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Volatility of Precious Metals: The Case of Platinum and Palladium

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Abstract

This paper investigates the relationship between the returns and their volatilities for Platinum and Palladium, by applying the known long-memory Fractionally Integrated-GARCH models. The SKEWED-FIAPARCH (1,d,1)-C seems to be the most suitable for modeling the volatility of Platinum's and Palladium's returns since we find that the returns of both metals are persistent processes over time. Our analysis suggests that the volatility of one metal negatively affects the returns of the other metal, while positive spillovers exist between them. It is also apparent that the effect of the volatility of platinum returns on the volatility of palladium returns is greater.

Keywords: volatility, returns, GARCH models, precious metals

1. Introduction

In modern economies, precious metals (e.g., Gold, Silver, Platinum, and Palladium) are considered viable investment alternatives for asset allocations (Folger, 2021). The investment community usually classifies precious metals as commodities whose prices are determined by the market's forces of demand and supply since they are assets with similar physical production and storage processing to broader commodity sectors such as energy, agriculture, and base metals. Unlike commodities, however, they also tend to act as currencies. Macroeconomic and monetary factors such as interest rates, exchange rates, and inflation affect their prices in the market (Vigne, Lucey, O'Connor, & Yarovaya, 2017). These distinctive properties make them an asset class separate from base commodities (Baur & Lucey, 2010).

In this paper, we investigate the volatility of Platinum and Palladium. Platinum is traded 24 hours a day on global commodity markets and is usually more expensive than Gold because of its scarcity. Many factors affect its price, but the most important is the concentration of its mines in South Africa and Russia (Baur & Lucey, 2010). These areas have a relatively high political risk, affecting its international supply and, therefore, its price. Platinum is mainly used as a catalyst in car manufacturing, with the demand from the automobile industry amounting to approximately 41% of its international production. It is also used in jewelry manufacturing. Platinum's use in coinage and investment accounts amounts to approximately 11% of its international production (Rand, 2021). Investing in Platinum can be achieved by buying/selling Platinum futures or by purchasing shares of ETFs.

Palladium is a lesser-known metal with a plethora of industrial uses. It is used at several stages of manufacturing processes, particularly for electronic and industrial products. Most of the world's metal supply comes from mines in the USA, Russia, South Africa, and Canada (Vesborg & Jaramillo, 2012). Demand is a critical factor that affects its price in international markets (McVey, 2018). The price of Palladium reached a 17-year high in 2017, surpassing even the price of Platinum for the first time since 2001. Investors can invest in it by buying or selling shares of Palladium-focused ETFs.

Many academic studies have been motivated by the need to produce trustworthy estimates of correlations among financial variables (Engle, 2002). Some standard methods for estimating correlations are the rolling average historical correlations and the correlation produced by the exponential smoothing approach. The multivariate generalized autoregressive conditional heteroscedasticity approach (GARCH) and the stochastic volatility approach are modern and more advanced techniques used widely in the econometric literature (Engle, 2002).

Existing literature has focused on the temporal variation in financial markets' volatility (Bollerslev, 1986). The two most essential parameterizations that prevailed in it were the Generalized ARCH (GARCH) developed by Bollerslev (1986) and the Exponential GARCH (EGARCH) introduced by Nelson (1991). However, this literature provides limited information regarding the variables that should be considered in determining the observed time variation in the conditional variances (Bollerslev, 1986). Especially for precious metals, their price volatility is influenced by several variables that are still less studied and understood. In contrast, the research concerning the factors affecting the pair-wise correlation of their prices is sparse (Zhang, Chang, Saliba, & Hasnaoui, 2022). This paper tries to fill this gap in the literature by investigating the relationship between the return and volatility of Platinum and Palladium. This study is among the first to model the volatility of these metals' returns using long-memory Fractionally Integrated-GARCH models. This is an essential element because the accurate estimation of the return and volatility features of Platinum's and Palladium's returns is crucial since alterations in their time-series structures can lead investors to great economic exposure (Diaz, 2015).

In the following section, we review the existing literature, while in Section 3, we describe our sample and present the results of statistical tests for modeling the volatility of the returns of these metals. In section 4, we describe our methodology, and in section 5, we analyze our results. Finally, in the last section, we present our conclusions.

2. Literature Review

Modeling and predicting financial data volatility has become increasingly popular recently (Zakaria & Winker, 2012). Volatility estimations are essential in a plethora of economic and financial applications, including portfolio management, risk management, asset pricing, and investing in general (Niyitegeka & Tewar, 2013; Zakaria & Winker, 2012; Parvaresh & Bavaghar, 2012). For example, volatility estimations are an indispensable prerequisite in derivatives instrument pricing or in estimating the hedging ratio of hedge funds in the market (Engle, 2002). Stock market investors are also interested in analyzing information and obtaining knowledge about the nature of stock market volatility. Excessive volatility can entail enormous losses or gains and increasing uncertainty (Parvaresh & Bavaghar, 2012).

Since the early 1980s, many models that estimate the conditional volatility of financial assets have been developed (Zakaria & Winker, 2012). The generalized conditional heteroscedastic models are the most popular (Zakaria & Winker, 2012). The Autoregressive Conditional Heteroscedasticity (ARCH) model, introduced by Engle (1982), was used in analyzing and simulating financial time series with time-varying conditional variance. Bollerslev (1986) improved and extended this model and introduced the generalized ARCH model (GARCH). Since the development of ARCH and GARCH models, there have been several empirical applications for modeling the volatility of financial time series. However, the standard GARCH models, when utilized with skewed data, could lead to misleading findings (Salisu & Fasanya, 2012). Therefore, new variants of these models appeared in the literature (e.g., GJR-GARCH, EGARCH) to alleviate this problem (Aliyev, Ajayi, & Gasim, 2020).

