DOI: 10.54254/2754-1169/2024.25087

Economic, Political Uncertainty Risks and Gold Market Volatility: Evidence from Multiplex Network Analysis of Global Spillovers

Xuechun Xu

Business School, Soochow University, Suzhou, China
2110411031@stu.suda.edu.cn

Abstract. With the accumulation of global economic risks and the intensification of geopolitical conflicts, the impact of uncertainty risk on gold market volatility has received increasing attention. This paper constructs a TVP-VAR-DY spillover effect model and a multilayer network model to comprehensively analyze the cross-country dynamic linkages between economic, political uncertainty risks and gold market volatility. Utilizing monthly data spanning from January 2000 to May 2024, the study focuses on regions including Asia-Pacific, Europe, and the Americas. The findings are twofold: (1) Economic policy uncertainty, geopolitical risk, and gold market volatility are intricately interconnected. (2) Key economies exhibit distinct roles and responses during major global events. This highlights the need for integrated economic and geopolitical strategies to navigate uncertainties and maintain stability.

Keywords: Spillover effect, Multiplex network, Uncertainty Risk

1. Introduction

The process of worldwide integration has significantly strengthened the interdependence and interconnectedness. Global markets can be viewed as a complex financial system constituted of interacting units [1], where risk shocks originating in one market can trigger multidimensional fluctuations. The numerous uncertainties, introduced by persistent economic frictions [2] and geopolitical conflicts [3,4], not only broaden the scope but also render it more contagious [5]. This, in turn, promotes rapid spillovers on the global scale, spreading these two systemic risks across interconnected areas beyond their original sectors.

While most of the existing research focuses on energy markets [6-10], further investigation is necessary into the significance of gold as a precious metal. In addition to its commodity properties, gold provides risk hedging, portfolio diversification in a risky market environment, accompanied by high volatility and stock market disengagement [11-14]. Its role as a "safe haven" makes it an attractive investment for investors seeking to preserve and expand their assets.

Typically, the gold market can be affected through various channels. At the macro level, countries may sell gold reserves during periods of global turbulence to influence supply levels, leading to short-term price surges and increased volatility. At the micro level, investors often withdraw from

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the stock market to safer assets like gold, which also impacts its price. Further at the market level, the spillover effect occurs as the interconnectedness of financial system allows economic and geopolitical risks to spread more rapidly, amplifying their impact on the gold market [15,16]. As the result of these factors. the volatility of gold market becomes a crucial indicator. It not only reflects underlying trend risks and sentiment changes, but also serves as a key metric for making investment decisions and risk management [17]. Thus, analyzing the spillover effects of uncertainty risks and the gold market, as well as their interactions, has significant theoretical and practical implications. Such analysis provides valuable insights for optimizing asset portfolio management for investors, and developing economic policies aimed at sustaining financial stability for policymaker.

Since earlier studies have failed to comprehensively investigate the relationship between uncertainty risks and the gold market, this paper addresses the gap by examining spillover effects and analyzing topological features within a three-layer multiplex network. It contributes to existing research in three ways: First, by broadening the analysis to encompass economic uncertainty risks, geopolitical risks, and gold market volatility, incorporating a broader array of risk and market factors. Second, by applying time-varying method, capturing the dynamic interactions and impact. Third, by investigating the topological features in a multiplex network, providing insights into their systemic linkages and characteristic.

The remainder of this paper is organized as follows. The next section is the review of existing literature, Section 3 introduce the data and methodology. The paper presents the empirical results in Section 4 and draw conclusions in Section 5.

2. Literature review

Due to the increase in risks, existing literature has explored various factors, channels, and predictors of gold price volatility. The impact of non-financial market factors, such as economic and geopolitical uncertainty, alongside traditional financial market factors, such as exchange rates, interest rates, equities and commodities, has drawn significant attention, particularly during periods of global economic downturn and geopolitical turmoil [18-20]

Regarding economic uncertainty policy, Baker et al [2]. first introduced the Economic Policy Uncertainty (EPU) index, constructed utilizing official news articles' relevant keywords correlated to finance and economic operations. Research employing this index indicates that economic uncertainty risk causes gold prices to rise, especially at lower quantiles [21], and improves the accuracy of short-term gold futures price fluctuations prediction [22]. Regarding geopolitical risks, Caldara and Iacoviello [4] developed the Geopolitical Risk (GPR) index based on newspaper articles, to capture risks associated with war, terrorism, and interstate tensions. Related studies find a significant positive effect on gold market volatility high-tension periods [15], and a time-varying correlation with stock markets, highlight gold's role as a good diversifier and safe haven. While much of aforementioned studies focuses on the function of uncertainty risks as a fitting factor, it often uses models like GARCH-MIDAS for mixed-frequency tracking and forecasting, without fully exploring their interconnectedness with the gold market.

