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Volatility Spillover: Garch Analysis of S&P 500's Influence on Precious Metals[1]

Abstract: In this study, the volatility spillovers from the S&P 500 to the precious metals (gold, silver and platinum) are investigated. By using the TGARCH and DCC GARCH model, the evidence is found that there are spillovers between the S&P 500 and these global commodity markets. However, there are some differences in times of crises which have occurred during the observed 15 years (global economic crisis, debt crisis and corona crisis). In the case of gold, despite extreme volatility, there is no clear evidence of the specific influence of the crises. In contrast, silver and platinum showed clearer situations, both demonstrating significant increases in correlation with the S&P 500 index during global economic crises.

Keywords: Spillover, Commodity markets, GARCH, crisis.

JEL Classification: C10, F36, G11, G15.

Introduction

According to modern portfolio theory, there is always a need to diversify a portfolio across different asset classes and different markets. This topic is probably of utmost importance for all portfolio managers around the world, but also for portfolio optimization theory. From a theoretical point of view, it makes sense to

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combine all assets that have the lowest possible correlation. On the other hand, as a direct result of globalization, there is increasing integration between financial markets through volatility and returns. The mechanism for transferring information from one market or asset to another is very important today. This can be seen in the spillover effects from the most developed markets to some other markets and global assets (oil, global commodities, gold and other precious metals, crypto markets, etc.). Of course, it is even more important to optimize the portfolio and use appropriate hedging strategies in times of crisis. Over the last 15 years, the world has experienced various crises with very specific causes.

The most developed market in the world is represented by the NYSE and its S&P 500 Index with the largest market capitalization. Accordingly, in this paper we explore the possibility of optimizing the portfolio through a combination of the S&P 500 and selected precious metals (gold, silver and platinum). The central hypothesis of the paper is therefore to investigate whether there is a spillover from the S&P 500 to the precious metals, and in particular how this has additionally changed during the crisis.

In this paper we have applied the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model alongside the Dynamic Conditional Correlation (DCC) GARCH model to investigate the co-movements between precious metals and the global equity markets represented by the S&P 500.

Literature Review

The financial markets and institutions have changed and developed rapidly in recent decades due to general trends of deregulation, liberalization, globalization and breakthroughs in computer technology (Fabris, 2019; Milojevic & Redzepagic, 2021). In times of instability, policymakers focus on maintaining price stability and amortizing external shocks that threaten to jeopardize the achievement of price stability (Fabris & Lazic, 2022; Ozer, Grubisic & Küçüksakarya, 2023), while investors focus on preserving capital value (Pazner & Razin, 1975; Fabris & Jesic, 2023; Kamıslı, Ozer, Sayılır, & Diallo, 2023). This dual focus on price stability and capital preservation is crucial for ensuring economic stability. In this regard, investors and policymakers have recently become increasingly interested in precious metals (Hillier, Draper & Faff, 2006). Studies examining the relationship between the capital market and precious metals (e.g. Sadeghi, Sanoubar, Marvasti & Karbor, 2014; Mensi, Vo & Kang, 2021) attempt to describe the dynamics between these asset classes and their role in investment portfolios. These studies usually focus on gold, silver and platinum, as these are the most traded and best-known precious metals (Al-Yahyaee, Mensi, Maitra & Al-Jarrah, 2019). Due to their inherent properties, these metals have always played a central role in the global commodities market. In times of stability, for example, gold is seen as a hedge against inflation and a reliable 'store of value' (Vukovic, Maiti, Grubisic, Grigorieva & Frommel, 2021; Adekoya, Oliyide & Tahir, 2021). In times of crisis, on the other hand, it is widely regarded as the epitome of a safe haven. In this context, Baur and Glover (2016) examined the role of gold as a safe haven and found that excessive investor confidence in its safety could undermine this role in practice. Shrydeh, Shahateet, Mohammad & Sumadi (2019), analyzing the US financial market from 2007-2017 using VAR-ADCC-BVGARCH, seem to confirm this conclusion. While the literature generally agrees that gold is a risk-mitigating asset relative to equities, the findings of Bauer and Glover (2012) and Shrydeh et al. (2019) suggest that this hedging aspect diminishes as the market capitalization of US equities increases, indicating a need for large gold investments relative to equities.

The main objectives of studies examining the relationship between the capital market and precious metals can be categorized into the following broad categories: (i) understanding the correlation between the movements of equity indices and precious metals to provide investors with more information on the potential benefits of diversifying portfolios with these commodities; (ii) exploring the role of precious metals as safe havens in times of financial shocks or market instability; (iii) exploring the impact of macroeconomic factors such as interest rates, inflation and exchange rates on the relationship between equity movements and precious metals. Below are the conclusions of the most significant works in this field.

Baur and Lucey (2010) examined the role of gold in the investment process. They aimed to gain a deeper understanding of gold's function in diversifying investment portfolios by analyzing its relationship to stocks and bonds under different market conditions. Using daily and monthly data from 1979 to 2008, the authors focused on stock market indices in the US, UK and Germany as well as ten-year government bonds of these countries. GARCH models and quantile regression are used for the analysis. The results are categorized as follows: 1. Gold as a hedge: The study shows that gold serves as a hedge against equities, but not against bonds. Gold has a low correlation with equities, indicating a positive impact on portfolio diversification. However, it does not have the same protective properties against bonds. 2. Gold as a safe haven: The authors find that gold acts as a safe haven for equities in times of extreme market stress, indicating its potential protective role in an investment portfolio in times of high market volatility or financial crises. The results also show that gold acts as a safe haven for bonds, but only in the short term. 3. Gold and inflation: The authors find evidence that gold acts as a hedge against inflation, supporting the idea that gold can help investors preserve their purchasing power in times of rising inflation.

