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Multi-Layer Spillovers between Volatility and Skewness in International Stock Markets Over a Century of Data: The Role of Disaster Risks

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Abstract

Measuring risk lies at the core of the decision-making process of every financial market participant and monetary authority. However, the bulk of literature treats risk as a function of the second moment (volatility) of the return distribution, based on the implicit unrealistic assumption that asset return are normally distributed. In this paper, we depart from centred moments of distribution by examining risk spillovers involving robust estimates of second and third moments of model-implied distributions of stock returns derived from the quantile autoregressive distributed lag mixed-frequency data sampling (QADL-MIDAS) method. Using a century of data on the stock indices of the G7 and Switzerland over the period May 1917 to February 2023 and applying the multilayer approach to spillovers, we show the following. Firstly, the risk spillover among stock markets is significant within each layer (i.e. volatility and skewness) and across the two layers. Secondly, geopolitical risks have the power to shape both risk layer values, based on an out-of-sample forecasting exercise involving machine-learning methods. Interestingly, the multi-layer approach offers a comprehensive and nuanced view of how risk information is transmitted across major stock markets, while global measures of geopolitical risk affect risk spillovers at shorter horizons up to 6 months, while, at longer horizons, the forecasting exercise is dominated by market-specific characteristics.

Key words: Risk spillover; advanced stock markets; multi-layer spillover approach; machine learning; geopolitical risks; forecasting.

JEL Codes: C22, C32, C53, G15

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1. Introduction

As per its definition, skewness is a measurement of the distortion of symmetrical distribution or a measure of asymmetry in a data set. Therefore, skewness (in asset returns) can be quantified as a representation of the extent to which a given distribution deviates from the normal distribution (of financial market returns), and hence can act as a metric of evolution of unbalanced (relative to a baseline) future risks (Dew-Becker, 2022; Salgado et al., 2022; Sheng et al., 2023). Not surprisingly, a burgeoning literature, post the global financial crisis (GFC) of 2007-2009, aims to relate volatility, the traditional estimate of risk, in equity markets[1] with the skewness in returns (see for example, Byun and Kim (2013), Chang et al. (2013), Amaya et al. (2015), Seo and Kim (2015), Mei et al. (2017), Jian and Li (2021), and Zhang et al. (2021)). A key rationale is that under extreme shocks and the resulting deviation of stock returns form the Gaussian distribution, volatility is not a comprehensive measure of risk but should be complemented by an analysis of skewness (Bouri et al., 2021).

Theoretically, the effect of skewness on volatility can be explained by the so-called “leverage effect” (Black, 1976), whereby (extreme) negative or positive returns are generally associated with corresponding upward or downward revisions of volatility. This inverse association effect implies that firms become more leveraged as the ratio of their debt value over equity rises, which in turn increases the leverage of their capital structures. The increased leverage deteriorates the financial state of the companies and, hence, increases the systematic risk of common stocks.[2] A similar effect may arise even if the firm has almost no debt because of the presence of an “operating leverage” (fixed costs that cannot be eliminated, at least in the short run, hence when expected revenues fall, profit margins decline as well). Alternatively, skewness is known to reflect investor sentiment, whereby increase (decrease) of skewness can result in optimistic (pessimistic) sentiment and buying (selling) behaviour in equity markets and hence, lead to an increase of aggregate volatility (Seo and Kim, 2015). Finally, as recently indicated by Iseringhausen et al. (2023), large increases (decreases) in skewness may result in economic expansions (downturns), associated with low (high) volatility in the financial sector (Schwert, 1989).

[1] There are also studies that link skewness with volatility in commodity, (crypto)currency, and real estate markets (see, for example, Gkillas et al. (2019), Bouri et al. (2021, 2023), Bonato et al. (2022, forthcoming), and Gupta et al. (2023)).

[2] Christie (1982) provides a theoretical explanation of the leverage effect under a Modigliani and Miller (1958) economy.

While Black (1976) calls the negative impact of returns on volatility a “direct causation”, the author also defines the idea of “reverse causation”, according to which the causal relationship runs from volatility changes to (extreme) stock returns. Specifically, changes in tastes and technology lead to an increase in uncertainty about payoffs from investments. Because of the increase in expected future volatility, stock prices must fall, so that the expected return from investments in the stock market rises to induce investors to continue to hold stocks. In other words, it is likely that skewness and volatility impact each other (see, Bekaert and Wu (2000) and Aït-Sahalia et al. (2013) for detailed discussions regarding the possibility of the issue of reverse causation in general).

Against this backdrop, the objective of this paper is twofold. Firstly, it extracts higher-order measures of risk for the monthly stock indices of eight advanced economies, namely Canada, France, Germany, Italy, Japan, Switzerland, the United Kingdom (UK), and the United States (US) based on a century of historical data (May 1917-February 2023), using the quantile autoregressive distributed lag mixed-frequency data sampling (QADL-MIDAS) method. Secondly, it analyses the spillover of both volatility and skewness for the eight stock markets based on not only a single-layer spillover network but also the multi-layer approach of Wang et al. (2021), which can fully capture all possible information spillover effects between volatility and skewness.

As pointed out by Ghysels et al. (2018), the QADL-MIDAS model mixes low and high frequency data, outperforming standard autoregressive conditional heteroskedasticity (ARCH), generalized ARCH (GARCH) and quantile autoregressive (QAR) approaches in extracting risk measures. Note that, besides the availability of the longest possible samples of stock market data, which prevents possible sample selection bias, the choice of these mature equity markets is primarily motivated by their importance in the global economy, with these countries representing nearly two-thirds of global net wealth, and nearly half of world output, making risk analysis of these countries of pivotal importance from the perspective of the stability of the world financial system (Das et al., 2019; Salisu et al., 2023).

Before we point out the importance of conducting a multi-layer risk spillover analysis, we must outline the two primary channels via real linkages and information through which risk can be transmitted across economies (Debarsy et al., 2018; Ji et al., 2020). The former type arises from trade or financial relationships across countries. For example, if a country is facing economic turbulences, its supply and demand for international goods and services are likely to be reduced, implying negative impact its trading patterns. According to this channel, the propagation mechanism that leads local turmoils to diffuse to the whole system basically depends on pairwise physical connections between countries through trade linkages. As fa as the mechanism underlying the informational channel is concerned, it builds on the existence of imperfect information in financial markets. It further assumes that market participants can use the characteristics (such as debt structure or bureaucratic quality) of one country for extracting a signal on those that are considered similar. Accordingly, if a country is economically disrupted, international investors will reassess the risk attached to those countries sharing similar characteristics, which, in turn, would cause them to adjust their trading strategy, and an associated transmission of the risk from one economy to another.

Carrying out a spillover analysis for the eight stock markets not only within the boundaries of one risk measure, evidence of which is widely discussed in Diebold and Yilmaz (2009), BenSaïda (2019), and Choi and Yoon (2023), but also across the two measures of risk, based on a multi-layer approach, is motivated by recent evidence that a single-layer spillover network cannot fully capture all possible information spillover effects (Foglia et al., 2023). As pointed out by Wang et al. (2021) while proposing the econometric methodology of multi-strata connectedness, the complexity of the financial system makes spillover analyses based on a single-layer network involving multiple countries not an optimal choice, because a single measure of risk cannot capture the diversity and heterogeneity of information transmission and its interconnectedness among markets. Thus, it is necessary to use multilayer networks, which consider heterogeneous information and the multilayer structure of a complex system, to understand the interaction behaviour in global stock markets. Multilayer networks, where links in each layer represent different types of connections among the same set of nodes (the eight advanced equity markets in our case), can combine various interconnectedness measures together to describe complex financial systems effectively across alternative metrics of risk simultaneously. Accordingly, we use a model of multilayer information spillover networks as an extension of the original work based on a single-layer by Diebold and Yilmaz (2012, 2014), including a volatility spillover layer and skewness (extreme risk) spillover layer, to comprehensively investigate the interconnectedness of developed stock markets. Due to the importance of risk spillover analysis from the perspective of portfolio allocation and risk management (Ji et al., 2020; Iqbal et al., 2021; Gong et al., 2023) and evidence of the utility of considering spillovers of higher-order moments and co-moments in portfolio allocation and risk management (Nekhili and Bouri, 2023), this multi-layer approach should be of paramount importance to investors, allowing them to get a complete understanding of the interconnectedness of volatility and skewness across developed stock markets, realizing the feedback effect between these two measures of risk (Bouri, 2023).

Finally, while a multi-layer risk spillover analysis is a pertinent issue for portfolio managers, an equally important issue is understanding the underlying reasons for connectedness within and across layers, i.e., volatility and skewness. In this regard, we analyse the role of the news-based measure of adverse geopolitical events and associated risks, i.e., the geopolitical risk (GPR) indexes developed by Caldara and Iacoviello (2022), both at the global and country level, with the former further categorized into geopolitical risks resulting from threats and the realization of adverse geopolitical events.

Our decision to concentrate on the GPR indexes is due to widespread acceptance that entrepreneurs and market participants view geopolitical risk as a key determinant of investment decisions and stock market dynamics ahead of political and economic uncertainty (Salisu et al., 2021; NguyenHuu amd Örsal, 2023). Higher geopolitical risk is an indication of lower investment, higher disaster probability and larger downside risks in the future, as documented by Caldara and Iacoviello (2022). Naturally, GPRs receive considerable attention from businesses, becoming a regular fixture in the agendas of many financial companies, newspapers, and consultancy firms (see, for example, McKinsey (2016), Morgan (2019), Blackrock Investment Institute (2023), and The Economist (2022)), as such risks can seriously threaten the stability of the world financial system. The fact that the GPR indexes are available over our long data sample, makes this an obvious variable to apply within and across the layers of volatility and skewness, especially given the extensive theoretical literature on the role of disaster risks, for which the GPR serves as a high-frequency empirical proxy (see, Berkman et al. (2011, 2017) for a detailed discussion of measurement issues involving rare disaster events), explaining various financial market phenomena, such as the equity premium, extreme risks and stock market volatility (Barro, 2006; Gourio, 2012; Wachter, 2013). Since actual forecasts of alternative measures of connectedness attributed to GPR would be of value to investors making portfolio decisions, we conduct an out-of-sample forecasting exercise using machine learning methods, which allow us to accommodate a large number of predictors while accounting for nonlinearities in the described relationships between variables.