Spillovers, a critical phenomenon in financial markets, have been extensively examined and quantified, particularly since the introduction of coefficients by Diebold and Yilmaz [23]. The method combines TVP-VAR models and generalized variance decomposition methods to depict spillovers and directional connectedness, and it turns out that connectedness measures are closely related to aspects of network connectedness [24]. Various studies have used the spillover matrices (taking variables as nodes and pairwise connection as edges to build the complex network) to analyze the topological aspects of the stock, carbon, and energy markets [25-28]. Studies related

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to volatility or uncertainty risk spillovers, though studies on the mechanisms of spillover that are often limited to a single dimension. For instance, Li et al [29].examined geopolitical and gold price dynamics of 18 emerging gold markets by using the global GPR index instead of country-specific variables to build a network, while Zhu et al [16]. explored relationship between gold market and extreme climatic change by testing causality-in-quantities to the gold market spillover network. These studies often overlook the external characteristics of risk, because they retain their independence even when discussing interconnectivity. Rather, a multilayer approach that charts each social group into a different laver of interactions and operates the spreading process separately on each layer [30], can lead actually to a series of significant and impactful insights.

To address these gaps, this paper introduces the method of complex multilayer networks to more comprehensively investigate the interactions between global economic, geopolitical uncertainty risks and gold market volatility. Although multilayer networks have been extensively discussed in the fields of medicine and social sciences, their application in finance has primarily focused on systemic stability [31-33], stock market risk contagion [34-36], investor sentiment [37], and trading networks [38]. By constructing a multiplex network on the basis of spillover effect measures, this paper aims to better capture both intra- and inter-layer interactions, providing theoretical and practical guidance for global investment and policy strategies.

3. Methodology

3.1. Spillover measurement

Traditional multivariate GARCH models, such as BEKK-GARCH and DCC-GARCH, have limitations in capturing the directionality and dynamics of spillovers. To overcome these limitations, Diebold and Yilmaz [39] used Cholesky decomposition to construct the index. They later enhanced their approach by adopting the generalized VAR framework of Koop et al [40]. and Pesaran and Shin [41], which allowed for variance decompositions independent of variable order [23]. Given that static models cannot fully represent dynamic interactions, this paper, following Antonakakis et al [6]., uses the TVP-VAR approach to provide time-varying spillover index characteristics. This approach reduces sample loss and smoothes estimation results, making it valuable to financial market spillover research.

To begin, the TVP-VAR model is developed. The H-step generalized variance decomposition matrix can be described as

$$d_{ij}^{gH} = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (e'_i \Theta_h \sum e_j)^2}{\sum_{h=0}^{H-1} (e'_i \Theta_h \sum \Theta'_h e_i)_{i,i}} \tag{1}$$

where e_j is a selection vector with j th element unity and zeros elsewhere, Θ_h is the coefficient matrix multiplying the h-lagged shock vector in the infinite moving-average representation of the non-orthogonalized VAR. Hence, the pairwise directional connectedness from j to i is defined as the element to construct the spillover network.

$$C_{ij}^{H} = d_{ij}^{gH} \tag{2}$$

Further, the grand total of the off-diagonal entries measures total connectedness in the whole system be calculated as follow.

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$$TCI^{H} = \frac{1}{N}\sum_{\substack{i,j=1 \\ i\neq j}}^{N} d_{ij}^{gH} \tag{3}$$

3.2. Network measurement

Based on the pairwise spillover connectedness of economic uncertainty risk (EPU), geopolitical uncertainty risk (GPR) and gold market volatility (GOLD), this paper construct a 3-layer multiplex networks $\Omega = \{L^1, L^2, L^3\}$ with $M = 3$ layers and $N = 9$ nodes. Inside each layer $L^{\lambda} = L(V, C^{\lambda})(\lambda = 1,2,3)$, $V = \{1,2,...,N\}$ denotes the node sets, C^{λ} denotes the edge set, and the element C_{ij}^{λ} denotes the directed and weighted link in the corresponding set, representing the pairwise spillover strength from economies i to j on layer λ .