The majority of the empirical applications of these GARCH-type models concern the prediction of the volatility of the daily stock returns (Niyitegeka & Tewar, 2013; Peters, 2001; Karmakar, 2005; Banumathy & Azhagaiah, 2013; Zakaria & Winker, 2012; Abd El Aal, 2011; Parvaresh & Bavaghar, 2012; Md. Qamruzzaman, 2015). Some of these models, especially GARCH (1,1), GARCH-M (1,1), exponential GARCH (1,1), threshold GARCH (1,1), and power GARCH (1,1), seem to be more frequently applied among all the GARCH family models (Ahmed & Naher, 2021). This is attributed to the fact that GARCH (1, 1) and GARCH-M (1, 1) are models that indicate the symmetry of previous shocks. In contrast, the other two models represent asymmetrical effects (Ahmed & Naher, 2021).

Precious metals have gained increasing interest over the last few years. The possible effects of the globalization of the precious metals markets drew researchers' attention to better understand the predictability and asymmetric volatility properties of platinum and palladium (Diaz, 2016). Its price volatility and the continuous rise of prices tend to entice individual and corporate investors (Zhang et al., 2022). Volatility in the prices of those metals is the outcome of the volatility of their demand in the market (Zhang et al., 2022). Therefore, proper forecasting is crucial since it can affect policy decision-makers and entrepreneurs' current and future investment and production choices (Bernard, Khalaf, Kichian, & Mcmahon, 2008).

Hammoudeh and Yuan (2008) found that short-term interest rates affect precious metals' return and volatility. According to Batten and Vo (2015), macroeconomic factors, including the business cycle, the monetary environment, and market sentiment, affect Palladium's price more than other precious metals. Using data from China and India, Mo, Gupta, Li, and Singh (2018) concluded that factors such as GDP and inflation rate tend to affect the precious metals market positively. Using the ARCH method, Zhang et al. (2022) examined the price volatility of precious metals between 2012 and 2020, including the incredibly unexpected and unstable COVID-19 pandemic era. They concluded that Palladium prices are most likely to be affected by adverse shocks.

Liberda (2017) indicates that financial variables such as interest rates, exchange rates, stock returns, and crude oil returns significantly impact precious metal markets more than macroeconomic variables such as GDP growth, inflation, and industrial production. The equity indexes negatively influence metals' returns (Zhang et al., 2022). Moreover, financial variables explain the fluctuation of Platinum and Palladium prices better than that of Gold and Silver (Liberda, 2017).

Recently, an increasing number of studies (e.g., Klein, 2017; Klein & Walther, 2022) have explored the influence of adverse events like the European Debt Crisis or the 9/11 terrorist attack on the correlation among the returns of precious metals. The Gold/Silver pair seems to respond quite differently than that of Palladium/Platinum to market shocks, whereas Platinum acts as a temporary haven during market uncertainty (Zhang et al., 2022; Klein & Walther, 2022).

3. Data

The data set includes the daily closing prices of Platinum and Palladium from January 5, 1977, to October 15, 2021, in order to calculate their respective daily returns. Consequently, 11, 249 daily returns for each of Platinum and Palladium are included in our sample. In Table 1, we present the descriptive statistics for the daily returns of the two precious metals. Platinum has an average daily return of about 0.02%, while Palladium has a daily return of about 0.03%. The Jarque-Bera (JB) test statistic provides evidence for rejecting the null hypothesis of normality for the return distributions of the two metals and favoring a skewed, heavy-tailed distribution for the metals' returns.

Table 1. Descriptive statistics of daily returns

	PLATINUM	PALLADIUM
Mean	0.000 172	0.000 329
Median	0.000 584	0.000 656
Maximum	0.111 762	0.229 381
Minimum	-0.123 158	-0.238 152
Std. Dev.	0.016 043	0.020 237
Skewness	-0.267 925	-0.249 116
Kurtosis	6.790 578	10.241 90
Jarque-Bera	6869.211	24 697.78
Probability	0.000 000	0.000 000
Sum	1.936 511	3.701 772
SumSq. Dev.	2.894 806	4.606 439
Observations	11 249	11 249

Note. This table includes average statistics for the daily returns of the two metals.

Figure 1 depicts the prices and the daily returns of Platinum and Palladium. Both metals fluctuate substantially over time. Platinum peaked in the second half of the 2000s, while Palladium did so recently.