The contributions of our paper are manyfold, being the first of its kind to: (a) estimate robust metrics of risks using QADL-MIDAS models involving over a century of data, the longest available, on the evolution of returns of important stock markets thus controlling for possible sample-dependent bias arising from the choice of specific sample periods; (b) provide an analysis of multi-layer spillovers across volatility and skewness of eight major stock markets, rather than taking a single-stand approach as is traditional in the existing literature, thereby providing a more complete understanding of risk spillover across alternative metrics; and (c) evaluate the path of spillover measures using a forecasting exercise based on the information content of various proxies of geopolitical risk, i.e., global and local geopolitical events, which are well-established drivers of the variability of asset market movements, using machine learning methods, with the predictions likely to be an invaluable source of information for investors gauging the future risk profile of equity markets and hence assist in optimal portfolio allocation across stock markets.

The remainder of the paper is organized as follows: Section 2 discusses the data. Section 3 lays out the QADL-MIDAS and multi-layer connectedness models. Section 4 presents the results of the multi-layer connectedness analysis and the associated forecasting exercise in relation to the GPRs. Finally, Section 5 concludes.

2. Data

The log-returns of stock market indices used in this study cover an extensive period, spanning May 1917 to February 2023 at monthly frequency, encompassing over a century of financial history. This extended time-series dataset allows us to analyse and capture various historical events, including major financial and economic crises, obtained from Global Financial Data.[3] Notable events within the timeframe include the 1929 US financial crash, the 1973 OPEC oil crisis, the Asian crisis of 1997-1998, the global financial crisis of 2008, the 2009 European sovereign debt crisis, the COVID-19 pandemic of 2020, and the recent Russian-Ukrainian conflict. These extreme events significantly impacted financial markets, increasing market volatility and making the description of the risk transmission analysis a central research issue. The dataset consists of the market indices of eight advanced economies, which include the G7: Canada (CAN; S&P TSX 300 Composite Index), France (FR; CAC All-Tradable Index), Germany (GER; CDAX Composite Index), Italy (IT; Banca Commerciale Italiana Index), Japan (JP; Nikkei 225 Index), the United Kingdom (UK; FTSE All Share Index), the United States (US; S&P500 Index), plus Switzerland (SW; All Share Stock Index). As measures of

[3] https://globalfinancialdata.com/.

geopolitical risk we consider the popular local and global geopolitical political risk (GPR) indices of Caldara and Iacoviello (2022).

The geopolitical risk historical (GPRH) index is derived through an automated text-search of the electronic archives of three popular newspapers (the Chicago Tribune, the New York Times, and the Washington Post), while the global index is constructed according to sentiment extraction from publications of the eight following categories: war threats, peace threats, military buildups, nuclear threats, terror threats, beginning of war, escalation of war, and terror acts. Based on the search groups, Caldara and Iacoviello (2022) construct two subindexes: the geopolitical risk historical Threats (GPRHT) index, which includes words belonging to the first five categories above, and the geopolitical risk historical Acts (GPRHA) index, based on words in the sixth, seventh and eighth categories. Caldara and Iacoviello (2022) calculate the country-specific index by counting the monthly share of all newspaper articles that simultaneously meet the criteria for inclusion in the GPRH index, and mention the name of the country or its major cities. Note that the indices are calculated by counting the number of articles related to adverse geopolitical events in each newspaper for each month (as a share of the total number of news articles).[4]

In doing so, as indicated, in this study we extract higher-order measures of risk for the aforementioned stock indices based on the QADL-MIDAS method. Specifically, we estimate two measures of risk: the inter-quartile range (IQR) and skewness (SKEW). The IQR is a robust measure of volatility, i.e., uncertainty risk based on conditional quantiles, and pertains to information about the possible future range of the realized stock returns. All else being equal, as the IQR increases, extreme stock returns realizations are more likely to occur. The other metric of stock market risk (i.e. skewness) measures the (a)symmetry of the distribution of future realizations of stock returns. A robust asymmetry measure, SKEW is defined as the deviation of the upper- and lower-tail regression quantiles from the median, standardized by the IQR. We provide more details of the methodological approach used to estimate the two measures in the methodology section.

[4] The various global and country-level GPRH indices are downloaded from: https://www.matteoiacoviello.com/gpr.htm.

Table 1: Descriptive statistics				
	Mean (1)	Variance (2)	Jarque-Bera statistic (3)	ERS (4)
Canada	16.37	23.67	156.44***	-7.23***
France	22.72	37.12	29.48***	-7.02***
Germany	11.62	17.41	6799.45***	-10.71***
Italy	16.03	28.41	981.14***	-6.07***
Japan	20.59	39.71	95.63***	-6.11***
Switzerland	13.23	16.12	45.37***	-7.32***
UK	12.38	8.69	551.88***	-7.96***
US	15.36	17.96	888.05***	-7.72***
Canada	0.48	36.27	65988549.14***	-15.79***
France	0.31	7.92	23588447.91***	-15.86***
Germany	-1.71	47.29	81016514.04***	-15.77***
Italy	-0.22	4.05	22436380.43***	-15.55***
Japan	-0.37	18.56	14554193.38***	-16.07***
Switzerland	4.76	167.28	81236051.39***	-16.13***
UK	-0.35	8.65	8642052.51***	-15.45***
US	-0.38	5.06	20054821.44***	-15.49***

In Table 1, we report the summary statistics of our measures. France (the UK) has the highest (lowest) average values of IQR volatility, while Switzerland (Germany) has the largest (smallest) value of skewness. All series are non-Gaussian distributions, as indicated by the Jarque-Bera (J-B) statistic. Finally, the Elliott et al. (1996) test (ERS) suggests no evidence of a unit root, implying that the stationarity requirement of VAR modelling is satisfied.

3. Methodology

In this section, we discuss the multilayer network model used to investigate the interplay between the inter-quartile range (IQR) volatility and skewness (SKEW) and the datasets considered, by first presenting the QADL-MIDAS model used to obtain these two metrics of risk. We compute a multilayer network following the framework developed by Wang et al. (2022, 2023) based on the Diebold and Yilmaz (2012, 2014) approach.

3.1. QADL-MIDAS model

In order to extract stock market risk measures, we are interested in modelling the τ-th quantile of h-step ahead series ($i_{t+h}^{(h)}$) using the information at time t ($\mathcal{F}_t$). The conditional quantile τ of h-step ahead will be given by:

$$q_{\tau,t+h}(i_{t+h}^{(h)}) = \mathcal{F}_{t+h|t}^{-1}(i^{(h)}) \tag{1}$$

Starting from the typical QAR model, assuming a 1-step ahead prediction to simplify notation, the quantile dependent AR coefficients are given by the equation:

$$q_\tau(i_{t+1}|\mathcal{F}_t) = \mu_\tau + \rho_\tau i_t + \sum_{j=0}^{q-1} \beta_{\tau,j} \Delta i_{t-j} \tag{2}$$

where μ is the intercept, $\rho = \sum_{j=0}^{q} a_j$ captures stock index persistence, α represents coefficients form a simple AR model of the stock index, q is the number of lags of the model, β is the autoregressive coefficient to be estimated, and $\tau \in (0,1)$ is the quantile level. Extending the QAR model to h-step ahead forecasting, the horizon is *h* months while the information remains monthly. Thus, the model becomes:

$$q_\tau(i_{t+1}|\mathcal{F}_t) = \mu_\tau + \rho_\tau i_t + \beta_\tau Z_t(\theta_\tau) \tag{3}$$

$$\text{given} \quad Z_t(\theta_\tau) = \sum_{j=0}^{q-1} \omega_j(\theta_\tau) \left|\Delta i_{t-j}\right|, \quad \omega_j = \frac{(1-x_j)^\theta}{\sum_{j=0}^{q-1}(1-x_j)^\theta} \text{ and } x_j = \frac{i-1}{h-1}$$

In this specification, the model can avoid over-fitting using a large number of lags and is able to specify coefficients at any given sampling frequency (i.e. quarterly) while keeping sampling at the monthly frequency. After estimating the QADL-MIDAS coefficients, we extract model-implied risk measures, where IQR is simply the difference between the upper and lower-tail quantiles at the τ (= 0.10) level:

$$IQR_{t|t-h}^{\tau} = \hat{q}_{1-\tau,t|t-h} - \hat{q}_{\tau,t|t-h} \tag{4}$$

and skewness measures the asymmetry of the distribution of future realizations as the deviation of the upper and lower tail quantiles from the median, standardized by IQR. At the τ (= 0.10) level:

$$SKEW_{t|t-h}^{\tau} = \frac{(\hat{q}_{1-\tau,t|t-h} - \hat{q}_{0.50,t|t-h}) - (\hat{q}_{0.50,t|t-h} - \hat{q}_{\tau,t|t-h})}{\hat{q}_{1-\tau,t|t-h} - \hat{q}_{\tau,t|t-h}} \tag{5}$$

When the distribution is symmetric, the two distances are similar and skewness is zero, while when $\hat{q}_{1-\tau,t|t-h} - \hat{q}_{0.50,t|t-h}$ is larger (smaller) the distribution is skewed to the right (left). The standardization makes the measure unit-free and between -1 and 1.

3.2. Multi-layer connectedness

We now turn our attention to the methodological background of multi-layer connectedness in a step-by-step manner.

