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Herding, Market Efficiency, and the Melting Pot Effect: Evidence from the Precious Metals Market

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Abstract

This study investigates the dynamics of market efficiency and herding behavior in four leading precious metals - gold, silver, platinum, and palladium - during and after the COVID-19 pandemic using 5-day-week data from December 9, 2019 to March 1, 2026. Employing Multifractal Detrended Fluctuation Analysis (MFDFA) to estimate generalized Hurst exponent (GHE), magnitude of long memory (MLM), and the predictability of return, the findings reveal heightened fractal spectrum and increased herding tendencies during the post-pandemic period for only gold. While the fractal dimension improves for these metals, excluding for gold, they all exhibited weaker long-memory characteristics and thereby an upward trend in the degrees of inefficiencies, implying resistance to persistent shocks, estimated by the MLM approach. Within this framework, the returns of silver, platinum, and palladium became more predictable during the post-pandemic period, implying lower volatility. These results highlight structural shifts in investor behavior and the patterns of market efficiency during crisis periods, providing important insights for enhancing market resilience and volatility management.

Keywords: precious metals; herding behavior; market efficiency; COVID-19; multifractality

JEL Classification: F3; G4; C22

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1. Introduction

The global population experienced one of the most significant global health threats of the last century started at the end of 2019, called the novel coronavirus (COVID-19) pandemic. In particular, from March 2020 onward, the disease spread from Wuhan, China to the entire world day by day, leading several countries to enforce quarantine and lockdown measures along with strict public health measures. Although COVID-19 had far-reaching consequences for global markets, it primarily induced distinct reactions in financial markets. In that vein, the International Monetary Fund (IMF) and the World Bank sharply revised growth rates downward due to disruptions in supply chains and slowdown in production caused by quarantine policies, which led global markets to encounter with potential crisis that were closely integrated with China through the import channel. For instance, starting in March 2020, the value of Dow Jones index dropped more than 30 percent within a few weeks. Additionally, millions of people in the United States applied for unemployment benefits during the subsequent month. Small-scale firms were then exposed to bankruptcy risk. Besides, the United Nations announced that the global economic impact of COVID-19 outbreak could require an additional budget of 2 trillion dollars (UNCTAD, 2020).

This turning point was also coincided with the U.S. Federal Reserve (Fed) actions towards reducing interest rates to near-zero levels for encouraging investment and thereby maintaining employment stability. It aimed at supporting price stability by engaging in extensive bond-buying programs in financial markets. A similar process was followed by the European Central Bank (ECB) and other major central banks, which implemented quantitative easing measures to stimulate economic growth and to prevent COVID-19 from turning into a global economic and financial crisis.

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Governments worldwide introduced large financial aid packages. Thus, increasing uncertainty and rising global concerns led financial investors to turn to certain key assets considered safe havens such as stocks and cryptocurrencies during the COVID-19 pandemic. The recent literature points out that some studies (Salisu et al., 2021; Wen et al., 2022) argue that precious metals such as gold serve as more robust safe havens compared to stocks, equities, and digital currencies, whereas the rest of the others (Choudhury et al., 2022) suggest that the crisis dynamics play a decisive role. Especially the financial disruptions during and after the pandemic have triggered a growing focus on alternative financial assets.

The investigation of a change in market efficiency lies at the very center of these problems whether to discuss the speed and accuracy with which prices reflect available information and how appropriate reactions are formed (Barucci et al., 2023; Nimalendran, 2024). Since market efficiency refers to the extent to which financial markets incorporate and reflect available information on asset prices, investors and traders do not follow their way of earning abnormal returns under certain conditions. However, if information can be predictable, prices may adjust through a nonlinear process. The efficient market hypothesis (EMH) is conducted to provide evidence against the existence of market anomalies where the level of information availability is divided into three forms: the weak form (all past trading prices), the semi-strong form (public information), and the strong form (all information) (Fama, 1991). Various multifactor-based models have been employed to assess the degree of market efficiency. These include rolling sample analysis (Fasanya et al., 2021), machine learning approaches (e.g., random forests, support vector machines, and linear models) (Sebastião & Godinho, 2021), BEKK-MGARCH analysis (Katsiampa et al., 2019), integrated cluster detection, optimization, and interpretation approach (Li et al., 2021), Markov regime-switching vector autoregressive with exogenous variables (MS-VARX) model (Shahzad et al., 2021), generalized vector autoregressive (GVAR) framework (Melki, 2020), bankruptcy prediction model (Kou et al., 2021a), a hybrid interval type-2 fuzzy multidimensional decision-making analysis (Kou et al., 2021b), and multivariate stochastic volatility model (Zhang & He, 2021). For instance, the machine learning-based approaches employ financial innovation techniques - such as artificial neural networks, support vector machines, random forests, and deep learning algorithms - to forecast future prices under the assumption that markets exhibit inefficiencies (Georges & Pereira, 2021; Feng & Liu, 2024; Vuković et al., 2024; Bustos et al., 2025). Moreover, time-varying procedures - such as rolling window regression, generalized spectral test, and state-space models - imply that efficiency considerably changes over time and then produces chronic instability in financial markets (Qi et al., 2022; Shao et al., 2025).

Analyzing the effect of herding behavior on price dynamics of metals market is also essential, as investor sentiment, crisis-driven uncertainty, safe-have demand, and speculative motive may induce collective trading patterns that temporarily weaken market efficiency. Banerjee (1992) and Bikhchandani et al. (1992) define herding behavior as rationally omitting private signals by assuming that others know better and by stemming from information cascades. When investors mimic others instead of relying on their own information (Sias, 2004), price movements can become more fluctuated, resulting in higher volatility and more pronounced market ups and downs (Fei & Liu, 2021). Although the short-run price movements are influenced by herd biased effects, institutional investors may trade similar types of assets since they may have reputation concerns (Lakonishok et al., 1992). This coordinated trading behavior can exacerbate liquidity shocks or periods of selling pressure (Nirei et al., 2012), which may be driven by asymmetric information. According to Forbes and Rigobon (2002), increased herding, low investor confidence, and higher uncertainty lead to stronger co-movement in the market. Accordingly, herding behavior may be categorized based on its determinants and market dynamics. While herding can depend on informational (Bikhchandani et al., 1998), reputational (Scharfstein & Stein, 1990), or behavioral (Banerjee, 1992) factors in terms of causes, the existing literature identifies crisis-induced herding (Bouri et al., 2021; Ferreruela & Mallor, 2021) and trend-following herding (King & Koutmos, 2021; Lin et al., 2023) indicators with respect to market conditions. Besides, the herd-biased behavior is attributed to a change in rationality where

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timing as simultaneous (Andrikopoulos et al., 2017; Scharnowski & Shi, 2024) or lagged (Park & Sabourian, 2011; Cipriani & Guarino, 2014), reflecting high-frequency trading and delayed responses to market signals. The group- (Lillo et al., 2008) and market-wide (Henker et al., 2006) classification is also relevant for herding. Notably, the alternative approach points out the importance of cross-sectional dispersion of betas (Hwang & Salmon, 2004) where Lakshman et al. (2013) state that this is statistically more pronounced than macro-induced variables to estimate herding, driven by sentimental and psychological factors.

This study examines the precious metals market to analyze the behavioral effects on market efficiency through the use of herding algorithms. Precious metals hold a prominent position among financial assets especially for both individual and institutional investors. Rising market uncertainty, the degree of inefficiency, and volatility concerns have recently led investors toward diversification and buying safe-haven assets. The behavior of returns is crucial for hedging and risk management decisions. Compared to traditional asset classes, precious metals have their own potential by protecting portfolios against price instability, currency risk, and systemic market shocks. Forecasts of returns in these markets tend to follow a nonlinear pattern, driven by economic, financial, and political forces. When traditional assets become highly volatile, investors stress the importance of diversification to improve risk-adjusted returns (Sadorsky, 2024). Moreover, market efficiency - or the degree of return predictability - directly affects how quickly information is reflected in prices or whether abnormal profit opportunities may arise (Charles et al., 2015).

