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Gold and Sustainable Stocks in the US and EU: Nonlinear Analysis Based on Multifractal Detrended Cross-Correlation Analysis and Granger Causality

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Abstract: Geopolitical risks and conflicts wield substantial influence on the global economy and financial markets, fostering uncertainty and volatility. This study investigates the intricate relationship between gold and representatives of green and sustainable stocks in the US and EU during the Russia-Ukraine conflict, employing multifractal detrended cross-correlation analysis (MF-DCCA) and nonlinear Granger causality. MF-DCCA reveals significant multifractal properties and nonlinear cross-correlations across all time series pairs. Notably, conflict weakened the multifractal cross-correlations between US stocks and gold, except for the TESLA/gold pair. A similar significant change in the EU market's multifractal properties was observed during the conflict. In conjunction with MF-DCCA, Granger causality tests indicate bidirectional nonlinear relationships between gold and green/sustainable stock markets in the USA and EU. Gold's past movements significantly influence changes in all the considered green and sustainable stocks, enabling predictions of their behavior. These findings shed light on multifractal dynamics during geopolitical crises and emphasize the bidirectional relationships between gold and green and sustainable stock markets. This comprehensive analysis informs investors and policy makers, enhancing their understanding of financial market behavior amid geopolitical instability.

Keywords: multifractal cross-correlation; nonlinear Granger causality; green and sustainable stocks: gold: Russia-Ukraine conflict

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1. Introduction

The conflict between Russia and Ukraine, which began in February 2014 over a dispute about the official status of Crimea and Donbas, escalated on 24 February 2022, and eventually became the most significant war in Europe since World War II [1]. This conflict had severe implications for global financial markets. Investor reactions to news about geopolitical risks and conflicts are often exaggerated [2], which does not help the overall market stability. As an example, Abbassi et al. [3] demonstrated that stock prices are vulnerable to geopolitical risks and trade dependence, underscoring the vulnerability of the stock markets in response to such events.

The economic consequences of the Russia-Ukraine (RU-UA) conflict range from supply chain shortages (especially in base metals and food) to higher inflationary pressures, weaker growth prospects, and other impacts as the battle has escalated [4]. Since the outbreak of the RU-UA conflict, global equity markets have experienced negative cumulative abnormal returns with significant heterogeneous effects [5], accompanied by substantial volatility [6]. As inflationary pressures continue to mount and the conflict shows no signs of abating, investor sentiment appears to have come under significant pressure. Bossman and Gubareva's [7] analysis of the financial impact of geopolitical risks triggered by the Russia-Ukraine conflict on the seven major stock markets in emerging and developed economies shows that the effect is asymmetric and market-specific, with Brazil, China, Russia, and Turkey being resilient to geopolitical risks during bear markets. The RU-UA conflict and the lingering consequences of COVID-19 are forcing central banks to raise interest rates to support currencies and social cohesion, fueling global economic concerns of a possible sharp slowdown or recession, which, combined with inflation, would lead to a highly adverse situation [8].

Stocks and gold prices are two important indicators of the health of the economy. However, the relationship between stocks and gold prices is complex and can be influenced by a number of factors. When the stock market rises, investors are generally optimistic about the future and willing to invest in companies. On the other hand, when the stock market falls, investors are more cautious and pull their money out of the market. Conversely, when there is economic uncertainty, gold is often seen as a safe haven for investors. When the price of gold rises, it indicates that investors are concerned about inflation or other economic factors that could negatively impact the value of traditional investments like stocks.

However, green and sustainable stocks are relatively less studied in the academic literature than traditional stocks, primarily due to the evolving nature of sustainable finance and environmental, social, and governance (ESG) investing. Traditional finance research has long focused on conventional metrics and analysis of standard stocks, for which well-established data sources and historical performance evidence exist. In contrast, green and sustainable stocks operate at the intersection of finance, environmental impact, and social considerations. As interest in green and sustainable investing continues to grow, academic research in these areas gradually expands; however, this growth has yet to fully bridge the relative scarcity of scholarly work. As sustainability and ESG factors gain prominence in investment decisions, we expect more research to be shedding light on the performance, risks, and impacts of green and sustainable stocks.

The main objective of this study is to examine how the Russia-Ukraine conflict has affected the relationship between the stock prices of selected green and sustainable companies in the US and the EU and the price of gold. To achieve that goal, we employ the multifractal detrended cross-correlation analysis (MF-DCCA) method to assess the cross-correlation between gold and sustainable stocks in the US and EU. Subsequently, we apply the nonlinear Granger causality test method to examine the causal relationship between these financial instruments. Furthermore, this study contributes to closing the existing research gap by exploring the impact of the Russia-Ukraine conflict on green and sustainable stocks and their relationship with gold prices. This analysis enhances our understanding of sustainable finance under geopolitical stress.

The MF-DCCA technique was first proposed by Zhou [9] and has since been successfully applied in a variety of fields, including financial markets [10–14], cryptocurrencies [15], Internet of Things [16], and various environmental phenomena [17–19]. Moreover, gold has also been an interesting research object when speaking about MF-DDCA. For instance, gold was analyzed in world markets [20], Chinese markets [21], and with Bitcoin and crude oil [22]. Multifractal analysis is commonly used to study crises' impact on markets. Bentes [23] investigated the safe haven attributes of gold in CIVETS countries and observed that, prior to the pandemic, gold did indeed exhibit safe haven characteristics; however, as the crises of COVID-19 and the RU-UA conflict unfolded, an increase in multifractality was detected, signifying the diminishing safe haven property of gold during these crises times. Aslam [24] applied multifractal analysis to evaluate the impact of the COVID-19 pandemic on agricultural futures markets and found significant changes in intraday multifractal properties and market efficiency. Mensi [25] used multifractal analysis to study Islamic stock markets and found different levels of efficiency across sectors and changes after the global financial crisis. In addition, multifractal analysis was used to evaluate the impact of the Russia-Ukraine conflict on the intraday efficiency of energy markets [26] and to investigate the multifractal characteristics of the cross-correlation between geopolitical risk and energy markets [27].

In addition to multifractal techniques, Granger causality analysis is widely used to explore nonlinear causal relationships among financial variables that provide insight into how different factors interact with and influence market dynamics. Linear models often cannot capture the complex dynamics during financial crises or significant geopolitical events such as the Russia-Ukraine conflict. Researchers can gain valuable insights into how financial markets nonlinearly respond to such events, providing important information for investors and decision makers. For example, Fernandez [28] used the nonlinear Granger causality test to study the spillover effects of the US subprime crisis on Asian and European economies and its impact on currency and stock markets. Similarly, Alzahrani et al. [29] examined the nonlinear Granger causality between wavelet-transformed spots and future oil prices. This method extends across various domains, encompassing stock markets [30] and their interactions with oil markets [31,32], investor sentiment [33], geopolitical risk assessments [34], responses to events like COVID-19 [35], and considerations of mental health [36].

The following sections of this paper are organized as follows: Section 2 explains the materials and methods used, Section 3 presents the results, and Section 4 presents our conclusions.

2. Methodology and Data

This section presents a concise overview of the MF-DCCA and nonlinear Granger causality test methodologies, outlining their key objectives and primary steps.

2.1. MF-DCCA

The MF-DCCA is one of the most predominant methods for examining multifractal patterns in cross-correlations of time series. Multifractal cross-correlation implies that shared underlying processes or factors influence both time series, but their relationship is more intricate and nuanced than a straightforward linear correlation can depict. MF-DCCA offers distinct advantages over comparable methods when it comes to examining the relationship between two time series. MF-DCCA excels at discovering hidden nonlinear relationships that are often missing in linear methods. Its ability to handle scale invariance makes it suitable for capturing both short-term fluctuations and long-term trends. This is particularly valuable in finance, where multifractal scaling is common due to complex interactions. MF-DCCA is also robust against noise, provides statistical significance testing, and can be used outside of finance, increasing its versatility. However, it requires computational resources that are sensitive to parameter settings and may not always provide direct causal insights.

To investigate the multifractal cross-correlation between the stock prices of selected green and sustainable companies in the US and EU and the price of gold, the following steps are taken.

Step 1. Let x_t and y_t be two time series of the same length N. The cumulative deviation series, $X(t)$ and $Y(t)$, are calculated for both time series using (1), where $\overline{x}$ and $\overline{y}$ represent the averages of the time series, and $t = 1,\ 2,\ \ldots,\ N$:

$$X\ (t) = \sum_{k=1}^{t}\ (x_k - \overline{x}\ ) \text{ and } Y\ (t) = \sum_{k=1}^{t}\ (y_k - \overline{y}\ ) \tag{1}$$

Step 2. The $X(t)$ and $Y(t)$ are divided into N_s non-overlapping segments, where s is the time scale. This process is also performed from the end to the start of the series to ensure all information is used. As a result, two sets of N_s non-overlapping segments are obtained.

