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Article

Empirical study on the volatility spillover effect of gold, silver and platinum prices

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Abstract: This study investigates the volatility dynamics of gold, silver, and platinum prices using daily closing data from the Shanghai Gold Exchange between 2012 and 2020. We employed ARCH and GARCH models to analyze volatility, asymmetry, and spillover effects among these precious metals. Our findings reveal that all three metals exhibit significant price fluctuations and volatility clustering. Silver demonstrated the highest volatility overall. Furthermore, all metals displayed asymmetric responses to market shocks, with gold and platinum demonstrating greater sensitivity to positive shocks (good news) compared to negative ones (bad news). Silver exhibited the opposite behavior. We also observed a one-way directional spillover effect where gold price volatility significantly impacts both silver and platinum, while silver price volatility primarily affects platinum. These results have important implications for investors, portfolio managers, and financial institutions. Understanding the volatility dynamics and spillover effects among these precious metals is crucial for effective risk management, portfolio diversification, and developing robust investment strategies.

Keywords: precious metals; ARCH effect; asymmetry; volatility spillover effects

1. Introduction

Precious metals such as gold, silver, and platinum, which have significant economic value and have historically been as essential as money, but are currently primarily employed for industrial or investment reasons, have recently piqued the interest of many decision-makers. The Shanghai Gold Exchange (SGE) is a significant player in the precious global metals. The largest and purely physical spot exchange in the world is the Shanghai Gold Exchange, created in October 2002. Gold, silver, and platinum are exchanged on China's Shanghai Gold Exchange. Since then, China's gold has begun to trade in the market, and precious metals trading is in its early stages. It serves as the primary trading platform for gold in China, the world's largest gold consumer. The SGE has been steadily increasing its international presence, attracting foreign investors, and expanding its global reach. The Shanghai Gold Benchmark Price, set by the SGE, is a significant reference point for gold prices in Asia. The SGE's daily turnover in precious metals is substantial, and it's clear that the SGE plays a significant role in the global gold market, especially in terms of physical gold trading [1].

The Tianjin Precious Metals Exchange was founded in 2009, and China also allowed over-the-counter (OTC) market operations. The flexible trading mechanism has allowed precious metals trade to enter a period of tremendous growth. Over the next several years, OTC market activities were disseminated across China.

Simultaneously, the rapid expansion of the precious metals trading market has led to various disruptions. However, with the proactive rectification and regulatory adjustments by relevant authorities, China's precious metals trading market has gradually transitioned into a phase of healthy development. In recent years, the internationalization of the renminbi has continued to advance, fostering the development of China's precious metals trading market in a more standardized and open manner.

In recent times, investment in precious metals has become increasingly attractive to investors, even amidst inflation, economic downturns, and political instability. Precious metals serve as effective hedging instruments and offer various derivative options. Regardless of the fluctuations in their prices, investors are able to monetize their investments. Historically, gold has been preferred for its high safety factor, making it the primary choice for investors seeking to preserve and enhance value. Silver, as an alternative to gold, offers a lower price point and lower investment threshold, which has contributed to its expanding transaction volume in recent years. Platinum and other precious metals are extensively utilized in both consumer applications and industrial sectors.

Several scholars [2–5] studied the factors that affect the price of gold and the relationship between the gold market and other markets. Although investors favor silver and platinum, which are also precious metals, they have limited attention of scholars. Various factors make the gold, silver, and platinum metal prices fluctuate by a big margin. Generally, investors will impact silver and platinum prices when gold price fluctuations and status changes. Therefore, empirical research on the precious metal market's volatility characteristics and the volatility spillover effects among the three precious metals, gold, silver, and platinum, has very important academic and practical application values. Many previous studies have focused on the volatility spillover effect between the domestic and foreign stock markets, oil markets, and gold markets but have not analysed the volatility spillover effect between various precious metals in the market. We empirically analyzed the volatility spillover effect between China's gold, silver, and platinum.

This paper consists of five sections. The introduction introduces the research background, purpose and significance, research ideas, and structural arrangements. The literature review section includes a literature review and the theoretical background of the study. The third section explains the methodology used in this study. The fourth section, empirical analysis, examines the volatility characteristics and asymmetry of the three precious metals. The last section includes the conclusion and policy recommendations.

2. Literature review

Practically, investors in the precious metals market have comprehensively considered various factors to predict future asset price trends, thereby making judgments and formulating investment strategies. The volatility spillover effect between precious metals is an important basis for predicting precious metals' future price trends. It refers to the fluctuation of a precious metals market affected by itself and other precious metal markets' previous fluctuations.

Malkiel and Fama [6] proposed the efficient market theory, which means that securities' prices reflect all available information and defined the market as three forms: Weak-form efficient market, semi-strong-form efficient market, and strong-form efficient market. In weak-form efficient markets, securities' prices reflect all historical trading information; in semi-strong-form efficient markets, securities' prices reflect all historical trading information and public information; in strong-form efficient markets, securities' prices reflect all public information and internal information. The Chinese precious metals market was established for a relatively short period, and its development is imperfect, and it is still in the stage of weak and efficient markets.

Volatility in financial markets denotes the degree of variation in asset prices over time. The volatility of financial asset prices typically exhibits characteristics such as volatility clustering, variance, peaks and tails, and long memory. Volatility clustering implies that large price fluctuations are often followed by large fluctuations, and small fluctuations by small ones. Variance, or conditional heteroscedasticity, is a key feature of financial time series, making the Autoregressive Conditional Heteroskedasticity (ARCH) model particularly suitable for analysis. The presence of spikes and thick tails indicates that financial time series do not conform to a normal distribution. Long memory suggests that historical data significantly influence future price movements.