Among the other precious metals, gold especially warrants distinct consideration given its substantial investment potential. Compared with the others, gold holds an average market share of 42% and thereby dominates the market. Thus, several previous studies highlight special importance for gold market. This focus is driven by gold's well-established role as a traditional "safe-haven" (Triki & Maatoug, 2021; Ryan et al., 2024). Gold is widely recognized for its capacity to enhance the portfolio risk-return trade-off and to provide hedging benefits during periods of economic downturn, heightened uncertainty, financial turmoil, geopolitical risk, and elevated risk aversion associated with weak investor sentiment (Tiwari et al., 2020; Salisu et al., 2023; Thuy et al., 2024). Instead of traditional EMH tests, several studies employ alternative advanced techniques, such as multifractal methods, inefficiency analyses, or fractal-based measures, which bring out the complex dynamics of gold market. For instance, Wang et al. (2022) indicate that there is an asymmetric herding during positive and negative return phases in China's gold futures market based on investor imitation, while Wang et al. (2024) analyzed gold spot market efficiency under major events (including COVID-19) and showed that efficiency weakens during such periods, implying deviations from weak-form efficiency. The main drivers of herding in the gold market can be grouped as: (i) market stress and uncertainty (Memon et al., 2022), (ii) speculation and investor sentiment (Niu et al., 2024; Nguyen et al., 2025), (iii) volatility and investor attention (Piccoli & de Castro, 2021), and (iv) cultural and regional differences (Liao, 2025). Hence, investors' collective behavior tends to prevail during periods of high market volatility. Additionally, the other factors such as currency denomination, trading structures (e.g., ETFs and futures), nonlinear dynamics, and information flows can affect the degree of efficiency in gold markets. Bidirectional interactions between herding and market efficiency may emerge. When investors copy the financial behaviors and imitate trading strategies, prices tend to follow trends rather than fundamental information, increasing herding and overall inefficiency. Moreover, investors are more likely to follow others' actions under conditions of asymmetric information.

The level of volatility in precious metal markets plays a decisive role in analyzing fractal dimensions and scale-dependent dynamics. This is particularly explained through modeling the dynamics of price fluctuations and investigating the underlying determinants for metals such as gold, silver, platinum, and palladium. Using GARCH and related models, the volatility dynamics of precious metals are investigated through conditional variance models, considering factors such as long memory, asymmetry, and spillover effects. According to Batten et al. (2010), the macroeconomic factors have different effects on volatility trends based on employing monthly price volatility of these

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metals. In particular, monetary policy variables explain gold's volatility, whereas this effect does not hold for silver. Nevertheless, volatility feedback effects are detected across all selected metals. Recent literature shows that such models as GARCH-MIDAS are used to test the impact of global economic policy uncertainty on precious metal price fluctuations, and uncertainty indices are found to significantly affect the volatility of gold, silver, platinum, and palladium (Raza et al., 2023). In addition, other empirical studies conducted within ARCH/GARCH framework reveal the presence of cross-market dynamics among precious metals, covering volatility clustering, asymmetry, and spillover effects (Fatima et al., 2022; Kakade et al., 2022; Madžar et al., 2023). For instance, some studies report that there is a unidirectional causality between silver and platinum driven by price volatility of gold (Rathnayake et al., 2025). Therefore, studies on volatility provide important insights when interpreting the results of multifractal algorithms. Since volatility measures the magnitude of fluctuations in a time series, multifractal methods uncover the scale-dependent organization of these fluctuations and determine whether the series is monofractal or not.

Conventional methods have certain limitations, whereas multifractal models tend to better capture stability patterns in financial markets. Based on Hurst exponent (Hurst, 1951; Mandelbrot, 1975), fractals are defined as complex geometric forms characterized by a single scaling attribute, which are especially important for identifying market turbulences. Mandelbrot (1963) and Mandelbrot and Hudson (2004) argue that financial price movements are inherently irregular and discontinuous, challenging the assumption of traditional models. However, they display scale-dependent and self-similar behavior, allowing them to capture fractal dimensions and the methods of fractal geometry. Kantelhardt et al. (2002) extended this framework by introducing the MFDFA method to assess multifractal features in non-stationary and stochastic time series, thereby facilitating to capture the intricate dynamics of financial markets. In that vein, fractal theory has been widely employed to test weak-form efficiency in financial markets, which captures features such as long-range dependence, scale invariance, and self-similarity (Patil & Rastogi, 2020; Metescu, 2022; Xu et al., 2022). Moreover, this theory is used in gold market to test weak and semi-strong form efficiency and to analyze complex market dynamics, particularly during periods of heightened uncertainty or major geopolitical events (Madani & Ftiti, 2019; Wang et al., 2024). Consistently, the impact of chaotic events has been used to explain financial market stability and to assess dynamic efficiency (Lahmiri & Bekiros, 2020; Jalan et al., 2021; Tanin et al., 2021).

This study contributes to literature in several ways. First, the precious metals market will be analyzed through the examination of short- and long-run fluctuations in gold, silver, platinum, and palladium across the COVID-19 outbreak and post-pandemic period, based on multifractality method. Second, this paper will capture deviations from the assumptions of weak-form market efficiency by measuring the persistence of large price fluctuations in precious metals. Third, the multifractal analyses will be complemented with the memory of long magnitude method to capture scale-dependent dynamics and long-term dependencies in precious metals market to assess complex financial behaviors during and after the COVID-19 pandemic. Consequently, the empirical findings will pave a way for capturing the long-run effects of large fluctuations which are technically useful for assessing the investment risk and the performance of predictive models.

The empirical results show that the generalized Hurst exponent (GHE) estimates have varying degrees of multifractal characteristics for selected precious metals over the sample period. The post-pandemic period exhibits weaker multifractal structures and reduced herd-driven behavior for silver, platinum, and palladium, in contrast to gold. The same finding is not relevant for the magnitude of long memory where the degree of inefficiency notably increased after the COVID-19 outbreak for each selected precious metal. In that vein, the herding behavior and the degree of market inefficiency differ from each other in terms of periodical dimension. In addition, the average level of multifractal spectrum positively changes only for gold, indicating an increase in multifractality during the post-pandemic period. However, the MLM-based inefficiency index suggests that all selected assets exhibited an increase over the sample period, suggesting that they all became less efficient in the aftermath of the COVID-19 pandemic. Within this framework, the returns of silver, platinum, and

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palladium, excluding gold, became more predictable during the post-pandemic period, implying lower volatility.

The rest of the paper is organized as follows: Section 2 describes the data, while Section 3 explains the methodological framework. Section 4 discusses empirical findings. Section 5 concludes the study.

2. Data

The sample of this study includes the financial data of four major precious metals' prices during the period between December 9, 2019 and March 1, 2026, extracted in 5-day-week frequency as per data available in "investing.com" database. Regarding the sample period of the study, the time dimension is divided into two separate sub-periods as the *COVID-19 pandemic* and the *post-pandemic period*. The prices of precious metals are also calculated by their returns on 5-day-week frequency to make comparisons among each other, to discuss diversification performance, and to forecast the future dynamics in prices. The precious metals' returns are calculated in Equation (1) as follows:

$$r_t = log\left(\frac{p_t}{p_{t-1}}\right) \tag{1}$$

Here, r_t and p_t are, respectively, the returns and prices at time *t*. p_{t-1} is the price at time *t-1*. Table 1 presents descriptive statistics, illustrating the asymmetrical features of upward price distributions across two periods. The results of the skewness and kurtosis tests suggest that each series does not follow normality and thereby deviates from Gaussian distribution.

Table 1. Descriptive statistics.

	GOLD	SILVER	PLATINUM	PALLADIUM
Mean	2252.6	28.03	1057.1	1704.8
Median	1922.8	24.56	977.2	1774.1
Maximum	5399.9	116.6	2796.2	3180.5
Minimum	1459.2	11.95	591.5	852.5
Std. Dev.	766.9	12.72	279.5	592.4
Skewness	1.857	3.325	3.037	0.179
Kurtosis	5.927	16.47	13.79	1.779
Jarque-Bera	1511.3***	15234***	10328***	108.9***
	(0.000)	(0.000)	(0.000)	(0.000)
ADF	-18.02***	-18.07***	-18.20***	-17.98***
PP	-39.71***	-40.94***	-41.29***	-38.52***
No. of Obs.	1621	1620	1615	1614

Figure 1 also describes the trends of precious metals' returns and prices over time. Accordingly, all selected prices of assets show considerable volatility during specific periods. Thus, it indicates that the pandemic period might have enduring implications for those prices, notably for predicting future trends.

