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RETURN VOLATILITY SPREAD IN COMMODITY VOLATILITY INDICES: SPOT AND FUTURE MARKET RESEARCH

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ABSTRACT

Volatility Indices are an important indicator for investors to accurately predict returns and risks in case of uncertainty in the markets. In this study, the effects of the gold, silver, and oil volatility indices (GVI, SVI and OVI) on the returns and volatility of both spot and futures assets were investigated using the VAR-EGARCH procedure. The findings of the study reveal that both the GVI and gold futures prices have a positive effect on gold spot prices. At the same time, it has been determined that gold futures prices are obtained from the GVI and gold spot prices. On the other hand, although SVI and future prices were effective on silver spot prices, only SVI lagged prices were effective on silver futures. Finally, OVI and oil future returns were ineffective on oil spot prices, and only OVI returns were effective on oil future prices.

Contribution/Originality: The most important contribution of this study to the literature is that it gives direction to portfolio selection strategies by measuring the effect of certain factors on the returns and volatility of precious metal and energy commodities volatility indices such as GVI, SVI, and OVI, which have recently shown the sensitivity of commodity market investors.

1. INTRODUCTION

In the finance literature, volatility, which is when the price of any financial asset exhibits very high increases or decreases relative to its average value in a certain period, is an important concept for investors (Karabiyik & Anbar, 2007). Because arbitrage transactions quickly translate any information in different markets to asset prices, information spreads quickly due to advanced technology, and investors move to more investment positions as a result of the emergence of different financial instruments and changing conditions, volatility in financial markets emerges (Mullins, 2000). In short, volatility generally arises from intense uncertainties in the markets. The subject of volatility has become the focus of researchers in recent years because investors are motivated to increase their returns through risk management in an environment of uncertainty.

Since volatility provides an important data point in portfolio optimization and risk calculations, together with option pricing, it is necessary to accurately estimate the volatility to estimate the returns of market participants (Chen, Liu, & Li, 2018). While investors take historical volatility into account (a measure of a financial asset's changes in returns over a historical period) to obtain information about past price movements while taking positions in financial markets, they evaluate indices of implied volatility (volatility derived from current prices of options contracts) to provide real-time information about future price fluctuations (Moran & Liu, 2020). The Chicago Options Exchange Volatility Index (COEVI) was the first volatility index to be created. This index, which was defined as a "fear meter" by Whaley (2000), started to calculate the 30-day expected volatility in 1993, based on the Black and Scholes option pricing model of the S&P 100 Index. It tries to predict future volatility by taking into account the weighted averages of the put-at-loss options (Chicago Opsiyon Borsası, 2019). Investors who estimate market volatility according to the volatility in option prices are comfortable with the low risk at Volatility Index (VIX) Index values of 20 and below. They act carefully because situations involving high risk are those with values of 30 and above (Taşpunar Altuntaş & Colak, 2015). Commodity volatility indices have been calculated as risk indicators for commodity investors because risk perceptions have increased with the growing uncertainty resulting from changes in the markets. CBOE GVI, CBOE OVI, and, in 2011, CBOE SVI were created by the CBOE by applying the VIX algorithm to options in 2008. These indices indicate the estimated 30-day implied volatility of SPDR gold stocks, US oil funds, and iShares silver ETF prices/returns, respectively. They are calculated by interpolating the middle bid values of gold, oil, and silver options between two time-weighted sums (CBOE).

In the literature, various observations have been made regarding the volatility spillover between volatility indices and commodity spot or futures prices/returns. Jubinski and Lipton (2013) held the view that there is a positive relationship between gold and silver futures returns and implied volatility, and a negative relationship between oil futures returns and implied volatility. Jin, Jie, and Zhang (2014) analyzed the relationship between gold futures price changes and A-share gold-stock price fluctuations in Shanghai and Shenzhen, China. They determined that the price changes of global gold futures caused the price fluctuations of Shanghai and Shenzhen A-share gold stocks, and the changes in foreign gold futures and spot prices were quite effective predictors of the domestic markets. Tanin, Sarker, Hammoudeh, and Shahbaz (2021) investigated whether different financial asset volatility indices changed the perception of gold as a safe haven before and during the COVID-19 pandemic. Using a NARDL model, they determined that while the volatility in finance, energy, gold, silver, and euro currency markets increased gold prices in the pre-COVID-19 period, only lagged negative oil volatilities reduced gold prices in the short term. In addition, they determined that only negative euro currency volatility reduced gold prices in the long term during the COVID-19 period, while positive gold, silver, emerging market, and (lagged) financial market volatility decreased gold prices in the short term. Echaust and Just (2021) investigated the relationship between the extreme returns of West Texas Intermediate crude oil prices and the changes in the OVI during the COVID-19 pandemic. They found that there was a strong correlation in the tail dependence between negative returns of crude oil and OVI changes and the tail independence for positive returns using a static and dynamic conditional copula methodology. Löwen, Kchouri, and Lehnert (2021) determined that there was a symmetrical causality relationship between the stock market and the gold and oil markets, and positive shocks in VIX cause positive shocks in GVI. Panagiotou (2021), using the non-linear quantile regression method, found that the changes in the implied volatility of gold generally did not affect the changes in its returns.

