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Technology–Finance Dual-Engine Dynamics: A Time-Varying Causality Analysis of the Global Semiconductor Index and Silver Prices

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Abstract: This study examines the causal relationship between the semiconductor index and silver prices, against the backdrop of the industry's growth, silver's dual attributes, and increasing macroeconomic and geopolitical volatility. Using monthly data from August 2012 to January 2026 and a bootstrap rolling-window causality test, we find a significant time-varying causal link. Specifically, a unidirectional causality from the semiconductor index (RSOX) to silver prices (RSP) is identified in periods such as June–August 2020, November 2022–January 2023, September–October 2024, and July 2025–January 2026. This effect is positive under conditions of ample liquidity and growth optimism but turns weakly negative during times of high policy uncertainty and geopolitical tension. Conversely, a weak positive causal effect from RSP to RSOX is observed from June to August 2016, likely driven by risk-aversion sentiment following events like the Brexit referendum and expectations of accommodative monetary policy. These findings suggest that silver has become a strategic asset with dual sensitivity to technological cycles and financial sentiment, offering important implications for managing critical resource supply chains.

Keywords: bootstrap rolling-window causality test; PHLX semiconductor index; COMEX silver futures; time-varying causality

JEL Classification: G15; F30; Q02; C32

1. Introduction

The semiconductor industry has become a pivotal engine of the global digital revolution and the green transition. Its technological progress underpins breakthroughs and deployment in frontier domains such as artificial intelligence, new energy vehicles, and advanced manufacturing [1]. In parallel, silver—an asset that combines critical industrial functionality with longstanding financial significance—plays an irreplaceable role in semiconductor packaging, photovoltaic conduction, and power electronics [2,3]. As a result, fluctuations in silver prices are simultaneously shaped by real-economy industrial demand and the global macro-financial environment [4]. Against this backdrop, identifying the dynamic transmission mechanism between the global semiconductor sector and silver prices is important not only for understanding cost dynamics and supply-chain resilience in high-technology value chains, but also for evaluating how macroeconomic cycles, monetary-policy shifts, and major technological revolutions propagate across markets and reprice assets.

From a practical perspective, the global semiconductor industry has remained in a sustained high-growth phase since 2020. According to the World Semiconductor Trade Statistics (WSTS), the global semiconductor market attained USD 520.1 billion in 2023 and is anticipated to grow to USD 588.4 billion in 2024, indicating an annual growth rate of 13%. Meanwhile, the application of silver in semiconductor packaging has increased steadily, particularly in advanced packaging technologies, where demand for materials such as silver paste, continues to rise. However, silver prices have not exhibited a simple or stable synchronous relationship with the semiconductor industry cycle. During the period of abundant global liquidity in 2020–2021, both silver prices and semiconductor-related assets rose in tandem. In contrast, during the Federal Reserve's aggressive monetary tightening cycle in 2022–2023, silver prices were significantly constrained by rising real interest rates, diverging from the continued strength of the semiconductor index. By around 2025, geopolitical tensions and supply chain disruptions once again underscored silver's safe-haven characteristics, giving rise to a new interaction with the semiconductor sector shaped by shifts in risk sentiment. This alternating pattern of co-movement and divergence raises a critical question: what dynamic transmission mechanisms link the semiconductor industry and silver prices under the combined influences of industrial demand, financial sentiment, and macroeconomic policy? Furthermore, does this mechanism undergo structural changes across different historical phases?

A substantial literature has explored linkages between commodity markets and equity markets, or the correlations between specific sector indices. Yet, evidence remains limited on the relationship between semiconductors—a highly cyclical, technology-intensive industry—and silver, an asset with dual industrial and financial attributes. Three limitations are particularly salient. First, much of the existing work relies on linear frameworks or full-sample static specifications that implicitly impose parameter constancy. This is restrictive in settings where both semiconductor activity and the silver market are highly exposed to extreme external shocks, making structural changes in their linkage plausible. Second, silver is often treated as a homogeneous "commodity" or "safe-haven asset", without sufficiently disentangling and testing the shifting dominance of industrial-demand-driven versus financial-attribute-driven forces in price formation across periods; dynamic comparisons from an event-based perspective are also scarce. Third, conventional approaches are ill-suited to capturing time-varying causality, leaving unanswered the key question of whether the direction and strength of influence vary systematically with historical context.

To address these gaps, the present study focuses on the PHLX Semiconductor Index (SOX) and COMEX silver futures prices (SP). Monthly data from August 2012 to January 2026 are analyzed using a bootstrap rolling-window causality test to examine time-varying causal relations between the two series. The study contributes in three respects. First, methodologically, the proposed framework relaxes the strong parameter-stability assumption embedded in standard Granger causality tests, enabling the identification and characterization of causal dynamics across rolling windows—an advantage for macro-financial time series repeatedly exposed to major events. Second, silver price fluctuations are examined within a dual perspective—silver as a critical input for the semiconductor industry and as a carrier of macro risk sentiment—thereby allowing an empirical assessment of how the dominant drivers of price formation shift across historical phases. Third, a significant time-varying Granger-causal effect from the semiconductor index to silver prices is documented, and the direction and magnitude of this effect are further related to specific macroeconomic policies, geopolitical events, and technological breakthroughs. Overall, these findings provide dynamic, mechanism-oriented evidence on the role of strategic industrial metals within complex technology–economic cycles.

2. Literature Review

The existing literature on the interaction between semiconductor indices and silver prices can be broadly organized into three strands.

First, existing studies have extensively examined the cyclical characteristics and key drivers of the semiconductor index. A broad consensus in the literature holds that the semiconductor industry exhibits pronounced and recurrent cyclical patterns. Price fluctuations not only reflect the pace of technological innovation but are also strongly shaped by the interaction of capital expenditure cycles, inventory adjustments, and variations in end-user demand. Moguilnaia et al. [5] analyze the formation mechanisms underlying cycles in the global semiconductor market, arguing that technological upgrading and investment expansion frequently generate supply–demand mismatches, thereby amplifying price volatility. Tan and Mathews [6] further emphasize that the semiconductor industry follows a distinct "investment–capacity–price" feedback loop, which intensifies cyclical fluctuations to a greater extent than in traditional manufacturing sectors. As semiconductors have increasingly become a foundational input for the digital economy and advanced manufacturing, their financial characteristics have continued to strengthen. Hilmola [7] finds that the semiconductor index has evolved into an important leading indicator of global manufacturing activity, technology investment cycles, and broader macroeconomic conditions, with its movements often preceding those of aggregate industrial production and technology-related equity indices. More recent research has incorporated geopolitical and technology policy factors into this analytical framework. Dadush [8] examines global trade policies and trends in technological decoupling, concluding that the semiconductor industry is particularly sensitive to trade barriers and export controls. Farrand [9] further document that technology sanctions, supply chain reconfiguration, and geopolitical tensions significantly amplify semiconductor index volatility through expectation-driven channels. As a result, fluctuations in the semiconductor index increasingly reflect not only industry fundamentals but also financial markets' pricing of systemic and geopolitical risks.