The study by Hood and Malik (2013) investigated the role of gold and precious metals as a hedge and safe haven at different levels of market volatility using US equity market data from 1995 to 2010. The results show that gold, unlike other precious metals (platinum and silver), is a weak hedge and safe haven for the US equity market. The authors find that the VIX serves as an extremely robust hedge and safe haven during the observed period. In both periods of low and high volatility, gold shows no negative correlation with the US equity market. In contrast, the correlation of the VIX with the overall equity market remains consistently negative and even strengthens during times of market turbulence (high volatility). Overall, the results suggest that the VIX is a better protective tool and a better safe haven than gold during the observed period.

In their study, the authors Arouri, Hammoudeh, Lahiani and Nguyen (2012) examine the return and volatility dynamics of precious metals — gold, silver, platinum and palladium — taking into account long memory and structural changes in their movements. Empirically, three tests for long memory are applied to analyze the long-term dependence in the conditional means and variances of these precious metals. In addition, a modified version of the Iterative Cumulative Sums of Squares (ICSS) algorithm by Inclan and Tiao (1994) is used to detect structural changes in the time series of the precious metals data. The results indicate that long memory is a significant empirical feature for precious metal series, and the conclusions remain unchanged when potential structural changes are considered. In six out of eight cases, there is significant evidence that double long memory models and ARFIMA-FIGARCH class models are better suited to describe temporal variations in precious metals returns and volatility. The out-of-sample analysis shows that the ARFIMA-FIGARCH class model provides more accurate volatility forecasts than other competing GARCH models in most cases. Comparing the empirical results among metals, the platinum futures return series has the highest degree of long memory in the variance equation, indicating that platinum may deviate from the average over a longer period of time. Therefore, platinum is not a suitable hedging instrument during bear or crisis markets. Furthermore, it is necessary to apply IGARCH conditional variance modelling for this series. Among the metals observed, gold can serve as a good hedge during market downturns as its return shows relatively low deviations from the mean and variance, confirming its prominent status as a safe haven. The results also highlight the importance of asymmetry in the dynamics of returns and volatility in precious metals, as the EGARCH-based model is best suited for predicting returns and volatility, respectively. Therefore, the extension of ARFIMA-FIGARCH models to include asymmetry in return and volatility series can improve their predictive power.

In their study, the authors Batten, Ciner and Lucey (2010) examine the macroeconomic factors that influence the instability of the precious metal markets, focusing specifically on gold, silver, platinum and palladium. The aim is to understand the factors that influence price changes and their impact on investors, policy makers and market participants. Through extensive data analysis and various econometric methods, the study demonstrates the correlation between macroeconomic variables and the instability of precious metal markets. With regard to individual precious metals, the authors find that gold is primarily influenced by monetary factors such as the money supply. This finding is consistent with the idea that gold can be considered a financial asset, perhaps even a currency substitute, making its price changes sensitive to the actions of monetary authorities (or central banks). Moreover, there is a significant dependence of the conditional volatility of the gold price on its own lags, which is consistent with the ARCH effects documented and known in the financial literature. Indeed, this phenomenon can also be observed in the prices of other precious metals. Furthermore, there is evidence that volatility spills over from the silver market to the gold market, as shown by the significance of the test statistic for the conditional volatility variable of silver with lag. The authors find that the conditional volatilities of the financial variables, both the S&P 500 and its dividend yield and the money supply, are significant determinants of the volatility of the palladium price. The results for platinum and silver show a different picture. In particular, the authors find that none of the macroeconomic factors explain the useful structure of volatility for these precious metals. This is particularly interesting for silver, as previous empirical research shows that silver has a significant economic use and can be considered an industrial metal.

Building on the existing literature, this paper focuses on the transmission of volatility between the commodity markets and the capital markets of developed countries. In this context, the study tests the following research hypotheses:

- H1: There is a transmission of volatility between the commodity markets and the capital markets of developed countries.
- H2: The transmission of volatility between commodity markets and capital markets of developed countries is greater during times of crisis compared to stable times.

Methodology

In this paper, we apply the GARCH model alongside the DCC-GARCH model to investigate the correlation between precious metals and global equity markets. The GARCH model serves as a fundamental tool for modelling and analyzing the volatility patterns contained in financial time series data. Due to its robustness and flexibility, it is particularly suitable for evaluating the market dynamics of precious metals. Complementing this, the DCC GARCH model is used to capture the evolving correlations between these asset classes, providing a more comprehensive view of their interdependencies. This combination of models allows us to analyze the complex, time-varying nature of the interactions between precious metals and equity markets. The integration of these econometric techniques is central to our efforts to provide a deeper, more nuanced understanding of these financial market relationships, thereby improving the precision and relevance of our findings.

Generalized Autoregressive Conditional Heteroskedasticity Model (GARCH model)

The Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model represents a significant advancement in econometric theory, building upon the foundational ARCH (Autoregressive Conditional Heteroskedasticity) models introduced by Robert F. Engle in 1982 (Engle, 1982). ARCH models aimed to capture the dynamic and variable nature of volatility in financial time series data, addressing the phenomenon of heteroskedasticity, where the variance of error terms changes over time.

