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Rare disasters and multilayer spillovers between volatility and skewness in international stock markets over a century of data: The role of geopolitical risk[☆]

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ABSTRACT

Measuring risk and understanding risk spillover across markets lie at the core of the decision-making process of every financial market participant and monetary authority. However, the bulk of the literature treats risk as a function of the second moment (volatility) of the return distribution, based on the implicit unrealistic assumption that asset returns are normally distributed. In this paper, we examine risk spillovers involving robust estimates of both second and third moments of model-implied distributions of stock returns using a multilayer approach; then, we assess the ability of geopolitical risk, as a proxy for rare disaster risk, to forecast layer-based risk spillovers using machine-learning methods. Considering a century of data on the stock indices of the G7 and Switzerland from May 1917 to February 2023, the results show the following: Firstly, the risk spillover among stock markets exists within each layer (i.e. volatility and skewness), with a stronger effect in the volatility layer. Secondly, the risk spillover is significant across the two layers, highlighting how various aspects of risk information are transmitted across major stock markets. Thirdly, geopolitical risk affects both risk layer values, based on an out-of-sample forecasting exercise. Specifically, global measures of geopolitical risk can forecast risk spillovers at shorter horizons up to 6 months, whereas, at longer horizons, the forecasting exercise is dominated by market-specific characteristics.

1. Introduction

In the context of asset returns, skewness reflects the extent to which a given return distribution deviates from the normal distribution, and hence represents a metric of evolution of unbalanced (relative to a baseline) future risk (Dew-Becker, 2022; Salgado et al., 2020; Sheng et al., 2023). A burgeoning literature, post the global financial crisis (GFC) of 2007–2009, relates volatility, a traditional

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estimate of risk in equity markets,[1] with the skewness of equity markets (see, for example, Amaya et al., 2015; Byun and Kim, 2013; Chang et al., 2013; Jian and Li, 2021; Mei et al., 2017; Seo and Kim, 2015; Zhang et al., 2021). A key rationale is that under extreme shocks and the deviation of stock returns form the normal distribution, volatility is not a comprehensive measure of risk but should be augmented by an analysis of skewness for completeness (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 an increase (decrease) of skewness can result in optimistic (pessimistic) sentiment and buying (selling) behaviour in equity markets leading 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). 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 flow 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, skewness and volatility impact each other (see, Bekaert and Wu, 2000; Aït-Sahalia et al., 2013) for detailed discussions regarding the issue of reverse causation in general).

Extensive theoretical literature underlines the role of disaster risk, for which geopolitical risk (GPR) serves as a high-frequency continuous empirical proxy (see, Berkman et al., 2011, 2017, for a detailed discussion of measurement issues involving rare disaster events),[3] explaining various financial market phenomena, such as the equity premium, extreme risks and stock market volatility (Barro, 2006; Gourio, 2012; Tsai and Wachter, 2015; Wachter, 2013). Entrepreneurs and market participants view geopolitical risk as a key determinant of investment decisions and stock market dynamics ahead of political and economic uncertainty (NguyenHuu and Örsal, 2024; Salisu et al., 2021). Higher geopolitical risk is an indication of lower investment, higher disaster probability, and larger downside risk in the future, as documented by Nakamura et al. (2013) and Caldara and Iacoviello (2022) for a panel of large number of countries (including the ones we consider in this paper), with the newspapers-based indexes of geopolitical risks created by the latter (discussed in detail later) serving as a continuous high-frequency metric of rare disaster events. Naturally, GPR receives considerable attention from businesses, becoming a regular fixture in the agendas of many financial companies, newspapers, and consultancy firms (see, McKinsey, 2016; Morgan, 2019; The Economist, 2022; Blackrock Investment Institute, 2023), as such risks can seriously threaten the stability of the world financial system.

Against this backdrop, the objective of this paper is twofold. Firstly, it analyses the spillover of both volatility and skewness for eight stock markets (Canada, France, Germany, Italy, Japan, Switzerland, the United Kingdom [UK], and the United States [US]). This is based on not only a single-layer approach but also a multilayer approach (Wang et al., 2021), which can fully capture all possible information spillover effects between volatility and skewness.[4] Secondly, it examines the ability of rare disaster risks, reflected by the news-based measure of adverse geopolitical events and associated risks such as the GPR indices of Caldara and Iacoviello (2022) covering both global and country levels,[5] to forecast layer-based risk spillovers.

At this stage, we must outline the two primary channels via which risk, i.e., volatility and skewness in our case, can be transmitted across economies (Debarsy et al., 2018; Ji et al., 2020). The first is the real linkages channel, which arises from trade or financial relationships across countries. For example, if a country is facing economic turbulence, its supply and demand for international goods and services are likely to be reduced, implying a negative impact on its trading patterns. According to this channel, the propagation mechanism that leads local turmoil to diffuse to the whole system basically depends on pairwise physical connections between countries through trade linkages. The second is the informational channel, which builds on the existence of imperfect information in

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[1] There are also studies that link skewness with volatility in commodity, (crypto)currency, and real estate markets (see, for example, Bonato et al., 2022, 2024; Bouri et al., 2021, 2023; Gkillas et al., 2019; Gupta et al., 2023).

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

[3] The basic definition of rare disaster events, in line with Barro (2006, 2009) is that, it is infrequent and significant in magnitude in terms of having a negative effect on an economy involving large cumulative decreases in Gross Domestic Product (GDP) growth and consumption growth of at least 10 % over one or more years. Given this, a major obstacle to full-fledged empirical verification of rare disaster models is that individual countries rarely face such major disasters, resulting in a small sample problem inherent in the use of actual rare disasters, which, in turn, is why earlier researchers studying the implications of rare disasters for asset pricing have relied on theoretical models calibrated on rare-disaster-risk probabilities derived from historical long-span cross-country evidence of major declines in output and/or consumption (Ćorić, 2018, 2021; Ćorić and Šimić, 2021). In this regard, Berkman et al. (2011, 2017) propose a solution to the small sample problem that would make the empirical estimation of such models feasible. They focus on a large sample of potential disasters, i.e., international geopolitical crises, which are likely to cause significant changes in perceived rare disaster probabilities.

[4] We also performed an analysis by adding both returns and kurtosis layers. Our results are qualitatively similar in terms of the two moments of concern in this paper, i.e., volatility and skewness – the theoretical link between which is outlined in detail above. Complete details of these results are available upon request from the authors.

[5] The global measure is further categorized into geopolitical risk resulting from threats and the realization of adverse geopolitical events.

financial markets. It assumes that market participants can use the characteristics of one country (such as debt structure or bureaucratic quality) to extract a signal on those considered similar. Accordingly, if a country is economically disrupted, international investors reassess the risk attached to countries sharing similar characteristics, which, in turn, causes them to adjust their trading strategy, and an associated transmission of risk from one economy to another.