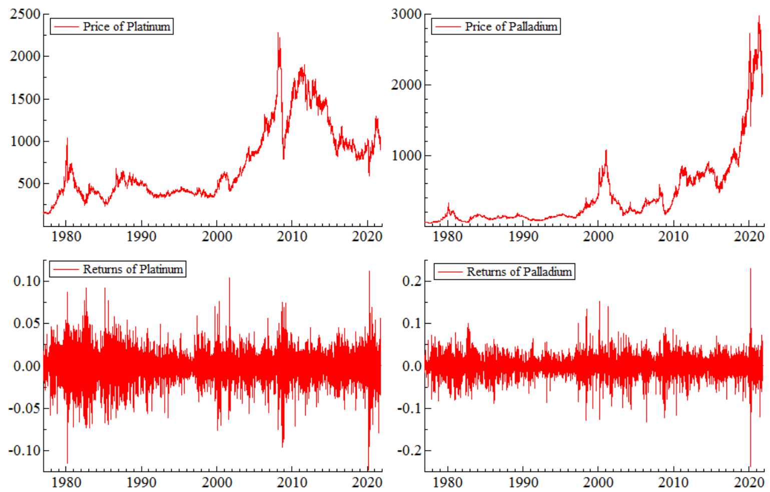

Figure 1. Time series plots of prices and daily returns for Platinum and Palladium (5/01/1977-15/10/2021)

To check for autocorrelation in our sample, we also performed the Box-Pierce and Ljung-Box statistic tests. More accurately, the Q-statistic for these two tests is estimated for 5, 10, 20, and 50-time lags. The results of these tests are shown in Tables 2 and 3, respectively. According to our findings, the null hypothesis of uncorrelated price changes for both metals is rejected. Evidence of no autocorrelation at 50-time lags is only present for Platinum.

Table 2. Box-Pierce Q-Statistic

LAGS	PLATINUM	PALLADIUM
5	16.3883 [0.005 818 5]	92.0668 [0.000 000 0]
10	23.6878 [0.008 473 7]	100.156 [0.000 000 0]
20	36.1387 [0.014 813 5]	112.766 [0.000 000 0]
50	56.6447 [0.240 981 1]	155.631 [0.000 000 0]

Note. This table includes the results from Box-Pierce statistic for the metals' returns using 5, 10, 20, and 50 lags. Probability values are inside the brackets.

Table 3. Ljung-Box Q-Statistics

LAGS	PLATINUM	PALLADIUM
5	2521.59 [0.000 000 0]	28.6313 [0.000 027 4]
10	4286.28 [0.000 000 0]	30.3474 [0.000 751 4]
20	6869.98 [0.000 000 0]	41.9141 [0.002 837 8]
50	12 597.0 [0.000 000 0]	71.1328 [0.026 359 3]

Note. This table includes the results from the Ljung-Box statistic for the metals' returns using 5, 10, 20, and 50 lags. Probability values are inside the brackets.

Long memory is a common feature of financial variables. Since any evidence of long memory would support the use of long memory-based volatility models, testing for long memory qualities is crucial. As a result, we conducted the Hurst exponent (1951) and Lo (1991) tests to check for the presence of long memory components in these precious metals' daily returns. The results of these tests are shown in Table 4, suggesting that metals' returns are persistent processes, and that small shocks tend to influence future returns for a long time.

Table 4. Long Memory Tests

	PLATINUM	PALLADIUM
Hurst exponent	0.552 67 [0.008 234 8]	0.570 66 [0.009 136 0]
Generalized Hurst exponent	0.553 473 [0.008 132 08]	0.570 265 [0.009 068 19]
Lo R/S test (q=1)	1.3179	1.37882
Lo R/S Test Critical Values: 90%[0.861, 1.747], 95% [0.809, 1.862], 99% [0.721, 2.098]		

Note. This table includes the results of the Hurst, Generalized Hurst exponent, and Lo R/S long memory tests for the metals' returns. Probability values are inside the brackets. In the last row, confidence intervals are in the brackets.

The findings presented in Tables 5 and 6 are consistent with volatility persistence for both metals' returns. As a result, this empirical study is in favor of predicting the volatility of metal returns using ARCH-based models.

Table 5. F-Tests

LAGS	PLATINUM	PALLADIUM
1-2	582.43 [0.0000]	429.01 [0.0000]
1-5	320.17 [0.0000]	222.68 [0.0000]
1-10	185.32 [0.0000]	164.84 [0.0000]

Note. This table includes the results of the F-test for the two metals. Probability values are inside the brackets.

Table 6. Box-Pierce Q-Statistics on Squared data

LAGS	PLATINUM	PALLADIUM
5	2521.59 [0.0000]	92.0668 [0.0000]
10	4286.28 [0.0000]	100.156 [0.0000]
20	6869.98 [0.0000]	112.766 [0.0000]
50	12 597.0 [0.0000]	155.631 [0.0000]

Note. This table includes the results of the Box-Pierce Q-Statistics on squared data for the two metals. Probability values are inside the brackets.

In Tables 7-9, we conduct unit root tests for stationarity. The results for the Augmented Dickey-Fuller test (ADF) are summarized in Table 7. We perform the test both for the prices and for the logarithmic returns of the two metals, both with a constant and with a linear time trend. The processes of the metals' prices are not stationary at the 5% level; therefore, we cannot reject the null hypothesis of the unit root existence. However, both metals' return time series are stationary. The same conclusions are reached by applying the Phillip-Perron (PP) and the Kwiatkowski–Phillips–Schmidt–Shintest (KPSS) tests for stationarity.

Table 7. ADF Tests

PRICES	PLATINUM	PALLADIUM
Constant	-1.915 043 [0.3256]	0.332 888 [0.9800]
Constant and Linear trend	-2.472 032 [0.3422]	-1.130 102 [0.9226]
RETURNS	PLATINUM	PALLADIUM
Constant	-70.863 40 [0.0001]	-97.065 01[0.0001]

Note. This table includes the results of the Augmented Dickey-Fuller test (ADF) for the prices and returns of the two metals. Probability values are inside the brackets.