The discussion of multiplex network measurement indicators in the financial domain now focuses on the node, edge, and layer measurements [29]. Following Wang et al [37]., Gong et al [1]., and Xiang et al [36]., the paper illustrates the topological features with measures below.

3.2.1. Spillover strength measures

The spillover effect strength of a single layer can be roughly measured by three indicators: in-strength (IS), out-strength (OS), and net-strength (NS) of node i , representing the sum of edges C_{ij}^{λ} to, and from all other nodes j to node i , and their difference.

$$IS_i^{\lambda} = \sum_{j=1,\, j\neq i}^{N} C_{ij}^{\lambda} \tag{4}$$

$$OS_i^{\lambda} = \sum_{j=1,\, j\neq i}^{N} C_{ji}^{\lambda} \tag{5}$$

$$NS_i^{\lambda} = OS_i^{\lambda} - IS_i^{\lambda} \tag{6}$$

where, C_{ij}^{λ} denotes the directed and weighted edge from nodes i to node j on layer λ .

3.2.2. Centrality measures

The problem of identifying the nodes that play a central structural role is one of the main topics in the traditional analysis of complex networks. There are many well-known parameters that measure the structural relevance and importance of each node [30], including the node degree, the closeness (facilitates efficient communication), the betweenness (controls information flow) and PageRank (determines node influence) centrality.

$$Closeness_i^{\lambda} = \sum_{j=1}^{N} \frac{N-1}{d_{ij}^{\lambda}} \tag{7}$$

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$$Betweenness_i^{\lambda} = \sum_{i \neq j \neq k}^{N} \frac{\sigma_{jk}(i)}{\sigma_{jk}} \tag{8}$$

$$PageRank_i^{\lambda} = \frac{1-f}{N} + f \sum_{j=1}^{N} \frac{PageRank_j^{\lambda}}{O_j^{\lambda}} \tag{9}$$

where, d_{ij}^{λ} denotes the shortest paths from nodes i to node j, σ_{jk} and $\sigma_{jk}(i)$ denote the numbers of shortest paths from nodes i to node j and numbers of those paths travelling through node i, f is the damping factor subtracted from 1, and O_j^{λ} is the number of outbound edges connected to node j on layer □.

3.2.3. Dependence measures

In order to examine the layer-layer correlations, the paper apply the following methods to analyze the similarity. Spearman rank correlation measures the strength of monotonic relationships between the ranks of two layers. Kendall rank correlation assesses the ordinal association between layers, reflecting the consistency of rank ordering.

$$\rho = 1 - \frac{6 \sum d_i^2}{n(n^2-1)} \tag{10}$$

$$\tau = \frac{2(P-Q)}{n(n-1)} \tag{11}$$

where d_i is the rank difference, n is the number of observations, and P and Q denote the numbers of concordant and discordant pairs, respectively.

3.3. Data and description

In order to capture the interaction between uncertainty risks and the gold market on the global scale, 9 economies are mainly focused across Asia-Pacific (Australia, China, Japan, India, Russia), Europe (the Eurozone and the UK), and Americas (the USA and Canada). Utilizing monthly data spanning from January 2000 to May 2024, the paper examines the spillover effects and their topological features among these regions.

Uncertainty risks are quantified using two prominent indices derived from text analysis: the Economic Policy Uncertainty (EPU) Index, developed by Baker et al [2]., which measures policy-related economic uncertainties through the frequency of newspaper coverage, and the Geopolitical Risk (GPR) Index, developed by Caldara and Iacoviello [4], which gauges adverse geopolitical events by analyzing articles from ten major newspapers. The gold market price trends, based on local currencies, are derived from public data from the World Gold Council (WGC). The gold volatility is calculated using the GARCH (1,1) model applied to the first log-differenced series of the gold price, which represents the return.

As shown in the table below, all three panels of data display the risk characteristics of high peaks and fat tails, and pass the ADF test at 1% level.