Regarding the rationale for analysing the role of geopolitical risk in forecasting layer-based risk spillovers across the eight stock markets, Berkman et al. (2011, 2017) highlight the theoretical role of disaster risk, such as GPR, in explaining equity premium, extreme risks and stock market volatility (Barro, 2006; Gourio, 2012; Tsai and Wachter, 2015; Wachter, 2013). The basic idea behind these models is that aggregate consumption follows a normal distribution with low volatility most of the time but with some probability of a far out-in-the-left-tail realization of consumption, creating risk associated with rare disaster events. The possibility of such a poor outcome substantially raises the equity premium, and the time-variation in the probability of such a disaster fosters high stock-market volatility. In addition, one of the key assumptions underlying rare-disaster models is that the entire universe of assets in an economy is exposed to an aggregate jump-risk factor. It follows that, even though in the cross-section some assets are more exposed to tail events than others, such a jump-risk factor should be an important driver of the time-series variation in the tails of individual asset returns (Barro, 2009; Rietz, 1988). In other words, we can hypothesize that the jump-risk factor associated with the dynamics of the GPR indices has predictive power for movements in the tail risks of the aggregate stock market, i.e., impacting the asymmetry in returns or skewness of the same, just like its volatility. Naturally, the risks associated with geopolitical events, being an empirical proxy for the theoretical concept of rare disaster risks, are likely to act as a common factor in driving the volatility and skewness of the stock markets of each country, and hence their spillovers within and across these two metrics of risk, given the channels outlined above involving risk transmission in globally integrated financial markets. As disaster events tend to increase both the second and third moment of stock returns, one would expect that the various geopolitical risks would also increase the indices capturing spillovers within and across the volatility and skewness of this similar set of advanced stock markets (Das et al., 2019; Krishnan et al., 2009; Longin and Solnik, 1995, 2001).

Given the above discussions, the contributions of our paper are multi-dimensional. It is the first of its kind to: (a) estimate robust metrics of two measures of risk involving over a century of data, the longest available, on the evolution of returns of important stock markets controlling for possible sample-dependent bias arising from the choice of specific sample periods; (b) provide an analysis of multilayer spillovers across volatility and skewness of eight major stock markets, rather than taking a single-strand approach as is traditional in the existing literature, thereby providing a more complete understanding of risk spillover across alternative metrics, especially given the theoretical interrelationship between these two measures of risk within and across countries; 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., aggregated and disaggregated 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 various stock markets.[6] In light of the importance of risk spillovers from the perspective of investment and policy decisions, our paper provides a unique empirical understanding of the nature of such linkages in advanced equity markets and how they are affected by geopolitical risk, and also an underlying explanation for these observations.

The remainder of the paper is organized as follows: Section 2 discusses the data. Section 3 lays out the quantile autoregressive distributed lag mixed-frequency data sampling (QADL-MIDAS) model used to extract higher-order measures of risk and the multilayer connectedness model. Section 4 presents the results of the multilayer connectedness analysis and the associated forecasting exercise in relation to GPR. Finally, Section 5 concludes.

2. Data

The log-returns of stock market indices used in this study cover the period May 1917 to February 2023 at monthly frequency, encompassing over a century of financial history. This extended time-series dataset is obtained from Global Financial Data[7] and allows us to analyse and capture various historical events, including major financial, economic, health, and geopolitical crises. Notable events within the timeframe include the US financial crash of 1929, the OPEC oil crisis of 1973, the Asian crisis of 1997–1998, the global financial crisis of 2007–2009, the European sovereign debt crisis of 2009–2010, the COVID-19 pandemic of 2020, and the recent Russian-Ukrainian conflict of 2022 (See Appendix Table A1). These extreme events significantly impacted financial markets, increasing market volatility and making risk transmission a central research issue. The dataset covers the stock market indices of eight advanced economies, which include the G7 and Switzerland, as described in Appendix Table A2 (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),

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[6] Note that the decision to use machine learning approaches emanates from the fact that we can have a large number of predictors, up to 16, and we can prevent the issue of overparametrization over each rolling sample used to compute the forecasts by using a data-driven approach which can select the best predictors at each iteration to compute forecasts, and hence reduce inefficiency in the forecast performance involving many GPRs indices. At the same time, the machine learning approach controls for the nonlinearity and regime-change which is likely to exist over this long period, especially in light of widespread evidence that moments of stock returns and its predictors are related in a way that is not linear and requires models that account for this issue to avoid model misspecification (see the detailed discussions in Breiman, 2001; Meinshausen, 2006).

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

plus Switzerland (SW; All Share Stock Index).

Our sample period is May 1917–February 2023 at monthly frequency, motivated as follows. With the advent of intraday data over the past years, daily time series metrics such as realized volatility and realized skewness can be easily computed. However, in our case, with stock price data not available even at daily frequency for the long-sample period covering more than a century (May 1917 to February 2023), we have to rely on monthly data, which is the highest-frequency available, to compute the second and third moments for our risk spillover analysis. Note that, besides the availability of the longest possible sample of stock market data, which prevents possible sample selection bias, the choice of eight advanced economies is primarily motivated by their importance in the global economy.[8] These economies combined represent nearly two-thirds of global net wealth, and nearly half of world output, which makes the analysis of their risk spillovers of pivotal importance from the perspective of the stability of the world financial system (Das et al., 2019; Salisu et al., 2023).

As measures of 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 eight categories: war threats, peace threats, military build-ups, nuclear threats, terror threats, beginning of war, escalation of war, and terror acts. An annotated plot of the GPRH index is provided in Figure A1 in the Appendix. Based on the search groups, Caldara and Iacoviello (2022) construct two subindices: 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).[9]

As indicated, we extract two measures of risk for the aforementioned stock indices based on the quantile autoregressive distributed lag mixed-frequency data sampling (QADL-MIDAS) model (described in subsection 3.1), and examine them using a multilayer spillover approach. The two estimated measures of risk are: the inter-quartile range (IQR) and skewness (SKEW). 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 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.

Table 1 gives the summary statistics of our measures of risk in Panel A (IQR) and Panel B (SKEW). 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 firstly present the QADL-MIDAS model used to obtain the two metrics of risk (volatility and skewness). We describe the multilayer connectedness approach employed to investigate the interplay between the inter-quartile range (IQR) volatility and skewness (SKEW) layers.

3.1. QADL-MIDAS model

To extract higher-order measures of risk (i.e. volatility and skewness) for the monthly stock indices of the eight advanced economies, we use the QADL-MIDAS approach. 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 at extracting risk measures. This quantiles-based approach allows us to compute the fitted time series of stock returns at each conditional (model) quantile, based on which robust estimates of volatility and skewness are obtained from the underlying distribution of the stock returns.

We model the τ-th quantile of h-step ahead series $\left(i_{t+h}^{(h)}\right)$ using the information at time t ($\mathscr{F}_t$). The conditional quantile τ of h-step ahead is given by:

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

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

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[8] While the choice of the G7 as appropriately representing the equity market of the developed world is understandable, the decision to include Switzerland is also justified due to its reliability as an investment destination, as outlined here: https://www.usnews.com/news/best-countries/best-countries-to-invest-in.