Many previous studies have only considered oil. Chen, He, and Yu (2015) argued that there was a negative dynamic relationship between changes in OVI and future crude oil spot returns, and that excessively high/low OVI levels fail to predict future crude oil spot positive/negative returns according to the Kalman filter model. Chen and Zou (2015) determined that time-varying coefficients showed a negative relationship between negative crude oil spot returns and OVI changes, but the relationship between positive crude oil spot returns and OVI changes was not significant. Ji, Liu, and Fan (2016) investigated the asymmetric dynamic dependence between returns and volatility in oil markets. According to the conditional Kendall coefficient, calculated to determine the Gumbel copula, and the excessive dependency coefficient, the existence of asymmetric dynamic dependence between oil price returns and OVI was determined. Chen et al. (2018) found that past OVI significantly influenced current oil spot volatility (despite all GARCH-type models). Molnár and Bašta (2017) found that there was a strong relationship between the implied volatility of the stock market and the implied volatility of the crude oil market; in particular, they stated that there was no leading/lag relationship between VIX and OVI on short time scales, but there was a leading/lag relationship on long time scales. Lin and Tsai (2019) stated that there was a long-run relationship between oil prices and VIX in all periods; there was a moderately negative correlation between oil price and OVI, and a moderate or high level of negative correlation between oil price and VIX in general. Shaikh (2019) found that WTI/USO could predict future crude oil prices with minimum error, using Barone, Adesi, and Whaley's (BAW) neural network model. According to the quantile regression results, there was a strong relationship between crude oil prices and OVI, and an asymmetric relationship between WTI/USO and OVI, while OVI had a feedback effect on crude oil price volatility. Alqahtani and Chevallier (2020) investigated the conditional correlations between the oil, gold, and S&P500 market returns of the Gulf Cooperation Council (GCC) member countries. They determined that the GCC stock market returns had a negative correlation with other volatility indices, and the correlations were stronger in crisis periods. In addition, GCC stock returns were found to be mostly associated with oil shocks, then with shocks in the global stock market, and least with gold shocks. Benedetto, Mastroeni, Quaresima, and Vellucci (2020) revealed an increase in information flow between the spot variance of OVI and Brent returns, and a decrease in information flow with WTI, based on the mutual information and transfer entropy approach. Lu, Ma, Wang, and Wang (2020) concluded that OVI caused short, medium, and long-term volatility in the Chinese oil futures market using Markov regime mixed data sampling (MRMDS) models.

When these studies are evaluated in general, it can be observed that the studies involving commodity prices and the VIX index are predominant, and gold and oil are chosen more often than commodities. No previous study has investigated the volatility spillover between the SVI and the spot and futures market price/returns. In addition, no prior study has been found in the literature that evaluates the volatility indices of commodities and the volatility spreads between spot and futures market prices/returns.

In this study, the volatility spillover between the CBOE gold, silver, and oil commodity volatility indices and these commodities' spot and futures market returns is analyzed using the VAR-EGARCH model. The motivation for this study is to close the gap in the literature. The results of the study will help potential investors and policymakers who want to take part in the gold, silver, and oil markets to manage their risk, in the context of the international integration of the markets and the increased sensitivity of commodity prices to different market dynamics and unpredictable economic situations.

2. METHODOLOGY

This study investigates the relationships between the implied (volatility), spot, and futures variables of gold, silver, and oil, which are among the commodities with the highest trading volumes. The data used in the study were obtained from "investing.com" and cover the period 16.03.2011–03.09.2021. In the application part of the study, the VAR-EGARCH model was run using the daily data of the indices.

Due to their structure, financial time series have characteristic features. Models made of financial time series are incomplete in calculating features such as excessive kurtosis, volatility clustering, and leverage effect. However, ARCH models, first introduced by Engle (1982), and GARCH models, developed by Bollerslev (1986), form the basis of models in which the properties of financial time series can be observed. GARCH models are a widely used method for estimating varying variances in financial time series. The VAR-EGARCH model, a variation of the GARCH model, was developed by Koutmos and Booth (1995) and allows the researcher to observe the asymmetric effect relationship that is often seen in time series. In this study, using the return series of the variables, phenomena such as the asymmetric effect, leverage effect, and volatility clustering in the series were examined with the multivariate VAR-EGARCH model.

The fact that error term variances in time series are related to past error terms and have high volatility causes the problem of varying variance. The problem of varying variance in the series, in turn, prevents statistically significant parameter estimates from being reached. To solve this problem, Engle introduced the Autoregressive Conditional Heteroscedasticity (ARCH) model in his 1982 study. With his ARCH model, Engle (1982) enabled the variance and covariance to change over time. In this model, error term variances are explained by squaring the values of the past period (Koutmos, 1996). The constant variance assumption used in traditional time series models is neglected, allowing the variance to change over time as the squares of the lagged values.