Step 3. Compute local trends with a kth-order polynomial fit via the least squares method for each sub-segment ν

$$\begin{aligned} x_\nu(i) &= a_1 i^k + \cdots + a_k i + a_{k+1} \\ y_\nu(i) &= b_1 i^k + \cdots + b_k i + b_{k+1} \end{aligned} \tag{2}$$

where $i = 1, 2, \ldots, s; k = 1, 2, \ldots; v = 1, \ldots, N_s$.
Step 4. For each of the $2N_s$ segments, we determine the local variance

$$F^2(v,s) = \frac{1}{s}\sum_{i=1}^{s} |X[(v-1)s+i] - x_v(i)||Y[(v-1)s+i] - y_v(i)| \tag{3}$$

for segments $v = 1, 2, \ldots, N_s$ and

$$F^2(v,s) = \frac{1}{s}\sum_{i=1}^{s}|X[N-(v-N_s)s+i] - x_v(i)||Y[N-(v-N_s)s+i] - y_v(i)| \tag{4}$$

for segments $v = N_s + 1, N_s + 2, \ldots, 2N_s$.
Step 5. Then, we compute the qth order wave function

$$\begin{aligned} F_q(s) &= \left\{ \tfrac{1}{2N_s} \sum_{v=1}^{2N_s} \left[F^2(v,s)\right]^{\frac{q}{2}} \right\}^{\frac{1}{q}}, \; q \neq 0 \\ F_0(s) &= \exp\{ \tfrac{1}{4N_s} \sum_{v=1}^{2N_s} \log F^2(v,s) \}, \; q = 0. \end{aligned} \tag{5}$$

If the series are long-range power-law correlated, $F_q(s)$ increases when s increases. In this case, the power-law correlations satisfy $F_q(s) \sim s^{h_{xy}(q)}$, where $h_{xy}(q)$ denotes the generalized Hurst exponent. If there is only short-range or no correlation in the time series, then $h_{xy}(2) = 0.5$. If there is a long-range power-law correlation, then $h_{xy}(2) \neq 0.5$. Furthermore, if $h_{xy}(2) > 0.5$, the long-range auto-correlations are persistent, while if $h_{xy}(2) < 0.5$, long-range auto-correlations are anti-persistent. To measure the strength of multifractal features, we compute $\Delta h_{xy} = h_{xy}\,(q_{min}) - h_{xy}(q_{max})$. The larger $\Delta H_{xy,}$ the stronger the multifractal feature.

The generalized Hurst exponent h_{xy} is directly related to the multifractal scaling exponent $\tau(q)$ via the following relation: $\tau(q) = qh_{xy}(q) - 1$. A linear form for the multifractal scaling exponent characterizes the monofractal time series.

The singularity strength $\alpha_{xy} = h_{xy}(q) + qh'_{xy}(q)$ describes the singular degree of each segment in a complex system. The singularity spectrum $f_{xy}(\alpha) = q\alpha_{xy} - qh_{xy} + 1$ describes the fractal dimension. The spectrum gives information about the relative dominance of various fractal exponents in the series. The wider the range of singularity strength $\Delta\alpha_{xy} = \alpha_{xy}^{max} - \alpha_{xy}^{min}$, the more intense data fluctuation exists.

2.2. Nonlinear Granger Causality

The Granger causality test method proposed by Granger [37] is widely used to analyze the risk conduction effect. Existing research proposes the nonlinear Granger Causality test method [38] based on the linear Granger causality test method, which compensates for the limitation of the linear Granger causality test method. Hence, the key advantage of the nonlinear Granger causality test is its ability to uncover complex, nonlinear causal relationships in data.

The process of conducting a nonlinear Granger causality test is outlined as demonstrated by [30,36]. Consider two time series, $\{X_t\}$ and $\{Y_t\}$, which are assumed to exhibit strict stationarity and weak dependence. The m-length leading vector of $\{X_t\}$ is represented as $\{X_t^m\}$, while the lag vectors of α-length and β-length for $\{X_t\}$ and $\{Y_t\}$ are denoted as $X_{t-\alpha}^{\alpha}$ and $Y_{t-\beta}^{\beta}$, respectively.

Formally, we define that

$$\begin{aligned} X_t^m &\equiv (X_t,\, X_{t+1},\, X_{t+2}, \ldots,\, X_{t+m-1}) \\ Y_t^m &\equiv (Y_t,\, Y_{t+1},\, Y_{t+2}, \ldots,\, Y_{t+m-1}) \\ X_{t-\alpha}^{\alpha} &\equiv (X_t,\, X_{t+1},\, X_{t+2}, \ldots,\, X_{t-\alpha}) \\ Y_{t-\beta}^{\beta} &\equiv (Y_t,\, Y_{t+1},\, Y_{t+2}, \ldots,\, Y_{t-\beta}). \end{aligned} \tag{6}$$

For given values of $m,\ \alpha$, and β (each greater than or equal to 1) and a positive constant e, the nonlinear Granger causality test indicates that $\{Y_t\}$ fails to Granger-cause $\{X_t\}$ if the following condition is met [30,36]:

$$\begin{aligned} Pr\big(\big|\big|X_t^m - X_s^m\big|\big| \quad &< e\big|\big|X_{t-\alpha}^{\alpha} - X_{s-\alpha}^{\alpha}\big|\big| < e,\ \big|\big|Y_{t-\beta}^{\beta} - Y_{s-\beta}^{\beta}\ \big|\big| < e\big) \\ &= Pr\big(X_t^m - X_s^m\big|\big| < e\big|\big|\ X_{t-\alpha}^{\alpha} - X_{s-\alpha}^{\alpha}\big|\big| < e\big). \end{aligned} \tag{7}$$

Here, $Pr(\cdot)$ denotes the probability and $\|\cdot\|$ denotes the maximum norm.

The left-hand side probability signifies the likelihood that two arbitrary m-length leading vectors of $\{X_t\}$ are within a distance of e from each other, provided their corresponding α-length lag vectors of $\{X_t\}$ are at a distance shorter than e from each other.

Testing the null hypothesis $H0:\ \{Y_t\}$ does not exhibit nonlinear Granger causality with respect to $\{X_t\}$ but becomes more insightful when expressing the conditional probabilities through ratios of their corresponding joint probabilities.

We utilize the ratios of joint probabilities, denoted as $\frac{C1(m+\alpha,\beta,e)}{C2(\alpha,\beta,e)}$ and $\frac{C3(m+\alpha,e)}{C4(\alpha,e)}$, to assess the left-hand and right-hand sides. We define joint probabilities as follows [30,36]:

$$\begin{aligned} C1(m+\alpha,\ \beta,\ e) &\equiv Pr\left(\left|\left|X_{t-\alpha}^{m+\alpha} - X_{s-\alpha}^{m+\alpha}\right|\right| < e,\ \left|\left|Y_{t-\beta}^{\beta} - Y_{s-\beta}^{\beta}\ \right|\right| < e\right) \\ C2(\alpha,\ \beta,\ e) &\equiv Pr\left(\left|\left|X_{t-\alpha}^{\alpha} - X_{s-\alpha}^{\alpha}\ \right|\right| < e,\ \left|\left|Y_{t-\beta}^{\beta} - Y_{s-\beta}^{\beta}\ \right| < e\right)\right. \\ C3(m+\alpha,\ e) &\equiv Pr\left(||X_{t-\alpha}^{m+\alpha} - X_{s-\alpha}^{m+\alpha}\right|\left| < e\right) \\ C4(\alpha,\ e) &\equiv Pr\big(\big|\big|X_{t-\alpha}^{\alpha} - X_{s-\alpha}^{\alpha}\ \big|\big| < e\big) \end{aligned} \tag{8}$$

Given the provided values of $m,\ \alpha$, and β (all of which are greater than or equal to 1) and a positive constant e, the null hypothesis $H0$ can be formulated as follows [30,36]:

$$H0\ :\ \frac{C1(m+\alpha,\ \beta,\ e)}{C2(\alpha,\ \beta,\ e)} = \frac{C3(m+\alpha,\ e)}{C4(\alpha,\ e)} \tag{9}$$

Let us define I as a kernel, denoted as $I = (Z_1,\ Z_2,\ e)$, which takes on the value of 1 when two compatible vectors Z_1 and Z_2 are within a maximum norm distance of e from each other, and 0 otherwise. This kernel function plays a crucial role in determining proximity based on the specified conditions, [30,36].

$$I = (Z_1,\ Z_2,\ e) = \begin{cases} 1,\ \|\ Z_1 - Z_2\ \| \leq\ e \\ 0,\ \|\ Z_1 - Z_2\ \| > e \end{cases} \tag{10}$$

The correlation-integral estimators of the joint probabilities can subsequently be expressed as follows [30,36]:

$$\begin{aligned}
C1(m+\alpha,\ \beta,\ e,\ \lambda) &\equiv \tfrac{2}{\lambda(\lambda-1)}\sum\sum_{t<s} I\left(x_{t-\alpha}^{m+\alpha},\ x_{s-\alpha}^{m+\alpha},\ e\right)\cdot I\left(y_{t-\beta}^{\beta},\ y_{s-\beta}^{\beta},\ e\right)\\
C2(\alpha,\ \beta,\ e,\ \lambda) &\equiv \tfrac{2}{\lambda(\lambda-1)}\sum\sum_{t<s} I\left(x_{t-\alpha}^{\alpha},\ x_{s-\alpha}^{\alpha},\ e\right)\cdot I\left(y_{t-\beta}^{\beta},\ y_{s-\beta}^{\beta},\ e\right)\\
C3(\alpha,\ \beta,\ e,\ \lambda) &\equiv \tfrac{2}{\lambda(\lambda-1)}\sum\sum_{t<s} I\left(x_{t-\alpha}^{m+\alpha},\ x_{s-\beta}^{m+\beta},\ e\right)\\
C4(\alpha,\ e,\ n) &\equiv \tfrac{2}{\lambda(\lambda-1)}\sum\sum_{t<s} I\left(x_{t-\alpha}^{\alpha},\ x_{s-\beta}^{\beta},\ e\right)
\end{aligned} \tag{11}$$

where $t,\ s = max(\alpha,\ \beta)+1,\ \ldots,\ T-m+1,\ n = T - max(\alpha,\ \beta) - m + 1$.

