects the SM. Yamaka (2024) and our results support the relationship between the SM and GM. The second causality is one-way causality from SM to GM. The stock prices cause a change in gold prices.

The shocks of the markets to themselves are more effective than the other markets' shocks. The most effective impulses are from GM for the GM. However, the severity of the impulse declines roughly in one and a half days, and this decline continues until day 4. The GM negatively responds to the gold price shocks between the 3th and 6th day. After 4th day, the price effect increases again. It moved around zero at the 7th and disappeared after the 8th day. The responses of SM by itself are strong from the beginning of the second day, similar to the other markets. The market's positive but less effects last until the 5th day when the effects vanish. Similar to the GM, the most severe impact of the CC price shocks is observed in the CC markets. The effect of the price shocks shows a downward trend from the beginning of 2th day and drops below zero. The negative impact of the price shocks stays below zero for the second and third days. From the beginning of the 4th day to the 6th day, the markets show some reactions to the price shocks. The responses of gold prices to CC and stock prices are around zero. The CC markets' first reaction to the gold price shocks occurs on the 2th day, initially positive, and then becomes negative on the 3th day as the price declines. The effect of the gold price on the CC market disappears. The response of the GM to CC price shocks is almost zero. After the initial shock, the GM doesn't show any reactions until the third day. The reactions remain slightly below zero for two days and completely disappear by day 5th. Although it is not as effective as gold price shocks, the SM reactions to the CC price shocks show the same paths. The SM remains unreacted during the first two days. Its first reaction is negative until the fourth day. Those negative responses become positive for a short time, which passes between the 4th and 5th days. The responses of the SM to GM shocks are slightly lower. The first real reaction of the SM is negative and observed at day 3th. However, it is around zero. Compared to the effect of GM on SM, the effect of SM on GM is strictly low. That implies a stronger effect of gold prices on stock prices. A shock of GM is more influential than a shock of SM for the markets' investors. The CC market responds to the impulses from SM with positive but unstable reactions during 5 days.

The variance decompositions demostrate how variables affect standard deviations. In period 1, 100% of changes in the standard deviation of gold prices come from itself. Similarly, 99.99% of changes in the standard deviation of CC prices come from CC prices. However, that is slightly different in the stock market. 99.972% of the standard deviation of SM prices can be explained by itself, 0.022% by gold prices, and 0.006% by CC prices. The variables' effects on the other variable increase over the 10 periods, though those effects are slight. The gold prices' effects on gold price variance change is 98.283%, it is 0.197% on CC prices, and it is 0.273% in SM prices in the 10th period. However, SM prices are more effective for gold prices. 1.554% of the variance changes of gold prices is because of SM prices.