A preferable ARCH model (Engle, 1982) can be described as:

$$y_t = \epsilon_t h_t^{1/2} \tag{1}$$

$$h_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i \, y_{t-i}^2 \tag{2}$$

Equation 1 is an example of an ARCH. It is not exactly a bilinear model, but approaches one (Engle, 1982). Under the assumption of normality, ψ_t, the ARCH regression model at time t is:

$$y_t \mid \psi_{t-1} \sim N \ (x_t \beta, h_t) \tag{3}$$

$$h_t = \alpha_0 \ + \ \alpha_1 y_{t-1}^2 \tag{4}$$

The variance function is also generalized:

$$h_t = h\left(y_{t-1}, y_{t-2}, \dots, y_{t-p}, \alpha\right) \tag{5}$$

The term h_t in Equations 2, 4, and 5 represents the conditional variance, ϵ_t represents the least squares residuals. Equation 2 describes the standard ARCH process. p represents the order of the ARCH model and α the unknown parameters vector. The conditional series of variances is a random variable in the estimation of ARCH models. Accordingly, to ensure the stationarity condition, the covariance of the random variables will be zero and the sum of the parameters will be less than one ($\sum_{i=1}^{p} \alpha_i < 1$). The conditional variance (h_t), must be positive for all realized values of y_t. In order to fulfill this condition, the parameters in the model are expected to take a positive value ($\alpha_0 > 0, \alpha_i \geq 0$).

Bollerslev developed the Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model in 1986 to avoid the necessary limitations of the parameters in the conditional variance equation in the ARCH model and to overcome the inconvenience of reaching parameter estimates with negative variance. This model, which aims to eliminate the deficiencies of the ARCH model, includes both more historical information and a more flexible delay structure. Bollerslev (1986) stated that in this model, the conditional variance over period t is not only related to the past values of the error terms, but also to the past conditional variances.

Here, ϵ_t is a real-valued discrete-time stochastic process, and ψ_t is the GARCH (p,q) model to represent the entire data set (Bollerslev, 1986):

$$\varepsilon_t | \psi_{t-1} \sim N(0, h_t) \tag{6}$$

$$h_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i \, \varepsilon_{t-i}^2 + \sum_{i=1}^{p} \beta_i \, h_{t-i} \tag{7}$$

The simplest but often useful GARCH(p,q) process is represented in Equation 7. Therefore, the GARCH(p,q) model can be interpreted as an autoregressive moving average process in ε_t^2 of orders p, respectively (Bollerslev, 1986). The GARCH model has successfully captured the thick tail and volatility clustering phenomena in the main characteristics of financial time series. However, because the unconditional variance is defined only as a function of the magnitudes of the lagged error terms, independent of the signs, the GARCH process fails to capture the asymmetrical relationship in the variance structure and cannot detect the leverage effect, which is another feature of financial time series.

Equation 8 represents the Exponential GARCH (EGARCH) model developed by Nelson in 1991; it captures the asymmetric response of volatility over time. In Nelson's (1991) model, the conditional variance is modeled logarithmically and the error delays are represented as a function of the magnitude and sign, so the constraints on the parameters required for the variance to be positive are not needed.

$$log\sigma_t^2 = \alpha_0 + \beta log\sigma_{t-1}^2 + \gamma \frac{|\mu_{t-1}|}{\sigma_{t-1}} \quad (8)$$

In Equation 8, γ is the coefficient of asymmetry. As long as this coefficient takes a non-zero value ($\gamma \neq 0$), the model is asymmetrical. A negative value of γ means that negative shocks have a greater effect on volatility than positive shocks, while a positive value of γ means that positive shocks affect volatility more than negative shocks (Wang, 2009). In the model, the β parameter indicates the persistence and the α parameter the ARCH effect.

The EGARCH model developed by Nelson (1991) was transformed into a multivariate structure by Koutmos and Booth (1995). Koutmos (1996) expanded this model further and developed the multivariate VAR-EGARCH model used in his study.

The VAR-EGARCH model offers advantages compared to the univariate EGARCH model. First, problems with predictive regression are avoided by performing the analysis in a single step. However, it increases the power of the tests to reveal the interaction between markets. It shows that news in one market provides information to investors who want to invest in the other market, both about the size of the market and whether it is under a negative or positive influence (Koutmos & Booth, 1995).

$$R_{i,t} = \beta_{i,0} + \sum_{j=1}^{n} \beta_{i,j} R_{j,t-1} + \varepsilon_{i,t} \quad i,j = 1,2, \dots n \quad (9)$$

$R_{i,t}$: percent return at time *t* in market *i*
$\sigma_{i,t}^2$: Conditional variance

In Equation 9, the returns of the markets are handled within the scope of the VAR model. The conditional mean of each market is a function of its lagged returns and the cross-lagged returns between markets. The coefficient $\beta i, j$, $i \neq j$ indicates the antecedent-lag relationship between the returns of the markets. This coefficient indicates that market *i* causes market *j* or can be used to predict returns in market j and future returns in market i. If $i = j$, it indicates the dependence of the i market return on its own lagged returns.

$$\sigma_{i,t}^2 = exp[\alpha_{i,0} + \sum_{j=1}^{n} \alpha_{i,j} f_j(z_{j,t-1}) + \gamma_i ln\,(\sigma_{i,t-1}^2)] \quad i,j = 1,2,\dots,n \quad (10)$$

Equation 10 describes a conditional equation of variance for the returns of each market. Here, it can be observed that conditional variance is an exponential function of the markets' own standardized changes (past shocks) and cross-market standardized changes.