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Table 1. Descriptive statistics of 9 economies

	Mean	Max	Min	Std.Dev.	Skew	Kurt	ADF
				Panel A: EPU			
Australia	109.350	337.044	25.662	59.784	1.244	4.533	-7.745***
China	148.867	661.828	10.111	119.164	1.456	4.962	-4.839***
India	106.830	239.024	48.399	31.153	1.057	4.993	-7.396***
Japan	89.571	283.689	23.353	45.484	1.476	5.763	-6.957***
Russia	190.486	964.141	12.399	159.449	1.755	6.403	-6.310***
Eurozone	144.819	344.613	53.851	58.900	0.745	3.161	-4.234***
UK	216.541	1141.796	29.027	149.794	1.645	8.374	-4.938***
USA	188.282	678.817	39.323	115.734	0.961	3.870	-5.067***
Canada	139.226	503.963	44.783	64.443	1.882	8.984	-6.403***
				Panel B: GPR			
Australia	0.107	0.515	0.013	0.075	1.993	8.527	-8.844***
China	0.561	2.475	0.161	0.307	1.657	7.839	-6.720***
India	0.240	1.237	0.059	0.166	2.248	9.828	-9.063***
Japan	0.220	0.946	0.064	0.130	2.985	15.284	-9.292***
Russia	0.864	8.801	0.218	0.816	4.694	37.476	-5.130***
Eurozone	0.146	0.864	0.046	0.095	3.206	18.779	-6.629***
UK	1.128	5.995	0.404	0.694	4.007	24.626	-7.223***
USA	0.225	1.724	0.057	0.171	4.655	34.990	-7.819***
Canada	2.447	13.229	0.820	1.355	4.380	30.995	-6/607***
				Panel C: GOLD			
Australia	0.012	0.208	0.003	0.014	9.569	122.087	-9.078***
China	0.011	0.069	0.003	0.009	3.249	17.845	-5.226***
India	0.012	0.083	0.003	0.01	3.591	21.52	-6.252***
Japan	0.011	0.075	0.004	0.008	3.364	19.449	-5.166***
Russia	0.019	0.694	0.005	0.044	12.544	185.448	-11.892***
Eurozone	0.01	0.071	0.003	0.008	3.183	17.409	-6.489***
UK	0.011	0.083	0.004	0.009	3.629	22.694	-7.280***
USA	0.011	0.09	0.004	0.009	4.377	32.475	-6.628***
Canada	0.011	0.065	0.004	0.008	3.31	18.236	-5.174***

Note: ***, **, and* indicate statistical significance at the 1%, 5% and 10% level, respectively. ADF stands for the Augmented Dickey-Fuller root tests, which is used to check the stationarity.

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4. Empirical results

The section examines the mechanism through the topological features of the multiplex network. The full-sample effect is first analyzed to illustrate the rough situation as shown in Figure 1. In addition, rolling sample analysis is used to estimate the dynamic characteristic of the multiplex network.

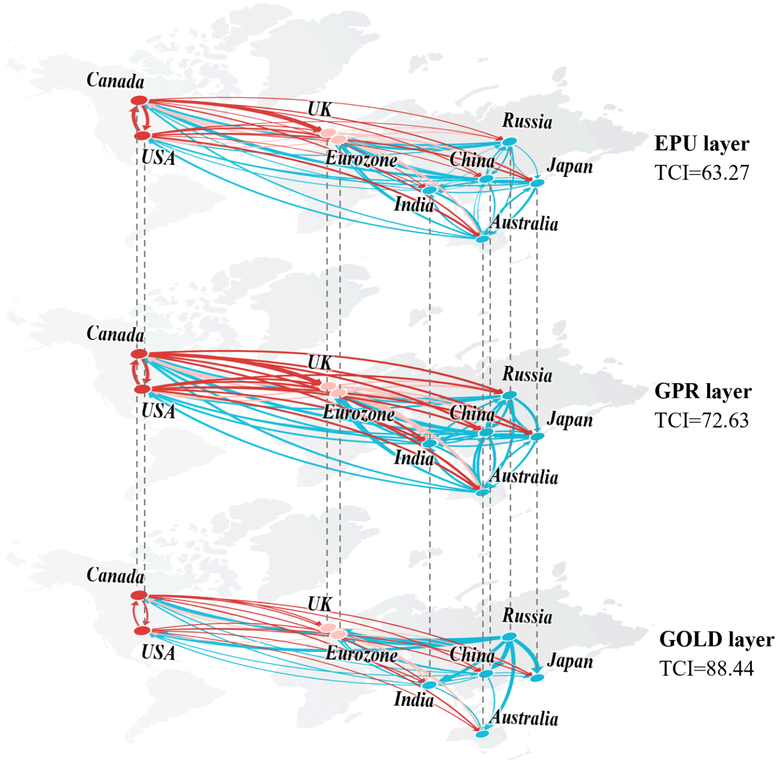

Figure 1. Multiplex network diagram of economic uncertainty risk (EPU), geopolitical uncertainty risk (GPR), and gold market volatility (GOLD)