[9] 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)
Panel A: IQR				
Canada	23.72	16.28	156.44***	−7.23***
France	35.28	25.46	29.48***	−7.02***
Germany	16.13	13.33	6799.45***	−10.71***
Italy	24.47	21.54	981.14***	−6.07***
Japan	34.18	28.82	95.63***	−6.11***
Switzerland	17.44	11.42	45.37***	−7.32***
UK	13.22	7.35	551.88***	−7.96***
US	20.15	12.35	888.05***	−7.72***
Panel B: SKEW				
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***

Notes: This table shows the summary statistics of the two measures of risk: the inter-quartile range (IQR) and skewness (SKEW). The sample period is May 1917 to February 2023, at monthly frequency. ERS is Elliott et al. (1996) unit root test.

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

where μ is the intercept, $\rho = \sum_{j=0}^{q} a_j$ captures stock index persistence, α represents coefficients of 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:

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

given $Z_t(\theta_\tau) = \sum_{j=0}^{q-1} \omega_j(\theta_\tau) |\Delta i_{t-j}|$, $\omega_j = \frac{(1-x_j)^\theta}{\sum_{j=0}^{q-1}(1-x_j)^\theta}$ 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 (e.g. quarterly) while keeping sampling at the monthly frequency. After estimating the QADL-MIDAS coefficients, we extract the model-implied risk measures. IQR is simply the difference between the upper and lower-tail quantiles at the τ (=0.10) level:

$$IQR^\tau_{t|t-h} = \widehat{q}_{1-\tau,t|t-h} - \widehat{q}_{\tau,t|t-h} \tag{4}$$

SKEW 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, it is given by:

$$SKEW^\tau_{t|t-h} = \frac{\left(\widehat{q}_{1-\tau,t|t-h} - \widehat{q}_{0.50,t|t-h}\right) - \left(\widehat{q}_{0.50,t|t-h} - \widehat{q}_{\tau,t|t-h}\right)}{\widehat{q}_{1-\tau,t|t-h} - \widehat{q}_{\tau,t|t-h}} \tag{5}$$

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

3.2. *Multilayer connectedness*

Our reliance on the multilayer spillover approach nicely complements previous studies and is motivated as follows. The existing literature includes spillover analyses for stock markets within the boundaries of one particular risk measure only (e.g. Ahmed et al., 2024; BenSaïda, 2019; Bouri et al., 2023; Choi and Yoon, 2023; Diebold and Yilmaz, 2009), ignoring the potential theoretical linkages between volatility and skewness (via the leverage effect). Foglia et al. (2023) argue that a single-layer spillover network cannot fully capture all possible information spillover effects. Wang et al. (2021), while proposing the econometric methodology of multi-strata connectedness, indicate that the complexity of the financial system makes the analysis of spillovers across various countries based on a single-layer network a suboptimal choice, because a single measure of risk cannot capture the diversity or heterogeneity of information transmission and its interconnectedness among markets. Thus, the use of a multilayer spillover network, which considers heterogeneous information and the multilayer structure of complex systems, is necessary to understand the interaction behaviour in global stock markets. This is more so, because, as indicated above, skewness and volatility are interconnected by theory, and this is also the case for these two individual measures of risk across countries. Multilayer spillover 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 to effectively describe complex financial systems across alternative metrics of risk simultaneously. In this regard, a multilayer network analysis across countries via the second and third moments of asset returns is crucial to reflect the well-known non-normality of return distribution (Ahmed et al., 2024) and thus the possible spillover effects between the volatility and skewness layers. While the individual layers of volatility and skewness capture risk spillovers within countries through real and information linkages, the multi(two)layer component of the analysis shows cross spillovers between two aspects of risks among the eight countries under study, driven by the leverage effect. As shown below in our empirical findings, analysing the spillovers across countries via both volatility and skewness can offer a complete picture of the interrelationships between the second and third moments of stock returns. Due to the importance of risk spillover analysis from the perspective of portfolio allocation and risk management (Gong et al., 2023; Iqbal et al., 2024; Ji et al., 2020) and evidence of the utility of considering spillovers of higher-order moments and co-movements in portfolio allocation and risk management (Nekhili and Bouri, 2023), this multilayer approach is of paramount importance to investors, allowing them to extend and refine their understanding of the interconnectedness of volatility and skewness across developed stock markets, realizing the feedback effect between these two measures of risk (Bouri, 2023).

Against this backdrop, we now turn our attention to the methodological background of multilayer 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 the IQR volatility and SKEW layers, respectively. It 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 at time t, 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 $N \times N$ coefficient 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), the contribution of each variable to the forecast error variance is calculated. Hence, the H-step ahead generalized forecast error variance is defined 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.

Each element of the H-step ahead matrix is normalized as:

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

3.2.2. Network measures

We consider multilayer information spillover networks, including the IQR volatility spillover layer and SKEW spillover layer. Each layer is built on the variance decomposition obtained from the VAR approach to spillover developed by Diebold and Yilmaz (2012, 2014). The network measures can be divided into two macro areas: system-level measures and multilayer information spillover measures, following the approach of Wang et al. (2023). These network 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[10].

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[10] 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 increasing and decreasing both configuration settings and exploring changes of up to 50 % from our fixed choices. 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 given in sub-section 4.2.2. Instead of IQR volatility, we use the volatility measure derived from the popular GARCH model. We report the GARCH-based finding in Appendix Figure A2, giving a snapshot of the multilayer network, which is similar to those reported in Fig. 1. In addition, we also used the Autoregressive Conditional Density (ACD) model of Hansen (1994) to obtain estimates of both volatility and skewness, and results, available upon request from the authors, produced qualitatively similar findings to those obtained from the moments (IQR and SKEW) computed using the QADL-MIDAS model.

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:

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

At the stock market level, we calculate market in-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 out-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 market i strength (NS) on the α layer, defined as the difference between the external and positive strength of stock markets i. Therefore, we have:

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

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

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

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

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. However, if each edge is exclusive to just one layer, then 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 ranges from 1 to 2. Values close to 2 indicate that the stock markets are similarly connected, while a value of 1 means that each edge only exists in one layer. The overlap index (O) is given by:

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

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

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

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

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

$$O_{NS,i} = O_{OS,i} - O_{IS,i} \tag{16}$$

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

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

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 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, representing characteristics of the node's interactions. When the coefficient equals 0, the node's connections are concentrated solely within one layer, meaning it plays a significant role in that 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 layers. 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 examine 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:

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

where N denotes the number of stock markets, in our case 8 (G7+Switzerland); 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:

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

By definition, $S_{i\leftarrow j}(H) + S_{i\leftarrow i}(H) = 1$. Accordingly, the cross-market connectedness matrix is given by:

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

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 Panel A of Table 2 we show 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 (G7+Switzerland) and *O* is the average edge overlap of the multilayer information spillover networks.

From a 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 layer. This implies that the G7+Switzerland stock markets are more strongly interconnected via their IQR volatility than via their skewness. Therefore, there are less significant ties between markets when low-probability events occur. This result is perfectly in line with the existing literature (e.g. Bouri et al., 2021; Bouri et al., 2023), which finds a higher level of volatility spillovers compared to skewness spillovers.