When considering the provided values of $m \geq 1$, $Lx \geq 1$, $Ly \geq 1$, and $e > 0$, the test statistics are defined utilizing the joint probability estimators as follows [30,36]:

$$\sqrt{n}\left[\frac{C1(m+\alpha,\ \beta,\ e)}{C2(\alpha,\ \beta,\ e)} - \frac{C3(m+\alpha,\ e)}{C4(\alpha,\ e)}\right]^{\alpha} \sim N\left(0,\ \sigma^2(m,\ \alpha,\ \beta,\ e)\right). \tag{12}$$

In this context, the variance is consistently estimated [39]. Assuming the values of m, α, and $\beta \geq 1$ and $e > 0$, if $\{X_t\}$ does not satisfy the nonlinear Granger cause with respect to $\{Y_t\}$, then the test statistic follows an asymptotic normal distribution with a zero mean and a constant variance. The conventional critical values are applicable when used to test the null hypothesis that the stock price $\{X_t\}$ does not nonlinearly Granger-cause $\{Y_t\}$, due to the asymptotic normality of the test statistics. A similar procedure is employed to test the hypothesis that $\{Y_t\}$ does not nonlinearly Granger-cause $\{X_t\}$.

2.3. Data

We selected 8 representatives of stocks of the greenest and sustainable companies from the United States and Europe. In selecting companies for this study, we were guided by several key criteria. First, we sought diversity across industries, encompassing renewable energy, waste management, utilities, and real estate, thus addressing various environmental challenges. Second, we focused on industry leaders renowned for their innovation, providing valuable insights into the intersection of innovation and sustainability. Third, we prioritized companies with significant global impact, actively shaping sustainability trends and supply chains. Fourth, to facilitate comparisons, we considered companies operating in both the United States and Europe, regions that are at the forefront of sustainability. Finally, and most crucially, the availability of robust and reliable data, critical to scientific research, strongly influenced our selection, leading us to the eight chosen companies. The data were obtained from the Yahoo Finance website. The selected time series spanned from August 4, 2014, to February 21, 2023, and a description of the gold and stocks series can be found in Table 1.

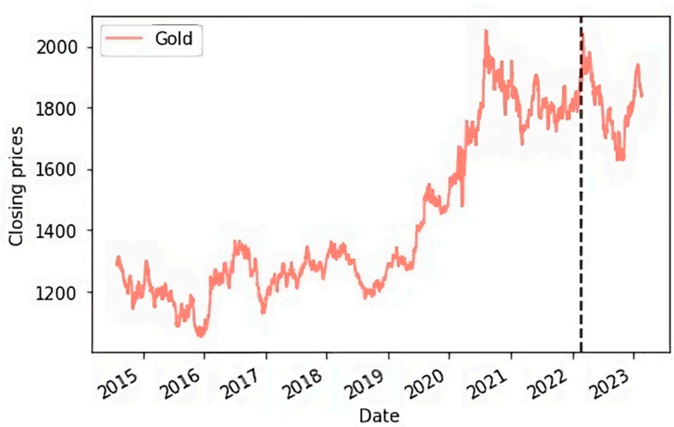
Table 1. Description of data.

Tesla (TSLA)	A sustainable energy company based in the United States that manufactures electric vehicles and renewable energy products to reduce the world's dependence on fossil fuels.
First Solar (FSLR)	A US-based environmentally friendly technology company that specializes in solar cell manufacturing and is driving the transition to renewable energy sources.
NextEra Energy (NEE)	A US-based clean energy company that generates electricity from renewable sources such as wind and solar power and is committed to reducing carbon emissions.

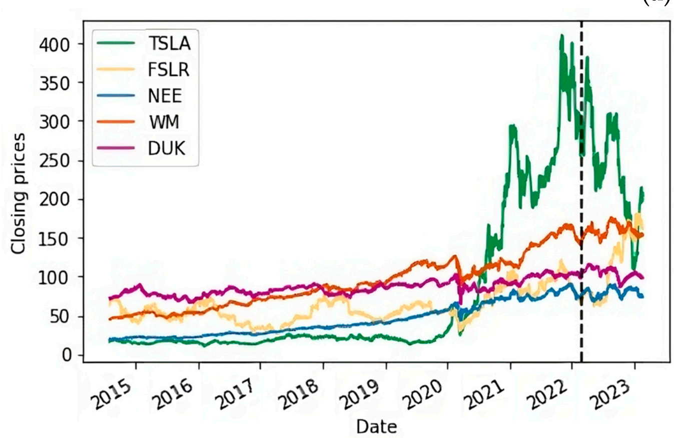
Table 1. *Cont.*

Waste Management (WM)	A US-based waste management and environmental services company that works to minimize waste and promote recycling to create a more sustainable future.
Duke Energy (DUK)	A US-based energy company that has made significant investments in renewable energy and has a goal of zero carbon emissions by 2050.
Vonovia SE (VNA.DE)	A German real estate company focused on sustainable housing, promoting energy efficiency, and reducing the carbon footprint of its buildings.
Vestas Wind Systems A/S (VWS.CO)	A Danish wind turbine manufacturer driving the shift to renewable energy sources and reducing carbon emissions.
Schneider Electric (SU.PA)	A French multinational company specializing in energy management and automation solutions that help optimize energy efficiency and reduce environmental impact.
Gold	Many factors, including global economic trends, political events, and changes in interest rates, influence the price of gold. In recent years, gold prices have fluctuated due to different uncertainties.

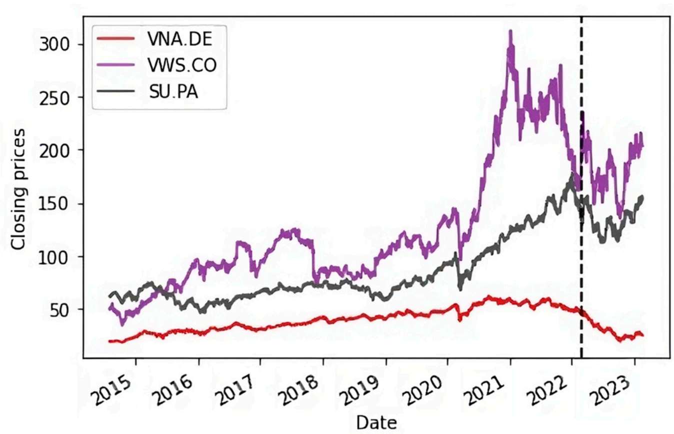
The evolution and development of prices are depicted in Figure 1, while the descriptive statistics and stationarity tests are presented in Table 2.



(**a**) Gold



(**b**) US green and sustainable companies



(**c**) EU green and sustainable companies

Figure 1. Evolution of prices.

Table 2. Descriptive statistics and unit root test results.

Whole Period	Mean	Med	Max	Min	SD	Ske	Kur	JB	ADF	PP	Obs
TSLA	87.56	21.68	409.97	9.58	107.61	1.21	2.95	438.99 **	−2.03	−2.13	1816
FSLR	66.14	59.92	180.19	26.33	28.95	1.74	6.35	1764.82 **	−1.60	−1.63	1816
NEE	47.11	39.44	90.25	18.53	22.58	0.38	1.64	183.64 **	−3.26	−3.40	1816
WM	98.04	91.08	175.29	44.05	37.53	0.37	1.94	127.08 **	−3.45 *	3.26	1816
DUK	87.16	85.82	115.43	64.15	10.77	0.45	2.41	88.89 **	−4.36 **	−4.46 **	1816
VNA.DE	38.78	29.16	62.22	18.12	11.17	0.14	1.96	87.61 **	−0.59	−0.42	1816
VWS.CO	129.64	110.02	312	34.06	61.32	0.82	2.68	212.8 **	−2.66	−2.47	1816
SU.PA	88.43	72.34	177.82	45.93	32.68	0.87	2.37	256.76 **	−2.24	−2.36	1816
GOLD	1458.49	1319.4	2051.5	1050.8	276.23	0.46	1.62	205.91 **	−3.21	−2.81	1816
Before RU-UA conflict											
TSLA	67.95	20.42	409.97	9.58	96.31	1.77	4.8	1056.91 **	−1.54	−1.52	1604
FSLR	59.41	55.66	121.14	26.33	18.62	0.76	3.17	156.54 **	−2.69	−2.69	1604
NEE	42.83	36.23	90.25	18.53	20.41	0.65	2.08	168.18 **	−2.87	−2.81	1604
WM	89.99	85.81	166.83	44.05	32.14	0.50	2.36	95.24 **	−2.53	−2.92	1604
DUK	84.96	83.99	107.93	64.15	9.17	0.43	2.54	63.22 **	−4.27 **	−4.20 **	1604
VNA.DE	39.98	40.49	62.22	18.12	11.02	0.02	1.99	67.92 **	−3.10	−2.96	1604
VWS.CO	122.72	105.45	312	34.06	61.52	1.14	3.29	353.37 **	−2.10	−1.86	1604
SU.PA	82.44	70.69	177.82	45.93	29.73	1.35	3.77	529.71 **	−1.85	−1.90	1604
GOLD	1412.17	1293.5	2051.5	1050.8	258.41	0.77	2.11	212.21 **	−2.73	−2.50	1604
After RU-UA conflict											
TSLA	235.96	236.82	381.82	108.1	63.95	−0.10	2.32	4.41	−2.06	−2.18	212
FSLR	117.12	122	180.19	61.4	40.23	0.00	1.40	22.51 **	−1.93	−2.03	212
NEE	79.50	80.16	89.77	67.02	5.4	−0.22	2.13	8.45 *	−1.93	−2.56	212
WM	158.93	157.95	175.29	141.91	7.33	0.28	2.57	4.48	−2.88 *	−2.91 *	212
DUK	103.82	104.75	115.43	85.97	6.56	−0.46	2.72	8.29 *	−2.60	−2.84	212
VNA.DE	26.69	27.07	47.5	18.97	7.52	0.87	2.68	27.92 **	−1.41	−1.23	212
VWS.CO	182.02	184.28	235.4	134.88	21.66	−0.30	2.22	8.51 *	−2.13	−2.02	212
SU.PA	133.76	133.38	156.28	112	11.59	0.03	2.08	7.53 *	−1.79	−1.68	212
GOLD	1808.9	1811.6	2040.1	1626.7	96.81	−0.00	2.05	7.95 *	−1.45	−1.42	212

Note: ** indicates significance at 1% level, * indicates significance at 5% level.