4.1. Full-sample analysis

The tables below illustrate the general topological features of spillover effect of nine economies across the three layers: economic uncertainty risk (EPU), geopolitical risk (GPR), and gold market volatility (GOLD). Through a static analysis of the full sample, the general features of the spillover effect network can be derived.

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Table 2. Spillover effect strength of 9 economies on 3 layers during full-sample period

	In-strength			Out-strength			Net-strength		
	EPU	GPR	GOLD	EPU	GPR	GOLD	EPU	GPR	GOLD
Australia	9.961	5.180	4.929	9.585	16.063	8.619	-0.376	10.883	3.690
China	16.210	1.243	10.787	8.885	19.055	0.631	-7.325	17.812	-10.156
India	4.143	1.994	11.282	16.700	41.985	1.327	12.556	39.991	-9.955
Japan	4.746	9.113	0.048	11.887	6.965	21.955	7.141	-2.147	21.907
Russia	5.857	6.927	3.535	19.691	7.768	17.487	13.833	0.841	13.952
Eurozone	11.381	16.977	2.467	6.210	1.333	10.746	-5.171	-15.644	8.279
UK	33.448	21.084	8.362	21.892	0.371	3.623	-11.557	-20.714	-4.739
USA	12.094	20.809	10.465	6.836	1.252	0.798	-5.258	-19.557	-9.667
Canada	12.103	14.579	13.763	8.258	3.112	0.450	-3.845	-11.466	-13.313

In terms of spillover effects, the paper primarily examines the impact paths from the perspectives of In-strength, Out-strength, and Net-strength across different layers. In the In-strength dimension, the UK in Europe exhibits the highest value in the EPU layer, with the Eurozone also showing significant influence in both the EPU and GPR layers. This indicates heightened economic and geopolitical risks in Europe throughout the period. Conversely, the Asia-Pacific region displays varied influence, with China and India reflecting substantial international impact on their gold markets. In the Out-strength dimension, India stands out in the GPR layer with a high value of 41.985. Russia also shows significant influence in the EPU layer. Meanwhile, the USA and Canada exhibit relatively low Out-strength across layers, suggesting a more domestically focused approach in these areas. The Net-strength analysis demonstrate the combined influence. Compared to the emerging Asia-Pacific areas where India and China stand out, European and American countries, despite showing significant inflows and outflows, tend to balance out and often act as net recipients in the global spillover network.

As to inter-layer similarity, the two systemic risks-the EPU and GPR layers-show a strong correlation, reflecting closely connected economic and geopolitical risks. However, the correlation between the GPR and GOLD layers is weaker, suggesting less influential the factor politic is.

Table 3. Centrality of 9 economies on 3 layers during full-sample period

	Closeness			Betweenness			PageRank		
	EPU	GPR	GOLD	EPU	GPR	GOLD	EPU	GPR	GOLD
Australia	0.112	0.085	0.096	0.334	0.229	0.418	0.100	0.058	0.062
China	0.099	0.095	0.105	0.448	0.381	0.598	0.187	0.057	0.115
India	0.084	0.062	0.099	0.200	0.073	0.121	0.047	0.053	0.194
Japan	0.102	0.107	0.057	0.437	0.585	0.088	0.046	0.069	0.051
Russia	0.094	0.103	0.072	0.333	0.667	0.029	0.055	0.066	0.086
Eurozone	0.111	0.093	0.094	0.476	0.220	0.506	0.086	0.236	0.057
UK	0.075	0.088	0.104	0.436	0.206	0.479	0.203	0.212	0.095
USA	0.110	0.090	0.107	0.282	0.241	0.477	0.164	0.161	0.101
Canada	0.106	0.105	0.092	0.338	0.361	0.116	0.110	0.089	0.240