Tim Bollerslev expanded on Engle's work in 1986 by developing the GARCH model (Bollerslev, 1986). This model integrates autoregressive elements (reflecting past errors) and moving average components (accounting for past variances), offering a more nuanced depiction of volatility dynamics in financial time series. GARCH models have since become indispensable in the fields of finance and economics, applied in forecasting market volatility, risk management practices, and option pricing strategies due to their robustness in modelling the volatility clustering frequently observed in financial markets. A critical aspect of financial time series, such as returns on investments, is their conditional variance instability, known as conditional heteroskedasticity. GARCH models formalize this concept through a set of equations that describe the return levels and their conditional variance or volatility.

In practice, the GARCH(1,1) model, a simplified version, is often used due to its efficacy in capturing the persistence of volatility shocks. It models conditional variance based on a combination of a long-term average variance, the impact of the previous period's forecast error, and the variance from the previous period. This model efficiently predicts future volatility, emphasizing the impact of recent shocks on predicted future variances.

The model's capacity to forecast long-term volatility hinges on specific parameter values that, when appropriately configured, allow for the prediction of conditional volatility over extended horizons. This feature is particularly relevant in risk management and strategic planning, where understanding future volatility patterns is crucial.

The GARCH framework thus offers a comprehensive and flexible approach for analyzing and forecasting the volatility in financial markets, embodying a significant contribution to econometric modelling and financial analysis. Its development reflects the complex nature of financial data and the need for sophisticated models that can accurately capture and predict dynamic changes in market conditions.

T-GARCH

The T-GARCH model, standing for Threshold GARCH, is a variant of the GARCH model designed to capture potentially asymmetric responses of volatility to positive and negative shocks. This model variation acknowledges that negative shocks from the previous period ($e_{t-1} < 0$) typically exert a greater impact on the current level of volatility compared to positive shocks ($e_{t-1} > 0$). In essence, negative information tends to trigger greater instability in return movements than positive information.

The T-GARCH model recognizes the asymmetry in volatility reactions, enabling a more nuanced understanding and prediction of volatility changes in financial markets. This model is particularly useful in scenarios where negative shocks, such as poor economic news or market downturns, have a more significant impact on volatility compared to positive shocks.

The volatility equation for the T-GARCH(1,1) model is formulated to include additional parameters related to negative shocks, allowing for an asymmetric response in volatility. These parameters are estimated based on available data, facilitating a more accurate understanding and modelling of volatility dynamics and its reactions to various types of shocks.

$$\sigma_t^2 = \alpha_0 + \alpha_1 e_{t-1}^2 + \alpha_1^* N_{t-1} e_{t-1}^2 + \beta_1 \sigma_{t-1}^2, \alpha_1^* > 0$$

$$N_{t-1} = \begin{cases} 1, e_{t-1} < 0 \\ 0, e_{t-1} \geq 0. \end{cases}$$

It is observed that the effect of asymmetric influence of shocks of different signs can be simply modelled using an artificial variable, N_{t-1}, which assumes a non-zero value of one exclusively for negative shock values from the period t-1. The impact of a positive shock is measured by the parameter α_1, while the influence of a negative shock on volatility is captured by an increased value (α_1+α_1^*). The model is structured such that the set threshold level is zero. This approach allows for a straightforward yet effective representation of asymmetric shock impacts in the volatility modelling process, highlighting the distinct influences of positive and negative market events on financial volatility.

DCC GARCH

The Dynamic Conditional Correlation (DCC) GARCH model, introduced by Robert Engle in 2002 (Engle, 2002), represents a statistical method employed for estimating time-varying conditional correlations between financial assets. It extends the traditional GARCH model, which focuses solely on estimating conditional variances, making the DCC GARCH model particularly valuable for portfolio management, risk management, and understanding the dynamics of financial markets.

Key features of the DCC GARCH model include:

1. Flexibility: It allows for changing correlations between financial assets over time, offering a more accurate insight into their relationships.
2. Economy: The model requires fewer parameters compared to alternative multivariate GARCH models, making it computationally more efficient.
3. Conditional Correlations: It estimates conditional correlations, reflecting the dynamic relationship between asset returns with consideration of information available up to a specific point in time.
4. Two-step Estimation Process: The DCC GARCH model utilizes a two-step estimation approach. The first step involves estimating univariate GARCH models for the return of each asset, while the second step estimates a time-varying conditional correlation matrix.

According to Engle (2002), the DCC GARCH model retains the flexibility of univariate GARCH models without the complexity of conventional multivariate GARCH models. These models, which directly parameterize conditional correlations, are naturally estimated in two stages – the first being a series of univariate GARCH estimates, followed by correlation estimation. This methodology offers clear computational advantages over multivariate GARCH models, as the number of parameters to be estimated in the correlation process is independent of the number of series to be correlated. Thus, it allows for the estimation of potentially large correlation matrices. In this study, the accuracy of correlations estimated by different methods is compared in bivariate settings where many methods are feasible, concluding that the DCC-GARCH model achieves superior results compared to other models.

Empirical results

In the empirical results section of our study, we present a detailed analysis of the co-movement patterns observed among three major precious metals — gold, silver, and platinum — and their interaction with global equity markets. Using the robust methods of the GARCH and DCC-GARCH models, this section highlights the complex dynamics and volatility behaviour of these metals. Our analysis not only describes the individual market reactions of gold, silver and platinum, but also sheds light on their collective behaviour in the broader context of global economic fluctuations. The insights gained here are critical to understanding the nuanced role these metals play in financial markets, both as individual assets and in the context of stock market movements. This part of our study aims to bridge the gap between theoretical models and practical market behaviour and provide empirical insights that are of key importance to investors, analysts and policy makers.