The Johansen-Juselius (1990) cointegration test found that at least two cointegrations and the variables move together in the long-run. The unnormalized cointegration equation supports Özer et al. (2011) which deduced cointegration of SM and GM. According to that cointegration equation, SM prices have inverse relationships both with gold and CC prices. -2.35% gold prices and -2.42% CC prices change stock prices by 1%. A rise at 1% level on stock prices causes a 2.35% and 2.42% decline in gold and CC prices, respectively. The results align with the conclusions of Sami and Abdallah (2021) and Wang et al. (2022). Because of that inverse relationship, CCs and stocks can be used for portfolio diversification and for hedging as Koy et al. (2021) mentioned. Klein et al. (2018) and Wang et al. (2022) explained the asymmetric relationship with market shocks, but Gambarelli et al.(2023) emphasized the effects of market conditions on that result. If the market is bearish, CCs can be a good opportunity to hedge stock market risks. The normalized coefficients concluded positive cointegration of the markets. When GM is normalized, only GM and CC prices show cointegration and 1% increase in GM prices causes a 0.69% rise in CC prices. Plus, when SM was normalized, the cointegration model was estimated with CC prices. If the gold price doesn't impact the stock price, only the SM and CC market has a cointegration and a 1% increase in stock prices raises the CC prices by 4.03%. Compared to the effect of stock prices by 4.03%, gold prices' effects on CC prices are slightly lower with 0.69%. Telek and Şit (2020) demonstrated similar results about the existence of a positive cointegration between CC and gold prices. On the other hand, our results argue with Junior et al. (2020) and González et al. (2021) which resulted in inverse relationships of the markets. Junior et al. (2020) mentioned that CCs can hedge risks of the gold market and vice versa. However, CCs cannot be used for hedging the GM risks, because they have a positive relationship and their movements are parallel to each other. Those differences in the articles' results may be associated with market structure or conditions. In this study, the relationships were tested in Turkish markets, while the other articles have focused on different markets. González et al. (2021) tested the relationships during the Covid-19 pandemic period. The pandemic had hazardous effects over many markets. Under those unusual conditions, markets may show different reactions than in normal conditions. The Granger causality test found causalities from CC prices to SM prices and from the SM prices to the GM prices. The CCs prices cause changes in the SM prices. This is a one-way short-run relationship. It means the SM prices are not causality for the CC prices. The second causality is from the SM prices to the GM prices. The SM prices impact or change the GM prices. Those relationships are not exactly in the same line with the short-run relationship mentioned by González et al. (2021). They concluded a one-way causality between CCs and gold prices during Covid-19 pandemic. According to our results, CC prices impact SM prices and SM prices impact GM prices in short-run. Therefore, the results imply an indirect effect of CC prices on GM prices.

Conclusions

Even though cryptocurrencies are accused of being speculative and having a risky structure and are banned in some countries, they are still accepted as an investment tool for tons of people. In common sense, the gold market is a safe haven to avoid stock market risks. This study aims to reveal whether cryptocurrencies are a safe haven for the stock and gold markets.

Three different tests were applied to 1513 daily price data. The time range of the data starts on 11/09/2017 and ends on 11/17/2023. The stock market is the BIST All Shares prices, the gold market is gold prices, and the cryptocurrencies are the price of the cryptocurrency basket in this study. The cryptocurrency basket is a weighted average of the five most traded cryptocurrencies. Although the cryptocurrency market is named as a volatile market, it is more stable than other markets during the time span of the research. The gold and stock prices seem similar, with an upward line. Whereas the volatilities were high in all markets (the stock market was the most volatile market), the market prices had increased during the Covid-19 pandemic.

The causality test found that a causality relationship from the cryptocurrency market to the stock market (prob.$\leq$ 0.05) and from the stock market to the gold market. The cryptocurrency prices cause changes in the stock market prices. This is a one-way short-run relationship. It means the stock market prices are not causality for the cryptocurrency prices. The SM prices impact or change the GM prices. Those results imply, an indirect effect of cryptocurrency markets on gold markets. The impulse-response function showed that price shocks from the other markets are not as effective as their own shocks. The other markets' responses to the other markets are around zero. Their own price shocks generally have negative effects on the markets. The negative effects of price shocks on gold markets disappear in five or six days. The gold prices may decrease in six days after the shocks. This is the longest reaction period compared to cryptocurrency and stock markets. The shocks positively impact the stock market for two days. Because of a price shock in the stock market, the stock prices will increase during two days. However, a price shock can decrease cryptocurrency prices in the first two days, and afterwards it moves towards zero until the 5th day of the post-shock period. In the first period, 100% of changes in the standard deviation of gold prices are explained by itself, 99.99% of changes in the standard deviation of cryptocurrency prices come from cryptocurrency prices, 99.972% of the standard deviation of stock market prices are explained by stock market prices, 0.022% by gold market prices, and 0.006% by cryptocurrency market prices. The variables' effects on the other variables increase over the 10 periods, though those effects are slight. The gold prices' effects on gold price variance change is 98.283%, it is 0.197% on cryptocurrency prices, and it is 0.273% in stock market prices in the 10th period. Whereas the stock market prices are more effective for the gold prices, 1.554% of the variance changes of gold prices are impacted by stock market prices. Those results show short-run relationships of stock, gold, and cryptocurrency markets. Though response-impulse functions and variance decompositions demonstrated that the markets have some kinds of relations, they are not strong enough to be causality for every market due to the causality test results.