Second, the price formation mechanism of silver has primarily been analyzed along two dimensions: its industrial attributes and its financial attributes. From a industrial standpoint, Kubesa and Černý [10] show that, as a key industrial metal, silver demand is closely associated with global manufacturing sentiment, industrial output, and developments in specific technology sectors, including electronics, photovoltaics, and precision manufacturing. Amidst the escalating demand for conductive and thermally conductive materials in new energy industries and high-end manufacturing, industrial demand for silver has exhibited clear structural growth characteristics. In terms of its financial attributes, a substantial body of literature characterizes silver as a hybrid asset that combines features of both precious metals and financial investment instruments. Shahzad et al. [11] find that silver prices are highly sensitive to real interest rates, the U.S. Dollar Index, and inflation expectations, with price volatility increasing markedly during periods of elevated financial uncertainty. Yıldırım et al. [12] further analyze silver through the lens of geopolitical risk, noting that, similar to other precious metals, silver displays pronounced safe-haven properties during episodes of intensified geopolitical conflict and global uncertainty. Comparative studies across precious metals provide additional insights into silver's unique price behavior. Lucey and Li [13] conduct a systematic examination of the safe-haven properties of gold, silver, platinum, and palladium, documenting significant temporal heterogeneity in their defensive roles. Their results indicate that during certain periods—such as the third quarter of 1996—silver, platinum, and palladium exhibited greater resilience to stock market downturns than gold. This evidence suggests that silver does not consistently follow gold's price dynamics and may display a higher degree of independence under specific market conditions.

Third, a related strand of literature investigates the linkages between resource- and energy-intensive industries and broader commodity markets. Creti et al. [14] examine the dynamic relationship between equity markets and commodity prices, finding that their correlation increased substantially amidst the global financial crisis, indicating that financialization has strengthened the connections between commodity markets and capital markets. Chen and Qi [15] further employ vector autoregression (VAR) and DCC-GARCH models to analyze volatility spillovers across multiple commodity categories and stock markets. Their findings indicate that commodity prices are no longer exclusively influenced by supply and demand fundamentals but are increasingly influenced by shifts in financial market risk appetite.

Despite these advances, the existing literature still lacks detailed analysis at the level of specific industrial linkages. Most studies either treat silver broadly as part of a precious metals portfolio or classify the semiconductor industry generically within the technology stock sector, without systematically examining the direct connections between the two from the perspectives of industrial chains and factor demand. In particular, the potential demand channels for silver—a critical industrial input—within semiconductor manufacturing processes are rarely incorporated into existing analytical frameworks.

3. Theory and Model

3.1. Theoretical Analysis

Based on silver's industrial role within the semiconductor value chain and its inherent financial attributes, a complex transmission mechanism arises between the global semiconductor index and silver prices. Fundamentally, fluctuations in the semiconductor index affect silver prices through two primary channels: industrial demand fundamentals and financial market sentiment.

Specifically, an increase in the semiconductor index influences silver prices through the following mechanisms. On the one hand, a rising semiconductor index provides fundamental support for silver prices via the industrial demand channel. Sustained strength in the semiconductor index is widely interpreted as a signal that the global semiconductor industry has entered an expansionary phase [16]. This signal reinforces expectations of higher industrial demand for silver through several pathways. First, an index upturn reflects increased capital expenditure, accelerated capacity expansion, and faster technological iteration within the industry, all of which point to future growth in chip production [17]. As a key bonding material and conductive filler in semiconductor packaging, silver demand is closely linked to chip output volumes [18]. Second, improved industry conditions tend to strengthen confidence along the supply chain, encouraging stockpiling and inventory accumulation, which further amplifies spot procurement demand for critical raw materials such as silver. Finally, technological breakthroughs in semiconductor manufacturing may create new application scenarios and higher performance requirements, potentially leading to structural increases in per-chip silver usage or demand for high-end silver materials. Through this channel, an increase in the semiconductor index exerts a positive demand-driven effect on silver prices by strengthening expectations of future physical consumption. On the other hand, a rising semiconductor index may exert pressure on silver prices through the financial sentiment channel by inducing liquidity reallocation [19,20]. In financial markets, the semiconductor sector is widely perceived as a representative high-growth, high-volatility technology asset, whereas silver combines the defensive characteristics of precious metals with the financial attributes of commodities [21]. When the semiconductor index—such as the SOX index—performs strongly, it is typically accompanied by heightened optimism regarding technological growth and a surge in investor risk appetite. Under such conditions, speculative and allocation capital seeking growth opportunities tends to flow out of traditional defensive assets, including government bonds, gold, and silver, and into growth-oriented sectors such as semiconductors. This cross-asset capital reallocation process generates a direct liquidity diversion effect on silver prices. The effect is particularly pronounced during periods of stable or tightening global liquidity, when shifts in risk preference play a more decisive role in capital allocation. Consequently, through the financial sentiment channel, an increase in the semiconductor index may exert a negative liquidity-driven effect on silver prices by altering investors' asset preferences and capital flows.

Conversely, a decline in the semiconductor index exerts a multifaceted impact on silver prices. Through the industrial demand channel, a falling index imposes fundamental downward pressure on silver prices. A sustained or sharp decline in the SOX index typically signals that the semiconductor industry has entered a downturn or is experiencing a major adverse shock [22]. This signal weakens the outlook for silver's industrial demand through several transmission mechanisms. First, a decline in the index often foreshadows contractions in capital expenditure, reductions in capacity utilization, and inventory adjustments within the industry. These developments directly slow the pace of chip production, thereby reducing the immediate consumption of silver used in semiconductor packaging materials [23]. Second, deteriorating conditions in the semiconductor sector propagate along the supply chain, triggering destocking behavior across upstream and downstream firms and further suppressing procurement orders for raw materials such as silver. Moreover, if the decline in the semiconductor index reflects stagnation in, or substitution away from, specific technological pathways, it may raise concerns about a long-term structural weakening of silver demand. Consequently, by signaling a deterioration in physical demand, a decline in the semiconductor index exerts negative demand-side pressure on silver prices. Through the financial sentiment channel, however, a decline in the semiconductor index may simultaneously provide support for silver prices by stimulating safe-haven demand. As the semiconductor sector functions as a barometer of technology-driven growth and global economic vitality, a pronounced weakening of the index is often interpreted as a leading indicator of rising systemic risk or a deteriorating growth outlook. Such developments can trigger a marked shift in financial market sentiment, accompanied by a sharp decline in investors' risk appetite. Under these conditions, silver—possessing both historical monetary attributes and tangible asset characteristics—tends to see its safe-haven role become more pronounced [24]. Capital flows out of risk assets such as equities and reallocates toward traditional safe-haven assets, including gold and silver, in order to hedge against heightened economic uncertainty and market volatility. This sentiment-driven inflow of funds generates a positive safe-haven support effect on silver prices [25].