Many scholars have studied the factors affecting the price of precious metals. They have confirmed the important role of fluctuations in the US dollar, oil prices, and changes in economic conditions. Tully and Lucey [7] studied macroeconomic variables affecting gold prices, using the Asymmetric Power Generalized Autoregressive Conditional Heteroskedasticity (APGARCH) model to confirm the important role of the US dollar in gold price changes. Zhang et al. [8] and Liu et al. [9] studied the impact of global oil price shocks on the Chinese precious metals market and found that the current jump in the crude oil market has a significant negative impact on the Chinese precious metals market. Kucher and McCoskeyb [10] and Churchill et al. [11] found that gold and silver, the periodical logarithmic price and gold and platinum seem to be a cointegrated long-term relationship using the vector error correction model between precious metal prices, which is strongly affected by economic conditions.

Simultaneously, the correlation between gold and silver is also a hot spot for scholars [12–14]. Liu and Su [15] explored the dynamic causality of gold and silver prices in the Chinese market with a rolling window bootstrap method. They found that gold's impact on silver has both significant positive and significant effects over multiple periods. Cunado, Gil-Alan and Gupta [16] found that cyclical behavior of gold and silver prices, gold (about seven years) is more cyclical than silver (4–5 years).

Scholars have also conducted empirical studies on the volatility spillover effects between various markets through various models. Dutta [3] studied the implied volatility between the gold and silver markets. It uses two forms of binary Value-at-risk (VAR)-GARCH models to confirm that returns and shocks vary significantly from gold to silver. Sarwar et al. [17] used the binary GARCH-BEKK model to explore the volatility spillover effect between the oil market and the Asian stock market. Volatility has a negative spillover effect, and the estimated results are different during the crisis period and at different data frequencies. Xu et al. [18] found an asymmetric spillover effect between the oil market and the stock market, and there was an asymmetry in the volatility shock of the oil stock markets.

Furthermore, several scholars have discussed the price discovery function of gold futures and spot markets, and the main conclusion is that US gold spot and futures dominate the price discovery. Chen [19] studied the possibility of establishing a VAR model using a price discovery function in China's gold futures market. The results showed that the market had not yet effectively realized the price discovery function. Guo and Xiao [20] examined the price discovery and dynamic correlation between China and the US gold market, and their results showed that the dominant position in the price discovery process is the US gold market, and the correlation between the US and Chinese gold markets changes over time. Also, many scholars have used various models to conduct an empirical analysis of the gold market risks and returns and have concluded that the gold market returns are positively related to risks. Sun [21], based on the Exponential Generalized Autoregressive Conditional Heteroskedastic (EGARCH) model and a study with the GARCH-M model, found that the gold market is positively correlated [22]. Pan et al. [23] developed a dynamic ARMA-GARCH model for gold prices. The GARCH (1, 1) model was used to study the significant volatility of the Shanghai Stock Index's daily return, which had persistent characteristics and high-risk stock market investment risk [24].

Li and Zhu [25] focused on the stock markets of Shanghai, Shenzhen, and Hong Kong, as well as the global gold spot market, using a ternary GARCH-BEKK (1, 1) model to analyze the volatility spillover effects among these markets. Their results indicated a two-way volatility spillover effect between the Shanghai and Shenzhen stock markets, while no such spillover existed between the other two markets. Panwen et al. [26] examined the stock cycle of the New York gold futures market and employed advanced empirical analysis to investigate the spillover effects of fluctuations in the gold sector and found that significant volatility spillover effects occurred during bull markets, while such effects were absent in other market conditions.

Li and Zhang [27] concluded that the prices of gold and silver are linearly correlated. Similarly, Zhang and Zhang [28] studied the impact of the US stock market on China's stock market using a VAR-GARCH model. They confirmed that the influence of the US market on the Chinese market is long-lasting, although the effect diminishes over time. Additionally, Chang et al. [29] investigated the spillover fluctuations in China's gold and silver spot markets and results indicated significant two-way volatility between the spillovers of gold and silver.

Scholars have primarily focused on studying the volatility spillover effects between domestic and foreign stocks, gold, oil, and other markets, drawing many valuable conclusions. Research has also been conducted on the price of gold, along with the associated risks and benefits of the gold market. Additionally, numerous research models related to the gold market have been proposed. These findings provide a theoretical foundation and technical support for further research. The volatility spillover effects between gold, silver, and platinum are important considerations for investors developing strategies for precious metals investment. However, scholars have not yet had the opportunity to study these effects in depth. Therefore, this study aims to explore the interactions within the gold, silver, and platinum markets in China. It will provide specific insights to help investors gain a more comprehensive understanding of the precious metals market and serve as a reference for their investment strategies.

3. Data and methodology

3.1. Data & sample

This study utilizes daily data spanning from 2012 to 2020, excluding statutory holidays, resulting in a total of 2003 observations. The data is employed to examine the volatility spillover effects among gold, silver, and platinum traded on the Shanghai Gold Exchange. The dataset, sourced from the Wind database, forms the basis for our analysis. Specifically, the logarithms of the daily closing prices of the three precious metals are used to conduct an empirical analysis of their rates of return. The calculation formula for the logarithmic returns is as follows

$$R = \ln(P_t / P_{t-1}) = lnP_t - lnP_{t-1} \tag{1}$$

where P_t and P_{t-1} are represented by t on and $t-1$ asset prices period, we used lrau, lrag, and lrpt to $t-1$ represent the logarithmic returns of gold Au9999, silver Ag (T + D), and platinum P_t9995, respectively.

3.2. Methodology

ARCH, GARCH, and TGARCH models are specifically designed to model and predict the volatility of time series data. Precious metal returns often exhibit volatility clustering, where high volatility periods tend to be followed by high volatility periods, and low volatility periods follow low volatility periods. These models effectively capture this characteristic. The TGARCH model, in particular, allows us to capture asymmetries in the volatility. This is crucial in financial time series where negative returns may have a different impact on volatility compared to positive returns of the same magnitude.

Non-linear causality methods, while useful, can be significantly more complex to implement and interpret. They require advanced statistical techniques and often rely on non-parametric methods, which might not always provide straightforward economic interpretations. The ARCH, GARCH, and TGARCH models are specifically designed for this purpose, making them more suited to our objectives compared to non-linear causality methods. Nevertheless, there is a strong precedent in financial literature for using ARCH, GARCH, and TGARCH models to study financial time series. This established framework provides a solid foundation for our methodology, ensuring that our methods are rigorous and aligned with the previous studies.