From a multilayer network perspective, the *O* measure shows that, on average, half the edges in each layer also exist in the other layer. Thus, the directional spillover between any two countries in each layer almost always exists in the other. This finding suggests that the two moments of the return distribution (volatility and skewness) capture somewhat distinct aspects of risk, but at the same

Table 2
Network metrics.

Panel A: Average connection strength (ACS) and overlap index (O)		
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
SSKEW spillover layer	13	87

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

time affect each other. In this regard, the Spearman rank measures based on PageRank centralities (see Panel B, Table 2) shows 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 but only be a peripheral node in the 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. The cross-layer risk spillover indicates risk transmission between the IQR and skewness layers, represented by 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. Notably, our 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 risk spillover effects. This empirical result points to the importance of understanding and managing risk within specific layers to effectively mitigate its impact on the overall risk.

4.2. Static analysis at the country level

To investigate the role of each stock market within the multilayer network, we evaluate several network measures. Table 3 shows the out-strength (OS) of the countries on the two layers, which is used to show the difference between the OS of stock markets across the two layers. The US market plays a dominant role in OS spillover. Indeed, it stands out as the preeminent stock market in both layers, securing the top position in terms of OS spillover, meaning that the US stock market exhibits the highest propensity for disseminating risk to other markets in both the IQR and skewness layers. These results affirm the influential role of the US stock market in modelling global risk dynamics (Gong et al., 2023; Iqbal et al., 2024; Ji et al., 2020; Smales, 2022). Other markets, such as Canada and France, maintain consistent positions across both layers. They specifically hold the same ranks in both the IQR and SKEW 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 SKEW layer and the 8th position in the IQR layer, indicating its smaller impact on risk transmission compared to other countries, regardless of the layer considered.

In Fig. 1, we present the evolving multiplex information spillover network over time. Within each layer, there are eight nodes, representing G7+Switzerland. 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. The IQR layer has a denser and more closely interconnected network than the SKEW layer. This reflects the differences in risk transmission dynamics between the layers.

To gain more complete 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 results show that 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. However, Canada has the highest level of overlapping in-strength among the sample markets, as it mainly absorbs variance spillovers from other countries. The US is the country with the highest overlapping net-strength, followed by Switzerland, Italy and the UK.

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

4.3. Dynamic analysis at the global level

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

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+Switzerland stock markets for volatility risk. This implies that changes in the volatility of one market have significant effects on related markets. When IQR is high, there is greater variability in returns and, consequently, a greater degree of uncertainty and risk in markets. The fact that this IQR connectivity is observed during periods of both normalcy and financial crisis suggests that the links between financial markets persist even during times of extreme volatility, highlighting a kind of interdependence between them. In contrast, the SKEW layer exhibits a lower level of connectivity, suggesting that the stock markets are less intertwined during low-probability events. The evidence that total skewness spillovers are lower than volatility spillovers indicates that asymmetry in the distribution of returns has a less significant impact on the transmission of risks between markets. Skewness measures asymmetry in the distribution of returns and may indicate the presence of abnormal or tail behaviours, such as extreme or anomalous events. The fact that skewness spillover is relatively low compared to the IQR layer suggests that markets do not transmit these deviations from normality as strongly with respect to volatility. These results are in line with the literature (see, for example, He

Table 3
Out-strength (OS) of stock markets.

Rank	Out-strength (OS)			
	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

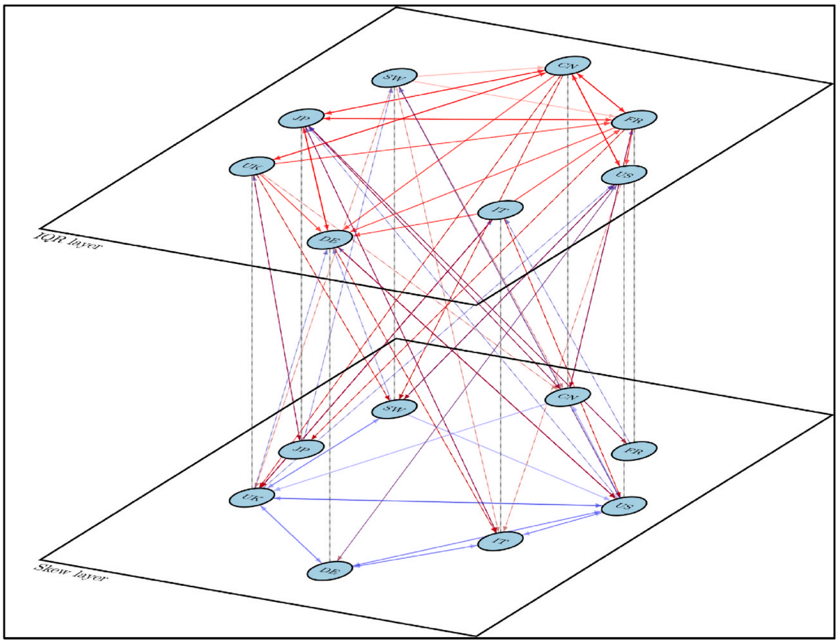

Fig. 1. Snapshot of multilayer network over time.

Table 4
Average overlapping strength of stock markets.

	O_{OS}-strength	O_{IS}-strength	O_{NS}-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

and Hamore, 2021; Bouri et al., 2021; Bouri et al., 2023), which shows that total skewness spillover is lower than total volatility spillover. The varying levels of connectedness in the two layers signify that stock markets respond differently to different types of risk (see Bouri et al., 2023).

Secondly, six phases of connection expansion are identified: i) the US financial crash of 1929; ii) the OPEC oil crisis of 1973; iii) the Asian crisis of 1997–1998; iv) the GFC of 2007–2009; v) the European debt crisis of 2009–2010; and vi) the COVID-19 health crisis of 2020. Throughout these phases, the IQR layer consistently exhibits larger connections than the SKEW layer, signifying that the G7+Switzerland stock markets are more interconnected via volatility risk than low-probability event risks. However, 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 of 1987, the early 1990s recession, and the 1998–2002 Argentine depression. These results further indicate

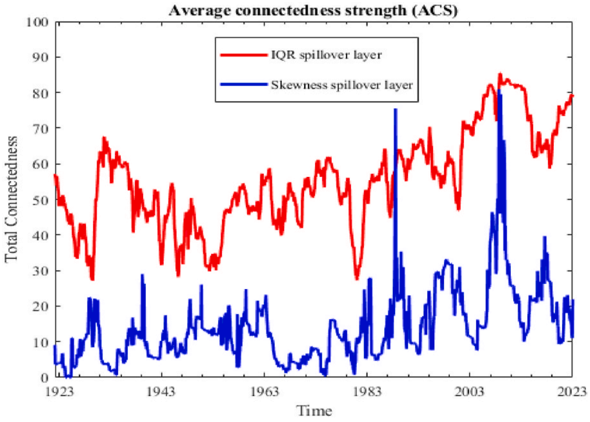

Fig. 2. Dynamic evolution of ACS over time.

the strong risk relationships among stock markets during crisis events.