According to the above analysis, this study proposes a central theoretical framework: Silver, owing to its pivotal industrial role within the semiconductor supply chain and its inherent financial attributes, forms a dynamic and complex transmission mechanism with the global semiconductor index. This mechanism is jointly driven by the industrial demand channel and the financial sentiment channel. The essence of this mechanism lies in the fact that fluctuations in the semiconductor index exert opposing forces on silver prices. Its ultimate net effect—whether positive pull, negative suppression, or negligible impact—is variable and contingent upon the macroeconomic situation, risk appetite structure, and nature of disruptive events during a specific period. This results in a pronounced time-varying kind of the causal connection between the two variables, which is difficult to capture within traditional static analytical frameworks, thereby forms the theoretical basis for employing a rolling window time-varying approach in this paper's empirical testing.

3.2. Bootstrap Rolling-Window Causality Test

Standard asymptotic distributions may not be followed by the test statistics in traditional Granger causality testing that is based on a vector autoregression (VAR) framework. Shukur and Mantalos [26] propose the RB critical values to enhance the precision of Granger causality inference and minimise potential size distortions. Even with small samples, this approach works well and is still applicable to standard asymptotic tests. Shukur and Mantalos [27] further show that the likelihood ratio (LR) test can be improved by correcting its power and size properties. Accordingly, the current study used a modified LR statistic based on the RB framework to examine Granger causality between the variables. The VAR(p) model is specified as follows:

$$Y_t = \alpha_0 + \sum_{k=1}^{p} \alpha_k Y_{t-k} + u_t, t = 1, 2, ..., T \quad (1)$$

Accordingly, p is first selected using the SIC, with the best lag order has been determined to be 2. Next, in each bivariate VAR(p), Y is specified as SOX_t and RSP_t. Equation (1) can therefore be rewritten as follows:

$$\begin{bmatrix} \mathrm{RSOX_t} \\ \mathrm{RSP_t} \end{bmatrix} = \begin{bmatrix} \alpha_{10} \\ \alpha_{20} \end{bmatrix} + \begin{bmatrix} \alpha_{11}(\mathrm{L}) & \alpha_{12}(\mathrm{L}) \\ \alpha_{21}(\mathrm{L}) & \alpha_{22}(\mathrm{L}) \end{bmatrix} \begin{bmatrix} \mathrm{RSOX_t} \\ \mathrm{RSP_t} \end{bmatrix} + \begin{bmatrix} \upsilon_{1t} \\ \upsilon_{2t} \end{bmatrix} \quad (2)$$

Here, $\upsilon_t = (\upsilon_{1t}, \upsilon_{2t})'$ is a zero-mean white-noise process with covariance matrix $\alpha_{ij}(L) = \sum_{k=1}^{p} \alpha_{ij,k} L^k$, $i, j = 1, 2$, where L denotes the lag operator and $L^k Y_t = Y_{t-k}$.

Equation (2) tests the null hypothesis that SOX does not affect RSP, i.e., $\alpha_{12,k} = 0$ for $k = 1, 2, \ldots, p$. Rejection of this null implies that SOX Granger-causes RSP; otherwise, it does not. Correspondingly, the null hypothesis positing that RSP exerts no influence on SOX, i.e., $\alpha_{21,k} = 0$ for $k = 1, 2, \ldots, p$, can be tested in the same manner.

3.3. Parameter Stability Assessment and Bootstrap Sub-Sample Rolling-Window Causality Examination

The bootstrap full-sample causality test relies on the premise that the parameters of the VAR model exhibit structural stability over time. However, this assumption is often violated in practice. When model parameters are not constant throughout the sample period, the results obtained from full-sample causality tests are likely to be unreliable. To address this issue, this study employs the Sup-F, Ave-F, and Exp-F tests proposed by Andrews [28] and Andrews and Ploberger [29] to examine parameter stability. The Sup-F test is used to detect abrupt structural changes, whereas the Ave-F and Exp-F tests are designed to assess whether model parameters evolve gradually along a time trajectory. In addition, to determine whether the parameters follow a random walk process, we apply the L_c statistic developed by Nyblom [30] and Hansen [31]. Through these tests, we are able to identify whether time-varying interactions exist between RSOX and RSP (used here as illustrative variables). If such interactions are present, we further investigate the Granger causality between the two variables using a bootstrap rolling-window sub-sample approach.

This approach, suggested by Balcilar et al. [32], partitions the full time-series dataset into a sequence of more compact sub-samples determined by a rolling window. These sub-samples are systematically rolled from the beginning to the end of the full sample. One major advantage of this technique is its ability to capture relationships between variables that evolve over time [33]. The specific procedure is as follows. Let T be the length of the time series, with a rolling window width designated as l. The endpoint of each sub-sample is defined as l, l+1,..., T, yielding a total of T−l+1 sub-samples. For each sub-sample, the RB modified LR test is employed to examine potential Granger causality. Subsequently, the p-values and LR statistics obtained from all sub-samples are compiled in chronological sequence to ascertain the outcomes of the bootstrap rolling-window causality test [34]. Let $N_b^{l} \sum_{k=1}^{p} \hat{\alpha}^{*}_{12,k}$ denote the average of a large number of bootstrap estimates, which represents the effect of RSP on RSOX. Here, N_b denotes the number of bootstrap replications, and $\hat{\alpha}^{*}_{12,k}$ is the parameter defined in Equation (2). This study constructs 90% confidence intervals, with the bottom and higher limits matching to the 5th and 95th percentiles of the bootstrap distribution, respectively [32]. The choice of the rolling window width involves a trade-off: a window that is too small may compromise the reliability of the test outcomes, while a larger window improves estimation precision but reduces the number of rolling iterations. Pesaran and Timmermann [35] suggest that when parameter stability cannot be assured, the rolling window width should not be less than 20.