Since the causality-in-variance test relies on the residuals obtained from the Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model, we first employ the GARCH model to analyze the return series of crude oil and precious metals. It is noteworthy that various studies in the literature employ different

GARCH models for modeling volatility. The choice of an appropriate model for volatility estimation is critically important. Mohammadi and Su [30] evaluated the performance of four different GARCH models namely GARCH, EGARCH, APARCH, and FIGARCH considering different aspects of volatility. Their findings indicated that the APARCH model provides a more accurate performance than other models in terms of modeling and forecasting the conditional mean and volatility of oil prices. Following the approach of Mohammadi and Su [30], we consider four GARCH models namely GARCH, EGARCH, APARCH, and FIGARCH to estimate the mean and volatility of oil and precious metal prices.

Extensive studies [4,30,31] have demonstrated the effectiveness of GARCH-type models in capturing the volatility dynamics of precious metals, including gold, silver, and platinum. These models have been widely adopted to analyze the Chinese precious metals market, owing to its growing significance in the global economy.

GARCH-type models are specifically designed to capture the phenomenon of volatility clustering, characterized by periods of high volatility followed by periods of both high and low volatilities. These models facilitate the analysis of dynamic relationships between the volatilities of various precious metals, thereby capturing spillover effects and correlations. By allowing the conditional variance of returns to change over time, GARCH models reflect the inherent dynamic nature of financial market volatility. Traders can utilize volatility forecasts generated by GARCH models to develop trading strategies that leverage volatility patterns.

3.2.1. ARCH model

Engle [32] proposed the Autoregressive Conditional Heteroskedasticity (ARCH) model as a solution to issues arising from constant variance. ARCH models acknowledge that asset return shocks, though uncorrelated, may still exhibit dependence. This sequence exhibits dependence that can be described using a simple quadratic function value, thereby producing hysteresis. The ARCH (*m*) model can be expressed as follows:

$$\mathrm{a}_t = \sigma_t \varepsilon_t, {\sigma_t}^2 = \alpha_0 + \alpha_1 {\mathrm{a}_{t-1}}^2 + \cdots + \alpha_m {\mathrm{a}_{t-m}}^2 \tag{2}$$

When the $\{{\mathrm{a}_{t-i}}^2\}\mathrm{i} = 1^m$ larger, the conditional variance σ_t^2 is greater, so that a_t is the absolute value will be greater. Under the framework of a large "disturbance" that appears, the ARCH model will immediately tend to show another larger "disturbance". This is similar to the "volatility aggregation" phenomenon we see in asset returns. Normally, we need to first perform the ARCH effect test on the residual sequence square $\{{\mathrm{a}_t}^2\}$. The specific methods are the LB test and the Lagrange multiplier test (ARCH-LM test). When we draw by any of the testing methods, the ARCH effect exists after. ARCH order model will be used $\{{\mathrm{a}_t}^2\}$ a sequence of the partial autocorrelation function (PACF) is determined, the subsequent parameter estimation is performed, and validation.

3.2.2. GARCH model

ARCH modeling has been considered a base model to analyze the volatility further developed as GARCH model [33,34]. Following previous studies GARCH model is used to identify the spillover effect. We represented r_t on the sequence number returns, *T* the time new information by express. The following Equation (3) expresses the GARCH (*m*, s) model:

$$a_t = \sigma_t \varepsilon_t, \ \ \sigma_t{}^2 = \alpha_0 + \sum_{i=1}^{m} \alpha_i a_{t-i}{}^2 + \sum_{j=1}^{s} \beta_j \sigma_{t-j}{}^2 \tag{3}$$

Similarly, when the $\{a_{t-i}{}^2\}i = 1^m$ is larger, conditional variance $[\sigma_t^2]$ will be greater so that a_t is the absolute value will be greater than zero ($\alpha_i \geq 0$.) Among them, α_i is called the ARCH parameter, β_j is called the GARCH parameter, the sum of the two is less than one（$\alpha_i + \beta_j$） < 1. The mean equation is $r_t = u_t + \alpha_t$.

3.2.3. TGARCH model

In financial markets, new information is typically categorized into two types: Positive news (good news) and negative news (bad news). Leverage, or asymmetry, refers to the phenomenon where good news and bad news have differing impacts on asset return fluctuations. To address this leverage effect, Glosten et al. [35] introduced the Threshold GARCH model (TGARCH model), also known as the GJR model. The TGARCH (*m*, s) model is as follows:

$$\sigma_t{}^2 = \alpha_0 + \sum_{i=1}^{m} (\alpha_i + y_i N_{t-i}) a_{t-i}{}^2 + \sum_{j=1}^{s} \beta_j \sigma_{t-j}{}^2 \tag{4}$$

where in N_{t-i} represents the negative of a_{t-i} indicator variable, to partition the effects of past disturbance, the model with 0 as the threshold. In other words:

$$N_{t-i} = \begin{cases} 1, if \ a_{t-i} < 0 \\ 0, if \ a_{t-i} \geq 0 \end{cases} \tag{5}$$

When the new interest is bad news, N_{t-1} is 1; when the new interest is good news, N_{t-1} is 0. As per the model, when $[a_{t-i}]$ is positive, the portion of $[\sigma_t^2]$ contributes to $\alpha_i a_{t-i}{}^2$; when a_{t-i} is negative, when the portion of $[\sigma_t^2]$ contributes more $\left(\alpha_i + \gamma_i\right) a_{t-i}{}^2$. The mean equation is $r_t = u_t + \alpha_t$. Wherein $0 \leq \alpha_1$, $\beta_1 \leq 1$, $(\alpha_1 + \beta_1) < 1$, α_i and β_j are respectively ARCH parameters and GARCH parameters.