In this model, the volatility persistence of the market i is determined by the term γ_i. For the γ_i term, the unconditional variance will be finite if $\gamma_i < 1$. In the case of $\gamma_i = 1$, the unconditional variance will not be encountered, and the conditional variance will continue depending on the first order. The coefficient $\alpha_{i,j}$ in the equation is $i \neq j$; it shows the volatility spread between the i and j markets. A positive and statistically significant coefficient of α_(i,j) means that j market shocks spread over i market volatility. However, in the case of $i = j$, i shows the dependence of market volatility on its own lagged shocks.

$$f_j(z_{j,t-1}) = (|z_{j,t-1}| - E(|z_{j,t-1}|) + \delta_j z_{j,t-1}) \quad j = 1,2,\dots,n \quad (11)$$

As dependent on Equation 10,
While $z_{j,t-1} < 0$, it is $(-1 + \delta_j)$

While $z_{j,t-1} > 0$, it is $(1 + \delta_j)$

In Equation 11, $i \neq j$; α_{ij}, shows the volatility between the i and j markets. Statistically significant and non-negative α_{ij} and negative δ_j indicate that the negative shocks in the j market and the volatility in the i market are relatively more effective than the positive shocks; however, the realized volatility spillover is asymmetrical.

δ_j measures the asymmetric effect of past shocks on volatility. Thus, it allows the markets' own lagged shocks and cross-market shocks to act asymmetrically on the conditional variances of the markets. When this coefficient is significant and negative, it means that negative shocks have a greater impact on volatility than positive shocks.

$$\sigma_{i,j,t} = \rho_{i,j}\, \sigma_{i,t}\, \sigma_{j,t} \qquad i,j = 1,2,\ldots,n \quad ve \quad i \neq j \qquad (12)$$

According to Equation 12, conditional variance indicates the simultaneous relationship between markets. This specification, which facilitates the estimation of the model, states that the correlation between the i and j variables is constant or that the covariance moves proportionally with the standard deviation (Koutmos & Booth, 1995).

3. FINDINGS

For the analysis of financial time data in GARCH-type models, the stationarity of the series is important, as emphasized in the methodology section. Figure 1 shows the graph of the price series of the variables used in the analysis. An examination of the graphs reveals that there are structural changes (structural breaks) in prices during the period and that the series contains a trend.