Table 8. PP Tests

PRICES	PLATINUM	PALLADIUM
Constant	-1.930 124 [0.3256]	0.309 285 [0.9788]
Constant and Linear trend	-2.500 933 [0.3277]	-1.187 760 [0.9120]
RETURNS	PLATINUM	PALLADIUM
Constant	-101.7817 [0.0001]	-96.934 51 [0.0001]

Note. This table includes the results of the Phillip-Perron (PP) test for the prices and returns of the two metals. Probability values are inside the brackets.

Table 9. KPSS Tests

PRICES	PLATINUM	PALLADIUM
Constant	8.595 631 [< 0.01]	7.375 878 [< 0.01]
Constant and Linear trend	1.036017 [< 0.01]	1.438 593 [< 0.01]
RETURNS	PLATINUM	PALLADIUM
Constant	0.107 921 [> 0.1]	0.052 959 [> 0.1]

Note. This table includes the results of the Kwiatkowski–Phillips–Schmidt–Shintest (KPSS) test for the prices and returns of the two metals. Probability values are inside the brackets.

4. Methodology

In this section, we present some fractionally integrated GARCH-type volatility models to examine whether a long memory exists in the daily volatility of these metals' returns. Then, these volatility models are ranked according to the information criteria of Akaike (AIC), Shibata (SIC), and Hannan–Quinn (HQC). Also, the log-likelihood value is used for the same purpose.

In the following volatility models, we assume that the mean process for the metals' return has the following form:

$$r_t = \mu_t + \varepsilon_t \tag{1}$$

where r_t is the metals' return at time t, μ_t is the conditional mean of r_t, and ε_t are identically normally-distributed residuals with zero-mean and time-dependent variances.

We initially used the Fractionally Integrated GARCH model (FIGARCH-BBM) introduced by Bailiie, Bollerslev, and Mikkelsen in 1996. Under the FIGARCH(1,d,1)-BBM approach, the conditional variance of ε_t in equation 1 is modeled as:

$$\sigma_t^2 = \omega + \beta_1 \sigma_{t-1}^2 + [1 - \beta_1 L - (1 - \phi_1 L)(1 - L)^d]\varepsilon_t^2 \tag{2}$$

where L is a lag operator and $0 \leq d \leq 1$ is the fractional differencing parameter.

According to Chung (1999), the method of parameterization of the FIGARCH model of Baillie et al. (1996) has a specification problem, among other weaknesses. So, we also used Chung's specification of the FIGARCH model [FIGARCH (1, d, 1)-C] in order to model the conditional variance of the ε_t in equation 1. The conditional variance of ε_t is written as:

$$\sigma_t^2 = (1-\beta)\sigma^2 + \beta_1\sigma_{t-1}^2 + [1-\beta_1 L - \phi_1 L\{1+ln(\alpha)(1-L)^d\}](\varepsilon_t^2 - \sigma^2) \quad (3)$$

where L is a lag operator and $0 \le d \le 1$ is the fractional differencing parameter. The σ^2 is the unconditional variance of ε_t.

The idea of fractional integration has been extended to other GARCH types of models, including the Fractionally Integrated EGARCH (FIEGARCH) of Bollerslev and Mikkelsen (1996), the Fractionally Integrated APARCH (FIAPARCH-BBM) of Tse (1998), and the FIAPARCH-C of Chung (1999).The conditional variance of ε_t according to the FIEGARCH (1, d, 1) model is given by:

$$ln(\sigma_t^2) = \omega + \beta_1 ln(\sigma_{t-1}^2) + [1-\beta_1 L - (1-\phi_1 L)(1-L)^d][\gamma_1\varepsilon_{t-1} + \gamma_2(|\varepsilon_{t-1}| - E|\varepsilon_{t-1}|)] \quad (4)$$

where $E|\varepsilon_{t-1}|$ represents the expected value of the residuals at time t-1 and $|\varepsilon_{t-1}|$ the absolute value of the residuals at time t-1. L again is a lag operator and $0 \le d \le 1$ is the fractional differencing parameter.

According to the FIAPARCH-BBM (1, d, 1) model, the conditional variance of ε_t is given by:

$$\sigma_t^\delta = \omega + \beta_1\sigma_{t-1}^\delta + [1-\beta_1 L - (1-\phi_1 L)(1-L)^d](|\varepsilon_t| - \gamma\varepsilon_t)^\delta \quad (5)$$

and the variance dynamics according to FIAPARCH-C model are:

$$\sigma_t^\delta = \beta_1\sigma_{t-1}^\delta + \sigma^2(1-\beta_1) + [1-\beta_1 L - (1-\alpha_1 L)(1-L)^d][(|\varepsilon_t| - \gamma\varepsilon_t)^\delta - \sigma^2) \quad (6)$$

where in equations 5 and 6, the parameter γ is the asymmetry coefficient, and δ is the power term of the long-memory persistence. L is a lag operator and $0 \le d \le 1$ is the fractional differencing parameter. The σ^2 is the unconditional variance of ε_t.We also estimated the previous FIAPARCH-C model by assuming that the residuals ε_t follow the skewed Student's t-distribution (SKEWED-FIAPARCH (1, d, 1)-C model).

Davidson (2004) extended the conditional variance of the FIGARCH model by introducing weights to the difference operator (HYGARCH), and we used this approach for our volatility modeling. Thus, the conditional variance of the residuals ε_t according to the HYGARCH (1, d, 1) model is:

$$\sigma_t^2 = \omega + \beta_1\sigma_{t-1}^2 + [1-\beta_1 L - \phi_1 L\{1+ln(\alpha)(1-L)^d\}]\varepsilon_t^2 \quad (7)$$

$where$ L is a lag operator and $0 \le d \le 1$ is the fractional differencing parameter.