3.2.4. Impulse response functions

In line with previous research [36,37], this study utilizes orthogonal impulse response functions (IRFs) to evaluate the spillover effects on yield, a methodology underpinned by several robust reasons. Orthogonal IRFs facilitate the disentanglement of concurrent shocks, enabling the attribution of observed responses to specific sources [38]. Furthermore, the use of orthogonal IRFs enhances the clarity of economic interpretations. In economic models, structural shocks such as demand, supply, monetary policy, or technology shocks are often assumed to be uncorrelated. Although non-orthogonal IRFs could provide insights into the combined effect of shocks, they lack the ability to separate these effects clearly. The resulting responses would be convoluted and harder to attribute to specific underlying shocks. This analysis focuses on linear spillover effects between the three precious metals. While linear models are useful for capturing the general dynamics between variables, they may not fully account for potential nonlinear relationships. Hence, for a clear and interpretable analysis, orthogonal IRFs are used.

4. Empirical analysis

4.1. Descriptive statistics

The descriptive statistics for all return series in **Table 1** indicate that the daily mean of all return series is positive for the sample periods, and it varies. Silver returns series provide the highest mean return, and they also exhibit higher volatility as measured by the standard deviation. Moreover, the average returns for silver and platinum are negative, with silver exhibiting the highest standard deviation, followed by platinum and gold, which has the smallest mean yield. Therefore, investments in silver and platinum are subject to greater fluctuations compared to gold, making gold more suitable for hedging and risk management purposes. Silver investments, characterized by high risk and high returns, may appeal to investors with a higher risk appetite. Platinum investments, although associated with greater risk and lower returns among the three metals, are potentially undervalued at present and may show promising future trends.

Table 1. Descriptive statistics.

	GOLD	SILVER	PLATINUM	LGOLD	LSILVER	LPLATINUM
Mean	281.636	4232.572	248.900	5.632	8.327	5.498
Median	273.595	3947.500	228.685	5.612	8.281	5.432
Maximum	376.900	7565.000	362.940	5.932	8.931	5.894
Minimum	216.870	2915.000	151.550	5.379	7.978	5.021
Std. Dev.	37.112	1000.104	50.046	0.128	0.207	0.195
Skewness	0.623	1.596	0.569	0.413	1.288	0.371
Kurtosis	2.418	4.467	1.991	2.319	3.726	1.839
Jarque-Bera	157.946	1030.110	192.935	95.536	597.442	158.395
Probability	0.000	0.000	0.000	0.000	0.000	0.000
Observations	2002	2002	2002	2002	2002	2002

Data source: Author's calculations using the data collected from the Wind database.

The normality test results for the daily logarithmic returns are presented in **Table 1**. Our analysis reveals that the daily logarithmic returns of gold, silver, and platinum are all left-skewed. The kurtosis values for all three metals exceed the normal distribution benchmark, indicating the presence of "fat tail" characteristics in the returns of these precious metals. The Jarque-Bera statistics are significantly high and reject the null hypothesis of normal distribution at the 1% significance level. Consequently, it is concluded that the returns of gold, silver, and platinum are non-normally distributed.

4.2. Unit root tests

We determined the return rate stability series by using the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) unit root tests on the three precious metals' daily logarithmic returns. The results in **Table 2** strongly suggest stationarity for all return series in levels at the significance level of 1%.

Table 2. ADF stationary test results.

	ADF Test		**PP test**	
Variable	*t*-statistic	*P* value	*t*-statistic	*P* value
Gold	−11.9653***	0.0000	−10.6749***	0.0000
Silver	−11.9163***	0.0000	−10.6235***	0.0000
Platinum	−12.1198***	0.0000	−11.3926***	0.0000

Data source: Author's calculations using the data collected from the Wind database. *** denotes a 1% significance level.

4.3. Zivot-Andrews unit root

To identify potential structural breakpoints in the daily precious metals market in China during the sample period from 2012 to 2020, we examined two breakpoints by considering major economic and financial events that could have significantly impacted the market. In mid-June 2013, the People's Bank of China (PBoC) tightened liquidity, resulting in a sharp rise in interbank lending rates and this financial stress affected multiple markets, including commodities and precious metals. Additionally, in August 2015, China unexpectedly devalued the yuan, triggering global market volatility which led to increased demand for gold as a safe-haven asset, likely causing a structural shift in the precious metals market.

The null hypothesis of the Zivot-Andrews [39] test suggests that the series has a unit root with a structural break in the constant, trend, or both. **Table 3** provides sufficient evidence to reject the null hypothesis of the presence of a unit root with structural breaks. Therefore, we conclude that the structural breaks in the series are not robust enough to generate any divergence from the results of conventional unit root tests.

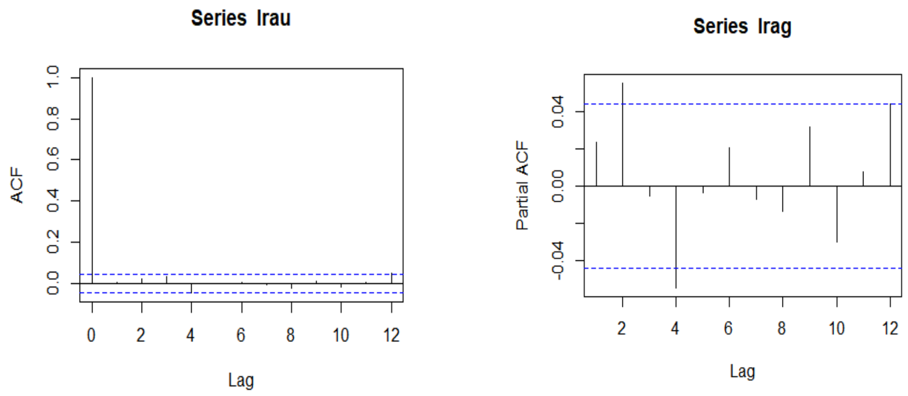
Table 3. Zivot-Andrews unit root test results.