In addition to the short-run tests, the markets were examined for the long-run relations. The first of two cointegrations showed that the stock market moves asymmetrically with gold and cryptocurrency markets. A 1% rise in the stock market will result in a 2.35% and 2.42% decline in gold and cryptocurrency prices, respectively. The normalized coefficients concluded positive cointegration of the markets. When gold market prices is normalized, only gold market and cryptocurrency market show cointegration and 1% increase in gold market prices causes a 0.69% rise in cryptocurrency prices. When stock market was normalized, the cointegration model was estimated with cryptocurrency prices. If the gold price doesn't impact the stock price, only the stock and cryptocurrency market has a cointegration and a 1% increase in stock prices raises the cryptocurrency prices by 4.03%. Compared to the effect of stock prices by 4.03%, gold prices' effects on cryptocurrency prices are slightly lower with 0.69%.

In our best knowledge, this study is the first study which shows how a cryptocurrency basket is associated with stock and gold markets. Further, it answers the questions of how the markets react the price shocks from itself and other markets, and variance decomposition ratios of the markets. Those results are important for investors, financial analysts, and financial markets. The results give detailed information for all three markets. The results can be used for hedging strategies and for portfolio management. Both gold and cryptocurrency markets can be used for hedging the risks of stock markets. Also, those results can be used to forecast future prices for stock, gold, and cryptocurrency markets. Policy makers can manage the markets and prices based on those results.

The tests concluded no causality from cryptocurrencies to the gold market, from the gold market to both the cryptocurrency and stock markets, and from the stock market to the cryptocurrency market. On the other hand, those markets have some kinds of cointegration relationships.

Moreover, the variables have heteroskedasticity, which supports the other variable effects over the relationship of markets. Also, the variables aren't normally distributed. Some macroeconomic factors or market structures, panics on the markets, and global markets' effects may cause a long-run relation, while they don't have any short-run relation. The differences in the results will be good research questions for the next studies. Examining the variables that cause long-run relationships for the markets can be an interesting and important research area.

Even though it has important results, this study has some limitations. The cryptocurrency basket structure can be changed. The five most traded cryptocurrencies were used for the basket, but it can be changed or extended. Also, the relationships were tested in Türkiye. As an emerging market, its market conditions are different from the developed and frontier markets. The relationships of the markets may be different in those countries because of market conditions, as previous studies mentioned.

References

Breusch, T.S. and Pagan, A.R. (1979). A simple test for heteroscedasticity and random coefficient variation. *Econometrica, 47*(5).

Breusch, T. and Pagan, A.R (1980). The LM test and its applications to model specification in econometrics. *Review of Economic Studies*, *47*. 239-254.

Caferra, R. and 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,* 101954. https://doi.org/10.1016/j.frl.2021.101954

Chen, K. and Wang, M. (2019). Is gold a hedge and safe haven for stock market? *Applied Economics Letters*, *26*(13)*,* 1080-1086. https://doi.org/10.1080/13504851.2018.1537469.

Corbet, S., Meegan, A., Larkin, C., Lucey, B. and Yarovaya, L. (2018). Exploring the dynamic relationships between cryptocurrencies and other financial assets. *Economics Letters*, *165*, 28-34. https://doi.org/10.1016/j.econlet.2018.01.004

Çifçi, G. (2025). Kahverengi kripto ve yeşil kripto paraların yatırımcı risk toleransı ile ilişkilisi: Yerli yatırımcılar bazında A-ARDL ve NARDL yöntemleri ile bir değerlendirme. *Afyon Kocatepe Üniversitesi İktisadi ve İdari Bilimler Fakültesi Dergisi, 27*(1), 130-153. https://doi.org/10.33707/akuiibfd.1551277