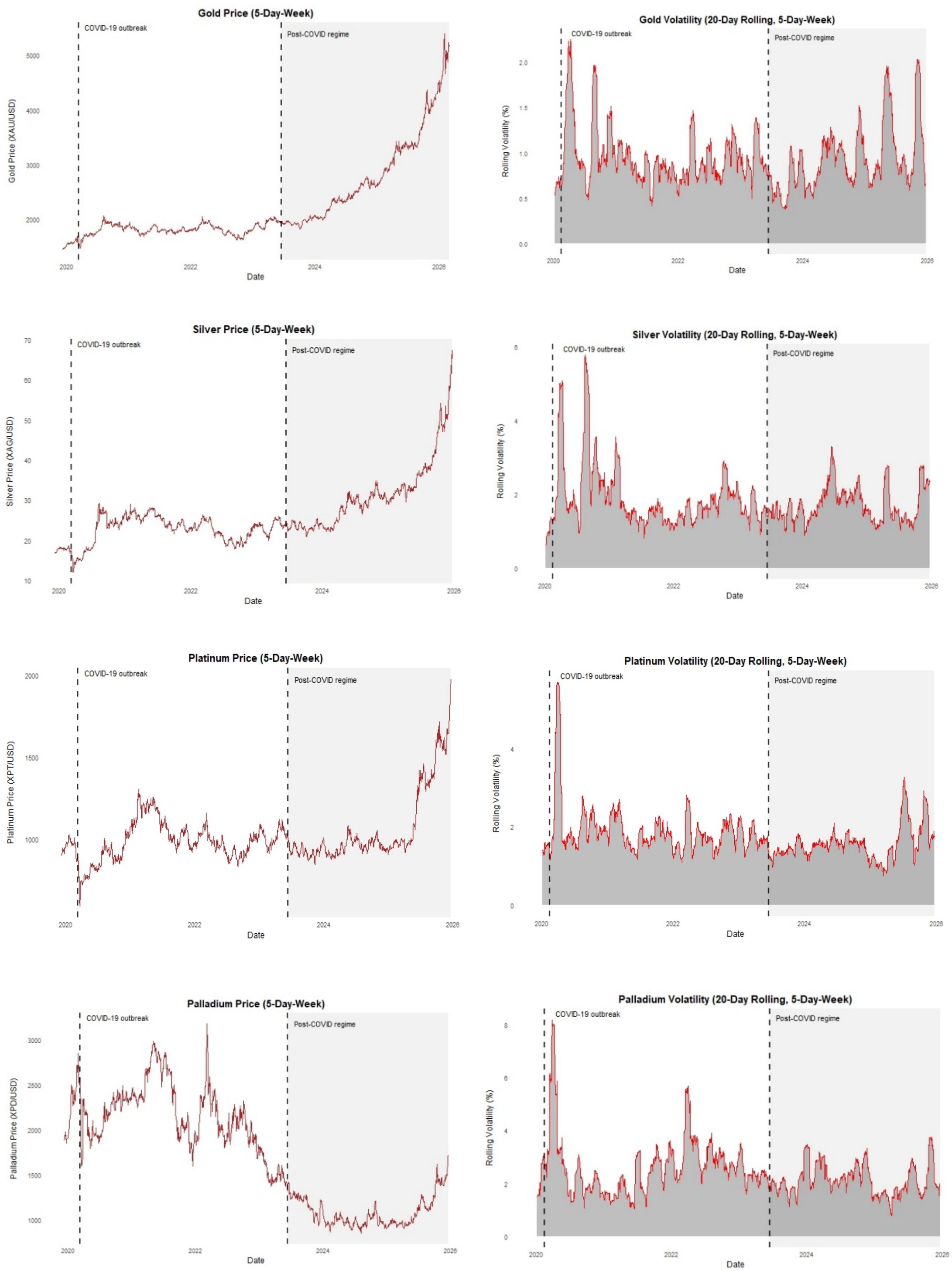

Figure 1. Price and return dynamics.

3. Methodology

3.1. STL Method

Prior to the MFDFA algorithm of the selected precious metal assets, the empirical framework utilizes the Seasonal and Trend Decomposition using Loess (STL) method introduced by Cleveland et al. (1990) to decompose the time series, allowing nonlinear correlations to be assessed within its components. Using locally fitted regression models, the STL approach provides a robust framework for decomposing time series into trend, seasonal, and remainder components. Hence, the usage of

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data is proper for each series along with informative feedback from the dataset obtained by recurring temporal patterns, which are captured as seasonal components.

The STL algorithm smooths the selected time series using Loess within inner and outer loops; the inner loop performs seasonal and trend smoothing, whereas the outer loop mitigates outlier effects. Within the STL framework, the seasonal component is primarily estimated within the inner loop and then adjusted to derive the trend component. The remainder component reflects the residual difference after removing the seasonal and trend factors.

As mentioned above, the Loess smoother developed by Cleveland et al. (1990) is also employed to decompose the daily fluctuation series of the selected precious metal assets into deterministic and stochastic components. Each series is classified as three different components: trend (T_i), seasonal (S_i), and stochastic remainder (R_i) (Laib et al., 2018a, 2018b). Given the daily fluctuations in selected precious metals assets, the STL components can be written as follows:

$$\gamma_i\,(t) = T_i + S_i + R_i \quad (2)$$

Here, γ_i depicts the daily fluctuations of time series of selected precious metals based on logarithms, T_i and S_i are the values of trend and seasonal components, and R_i is the value of remainder component at point *i*. STL composition of the series is carried out using the "STL" package in RStudio (Cleveland et al., 1990; Laib et al., 2018a; Miloş et al., 2020). For seasonal extraction, the Loess window span is specified as 30 in the daily fluctuation series of selected precious assets. Accordingly, Figure 2 represents the STL decomposition of fluctuations in those assets. Each graph illustrates the daily fluctuations in the selected series of precious metals market, along with their trend, seasonal, and remainder components.

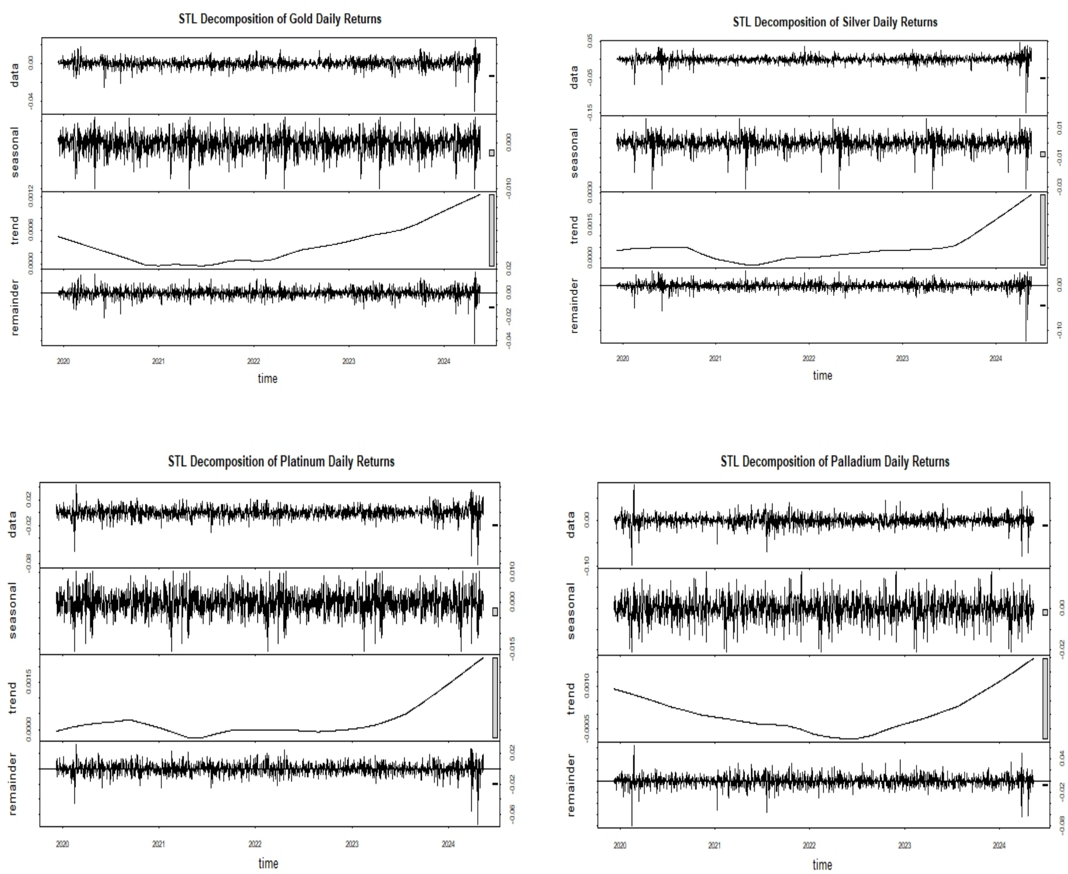

Figure 2. STL of precious metals.

3.2. The MFDFA Algorithm

The behavior of precious metals market is analyzed in terms of short- and long-run benefits; accordingly, this study employs fractal theory to identify the presence of herd-biased impact and the degree of market inefficiency. MFDFA represents a generalized form of the standard DFA method to test the presence of correlations and multifractal features in non-stationary time series data (Kantelhardt et al., 2002). The methodological structure of MFDFA builds upon five main steps (Martínez et al., 2021; Mnif et al., 2022). The initial procedure starts by assuming that $\{x_k, k = 1,2,..,N\}$ where the series of length N does not decay to zero within a closed set. Thus, $x_k = 0$ is possible for an empty set of values.