Descriptive statistics for eight stocks and gold were analyzed for three periods: the whole period, before the RU-UA conflict, and after the conflict. The analysis revealed some interesting findings about the behavior of these assets during the different periods.

First, the average price of most stocks and gold increased after the RU-UA conflict compared with the period before. This can be attributed to the market's response to geopolitical events, where investors tend to favor safe assets such as gold and utility stocks during periods of uncertainty. In contrast, the average price of Vonovia SE (VNA.DE) declined after the RU-UA conflict, which could be attributed to factors such as increased competition, supply chain disruptions, and/or regulatory issues. The median values are not significantly different from the mean values.

Second, the standard deviation (SD) for all stocks and gold declined after the RU-UA conflict compared with the pre-conflict period. This can be explained by the significantly lower number of observations after the conflict and the fact that they are green and sustainable companies since, from a theoretical point of view, we could expect increased volatility in the market due to geopolitical tensions.

The results also suggest that investors should carefully consider the risks associated with investing in individual stocks, especially those with high volatility. These conclusions are important for both investors and policy makers, as they highlight the need for careful analysis and monitoring of market behavior in times of uncertainty.

Unit root tests determine whether a time series data set is stationary or not. A stationary series has a constant mean, variance, and autocorrelation, facilitating its modelling and analysis. The Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests are commonly used unit root tests. From the results, it can be seen that all time series are stationary over the entire period, except Duke Energy (DUK) for the whole period and before the conflict and Waste Management (WM) after the conflict.

3. Results

3.1. MF-DCCA

In this section, we present results of MF-DCCA used to examine the cross-correlation between selected US (TSLA, FLSR, NEE, WM, DUK) and EU stock prices (VNA.DE, VWS.CO, SU.PA) and the gold price. The analysis was conducted for the entire period and separately for the series before and after the RU-UA conflict in order to examine the impact of the conflict. The reason is that previous crises, such as COVID-19, have significantly affected the gold price and may have affected the multifractality and persistence of both the gold market and green and sustainable stocks.

We first present results from MF-DCCA for the entire period to determine whether the degree of multifractal cross-correlation between the price of gold and stocks increases with the time scale. Figures 2 and 3 illustrate the fluctuation functions for the US and EU companies, respectively. We only show the results for q-orders -10, -6, -2, 2, 6, and 10. All fluctuation functions exhibit an upward slope, suggesting that the cross-correlated multifractal behavior of assets increases with the time scale. This is the first evidence that the gold price amplifies the multifractal behavior of both US and EU stocks.

The values of the cross-correlation generalized Hurst exponents for both the US and EU markets decline as the values of q increase, validating a strong multifractal behavior, as shown in Figure 4a,d. Moreover, we can observe persistence, since $h_{xy}(2)$ is greater than 0.5. Another indication of multifractality is provided by the scaling exponent properties, which exhibit a nonlinear relationship with q (Figure 4b,f). Lastly, we examine the strength and spectrum of multifractality to analyze the time series pair. The width of the multifractal spectra is considerably larger than zero, which demonstrates that the series are multifractal (Figure 4c,f).

Now, we compare time series pairs in the pre-conflict and conflict periods. First, we analyze the results for US stocks (Figure 5). Focusing on green and sustainable stocks in the US market during the pre-conflict period, we found that the generalized Hurst exponent decreases with increasing q, indicating that each series pair possesses a multifractal property (Figure 5a,b). Furthermore, when $q = 2$, the exponents are larger than 0.5, indicating that all time series pairs have persistence. During the conflict period, we observed a lower decay rate of the exponent for all stocks except for DUK. The exponent for DUK did not follow the same pattern as in the pre-conflict period. The values of the generalized Hurst exponents during the conflict period were larger than those in the pre-conflict period, indicating that the cross-correlation was more persistent during the conflict period. The scaling exponents for US markets are nonlinearly dependent on q, showing further evidence of multifractality for both periods (Figure 5c,d). Lastly, we use multifractal strength and spectra to examine time series pairs in the pre- and post-conflict periods. The widths of multifractal spectra are significantly nonzero, indicating that all the series are multifractal (Figure 5e,f).

Overall, we can conclude that multifractal cross-correlation exists between US stocks and gold prices in both periods. These results mean that the time series are correlated in a complex, nonlinear way that a single correlation coefficient cannot fully describe.

Regarding the EU market, we found that during the pre-conflict period, there was evidence of multifractal cross-correlation between gold and the selected green and sustainable stocks (Figure 6). Specifically, we observed that the scaling exponents decrease with increasing q, indicating multifractality in the cross-relations (Figure 6a,b). The scaling exponents for $q < 0$ are larger than those for $q > 0$, although they are all larger than 0.5. This suggests that the cross-correlated behavior of small fluctuations is more persistent than that of large fluctuations. The nonlinear dependency and multifractality of the analyzed relationships are further supported by the fact that the multifractal exponents are nonlinearly dependent on q. To better understand the nonlinear relationship between gold and the selected green and sustainable stocks in the EU market, we conducted a further analysis using multifractal spectra. Our results showed that during the pre-conflict period, there were clear departures from a random walk process for all cases, supporting the presence of multifractality in the cross-correlations. However, during the conflict period, we observed significant changes in the results and cross-correlation properties, suggesting a possible impact on the underlying dynamics of the system—specifically, the generalized Hurst exponent of VNA.DE/Gold and VWS. CO/Gold was no longer a decaying function of q for $q > 0$. This suggests that the conflict may have affected the strength or nature of the interactions between the components of the system. Furthermore, our analysis showed that the functions were monotonically increasing for $0 < q < 2$, indicating an increase in the persistence of the cross-correlations, with the "normal" fluctuations enhancing. The multifractal exponents did not show an obvious nonlinear dependence with q (Figure 6c,d), while the multifractal spectra no longer had a reversed U shape (Figure 6e,f). Regarding the pair SU. PA/Gold, the results still exhibited multifractal properties as in the pre-conflict period, but they were much weaker. Overall, our findings suggest that the conflict significantly impacted the multifractal nature and cross-correlations of the relationships between gold and the selected green and sustainable stocks in the EU market.