3.2.1. Spillover methodology

We apply the Diebold-Yilmaz (2012, 2014) model to calculate spillover of risk measures, which allows us to calculate the spillover indices for IQR volatility and skewness layers, respectively. The Diebold-Yilmaz model is based on the vector autoregression (VAR) model expressed as:

$$Y_t = \sum_{i=1}^{p} \Theta_i Y_{t-i} + \varepsilon_t \tag{6}$$

where, Y_t stands for an $N \times 1$ vector of endogenous variables t time, Θ_i are $N \times N$ coefficient matrices for each lag, p denotes the lag order, and finally $\varepsilon_t \sim (0, \Sigma)$ is an $N \times 1$ white noise vector. The VAR (p) model can be regarded as a moving average process, i.e., $Y_t = \sum_{j=0}^{\infty} \Psi_j \, \varepsilon_{t-j}$ where, Ψ_j is a an $N \times N$ coefficients matrix defined as $\Psi_j = \Theta_1 \Psi_{j-1} + \Theta_2 \Psi_{j-2} + \ldots + \Theta_k \Psi_{j-k}$ with Ψ_0 as an $N \times N$ identity matrix, and $\Psi_j = 0$ for $j < 0$.

Based on the generalized variance decomposition (GVD) framework (Koop et al., 1996; Pesaran and Shin, 1998), we calculate the contribution of each variable to the forecast error variance. Hence, we define the H-step ahead generalized forecast error variance as:

$$\theta_{ij}^{g}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} \left(e_i' B_h \Sigma e_j\right)^2}{\sum_{h=0}^{H-1} \left(e_i' B_h \Sigma B_h' e_i\right)} \tag{7}$$

where, Σ represents the $N \times N$ covariance matrix of the error vector ε, σ_{jj} shows the standard deviation of the error term, and e_i is an $N \times 1$ selection vector. Finally, we normalize each element of the H-step ahead matrix:

$$\tilde{\theta}_{ij}(H) = \frac{\theta_{ij}(H)}{\sum_{j=1}^{N} \theta_{ij}(H)} \tag{8}$$

3.2.2 Network measures

Furthermore, we consider multilayer information spillover networks, including the IQR volatility spillover layer and the SKEW spillover layer. Each layer is built on the variance decomposition obtained from the VAR approach to spillover developed by Diebold-Yilmaz (2012, 2014). The network measures can be divided into two macro areas: system-level measures and multilayer information spillover measures. In addition, these measures are calculated based on both static and dynamic perspectives. For the latter, we follow Balcilar and Usman (2021) and use a 60-month (5 year) rolling sample on 12-step horizons[5].

3.2.2.1. System-level measures from static and dynamic perspectives

We compute the system-level measures, namely the average connection strength (ACS), defined as:

$$ACS = \frac{1}{N}\sum_{i=1}^{N}\sum_{j=1,i\neq j}^{N}\tilde{\theta}_{ij}(H) \tag{9}$$

At the stock markets level, we calculate market strength *i* (IS) on the α layer, which is defined as the sum of the connection strength or weight of incoming edges from all other stock markets *j* to market *i,* and market strength *i* (OS) on the α layer, which is defined as the sum of the connection strength or weight of outgoing edges from stock market *i* to all other stock markets *j.* We also consider the net financial market *i* strength (NS) on the α layer, defined as the difference between the external and positive strength of stock markets *i*. Mathematically, we have:

a. *IS* ($C_{i\leftarrow j}$) measures the influence from other markets j to market i:

$$C_{i\leftarrow j}(H) = \sum_{ij=1,i\neq j}^{N}\tilde{\theta}_{ij}(H) \tag{10}$$

b. *OS* ($C_{i\rightarrow j}$) measures the influence from market i to other markets j:

[5] We assess the robustness of our findings by conducting the analysis with various alternatives for the rolling estimation window and forecast horizon steps. This includes both increasing and decreasing both configuration settings and exploring changes of up to 50% from our fixed choices. Additionally, instead of the IQR volatility, we use the volatility measure derived from the GARCH model. The results indicate a consistency in the qualitative outcomes, reaffirming the robustness of our findings to the choice of the volatility proxy. Detailed results are available from the authors upon request, though we report the GARCH-based findings in Figure A1 in the Appendix, giving a snapshot of the multilayer network.

$$C_{i\rightarrow j}(H) = \sum_{ij=1,i\neq j}^{N} \tilde{\theta}_{ji}\,(H) \tag{11}$$

c. *NS* measures the net risk spillovers for market i, which is the difference between *Out-strength* and *In-strength* as follows:

$$NS_i(H) = C_{i\rightarrow j}(H) - C_{i\leftarrow j}(H) \tag{12}$$

3.2.2.2 Multilayer information spillover network measurements

We compute the average edge overlap (O), a metric that quantifies the average number of edges present among all pairs of nodes within the M layers (in our case, M = 2). When the edge structures across the M layers are identical, the average edge overlap equals M. On the other hand, if each edge is exclusive to just one layer, the value of the average edge overlap is 1. This metric serves to gauge the degree of similarity between the edge structures of each layer within a multiplex network, effectively capturing how these layers intersect with one another. Given that our network comprises two layers (M = 2), the overlap index spans from 1 to 2. Values close to 2 indicate that the stock markets are similarly connected, while values of 1 mean that each edge only exists on one layer. The overlap index is given by:

$$O = \frac{1}{K}\sum_{i=1}^{N}\sum_{j=1,i\neq j}^{N}\sum_{\alpha=1}^{M} a_{ij}^{[\alpha]} \tag{13}$$

where $a_{ij}^{[\alpha]} = \sin(g\,(\tilde{\theta}_{ij}))$, and k is the number of edges for layers.

Furthermore, we measure the importance of nodes in multilayer networks, by computing the average overlapping strength as a basic topological indicator based on the market strength (IS), market strength (OS), and net market strength (NS) of each layer as follows:

$$O_{IN,i} \;=\; \frac{1}{M}\sum_{\lambda=1}^{M} IS_i^{\lambda} \tag{14}$$

$$O_{OS,i} \;=\; \frac{1}{M}\sum_{\lambda=1}^{M} OS_i^{\lambda} \tag{15}$$

$$O_{NET,i} = O_{OS,i} - O_{IN,i} \tag{16}$$

In order to measure the distribution of the nodes in each layer, we compute the multiplex participation coefficient as follows:

$$P_i = \frac{L}{L-1}\left[1 - \sum_{\alpha=1}^{L}\left(\frac{k_i^{[\alpha]}}{o_i}\right)^2\right] \tag{17}$$

where $k_i^{[\alpha]}$ is the degree of node i on layer α. The multiplex participation coefficient is a valuable metric that characterizes a node's centrality across different layers within a network. It quantifies the extent to which a node acts as a hub within one layer compared to the other layers. This coefficient is a critical indicator of the distribution of connections between the node and other nodes across various layers. A multiplex participation coefficient varies from 0 to 1, each representing different characteristics of the node's interactions. When this coefficient equals 0, the node's connections are concentrated solely within one layer, meaning it plays a significant role in one layer while having minimal interactions in the others. Conversely, when the multiplex participation coefficient equals 1, it suggests that the node's connections are evenly distributed across multiple layers, making it a well-connected hub with similar importance in each layer. In this case, the node's influence is spread uniformly across the network's different layer. In practical terms, the magnitude of the multiplex participation coefficient indicates the degree of uniformity in a node's direct connections across network layers. A higher coefficient implies that the node's influence is more evenly spread across the layers, resulting in a more uniform impact on the network. This may manifest as a node (e.g., a stock market) having varying levels of prominence, serving as a hub in one layer while acting as a peripheral node in another.

After establishing the system's level of connectedness, we proceed to explore the structural similarity between two pairs of layers. To this end, following Musmeci et al. (2017), we apply Spearman's rank correlation between layers α and β, as:

$$\rho^{[\alpha,\beta]} = 1 - \frac{6\sum_i\left(R_i^{[\alpha]} - R_i^{[\beta]}\right)^2}{N(N^2-1)} \tag{18}$$

where N denotes the number of stock markets, in our case 8 (G7+W); while $R_i^{[\alpha]}$ and $R_i^{[\beta]}$ are the degree rankings of market i on layers α and β, respectively.

Finally, following Wang et al. (2023), we compute the spillover between the two types of risk (IQR and skewness) using the block aggregation methodology developed by Greenwood-Ninno et al. (2021). This so-called block aggregation spillover index allows us to quantify the spillovers between the two layers. It is represented as follows:

$$S_{i\leftarrow j}(H) = \frac{1}{d}\sum_{i=1}^{d} G_{\leftarrow j}\,(H) = \frac{1}{d}\sum_{i=1}^{d}\sum_{ij=1,i\neq j}^{d} \tilde{\theta}_{ij}\,(H) \tag{19}$$

By definition, $S_{i\leftarrow j}(H) + S_{i\leftarrow i}(H) = 1$. Accordingly, we define the cross-market connectedness matrix as follows:

$$\begin{bmatrix} \Theta^{g}_{IQR\rightarrow \mathrm{IQR}} & \Theta^{g}_{\mathrm{SKEW}\rightarrow IQR} \\ \Theta^{g}_{IQR\rightarrow \mathrm{SKEW}} & \Theta^{g}_{\mathrm{SKEW}\rightarrow \mathrm{SKEW}} \end{bmatrix} \tag{20}$$

where $\Theta^{g}_{IQR\rightarrow \mathrm{SKEW}}$ and $\Theta^{g}_{\mathrm{SKEW}\rightarrow IQR}$ are the total cross-risk spillover from the IQR layer to the SKEW layer and from the SKEW layer to the IQR layer, respectively.

4. Empirical Findings

4.1 Static global analysis

In order to investigate the topological features of the two layers, in Panel A of Table 2 we report the estimates of the topological measures (*ACS* and *O*) of the two layers of multilayer information spillover. *ACS* is the average connection strength across the stock market indices of the 8 countries and *O* is the average edge overlap of the multilayer information spillover networks.