Step 1. The profile or accumulated deviation of the seasonally adjusted series x_k is measured by the cumulative sum $Y(i)$ as:

$$Y(i) = \sum_{k=1}^{i} |x_k - \bar{x}| \tag{3}$$

Here, $\bar{x}$ represents the mean of x_k and thereby captures the transition from a white noise series to its cumulative random walk form. Equation (4) denotes $\bar{x}$ in a formal illustration and will be eliminated in the trend analysis undertaken in step 3.

$$\bar{x} = \frac{1}{N}\sum_{i=1}^{N} x_i \tag{4}$$

Step 2. The profile or cumulative sum $Y(i)$ is divided into $N_s = \left\lfloor \frac{N}{s} \right\rfloor$ non-overlapping continuous segments (v) of equal length scale (s). $\left\lfloor \frac{N}{s} \right\rfloor$ is the integer part of N divided by s. As the series length N may not necessarily multiple of the time scale s, a small segment at the end of profile or cumulative sum may be excluded from the local segments. Therefore, this leads to be concluded with $2N_s$, which is conducted by repeating the older segmentation process in reverse order.

Step 3. For each of the $2N_s$ segments, the local trend is estimated through the least squares regression of the series. Additionally, the polynomial trend function $\tilde{Y}_v(i)$ is estimated by sections adjusted in each segment v through the detrending approach over a range of different window sizes s within the variance equation as:

$$F_s^2(v) = \frac{1}{s}\sum_{k=1}^{s} (Y_v(k) - \tilde{Y}_v(k))^2 \tag{5}$$

The fitting procedure is based on linear (m = 1), quadratic (m = 2), and cubic (m = 3) polynomials.

Step 4. The fluctuation function or average fluctuation of the qth order is measured by taking the mean of all segments. For $q = 0$, it is defined as:

$$F_q(s) = \left\{\frac{1}{2N_s}\sum_{v=1}^{2N_s} [F_s^2(v)]^{\frac{q}{2}}\right\}^{\frac{1}{q}} \tag{6}$$

and for $q \neq 0$, the equation is expressed as:

$$F_q(s) = exp\left\{\frac{1}{4N_s}\sum_{v=1}^{2N_s} lnF^2(v,s)\right\} \tag{7}$$

To determine how $F_q(s)$ depends on the scale s for different q values, steps 2-4 are required to be repeated across various time scales. This study restricts q within the interval $-5 \leq q \leq 5$.

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Step 5. The scalar behavior of $F_q(s)$ is identified by means of log-log graphs $F_q(s)$ against *s* for each value of *q* order. Fractal time series may possibly exhibit a range of scales, $m + 2 = s_{min} \leq s \leq s_{max} = \frac{N}{4}$ in a given order $q \neq 0$, for which Equation (8) can be conducted:

$$F_{q(s)} \sim s^{h(q)} \quad (8)$$

Hence, the profile or accumulated deviation of the seasonally adjusted series x_k has long-term correlation. Since $F_q(s)$ is not a constant function of *s*, the value of $F_0(s)$ is measured by Equation (9), subject to $q = 0$ (Philippopoulos et al., 2019):

$$F_{0(s)} \sim s^{h(0)} \quad (9)$$

The least squares method is also employed to adjust functions $\ln\left(F_q(s)\right)$ and $\ln(s)$ (Zhang et al., 2019). $h(q)$ is the generalized Hurst exponent and it can be related to the classical Hurst exponent *h* (Chen et al., 2002; Movahed et al., 2006):

$$H = \begin{cases} h(2), & for\ stationary\ time\ series \\ h(2) - 1, & for\ non-stationary\ time\ series \end{cases} \quad (10)$$

It can be shown that, for such a non-stationary signal, the mean sample variance corresponding to $q = 2$ follows a proportionality $s^{h(q)}$, with $h(2) = h + 1$.

When $h(q)$ shows no dependence on *q*, the values of $h(q)$ do not change, thereby the variance $F_s^2(v)$ stays constant for all local segments. The average fluctuation of the *q*th order, $F_q(s)$, takes the same value for all *q*. This means that the time series is monofractal and thereby has no multifractal characteristics. By contrast, if $h(q)$ is determined by *q*, the data of time series has a multifractal structure. Then the velocity of local fluctuations in $F_q(s)$ is considerably driven by selected window size. Positive and negative *q* values highlight large and small fluctuations, respectively, capturing the scaling behavior of each segment (Kantelhardt, 2015). In a multifractal time series, $h(q)$ is a nonlinear decreasing function of q; thus, for $q < 0$, $h(q)$ values are larger than for $q > 0$. The exponent $h(2)$ is corresponded to the value between 0 and 1. In multifractal series, positive q corresponds to lower $h(q)$ values, potentially requiring more iterations for estimations, with the multifractal spectrum spanning m from 1 to 3. To mitigate overfitting problems, this study applies a first-order polynomial with order $m = 1$ (Lashermes et al., 2004; Mnif et al., 2022).

3.3. Generalized Hurst Exponent

The generalized Hurst exponent (GHE), $h(q)$, extends the traditional Hurst (Hölder) exponent introduced by Hurst (1951). It is commonly used to identify financial bubbles or explosive behavior in a time series. Therefore, as a key method for assessing scaling behavior, the GHE provides a way for underlying dynamics of financial markets (Di Matteo et al., 2005; Barunik & Kristoufek, 2010). The estimation procedure leans on the following equation:

$$K_q(\tau) = \sum_{t=0}^{N-\tau} |X(t+\tau) - X(t)|^q / \sum_{t=0}^{N-\tau} |X(t)|^q \quad (11)$$

If $0 < h < 0.5$, the series x_k exhibits long-term negatively correlated behavior where the process frequently reverses its trend direction. Thus, it is described as anti-memory or anti-persistent. This also means that the series lacks from fractal characteristics, thereby preventing the bubble formation and indicating the absence of herding behavior. If $h = 0.5$, the series follows random walk and shows no correlation. If $0.5 < h < 1$, the process is persistent with a clear shape, higher fractal features, and herding behavior. Moreover, it has a long-term memory with a long-term correlation and continuous trend (Movahed et al., 2006; Martínez et al., 2021).

Along with detecting the herding behavior, the roughness in financial markets was first introduced by Mandelbrot (1963), which is particularly estimated by the Hurst exponent *h*

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(Mandelbrot & van Ness, 1968). The following Equations (12) and (13) calculate the fractal dimension *d*, represented as:

$$d = 2 - h \; when \; 0 < h < 1 \quad (12)$$

and

$$d = 1.5 - \alpha \; when - 0.5 < \alpha < 0.5 \quad (13)$$

The generalized Hurst exponent (GHE), $h(q)$, is calculated by multifractal scaling exponent, $\tau(q)$, defining as Rényi exponent (Paladin & Vulpiani, 1984), to explain multifractal behavior, as follows:

$$\tau(q) = qh(q) - 1 \quad (14)$$

Here, the Rényi exponent tends to be concave if the process is multifractal or linear if it is monofractal. This can be also explained based on the independence of $\tau(q)$ and q where $h(q) = h$; then they are linearly correlated and are defined as monofractal, $\tau(q) = qh - 1$. On the contrary, there may be concave nonlinear relationship between $\tau(q)$ and q, then, the time series can be assumed to be multifractal. Thus, the degree of multifractality intensifies with the strength of the nonlinear relationship (Zhang et al., 2019). Additionally, $\tau(q)$ estimates $h(q)$ by using: (i) the generalized Hurst exponent or (ii) the generalized fractal dimension.

The first one is estimated by:

$$h(q) = \frac{1 + \tau(q)}{q} \quad (15)$$

and the latter is computed by the following equation:

$$d(q) = \frac{\tau(q)}{q - 1} \quad (16)$$

Another approach to characterizing the multifractality of a time series is to utilize the singularity spectrum $f(\alpha)$. The first-order Legendre transformation is employed to calculate $f(\alpha)$ in relation with $\tau(q)$:

$$\alpha = h(q) + q\frac{dh_q}{d_q} - \tau_q \quad (17)$$

where the singularity spectrum $f(\alpha)$ is calculated as:

$$f(\alpha) = q\alpha - \tau_q \quad (18)$$

The Hölder exponent (singularity index) is represented by α and $f(\alpha)$ and it describes the fractal dimension of those segments of the time series identified by a given α. In that vein, the plot of α against $f(\alpha)$ is known as the singularity spectrum, also referred to as the multifractal spectrum where $f(\alpha)$ gets the maximum value when $q = 0$. For monofractal signals, the $f(\alpha)$ spectrum collapses to a single point. In a practical framework, the strength of multifractality $\Delta h(q)$ indicates deviation from monofractal behavior. Thus, the higher values of $\Delta h(q)$ correspond to a more developed multifractal characteristics and the stronger its dynamics (Oświkecimka et al., 2013). The same structure is also valid for the width of multifractal spectrum, $\Delta\alpha$, which also serves as indicator of the degree of multifractality. A marked variation in multifractal behavior necessarily reflects a substantial transformation of the series spectrum. The scale range is selected between $s_{min} = 10$ to $s_{max} = (T/4)$ (Rizvi et al., 2014) for this study, where *T* denotes the total length of the time series of selected precious metals.