Preliminary Data Analysis

In the observed period, gold showed the most remarkable performance with an increase of 236%, while silver also achieved significant growth of 180%. Platinum, on the other hand, recorded a minimal increase of 1% over the same period. Additionally, in terms of volatility measured by standard deviation, gold attained the most stable return with a standard deviation of 2.4%, while platinum was slightly more volatile at 3.4% and silver was even more volatile at 4.4%.

Examining the performance of these metals during the global economic crisis, both silver and platinum have lost considerable value. In contrast, gold recovered quickly despite an initial decline and continued its upward trend. Silver in particular recorded the strongest growth among the metals after the crisis, but also suffered a significant decline during the European debt crisis.

Overall, the data examined in this study exhibit typical characteristics of financial time series. In addition, the analysis of skewness and kurtosis, measured with the Jarque-Bera (JB) test, yielded results below the significance levels (1%, 5%, 10%), indicating the null hypothesis of normal distribution for all observed metals in this time period can be rejected.

The correlation between the observed metals and the S&P 500 Index, as shown in Table 1, shows lower results compared to the correlation of the other indices examined in the study with the S&P 500. Gold in particular showed an exceptionally low correlation of 0.04 with the S&P 500 during the period under review. However, the metals themselves showed a significant degree of correlation with each other, with the highest correlation between gold and silver at 0.8, while the correlation between these metals and platinum was slightly lower, but still remarkably high at 0.6.

Table 1 Descriptive Statistics and Jarque-Bera Test for Metal Returns

Metric	Gold	Platinum	Silver
Mean Return	0.2%	0.1%	0.2%
Median Return	0.3%	0.1%	0.2%
Minimum Return	-8.6%	-19.8%	-25.8%
Maximum Return	14.1%	21.3%	17.8%
Standard Deviation	2.4%	3.4%	4.4%
Skewness	-0.10	-0.28	-0.55
Excess Kurtosis	2.21	4.73	3.84
Number of Observations	787	787	787
Jarque-Bera*	160.87	743.68	523.17
p-value	0.00%	0.00%	0.00%

* Note: The Jarque-Bera test is a goodness-of-fit test of whether sample data have the skewness and kurtosis matching a normal distribution. The p-values indicate the probability of the sample data coming from a normal distribution. In this case, the extremely low p-values (0.00%) for all three metals suggest a rejection of the null hypothesis of normal distribution for their returns.

Source: Authors' own representation

Table 2: Correlation of Metals in the Sample and the S&P 500

	S&P 500	Gold	Platinum	Silver
S&P 500	1			
Gold	0.047028	1		
Platinum	0.330631	0.61896	1	
Silver	0.271504	0.805545	0.66304	1

Note: The correlation coefficient values indicate the strength of the relationship between two indices. Values of +1 or -1 signify a perfect positive or negative correlation, respectively, while a value of 0 indicates no correlation.

Source: Authors' calculations.

Unit Root Tests

The results of the unit root tests are presented in Table 3. This table contains the results of the Dickey-Fuller (DF) test without trend, with trend and the Augmented Dickey-Fuller (ADF) test. The test results show that the null hypothesis of non-stationarity is rejected at the 1% and 5% significance levels.

Table 4 shows the results of the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test. Since the t-statistics are higher than the critical values, the null hypothesis of stationarity is accepted at the 1% and 5% significance levels. This means that all data sets show stationarity.

In view of the unit root tests performed, no transformation of the original data is required for further econometric modelling. Such a transformation is usually required when non-stationary variables are identified in the data. Therefore, the stability of the data series allows the direct application of econometric modelling techniques without prior data transformations, which increases the reliability of subsequent analyzes and interpretations.

Table 3: DF and ADF

DF i ADF test		Platinum	Gold	Silver
no drift	coefficient	-0.99	-1.00	-0.97
	standard error	0.04	0.04	0.04
	t-stat	**-27.67**	**-28.11**	**-27.13**
drift + trend	coefficient	-0.99	-1.01	-0.97
	standard error	0.04	0.04	0.04
	t-stat	**-27.65**	**-28.26**	**-27.18**
			0.00	0.00
augmented (2 lags)	coefficient	-0.89	-1.05	-1.02
	standard error	0.06	0.06	0.06
	t-stat	**-14.68**	**-16.63**	**-16.83**

DF critical values	no trend	trend
1%	-3.43	-3.96
5%	-2.86	-3.41

Source: Authors' calculations.

Table 4 KPSS

	Platinum	Gold	Silver
KPSS Statistic	0.11	0.21	0.16
Critical value (95%)	0.46		
Critical value (99%)	0.74		

Source: Authors' own representation

Heteroskedasticity Test – Detection of ARCH Effects

A decisive prerequisite for the application of the GARCH model is the existence of the so-called ARCH effect (Autoregressive Conditional Heteroskedasticity), for which the ARCH LM (Autoregressive Conditional Heteroskedasticity Lagrange Multiplier) test is used. The test's statistic for detecting the ARCH effect is based on a concept similar to the Q statistic. It examines whether the variance of a time series at a given moment t is dependent on variances at previous moments.

Table 5 shows that the f-statistics and the chi-square statistics are statistically significant at the 1% level for all observed indices. This result confirms the presence of the ARCH effect in the data, indicating heteroscedasticity. This conclusion is also confirmed by the graphical representations of the returns, in which the clusters of variability are clearly visible. The results of the ARCH LM test are consistent with numerous other studies that have documented the presence of the ARCH effect in the financial markets.

These results emphasize the dynamic nature of financial market volatility and the need to use models such as GARCH that can adequately capture and account for such time-varying volatility characteristics in financial time series analysis.