4. Data and Variable Description

4.1. Data Sources and Sample Selection

To investigate the bidirectional causality between the semiconductor index and silver prices, this study employs the PHLX Semiconductor Index as a proxy for global semiconductor market performance and COMEX silver futures prices to represent global silver prices. All variables are measured monthly, from August 2012 to January 2026, and all data are obtained from the Choice database (https://www.choice-china.com/ (accessed on 31 January 2026)). Monthly-frequency data are employed to effectively capture the long-term co-movement between semiconductor industry cycles and silver prices, while mitigating the noise that may arise from high-frequency data. All raw data undergo rigorous quality screening and cleaning procedures to ensure the absence of missing values over the sample period. To satisfy the stationarity requirements of time-series modeling, the original series—SOX and SP—are transformed using first-order natural logarithmic differencing, yielding the return series RSOX and RSP, respectively. These transformed series serve as the fundamental variables for the subsequent bootstrap rolling-window causality analysis.

4.1.1. PHLX Semiconductor Index

The PHLX Semiconductor Index serves as a substitute for global semiconductor market performance in this study. Introduced by the Philadelphia Stock Exchange on 1 December 1993, it has a base value of 200 points. Widely used as a barometer of conditions in the global semiconductor industry, the index covers major segments of the semiconductor value chain, including design, equipment, manufacturing, and sales, and comprises 30 leading firms worldwide. Its constituent stocks account constitutes the predominant portion of the overall market capitalization of publicly traded semiconductor firms globally, granting the index a high degree of industry representativeness and market influence. The index is calculated using a market-capitalization-weighted methodology, enabling it to sensitively reflect global semiconductor technological advancement, capital expenditure cycles, and fluctuations in end-market demand.

4.1.2. COMEX Silver Futures Price

COMEX silver futures prices refer to the pricing of silver futures contracts on COMEX, one of the most influential silver derivatives markets worldwide. Their price movements are widely regarded as a benchmark for international silver pricing. This futures contract offers high liquidity, transparency, and a well-established delivery mechanism, attracting a broad range of participants worldwide, including industrial users, investors, and financial institutions. As a key instrument for price discovery and risk management, its quoted prices not only reflect the spot supply–demand conditions of physical silver but also deeply incorporate the influence of multiple factors such as the macro-financial environment, inflation anticipations, fluctuations in the exchange rate of the U.S. dollar, and safe-haven sentiment. Consequently, it is able to comprehensively and sensitively capture price signals associated with the dual attributes of silver. Accordingly, this study uses COMEX silver futures prices as a proxy for global silver prices.

All variable definitions and characteristics are reported in Table 1.

Table 1. Variable definitions.

Variable	Symbol	Description/Transformation	Frequency
PHLX Semiconductor Index	SOX	Level (index)	Monthly
COMEX silver futures price	SP	Level (index)	Monthly
Change rate of PHLX Semiconductor Index	RSOX	First difference of ln(SOX)	Monthly
Change rate of COMEX silver futures price	RSP	First difference of ln(SP)	Monthly

4.2. Descriptive Statistics

Table 2 provides a summary of the descriptive statistics for the variables. From the perspective of skewness, the skewness coefficients of SOX and SP are 1.106 and 3.341, respectively, both significantly greater than zero. This indicates that the distributions of the two series are markedly right-skewed, characterized by relatively long right tails. In such distributions, the mean exceeds the median, and the probability of observing extreme high values during the sample period is relatively high. Regarding kurtosis, the kurtosis values of SOX and SP are 3.462 and 21.052, respectively, both exceeding the benchmark value of 3 associated with a normal distribution. This suggests that both series exhibit pronounced leptokurtic and fat-tailed characteristics, implying a higher concentration of observations around the mean as well as a greater likelihood of extreme values compared with the normal distribution—characteristics that align with the stylized facts of financial time series. To further investigate the stationarity characteristics of the series, this study employs the ADF test, the PP test, and the KPSS test. The results indicate that the ADF and PP statistics for both SOX and SP unable to reject the null hypothesis of a unit root at standard significance levels, while the KPSS statistics significantly refute the null hypothesis of stationarity at the 1% significance level. Taken together, these three tests provide consistent evidence that SOX and SP are non-stationary time series over the sample period and therefore do not satisfy the requirements for subsequent time-series modeling.

Accordingly, to meet the fundamental stationarity requirement for time-series analysis, the original series SOX and SP are transformed by taking first-order natural logarithmic differences, yielding the corresponding return series denoted as RSOX and RSP. These series measure changes in the semiconductor index and silver futures prices, respectively. An examination of the statistical properties of the differenced series shows that RSOX exhibits a negative skewness coefficient, indicating a pronounced left-skewed distribution, whereas RSP displays a positive skewness coefficient, reflecting a clear right-skewed distribution. The kurtosis values of both RSOX and RSP remain significantly greater than 3, indicating that the leptokurtic and fat-tailed characteristics persist, which is typical of financial return series. Crucially, the stationarity test results undergo a fundamental shift after differencing. The ADF and PP statistics for both RSOX and RSP strongly disregard the null hypothesis of a unit root at the 1% significance threshold. At the same time, the KPSS statistics become insignificant and unable to reject the null hypothesis of stationarity. Based on the combined evidence from these three tests, it can be unambiguously concluded that RSOX and RSP are stationary time series after first-order differencing, thereby satisfying the prerequisite conditions for constructing vector autoregressive (VAR) models and conducting rolling-window Granger causality tests.

Table 2. Descriptive statistics.

Variable	SOX	SP	RSOX	RSP
Obs	162	162	162	162
Mean	2066.524	23.344	0.017	0.005
Median	1361.760	21.120	0.021	0.001
Maximum	7927.410	94.635	0.170	0.288
Minimum	326.370	13.825	−0.192	−0.310
Std. Dev.	1747.920	9.815	0.070	0.087
Skewness	1.106	3.341	−0.305	0.284
Kurtosis	3.462	21.052	3.199	4.127
ADF	2.697	5.039	−14.919 ***	−12.217 ***
PP	2.438	3.157	−14.955 ***	−12.249 ***
KPSS	15.595 ***	31.373 ***	0.261	0.752

Note: The ADF statistic is the Augmented Dickey-Fuller test statistic; The PP statistic is the Phillips Perron test statistic. The KPSS statistic is the Kwiatkowski-Phillips-Schmidt-Shin test statistic; *** indicate significance at the confidence levels of 1%.