3.4. Magnitude of Long-Memory and Predictability Index

To analyze how time-varying market efficiency changes, this section uses a measure of long-range dependence based on the generalized Hurst exponent. The magnitude of long memory (MLM) reflects fluctuations in the level of market efficiency across different periods. Market efficiency is further evaluated by estimating the multifractal dimension, which reflects a random walk process across the spectrum from lower bound $h(-0.5)$ to upper bound $h(5)$. When the magnitude of long

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memory is zero, the volatilities of selected precious metals' returns are considered fully efficient, exhibiting neither long memory nor explosive behavior.

Accordingly, larger (smaller) MLM values correspond to a stronger (weaker) degree of long memory and a greater (lower) tendency toward explosive dynamics, thereby implying a higher (lower) level of herding behavior. Following Khuntia and Pattanayak (2020), market efficiency is proxied by the inefficiency index (MLM), and together with the indicators of explosive behavior, is formally presented as follows:

$$MLM = \frac{1}{2}\left(|h(-5) - 0.5| + |h(5) - 0.5|\right) \tag{19}$$

On the other hand, the predictability index (PI) is also defined as:

$$PI = 2\,|d - 1.5| = 2\,|0.5 - h| \tag{20}$$

The fractal dimension, d, is expressed in absolute term since predictability rises under two conditions: (i) $d < 1.5$ (corresponding to $0.5 < h < 1$) and (ii) $d > 1.5$ (corresponding to $0 < h < 0.5$) (Rehman & Siddiqi, 2009). If the first case $(d < 1.5)$ holds, there is a persistence behavior or correlation. Otherwise, the second case $(d > 1.5)$ shows anti-persistence behavior or negative correlation. Similarly, if PI tends toward zero, the process approximates a random walk (classical Brownian motion), thereby rendering precious metals inherently unpredictable in terms of their future trends. Hence, variations in amplitude over two consecutive periods are independent from each other. However, the closer PI is to one, the more predictable returns become, thereby increasing the likelihood of trend persistence.

4. Empirical Findings

The multifractal series with non-normal distribution is analyzed within the initial phase to determine whether it is driven by multiple signals. Figures 3–6 highlight the standard MFDFA results for the remaining inputs of four major precious metals - gold, silver, platinum, and palladium. As illustrated in each figure, the log-log relationship between $F(q)$ and s exhibits a distinct straight-line pattern. Regarding Equations (5) and (6), they are used to derive Hurst exponent, and the stationarity of the series is calculated under the condition that $q = 2$ for assessing the scaling behavior.

The qth-order Hurst exponents $h(q)$ for precious metals vary across q, indicating multifractal scaling exponents rather than a single, unique exponent, represented in Figure 3. Besides, each value with negatively sloped trend implies a presence of multifractality in the temporal dynamics of time-varying residual components. The $h(q)$ estimates are confined to the interval between $q = 5$ and $q \neq 5$, given that the slopes have consistent and gradual changes beyond $q > 5$. Furthermore, for further estimations of multifractal dimensions, the empirical analysis consists of the Rényi exponent τ_q (Figure 4) and the singularity spectrum $f(\alpha)$, through estimating Equations (14)–(18). The overall findings suggest that monofractal series are characterized by linear scaling, while multifractal series demonstrate nonlinear patterns. The exponent form (nonlinear behavior) of the Rényi exponent τ_q provides some evidence that all series exhibit multifractal spectra. In addition, a single-peaked (single-humped) shape of the multifractal spectra indicate that the whole series follow a multifractal structure. The colored dots representing different orders of the Hurst exponent - q = 5 (green), q = 0 (red), and q = -5 (black) - indicate changes in the slope of $h(q)$ across the series, as highlighted in Figure 5. The final step measures the range of $\Delta h(q)$ to analyze the presence of multifractal spectrum and to evaluate the strength of multifractality, indicating a deviation from monofractal behavior. The larger (smaller) the range, the higher (lower) the multifractality (Kantelhardt et al., 2002).

The estimated fluctuation functions of selected precious metals indicate a largely symmetric multifractal spectrum over the years, suggesting that the returns are self-affine fractals with axis-dependent scaling. While past patterns influence returns, they may introduce bias due to value changes and estimation errors. Figure 6 shows that the spectrum becomes slightly skewed right

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during the post-pandemic, highlighting the impact of certain variations on those assets during this period.

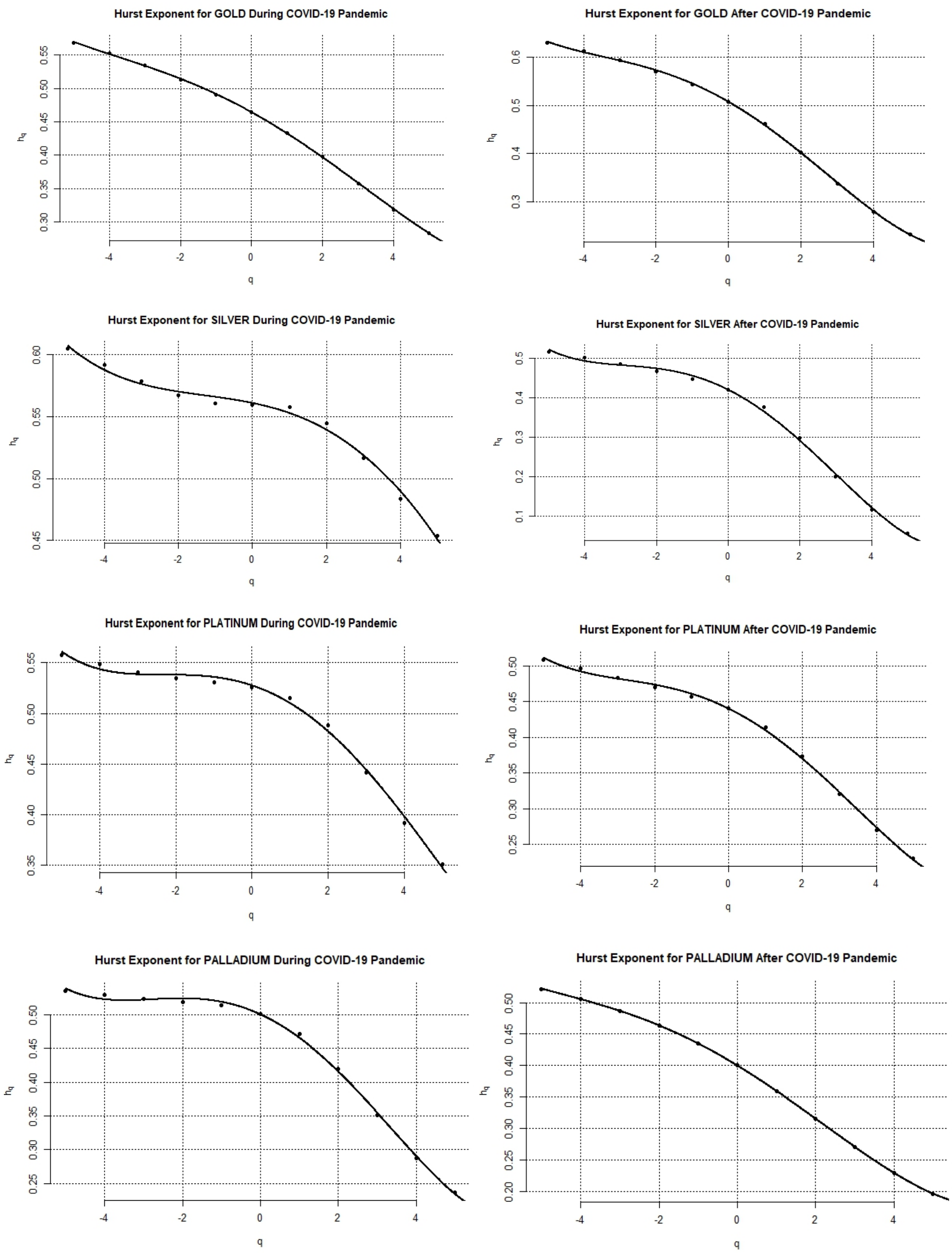

Figure 3. Hurst exponent.