Next, we estimate the following linear equations to examine the relation between the volatility of Platinum and Palladium's returns. The equations are written as:

$$VPL_t = c_1 + b_1 VPA_t + u_{1,t} \quad (8)$$

$$VPA_t = c_2 + b_2 VPL_t + u_{2,t} \quad (9)$$

where VPL_t and $VPA_t$are the volatilities of Platinum and Palladium's returns at time t respectively. The $u_{1,t}$ and $u_{2,t}$ are the zero-mean expected residuals of equations 8 and 9 respectively.

To further examine the possibility of spillover effects, equations 8 and 9 are extended by taking into account the ARCH effects for the residuals. We also include the squared residuals of the SKEWED-FIAPARCH-C model as an explanatory variable. Thus, our models' metals' returns are written as:

$$RPL_t = c_1 + b_1 RPA_t + \zeta_1 e_{A,t}^2 + \varepsilon_{1,t}$$

$$\sigma_{1,t}^{\delta_1} = \omega_1 + \beta_1\sigma_{1,t-1}^{\delta_1} + \phi_1\left(|\varepsilon_{1,t-1}| - \gamma_1\varepsilon_{1,t-1}\right)^{\delta_1} + \psi_1 e_{A,t}^2 \quad \mathit{(10)}$$

$$RPA_t = c_2 + b_2 RPL_t + \zeta_2 e_{L,t}^2 + \varepsilon_{2,t}$$

$$\sigma_{2,t}^{\delta_2} = \omega_2 + \beta_2\sigma_{2,t-1}^{\delta_2} + \phi_2\left(|\varepsilon_{2,t-1}| - \gamma_2\varepsilon_{2,t-1}\right)^{\delta_2} + \psi_2 e_{L,t}^2 \quad (11)$$

where RPL_t and RPA_t are the Platinum and Palladium's returns at time t respectively while $e_{A,t}$ and $e_{L,t}$ are the Platinum and Palladium residuals from the SKEWED-FIAPARCH-C model respectively at time t. The entities $\varepsilon_{1,t}$ and $\varepsilon_{2,t}$ are the zero-mean expected error terms for equations 10 and 11 respectively.

Finally, a multivariate model is estimated to investigate the covariance between the volatilities of the two metals' returns. More specifically, the multivariate VARFIMA (1,d,1)-FIAPARCH(1,d,1)-DCC model is used. The model may be written as:

$$(1-L)(1-L)^{d_1}(y_t - \mu) = (1-L)\varepsilon_t$$

$$\varepsilon_t = H_t^{1/2} z_t \quad (12)$$

where y_t is the vector of daily returns of the metals, μ is the vector of the conditional means of y_t, ε_t is an error vector with zero mean, H_t is the conditional variance-covariance matrix, and z_t is a vector of t-distributed random variables with zero mean and identity variance-covariance matrix. The conditional variance-covariance matrix can be split as $H_t = D_t R_t D_t$, where R_t is the conditional correlation matrix, and D_t is a diagonal matrix with its diagonal elements being the standard deviations $h_{it}^{1/2}$obtained from the FIAPARCH(1,d,1) model:

$$\sigma_t^\delta = \omega + \beta_1 \sigma_{t-1}^\delta + [1 - \beta_1 L - (1 - \phi_1 L)(1 - L)^d](|\varepsilon_t| - \gamma \varepsilon_t)^\delta \quad (13)$$

Engle (2002), based on the cross products of the standardized residuals $\eta_t = D_t^{-1}(y_t - \mu)$, suggests that the most common Dynamic Conditional Correlation (DCC) representation is:

$$Q_t = (1 - \alpha - \beta)\bar{Q} + \alpha \eta_{t-1} \eta'_{t-1} + \beta Q_{t-1} \quad (14)$$

where Q_t is the conditional correlation matrix and is assumed to be a positive definite matrix with unit elements along the main diagonal, whereas the two scalar parameters satisfy a stability constraint of the form $\alpha + \beta < 1$.Finally, the sequence Q_t drives the dynamics of the conditional correlations.

5. Results

The results from the information criteria and that of the log-likelihood function concerning the fitting of the fractionally integrated extended memory volatility models described in the previous section are summarized in Tables 10 and 11. Table 10 contains the results for the volatility of Platinum's return, while Table 11 contains the results for the volatility of Palladium's return. According to our findings, the SKEWED-FIAPARCH (1, d, 1)-C model best fits the description of the volatility of the returns for both metals. The diagnostic tests of this best fitting model appeared analytically in the appendix, both for Platinum and Palladium.

Table 10. Information criteria for the long-memory volatility models of Platinum's return

MODEL	log-likelihood	SIC	HQC	AIC
FIGARCH (1, d, 1)-BBM	32 257.656	5.7302	5.7328	5.7341
FIGARCH (1, d, 1)-C	32 257.042	5.7301	5.7327	5.7340
FIEGARCH (1, d, 1)	32 252.697	5.7277	5.7311	5.7329
FIAPARCH (1, d, 1)-BBM	32 267.784	5.7304	5.7338	5.7356
FIAPARCH (1, d, 1)-C	32 267.846	5.7304	5.7338	5.7356
SKEWED-FIAPARCH (1, d, 1)-C	**32 286.152**	**5.7353**	**5.7379**	**5.7392**
HYGARCH (1, d, 1)	32 261.430	5.7301	5.7331	5.7346

Note. This table includes the results for various information criteria for the long-memory volatility models of Platinum's return.