Variable	**Intercept**			**Trend**			**Intercept and Trend**		
	***t*-statistic**	***P* value**	**Breakpoint**	***t*-statistic**	***P* value**	**Breakpoint**	***t*-statistic**		**Breakpoint**
Gold	−6.8752***	0.0000	26/06/2023	−5.9741***	0.0000	26/06/2023	−5.8864***	0.0000	26/06/2023
Silver	−6.1142***	0.0000	07/08/2015	−5.7337***	0.0000	07/08/2015	−5.8472***	0.0000	07/08/2015
Platinum	−5.3697***	0.0000	07/08/2015	−5.2915***	0.0000	07/08/2015	−4.8526***	0.0000	07/08/2015

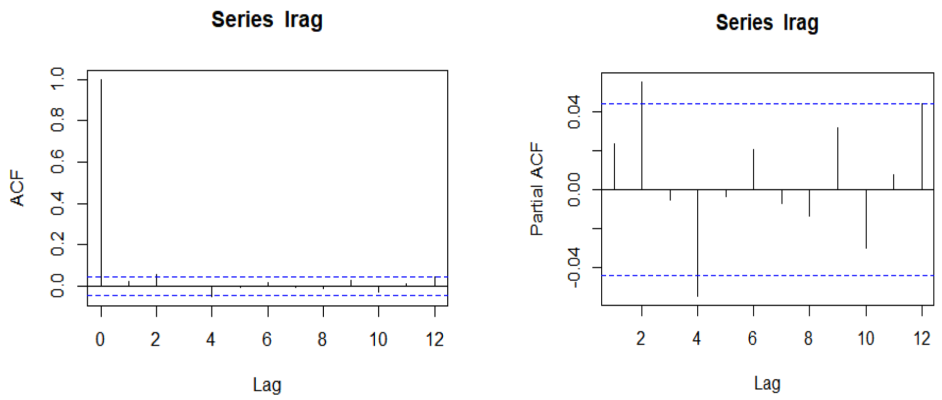
Data source: Author's calculations using the data collected from the Wind database. *** denotes a 1% significance level.

4.4. Autocorrelation test

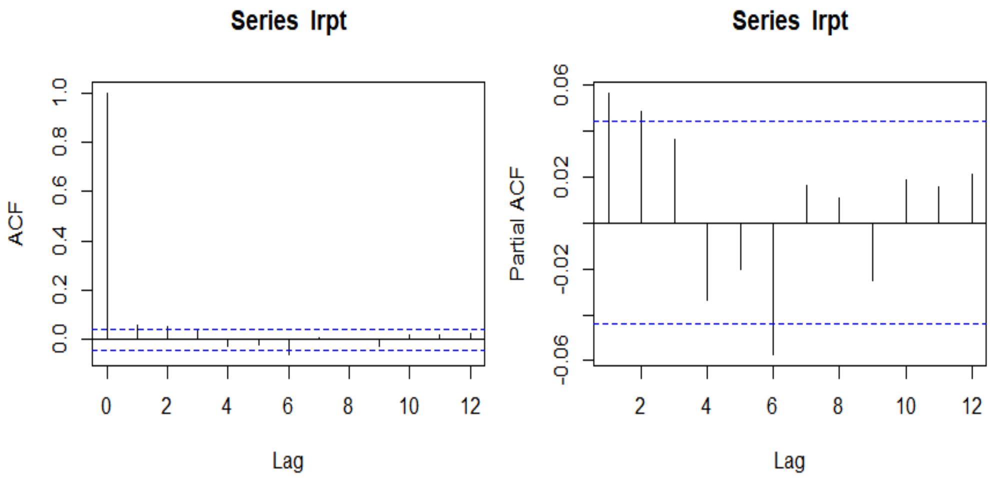
Figure 1 illustrates the autocorrelation function (ACF) and partial autocorrelation function (PACF) plots for the logarithmic yields of precious metals. The ACF plot for gold shows a gradual decay with no significant spikes after the first lag, suggesting some persistence in gold returns. However, the effect of past returns on future returns diminishes quickly. The PACF plot for gold shows a significant spike at lag 1 and then decays to insignificant levels, indicating that gold returns are likely to be influenced by immediate past values, but not by more distant past values. The ACF plot for silver shows a similar pattern, with a gradual decay and no significant spikes after the first lag. The PACF plot for platinum shows a significant spike at lag 1 and then decays to insignificant levels, indicating that platinum returns are likely to be influenced by immediate past values, but not by more distant past values. The ACF plots for all three metals suggest that past returns can have a small influence on future returns, while the PACF plots for all three metals indicate that immediate past returns are the most significant predictor of future returns.



(a)



(b)

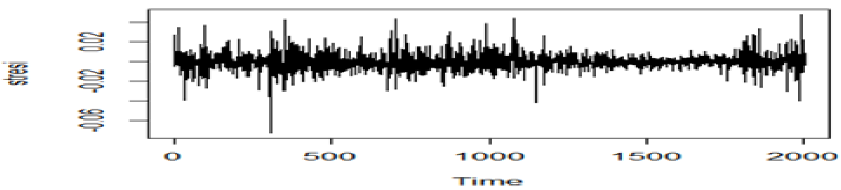


(c)

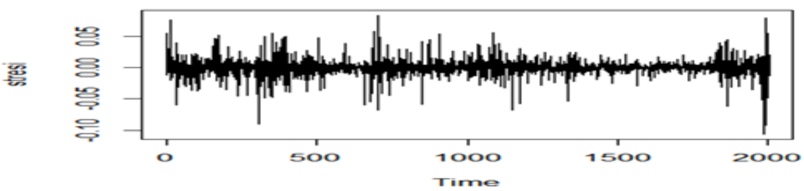
Figure 1. Autocorrelation function (ACF) and Partial autocorrelation function (PACF) plots. **(a)** Gold; **(b)** silver and **(c)** platinum the ACF graph and PACF.
Data source: Author's calculations.