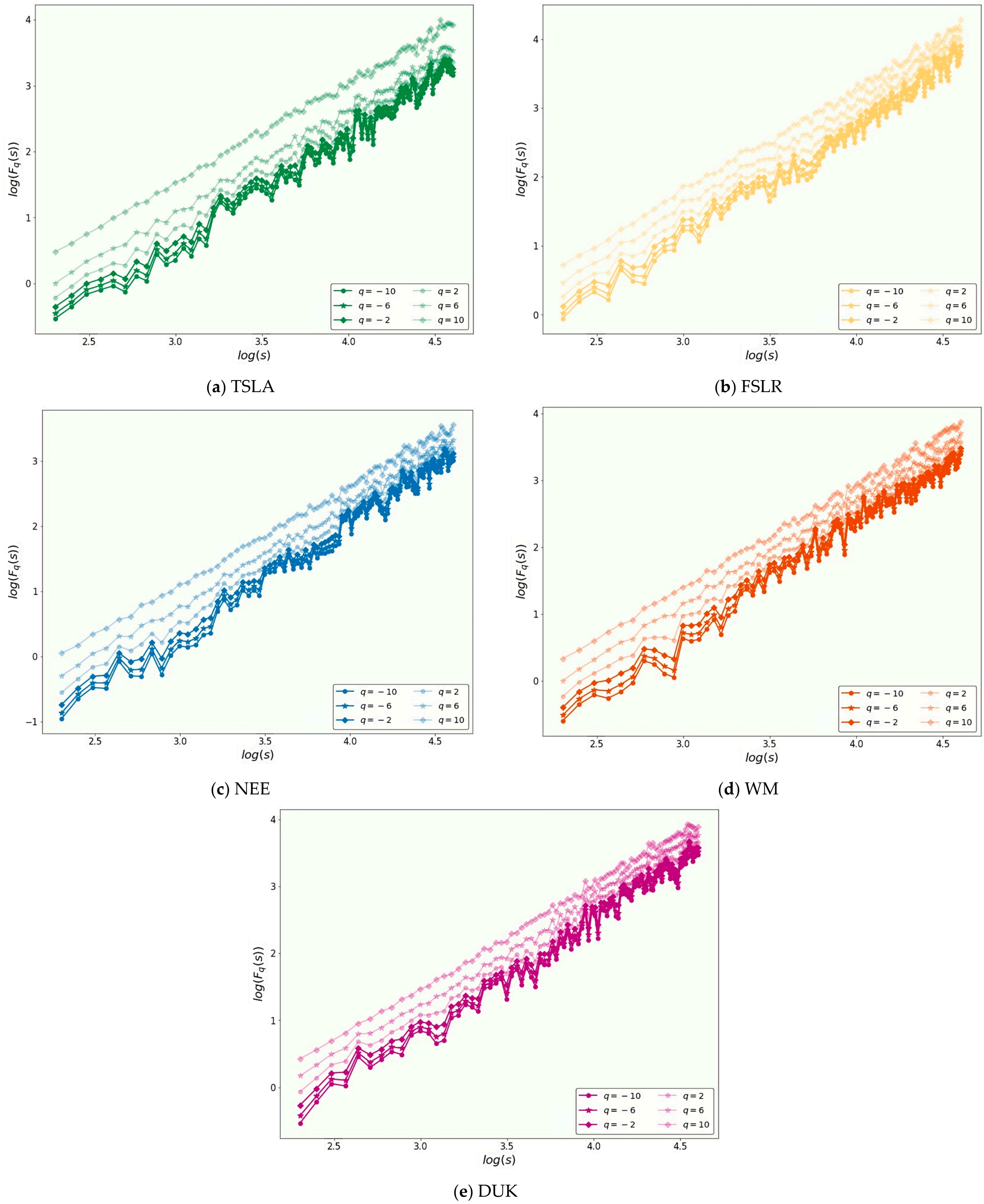
A consistent fall in the generalized Hurst exponents further strengthens the multifractality of time fluctuations of the cross-correlation between the gold price and the US green and sustainable stock markets. Turning to the specific case of q-order 2, it is clearly seen that the generalized Hurst exponents are higher in the conflict than in the pre-conflict period. The implication is that the conflict intensifies the impact of gold prices on the persistence of all the stock markets, making them less efficient than before the conflict. All time series pairs have a larger Δh_{xy} and a larger $\Delta\alpha_{xy}$ in the pre-conflict period, suggesting stronger multifractality and greater cross-correlations, except TSLA, where all the values are larger in the conflict period. The implication is that the conflict intensifies the impact of gold prices on the persistence of all the stock markets, making them less efficient than before the conflict. All the stock markets' generalized Hurst exponents rise significantly above 0.5. Thus, the null hypothesis of random walk is rejected in favor of persistence and market inefficiency.

The prices of selected EU green and sustainable companies show the same dynamics concerning gold prices. The multifractal features of cross-correlation are weaker in the period after the conflict. This can be viewed in terms of lower values of Δh_{xy} and $\Delta\alpha_{xy}$.

The results in Tables 3 and 4 could be interpreted [in several ways. First, the time series pairs are still correlated after the conflict, but the nature of the correlation has changed. The larger value of Δh_{xy} and $\Delta\alpha_{xy}$ in the pre-conflict period could indicate a stronger, more complex correlation between the time series pairs during that time, which has since weakened or become more linear. Second, the conflict itself may have affected the dynamics of one or both of the time series, leading to changes in their multifractal properties. Finally, it is important to consider the possibility of spurious correlations or other confounding factors that could affect the MF-DCCA analysis. For example, if other significant events or trends are happening around the same time as the conflict, these could influence the analysis results. In any case, further analysis and contextual information would be needed to fully interpret the results of the MF-DCCA analysis and understand the implications of the results before and after the RU-UA conflict.

3.2. Nonlinear Granger

While the MF-DCCA methodology is proficient in detecting cross-correlations, it does not possess the capacity to discern the direction of a relationship. Hence, we employ the nonlinear Granger causality test method to establish and characterize causal relationships, subsequently comparing the obtained results using the multifractal approach on the whole considered period. It is imperative to maintain stationarity in the time series utilized for the Granger causality test in order to mitigate the influence of any autoregressive phenomena.

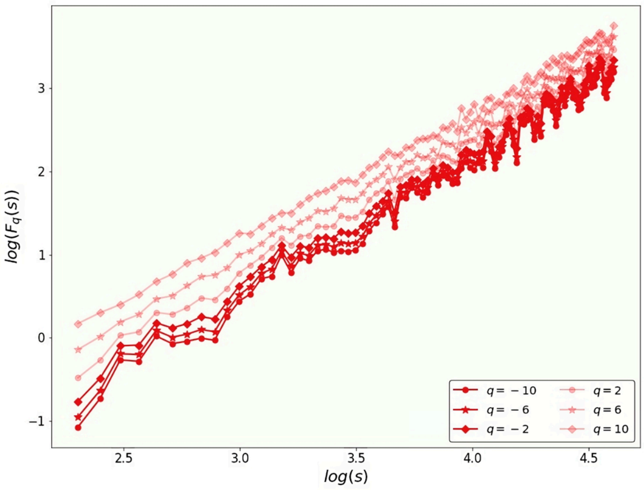


(**a**) TSLA (**b**) FSLR

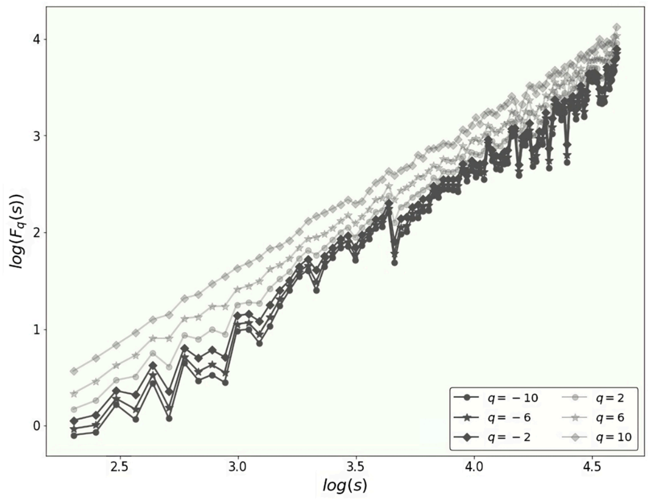
(**c**) NEE (**d**) WM

(**e**) DUK

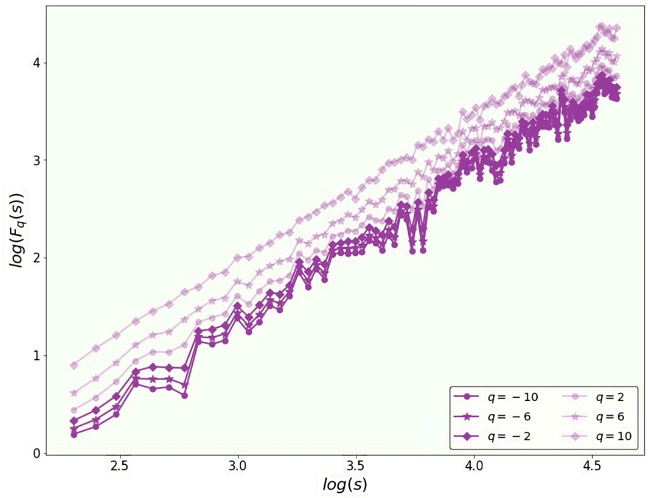
Figure 2. Fluctuation functions for US green and sustainable companies.



(**a**) VNA.DE



(**b**) VWS.CO

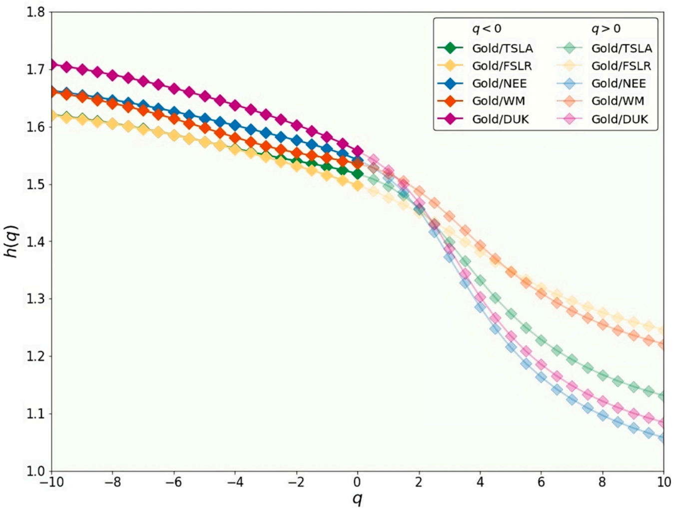


(**c**) SU.PA

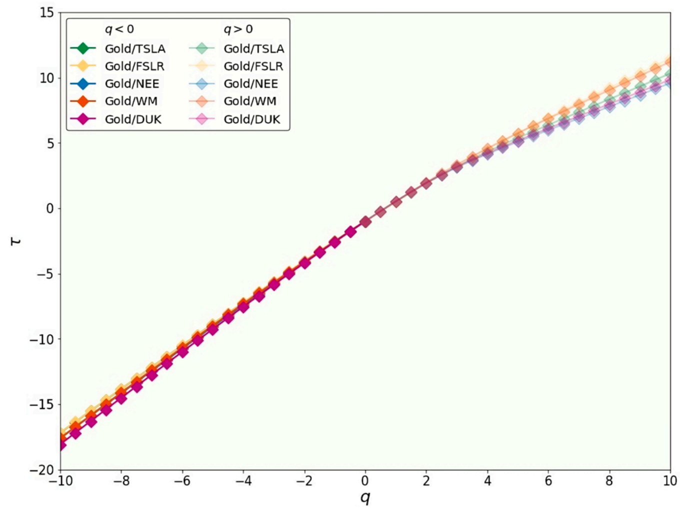
Figure 3. Fluctuation functions for EU green and sustainable companies.