Overall, the dynamics of interconnectedness of risk indicators across the G7+Switzerland stock markets, particularly during major crisis events, align with the existing literature (Bouri et al., 2021; Do et al., 2016; Finta and Aboura, 2020). The spillover indices associated with these two risk measures are useful for monitoring and understanding changes in risk dynamics under various market conditions. The findings suggest that volatility risks exert a significant influence on the intensity of stock market interconnectedness, which can be ascribed to the inherent characteristics of volatility itself. Compared to higher-order moments, which are infrequent and exhibit lower predictability, volatility manifests as a more prevalent and pervasive phenomenon. Consequently, the transmission of volatility across markets occurs in a more constant and continuous manner, fostering the development of more robust linkages. While our results suggest that 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 not captured exclusively by volatility measures, we compute the average edge overlap and cross-layer spillover index. Starting with the dynamic average edge overlap index within the multilayer information spillover network, as illustrated in Fig. 3, the index shows 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 edges within the multilayer information spillover network are more likely to be present across multiple layers than confined to individual layers. An interesting observation pertains to the index's behaviour in various market conditions. The increasing index during financial turmoil, notably the GFC of 2007–2009, 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.

Focusing on the within-spillover and cross-spillover between layers, Fig. 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 Fig. 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 than 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 timeframe analysed. Notable examples include the US financial crash of 1929, GFC of 2007–2009, and European sovereign debt crisis of 2009–2010, 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 skewness in spillover analyses (Bouri, 2023).[11] In fact, our detection of significant spillover effects between the volatility layer and 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

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[11] 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.

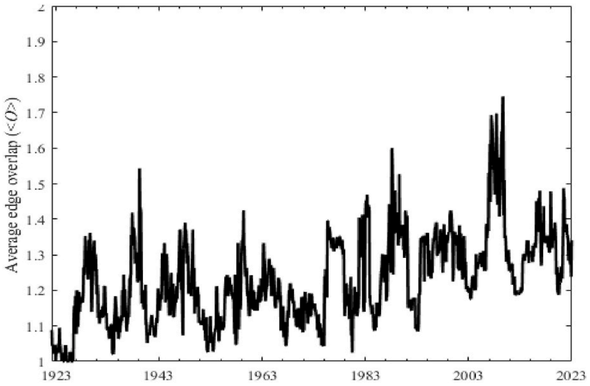

Fig. 3. Overlap index.

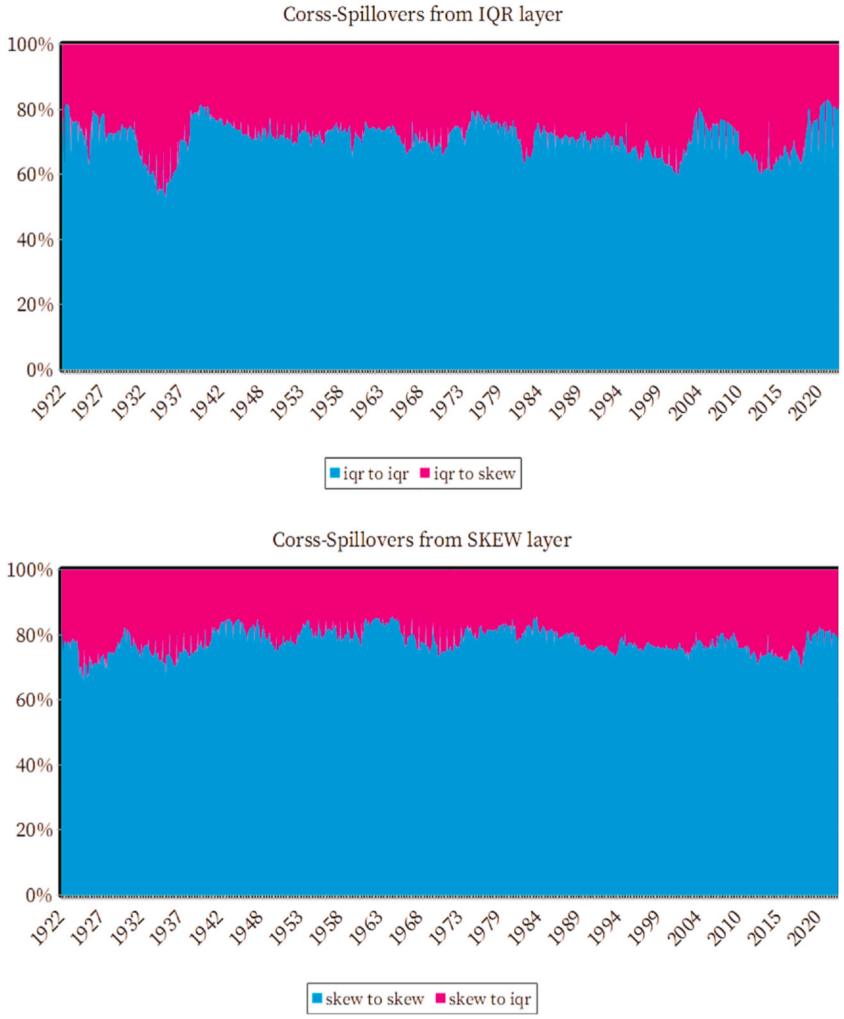

Fig. 4. Dynamics of cross-spillover measures.

level of systemic risk in the G7+Switzerland stock market indices.

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 the G7+Switzerland 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 more accurate and robust insight into the intricate interplay of information transmission paths across advanced stock market indices.

4.4. Dynamic analysis at the country level

We expand the dynamic analysis of risk information spillovers to each stock market. The heatmaps shown in Fig. 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 three 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 in the global financial system (see, e.g., Finta and Aboura, 2020; Ji et al., 2020; Gong et al., 2023). The US economy is the largest, accounting for around 11 % of global trade and constituting the top destination for foreign direct investment (FDI) inflows worldwide.[12]

The overlapping net-strength provides an overview of the dynamic behaviours of risk 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 stock markets in Switzerland, the UK, Japan, and the US predominantly serve as major emitters of risk shocks, while other countries function as recipients of risk 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 US financial crash of 1929 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 2007–2009, 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, or 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 a synchronous impact on multiple economies, with various countries acting as both spillover emitters and recipients.