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In terms of centrality, closeness centrality, betweenness centrality, and PageRank centrality are examined to assess the status of different regions. At the closeness centrality level, regions like the Eurozone and the USA demonstrate high closeness in the EPU layer, indicating efficient information dissemination, while the UK (0.075) shows lower closeness, suggesting less efficiency despite strong spillover effects. Developed Asia-Pacific countries, such as Australia and Japan, also play important roles. At the betweenness centrality level, China leads in the GOLD layer, serving as a crucial bridge, while Japan is significant in the GPR layer, highlighting the Asia-Pacific region's intermediary role in the global network. At the PageRank centrality level, the UK has strong influence in both systemic risk layers, with scores above 0.2, although its impact on gold market risk is weaker. Similar trends are observed in other European and American countries, which are more central in risk layers, while the Asia-Pacific region gains prominence in gold market volatility.

The inter-layer centrality similarity analysis also shows a strong correlation (0.307) between the economic and geopolitical uncertainty layers similar to edge similarity, particularly in Europe and America. In contrast, the connection between these risks and the gold market is weaker, with more independent central positions and even negative correlations between the GPR and GOLD layers. This indicates that Europe and America are central in risk layers, whereas emerging markets in the Asia-Pacific region show greater influence in the gold market.

Table 4. Intra-layer rank correlations of key measures on 3 layers during full-sample period

	Edge		PageRank	
	Spearman	Kendall	Spearman	Kendall
EPU-GPR	0.307	0.307	0.074	0.053
EPU-GOLD	0.162	0.162	0.124	0.137
GPR-GOLD	0.059	0.059	-0.086	-0.081

4.2. Dynamic-sample analysis

Furthermore, this study investigates the time-varying characteristics using 293 months of monthly data from January 2000 to May 2024, providing a comprehensive analysis of temporal dynamics over an extended period.

The window width and prediction horizon are set to $W = 12$ and $H = 36$. The VAR lag order of two uncertainty risks and the gold market volatility is $p = 1$ and $p = 2$, respectively.

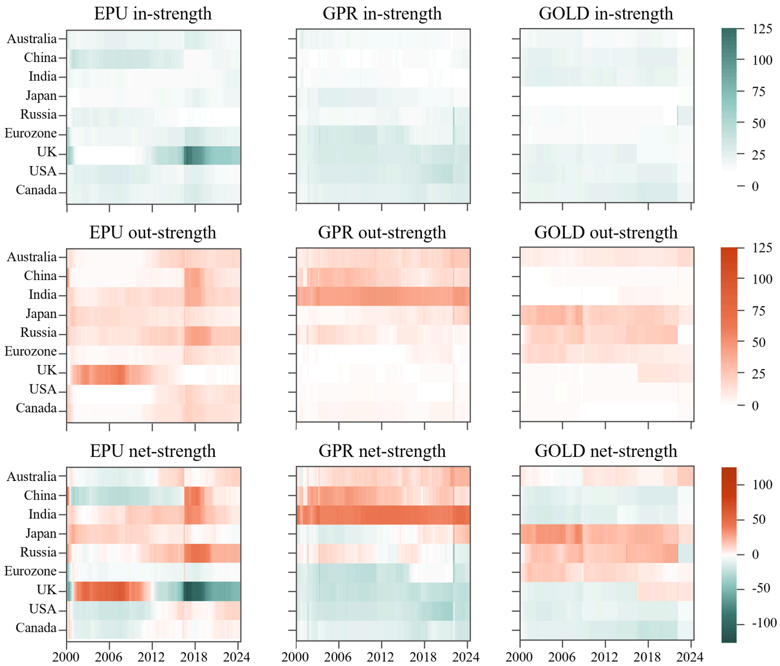

Figure 2. Dynamic spillover in, out and net-strength of 9 economies on 3 layers

As show in Figure 2, it is evident that events are a crucial factor beyond region. Regarding In-strength, similar to the static analysis, the Asia-Pacific region generally exhibits weaker In-strength over the entire period, while European and American countries are more significantly impacted. Notably, the UK experienced a significant increase in In-strength during the 2008 financial crisis and the 2016 Brexit referendum, indicating that it was most affected by the heightened global economic policy uncertainty during its related events. Additionally, in 2022, Russia and the Eurozone saw a sharp rise in In-strength in the GPR layer, reflecting the geopolitical impact of the Russia-Ukraine conflict. Following this event, Russia's gold volatility also showed a long-term increase, indicating lasting effects. Regarding Out-strength, prior to the 2008 financial crisis, the UK had the most significant global external influence. While after the crisis, particularly after 2016, emerging Asia-Pacific countries like China, India, and Russia began to exhibit more prominent influence. However, the GPR layer showed stronger country-specific characteristics, with the nature of GPR being more dependent on national attributes, similar to the characteristics observed in the GOLD layer.