4.3. Time-Series Trends of the Variables

The variables' time-series trends are shown in Figure 1. As shown in Figure 1, SOX and SP display broadly similar long-run movements, and both series exhibit pronounced short-term fluctuations. Specifically, prior to 2018, the co-movement between SOX and SP was relatively weak, with each series being driven primarily by its own idiosyncratic fundamentals. However, beginning in late 2018 or early 2019, both variables entered a pronounced upward phase, during which the synchronization of their trends became markedly stronger. This period of simultaneous growth coincided closely in time with a series of major technological, economic, and financial events. Subsequent to the emergence of the COVID-19 pandemic in 2020, ultra-accommodative monetary policies implemented by major central banks worldwide have provided abundant liquidity support for risk assets and certain commodity markets. Since late 2022, breakthrough advances in generative artificial intelligence technologies—represented by ChatGPT—and the subsequent iteration of large-scale models such as DeepSeek have substantially boosted market expectations regarding long-term semiconductor demand, as well as the application of silver in advanced computing and electronic devices. Meanwhile, strategic mergers and acquisitions and large-scale capital expenditures undertaken by leading semiconductor firms, including Microsoft and NVIDIA, have further reinforced signals of heightened industry prosperity. Together, these developments constitute the macroeconomic and technological backdrop underlying the synchronous rise of SOX and SP in the latter part of the sample period.

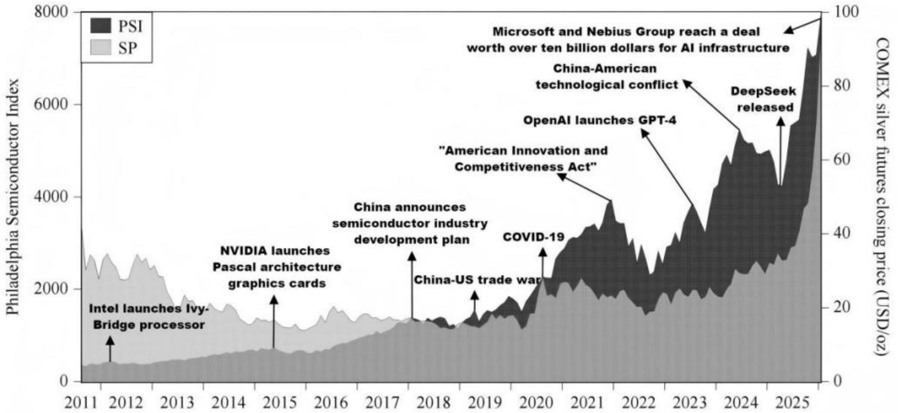


Figure 1. Time-series trends of the variables.

5. Empirical Analysis

This research employs a bootstrap sub-sample rolling-window causality test to examine the time-varying causal relationship between RSOX and RSP, and further analyzes how the direction and amount of causal effects change throughout various timeframes.

5.1. Full-Sample Granger Causality Test

Following Balcilar, Gupta, Kyei and Wohar [32], a bootstrap sub-sample rolling-window causality testing procedure is adopted to assess time-varying causality between RSOX and RSP. Consistent with [36–38], the rolling-window width is set to 12 periods, and the lag order is established as 1 according to the AIC. The findings are delineated in Table 3.

Table 3 shows the comprehensive Granger causality results derived from the residual-based bootstrap (RB) modified likelihood ratio test. All reported p-values exceed 0.10, therefore it is impossible to reject the null hypotheses. This signifies that, for the whole sample period, RSOX does not Granger-cause RSP, nor does RSP Granger-cause RSOX.

Table 3. Full-sample Granger causality test.

Null Hypothesis	Test Statistic	*p*-Value
RSOX does not Granger-cause RSP	0.318	0.600
RSP does not Granger-cause RSOX	0.456	0.497

5.2. Parameter Stability Tests

In conventional full-sample Granger causality testing, structural changes in model parameters may lead to biased inference by violating the assumption of parameter constancy [39,40]. Accordingly, to guarantee the reliability of the ensuing findings, parameter stability should be evaluated first.

To examine whether structural change is present, this study implements a set of parameter stability tests, including the Sup-F, Ave-F, and Exp-F tests proposed by Andrews and Ploberger [29], as well as the Lc test created by Nyblom [30] and Hansen [31]. The results are reported in Table 4. The evidence indicates structural change between RSOX and RSP, suggesting that full-sample Granger causality tests based on the supposition of parameter constancy may be unreliable.

Table 4. Parameter Stability Tests for RSOX and RSP.

	RSOX		RSP		VAR System	
Test	**Statistic**	**Bootstrap *p*-Value**	**Statistic**	**Bootstrap *p*-Value**	**Statistic**	**Bootstrap *p*-Value**
Sup-F	26.382 ***	0.002	32.542 ***	0	31.192 **	0.013
Ave-F	5.267	0.378	16.530 ***	0	15.969 **	0.039
Exp-F	8.964 ***	0.004	11.650 ***	0	12.276 **	0.011
Lc					0.827	0.440

Note: *** and ** respectively indicate significance at the confidence levels of 1%, 5%.

5.3. Sub-Sample Rolling-Window Analysis

Figure 2 provides the outcomes of the rolling-window causality examinations between RSOX and RSP. Panels (a) and (c) report the p-values of the LR statistics under the null hypotheses that “RSOX does not Granger-cause RSP” and “RSP does not Granger-cause RSOX”, respectively. Panels (b) and (d) report the rolling-window sums of the estimated coefficients capturing the effects of RSOX on RSP and of RSP on RSOX, along with their bootstrap estimates.

As reported in Figure 2a, the null of no Granger causality running from RSOX to RSP is rejected at the 10% significance threshold for four sub-periods: June–August 2020, November 2022–January 2023, September–October 2024, and July 2025–January 2026. Combining the evidence from Figure 2b, RSOX exerts only a weak positive effect on RSP during June–August 2020. This pattern can be attributed to the following mechanisms. Silver possesses pronounced industrial attributes, and the semiconductor industry represents one of its key sources of industrial demand, particularly in chip packaging processes that require substantial silver inputs. However, the onset of the COVID-19 pandemic in early 2020 precipitated widespread industrial shutdowns globally, which caused a general slowdown in semiconductor manufacturing activity. In response to mounting economic pressure, the Federal Reserve implemented highly accommodative monetary policies between June and August 2020, creating an environment of abundant liquidity that lifted prices across a broad range of assets. While both liquidity conditions and inflation expectations supported semiconductor equities and silver prices, rising RSOX would, under conventional logic, tend to attract capital away from traditional safe-haven assets such as silver, generating a liquidity-diversion effect. Meanwhile, the recovery of the semiconductor sector affects actual industrial demand for silver with a lag: real-economy demand tends to normalize gradually, whereas financial markets react more quickly. Consequently, under the combined influence of liquidity expansion and demand-side adjustment delays, the impact of RSOX on RSP remains positive but relatively weak.