Çetin, M. and Sezen, S. (2018). Türkiye'de yenilenebilir ve yenilenemeyen enerji tüketimi, ekonomik büyüme ve karbondioksit salınımı arasındaki ilişki: Bir SVAR (yapısal var) analizi. *Journal of Management and Economics Research, 16(1),* 136-157. https://doi.org/10.11611/yead.385401

Dickey, D. A., and Fuller, W. A. (1979) Distribution of the estimators for autoregressive time series with a unit root. Journal of the American Statistical Association 74(366a): 427-431. https://doi.org/10.1080/01621459.1979.10482531.

Dwyer, G. P. (2015). The Johansen tests for cointegration. *White Paper*, *516*.

Gambarelli, L., Marchi, G. and Muzzioli, S. (2023). Hedging effectiveness of cryptocurrencies in the European stock market. *Journal of International Financial Markets, Institutions and Money*, *84*, 101757. https://doi.org/10.1016/j.intfin.2023.101757

Garda, N. and Şahin, İ. E.(2025). Kripto paraların psikolojik çekiciliği ve yatırımcı davranışları: Davranışsal finans perspektifinden bir inceleme. *Selçuk Üniversitesi Akşehir Meslek Yüksekokulu Sosyal Bilimler Dergisi*, (19), 107-121.

Gemici, E., Gök, R., and Bouri, E. (2023). Predictability of risk appetite in Turkey: Local versus global factors. *Emerging Markets Review*, 55, 101018. https://doi.org/10.1016/j.ememar.2023.101018

Granger, C. W. (1969). Investigating causal relations by econometric models and cross-spectral methods. *Econometrica: journal of the Econometric Society*, 424-438.

González, M. D. L. O., Jareño, F. and Skinner, F. S. (2021). Asymmetric interdependencies between large capital cryptocurrency and Gold returns during the COVID-19 pandemic crisis. *International Review of Financial Analysis*, *76*, 101773. https://doi.org/10.1016/j.irfa.2021.101773

Gökalp, B. T. (2022). Kripto para piyasasının Borsa İstanbul endeksleri üzerindeki etkileri. *Ekonomi Politika ve Finans Araştırmaları Dergisi*, *7*(2), 481-499. https://doi.org/ 10.30784/epfad.1081705

Ha, L.T. (2023), Interlinkages of cryptocurrency and stock markets during COVID-19 pandemic by applying a TVP-VAR extended joint connected approach, *Journal of Economic Studies*, *50(3)*, 407-428. https://doi.org/:10.1108/JES-01-2022-0055

Klein, T., Thu, H. P. and Walther, T. (2018). Bitcoin is not the new gold–a comparison of volatility, correlation, and portfolio performance. *International Review of Financial Analysis*, *59*, 105-116. https://doi.org/10.1016/j.irfa.2018.07.010

Koy, A. Yaman, M. and Mete, S. (2021). Kripto paraların volatilite modelinde ABD borsa endekslerinin yeri: Bitcoin üzerine bir uygulama. *Finansal Araştırmalar ve Çalışmalar Dergisi*, *13*(24), 159-170. https://doi.org/10.14784/marufacd.880672

Maggiora, D. D. and Skerman, R. (2009). Johansen cointegration analysis of American and European stock market indices: An empirical study. Master Thesis.

Johansen, S. and Juselius, K. (1990) Maximum likelihood estimation and ınference on cointegration—with applications to the demand for money. *Oxford Bulletin of Economics and Statistics*, *52*, 169-210. https://doi.org/10.1111/j.1468-0084.1990. mp52002003.x

Junior, P.O., Adam, A. M. and Tweneboah, G. (2020). Connectedness of cryptocurrencies and gold returns: Evidence from frequency-dependent quantile regressions. *Cogent Economics & Finance*, *8*(1), 1804037. https://doi.org/10.1080/23322039.2020.1804037