Table 11. Information criteria for the long-memory volatility models of Palladium's return

MODEL	log-likelihood	SIC	HQC	AIC
FIGARCH (1, d, 1)-BBM	29 761.815	5.2865	5.2891	5.2904
FIGARCH (1, d, 1)-C	29 762.612	**5.2866**	5.2892	5.2905
FIEGARCH (1, d, 1)*	-	-	-	-
FIAPARCH (1, d, 1)-BBM	29 764.386	5.2853	5.2887	5.2905
FIAPARCH (1, d, 1)-C	29 769.131	5.2861	5.2896	5.2913
SKEWED-FIAPARCH (1, d, 1)-C	**29 775.482**	5.2864	**5.2903**	**5.2923**
HYGARCH (1, d, 1)	29 765.768	5.2864	5.2894	5.2909

Note. This table includes the results for various information criteria for the long-memory volatility models of Palladium's return. The * means that the estimation failed to converge.

The estimated coefficients of the best-fitted model [SKEWED-FIAPARCH (1, d, 1)-C] appear in Table 12, while its diagnostic tests appear in the Appendix of this paper. As shown, the fractional coefficient d value indicates a high persistence level for the conditional variance of both metal returns. Also, in Figures 2 and 3, we plot the estimated values of the conditional volatilities of the returns for Platinum and Palladium, respectively.

Table 12. SKEWED-FIAPARCH (1, d, 1) model estimated with Chung's Method

	PLATINUM	PALLADIUM
c	0.000 110 [0.3370]	0.000 253 [0.0726]
ω	1.044 485 [0.0667]	0.552 870 [0.1889]
d	0.478 662 [0.0000]	0.397 048 [0.0000]
φ	0.371 519 [0.0000]	0.288 549 [0.0002]
β	0.738 064 [0.0000]	0.474 450 [0.0000]
γ	-0.129 736 [0.0000]	-0.051 386 [0.0176]
δ	2.044 068 [0.0000]	2.148 733 [0.0000]
Asymmetry	-0.089 559 [0.0000]	-0.045 120 [0.0003]
Tail	7.003 952 [0.0000]	5.564 351 [0.0000]

Note. This table contains the coefficient estimates for the SKEWED-FIAPARCH (1, d, 1) model for Platinum and Palladium. Probability values are inside the brackets.

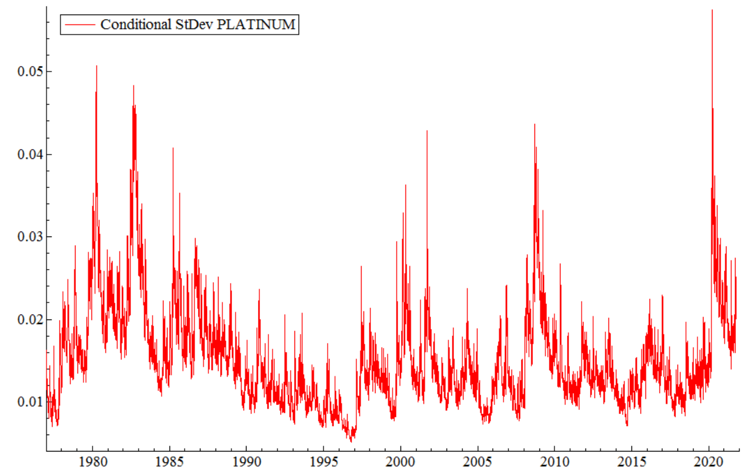

Figure 2. Estimated conditional volatility of the return of the Platinum according to the SKEWED-FIAPARCH (1, d, 1)-C model

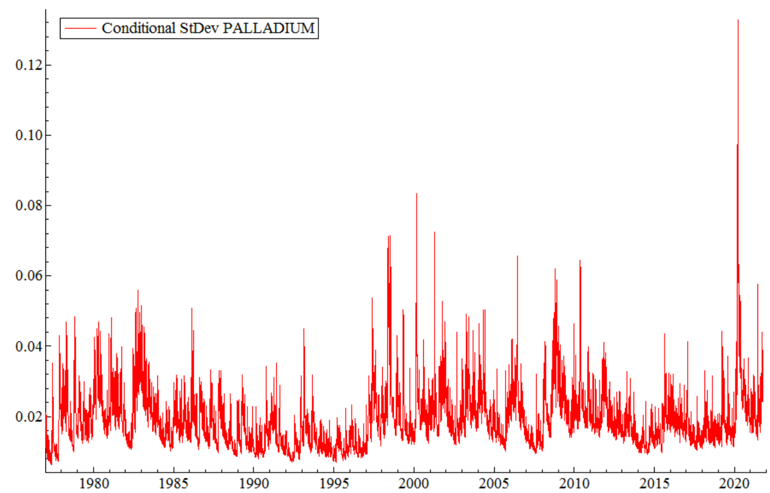

Figure 3. Estimated conditional volatility of the return of the Palladium according to the SKEWED-FIAPARCH (1, d, 1)-C model

Table 13 displays the OLS estimations of equations 8 and 9, respectively. In Equations 8 and 9, the coefficients for b_1 and b_2 are statistically significant, implying an interaction between the two volatilities. According to these findings, a unit change in the volatility of Palladium's return causes a change of approximately 0.44 units in Platinum's return. However, the effect of the volatility of Platinum's return on the volatility of Palladium's return is more significant since a standard deviation change in the volatility of Platinum's return causes a 0.81 standard deviation change in the volatility of Palladium's return.