Table 3. US: multifractal metrics.

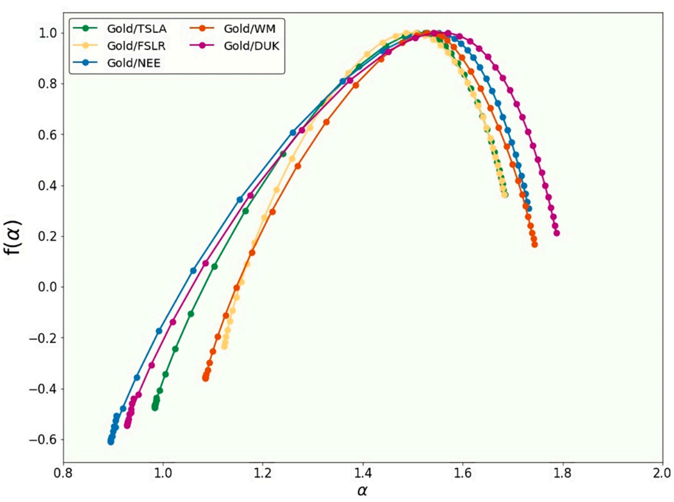
Stock	Metric	Total	Pre	Post
TSLA	$h_{xy}(2)$	1.516	1.509	1.497
	Δh_{xy}	0.323	0.368	0.526
	$\Delta \alpha_{xy}$	0.474	0.525	0.714
FSLR	$h_{xy}(2)$	1.495	1.496	1.423
	Δh_{xy}	0.310	0.289	0.215
	$\Delta \alpha_{xy}$	0.446	0.415	0.344
NEE	$h_{xy}(2)$	1.537	1.522	1.638
	Δh_{xy}	0.564	0.698	0.413
	$\Delta \alpha_{xy}$	0.782	0.928	0.559
WM	$h_{xy}(2)$	1.530	1.520	1.539
	Δh_{xy}	0.453	0.505	0.375
	$\Delta \alpha_{xy}$	0.681	0.722	0.525
DUK	$h_{xy}(2)$	1.554	1.547	1.652
	Δh_{xy}	0.591	0.681	0.170
	$\Delta \alpha_{xy}$	0.803	0.903	0.292



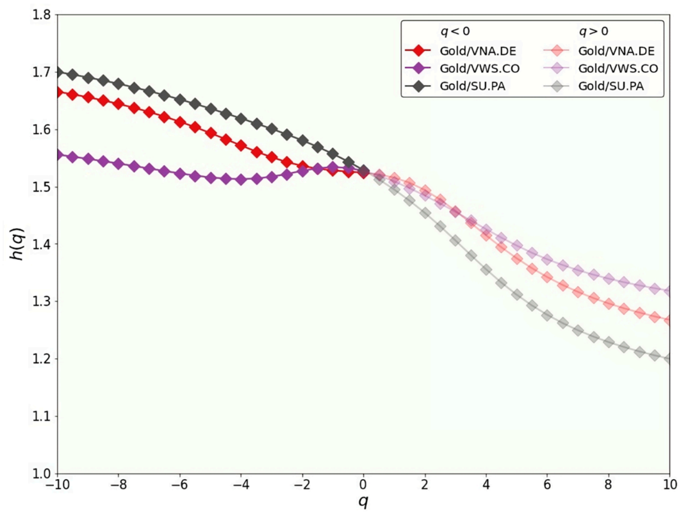
(**a**) Hurst (US)



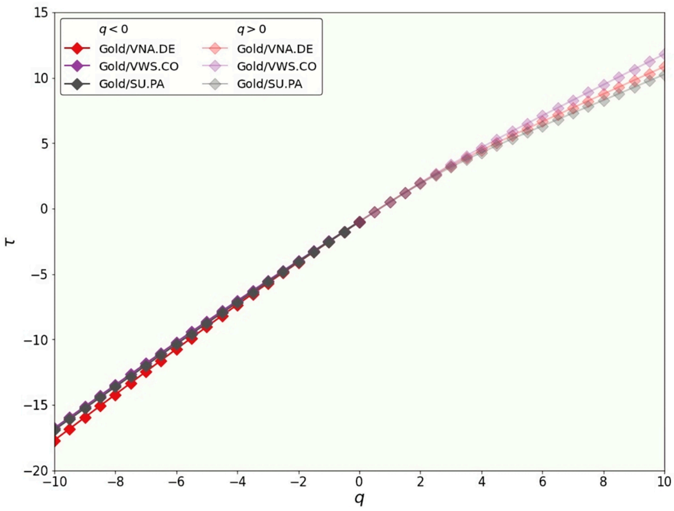
(**b**) Tau (US)



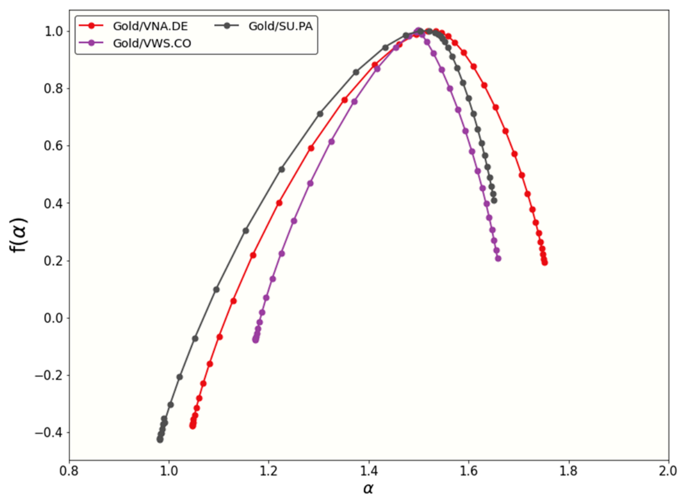
(**c**) Multifractal spectrum (US)



(**d**) Hurst (EU)

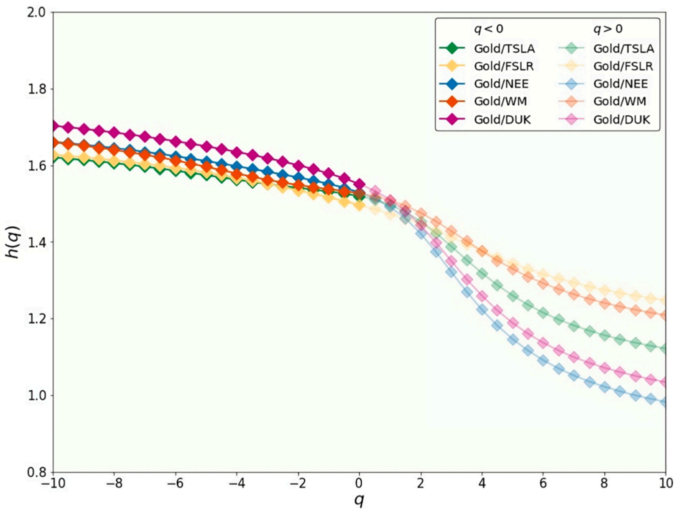


(**e**) Tau (EU)

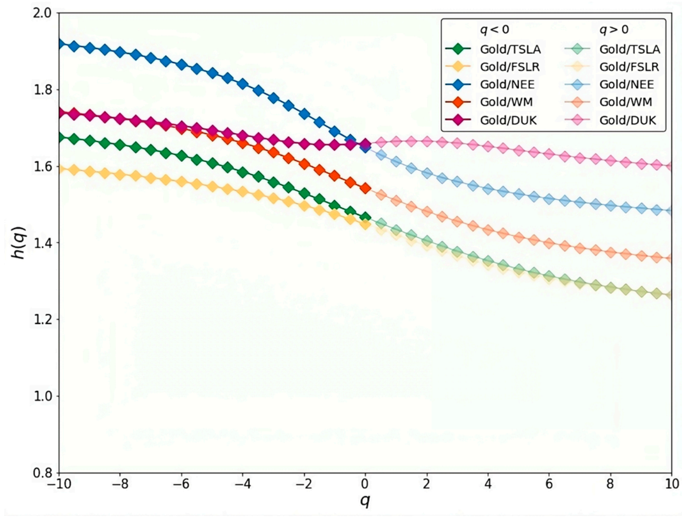


(**f**) Multifractal spectrum (EU)

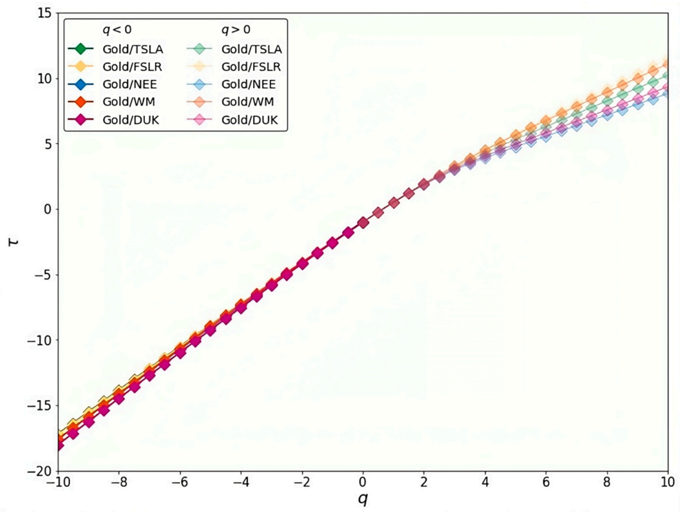
Figure 4. MF-DCCA results.