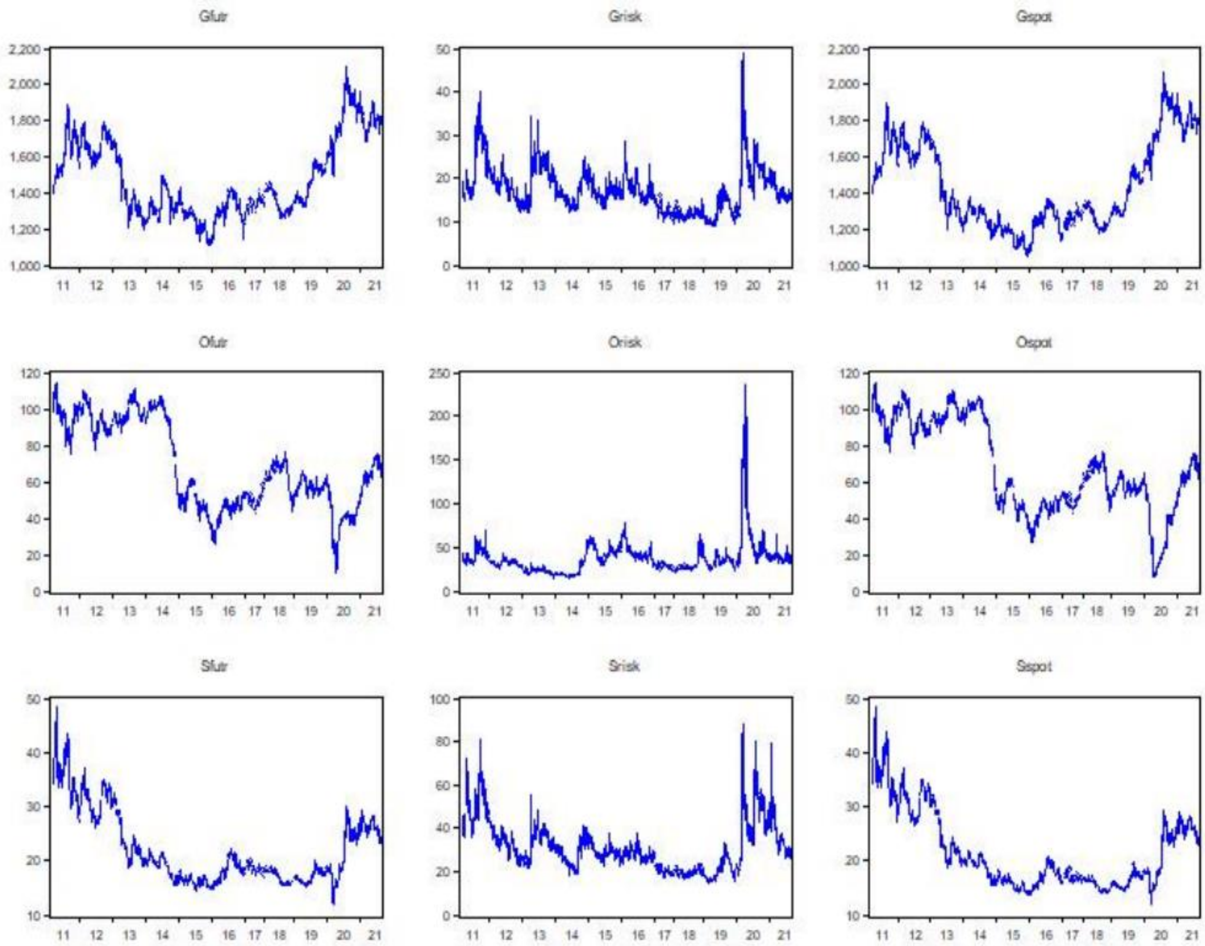

Figure 1. Graphs of price series of variables.

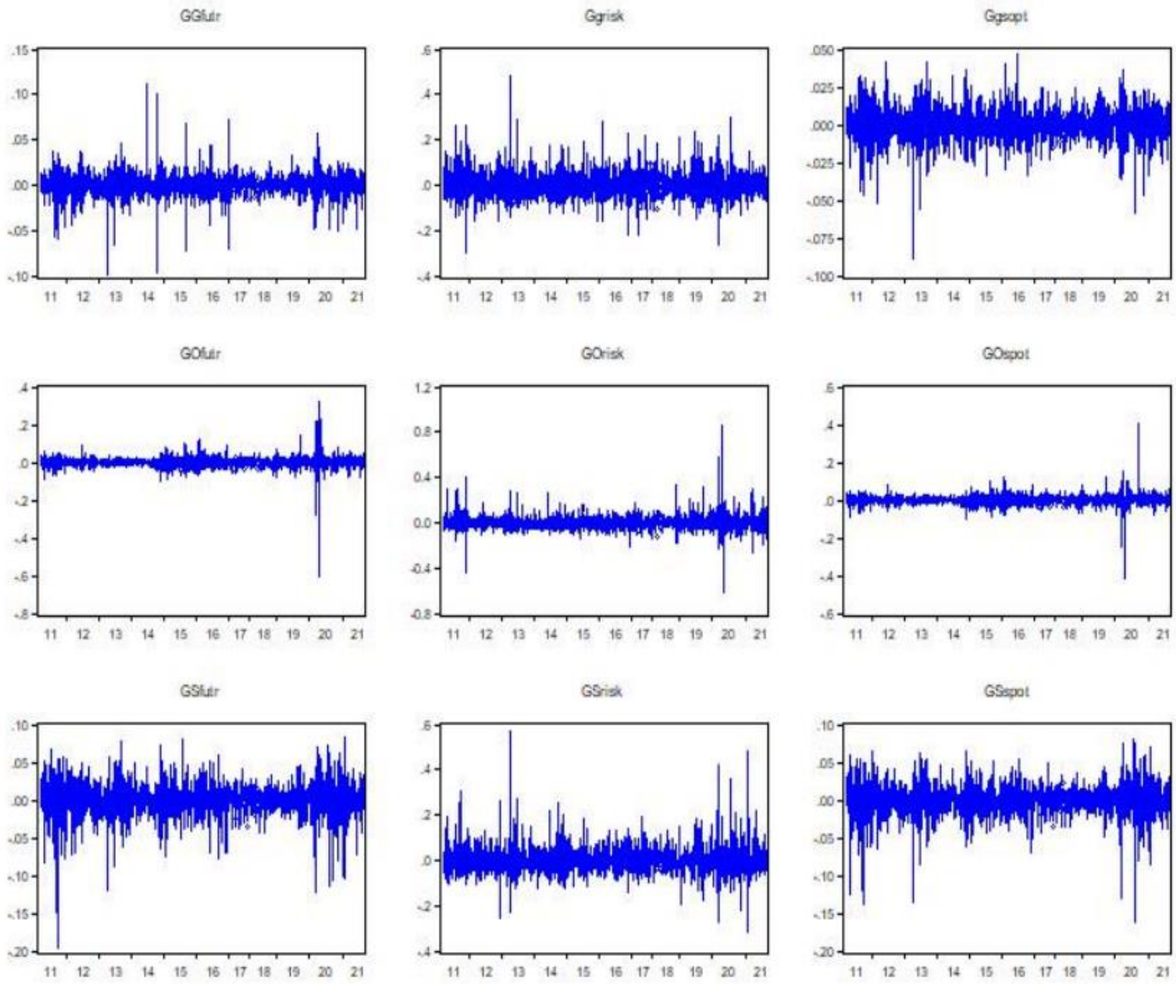

Figure 2. Graphs of return series of variables.

Figure 2 shows that there is volatility clustering in both spot and futures return series; low volatility periods are followed by low volatility, and high volatility periods are followed by high volatility. In this way, it is determined that there is heteroscedasticity in both spot and futures returns. Thus, it can be said that there is varying variance in both spot and forward returns. In addition, it is determined that volatility increased in all volatility indices, especially during periods of turbulence, such as COVID-19.

Table 1. Dataset information.