Table 13.Estimation of regression equations 8 and 9

Dependent Variable	c_i	b_i
VPL	0.006 664 [0.0000]	0.436 907 [0.0000]
VPA	0.006 854 [0.0000]	0.808 311 [0.0000]

Note. This table describes the estimation results for the regressions in equations 8 and 9. The index i under each estimate takes the values 1 and 2.

We also perform Granger-casualty tests to determine whether one metal's return may be an estimator for the other and vice versa. The results of the Granger causality tests are summarized in Table 14. As we can see, the volatility of Palladium's return Granger causes the volatility of Platinum's return. At the same time, the volatility of Platinum's return also Granger causes the volatility of Palladium's return. Therefore, the results suggest a mutual volatility spillover effect between the returns of Platinum and Palladium.

Table 14. Granger Causality F Tests

Lags:2	Test
VPA does not Granger CauseVPL	4.129 59 [0.0161]
VPL does not Granger CauseVPA	46.8751 [0.0000]

Note. This table includes the results of Granger Causality F Tests. Probability values are inside the brackets.

The estimated coefficients of models 10 and 11 are given in Table 15 below. There is a negative relationship between the volatility of each metal and the return of the other one: Palladium's volatility of return strongly affects Platinum's return, and vice versa. This is likely attributed to investors trying to exploit the fluctuations occurring in each metal. They move invested funds from the less volatile metal to the other in order to take advantage of higher returns. This may trigger a demand fall for the less volatile metal and its corresponding return. Also, we notice positive volatility spillover effects between the volatility of the returns of the two metals.

Table 15.Estimates of Equations 10 and 11

Coefficients	Equation 9 (PLATINUM)	Equation 10(PALLADIUM)
C_i	0.000 278 [0.0039]	0.000 305 [0.0114]
b_i	0.440 198 [0.0000]	0.698 597 [0.0000]
ζ_1	-0.970 036 [0.0000]	-1.404 606 [0.0000]
ω_i	0.000 083 [0.1512]	0.00002 [0.1576]
β_1	0.931 796 [0.0000]	0.758 146 [0.0000]
ϕ_1	0.068 670 [0.0000]	0.166 088 [0.0000]
γ	-0.083 091[0.0621]	-0.066 964 [0.0143]
δ	-0.089 559 [0.0000]	1.791 638 [0.0000]
Ψ_i	0.134 849 [0.0000]	0.157 298 [0.0479]

Note. This table gives the coefficient estimates of equations 10 and 11 for Platinum and Palladium. Probability values are inside the brackets. Index i takes the values 1 and 2 for Platinum and Palladium respectively.

The estimates of the system of equations 12 and 13 are presented in Table 16. Most coefficient estimators for Platinum are statistically significant, while those for Palladium are not. Parameter δ is significant for both metals.

Table 16. Estimated Multivariate Model for Metal Returns

Coefficients	PLATINUM	PALLADIUM
μ	0.000 119 [0.3645]	0.000 354 [0.0105]
d_1	0.056 282 [0.0003]	-0.015 599 [0.3164]
AR(1)	0.919 116 [0.0000]	0.074 450 [0.4595]
MA(1)	-0.946 035 [0.0000]	-0.001 776 [0.9852]
ω	1.031 496 [0.1024]	0.926 900 [0.1115]
d_2	0.429 602 [0.0000]	0.336 887 [0.0000]
ϕ_1	0.414 443 [0.0000]	0.261 486 [0.1552]
β_1	0.721 493 [0.0000]	0.396 825 [0.0471]
γ	-0.059 090 [0.0506]	-0.015 805 [0.5373]
δ	2.049 957 [0.0000]	2.111 693 [0.0000]

Note. This table gives the coefficient estimates for the multivariate model in equation 12 both for Platinum and Palladium. Probability values are inside the brackets.

An estimation of the DCC part derived from the multivariate model is shown in Table 17. The dynamic correlation coefficient is statistically significant at the 1% level ($p<0.05$) and takes a relatively high value. Therefore, we can conclude that a robust dynamic correlation between the metals' returns is present despite the dynamic correlation coefficient being highly volatile over time (Figure 4). There are also positive spillover effects between the volatilities of the two metals since the dynamic correlation coefficient remains positive (Figure 4).

Table 17. DCC- Estimation of conditional correlation

ρ	α	β	df
0.591 03 [0.0000]	0.009 486 [0.0000]	0.989 240 [0.0000]	6.477 044 [0.0000]

Note. This table includes the estimates for the DCC model of conditional correlation. Probability values are inside the brackets.