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 Fig. 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 is less evenly balanced, with coefficients consistently less than one. This suggests that spillover behaviours evolve 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. This could be attributed to the predominant role of the US in the global economy and the fact that the US stock market is considered a key barometer of the health of the global economy. Therefore, large fluctuations and crises in the US stock market have a significant impact on other financial markets around the world, reflecting the interconnectedness and interdependence of global stock markets. Observing non-uniform spillover strength in various periods, especially during financial stress, underscores the

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

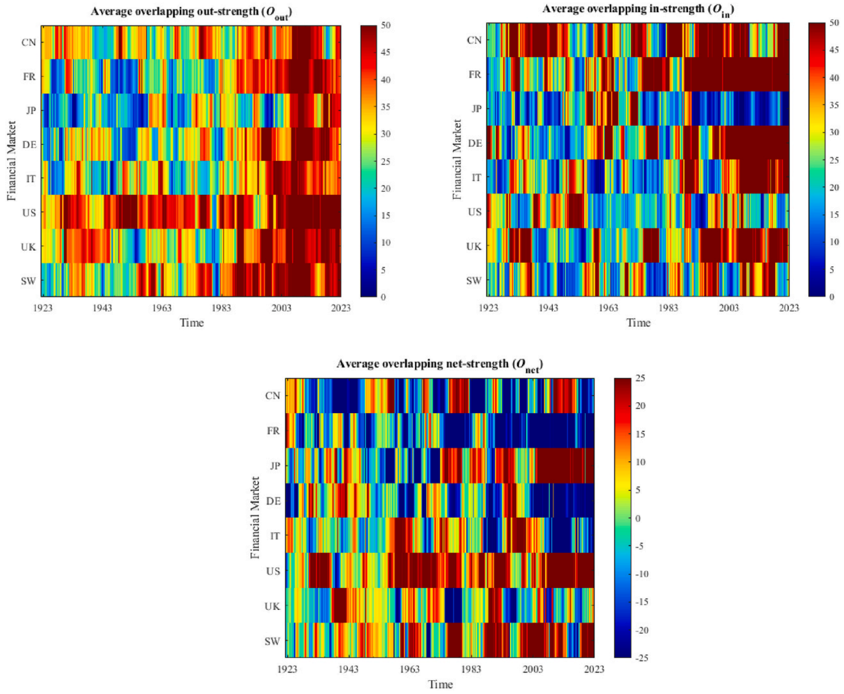

Fig. 5. Country dynamics of overlapping indices.

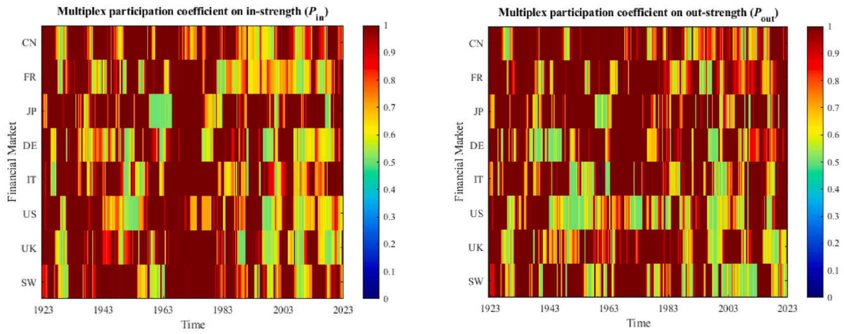

Fig. 6. Country dynamics of multiplex participation coefficient.

complexity of market risk dynamics.

4.5. Discussion about the volatility-skewness connectedness results

Our analysis combines two central dimensions of risk, i.e., volatility (second moment) and skewness (third moment), within a multilayer network structure for G7+Switzerland equity markets. This framework derives from a substantial body of theoretical and empirical work underscoring the interconnected nature of volatility and skewness (see, for example, Amaya et al., 2015; Byun and Kim, 2013; Zhang et al., 2021). Theoretically, the interaction between volatility and skewness is based on several mechanisms. The first is the leverage effect (Black, 1976). Strongly negative or strong positive returns can amplify a firm's leverage (debt-to-equity ratio), increasing systematic risk and contributing to future volatility. The second mechanism is reverse causation (Aït-Sahalia et al., 2013; Bekaert and Wu, 2000), meaning that changes in volatility can affect the distribution of returns, producing extreme tails and thus modifying skewness. The third is investor sentiment (Seo and Kim, 2015). An increase in skewness can reflect investor optimism (or pessimism), triggering buying (or selling) pressures and subsequently affecting aggregate volatility. Finally, economic cycles and market conditions (Iseringhausen et al., 2023; Schwert, 1989). Significant changes in skewness may accompany phases of economic expansion (or recession), suggesting lower (or higher) levels of volatility.

From a single-layer perspective, our empirical findings indicate that the average connectedness (ACS) measure is significantly higher for the volatility (IQR) layer compared to the skewness layer. This result is consistent with the leverage effect (Black, 1976) and related theories (Aït-Sahalia et al., 2013; Bekaert and Wu, 2000), suggesting that large negative or large positive equity returns typically generate more significant immediate revisions to volatility than skewness. The volatility channel is thus naturally more reactive, leading to a higher degree of spillover transmission across markets. In other words, when shocks occur, the second moment adjusts quickly, creating a significant spillover effect among countries in the volatility layer. By contrast, skewness captures the degree of low-probability, high-impact events (Salgado et al., 2020; Sheng et al., 2023). These extreme risks do not always manifest themselves with the same frequency (or intensity) as volatility shocks. Hence, the global spillover of skewness tends to be lower on average, as revealed by our empirical findings. However, this does not imply that skewness is unimportant. Rather, it highlights that skewness-based spillovers become crucial, especially when (1) markets exhibit extreme deviations from normality and (2) investor sentiment strongly changes, leading to asymmetric return distributions (Seo and Kim, 2015).

Focusing on the multilayer analysis shows that about half the spillover edges in one layer are also present in the other layer. However, the within-layer spillovers dominate. This aligns with the theoretical premise that, while volatility and skewness are interlinked, each moment can propagate risk predominantly within its own dimension. Skewness does feed into volatility, and vice versa (the so-called "reverse causation" in Black, 1976), but the degree of these cross-layer transmissions is comparatively smaller than the within-layer channels.

Our dynamic analysis identifies six phases of strong connectivity (1929, 1973, 1997–98, GFC of 2007–2009, European debt crisis of 2009–2010, COVID-19 of 2020). In all of these, skewness shows more intense connections, supporting the idea that the second moment is the main vehicle of contagion (He and Hamore, 2021; Bouri et al., 2021, 2023). However, skewness becomes significant at certain periods (e.g., the early 1980s recession, Black Monday of 1987, and Argentina crisis of 1998–2002), showing tail risk dynamics that volatility alone may not capture. This confirms Bouri's (2023) findings that ignoring skewness risks underestimating the financial system's vulnerability during exceptional events. Indeed, our results provide useful information about the role of each financial market depending on network layers. By considering the iteration between the layers (i.e., the two types of risks), we can better identify the systemically important countries, i.e., crucial nodes in our case, from a multilayer network perspective.

Overall, empirical evidence supports the theoretical assumptions that volatility and skewness interact dynamically, especially during phases of high uncertainty (Black, 1976; Bekaert and Wu, 2000; Aït-Sahalia et al., 2013). Using a multilayer approach allows us to capture the complexity of this interaction, suggesting how the second and third moments show different but complementary aspects of market risk spillovers.