Table 5 Results of ARCH LM Test

Metal	Test	F-Statistic	p-Value (F-stat)	Chi-sq Statistic	p-Value (Chi-sq)
Gold	ARCH (2)	13.5068	0.0000	41.8870	0.0000
Platinum	ARCH (2)	78.2754	0.0000	209.2786	0.0000
Silver	ARCH (2)	10.4796	0.0000	32.7439	0.0000

Note: The test involves examining the first two lags (ARCH (2)) for each metal. The extremely low p-values (0.0000) for both F-statistic and Chi-squared statistic across all metals strongly indicate the presence of ARCH effects. This suggests that the variance of the time series data for these metals is influenced by variances in previous periods, confirming the existence of heteroskedasticity.

Source: Authors' calculations.

Autocorrelation in Commodity Data

Table 6 illustrates the results of the autocorrelation tests for platinum, gold and silver. The test results of both the Box-Pierce and Ljung-Box statistics show that there is significant autocorrelation. This finding is consistent with a considerable body of prior research, which has identified autocorrelation in financial market data.

The existence of autocorrelation serves as an additional indicator that the GARCH model is suitable for modelling the volatility of these commodity indices.

Table 6: Autocorrelation in Commodity Data

Metal	Box-Pierce	p-Value (Box-Pierce)	Ljung-Box	p-Value (Ljung-Box)
Platinum	41.95	0.00000	42.14	0.00000
Gold	28.38	0.00000	28.51	0.00000
Silver	31.18	0.00000	31.34	0.00000

Note: The null hypothesis for these tests is the absence of autocorrelation. The null hypothesis is rejected for all significance levels greater than the observed p-values and not rejected for levels lower than the p-values. The extremely low p-values (0.00000) for both the Box-Pierce and Ljung-Box tests across all metals strongly suggest the rejection of the null hypothesis, indicating a significant presence of autocorrelation.

Source: Authors' calculations.

These results support the appropriateness of using the GARCH model for modelling volatility in the financial time series of these commodities, as GARCH can effectively capture and incorporate the features of autocorrelation in the data.

TGARCH Volatility Modelling

This study presents the results of volatility modelling by ARCH, GARCH and TGARCH processes. Among these, the TGARCH model (Threshold GARCH) provided the most favourable results and was subsequently used as the basis for dynamic correlation modelling (DCC). The purpose of the TGARCH variant of the GARCH specification is to model the potential asymmetric response of volatility to positive and negative shocks, where a negative shock from a previous period usually has a greater impact on the current level of volatility than a positive shock.

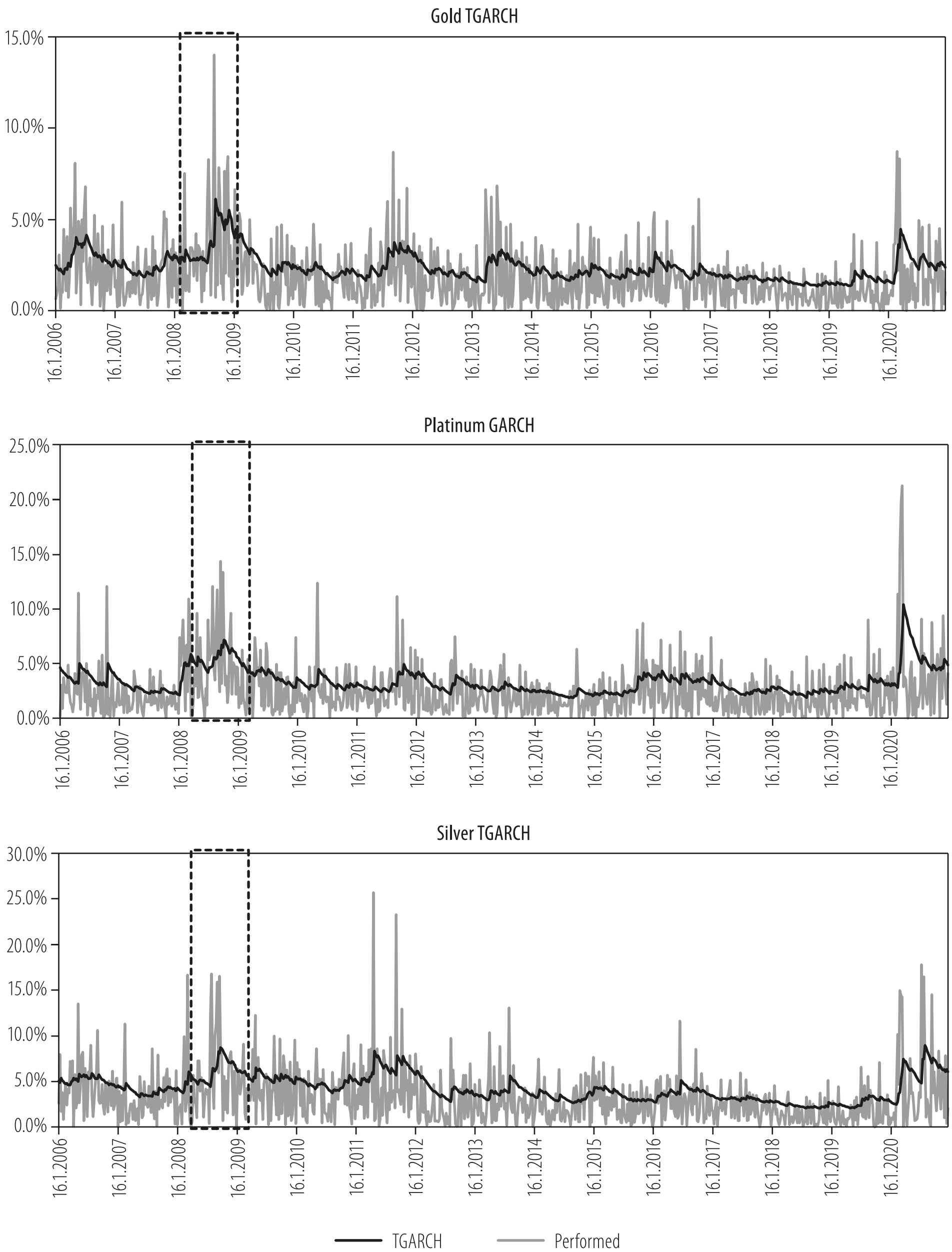
In Graph Set 1, we observe the estimated volatility of the TGARCH model alongside the actual market volatility. The horizontal axis represents the time period, while the vertical axis shows the level of volatility. The actual market volatility, shown with a gray line, represents the real market volatility recorded over the observed period. Estimated volatility, shown in black is derived from the TGARCH model using historical data.