Table 2: Network metrics

Panel A: Average connection strength and overlap index		
Layer	ACS	O
IQR spillover layer	55.3	1.4
Skew spillover layer	14.17	
Panel B: Correlation between layers		
Layer-Layer	Spearman Rank correlation	
IQR layer and SKEW layer	-0.264**	
Panel C: Cross-spillover layer		
Layer	IQR spillover layer	Skew spillover layer
IQR spillover layer	91	9
Skew spillover layer	13	87

Note: ACS (average connection strength); O (overlap index); IQR (inter-quartile range). ** denotes statistical significance at the 5% significance level.

From the single layer perspective, the ACS measure indicates that the level of IQR connectedness in the IQR layer is much higher than that in the skewness layers. This implies that the G7+SW stock markets are more strongly interconnected via their IQR volatility than via their higher-order moment (i.e., skewness). Therefore, there are less significant ties between markets when low-probability events occur. These findings are perfectly in line with the literature (Bouri et al. 2021; Bouri et al., 2023), which finds a higher level of volatility spillover compared to the skewness spillovers.

From a multilayer network perspective, the *O* measure shows that, on average, half of the edges in each layer also exist in the other layer. Thus, the directional spillover between any two countries on each layer almost always exists on the other. This finding suggests that the two different moments capture somewhat distinct aspects of risk, but at the same time risks affect each other. In this regard, we report the Spearman rank measures based on PageRank centralities (Panel B, Table 2) and show a relatively low but negative rank correlation between the two layers. This means that a stock market can take a hub role in a given IQR layer and may only be a peripheral node on skew layer, highlighting the somewhat distinct roles played by these layers.

In Panel C of Table 2 we present the spillover aggregation matrix, which provides valuable insight into the magnitude of risk spillovers in the context of cross-spillover analysis. We employ Greenwood's methodology to dissect the risk emanating from the IQR and skewness layers, differentiating between within-layer and cross-layer risk spillovers. Finally, we evaluate the proportion of these spillovers to the overall risk. Recall that the within-layer risk spillovers refer to the transmission of risk within the same layer. In our case, this means that risk within the IQR layer tends to propagate primarily to other nodes (countries) within the same IQR layer, while risk within the skewness layer mostly remains confined to the skewness layer. This within-layer risk transmission is notably more significant (91 for the IQR layer and 87 for the skewness layer), as shown in Panel C of Table 2. On the other hand, the cross-layer risk spillovers indicate risk transmission between the IQR and skewness layers. This cross-layer risk transmission is represented in the non-diagonal elements of the matrix. This can be compared to Bouri (2023) who examines spillovers in the joint system of higher-order moments for green energy, brown energy, and technology stocks, reporting evidence of significant interactions between volatility and skewness. We note that these cross-layer spillovers are less intensive than within-layer spillovers. The dominance of within-layer risk spillovers suggests that risk transmission within each layer significantly influences the overall risk dynamics. In contrast, across-layer spillovers play a comparatively smaller role in the broader context of spillover effects. This empirical result points to the importance of understanding and managing risks within specific layers to effectively mitigate their impact on the overall risk.

4.1.1. Static analysis at the country level

To investigate the role of each stock market within the multilayer network, we evaluate several network measures. To understand the difference between the out-strength of financial markets across two layers, Table 3 lists the OSs of the countries on two layers. As we observe, the US market plays a dominant role in out-strength spillover. Indeed, it stands out as the preeminent stock market in both layers, securing the top position in terms of out-strength spillover, meaning that the US stock market exhibits the highest propensity to disseminate risk to other markets in both the IQR and skewness layers. These results affirm the influential role of the US financial market in shaping global risk dynamics (Ji et al. 2020; Iqbal et al., 2021; Smales, 2022; Gong et al., 2023). Notably, some markets, such as Canada and France, maintain a consistent position across both layers. Specifically, they hold the same ranks in both the IQR and skewness layers, suggesting that they exhibit a similar role in risk transmission within both layers, albeit with varying degrees of influence. Japan occupies the 7th position in the skewness layer and the 8th position in the IQR layer, indicating its modest impact on risk transmission compared to other countries, regardless of the layer considered.

Table 3: Out-strength of countries

Rank	Out-strength			
	Stock market	IQR layer	Stock market	SKEW layer
1	US	0.637	US	0.499
2	SW	0.613	IT	0.249
3	UK	0.524	GER	0.133
4	CAN	0.375	CAN	0.119
5	IT	0.298	UK	0.012
6	FR	0.290	FR	0.008
7	GER	0.160	JP	0.002
8	JP	0.115	SW	0.001

In Figure 1, we present the evolving multiplex information spillover network over time. Within each layer, there are eight nodes, representing the G7+SW stocks markets. Directed edges are used to illustrate the flow of risk spillovers from one market (the emitter) to another (the recipient), and the thickness of each edge reflects the strength of the spillover between them. As we observe, the IQR layer exhibits a denser and more closely interconnected network in comparison to the SKEW layer. This reflects the differences in risk transmission dynamics between layers.

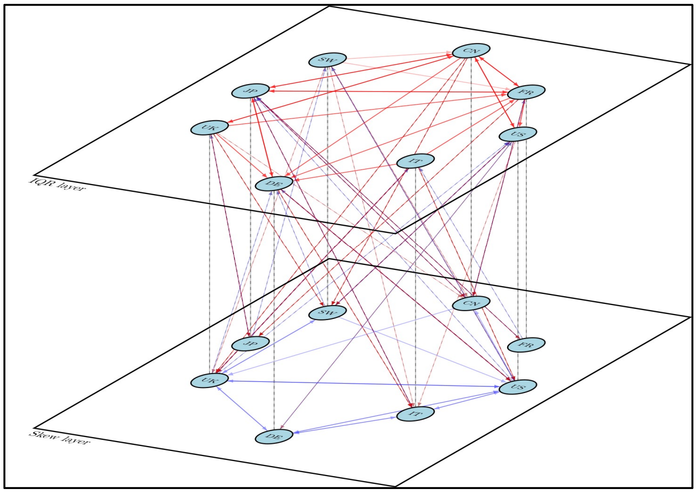


Figure 1: Snapshot of multilayer network over time

To gain a more comprehensive insight into the market interrelationships within the volatility spillover multiplex network, it is crucial to analyse market behaviour from a holistic viewpoint. For this purpose, in Table 4, we rank the eight markets by their average overlapping out-strength, average overlapping in-strength, and overlapping net-strength. The US is again the market with the largest magnitude of overlapping out-strength, reflecting its dominant role as a transmitter of variance spillovers to the other stocks markets. Meanwhile, Canada has the highest level of overlapping in-strength among the sample markets, as it mainly absorbs variance spillovers from other countries. The US has the highest overlapping net-strength, followed by Switzerland, Italy and the UK.

Table 4: Average overlapping strength

Rank	Average overlapping strength per financial market		
	Out-strength	In-strength	Net-strength
1	US	CAN	US
2	SW	FR	SW
3	UK	UK	IT
4	CAN	SW	UK
5	IT	US	JP
6	FR	GER	GER
7	GER	IT	FR
8	JP	JP	CAN

Overall, the static overview provides a description of market behaviours interconnections, and the role of stock markets within the multilayer information spillover network. The findings emphasize the dominance of IQR spillovers, the interconnectedness of the two layers, and the influence of specific markets, such as the US market, on global risk dynamics. Understanding these dynamics is crucial for effective risk management and policy decisions in the context of financial markets.

4.2. Dynamic analysis at the global level

To gain more insight into the evolution of network connections across time, Figure 2 depicts the time-varying ACS of the IQR spillover layer (solid red line) and skewness spillover layer (solid blue line) over the entire sample period 1922–2023, covering 100 years of history.

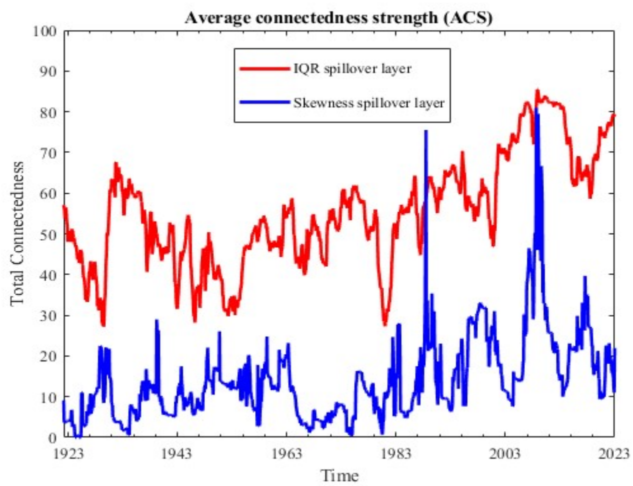


Figure 2: Dynamic evolution of ACS over time

Several key observations can be made. Firstly, the significantly higher levels of ACS in the IQR layer indicate a larger degree of connectivity among G7+SW markets regarding volatility risk. In contrast, the SKEW layer exhibits lower levels of connectedness, suggesting that the stock markets are less intertwined during low-probability events. The varying levels of connectedness in these two layers signify that stock markets respond differently to different types of risk (see Bouri et al., 2023). Secondly, we can identify several phases of connection expansion. The measures identify six significant phases of connection expansion: i) the 1929 crisis, ii) the 1973 OPEC oil crisis, iii) the Asian crisis of 1997-1998, iv) the GFC of 2008, v) the European debt crisis, and vi) the COVID-19 health crisis. Throughout these phases, the IQR layer consistently exhibits larger connections than the SKEW layer, signifying that G7+SW stock markets are more interconnected via volatility risk compared to low-probability event risks. However, we observe that the skewness spillover layer captures changes in market risk associated with events that the IQR layer does not, for example, the early 1980s recession, Black Monday (1987), the early 1990s recession and the 1998–2002 Argentine great depression. These results further indicate the strong relationships among stock markets during crisis events.