Variables	Variable Description	Period	Source
GVI	CBOE Gold ETF Volatility Index	16.03.2011- 03.09.2021	Investing.com
G_spot	Gold Spot Price		
G_future	Gold Futures Price		
SVI	CBOE Silver Etf Volatility		
S_spot	Silver Spot Price		
S_future	Silver Futures Price		
OVI	CBOE Crude Oil Volatility Index		
O_spot	Oil Spot Price		
O_future	Oil Futures Price		

Table 2. Results of VAR (1)-EGARCH (1,1) model for gold.

$R_{i,t} = \beta_{i,0} + \sum_{j=1}^{n} \beta_{i,j} R_{j,t-1} + \varepsilon_{i,t} \quad i,j = 1,2,\ldots n$			
Gspot		**Gfutures**	
$\beta_{G\_spot,Sabit}$	-0.093 (-9.397)*	$\beta_{G\_futures,Sabit}$	-0.108 (-11.282)*
$\beta_{G_{spot},GVI(-1)}$	0.136 (6.278)*	$\beta_{G\_futures,GVI(-1)}$	0.814 (11.241)*
$\beta_{G\_spot,G\_spot(-1)}$	0.0007 (0.656)	$\beta_{G\_futures,G\_spot(-1)}$	-0.728 (-8.963)*
$\beta_{G\_spot,G\_futures(-1)}$	-0.108 (-7.968)*	$\beta_{G\_futures,G\_futures(-1)}$	-0.004 (-0.596)
$\sigma_{i,t}^2 = exp[\alpha_{i,0} + \sum_{j=1}^{n} \alpha_{i,j} f_j(z_{j,t-1}) + \gamma_i \ln(\sigma_{i,t-1}^2)] \quad i,j = 1,2,\ldots,n$			
$\alpha_{G\_spot,Sabit}$	-0.045 (-6.865)*	$\alpha_{G\_futures,Sabit}$	0.022 (0.136)
$\alpha_{G\_spot,GVI(-1)}$	0.060 (16.117)*	$\alpha_{G\_futures,GVI(-1)}$	0.035 (0.595)
$\alpha_{G\_spot,G\_spot(-1)}$	-0.066 (-5.853)*	$\alpha_{G\_futures,G\_spot(-1)}$	-0.523 (-1.639)
$\alpha_{G\_spot,G\_futures(-1)}$	0.071 (17.154)*	$\alpha_{G\_futures,G\_futures(-1)}$	0.550 (5.466)*
$\delta_{G\_spot\_Kaldıraç}$	0.171 (1.199)	$\delta_{G\_futures\_Kaldıraç}$	-0.133 (-0.944)
$\gamma_{G\_spot\_GARCH}$	0.973 (230.675)*	$\gamma_{G\_futures\_GARCH}$	0.716 (9.092)*
LB-Q	5.461 (0.941)	LB-Q	13.529 (0.332)
ARCH-LM	15.406 (0.220)	ARCH-LM	54.715 (0.000)*

Note: Values in ( ) are standard errors. (*) indicates that the results are at the 1% significance level.

The coefficients of 0.137 and 0.814 in Table 2 show that the lagged returns of the GVI have a statistically significant positive effect on both spot gold (G_spot) and gold futures (G_futures) returns. It can be seen from the coefficient of 0.814 that the return spread effect of the GVI has a greater effect in the futures markets than in the spot market. The fact that uncertainties about gold prices have a greater impact on futures markets than spot markets may be because GVI is an ETF calculated on options contracts.

When the spillover effect of the gold implied-volatility ETF on the volatility of both the spot and futures markets is analyzed, the results in Table 2 show that the GVI has the effect of increasing the spot gold yield volatility. The change in GVI expressed by the coefficient value of 0.060 can be interpreted as an increase in the G_spot return volatility. It is further understood from the results in Table 2 that, unlike spot gold return volatility, GVI does not have a significant effect on futures return volatility.

The leverage parameters indicate that the volatility persistence in both spot and futures gold markets is high. Spot gold volatility persistence is at 0.973, while that of futures is at 0.716. The leverage parameter obtained from the VAR-EGARCH model is statistically insignificant. This result can be interpreted to mean that negative and positive information shocks have similar effects on both spot and futures markets. The fact that volatility persistence is lower in gold futures compared to low spot gold and that the GVI is statistically ineffective on the volatility of gold futures can be interpreted to mean that gold futures are more effective than spot gold prices in terms of market efficiency.

Table 3. VAR(1)-GARCH(1,1) model results for silver.