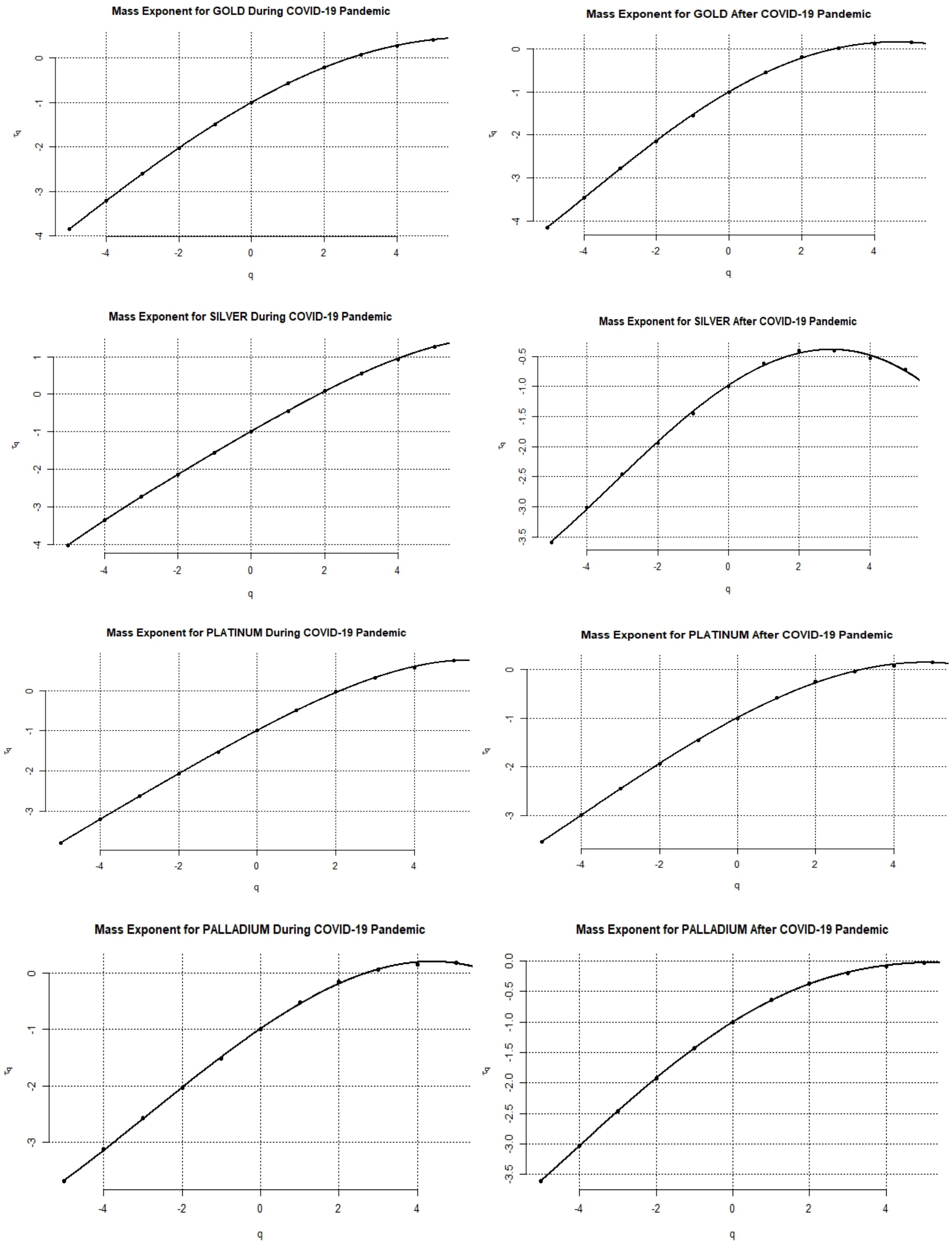

Figure 4. Mass exponent.

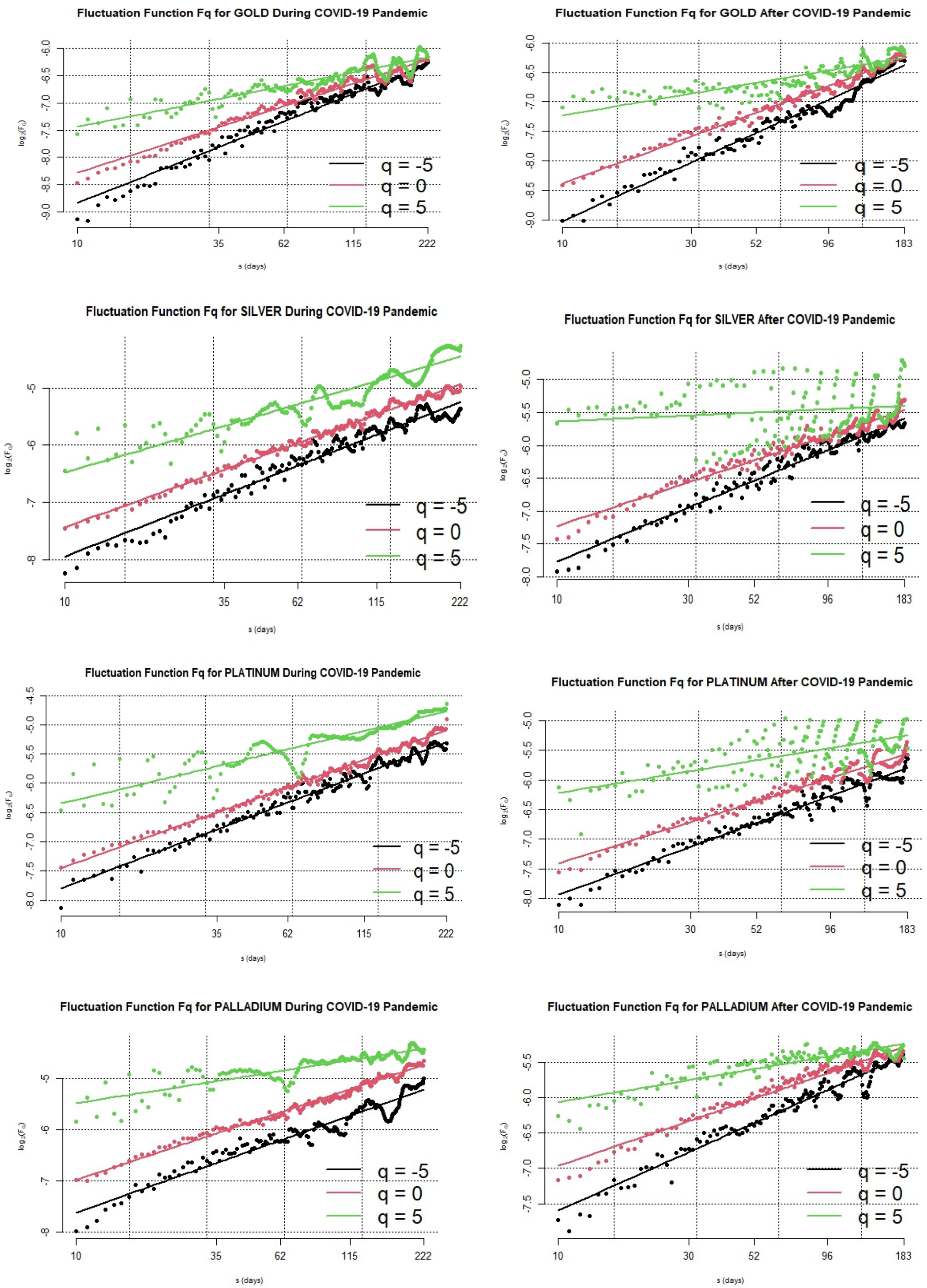

Figure 5. Fluctuation function.