Overall, the dynamics of interconnectedness of risk indicators across G7+SW stock markets, particularly during major crisis events, align with the existing literature (Do et al., 2016; Finta and Aboura, 2021; Bouri et al., 2021). The spillover indices associated with these two risk measures are useful for monitoring and understanding changes in risk dynamics under various market conditions. While the spillover effect in the IQR volatility layer is informative and crucial, it is not enough and thus should be examined in association with the spillover effects in the higher-order moment of skewness, which seems to play a significant role in detecting critical events that may not be fully captured by the volatility measure alone (see, among others, Bouri et al., 2021, 2023).

To evaluate similar phenomena that are not captured exclusively by volatility measures, we compute the average edge overlap and the cross-layer spillover index. Starting with the dynamic average edge overlap index within the multilayer information spillover network, as illustrated in Figure 3, the index exhibits variations, ranging from a minimum value of 1 to a maximum of 1.77, with a mean value of approximately 1.4. This suggests that the edges within the multilayer information spillover network are more likely to be present across multiple layers than to be confined to individual layers. An interesting observation pertains to the index's behaviour in different market conditions. The increasing index during financial turmoil, notably the GFC of 2008, reflects a higher degree of overlap and interaction among the layers, emphasizing the dynamic nature of information transmission within the multilayer framework. In contrast, during market stability, the index tends to decrease, indicating a reduced overlap and interaction among the layers. This pattern of behaviour aligns with the overall connectedness of the network.

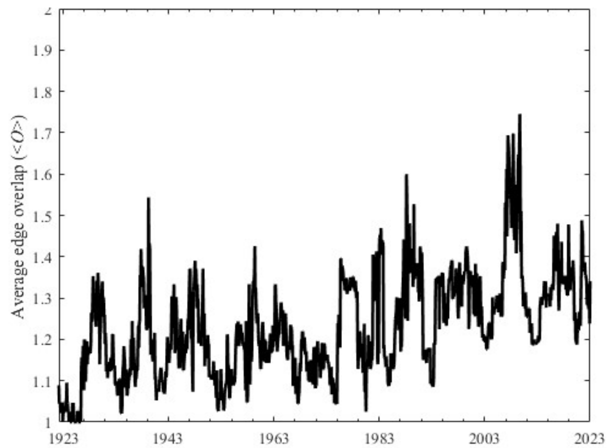
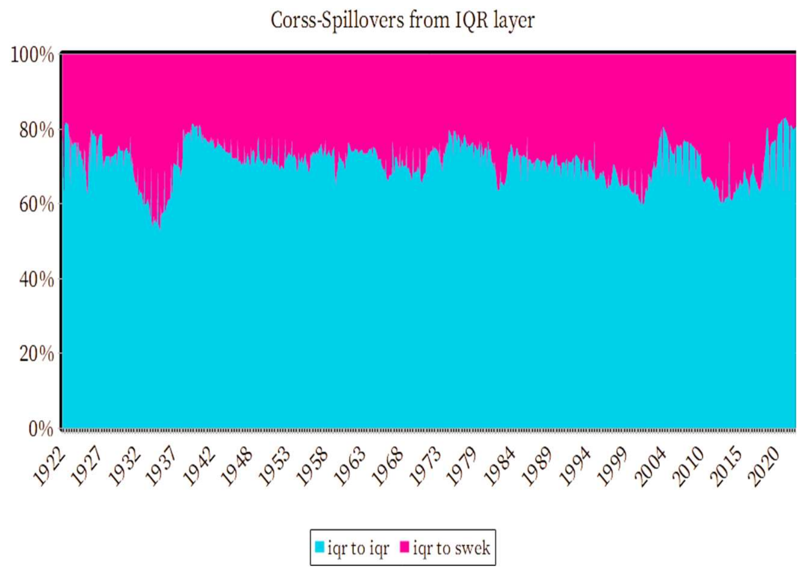


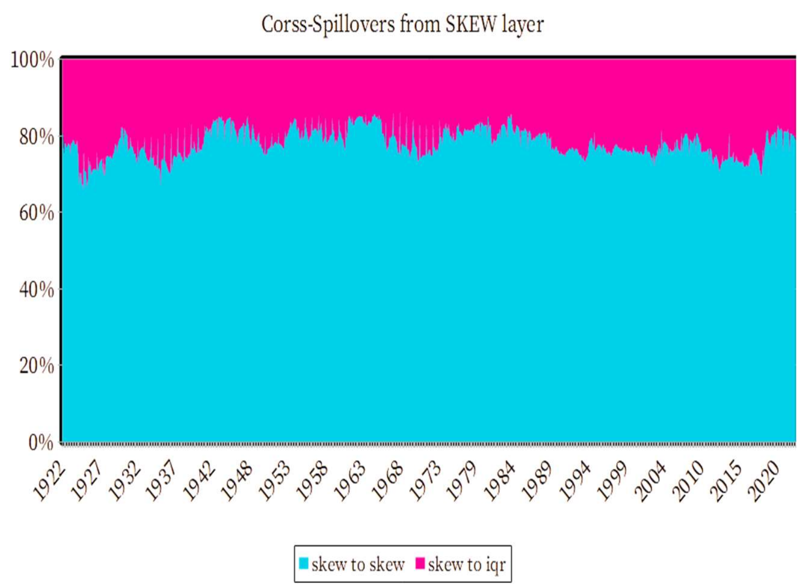
Figure 3: Overlap index

Focusing on the within-spillover and the cross-spillover between the layers, Figure 4 provides valuable insights into how risk propagates within distinct measures. Within-market spillovers pertain to risk transmission within a specific layer, IQR or skewness. As revealed in Figure 4, within-market spillovers dominate in magnitude compared to cross-market spillovers. In simpler terms, most risk is disseminated within the same layer, with relatively less transfer between the layers.

Cross-market spillovers, on the other hand, involve the transmission of spillover between layers. To provide specific figures, on average, the IQR layer transmits approximately 24% of its spillovers into the skewness layer. In contrast, the skewness layer transmits a lower level of risk to the IQR layer, averaging around 20%. This discrepancy underscores the distinct risk profiles inherent in each of these measures. While these spillovers are less pronounced when compared to within-market spillovers, they exhibit dynamic patterns over time. The results indicate that the intensity of cross-market spillovers experiences fluctuations in response to evolving global economic events and financial crises. A significant observation is the changing nature of risk transmission during specific periods. This phenomenon, characterized by heightened cross-market and within-market spillovers, is closely linked to extreme events within the analysed timeframe. Notable examples include the Great Depression (1929-1939) and the GFC of 2006-2010, which exposed vulnerabilities within global financial markets. These events prompt an increased flow of risk from the skewness layer to the IQR layer, marking shifts in the interconnectedness of risk transmission paths during periods of exceptional economic and financial stress.

Under extreme events, and possibly large deviations of stock returns from the Gaussian distribution, volatility as a measure of risk becomes partial and suboptimal, suggesting the relevance of considering a higher-order moment such as skewness in spillover analyses (Bouri, 2023)[6]. In fact, our detection of significant spillover effects between the volatility layer and the skewness layer is new to the literature on the interconnectedness across international stock markets (Finta and Aboura, 2020; Jian and Li, 2021), providing a more comprehensive view of the level of systemic risk in the G7+SW stock market indices.





[6] Bouri (2023) recently highlights significant interactions across the higher-order moments of green and brown energy and technology stocks relying on a VAR-based spillover framework, in the joint system of higher-order moments.

Figure 4: Dynamics of cross-spillover measures

Our findings provide compelling evidence that each layer within the multilayer information spillover network contributes complementarily to the risk spillover analysis across the system of G7+SW stock markets. Therefore, neglecting any one layer would result in an incomplete understanding of information transmission dynamics. In essence, the multilayer approach offers a more comprehensive and nuanced view of how information flows across major stock markets, highlighting the necessity of considering both layers to gain a more accurate and robust insight into the intricate interplay of information transmission paths across advanced stock market indices.

4.2.1. Dynamic analysis at the country level

We expand the dynamic analysis of variance information spillovers to each stock market. The heatmaps shown in Figure 5 illustrate the time-varying aspects of overlapping in-strength, overlapping out-strength, and overlapping net-strength for each market individually. Darker colours signify higher spillover strengths. Canada appears to consistently exhibit the highest level of overlapping in-strength, followed closely by France and Germany. This suggests that these stock markets are more inclined to absorb external risk spillovers from other stock markets. This observation aligns with the notion that some markets might serve as “shock absorbers” by actively receiving risk from other markets, which reflects their high sensitivity and responsiveness to shocks arising from other influential markets. In contrast, the US exhibits notably higher overlapping out-strength, which is consistent with the US’s pivotal role in influencing risk levels worldwide due to its centrality within the global financial system (see, e.g., Finta and Aboura, 2020; Ji et al., 2020; Gong et al., 2023). The US accounts for around 11% of global trade and constitutes the top destination for foreign direct investment (FDI) inflows worldwide[7].

The overlapping net-strength provides an overview of the dynamic behaviours of variance information spillovers. In this plot, red represents a positive value, reflecting the emission of spillover shocks, while blue represents a negative value, reflecting the absorption of shocks. Our analysis corroborates the findings from the static analysis, emphasizing that financial

[7] See: https://blogs.worldbank.org/developmenttalk/us-post-crisis-trade-weakness-4-charts and https://www.oecd.org/investment/statistics.htm.

markets in Switzerland, the UK, Japan, and the US predominantly serve as major emitters of variance shocks, while other countries function as recipients of variance shocks.