Visual inspection shows that the estimated volatility of the TGARCH model closely follows the actual market volatility over the entire period. The black line consistently follows the fluctuations of the gray line, indicating that the TGARCH model effectively captures the changes in market volatility.

Similar to the equity indices, it can be observed that both the estimated TGARCH volatility (black line) and the actual market volatility (gray line) rise sharply during the global economic crisis, with both lines reaching their peak values during this period. The increased uncertainty during the crisis and structural disruptions in the banking sector led to periods of heightened market uncertainty that affected both the equity and commodity markets.

In addition to the considerable volatility in 2008, the crisis triggered by the COVID-19 pandemic led to further market shocks. The pandemic caused considerable volatility on the global markets and had a significant impact on the markets of the commodities under review.

Graph set 1: Graphical Representation of Commodity Market Volatility Modelling Using TGARCH Model



Source: Authors' calculations.

Maximum Likelihood Test

The evaluation of the TGARCH model was carried out analogously to the approach used for the indices with the aid of the maximum likelihood test, supplemented by autocorrelation tests, namely Box-Pierce and Ljung-Box. The results of these tests confirm that the TGARCH model is well fitted to the data. While the methodology of these tests was summarized earlier in this paper, we focus here on the discussion of the results. The application of the maximum likelihood test and the autocorrelation tests (Box-Pierce and Ljung-Box) to evaluate the performance of the TGARCH model demonstrates its suitability for modelling the volatility of the observed indices. However, in the case of platinum, the GARCH model produced higher values in the maximum likelihood test. Therefore, the GARCH model was used to model the volatility of platinum instead of the TGARCH model.

Table 7: Model Testing using Maximum Likelihood Method

Metal	Model	Chi-sq	df	p-value
Gold	ARCH	43.89	1.00	0.00
	GARCH	120.62	2.00	0.00
	TGARCH	123.72	3.00	0.00
Platinum	ARCH	63.87	1.00	0.00
	GARCH	125.84	2.00	0.00
	TGARCH	118.84	3.00	0.00
Silver	ARCH	20.25	1.00	0.00
	GARCH	129.12	2.00	0.00
	TGARCH	134.00	3.00	0.00

Source: Authors' calculations.

Table 8: Autocorrelation of Standardized Residuals of TGARCH (GARCH) Model

Metal	Test	Box-Pierce Stat	p-Value	Ljung-Box Stat	p-Value
Gold	Autocorrelation	2.16	0.53943	2.17	0.53742
Platinum	Autocorrelation	1.66	0.64601	1.67	0.64372
Silver	Autocorrelation	1.34	0.71998	1.35	0.71812

Note: The null hypothesis for these tests is the absence of autocorrelation. The null hypothesis is rejected for all significance levels greater than the observed p-values and not rejected for levels lower than the p-values.

Source: Authors' calculations.

These results show that the TGARCH model (and the GARCH model in the case of platinum) effectively captures the dynamics of market volatility with minimal signs of autocorrelation in the standardized residuals, confirming the robustness of the model and its suitability for the financial time series data under investigation.

DCC GARCH and Correlation Matrix Analysis

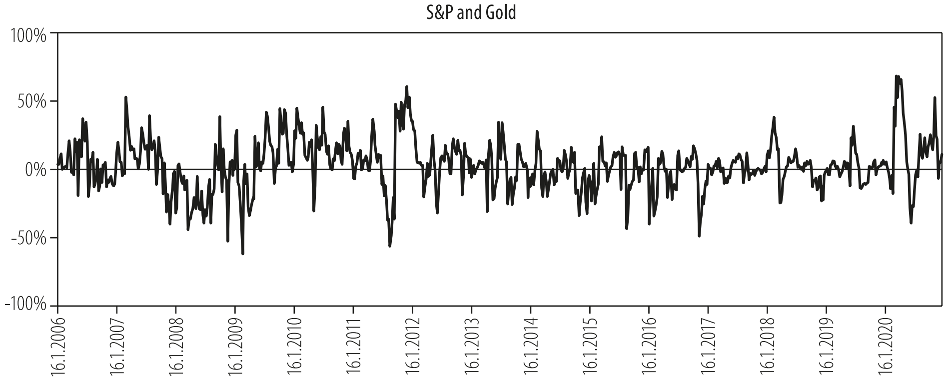
As previously discussed, the DCC (Dynamic Conditional Correlation) GARCH model was employed to investigate the extent of volatility spillover between the S&P 500 Index and the commodity markets. The correlation modelled by DCC GARCH shows remarkable volatility, especially in the case of gold. Even in times of crisis, it is difficult to determine conclusively how the crisis has affected gold price movements. The situation is clearer for silver and platinum. For both metals, the correlation with the S&P 500 Index increased significantly during the global economic crisis. A common trend for all commodity markets is the increase in volatility during the COVID-19 pandemic crisis. In the period under review, gold has the lowest correlation with the S&P 500 and frequently dips into negative territory, while platinum has the highest average correlation with the index.