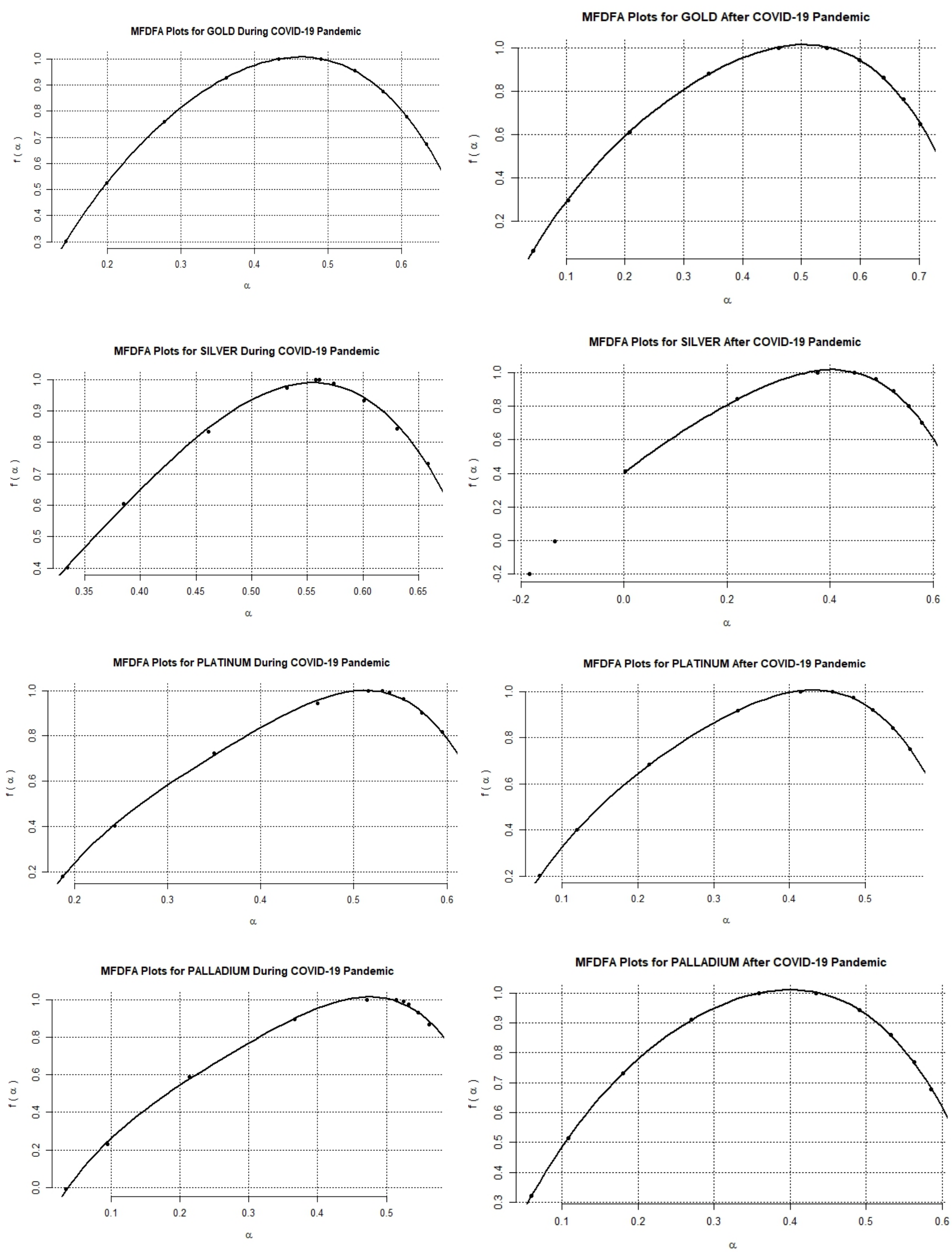

Figure 6. MFDFA plots.

The empirical findings of the generalized Hurst exponent are also summarized in Tables 2–5 through the range of $q \in$ [-5, 5] for given precious metals. For instance, $-5 \leq h(q) \leq 0$ values for $h(q)$ refer to the small price fluctuations effect on returns, while $1 \leq h(q) \leq 5$ means otherwise. Accordingly, as the $h(q)$ values are bound between 0 and 1, the return series of each selected precious metals exhibits fractional Gaussian motion over the given periods. Furthermore, the $h(q)$ values have downward trends from negative to positive q orders, thereby the temporal dynamics of the remaining components reveal multifractal behavior (Laib et al., 2018a, 2018b).

Table 2. Generalized Hurst exponent: Gold.

	COVID-19 outbreak				Post-COVID-19 period			
$q^{th}order$	τ_q	h_q	α	$f(\alpha)$	τ_q	h_q	α	$f(\alpha)$
-5	-3.8430	0.5686	0.6338	0.6740	-4.1550	0.6310	0.7014	0.6480
-4	-3.2092	0.5523	0.6338	0.6740	-3.4536	0.6134	0.7014	0.6480
-3	-2.6017	0.5339	0.6075	0.7792	-2.7805	0.5935	0.6731	0.7612
-2	-2.0266	0.5133	0.5751	0.8764	-2.1412	0.5706	0.6393	0.8626
-1	-1.4903	0.4903	0.5363	0.9540	-1.5430	0.5430	0.5982	0.9448
0	-1.0000	0.4641	0.4903	1.0000	-1.0000	0.5079	0.5430	1.0000
1	-0.5665	0.4335	0.4335	1.0000	-0.5386	0.4614	0.4614	1.0000
2	-0.2048	0.3976	0.3617	0.9282	-0.1956	0.4022	0.3430	0.8816
3	*0.0731*	*0.3577*	*0.2779*	*0.7606*	*0.0119*	*0.3373*	*0.2075*	*0.6106*
4	0.2728	0.3182	0.1997	0.5260	0.1148	0.2787	0.1029	0.2968
5	0.4165	0.2833	0.1437	0.3020	0.1590	0.2318	0.0442	0.0620
Efficiency index	*0.1427*				*0.1996*			
Predictability index	*0.1068*				*0.0598*			

Table 3. Generalized Hurst exponent: Silver.

	COVID-19 outbreak				Post-COVID-19 period			
$q^{th}order$	τ_q	h_q	α	$f(\alpha)$	τ_q	h_q	α	$f(\alpha)$
-5	-4.0245	0.6049	0.6585	0.7320	-3.5885	0.5177	0.5777	0.7000
-4	-3.3660	0.5915	0.6585	0.7320	-3.0108	0.5027	0.5777	0.7000
-3	-2.7352	0.5784	0.6308	0.8428	-2.4577	0.4859	0.5531	0.7984
-2	-2.1346	0.5673	0.6006	0.9334	-1.9352	0.4676	0.5225	0.8902
-1	-1.5606	0.5606	0.5740	0.9866	-1.4470	0.4470	0.4882	0.9588
0	-1.0000	0.5591	0.5606	1.0000	-1.0000	0.4202	0.4470	1.0000
1	-0.4425	0.5575	0.5575	1.0000	-0.6241	0.3759	0.3759	1.0000
2	*0.0890*	*0.5445*	*0.5315*	*0.9740*	*-0.4040*	*0.2980*	*0.2201*	*0.8442*
3	0.5501	0.5167	0.4611	0.8332	-0.4009	0.1997	0.0031	0.4102
4	0.9352	0.4838	0.3851	0.6052	-0.5360	0.1160	-0.1351	-0.0044
5	1.2695	0.4539	0.3343	0.4020	-0.7195	0.0561	-0.1835	-0.1980
Efficiency index	*0.0755*				*0.2309*			
Predictability index	*0.0942*				*0.2934*			

Table 4. Generalized Hurst exponent: Platinum.

	COVID-19 outbreak				Post-COVID-19 period			
$q^{th}order$	τ_q	h_q	α	$f(\alpha)$	τ_q	h_q	α	$f(\alpha)$
-5	-3.7900	0.5580	0.5948	0.8160	-3.5460	0.5092	0.5592	0.7500
-4	-3.1952	0.5488	0.5948	0.8160	-2.9868	0.4967	0.5592	0.7500
-3	-2.6221	0.5407	0.5731	0.9028	-2.4505	0.4835	0.5363	0.8416

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-2	-2.0690	0.5345	0.5531	0.9628	-1.9406	0.4703	0.5099	0.9208
-1	-1.5304	0.5304	0.5386	0.9918	-1.4567	0.4567	0.4839	0.9728
0	-1.0000	0.5261	0.5304	1.0000	-1.0000	0.4402	0.4567	1.0000
1	-0.4845	0.5155	0.5155	1.0000	-0.5855	0.4145	0.4145	1.0000
2	-0.0238	0.4881	0.4607	0.9452	-0.2536	0.3732	0.3319	0.9174
3	*0.3257*	*0.4419*	*0.3495*	*0.7228*	*-0.0385*	*0.3205*	*0.2151*	*0.6838*
4	0.5688	0.3922	0.2431	0.4036	0.0816	0.2704	0.1201	0.3988
5	0.7560	0.3512	0.1872	0.1800	0.1525	0.2305	0.0709	0.2020
Efficiency index		*0.1034*				*0.1394*		
Predictability index		*0.0132*				*0.1882*		

Table 5. Generalized Hurst exponent: Palladium.

	COVID-19 outbreak				Post-COVID-19 period			
$q^{th}order$	τ_q	h_q	α	$f(\alpha)$	τ_q	h_q	α	$f(\alpha)$
-5	-3.6800	0.5360	0.5624	0.8680	-3.6085	0.5217	0.5861	0.6780
-4	-3.1176	0.5294	0.5624	0.8680	-3.0224	0.5056	0.5861	0.6780
-3	-2.5714	0.5238	0.5462	0.9328	-2.4589	0.4863	0.5635	0.7684
-2	-2.0386	0.5193	0.5328	0.9730	-1.9258	0.4629	0.5331	0.8596
-1	-1.5138	0.5138	0.5248	0.9890	-1.4346	0.4346	0.4912	0.9434
0	-1.0000	0.5013	0.5138	1.0000	-1.0000	0.4003	0.4346	1.0000
1	-0.5278	0.4722	0.4722	1.0000	-0.6404	0.3596	0.3596	1.0000
2	-0.1610	0.4195	0.3668	0.8946	-0.3706	0.3147	0.2698	0.9102
3	*0.0533*	*0.3511*	*0.2143*	*0.5896*	*-0.1903*	*0.2699*	*0.1803*	*0.7312*
4	0.1480	0.2870	0.0947	0.2308	-0.0820	0.2295	0.1083	0.5152
5	0.1830	0.2366	0.0350	-0.0080	-0.0220	0.1956	0.0600	0.3220
Efficiency index		*0.1497*				*0.1630*		
Predictability index		*0.1110*				*0.2398*		

The results also exhibit that the mean estimates of Hurst exponent for selected precious metal assets are approximately below 0.5, except for silver (at $q = 2$), during the COVID-19 when $q = 3$. The *q*-order is selected based on the scaling behavior and the Rényi exponent, τ_q, where the large fluctuations in the series exhibit strong scaling behavior if $\tau_q > 0$. This is generally associated with persistence or long-term dependence, which refers that clusters of high volatility tend to follow each other over time. However, the post-pandemic period shows that the return series of only gold exhibits persistent trend with herding behavior since the mean of $h(q)$ is higher than 0.5 for $q = 3$ in case of τ_q becomes positive. The observed sharp shifts in $h(q)$ with respect to *q*-order indicate higher fractal complexity in gold asset following the pandemic, as represented in Figure 5, indicating a relatively larger width of MFDFA plot. The rest of the other selected precious metal assets indicates that they show persistent behavior, meaning that any positive or negative change during the COVID-19 outbreak would be followed by the same attitude at the latter period. Therefore, regarding the predictability index (PI), all selected precious metals - silver, platinum, and palladium - excluding gold, are more predictable across two periods. Hence, trend-following strategies could result in

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spikes of abnormal returns for these precious metals, except for gold, within the given time frame (Caporale et al., 2018).