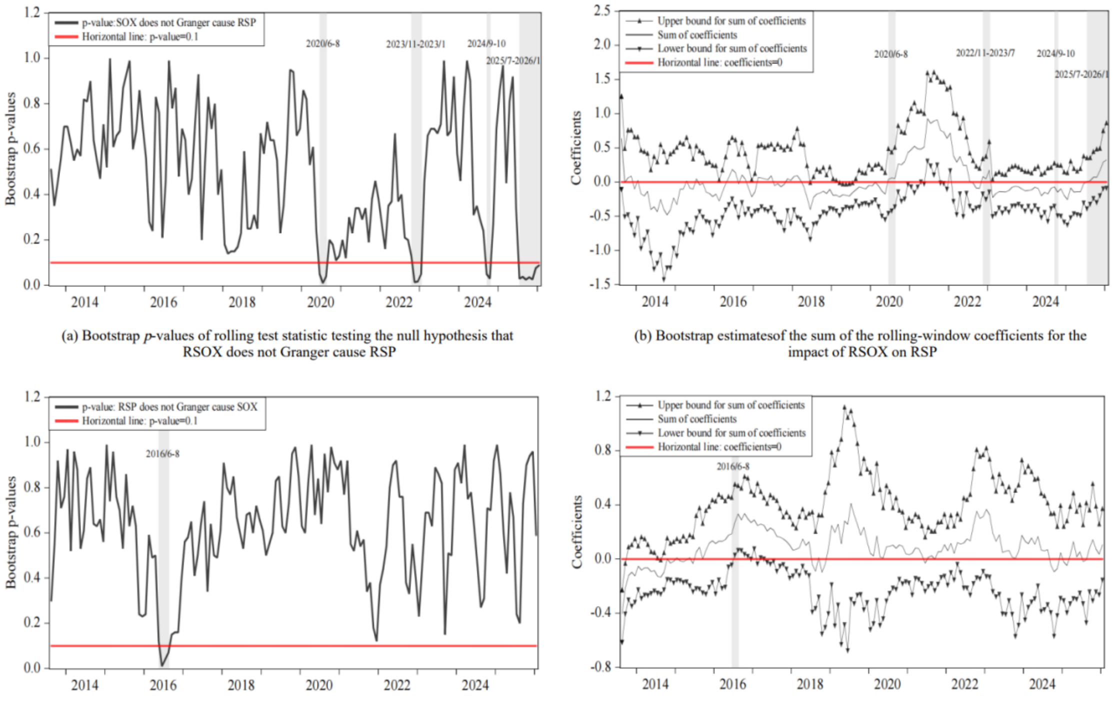
During November 2022 to January 2023, RSOX continues to exert a positive effect on RSP, although the magnitude of this effect increases only modestly relative to the previous episode. This pattern reflects changes in the macro-financial environment. As the Federal Reserve's aggressive tightening cycle approached its end, market expectations of a slowdown in rate hikes emerged from November 2022 onward, accompanied by renewed optimism regarding the prospects for a "soft landing". As a barometer of technology-sector performance and future economic growth, strengthening movements in the SOX index were interpreted as early signals of potential recovery in global manufacturing and consumer electronics demand, thereby improving expectations of future industrial demand for silver and supporting its price. Under normal circumstances, increases in RSOX might draw capital away from silver, resulting in a negative return correlation. However, in the specific context in which the tightening cycle was approaching its end, structural shifts in market risk preferences generated offsetting effects. As a result, the positive impact of RSOX on RSP did not strengthen markedly and remained relatively limited in magnitude.

During September–October 2024, RSOX exerts a weak negative effect on RSP. This outcome is primarily associated with heightened policy uncertainty and conflicting macroeconomic signals. During this period, intensifying technological competition between the United States and China, together with discussions of tighter U.S. export controls on semiconductor technologies, directly undermined the stability of global semiconductor supply chains. Given the industry's high sensitivity to trade policy, such uncertainty dampened profit expectations. Meanwhile, optimism regarding the long-term prospects of artificial intelligence—supported by developments such as the release of GPT-4—helped keep RSOX at elevated levels. Meanwhile, U.S. macroeconomic indicators conveyed mixed signals: non-farm payroll growth fell short of expectations and earlier data were revised downward, while manufacturing PMI readings remained in contractionary territory, pointing to weakness in the real economy, even as inflationary pressures persisted. This coexistence of weak manufacturing activity and sticky inflation led to divergent market views on the Federal Reserve's rate-cut path. Under these conditions, the financial channel linking semiconductor performance to silver prices provided limited support, resulting in a mildly negative effect of RSOX on RSP.

During July 2025 to January 2026, the positive impact of RSOX on RSP strengthens markedly relative to the preceding periods, indicating a more pronounced positive correlation. This intensification can be attributed to several concurrent factors. First, global semiconductor sales continued to expand, while downstream industries such as artificial intelligence and new energy vehicles generated strong industrial demand for silver. Applications of silver in key components—including controllers for electric vehicles and AI servers—further tightened supply–demand conditions. Second, expectations of Federal Reserve rate cuts contributed to declining real interest rates, simultaneously lowering the opportunity cost associated with retaining silver and supporting higher valuations for technology equities through improved liquidity conditions. In addition, heightened geopolitical risk—driven by concerns over U.S. dollar credibility and military actions by the United States against Venezuela in early January 2026—led to increased risk aversion among investors. In this environment, capital flows may have favored both precious metals with safe-haven attributes, such as silver, and semiconductor equities representing long-term growth potential. As a result, under the combined influence of strong industrial demand, accommodative monetary expectations, and geopolitically induced safe-haven demand, the positive impact of RSOX on RSP becomes significantly stronger.