The analysis of systemic shocks over time, represented by vertically aligned darker colour bars in the heatmap, gives important insight into the evolution of systemic risk across advanced economies. These observations underscore the interconnectedness of stock markets and the varying triggers of systemic shocks throughout history. In the analysis, the systemic shock related to the 1929 crisis stands out prominently. This major event corresponds to the Great Depression, which had devastating consequences at a global scale. The heatmap demonstrates that major economies such as Canada, the US and the UK played significant roles in transmitting risk shocks during this crisis. The heatmap also indicates a systemic shock from the early 1980s to the 1990s recession. This recession, characterized by global economic challenges, had a discernible impact on various advanced economies. Moreover, the heatmap reveals a substantial systemic shock during the GFC of 2008, which was marked by the collapse of major financial institutions, plummeting stock market indices, intensifying stock market volatility, and a severe credit crunch. The systemic shock associated with the GFC is represented by dark bars spanning multiple countries, reflecting how interconnected and interdependent global financial markets had become by that time due to globalization and technological advancements that ease transnational flows of information, goods and capital. Finally, the COVID-19 pandemic represents another systemic shock visible in the sample analysis. It is evident that virtually all countries experienced this shock (Abuzayed et al., 2021), as indicated by the dark bars extending across the heatmap. The pandemic resulted in a global economic recession, supply chain disruption and considerable market uncertainty. The fact that it affected nearly all economies reaffirms the systemic nature of this particular global health crisis.

These findings show that systemic shocks have historically been triggered by major economic events, recessions, financial crises and health crises. They underscore the fact that the global financial system is highly interconnected, and shocks in one part of the world can rapidly propagate to affect markets globally. The presence of dark bars in the heatmaps during these events and crises signifies the synchronous impact on multiple economies, with various countries acting as both spillover emitters and recipients.

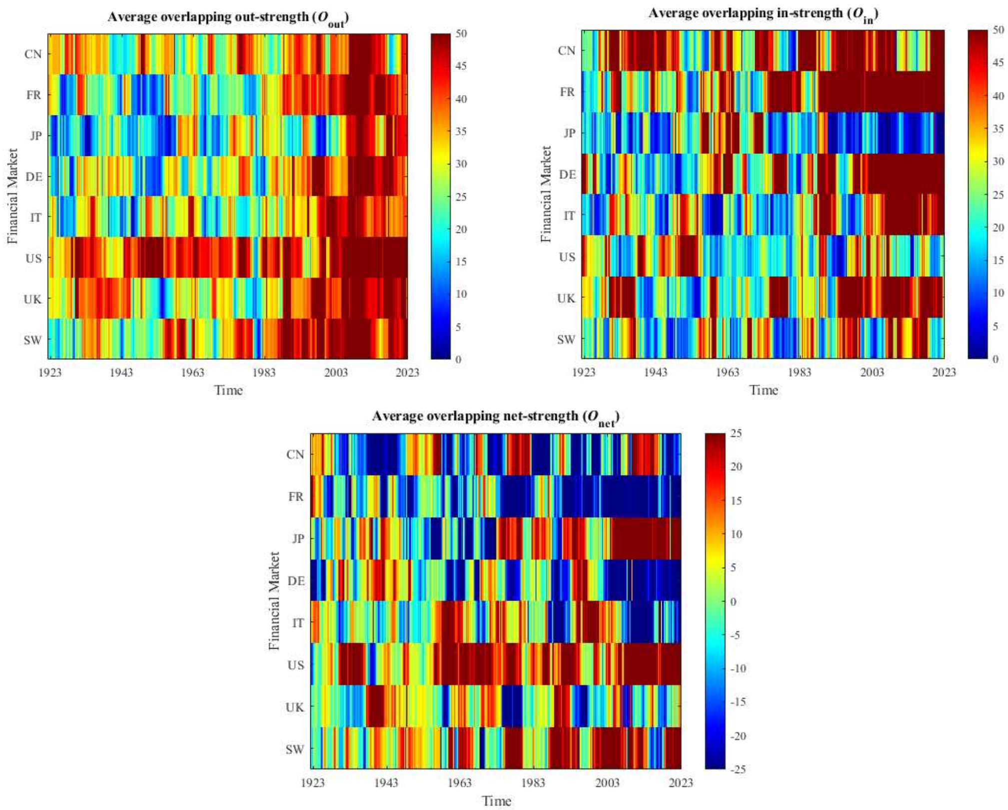


Figure 5: Country dynamics of overlapping indexes

The dynamic analysis of out-strength (P_{OUT}) and in-strength (P_{IN}) participation coefficients trains a powerful lens on the features of risk spillovers within global stock markets. The coefficients are invaluable for understanding how risk transmission behaviours differ among layers and individual markets. As Figure 6 illustrates, the P_{OUT} and P_{IN} coefficients range from 0 to 1, revealing important information about the distribution of spillover strengths within the layers. When these coefficients converge to 0, it indicates that a stock market's spillover strength is predominantly concentrated in one of the two layers. On the other hand, when P_{OUT} and P_{IN} approach 1, it suggests that the market spillover strength is more uniformly distributed across the layers.

The average distribution of in-strength coefficients across the two layers indicates that stock markets are generally influenced by similar spillover sources in different layers. This homogeneity is more evident during stable periods. However, the dynamic analysis reveals interesting market behaviours. Over the past 40 years, the risk distribution between the two layers has been less evenly balanced, with coefficients consistently less than one. This suggests that spillover behaviours have evolved over time and are not uniform between the layers, and this disparity persists over time. Particularly, the dynamic behaviour of the US in terms of risk spillover is noted. Only during periods of high financial stress is the risk spillover emitted by the US distributed more evenly across the two layers. This indicates that during crisis periods or elevated systemic risk the US's impact becomes more pronounced and widely distributed. This disparity in spillover activity between the IQR and skewness layers for the US highlights its ability to influence various aspects of risk in the global financial system. Observing non-uniform spillover strength in various periods, especially during financial stress, underscores the complexity of market risk dynamics.

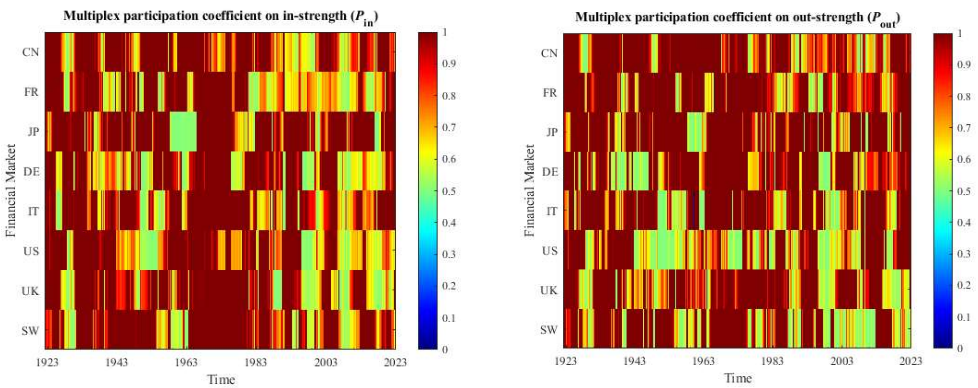


Figure 6: Country dynamics of multiplex participation coefficient

4.3 Forecasting spillover indices

The spillover analysis reveals a significant degree of within-layer risk spillover but a relatively lower degree in the across-layer spillover, with the US market exhibiting a predominant role in the risk transmission in both cases. Nevertheless, the spillover analysis is silent regarding the role of exogenous factors, notably disaster risks, in shaping the various risk spillovers considered. Thus, we evaluate the forecasting power of geopolitical risk (as an empirical proxy of disaster risk) for the risk spillovers across several forecast horizons. Specifically, the dependent variable is the total connectedness index of each of the IQR and SKEW layers (see Figure 2), and the within-layer spillover index and the cross-layer spillover index for each of the IQR and the SKEW layers (see Figures 4). As possible predictors, we evaluate three distinct sets of variables: a) the global GPRH index of Caldara and Iacoviello (2022) along with the respective country-specific GPR indices of our sample; b) the two components of GPR that account for terrorist acts (GPRHA) and terrorist threats (GPRHT) along with the country specific indices;[8] and c) the categories of words used to construct the weighted global GPR index and the eight individual country indices.

Our forecasting exercise evaluates the forecasting performance of an autoregressive integrated moving average (ARIMA), random forest (RF), artificial neural network (ANN), support vector regression (SVR) and XGBoost model,[9] the last of which is an ensemble of decision trees based on the boosted approach. In order to account for possible structural breaks in the series, we train all models on a rolling-window approach where 120 observations (5 years) are used for training the model parameters, which are evaluated using 1, 3, 6, 12 and 24-month ahead forecasting. A 1-month sliding window is used, while all models are trained based on a cross-validation scheme to avoid overfitting in their respective windows.

Table 5: Total connectedness forecasts for the IQR layer

Horizon(months)	RW	ARIMA	RF	ANN	SVR	XGBoost
Panel A: Global GPR and country GPR indices						
1	6.787	0.237	1.457	1.751	1.699	2.600
3	6.784	0.471	1.482	1.756	1.765	2.630
6	6.788	0.882	1.528	1.970	1.845	2.658
12	6.792	1.496	1.511	1.869	1.716	2.755
24	6.785	2.532	1.640	1.959	1.887	2.486
Panel B: GPRHT, GPRHA and country GPR indices						
1	6.787	**0.224**	1.382	1.533	1.602	2.727
3	6.784	**0.465**	1.412	1.655	1.570	2.583
6	6.788	**0.856**	1.449	1.879	1.641	2.673
12	6.792	1.478	1.421	1.608	1.546	2.502
24	6.785	2.417	1.552	1.971	1.817	2.730
Panel C: Individual for each category and country specific GPR indices						
1	6.787	0.303	1.230	1.534	1.397	2.410
3	6.784	0.512	1.218	1.496	1.312	2.406
6	6.788	0.901	1.237	1.491	1.410	2.622
12	6.792	12.217	**1.238**	1.663	1.313	2.668
24	6.785	18.393	**1.227**	1.575	1.376	2.467

Note: This table shows the average out-of-sample root mean square error (RMSE) across five horizons (1, 3, 6, 12, and 24 months). The models considered are a random walk (RW), an autoregressive integrated moving average (ARIMA), random forest (RF), an artificial neural network (ANN), a support vector regression (SVR) and an extreme gradient boosting (XGBoost) model. Apart from the global index, we also consider the geopolitical risk historical (GPRH), the geopolitical risk historical Threats (GPRHT) and the geopolitical risk historical acts (GPRHA) index. The most accurate forecast per horizon is shown in bold.