4.5. ARCH effect test

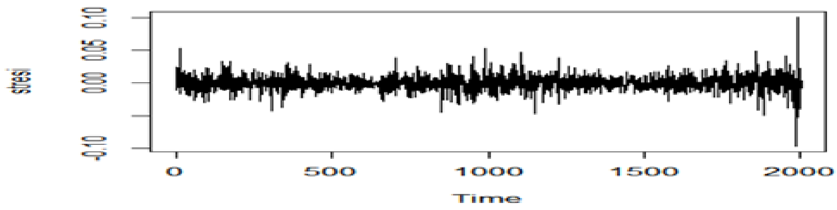
Following the methodologies of Raza et al. [40] and Yıldırım et al. [4], residual sequence charts for the return rates of three precious metals were developed and are presented in **Figure 2**. These charts reveal pronounced volatility clustering phenomena, characterized by periods of high volatility followed by further high volatility, and periods of low volatility followed by further low volatility. This pattern indicates a potential presence of ARCH effects in the error terms of the return series for gold, silver, and platinum.



(a)



(b)



(c)

Figure 2. Residual sequence diagram, **(a)** gold; **(b)** silver; **(c)** platinum.
Data source: Author's calculations.

Furthermore, the Ljung-Box test was applied to the squared residuals $\{a_t^2\}$, utilizing the LB statistic {Q(m)} to assess the presence of the ARCH effect. The Ljung-Box (LB) test, conducted on the residuals of gold, silver, and platinum yield series, yielded Q(12) statistics of 222.54, 555.87, and 454.12, respectively. These highly significant Q-statistics provide strong evidence of ARCH effects in the residuals of all three precious metal yield series. As a result, a GARCH (1, 1) model was employed to capture the time-varying volatility present in the daily logarithmic return series of gold, silver, and platinum.

4.6. GARCH (1, 1) model estimation

From the analysis, we found that the volatility equations for the noble metals exhibit highly significant ARCH and GARCH terms, indicating significant volatility in the returns of these metals. Based on the **Table 4** α_0 values, silver appears to be the most volatile of the three metals, followed by platinum and then gold. Higher α_1 values suggested that recent large returns have a stronger influence on future volatility. Silver has the highest α_1 (0.1644), indicating that recent shocks will have a greater impact on its future volatility compared to gold and platinum. The high α_1 values for all three metals suggested that these markets are prone to volatility clustering. Periods of high volatility are likely to be followed by more periods of high volatility, and vice versa.

All three metals exhibit high β_1 values, suggesting that volatility shocks tend to persist for a relatively long time. The high β_1 values indicate that past volatility shocks will have a long-lasting impact on future volatility. Once volatility increases, it may take a considerable time for it to return to its long-term average. $\alpha_1 + \beta_1$ measures the overall persistence of the volatility process. All three metals have values close to 1, suggesting that volatility shocks tend to persist strongly in all three markets. μ represents the mean return of the asset. The values are relatively small and positive for all three metals, suggesting a slight upward trend in returns.

After establishing the GARCH (1, 1) model, the residual sequence was subjected to the Ljung-Box (LB) test. The corresponding *p*-values were 0.8336, 0.2868, and 0.2271 for gold, silver, and platinum, respectively. These results indicate the absence of significant ARCH effects in the residuals, confirming that the GARCH (1, 1) model is appropriate for fitting the return rate series of these noble metals. The mean equation for gold does not include the fourth-order lag, while the mean equations for silver and platinum exclude the first and sixth-order lags. This exclusion is due to the insignificance of these coefficients in the GARCH model.

Table 4. GARCH model estimation.

	Gold	Silver	Platinum
α_0	1.6467	6.8736	3.3377
α_1	0.0413	0.1644	0.0304
β_1	0.9586	0.8200	0.9689
$\alpha_1 + \beta_1$	0.9999	0.9844	0.9993
μ	0.0531	0.0388	0.0390

Data source: Author's calculations using the data collected from the Wind database.

4.7. TGARCH (1, 1) model estimation

Table 5 presents the estimated parameters of the TGARCH (1, 1) model for the daily rate of returns of gold, silver, and platinum. For gold, all parameters are statistically significant at the 5% level, confirming the presence of volatility clustering and leverage effects in the gold market. The coefficient on the positive shock (0.0349) is greater than the coefficient on the negative shock (0.0179), indicating that good news has a larger impact on gold price volatility than bad news.

Table 5. Gold, silver and platinum daily rate of returns TGARCH (1, 1) model test results.