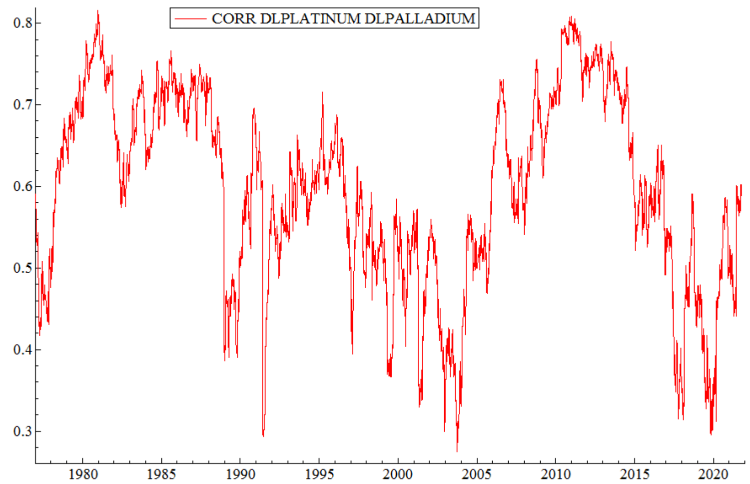

Figure 4. The estimated dynamic correlation coefficients throw the time horizon

6. Conclusions

In this study, we examine the presence of spillover effects among the returns and volatilities of Platinum and Palladium. A SKEWED-FIAPARCH (1, d, 1)-C model was estimated and applied for daily data for more than 24 years. According to our findings, there is a high level of persistence for the conditional variance of both metals' returns. Additionally, we observed the existence of significant interrelationships between the two metals' volatilities.

This study contributes to academic literature by providing evidence that the volatilities of Platinum's and Palladium's returns are highly persistent and there are positive spillover effects between these volatilities.

Interchangeability in particular industrial applications is the first factor to consider when attempting to understand the significant spillover impact between Platinum and Palladium. As such, a spillover effect triggered by fluctuations in a metal's return might affect the demand for the other and vice versa. Both metals share similar mining processes and are found in the same geographical areas, which supports our findings of spillover effects.

The leading cause, though, might be found in investors' sentiments and speculations, just as in market dynamics. The fact that most investors deal in both metals and the precious metals market is small may explain the seeming strong link. The tendency for one metal's higher volatility to have a negative spillover effect on the returns of the other metal while there are positive spillovers for volatility may eventually, to some extent, deconstruct the positions of the investors.

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Appendix

Diagnostic tests of SKEWED- FIAPARCH (1, d, 1)-C model for Platinum and Palladium

PLATINUM		
Q-Statistics on Standardized Residuals		
Q(5) =	22.8846	[0.000 355 2]**
Q(10) =	30.7825	[0.000 637 3]**
Q(20) =	43.0818	[0.001 994 0]**
Q(50) =	77.6456	[0.007 369 1]**
Q-Statistics on Squared Standardized Residuals		
Q(5) =	6.523 27	[0.088 749 2]
Q(10) =	15.2917	[0.053 716 5]
Q(20) =	19.7217	[0.348 701 7]
Q(50) =	52.7453	[0.295 709 4]

ARCH 1-2 test:	F(2,11 242)=	2.5528 [0.0779]	
ARCH 1-5 test:	F(5,11 236)=	1.3118 [0.2556]	
ARCH 1-10 test:	F(10,11 226)=	1.5009 [0.1319]	
Joint Statistic of the Nyblom test of stability: 3.516 79			
Individual Nyblom Statistics:			
Cst(M)		0.257 28	
Cst(V) x 10^4		0.135 53	
d-Figarch		0.712 55	
ARCH(Phi1)		0.328 54	
GARCH(Beta1)		0.571 82	
APARCH(Gamma1)		0.598 80	
APARCH(Delta)		0.419 95	
Asymmetry		0.262 99	
Tail		1.057 51	
Asymptotic 5% critical value for individual statistics = 0.47			
Adjusted Pearson Chi-square Goodness-of-fit test			
Cells(g)	Statistic	P-Value(g-1)	P-Value(g-k-1)
40	37.8735	0.521 151	0.153 025
50	59.0674	0.153 638	0.026 417
60	62.4855	0.353 503	0.110 666
PALLADIUM			
Q-Statistics on Standardized Residuals			
Q(5) =	75.2871	[0.000 000 0]**	
Q(10) =	77.4572	[0.000 000 0]**	
Q(20) =	87.6947	[0.000 000 0]**	
Q(50) =	124.189	[0.000 000 0]**	
Q-Statistics on Squared Standardized Residuals			
Q(5) =	5.744 26	[0.124 737 3]	
Q(10) =	11.1097	[0.195 560 2]	
Q(20) =	19.3852	[0.368 474 8]	
Q(50) =	46.9857	[0.514 371 4]	
ARCH 1-2 test:	F(2,11 242)=	0.044 378 [0.9566]	
ARCH 1-5 test:	F(5,11 236)=	1.1556 [0.3285]	
ARCH 1-10 test:	F(10,11 226)=	1.1391 [0.3280]	
Joint Statistic of the Nyblom test of stability: 7.24604			
Individual Nyblom Statistics:			
Cst(M)		1.136 55	
Cst(V) x 10^4		0.194 08	
d-Figarch		3.762 51	
ARCH(Phi1)		3.125 44	
GARCH(Beta1)		3.415 29	
APARCH(Gamma1)		0.719 54	
APARCH(Delta)		0.642 08	
Asymmetry		1.009 64	
Tail		0.477 29	
Asymptotic 5% critical value for individual statistics = 0.47			
Adjusted Pearson Chi-square Goodness-of-fit test			
Cells(g)	Statistic	P-Value(g-1)	P-Value(g-k-1)
40	76.8387	0.000 285	0.000 006
50	83.5407	0.001 528	0.000 066
60	79.1376	0.041 211	0.005 389

Cells(g)	Statistic	P-Value(g-1)	P-Value(g-k-1)
40	76.8387	0.000 285	0.000 006
50	83.5407	0.001 528	0.000 066
60	79.1376	0.041 211	0.005 389