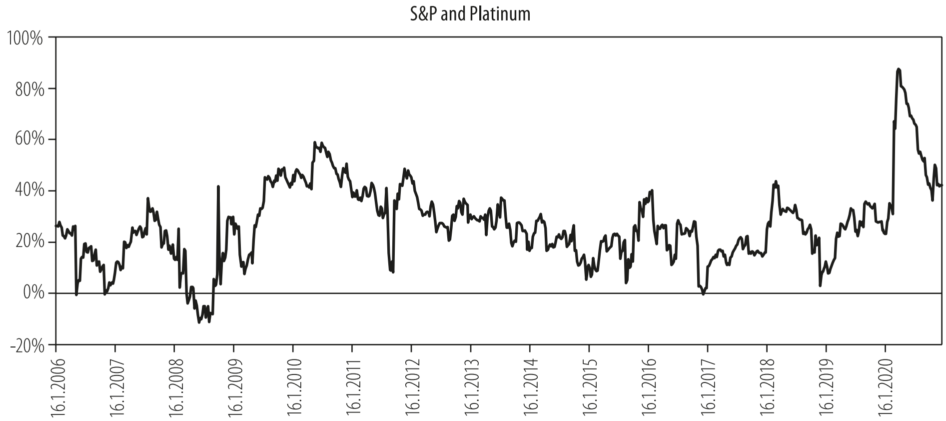
In order to isolate the crisis moments and observe the reactions of the commodity markets, we have created a conditional correlation matrix. This matrix shows that the correlation between the commodity markets and the observed index is highest during the most volatile moments of the S&P 500 index (95% to 100% in Table 98 and Graph Set 3). This is clear evidence that volatility spills over to the commodity markets in times of crisis.

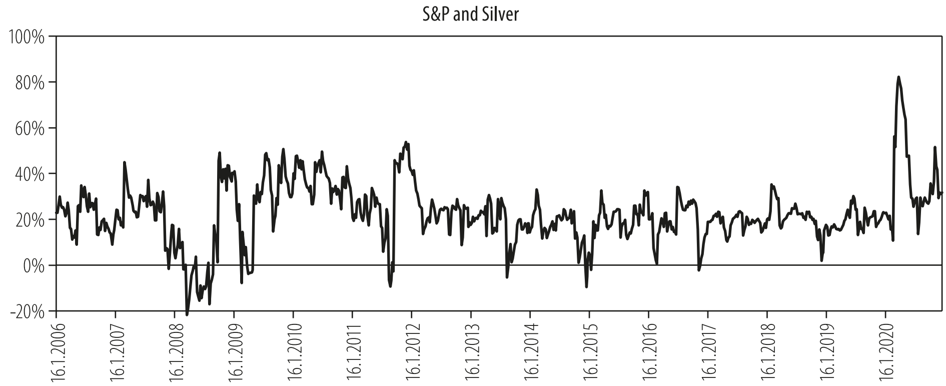
In the case of gold, on the other hand, the S&P 500 showed no correlation with the observed index in times of crisis (0% to 5% in table 109 and Graph Set 4). This is in line with the perception of gold as a safe haven in times of crisis, while platinum and silver showed a significant correlation of returns in the same range.

Given the overall positive correlation between the commodity markets and the S&P 500, it can be concluded that there is a transmission of volatility between these markets that intensifies when there are shocks in the financial markets. This observation supports hypotheses 1 and 2 and confirms the interconnectedness and dynamic interplay between these market segments in times of financial turmoil.

Graph set 2 Graphical Analysis: DCC-GARCH – Commodities and the S&P 500







Source: Authors' calculations.

Table 9: Correlation matrix – TGARCH

Conditional correl.	Rank	S&P 500	Platinum	Gold	Silver
0%	5%	1.00	0.27	0.11	0.18
5%	10%	1.00	-0.30	-0.03	0.01
10%	20%	1.00	0.05	0.02	-0.02
20%	30%	1.00	-0.10	-0.09	-0.02
30%	40%	1.00	0.10	0.13	0.10
40%	50%	1.00	-0.02	0.19	0.06
50%	60%	1.00	0.11	0.16	0.01
60%	70%	1.00	0.02	-0.05	0.06
70%	80%	1.00	0.13	-0.10	-0.07
80%	90%	1.00	0.03	0.05	0.09
90%	95%	1.00	0.15	0.29	0.29
95%	100%	1.00	0.65	0.53	0.50

Note: The correlation matrix presented here illustrates the correlation of various commodities with the benchmark S&P 500 index. This correlation is conditioned on the volatility level of the base index, with a range from 95% to 100% representing periods during which the index exhibited its top 5% volatility levels.

Source: Authors' calculations.