$$R_{i,t} = \beta_{i,0} + \sum_{j=1}^{n} \beta_{i,j} R_{j,t-1} + \varepsilon_{i,t} \quad i,j = 1,2,\dots n$$			
Sspot		**Sfutures**	
$\beta_{S\_spot,Sabit}$	-0.041 (-2.471)**	$\beta_{S\_futures,Sabit}$	-0.027 (-1.095)
$\beta_{S\_Spot,SVI(-1)}$	0.186 (2.847)*	$\beta_{S\_futures,SVI(-1)}$	0.747 (9.508)*
$\beta_{S\_spot,S\_spot(-1)}$	-0.005 (-0.972)	$\beta_{S\_futures,S\_spot(-1)}$	-0.735 (-9.598)*
$\beta_{S\_spot,S\_futures(-1)}$	-0.214 (-3.492)*	$\beta_{S\_futures\_futures(-1)}$	-0.004 (-0.653)
$$\sigma_{i,t}^2 = exp[\alpha_{i,0} + \sum_{j=1}^{n} \alpha_{i,j} f_j(z_{j,t-1}) + \gamma_i \ln(\sigma_{i,t-1}^2)] \quad i,j = 1,2,\dots,n$$			
$\alpha_{S\_spot,Sabit}$	-0.122 (-4.310)*	$\alpha_{S\_futures,Sabit}$	-0.114 (-4.325)*
$\alpha_{S\_spot,SVI(-1)}$	0.102 (3.657)*	$\alpha_{S\_futures,SVI(-1)}$	0.090 (3.434)*
$\alpha_{S\_spot,S\_spot(-1)}$	0.119 (2.463)**	$\alpha_{S\_futures,S\_spot(-1)}$	0.116 (2.480)**
$\alpha_{S\_spot,S\_futures(-1)}$	0.002 (1.124)	$\alpha_{S\_futures\_futures(-1)}$	0.001 (1.151)
$\delta_{S\_spot\_Kaldıraç}$	-1.237 (-1.193)	$\delta_{S\_futures\_Kaldıraç}$	1.071 (2.078)**
$\gamma_{S\_spot\_GARCH}$	0.964 (52.359)*	$\gamma_{S\_futures\_GARCH}$	0.968 (58.037)*
LB-Q	14.261 (0.284)	LB-Q	12.844 (0.380)
ARCH-LM	13.860 (0.310)	ARCH-LM	19.957 (0.068)*

Note: Values in ( ) are standard errors. (*) indicates that the results are at the 1% significance level and (**) indicates that the results are at the 5% significance level.

According to the results in Table 3, the lagged values of the SVI have a positive effect on the returns of S_spot and S_futures. This conclusion can be drawn from the significance of the coefficients calculated for the variables (0.186) S_spot and (0.747) S_futures. It can even be understood from the coefficient (0.747) that VXSLV lagged values are more dominant in S_futures returns, as is the case with the GVI index.

On the other hand, the results show that the change in the SVI index affects the returns of S_spot and S_futures. It is understood from the coefficients (0.102, 0.090) that SVI volatility has an increasing effect on S_spot and S_futures returns, respectively. Here, it can be understood from the coefficient value of 0.102 that the SVI volatility has a more increasing effect on the S_spot return volatility. Compared to gold, the use of silver in the manufacturing industry and the disruptions in production due to COVID-19 caused the volatility of silver futures to increase as well as the spot silver return volatility of SVI, which, as a global uncertainty indicator, is an indicator of investor sensitivity, unlike gold.

According to the results of the γ parameter, volatility persistence was found to be at the level of .96 for both variables. In this case, it can be interpreted to mean that shocks persist for a long time for both S_spot and S_futures. This result can be interpreted to indicate that there is no difference in the market efficiency of spot and futures silver. In addition, it can be understood from the probability values that SVI volatility affects S_spot and S_futures return volatility in different directions. When the leverage parameters obtained from the model are examined, it becomes clear that the leverage parameter is meaningless for S_spot and significant for S_futures. This situation can be interpreted to mean that negative and positive information shocks do not have the same effect on S_spot and S_futures markets.

Table 4. Results of VAR(1)-EGARCH(1,1) model for oil.

$$R_{i,t} = \beta_{i,0} + \sum_{j=1}^{n} \beta_{i,j} R_{j,t-1} + \varepsilon_{i,t} \quad i,j = 1,2,\dots n$$

Ospot		**Ofutures**	
$\beta_{O\_spot,Sabit}$	-0.153 (-1.636)	$\beta_{O\_futures,Sabit}$	-0.144 (-1.819)***
$\beta_{O\_spot,OVI(-1)}$	-0.186 (-1.167)	$\beta_{O\_futures,OVI(-1)}$	0.307 (1.968)**
$\beta_{O\_spot,O\_spot(-1)}$	-0.025 (-1.523)	$\beta_{O\_futures,O\_spot(-1)}$	-0.401 (-2.130)**
$\beta_{O\_spot,O\_futures(-1)}$	0.055 (0.289)	$\beta_{O\_futures,O\_futures(-1)}$	-0.019 (-1.191)

$$\sigma_{i,t}^2 = exp[\alpha_{i,0} + \sum_{j=1}^{n} \alpha_{i,j} f_j(z_{j,t-1}) + \gamma_i \ln(\sigma_{i,t-1}^2)] \quad i,j = 1,2,\dots,n$$