The data presented in Figure 2c indicate that the p-values fall below 0.1 during the period from June to August 2016, permitting the null hypothesis to be dismissed at standard significance thresholds and indicating that RSP Granger-causes RSOX. In conjunction with the evidence presented in Figure 2d, it can be observed that RSP exerts only a weak positive effect on RSOX over the same period. The United Kingdom's "Brexit" referendum held in late June 2016, as a major political risk event, initially triggered a surge in global risk-averse sentiment, thereby driving an increase in silver prices due to silver's safe-haven properties. However, the market response was not limited to a flight-to-safety effect. The uncertainty induced by Brexit strengthened expectations that central banks would maintain accommodative liquidity conditions for a prolonged period. These pronounced easing expectations, in turn, provided a modest boost to the valuation outlook within the semiconductor industry, which is acutely responsive to interest rate fluctuations.

Combining the evidence from Figure 2a,c, no bidirectional causality between RSOX and RSP is detected over the same period, and the empirical results are therefore considered robust.



(a) Bootstrap *p*-values of rolling test statistic testing the null hypothesis that RSOX does not Granger cause RSP

(b) Bootstrap estimatesof the sum of the rolling-window coefficients for the impact of RSOX on RSP

(c) Bootstrap *p*-values of rolling test statistic testing the null hypothesis that RSP does not Granger cause RSOX

(d) Bootstrap estimatesof the sum of the rolling-window coefficients for the impact of RSOX on RSP

Figure 2. Rolling-Window Causality Test between RSOX and RSP.

6. Conclusions and Policy Implications

Against the backdrop of the explosive growth of the global semiconductor industry, the intertwined industrial and financial attributes of silver, and the frequent occurrence of macroeconomic policy shifts and geopolitical events, this paper investigates the causal relationship between the global semiconductor index and silver prices. Drawing on monthly data from August 2012 to January 2026, a bootstrap sub-sample rolling-window causality test is employed. The outcomes indicate a significant time-varying causal relationship between RSOX and RSP. However, this relationship is not globally stable and emerges only within specific event-driven windows shaped by major external shocks, namely June–August 2020, November 2022–January 2023, September–October 2024, and July 2025–January 2026. During periods dominated by abundant liquidity and optimistic growth expectations, RSOX exerts a positive effect on RSP, reflecting the fundamental mechanism of industrial-demand-driven linkage. By contrast, in phases characterized by heightened policy uncertainty and intensified geopolitical tensions, shifts in risk preferences may weaken this linkage or even render it mildly negative. Meanwhile, during June to August 2016, the study also captured a weak positive Granger causality effect from RSP to RSOX. This primarily stemmed from risk aversion triggered by events such as the UK's Brexit referendum and the subsequent strengthening of expectations for global monetary easing. Overall, the findings indicate that silver has evolved from a traditional commodity into a strategic asset deeply embedded in global technology cycles and financial sentiment.

This study presents policy recommendations at three levels based on the aforementioned findings: national strategy, industrial coordination, and firm-level practice.

At the national level, priority should be given to strengthening international cooperation and rule-shaping capabilities in resource security. Against the backdrop of global supply chain reconfiguration, policymakers should actively leverage multilateral and bilateral dialogue mechanisms to promote the establishment of a critical metals supply chain resilience partnership. On the one hand, deeper interest alignment with major resource-producing and processing countries should be fostered through long-term trade agreements, joint development projects, and co-investment initiatives. On the other hand, proactive participation in—and guidance of—discussions on relevant international rules, standards, and pricing mechanisms is essential to enhance China's voice and influence in global resource governance. Such efforts would help create a stable, fair, and predictable international resource market environment for domestic industries.

At the industry level, materials science and technological innovation should be elevated to a strategic priority on par with chip design and manufacturing processes. Through national key science and technology programs and industry-guided investment funds, greater support should be directed toward research and development in silver-saving technologies, novel composite conductive materials, and potential substitute materials. The objective is to fundamentally reduce the downstream high-end manufacturing sector's absolute dependence on a single scarce resource. At the same time, leading firms in the semiconductor industry should be encouraged to establish long-term strategic partnerships and risk-sharing platforms with upstream suppliers of critical materials such as silver. This can be achieved through long-term procurement agreements, joint R&D investments, equity participation, or cross-shareholding arrangements, thereby deepening mutual interests, jointly addressing cyclical fluctuations and geopolitical risks, and enhancing the overall resilience and coordination efficiency of the industrial chain.

At the firm and market level, it is recommended that financial institutions collaborate with commodity exchanges to develop and promote more sophisticated risk management instruments centered on strategic metals such as silver. For example, silver price index futures and options linked to semiconductor industry sentiment indices could be introduced, or tailored hedging strategies could be designed to provide firms with more precise financial tools for managing cost volatility. In addition, efforts should be made to actively promote—and take a leading role in—the establishment of responsible resource sourcing and environmental, social, and governance (ESG) standards. By incorporating ESG criteria such as supply chain transparency, carbon footprint reduction, and community development into procurement guidelines, global resource supply chains can be guided toward a greener, more inclusive, and sustainable trajectory. Such initiatives would enhance the sustainability and credibility of high-tech supply chains and improve engagement in global resource governance. In the long run, they would contribute to greater supply chain resilience and cost stability within the global technology and industrial system.

Author Contributions

X.S.: conceptualization, methodology, data curation, software, formal analysis, writing—original draft preparation; T.Z.: supervision, validation, writing—reviewing and editing, project administration. All authors have read and agreed to the published version of the manuscript.

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Use of AI and AI-Assisted Technologies

This manuscript and all related research (including design, analysis, and interpretation) were carried out entirely by the authors without the use of any AI tools.

References

1. Bhosle, S.M.; Mahadik, S.C. A review of microelectronics as a catalyst for intelligent manufacturing: Trends, sectoral applications, and future directions. *Aust. J. Multi-Discip. Eng.* **2025**, 1–20.
2. Dutta, A. Impact of silver price uncertainty on solar energy firms. *J. Clean. Prod.* **2019**, *225*, 1044–1051.
3. Apergis, I.; Apergis, N. Silver prices and solar energy production. *Environ. Sci. Pollut. Res.* **2019**, *26*, 8525–8532.