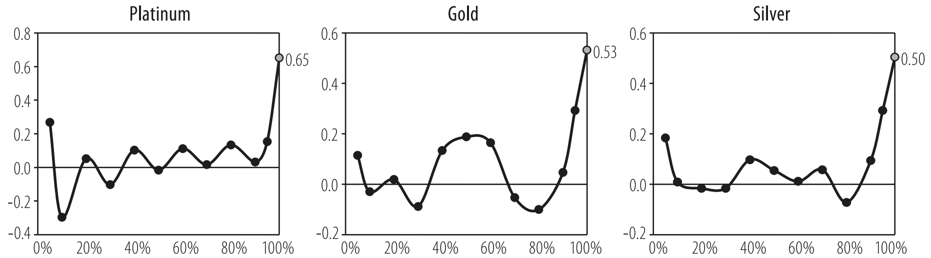
Table 10: Correlation matrix – return

Conditional correl.	Rank	S&P 500	Platinum	Gold	Silver
0%	5%	1.00	0.38	0.07	0.40
5%	10%	1.00	0.18	0.09	-0.01
10%	20%	1.00	0.21	0.21	0.23
20%	30%	1.00	-0.08	-0.14	-0.09
30%	40%	1.00	0.22	0.11	0.08
40%	50%	1.00	-0.13	0.09	0.07
50%	60%	1.00	-0.16	-0.02	-0.11
60%	70%	1.00	-0.01	-0.03	0.07
70%	80%	1.00	0.02	0.05	-0.06
80%	90%	1.00	0.25	0.01	0.16
90%	95%	1.00	0.03	0.04	-0.01
95%	100%	1.00	0.40	0.20	0.26

Note: The correlation matrix provided showcases the correlation of various commodities with the benchmark S&P 500 index. This correlation is conditional on the return level of the base index. Specifically, a range of 0% to 5% represents periods during which the base index experienced its lowest 5% of returns.

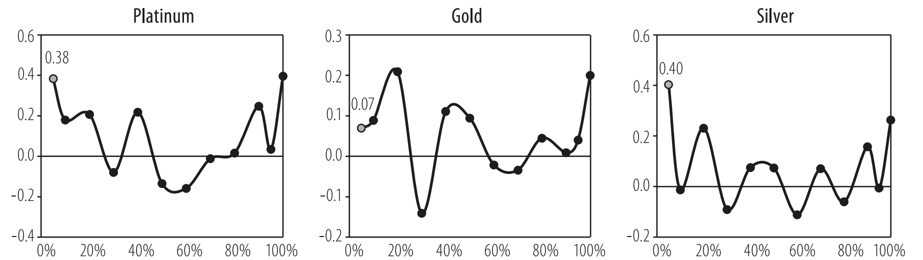
Source: Authors' calculations.

Graph set 3: Correlation – GARCH



Source: Authors' calculations.

Graph set 4: Correlation – return



Source: Authors' calculations.

Conclusion

This paper provides an in-depth analysis of volatility spillover from the global economic crisis that originated in the US to the precious metals markets, including gold, silver and platinum. Although the main focus is on the global economic crisis, the analysis also extends to spillover effects during other major crisis periods, namely the European debt crisis and the COVID-19 pandemic crisis.

Prior to the volatility analysis, comprehensive statistical tests were performed on the time series of the S&P 500 Index and precious metal prices for the period between 2006 and 2020. The tests for normal distribution, stationarity, heteroscedasticity and autocorrelation showed, in line with a large number of studies, that the data does not follow a normal distribution but a leptokurtic distribution and that the data is stationary. The ARCH LM test confirmed the existence of ARCH effects and heteroscedasticity, as indicated by statistically significant f-statistics and chi-sq statistics at the 1% level for all indices examined, consistent with graphical plots showing recognizable clusters of variability.

The application of the maximum likelihood test and autocorrelation tests (Box-Pierce and Ljung-Box) indicates that the TGARCH model fits the data well and is suitable for modelling the volatility of the observed indices. For platinum, however, the GARCH model showed higher values in the maximum likelihood test, which led to it being preferred to the TGARCH model for modelling the platinum's volatility.

The correlation modelled by DCC-GARCH showed extreme volatility in the case of gold, with no definitive conclusion on how the crisis affected gold price movements, even in times of crisis. For silver and platinum, however, the picture was clearer: both showed a significant increase in correlation with the S&P 500 Index during global economic crises. A common trend for all commodity markets was the increased volatility during the COVID-19 pandemic crisis. During the period observed, gold showed the lowest correlation with the S&P 500 and often turned negative, while platinum showed the highest average correlation with the index.

However, in the case of gold, the application of the correlation matrix revealed a lack of correlation with the S&P 500 during periods of lowest returns (0% to 5%), which is consistent with the perception of gold as a safe haven in times of crisis, while platinum and silver showed a significant correlation of returns in this range.

Given the overall positive correlation in terms of volatility between the commodity markets and the S&P 500, it can be concluded that there is a transmission of volatility between these markets. This transmission is amplified during financial market shocks, so our results suggest that there is insufficient evidence to reject Hypotheses 1 and 2.

These findings hold significant implications for monetary policy makers and portfolio managers, underscoring the need for a deeper understanding of the transmission mechanisms through which instability in one market can spread to the entire financial system and affect commodity markets, in this case precious metals. The research is consistent with existing views on the relationship between capital and commodity markets. Many studies emphasize the role of gold as a safe haven or hedging instrument, while the other two metals do not have such favourable characteristics in terms of the benefits they can offer portfolio managers.

A limitation of the research and findings presented in this paper is that they only relate to the influence and, therefore, spillover effects from the S&P 500 to the precious metals` markets. Although the S&P 500 is probably the most respected representative of the stock exchange markets, it is no longer the only important market today. Therefore, a recommendation for future research in this area would be to investigate the spillover effects of several highly developed stock exchanges to the global commodity markets.

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