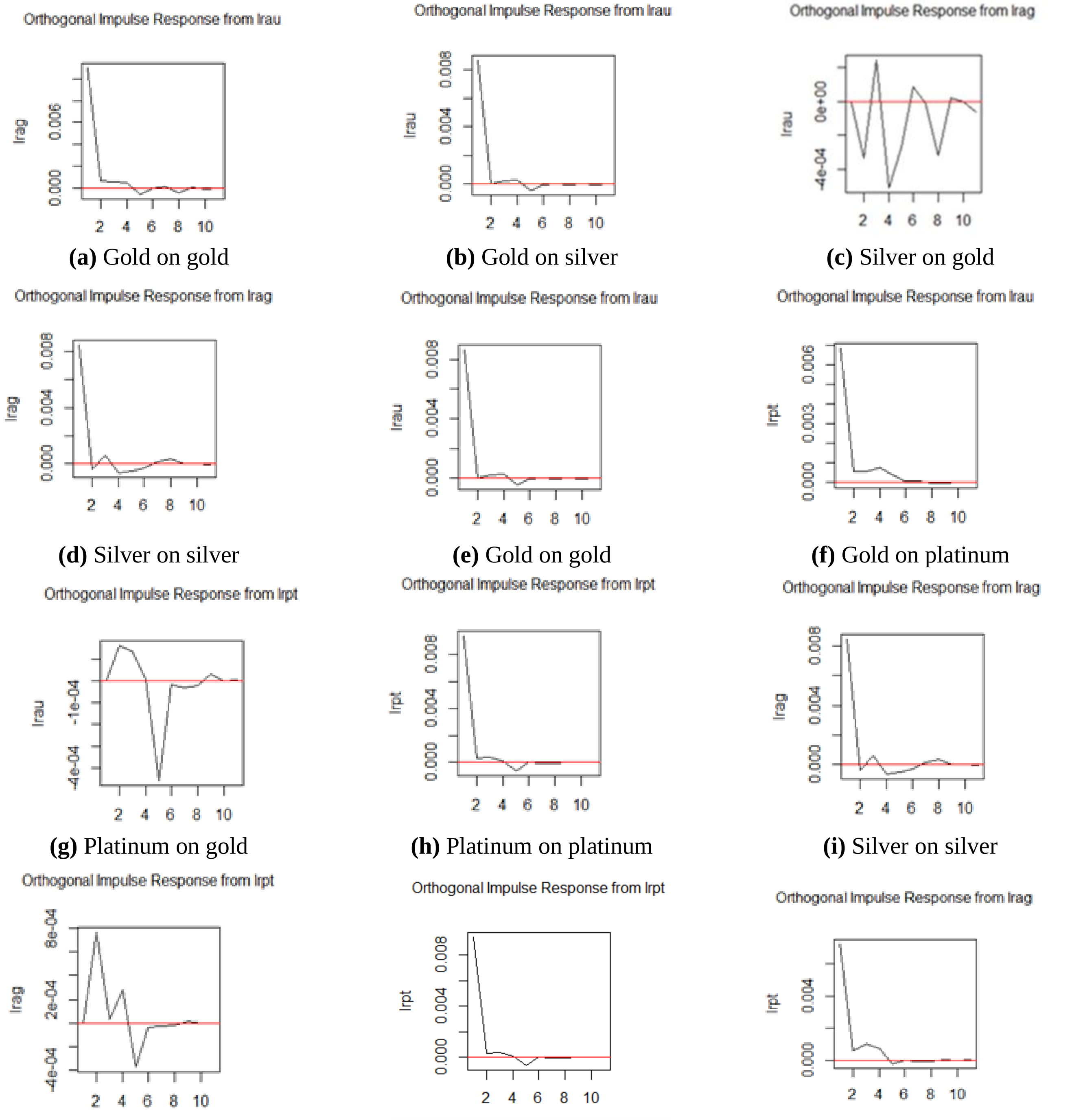
	Gold			Silver			Platinum		
	Estimate	**Std. Error**	**Pr(> |*t*|)**	**Estimate**	**Std. Error**	**Pr(> |*t*|)**	**Estimate**	**Std. Error**	**Pr(> |*t*|)**
alpha1	0.0349	0.0081	0.0000	0.1648	0.0236	0.0000	0.0161	0.0045	0.0003
beta1	0.9551	0.0076	0.0000	0.8258	0.0149	0.0000	0.9704	0.0064	0.0000
gamma1	0.0179	0.0082	0.0291	0.0128	0.0239	0.0593	0.0251	0.0069	0.0003

Data source: Author's calculations using the data collected from the Wind database.

For silver, the leverage effect is present, but in the opposite direction to gold, with the coefficient on the negative shock 0.1776 (0.1648 + 0.0128) exceeding the coefficient on the positive shock (0.1648). Our findings suggested that bad news has a greater impact on silver price volatility compared to good news. Furthermore, the estimated coefficients for silver are generally larger than those for gold, implying higher volatility and sensitivity to shocks in the silver market. Finally, for platinum, all parameters are significant at the 1% level. The leverage effect is present, with the coefficient on the positive shock (0.0161) being greater than the coefficient on the negative shock -0.0090 (0.0161–0.0251). Therefore, good news has a larger impact on platinum price volatility than bad news. The estimated coefficients for platinum are generally smaller than those for gold and silver, suggesting lower volatility and sensitivity to shocks in the platinum market. Hence, the results provide evidence for volatility clustering and leverage effects in the daily returns of all three precious metals. However, the direction and magnitude of the leverage effects differ across the metals.

4.8. Spillover effect analysis using impulse response functions

Market volatility is influenced by its own historical volatility as well as the historical volatility of other markets. This influence is characterized by the magnitude of the difference rather than a directional bias. Volatility is typically quantified using variance, and this phenomenon is referred to as the volatility spillover effect [41]. The correlation coefficients for the daily logarithmic returns between gold and silver, gold and platinum, and silver and platinum are 0.7915, 0.5888, and 0.6217, respectively, indicating substantial correlations. We used impulse response functions to measure the spillover effect of precious metals, and our results are illustrated in **Figure 3**.



(a) Gold on gold **(b)** Gold on silver **(c)** Silver on gold

(d) Silver on silver **(e)** Gold on gold **(f)** Gold on platinum

(g) Platinum on gold **(h)** Platinum on platinum **(i)** Silver on silver

(j) Silver on platinum **(k)** Platinum on silver **(l)** Platinum on platinum

Figure 3. Impulse response functions.

Figure 3a–d illustrates that the lagged spot gold yield exerts a positive influence on the current spot gold yield, with an impact value of 0.008. Conversely, the current silver spot yield has an almost negligible effect on the current spot gold yield. Both the silver spot yield and the current gold spot yield positively influence the current silver spot yield, with impact values of 0.008 and 0.01, respectively. From this analysis, we can infer that the volatility of the gold spot rate of return significantly impacts the fluctuations in spot silver yields. In contrast, the volatility of the spot silver yield does not affect the gold spot rate of return. However, the lagged spot silver yield has a greater impact on the current silver spot return volatility.

Figure 3e–h demonstrates that the lagged spot gold rate of return positively influences the current spot gold rate of return, with an impact value of 0.008. However, the current platinum spot rate of return does not affect the current gold spot rate of return. Similarly, the lagged platinum spot rate of return positively impacts the current platinum spot rate of return, also with an impact value of 0.008. Additionally, the current gold spot rate of return positively influences the current platinum spot yield, with an impact value of 0.006. As per the given results, the volatility of the gold spot rate of return and the lagged volatility of the platinum yield positively impact the volatility of the spot platinum yield. In contrast, the volatility of the spot platinum yield does not affect the volatility of the spot gold rate of return.