4. Apergis, N.; Christou, C.; Payne, J.E. Precious metal markets, stock markets and the macroeconomic environment: A FAVAR model approach. *Appl. Financ. Econ.* **2014**, *24*, 691–703.
5. Moguilnaia, N.A.; Vershinin, K.V.; Sweet, M.R.; et al. Innovation in power semiconductor industry: Past and future. *IEEE Trans. Eng. Manag.* **2005**, *52*, 429–439.
6. Tan, H.; Mathews, J.A. Identification and analysis of industry cycles. *J. Bus. Res.* **2010**, *63*, 454–462.
7. Hilmola, O.-P. Stock market performance and manufacturing capability of the fifth long-cycle industries. *Futures* **2007**, *39*, 393–407.
8. Dadush, U. The policy response to global value chain disruption. *Glob. Policy* **2023**, *14*, 548–557.
9. Farrand, B. The economy–security nexus: Risk, strategic autonomy and the regulation of the semiconductor supply chain. *Eur. J. Risk Regul.* **2025**, *16*, 279–293.
10. Kubesa, J.; Černý, I. A study of the influence of economic factors on world silver production. *GeoScience Eng.* **2023**, *69*, 69–81.
11. Shahzad, U.; Mohammed, K.S.; Tiwari, S.; et al. Connectedness between geopolitical risk, financial instability indices and precious metals markets: Novel findings from Russia Ukraine conflict perspective. *Resour. Policy* **2023**, *80*, 103190.
12. Yıldırım, D.; Eren, M.; Dogan, M. Investor Trends During Periods of Geopolitical Risk in Turkey: Which Assets Serve as Safe Havens? *Borsa Istanb. Rev.* **2025**, 25, 801-815.
13. Lucey, B.M.; Li, S. What precious metals act as safe havens, and when? Some US evidence. *Appl. Econ. Lett.* **2015**, *22*, 35–45.
14. Creti, A.; Joëts, M.; Mignon, V. On the links between stock and commodity markets' volatility. *Energy Econ.* **2013**, *37*, 16–28.
15. Chen, Y.; Qi, H. Dynamic interplay between Chinese energy, renewable energy stocks, and commodity markets: Time-frequency causality study. *Renew. Energy* **2024**, *228*, 120578.
16. Liu, Q.; Xue, D.; Li, W. A Sustainable Production Segment of Global Value Chain View on Semiconductors in China: Temporal and Spatial Evolution and Investment Network. *Sustainability* **2024**, *16*, 8617.
17. Nazir, M.; Rasheed, M.Q.; Yu, X.H.; et al. Can Computer Technology, Semiconductors, and Artificial Intelligence Shape a Sustainable Future? Evidence From Leading Semiconductor-Producing Countries. *Sustain. Dev.* **2025**, 33, 5214–5233.
18. Ju, Y.-M.; Kim, T.-W.; Lee, S.-H.; et al. Advanced WBG power semiconductor packaging: Nanomaterials and nanotechnologies for high-performance die attach paste. *Nano Converg.* **2025**, *12*, 38.
19. Baker, M.; Stein, J.C. Market liquidity as a sentiment indicator. *J. Financ. Mark.* **2004**, *7*, 271–299.
20. Liu, S. Investor sentiment and stock market liquidity. *J. Behav. Financ.* **2015**, *16*, 51–67.
21. Li, S.; Lucey, B.M. Reassessing the role of precious metals as safe havens–What colour is your haven and why? *J. Commod. Mark.* **2017**, *7*, 1–14.
22. Yen, C.-H.; Chang, C.-H.; Yu, W.W. Asymmetric Impact of Inverted Yield Curve, FRAC Spread Count, and Billings Trends for Semiconductor Equipment Manufacturers on SOX Index. *IEEE Access* **2023**, *11*, 139849–139859.
23. Ayres, R.U.; Williams, E. The digital economy: Where do we stand? *Technol. Forecast. Soc. Change* **2004**, *71*, 315–339.
24. Gorton, G. The history and economics of safe assets. *Annu. Rev. Econ.* **2017**, *9*, 547–586.
25. Ullah, M.; Sohag, K.; Doroshenko, S.; et al. Examination of Bitcoin Hedging, diversification and safe-haven ability during financial crisis: Evidence from equity, bonds, precious metals and exchange rate markets. *Comput. Econ.* **2025**, *66*, 835–867.
26. Shukur, G.; Mantalos, P. A simple investigation of the Granger-causality test in integrated-cointegrated VAR systems. *J. Appl. Stat.* **2000**, *27*, 1021–1031.
27. Shukur, G.; Mantalos, P. Size and power of the RESET test as applied to systems of equations: A bootstrap approach. *J. Mod. Appl. Stat. Methods* **2004**, *3*, 10.
28. Andrews, D.W. Tests for parameter instability and structural change with unknown change point. *Econometrica* **1993**, *61*, 821-856.
29. Andrews, D.W.; Ploberger, W. Optimal tests when a nuisance parameter is present only under the alternative. *Econometrica* **1994**, *62*, 1383-1414.
30. Nyblom, J. Testing for the constancy of parameters over time. *J. Am. Stat. Assoc.* **1989**, *84*, 223–230.
31. Hansen, B.E. Tests for Parameter Instability in Regressions with I(1) Processes. *J. Bus. Econ. Stat.* **1992**, *10*, 321–335. https://doi.org/10.2307/1391545.
32. Balcilar, M.; Gupta, R.; Kyei, C.; et al. Does economic policy uncertainty predict exchange rate returns and volatility? Evidence from a nonparametric causality-in-quantiles test. *Open Econ. Rev.* **2016**, *27*, 229–250.
33. Su, C.-W.; Song, X.Y.; Dou, J.; et al. Fossil fuels or renewable energy? The dilemma of climate policy choices. *Renew. Energy* **2025**, *238*, 121950.
34. Qin, M.; Su, C.-W.; Umar, M; et al. Are climate and geopolitics the challenges to sustainable development? Novel evidence from the global supply chain. *Econ. Anal. Policy.* **2023**, *77*, 748–763.
35. Pesaran, M.H.; Timmermann, A. Small sample properties of forecasts from autoregressive models under structural breaks. *J. Econom.* **2005**, *129*, 183–217.

36. Su, C.-W.; Li, Z.-Z.; Chang, H.-L.; et al. When will occur the crude oil bubbles? *Energy Policy* **2017**, *102*, 1–6.
37. Su, C.-W.; Liu, Y.; Chang, T.; et al. Can gold hedge the risk of fear sentiments? *Technol. Econ. Dev. Econ.* **2023**, *29*, 23–44.
38. Su, C.-W.; Qin, M.; Zhang, X.-L.; et al. Should Bitcoin be held under the US partisan conflict? *Technol. Econ. Dev. Econ.* **2021**, *27*, 511–529.
39. Sun, Y.; Song, Y.; Long, C.; et al. How to improve global environmental governance? Lessons learned from climate risk and climate policy uncertainty. *Econ. Anal. Policy* **2023**, *80*, 1666–1676.
40. Zeileis, A.; Leisch, F.; Kleiber, C.; et al. Monitoring structural change in dynamic econometric models. *J. Appl. Econom.* **2005**, *20*, 99–121.