[8] The use of sub-variants of the GPR (historical) index, namely the GPRHA and GPRHT indices, is justified by the various aspects of geopolitical risk captured by each sub-variant. GPRHA is constructed based on a count of newspaper articles covering three categories of geopolitical events reflecting phrases related to the realization or escalation of adverse events, whereas GPRHT is based on a count of newspaper articles associated with five categories of geopolitical tension reflecting words related to military or nuclear tensions.

[9] A detailed description of each methodology is not provided due to the wide popularity of the methods used in the forecasting literature.

In Table 5 we report the average out-of-sample root mean square error (RMSE) for the total connectedness forecasts for the IQR layer. The forecasting performance of each method is compared with the Random Walk (RW) model that is referred to as the benchmark, since the RW model assumes that no model can forecast future values with consistency and all the available information is included in the observed value of the dependent variable. As we observe from Table 5, all models outperform the RW model in terms of RMSE, suggesting that it is feasible to forecast the evolution of the total connectedness index. The most accurate model is the ARIMA model at the 1-, 3-, and 6-month horizons and the RF at the longer 12- and 24-month horizons. Interestingly, the information included in GPRHT and GPRHA provides higher accuracy in forecasting the connectedness index at shorter horizons that the weighted GPR and the full information content of all categories, presumably due to the lack of information with the weighting scheme and the inherent noise content with the full word spectrum. At longer horizons, the more detailed informational content of the full wording categories outperforms all other alternatives. Moreover, in contrast to RF, the ARIMA model exhibits high instability at longer forecasting horizons, suggesting that the appearance of trend components and seasonal patterns in longer horizons affect the model performance. The SVR, XGBoost and ANN include more complex models than the RF, but fail to outperform it, suggesting that they tend to overfit.

In Table 6, we report the respective results for the SKEW layer, where we observe exactly the same patterns as previously reported for the IQR layer in Table 5 in terms of the most accurate model and the performance of all models in total. This suggests the importance of geopolitical risks for forecasting each of the volatility and skewness spillover effects across the volatility of G7+SW stock markets. This can be understood under the theoretical framework linking disaster risks, for which the GPR serves as an empirical proxy, driving equity premium, extreme risks, and stock market volatility (Barro, 2006; Wachter, 2013).

Table 6: Total connectedness forecasts for the SKEW layer						
Panel A: Global GPR and country GPR indices						
Horizon (months)	RW	ARIMA	RF	ANN	SVR	XGBoost
1	2.079	0.438	1.063	1.260	1.240	1.538
3	2.081	0.601	1.107	1.332	1.343	1.446
6	2.083	0.854	1.119	1.283	1.314	1.610
12	2.087	1.202	1.079	1.289	1.283	1.476
24	2.094	1.830	1.077	1.255	1.325	1.536
Panel B: GPRHT, GPRHA and country GPR indices						
1	2.079	**0.426**	1.003	1.171	1.173	1.439
3	2.081	**0.590**	1.049	1.317	1.262	1.497
6	2.083	**0.852**	1.082	1.560	1.296	1.431
12	2.087	1.178	1.026	1.374	1.161	1.536
24	2.094	1.832	1.019	1.245	1.158	1.451
Panel C: Individual for each category and country specific GPR indices						
1	2.079	0.632	0.917	0.986	1.023	1.479
3	2.081	0.999	0.962	1.042	1.059	1.369
6	2.083	1.470	0.977	1.035	1.149	1.501
12	2.087	2.172	**0.947**	0.988	1.082	1.426
24	2.094	4.393	**0.971**	1.026	1.171	1.638

Note: This table shows the average out-of-sample root mean square error (RMSE) across five horizons (1, 3, 6, 12, and 24 months). The models considered are a random walk (RW), an autoregressive integrated moving average (ARIMA), random forest (RF), an artificial neural network (ANN), a support vector regression (SVR) and an extreme gradient boosting (XGBoost) model. Apart from the global index, we also consider the geopolitical risk historical (GPRH), the geopolitical risk historical Threats (GPRHT) and the geopolitical risk historical acts (GPRHA) index. The most accurate forecast per horizon is shown in bold.

Shifting our focus from the total connectedness of each layer to the within-layer risk spillover index (i.e. spillovers between markets within the same layer), we reach similar conclusions, reported in Tables 7 and 8 for the IQR and SKEW layers, respectively. The ARIMA model is the most accurate model at shorter forecasting horizons, while the RF model supersedes all competing models at the longer 12- and 24-month horizons. Nevertheless, the most accurate measures for forecasting connectedness are not the GPRHT and GPRHA indices, but the global GPR index, reported in Panel A of Tables 7 and 8. This finding suggests that regarding the spillover of risk among stock markets, the disaggregated country geopolitical risk indices include more noise than the “filtered” global GPR index.

Table 7: Within layer spillover forecasts for the IQR layer						
Panel A: Global GPR and country GPR indices						
Horizon (months)	RW	ARIMA	RF	ANN	SVR	XGBoost
1	10.079	**1.303**	2.454	3.373	2.770	4.105
3	10.087	**1.472**	2.402	3.583	2.638	4.121
6	10.069	**1.726**	2.463	3.484	2.680	4.316
12	10.073	2.574	2.474	3.155	2.817	4.119
24	10.055	3.732	2.438	3.562	2.787	3.876
Panel B: GPRHT, GPRHA and country GPR indices						
1	10.079	1.352	2.249	3.215	2.542	3.836
3	10.087	1.720	2.119	3.303	2.396	4.019
6	10.069	1.934	2.254	3.323	2.526	4.132
12	10.073	3.088	2.182	3.033	2.500	3.791
24	10.055	4.959	2.178	3.058	2.509	3.906
Panel C: Individual for each category and country specific GPR indices						
1	10.079	1.763	1.962	2.814	2.278	3.794
3	10.087	2.142	2.008	2.787	2.157	4.076
6	10.069	3.177	2.012	2.790	2.312	4.100
12	10.073	19.150	**2.089**	2.672	2.303	4.005
24	10.055	24.126	**1.932**	2.672	2.241	3.702

Note: This table shows the average out-of-sample root mean square error (RMSE) across five horizons (1, 3, 6, 12, and 24 months). The models considered are a random walk (RW), an autoregressive integrated moving average (ARIMA), random forest (RF), an artificial neural network (ANN), a support vector regression (SVR) and an extreme gradient boosting (XGBoost) model. Apart from the global index, we also consider the geopolitical risk historical (GPRH), the geopolitical risk historical Threats (GPRHT) and the geopolitical risk historical acts (GPRHA) index. The most accurate forecast per horizon is shown in bold.

Table 8: Within layer spillover forecasts for the SKEW layer						
Panel A: Global GPR and country GPR indices						
Horizon (months)	RW	ARIMA	RF	ANN	SVR	XGBoost
1	10.242	**1.161**	1.747	2.270	2.091	2.882
3	10.249	**1.373**	1.848	2.232	2.208	2.959
6	10.212	**1.592**	1.737	2.211	2.091	3.020
12	10.205	2.214	1.773	2.181	2.119	2.798
24	10.212	3.093	1.730	2.086	1.941	2.857
Panel B: GPRHT, GPRHA and country GPR indices						
1	10.242	1.263	1.648	2.143	1.979	2.952
3	10.249	1.562	1.678	2.175	2.082	2.891
6	10.212	1.807	1.650	2.242	1.965	2.758
12	10.205	2.414	1.664	2.154	1.938	2.763
24	10.212	3.096	1.597	2.094	1.885	2.808
Panel C: Individual for each category and country specific GPR indices						
1	10.242	11.906	1.519	1.788	1.720	2.980
3	10.249	16.712	1.562	2.037	1.850	2.926
6	10.212	17.016	1.536	1.841	1.834	2.666
12	10.205	11.159	**1.528**	1.876	1.803	2.618
24	10.212	8.274	**1.501**	1.901	1.750	2.640

Note: This table shows the average out-of-sample root mean square error (RMSE) across five horizons (1, 3, 6, 12, and 24 months). The models considered are a random walk (RW), an autoregressive integrated moving average (ARIMA), random forest (RF), an artificial neural network (ANN), a support vector regression (SVR) and an extreme gradient boosting (XGBoost) model. Apart from the global index, we also consider the geopolitical risk historical (GPRH), the geopolitical risk historical Threats (GPRHT) and the geopolitical risk historical acts (GPRHA) index. The most accurate forecast per horizon is shown in bold.

Besides the importance of geopolitical risk for within-layer risk spillover, we are also interested in the cross-layer risk spillover and whether geopolitical risk measures have the power to forecast it. Table 9 reports the forecasting models from the IQR layer to the SKEW layer, while Table 10 reports the same for the opposite direction (i.e. the spillovers from the SKEW layer to the IQR layer). As we observe, once again, at the short 1-6 month horizons, the ARIMA model is the most accurate, while at the longer horizon the RF supersedes all other models. The most interesting finding lies in the ability of the disaggregated GPR measures to forecast cross-layer risk spillovers better than the global weighted version of GPR.