$\alpha_{O\_spot,Sabit}$	-0.171 (-3.927)*	$\alpha_{O\_futures,Sabit}$	-0.166 (-4.165)*
$\alpha_{O\_spot,OVI(-1)}$	0.112 (6.390)*	$\alpha_{O\_futures,OVI(-1)}$	0.105 (6.068)*
$\alpha_{O\_spot,O\_spot(-1)}$	0.114 (2.850)*	$\alpha_{O\_futures,O\_spot(-1)}$	0.114 (3.094)*
$\alpha_{O\_spot,O\_futures(-1)}$	0.025 (3.281)*	$\alpha_{O\_futures,O\_futures(-1)}$	0.025 (3.687)*
$\delta_{O\_spot\_Kaldıraç}$	2.370 (7.938)*	$\delta_{O\_futures\_Kaldıraç}$	-12.761 (-10.004)*
$\gamma_{O\_spot\_GARCH}$	0.994 (289.890)*	$\gamma_{O\_futures\_GARCH}$	0.995 (267.662)
LB-Q	34.093 (0.001)*	LB-Q	19.348 (0.080)*
ARCH-LM	20.375 (0.060)	ARCH-LM	0.080 (0.712)

Note: Values in ( ) are standard errors. (*) indicates that the results are at the 1% significance level, (**) indicates that the results are at the 5% significance level, and (***) indicates that the results are at the 10% significance level.

Table 4 presents the results of the lagged prices and OVI index returns spread over O_spot and O_futures prices. According to the results obtained from the model, there is no return spread on O_spot, neither on its own lagged values nor on OVI or O_futures lagged values. These results were obtained from the coefficients (-0.186, -0.025, 0.055) and probability values calculated for the model. However, it is statistically significant that the past values of the OVI index and O_spot index have positive and negative return spreads on O_futures. While the OVI affected O_futures price returns positively (0.105), O_spot (-0.401) had a negative spillover. Here, it can be understood from the coefficient (-0.401) that O_spot prices are more dominant over O_futures prices.

However, other findings indicate that OVI volatility shocks increase O_spot and O_futures return volatility. These results were obtained from the coefficients of statistically significant results (0.112, 0.105) on the O_spot and O_futures return volatility of the OVI. Similar to what was expressed above regarding silver, it can be seen that the increase in investor sensitivity parallels the increase in the uncertainty of the future in oil spot and futures, which is one of the important input elements of production processes – COVID-19 caused a statistically significant increase in oil spot and futures volatility. In addition, volatility persistence was observed to be as high as 0.99 on both O_spot and O_futures. The fact that the persistence in oil volatility is very close to 1 can be interpreted to mean that the shocks that occur with the increase in global fear about oil do reach an equilibrium value in the long run. Compared to precious metals, the effect of oil on global production can be interpreted to indicate that global uncertainties have a greater impact on oil volatility than on precious metals. Finally, since the leverage parameter of the model is statistically significant, it is evident that O_spot and O_futures do not affect the markets in the same direction. Positive and negative information affects the two markets differently.

4. CONCLUSION

Regardless of their source, it is a frequently researched issue in the finance literature that global uncertainties have an increasing effect on the portfolio diversification of both individual and institutional investors. Although many asset pricing theories are based on the assumption that investors are rational, global developments, whether in the political or health arena, can trigger investors to make irrational choices. Implied volatility indices are calculated by the Chicago Board Options Exchange on the principle that they will supply foresight over futures contracts of related assets as an indicator of investor sensitivity. These indices help investors make inferences about the possible future movements of asset prices. Since implicit volatility indices are based on uncertainties about a fluctuation occurring in the prices of related assets, they are described in the literature as fear indices. Whether they make rational or irrational investment decisions, the need for potential investors to obtain certain returns using portfolios with minimum variance in portfolio diversification makes it essential to examine the possible effects of such fears on asset returns and return volatility.

This study was conducted to allow investors the opportunity to make inferences about portfolio diversification by measuring the effect of fear indices on gold, silver, and crude oil returns and volatility, which can be considered both an investment tool and an input element in production. Using the VAR-EGARCH procedure, the effects of the implied volatility (fear) indices OVI, GVI, and SVI on the returns and volatility of both spot and futures assets were examined separately. The findings show that each financial asset responds differently. Both the GVI and gold futures (G_futures) prices have a positive effect on gold spot prices. At the same time, it has been determined that gold futures (G_futures) prices are obtained from the GVI and gold spot prices. On the other hand, while the SVI and futures prices affected silver spot prices, only the SVI lagged prices affected S_futures. Finally, while the OVI index and O_futures returns did not affect oil spot prices, only the OVI index returns affected O_futures prices. These results are similar to those obtained in the studies of Jubinski and Lipton (2013); Jin et al. (2014); Chen et al. (2015); Chen and Zou (2015); Ji et al. (2016); Chen et al. (2018); Molnár and Bašta (2017); Lin and Tsai (2019); Shaikh (2019); Alqahtani and Chevallier (2020); Benedetto et al. (2020); Lu et al. (2020); Echaust and Just (2021); Tanin et al. (2021).

Although this research obtained different findings for the different asset types, we observed that the fear indices, an indicator of investor sensitivity, affect the returns and volatility of both spot and futures assets. The most striking result of the research is that compared to the climate of fear in the markets, the futures assets of silver and crude oil, which are also used as input elements in the manufacturing industry, increase their volatility and have a more negative effect on the persistence of volatility. When evaluated in terms of market efficiency, the fact that gold spot and futures markets are relatively less affected by the climate of increasing fear compared to silver and oil markets emerges as another result of the research. To enrich the literature on this subject, the effect on spot and futures markets of price or return volatility of different commodities and other market instruments should be investigated in further studies.

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