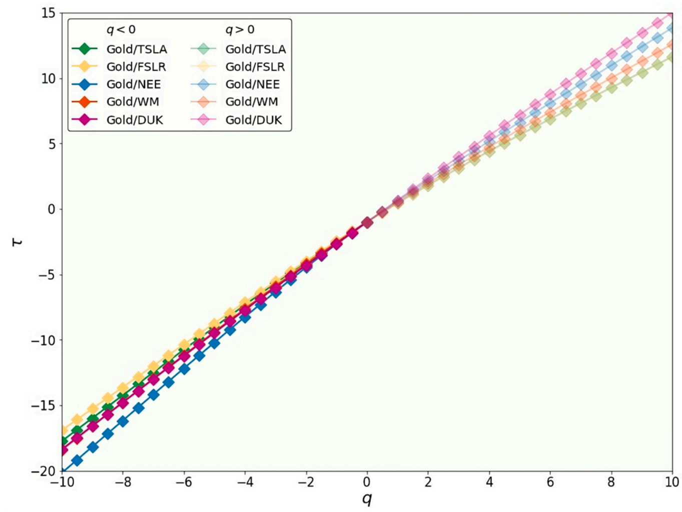
(**a**) Generalized Hurst exponent (pre-conflict)



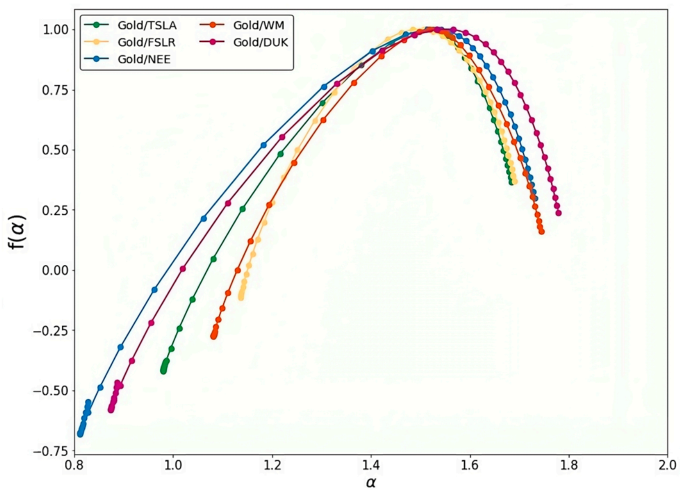
(**b**) Generalized Hurst exponent (post-conflict)



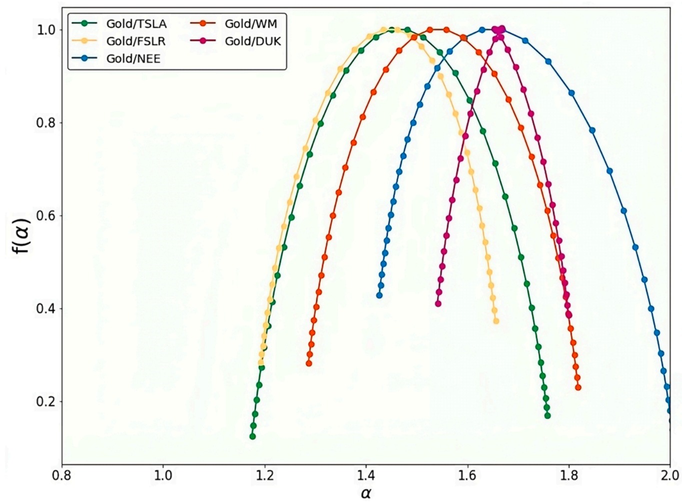
(**c**) Multifractal scaling exponent (pre-conflict)



(**d**) Multifractal scaling exponent (post-conflict)

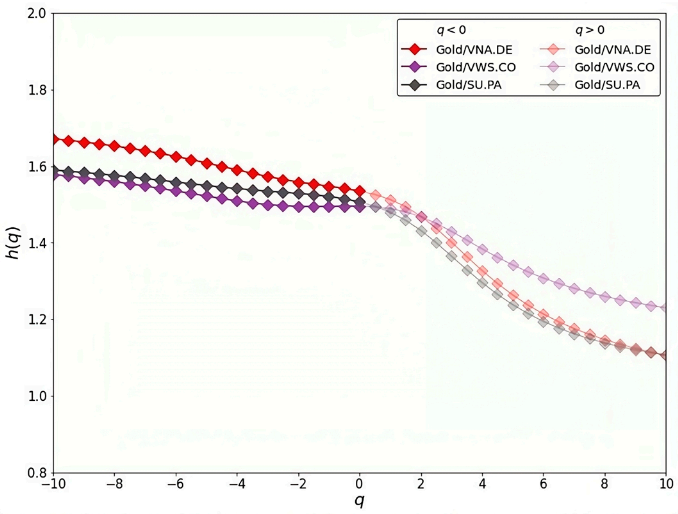


(**e**) Multifractal spectrum (pre-conflict)

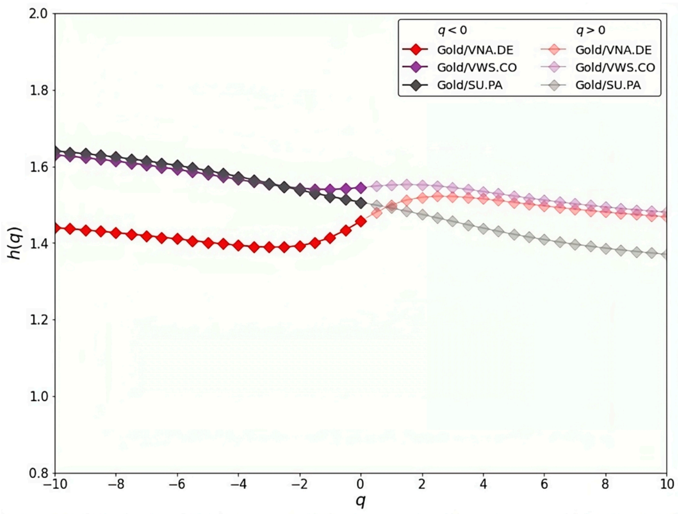


(**f**) Multifractal spectrum (post-conflict)

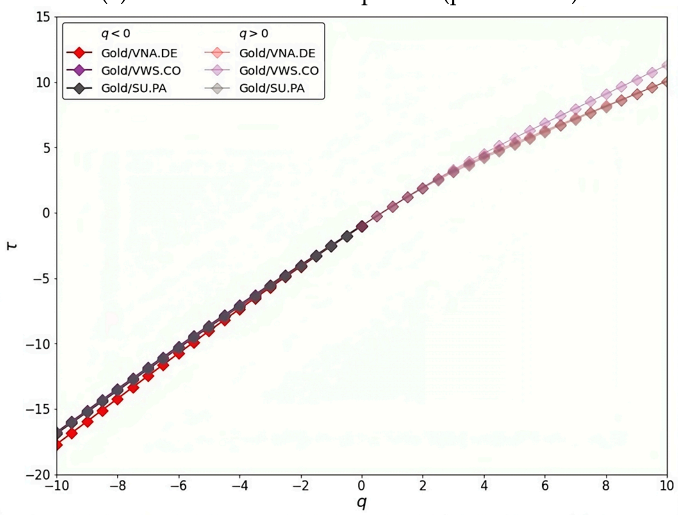
Figure 5. US: pre- vs. post-conflict.