Table 9: Cross-layer spillover from IQR to SKEW forecasts

Horizon (months)	RW	ARIMA	RF	ANN	SVR	XGBoost
Panel A: Global GPR and country GPR indices						
1	10.079	1.164	2.456	3.520	2.770	4.088
3	10.087	1.339	2.404	3.476	2.638	4.035
6	10.069	1.711	2.455	3.388	2.679	4.098
12	10.073	2.499	2.454	3.111	2.817	3.961
24	10.055	3.632	2.420	3.062	2.787	3.891
Panel B: GPRHT, GPRHA and country GPR indices						
1	10.079	1.418	2.244	3.207	2.542	3.698
3	10.087	1.681	2.121	3.063	2.396	4.880
6	10.069	1.850	2.270	3.007	2.526	3.899
12	10.073	3.097	2.192	2.947	2.499	3.853
24	10.055	4.927	2.172	3.070	2.509	3.888
Panel C: Individual for each category and country specific GPR indices						
1	10.079	**0.303**	1.230	1.534	1.397	2.410
3	10.087	**0.512**	1.218	1.496	1.312	2.406
6	10.069	**0.901**	1.237	1.491	1.410	2.622
12	10.073	12.217	**1.238**	1.663	1.313	2.668
24	10.055	18.393	**1.227**	1.575	1.376	2.467

Note: This table shows the average out-of-sample root mean square error (RMSE) across five horizons (1, 3, 6, 12, and 24 months). The models considered are a random walk (RW), an autoregressive integrated moving average (ARIMA), random forest (RF), an artificial neural network (ANN), a support vector regression (SVR) and an extreme gradient boosting (XGBoost) model. Apart from the global index, we also consider the geopolitical risk historical (GPRH), the geopolitical risk historical Threats (GPRHT) and the geopolitical risk historical acts (GPRHA) index. The most accurate forecast per horizon is shown in bold.

Taken together, we highlight the importance of geopolitical risk in forecasting the spillover index in each of the two layers and the spillover effects across the two layers. This nicely complement studies on the importance of geopolitical risk for the transmission of systemic risk based on volatility only (Lai et al., 2023). This suggests that geopolitical risk as proxy for disaster risk has the power to predict the transmission of various aspects of risk within the system of G7+SW stock markets.

Table 10: Cross-layer spillover from SKEW to IQR forecasts						
Panel A: Global GPR and country GPR indices						
Horizon (months)	RW	ARIMA	RF	ANN	SVR	XGBoost
1	10.242	0.438	1.063	1.260	1.240	1.538
3	10.249	0.601	1.107	1.332	1.343	1.446
6	10.212	0.854	1.119	1.283	1.314	1.610
12	10.205	1.202	1.079	1.289	1.283	1.476
24	10.212	1.830	1.077	1.255	1.325	1.536
Panel B: GPRHT, GPRHA and country GPR indices						
1	10.242	**0.426**	1.003	1.171	1.173	1.439
3	10.249	**0.590**	1.049	1.317	1.262	1.497
6	10.212	**0.852**	1.082	1.560	1.296	1.431
12	10.205	1.178	1.026	1.374	1.161	1.536
24	10.212	1.832	1.019	1.245	1.158	1.451
Panel C: Individual for each category and country specific GPR indices						
1	10.242	0.632	0.917	0.986	1.023	1.479
3	10.249	0.999	0.962	1.042	1.059	1.369
6	10.212	1.470	0.977	1.035	1.149	1.501
12	10.205	2.172	**0.947**	0.988	1.082	1.426
24	10.212	4.393	**0.971**	1.026	1.171	1.638

Note: This table shows the average out-of-sample root mean square error (RMSE) across five horizons (1, 3, 6, 12, and 24 months). The models considered are random walk (RW), autoregressive integrated moving average (ARIMA), random forest (RF), artificial neural network (ANN), support vector regression (SVR) and extreme gradient boosting (XGBoost). Apart from the global index, we also consider the geopolitical risk historical (GPRH) index, geopolitical risk historical Threats (GPRHT) index, geopolitical risk historical Acts (GPRHA). The most accurate forecast per horizon is shown in bold.

5. Conclusions and discussion

In this paper, we conduct a comprehensive analysis of the transmission of systemic risk across the G7 plus Switzerland economies, captured by both the second (volatility) and third (skewness) moment of stock returns extracted from QADL-MIDAS modelling, over the period May 1917 to February 2023 corresponding to the entire financial history of the markets under examination. Using the multi-layer spillover approach, we evaluate the risk spillover effects between stock markets for each risk measure in a one-layer analysis and for the two risk measures jointly in a two-layer analysis. By allowing for not only within-layer but also cross-layer spillovers, where one risk measure affects the other, we describe in better detail the transmission mechanism of risk across developed stock markets.

Our empirical results suggest that the larger stock markets of the US and UK tend to transmit risk to other markets and with a higher degree during various turbulent periods. This extends the evidence from the less comprehensive but typical within-layer analyses often used in the existing literature to show the intensity and occurrence of risk spillover effects. Therefore, our main analysis points to the significance of considering both volatility and skewness when studying the spillover effect across advanced stock markets using a multi-layer approach. Accordingly, investors and policymakers concerned with the systemic risk transmission among advanced stock markets should not overlook either of the two layers or, importantly, the significant cross-layer spillovers when examining information transmission dynamics. Otherwise, an important part of the risk transmission would be missed, possibly making any investment and risk management decision or policy formulation incomplete and suboptimal. This evidence also has implications for portfolio allocation and risk inferences because limiting the optimization analysis to the second moment of stock returns without considering skewness or volatility-skewness interactions might lead to incomplete portfolio implications and thereby decisions, especially under the frequent stress experienced by global stock markets. Accordingly, the development of portfolio allocation models using both volatility and skewness is required for the sake of completeness.

In a different strand of research, we evaluate the role of country-specific and global geopolitical risk indices in forecasting layer-based risk spillovers. We conclude that global geopolitical risk drives the financial risk up to 6 months, while country-specific indices forecast financial risk more accurately at longer horizons. This new evidence has direct policy implications, as it provides a structured approach to link volatility and skewness risk spillovers with disaster risk such as geopolitical risk. This implies that portfolio managers and policymakers concerned with stock market stability and the well-functioning stock markets of developed economies should take a close look at geopolitical risk and accordingly formulate preventive policies to make stock markets more resilient to geopolitical shocks and improve their stability.

Future research strands could include the examination of a broader sample of financial markets or regions or add higher distribution moments such as kurtosis, while highlighting the portfolio implications.

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Appendix

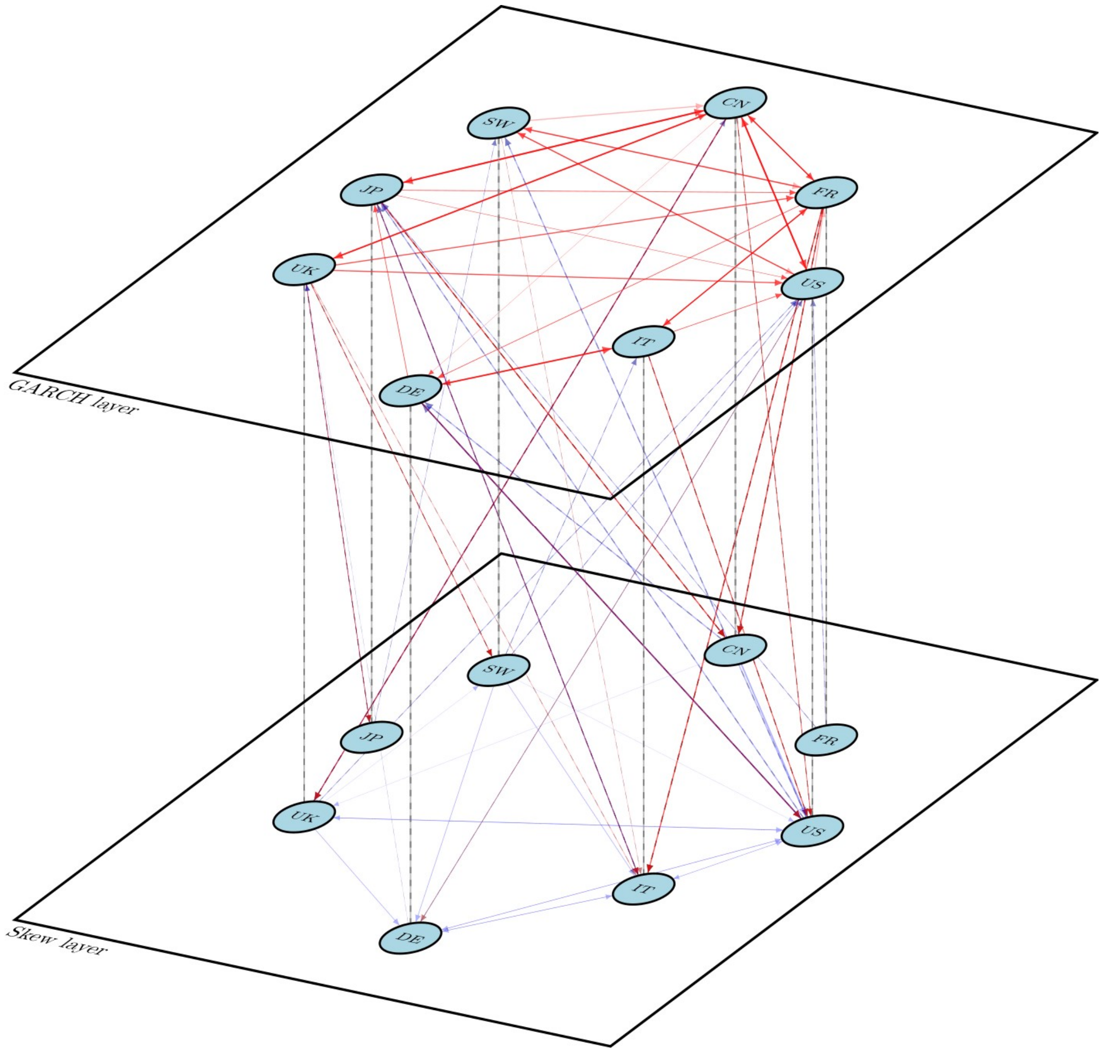

Figure A1: Snapshot of multilayer network over time using a GARCH-based model of stock returns volatility