Thus, in terms of Net-strength, economic uncertainty risks displayed more variability. Policy adjustments before and after 2008 and 2016 in developed regions and emerging markets caused significant shifts in the global landscape. However, in the geopolitical and gold layers, countries generally maintained consistent characteristics. The former saw greater influence from emerging countries, while the latter remained dominated by developed nations.

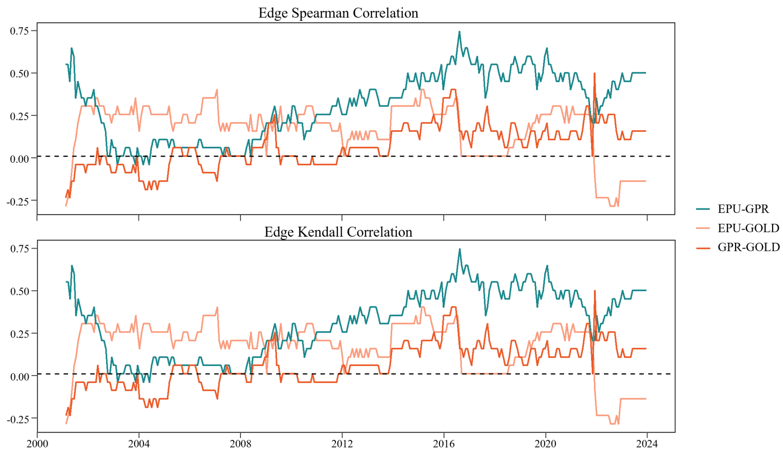

Figure 3. Dynamic Spearman and Kendall edge rank correlation

In the Spearman and Kendall rank correlations, the overall correlation is positive. The correlation between EPU and GPR significantly strengthened during the 2008 financial crisis, indicating a high level of interdependence between these two systemic during major events. In terms of their connection to the gold market, both EPU and GPR correlations surged during major events such as 9/11, the financial crisis, the European debt crisis, and the Russia-Ukraine conflict. Although the correlation between EPU and the GOLD layer was initially higher but sharply turned negative after the 2022 pandemic, the correlation between GPR and GOLD, while initially low, gradually increased after 2008.

Dynamic analysis reveals that the roles and influence of countries within the global network have changed significantly over time and with events. The Asia-Pacific region, particularly China and India, has transitioned from being receivers to becoming important transmitters in the global network as international events progressed. In contrast, European and American countries tend to balance their spillover effects during relatively stable periods. Inter-layer similarity analysis further highlights the close link between economic policy and geopolitical risks while also reflecting the independence of the gold market.

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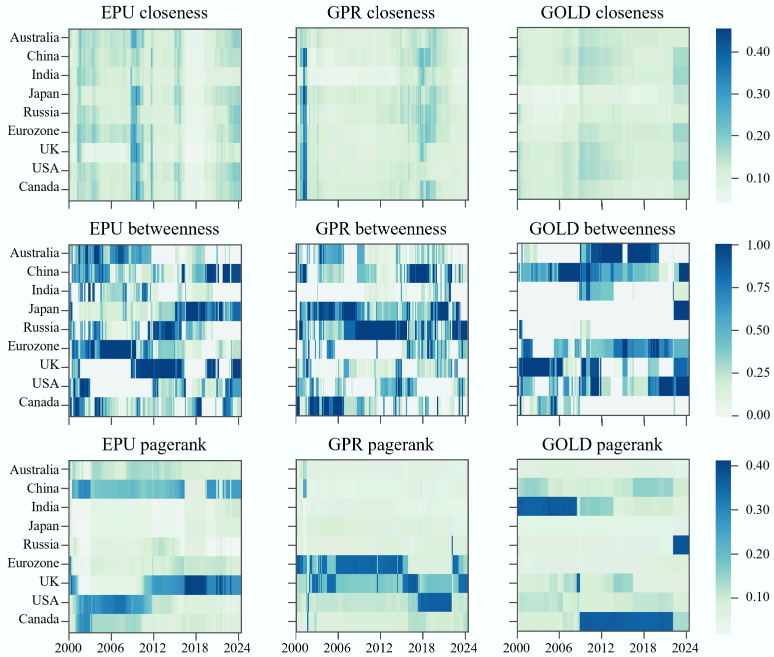