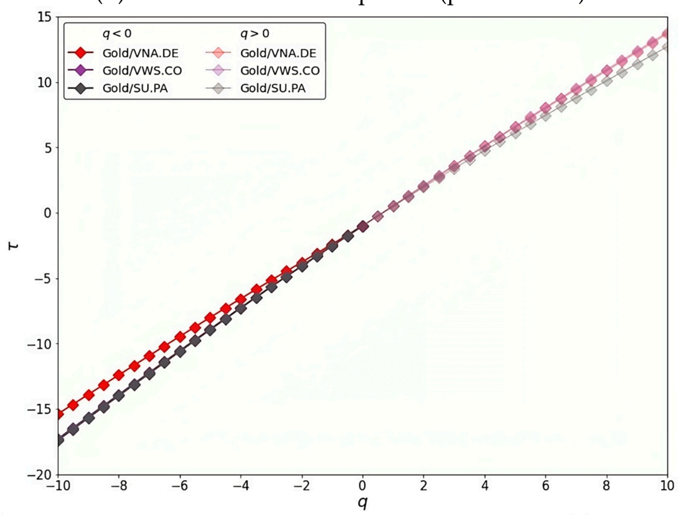
(**a**) Generalized Hurst exponent (pre-conflict)



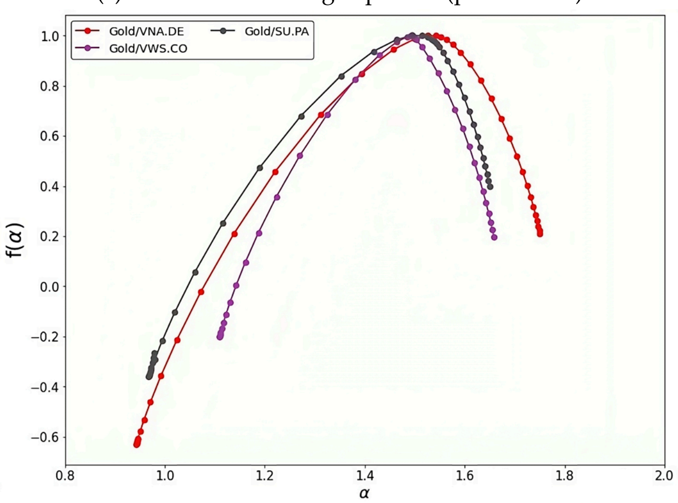
(**b**) Generalized Hurst exponent (post-conflict)



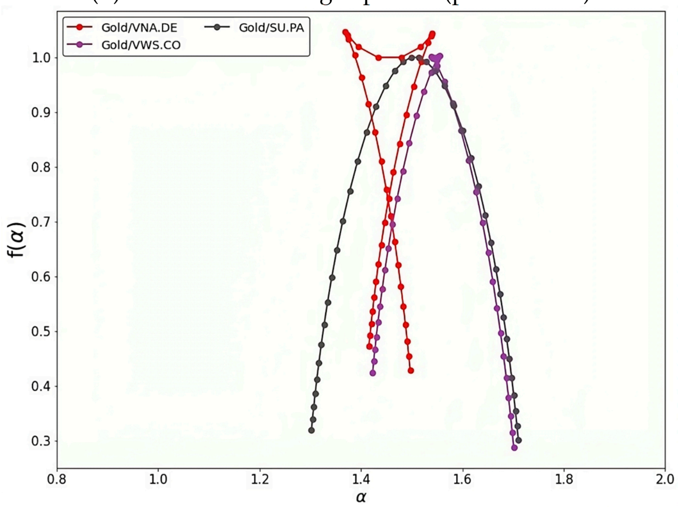
(**c**) Multifractal scaling exponent (pre-conflict)



(**d**) Multifractal scaling exponent (post-conflict)



(**e**) Multifractal spectrum (pre-conflict)



(**f**) Multifractal spectrum (post-conflict)

Figure 6. EU: pre- vs. post RU-UA conflict.

Table 4. EU: multifractal metrics.

Stock	Metric	Total	Pre	Post
VNA.DE	$h_{xy}(2)$	1.527	1.532	1.486
	Δh_{xy}	0.579	0.616	0.204
	$\Delta\alpha_{xy}$	0.797	0.840	0.343
VWS.CO	$h_{xy}(2)$	1.497	1.489	1.525
	Δh_{xy}	0.219	0.271	0.203
	$\Delta\alpha_{xy}$	0.346	0.396	0.339
SU.PA	$h_{xy}(2)$	1.505	1.495	1.499
	Δh_{xy}	0.454	0.603	0.294
	$\Delta\alpha_{xy}$	0.643	0.831	0.434

Tables 5 and 6 show that bidirectional nonlinear Granger causality relationships exist between gold and two sustainable and green stock markets (EU and USA), where α = β = 1, 2, 3, 4.

Table 5. Nonlinear Granger causality test results: USA.

$\alpha = \beta$	Test	TSLA → Gold	Gold → TSLA	FSLR → Gold	Gold → FSLR	NEE → Gold	Gold → NEE	WM → Gold	Gold → WM	DUK → Gold	Gold → DUK
1	Statistics	1.145	65.220	1.011	65.574	1.180	68.139	1.895	74.430	3.611	3.611
	p-value	0.325	<0.01	0.431	<0.01	0.299	<0.01	1	<0.01	<0.01	<0.01
2	Statistics	1.4778	56.839	1.407	57.151	2.661	57.389	0.194	59.542	4.373	57.800
	p-value	0.1	<0.01	0.129	<0.01	<0.01	<0.01	1	<0.01	<0.01	<0.01
3	Statistics	0.907	36.639	0.877	36.504	1.614	36.613	0.233	37.471	2.557	36.946
	p-value	0.585	<0.01	0.627	<0.01	0.036	<0.01	1	<0.01	<0.01	<0.01
4	Statistics	0.5428	23.868	0.525	22.962	0.900	23.213	0.115	24.103	1.424	23.427
	p-value	0.976	<0.01	0.981	<0.01	0.615	<0.01	1	<0.01	0.070	<0.01

Note: α = β denotes the residual series of lag order numbers; TSLA → Gold means the original hypothesis: TSLA is not a Granger causality of gold. The others have the same meaning; $e = 1.5\sigma, m = 1$.

Table 6. Nonlinear Granger causality test results: EU.

$\alpha = \beta$	Test	VNA.DE → Gold	Gold → VNA.DE	VWS.CO → Gold	Gold → VWS.CO	SU.PA → Gold	Gold → SU.PA
1	Statistics	5.837	59.587	0.864	73.112	−0.828	74.123
	p-value	<0.01	<0.01	1	<0.01	1	<0.01
2	Statistics	5.074	55.914	0.121	58.703	0.261	60.142
	p-value	<0.01	<0.01	1	<0.01	1	<0.01
3	Statistics	2.988	36.354	0.171	37.032	0.2756	38.078
	p-value	<0.01	<0.01	1	<0.01	1	<0.01
4	Statistics	1.688	23.110	0.123	23.464	0.193	24.348
	p-value	0.014	<0.01	1	<0.01	1	<0.01

Note: α = β denotes the residual series of lag order numbers; VNA.DE → Gold means the original hypothesis: VNA.DE is not a Granger causality of gold. The others have the same meaning; $e = 1.5\sigma, m = 1$.

The past values of TSLA, FSLR, NEE, WM, and DUK do not significantly Granger-cause changes in Gold's value for most lag orders. The p-values for these cases are above 0.01, indicating a lack of significant causal influence. On the other hand, gold's past values significantly Granger-cause fluctuations in TSLA, FSLR, NEE, WM, and DUK for most lag orders ($p < 0.01$). This suggests that gold's past movements can predict changes in these stocks. As the lag order decreases, the p-values generally remain below 0.01 for gold's influence on the stocks, confirming the consistent predictive relationships.

The nonlinear Granger causality test reveals significant relationships between gold and EU stocks, investigated in both directions. Our analysis indicates that gold's past values exhibit a robust and nonlinear influence on changes in the value of all three stocks, VNA.DE, VWS.CO, and SU.PA. The past values of VNA.DE significantly and nonlinearly influence changes in gold's value, suggesting a predictive relationship. On the other hand, p-values for the relationships VWS.CO$\rightarrow$Gold and SU.PA$\rightarrow$Gold are consistently greater than 0.01 for all lag orders. This indicates that the past values of VWS.CO and SU.PA do not significantly Granger-cause changes in gold's value, suggesting an absence of predictive influence.

4. Conclusions

In this paper, we investigate the impact of gold prices on the persistence and efficiency of green and sustainable stocks in the US and EU markets. Our results are of great importance to investors, financial institutions, governments, and policy makers as they shed light on the complex relationship between these variables and their implications for financial markets and economic policies.

First, we use MF-DCCA to uncover multifractal cross-correlations between the prices of selected green and sustainable stocks and the price of gold. Our analysis reveals significant multifractal properties and nonlinear cross-correlations between all pairs of time series examined. In particular, we observe a distinct shift in multifractal properties within the EU market, especially during the period of the RU-UA conflict. This highlights the differential resilience of green and sustainable stock markets during geopolitical events and underscores the need to assess market dynamics and their potential impact on asset prices during periods of uncertainty.

To further explore these cross-correlations, we use the nonlinear Granger causality test method, which uncovered bidirectional nonlinear Granger causality relationships between gold and both US and EU green and sustainable stocks. This finding deepens our understanding of the complex linkages within financial markets and underscores the importance of considering gold as a relevant risk factor in portfolio construction. Consequently, this finding has direct implications for the risk management and diversification strategies of investors and portfolio managers.

Financial institutions should take these insights into account when designing and managing financial products and services, as they play a central role in facilitating investment in these markets. Recognizing the potential substitution effect between the two markets can inform the development of financial instruments that are aligned with investors' risk exposures and sustainability preferences. In addition, institutions need to actively monitor and manage risks arising from market spillover effects to ensure portfolio stability.

For governments and policy makers, especially those committed to sustainable finance and climate-friendly investing, this study offers valuable insights. Policy makers should consider potential spillover effects and contagion risks when creating regulatory frameworks and incentives to encourage investment in green and sustainable stocks. Recognizing that these markets are interconnected is essential to a holistic and adaptive approach to sustainable finance. This allows investors and policy makers to navigate evolving market dynamics while aligning financial goals with global sustainability goals, ensuring the stability of financial markets.

It is vital to explore the causes of these dynamic changes for a more comprehensive understanding. Therefore, future research should examine these series using additional methods such as wavelet analysis or empirical mode decomposition to gain further insight into the changes in time series properties before and after the conflict.

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Data Availability Statement: Publicly available datasets were analyzed in this study. This data can be found here: https://finance.yahoo.com (accessed on 29 September 2023).

Conflicts of Interest: The authors declare no conflict of interest.

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