4.6. Robustness check

We employ robustness checks to mitigate concerns that the selection of parameters might influence the empirical results. We calculate the dynamics of average connection strength (ACS) using various window widths (w = 60 and 90) and forecast horizons (h = 6, 12, and 18). Fig. 7 illustrates the results. As observed in the figure, the dynamics of ACS exhibit similar behaviour across the various parameter configurations. This consistency strengthens the robustness of our findings, implying that the core results are not contingent upon specific parameter choices.

4.7. Forecasting spillover indices

The spillover analysis reveals a significant degree of within-layer risk spillover but a relatively lower degree of across-layer spillover, with the US market showing 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 for disaster risk) for the risk spillovers across several forecast horizons. As actual forecasts of alternative measures of connectedness attributed to geopolitical risk 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.

Specifically, the dependent variable is the total connectedness index of each of the IQR and SKEW layers (see Fig. 2), and the within-layer spillover index and cross-layer spillover index for each of the IQR and SKEW layers (see Fig. 4). As possible predictors, we evaluate three distinct sets of variables: a) the global GPRH index of Caldara and Iacoviello (2022) [13] 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

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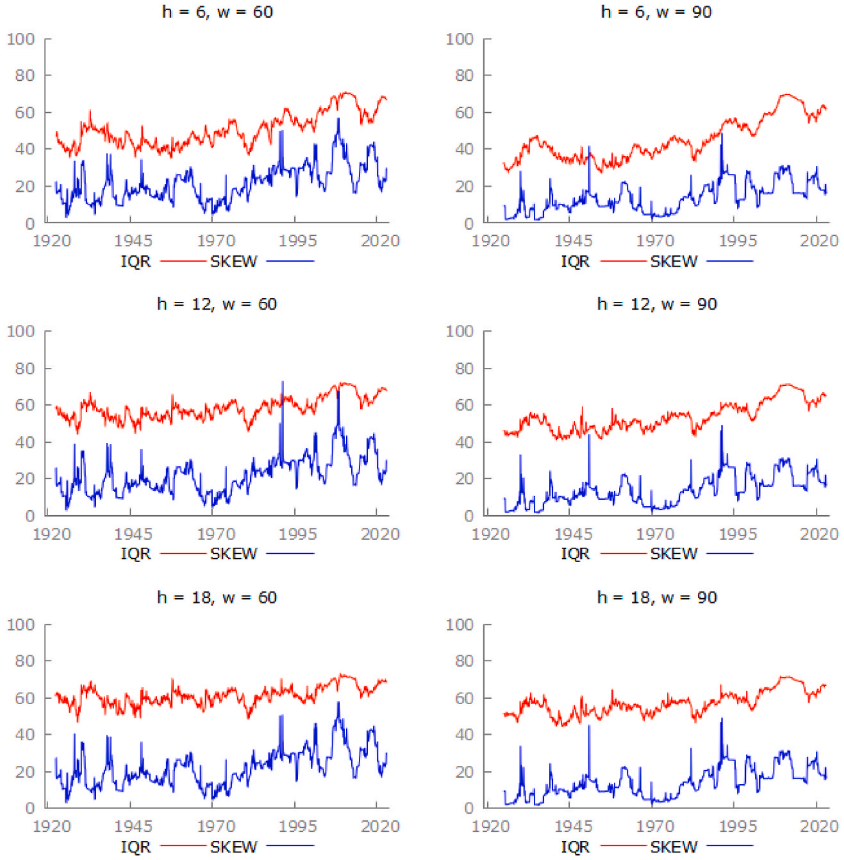
[13] We used the quantile on quantile (QQ) regression of Sim and Zhou (2015) to check the underlying relationship between the levels (quantiles) of the GPRH index and its effect on the conditional quantiles, capturing the conditional states of the within and across spillover indices of IQR and SKEW. As expected, higher GPRH, serving as a metric of bad news, i.e., rare disaster risks, tends to increase the spillover within and across the markets in terms of the two metrics of risk, with this result being consistent across the various levels of spillover indices. Complete details of these results are available upon request from the authors. Understandably, our machine learning methods do not yield an explicit expression for the impact of the various measures of rare disaster risks on the spillover indicators, and hence we rely on the QQ regression to get an underlying picture of this relationship.


h = 6, w = 60

h = 6, w = 90

h = 12, w = 60

h = 12, w = 90

h = 18, w = 60

h = 18, w = 90

Fig. 7. Robustness results based on alternative rolling windows and forecast horizons.

(GPRHT) along with the country specific indices[14]; 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,[15] 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 (10 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.

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 which 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 shown in 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 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 of the weighted GPR and the full information content of all categories, presumably due to the lack of information in the weighting scheme and the inherent noise content of 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 at longer horizons affect the model performance. SVR, XGBoost and ANN are more complex models than RF, but fail to outperform it, suggesting that they tend to overfit.

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[14] 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.

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

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 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), geopolitical risk historical threats (GPRHT), and geopolitical risk historical acts (GPRHA) indices. The most accurate forecast per horizon is shown in bold.

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 risk for forecasting each of the volatility and skewness spillover effects across the G7+Switzerland stock markets. This can be understood under the theoretical framework linking disaster risks, for which the GPR serves as an empirical proxy, equity premium, extreme risks, and stock market volatility (Barro, 2006; Wachter, 2013).

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, as shown in Tables 7 and 8 for the IQR and SKEW layers, respectively. The ARIMA model is the most accurate 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 or GPRHA indices, but

Table 6
Total connectedness forecasts for the SKEW layer.

Horizon (months)	RW	ARIMA	RF	ANN	SVR	XGBoost
Panel A: Global GPR and country GPR indices						
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 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), geopolitical risk historical threats (GPRHT), and geopolitical risk historical acts (GPRHA) indices. The most accurate forecast per horizon is shown in bold.

the global GPR index, as shown 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.

Alongside the results for the importance of geopolitical risk to 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 shows the results of the forecasting models from the IQR layer to the SKEW layer, while Table 10 shows the same for the opposite direction (i.e. spillovers from the SKEW layer to the IQR layer). Once again, at the short 1–6 month horizons the ARIMA model is the most accurate, while at the longer horizons, RF supersedes all other models. The most interesting finding lies in the ability of the disaggregated GPR measures to forecast cross-layer risk spillover better than the global weighted version of GPR.

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 complements studies of the importance of geopolitical risk for the transmission of systemic risk based on volatility only (Lai et al., 2023). It 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+Switzerland stock markets.

5. Conclusions

In this paper, we conduct a complete 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. The sample period is May 1917 to February 2023, corresponding to the entire financial history available for the markets under examination. Using the multilayer 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 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 multilayer 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 or suboptimal. The implications concern 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.

We also evaluate the role of country-specific and global geopolitical risk indices in forecasting layer-based risk spillovers. 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. At the same time, as shown by Caldara and Iacoviello (2022), geopolitical events have a recessionary impact on the global economy, and with these disaster risks also impacting the future path of stock volatility and skewness, i.e., financial market risks, of the developed stock markets, a second-round recessionary impact is possible through the second and third moments (Iseringhausen et al., 2023; Ludvigson et al., 2021). Naturally, policy authorities need to take account of this issue when determining the strength and duration of expansionary monetary and fiscal policies to revive the macroeconomic environment.