Table 6 summarizes the multifractality results. The widest range of $\Delta h(q)$ for the COVID-19 period is attributed to the palladium (0.2994), followed by gold (0.2853), implying that the highest levels of multifractality and thus the least efficient precious metal assets. Besides, the narrowest range of $\Delta h(q)$ is tracked by the silver (0.1510) and platinum (0.2068), respectively, referring that they have the lowest multifractality levels along with highest market efficiency during the COVID-19 pandemic. On the other hand, the post-pandemic period reveals that the highest multifractality is shown in silver (0.4616) and gold (0.3992) with the highest level of market inefficiency, respectively, but the lowest multifractality belongs to the platinum (0.2787) and palladium (0.3261).

The dynamics of market efficiency is also captured in Table 6 for each precious metal asset, based on the MLM inefficiency index. This index quantifies the extent to which past fluctuations influence future dynamics and captures the degree of persistence in the series, serving as a measure of predictability and reflecting potential inefficiencies in the market. In essence, the width of multifractal spectrum, $\Delta\alpha$, highlights that the rise in the average coincides with the increase in multifractality (Lu et al., 2013). Therefore, to verify the strength of this connection, the MLM approach provides key points for assessing the empirical validity of the multifractality results where it is measured based on generalized Hurst exponent $h(q)$ and thus the higher values of MLM index refers to a higher degree of market inefficiency.

In this regard, the transition period from coronavirus outbreak to its aftermath shows that all indices increased over time, meaning that the selected precious metals demonstrate increased market inefficiency relative to the pandemic period, as reflected by higher MLM values. This particularly occurs because, once the market stabilizes, past fluctuations exert a strong influence on future returns, leading to persistent patterns. During the pandemic, extreme uncertainty and rapid information flow often temporarily limited long memory. However, after the pandemic, the market stabilizes together with persistent trends re-emerge which leads to more predictable patterns and higher measured inefficiency in the precious metal markets. Additionally, MLM index for each metal asset confirms that this enhanced long memory is not just short-term noise but reflects inherent persistent behavior, reinforcing the observed increase in inefficiency during the post-pandemic period. Some recent studies highlight that the COVID-19 outbreak caused to a sudden negative change in that market regarding the market inefficiency (Mensi et al., 2020, 2021a, 2021b; Faraj et al., 2025). All in all, the causal relations are summarized in Table 7 in terms of changes in herding, market inefficiency, and predictability of returns.

Table 6. Multifractality results.

	Period	Δh_q	$\Delta\alpha$	Hurst Average	Multifractal Spectrum Average (α)	Fractal Dimension (d)	MLM (Inefficiency) Index	Predictability Index (PI)
GOLD	During	0.2853	0.4901	0.4466	0.4259	1.5534	0.1427	0.1068
	After	0.3992	0.6572	0.4701	0.4314	1.5299	0.1996	0.0598
SILVER	During	0.1510	0.3242	0.5471	0.5294	1.4529	0.0755	0.0942

	After	0.4616	0.7612	0.3533	0.2869	1.6467	0.2309	0.2934
PLATINUM	During	0.2068	0.4076	0.4934	0.4546	1.5066	0.1034	0.0132
	After	0.2787	0.4883	0.4059	0.3698	1.5941	0.1394	0.1882
PALLADIUM	During	0.2994	0.5274	0.4445	0.3863	1.5555	0.1497	0.1110
	After	0.3261	0.5261	0.3801	0.3587	1.6199	0.1630	0.2398

Table 7. Summary results for precious metals.

Precious Metals	Change in Herding	Change in Market Inefficiency	Change in Predictability
GOLD	↑	↑	↓
SILVER	↓	↑	↑
PLATINUM	↓	↑	↑
PALLADIUM	↓	↑	↑

5. Concluding Remarks

This study offers an in-depth analysis of herding behavior and market efficiency in four major precious metals, covering gold, silver, platinum, and palladium. Accordingly, the generalized Hurst exponent (GHE) and the magnitude of long memory (MLM) methods were employed to assess the degree of fractality using multifractal detrended fluctuation analysis (MFDFA) for two distinctive periods: (i) the COVID-19 outbreak and (ii) the post-pandemic era. Prior to conducting the MFDFA, the seasonal and trend decomposition using Loess (STL) method was utilized to investigate whether there is a multifractality in the fluctuations of selected series of precious metals. Since MFDFA assumes that large deterministic components (trend or seasonality) are not dominant on fluctuations, STL helps MFDFA by way of removing seasonal components, isolating the trend, improving multifractal scaling results, and avoiding pseudo-multifractality due to seasonality or deterministic structure. Hence, the central objective of this study was to assess whether the series of precious metals became increasingly prone to herd-driven investment behavior during and after the COVID-19 pandemic. Based on the existing literature, limited evidence exists regarding both the GHE and MLM methods together with the STL approach that are jointly used in precious metals market.

The results based on the GHE estimates reveal that the selected precious metals exhibited varying degrees of multifractal properties throughout the sample period. The intensities of multifractal structures differ from coronavirus to its aftermath, but the trend is less pronounced for the latter phases of COVID-19 pandemic, except for gold. Additionally, the same attitude is not relevant for market efficiency where the herd-driven behavior strictly decreased for silver, platinum, and palladium after the outbreak but the market became increasingly inefficient for each asset.

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Therefore, the degree of herding behavior and market inefficiency differed markedly between the two sub-periods. It is noteworthy that changes in the average values of the multifractal spectrum indicate an increase in multifractality only for gold during the post-pandemic period. This means that the latter phase appears to have intensified herding behavior and market inefficiency in gold transactions. However, the MLM-based inefficiency index indicated that all selected assets became less efficient in the aftermath of COVID-19 pandemic. Within this framework, following the coronavirus disease, the returns of silver, platinum, and palladium - excluding gold - became increasingly predictable, indirectly suggesting reduced volatility.

Besides, the scaling behavior of each selected precious metal series is reflected by the fractal dimension, d, to provide evidence for persistence and collective dynamics such as herding in that market. This was calculated for each series to assess the changes in herd-driven behavior after the pandemic, further supporting these findings. In line with the multifractal spectrum results, the evaluation of post-COVID-19 changes in herding behavior through the fractal dimension scale indicates that, during the given period in the precious metals market, herding increased only in gold, while the rest of the metal assets exhibited a decline in herding tendencies. Based on the ranking of fractal dimension values, the silver had the greatest level of herding (0.4529) during the pandemic, whereas gold recorded the strongest herding tendency (0.5299) afterward. Furthermore, the MLM (inefficiency) index suggests that the selected precious metals display varying degrees of inefficiency, but the crucial point is that all of them revealed an upward trend during the post-pandemic period, which means that the market became increasingly inefficient throughout the time. During the COVID-19 pandemic, the palladium (0.1497), followed by gold (0.1427), had the highest inefficiencies, whereas the silver (0.2934), followed by the palladium (0.2398), showed the greatest inefficiencies in the subsequent period. In addition, the rise in the inefficiency index for all precious metals between the two periods indicates that they were exposed to wider market-wide effects related to transaction volumes.

The multifractality analysis based on MFDFA method provides important insights into measuring the sensitivity of highly traded precious metals and to evaluate multiscale and nonlinear dynamics in the market. However, further studies will be also done to enhance its analytical capability in this market and to improve the robustness of the results in the future. The multifractal cross-correlations between gold, silver, platinum, and palladium will be also considered for further studies along with the analysis of asymmetric market responses by distinguishing between upward and downward market movements, which is highly significant in times of market stress and during periods of financial turmoil. Therefore, future studies will be based on new dimensions of herd-driven behavior together with market inefficiency and robustness checks for these findings across the precious metals market by expanding the scope to cover additional approaches.

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