Figure 4. Dynamic closeness centrality, betweenness centrality, and PageRank centrality of 9 economies on 3 layers

In terms of closeness centrality, countries show significant increases in the EPU layer during the 2008 financial crisis, the 2016 Brexit, and the 2022 pandemic. While the GPR layer reacts strongly around the 9/11 attacks, its impact on the GOLD layer remains relatively stable except during the financial crisis. However, in betweenness centrality, after standardization, roles shift significantly with localized shocks. Overall, emerging Asia-Pacific countries act as intermediaries in systemic risks, while developed countries like Australia, the Eurozone, and the USA dominate in transmitting gold market volatility. Regarding PageRank influence, despite the UK's rising EPU influence post-Brexit and Russia's increased GOLD influence after the 2022 conflict, developed Western countries still primarily lead the market, with notable emerging country influence only in specific periods. The PageRank indicators for the UK and Eurozone in the GPR layer rose significantly during the 2008 financial crisis, indicating their increased importance in global geopolitical risk.

Inter-layer similarity shows that while there have been recent fluctuations, the PageRank similarity between two risk layers remains high, particularly the increase during the 2008 financial crisis, reflecting increased global interconnectedness. However, the similarity between the EPU, GPR and GOLD layers is low, indicating weak direct linkage between risks and gold market volatility.

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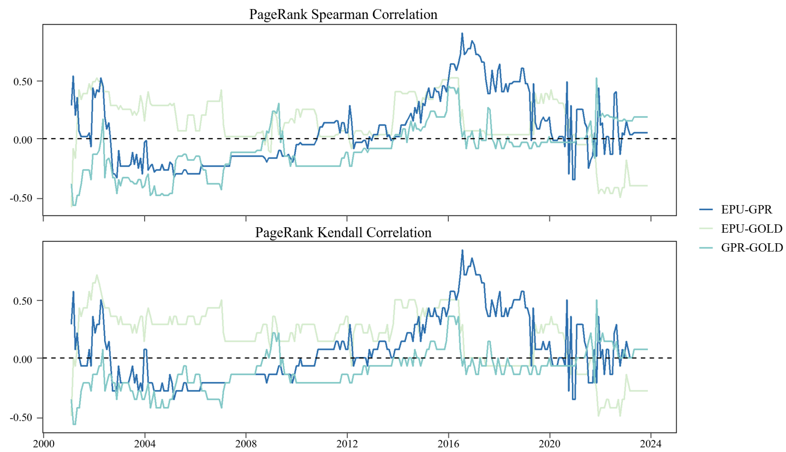

Figure 5. Dynamic Spearman and Kendall PageRank centrality rank correlation

5. Conclusion

To conduct a comprehensive and systematic inquiry into the interaction of economic and political un certainty risks and gold market volatility, this paper built a multiplex network model based on spillover effect. The full-sample and dynamic-sample analyses underscore the intricate interplay between economic policy uncertainty, geopolitical risk, and gold market volatility. Key economies exhibit distinct roles and responses, reflecting their strategic positions and adaptability during major global events. The UK and Eurozone show strong influence in EPU, while China and India are significant in GOLD. Emerging Asia-Pacific countries increasingly influence global networks, while developed Western countries dominate systemic risks and gold market volatility. Time-varying analysis reveals shifts in influence, particularly during major events like the 2008 financial crisis and 2022 Russia-Ukraine conflict. Inter-layer correlations indicate strong connections between economic and geopolitical risks but weaker ties to the gold market.

However, the proposed multilayer network analysis overlooks the inter-layer spillover effects, which could be further explored within an interdependent structure. Additionally, the mechanisms of the system are primarily discussed through topological features and correlations. Future research could extend this analysis to examine model resilience, percolation, and synchronization, drawing on similar methodologies used in medical research to provide a more comprehensive understanding of the system's dynamics and robustness.

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