Future research could include the examination of a broader sample of financial markets or regions (especially those that are more prone to geopolitical risks, but this is likely to involve shorter data sample) or add higher distribution moments such as kurtosis, while highlighting the portfolio implications by extending the single-layer spillover analysis of Umar et al. (2022).[16] Moreover, our work can be further extended by investigating how the multilayer model operates at different temporal lags within the frequency domain. By examining short, medium, and long-term spillovers, this approach could reveal insights into the temporal spillover hierarchy of influences and their interplay across timescales, along the lines of Ouyang et al. (2023).[17] Furthermore, a robustness analysis of our

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[16] While detailed portfolio analysis is beyond the scope of this paper, when we computed hedge ratios based on fitted returns from two VAR models involving returns and IQR and returns, IQR and SKEW, we found that in general the latter model produced higher ratios, suggesting the need to accommodate simultaneously the information of volatility and skewness in portfolio decisions. Complete details of these results are available upon request from the authors.

[17] As a preliminary analysis, we use the ensemble empirical mode decomposition (EEMD) approach to decompose the IQR and SKEW series for each country into short-, medium- and long-run frequencies, then conduct cross-layer spillover analysis. The unreported results to save space, available upon request from the authors, show that cross-layer spillovers are more strongly connected in the long-term, rather than short or medium-term, possibly suggesting the existence of idiosyncratic movements rather than fundamentally-driven spillovers at the latter two frequencies.

Table 7
Within layer spillover forecasts for the IQR layer.

Horizon (months)	RW	ARIMA	RF	ANN	SVR	XGBoost
Panel A: Global GPR and country GPR indices						
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 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), geopolitical risk historical threats (GPRHT), and geopolitical risk historical acts (GPRHA) indices. The most accurate forecast per horizon is shown in bold.

Table 8
Within layer spillover forecasts for the SKEW layer.

Horizon (months)	RW	ARIMA	RF	ANN	SVR	XGBoost
Panel A: Global GPR and country GPR indices						
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 random walk (RW), autoregressive integrated moving average (ARIMA), random forest (RF), artificial neural network (ANN), support vector regression (SVR), and an extreme gradient boosting (XGBoost). Apart from the global index, we also consider the geopolitical risk historical (GPRH), geopolitical risk historical threats (GPRHT), and geopolitical risk historical acts (GPRHA) indices. The most accurate forecast per horizon is shown in bold.

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 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), geopolitical risk historical threats (GPRHT), and geopolitical risk historical acts (GPRHA) indices. The most accurate forecast per horizon is shown in bold.

Table 10

Cross-layer spillover from SKEW to IQR forecasts.

Horizon (months)	RW	ARIMA	RF	ANN	SVR	XGBoost
Panel A: Global GPR and country GPR indices						
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), geopolitical risk historical threats (GPRHT), and geopolitical risk historical acts (GPRHA) indices. The most accurate forecast per horizon is shown in bold.

findings by including additional metrics of rare disaster events, such as extreme weather shocks, can also be conducted.[18]

Declaration of competing interest

The authors declare no conflict of interest.

Appendix

Table A1
Major historical events affecting the international stock markets

Number	Event details
1	US financial crash of 1929
2	OPEC oil crisis of 1973
3	Asian crisis of 1997–1998
4	Global financial crisis of 2007–2009
5	European sovereign debt crisis of 2009–2010
6	COVID-19 pandemic of 2020
7	Russian-Ukrainian conflict of 2022

Notes: This table indicates the timing of various historical events, including major financial, economic, health, and geopolitical crises, obtained from Global Financial Data (https://globalfinancialdata.com/).

Table A2
List of G7 and Switzerland stock market indices

Country name	Abbreviation	Stock index name
Canada	CA	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
Switzerland	SW	All Share Stock Index
United Kingdom	UK	FTSE All Share Index
United States	US	S&P500 Index

Notes: This table presents the eight advanced economies under study and their stock market indices.

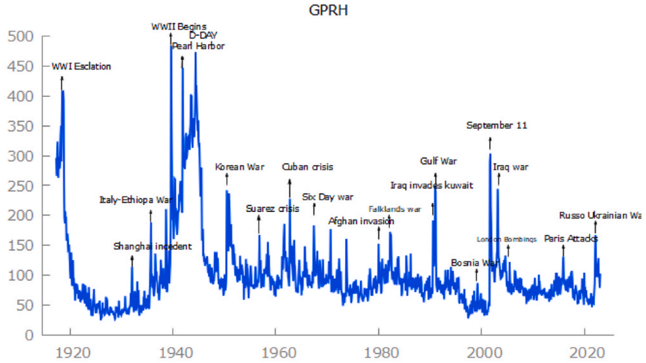

Fig. A1. Annotated plot of the historical geopolitical risks (GPRH) index.

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[18] Quantiles-based causality testing, which allows us to control for both nonlinearity and provide evidence of predictability over the entire conditional distribution of the dependent variable, revealed that the various global geopolitical risks indexes continued to cause, in general, the entire conditional distributions of the within and across spillover measures of volatility and skewness, with year-on-year changes in global temperature anomaly and its volatility (derived from the National Oceanic and Atmospheric Administration of the National Centers for Environmental Information) as control variables. These findings should not come as a surprise, because, even physical climate risks often gets reflected in conflicts (Burke et al., 2015; Jin et al., 2023; Xie et al., 2024). Complete details of these results are available upon request from the authors.

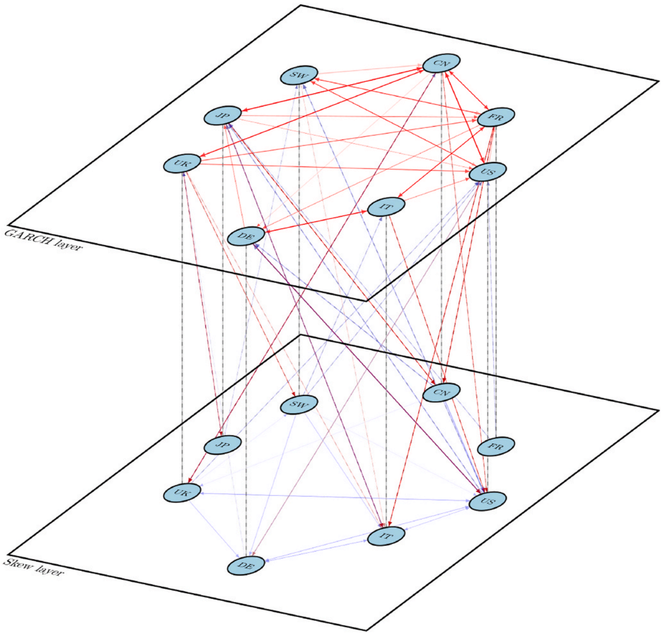

Fig. A2. Snapshot of the multilayer network over time using a GARCH-based model of stock returns volatility.

Data availability

Data will be made available on request.

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