Figure 3i–l reveals that the lagged silver spot yield positively influences the current silver spot yield, with an impact value of 0.008. In contrast, the current platinum spot yield has no significant effect on the current silver spot yield, as indicated by an impact value of 0. Similarly, the lagged platinum spot rate of return positively affects the current platinum spot yield, with an impact value of 0.008, while the current silver spot rate of return positively influences the current platinum spot yield, with an impact value of 0.006. The fluctuations in the silver spot yield and the lagged platinum yield positively impact the fluctuations in the platinum spot yield. However, the lagged platinum yield has a more substantial effect. Conversely, the volatility of the platinum spot rate of return does not affect the volatility of the spot silver yields.

Through the analysis of impulse response functions, we observed that fluctuations in the gold spot yield positively influence fluctuations in both silver and platinum spot yields. Similarly, fluctuations in the silver spot yield positively impact fluctuations in the platinum spot yield. However, fluctuations in the gold spot yield are not affected by fluctuations in the silver or platinum spot yields, and fluctuations in the silver spot yield are not influenced by fluctuations in the platinum spot yield. Additionally, the lagged one-period yield fluctuations of gold, silver, and platinum spot yields positively affect their respective current yield fluctuations.

5. Conclusion

In this paper, we empirically study the volatility and asymmetry of the daily logarithmic returns of gold, silver and platinum through the ARCH family model and empirically analyze the volatility spillover effect among the three precious metals in the impulse response function. Gold, silver and platinum daily logarithmic return sequences are not normally distributed, are showing a “fat tail” feature, and all three have a significant ARCH effect. The GARCH (1, 1) model fits the three types of precious metal daily return series well, eliminating the three daily return series' conditional heteroscedasticity. The sum of the ARCH term's coefficients and the GARCH term in the volatility equation is close to 1, indicating that the three daily return rates' fluctuation is persistent. The three precious metals have obvious asymmetric effects on the new interest. Gold and platinum showed good news that is greater than the volatility caused by the same bad news; silver is the opposite: three, the same impact on the innovation of the largest silver confirms high silver risk and high return of the future, namely the whole, the silver investment fluctuations greater. Gold-silver, gold-platinum and silver-platinum all have unidirectional asymmetric fluctuation spillover effects. Fluctuations in the gold market can cause fluctuations in the silver and platinum markets. Fluctuations in the silver market can also cause fluctuations in the platinum market. However, fluctuations in the silver and platinum markets cannot cause fluctuations in the gold market, nor can fluctuations in the platinum market cause fluctuations in the silver market. Simultaneously, the price lag of gold, silver and platinum by one period has a significant impact on the price fluctuation of their respective periods.

In light of our empirical findings, we offer the following recommendations for investors and policymakers in the Chinese precious metals market. Investors can leverage the spot prices of gold to predict the spot prices of silver and platinum. Given the observed volatility spillover effects, the past prices of gold, silver, and platinum can be used to forecast their respective future prices, aiding in more informed investment decisions. Although the Chinese precious metal market is becoming more sophisticated, it has not yet significantly influenced international precious metal price trends. Investors should continue to base their predictions of domestic precious metal prices on global price trends, reflecting the integration of international economic factors. The prices of precious metals are influenced by various factors such as economic conditions, oil prices, the US dollar, and inflation levels. Investors need to analyze these factors comprehensively to make investment decisions that maximize their returns.

Given silver's high volatility and speculative nature, it is suitable for investors with a high risk appetite. Investors should consider a diversified portfolio that includes silver to achieve higher returns. For those seeking risk aversion, gold remains a reliable option for hedging against market volatility. Additionally, platinum, being currently undervalued, may offer significant future upside. The maturity of China's gold, silver, and platinum spot trading markets varies, with a notable disparity in investor expertise. Efforts should be made to enhance investor education, guiding them to formulate investment strategies that suit their risk profiles and financial goals. Precious metals trading institutions should actively promote relevant financial products and allocate resources more effectively. Further, developing and marketing products tailored to different investor needs and preferences. Strengthening the construction of the precious metals market is essential. It is important to establish strict supervision mechanisms to improve the efficiency of resource allocation and mitigate risks. Policymakers should implement a robust regulatory framework to prevent and manage risks associated with rapid resource allocation and risk propagation.

Based on our empirical findings on the volatility and asymmetry of precious metal returns, here are specific recommendations to manage or mitigate the identified spillover effects. Investors should adopt dynamic hedging strategies to protect against volatility spillovers. Given the unidirectional spillover effects from gold to silver and platinum, hedging positions in silver and platinum when holding substantial gold investments can help manage risks. A well-diversified investment portfolio that includes a mix of precious metals can help mitigate the impact of spillovers. By spreading investments across gold, silver, and platinum, investors can reduce the risk associated with the volatility of any single metal.

Utilizing financial derivatives such as futures, options, and swaps on precious metals can provide effective tools for managing spillover risks. These instruments allow investors to hedge against unfavorable price movements and enhance portfolio stability. Regularly monitoring key economic indicators such as oil prices, exchange rates, and inflation levels can provide early warning signals for potential spillovers. Investors can adjust their positions accordingly to manage the anticipated impacts.

Adjusting asset allocation strategies based on market conditions and spillover effects can help optimize returns. For instance, during periods of high volatility, increasing the allocation to gold can provide a safe haven, while in periods of stability, reallocating towards silver and platinum may offer higher returns. Leveraging historical price data and models to predict future price movements and spillover effects can enhance decision-making. Investors should incorporate past price trends of gold, silver, and platinum into their analysis to anticipate and manage spillovers more effectively.

Active management of investment positions, including regular rebalancing of the portfolio, can help mitigate the impact of spillovers which involves continuously reviewing and adjusting holdings to maintain an optimal risk-return balance. Conducting cross-market analysis to understand how global precious metal markets influence each other can provide insights into managing spillovers. Investors should consider international market trends and their potential impact on domestic precious metal prices. Policymakers and regulatory bodies should ensure that robust frameworks are in place to manage systemic risks in the precious metals market. It includes establishing clear guidelines for trading practices and providing oversight to prevent excessive speculation that could exacerbate spillovers.

By implementing these recommendations, investors can better manage the spillover effects identified in our analysis, thereby enhancing their investment strategies and optimizing their financial outcomes in the precious metals market.

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