Öget**,** E. (2023). Bitcoin'in kriz dönemindeki çeşitlendirici etkisi: G7'den kanıtlar. *Muhasebe ve Finansman Dergisi*, (100), 105-120. https://doi.org/10.25095/mufad.1311409

Öncü, M. A., Çömlekçi, İ., Yazgan, H. İ. and Bar, M. (2015). Yatırım araçları arasındaki eşbütünleşme (BIST 100, altın, reel döviz kuru). *Abant İzzet Baysal Üniversitesi Sosyal Bilimler Enstitüsü Dergisi*. 15(1), 43-57. https://www.researchgate.net/profile/Halil_Yazgan/publication/386274021_.pdf

Özer, A., Kaya, A. and Özer, N. (2011). Hisse senedi fiyatlari ile makroekonomik değişkenlerin etkileşimi. *Dokuz Eylül Üniversitesi İktisadi İdari Bilimler Fakültesi Dergisi*, *26*(1), 163-182. https://dergipark.org.tr/en/download/article-file/210999

Phillips, P.C.B. & P. Perron (1988) Testing for a unit root in time series regression. *Biometrika* 75, 335-346.

Sami, M. and Abdallah, W. (2021), How does the cryptocurrency market affect the stock market performance in the MENA region?, *Journal of Economic and Administrative Sciences*, *37(4)*,741-753. https://doi.org/10.1108/JEAS-07-2019-0078

Sevüktekin, M. and Çınar, M. (2017). *Ekonometrik zaman serileri analizi: EViews uygulamalı*. Dora Yayınları. İstanbul

Statista, (2024, February 10) *Share of respondents who indicated they either owned or used cryptocurrencies in 56 countries and territories worldwide from 2019 to 2023.* https://www.statista.com/statistics/1202468/global-cryptocurrency-ownership/

Stensås, A., Nygaard, M. F., Kyaw, K. and Treepongkaruna, S. (2019). Can Bitcoin be a diversifier, hedge or safe haven tool?. *Cogent Economics & Finance*, *7*(1), 1593072. https://doi.org/10.1080/23322039.2019.1593072

Şenol, Z., Gülcemal, T. and Çakan, O. (2022). Kripto paralarla borsalar arasındaki volatilite yayılımı. *Ekonomi Politika ve Finans Araştırmaları Dergisi*, *7*(4), 925-943. https://doi.org/10.30784/epfad.1200423

Telek, C. and Şit, A. (2020). Kripto paraların altın ve dövizle ilişkisi: Bitcoin örneği. *Turkish Studies-Economy*, *15*(2), 913-924. https://dx.doi.org/10.29228/TurkishStudies

Toprak, Y.D. and Kubar, Y. (2023). Seçilmiş borsa endeksleri ile kripto para birimleri arasındaki ilişki üzerine ekonometrik bir analiz. *Karamanoğlu Mehmetbey Üniversitesi Sosyal ve Ekonomik Araştırmalar Dergisi*, *25*(44), 21-45. https://dergipark.org.tr/en/download/article-file/2607128

Velip, S., Jambotkar, M. and Velip, S. (2023). A wavelet-based time-frequency dependency and safe haven attributes of gold: evidence from the Russia–Ukraine war. *Applied Economics Letters*, 1-6. https://doi.org/10.1080/13504851.2023.2275644

Wang, H., Wang, X., Yin, S. and Ji, H. (2022). The asymmetric contagion effect between stock market and cryptocurrency market. *Finance Research Letters*, *46*, 102345. https://doi.org/10.1016/j.frl.2021.102345

Yamaka, W. (2024). Understanding the Nexus Between Emerging Stock Market Volatility and Gold Price Shocks. In: Ngoc Thach, N., Kreinovich, V., Ha, D.T., Trung, N.D. (eds) Optimal Transport Statistics for Economics and Related Topics. Studies in Systems, Decision and Control, vol 483. Springer, Cham. https://doi.org/10.1007/978-3-031-35763-3_48

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