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Long-Span Multi-Layer Spillovers between Moments of Advanced Equity Markets: The Role of Climate Risks

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Abstract

In this paper, we examine the potential spillovers between returns, volatility, skewness and kurtosis of developed stock markets under the lenses of rare disaster events, proxied by climate risks. The goal of this study is to depict the transmission mechanism of rare disaster events involving moments within and between advanced equity markets. In doing so, we provide estimates of the aforementioned moments based on model-implied distributions of stock returns, derived from the quantile autoregressive distributed lag mixed-frequency data sampling (QADL-MIDAS) method, using a long span of data. Our research framework includes the G7 and Switzerland over the period December 1924 to February 2023, where we apply a multilayer approach to spillovers, adding the effect of climate risk to our analysis. Our empirical findings are as follows: firstly, spillovers are significant within- and across stock markets for each of the four moments. Secondly, based on a nonparametric causality-in-quantiles approach, changes in temperature anomalies, have the predictive power to shape the entire conditional distribution of various metrics of spillover involving single- and multiple-layers of returns and risks layers. In sum, we show that the multi-layer approach offers a comprehensive and nuanced view of how stock market-related information is transmitted across the stock markets of advanced economies, carrying implications for investors and policymakers.

Key words: Returns and risk spillovers; advanced equity markets; multi-layer spillover approach; nonparametric causality-in-quantiles method; climate risks; predictability.

JEL Codes: C22, C32, C53, G15, Q54

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1. Introduction

Climate change-related extreme weather conditions, due to increased levels and variability of global temperature, poses a large aggregate risk to the stock markets, and the overall financial system in general (Del Fava et al., 2024), due to occurrences of rare disaster events impacting far out-in-the-left-tail realizations of the underlying states of the economy (Giglio et al., 2021; Stroebel and Wurgler, 2021; van Benthem et al., 2022). Theoretically speaking, the key assumption underlying rare-disaster models used to explain this nexus is that, the entire universe of assets in an economy is exposed to an aggregate jump-risk factor (Rietz, 1988; Barro, 2006, 2009). It follows that, even though in the cross section, some assets are more exposed to such a tail events than others, a jump-risk factor should be an important driver of the time-series variation in the various moments of individual asset prices, as detected recently in the context of the international stock markets by, for example, Choi et al. (2020), Balcilar et al. (2023), Bonato et al. (2023) Salisu et al. (2023a), due to reduction in productivity and/or the increase in the stochastic depreciation rate of capital to produce adverse impact on equity valuations (Donadelli, 2017, 2021a, b, 2022).

Against this theoretical backdrop, one can hypothesize that the jump-risk factor associated with global warming, involving changes in temperature anomalies and its volatility, is likely to cause the spillover of not only the non-normal returns and volatility, but also skewness and kurtosis of the interconnected international stock markets (see, among others, the detailed discussions in Bouri et al. (2021, 2023), Bouri (2023), and Ahmed et al. (2024) in this regard). In this regard, recall that, there are primarily two channels, namely real (trade) linkages and information involving market characteristics, which connects the financial sectors of the world economies (Debarsy et al., 2018). With adverse global shocks associated with weather-related risks impacting both these channels, it is not far-fetched to propose our above-mentioned hypothesis.

To econometrically test our hypothesis, we obtain measures of volatility, skewness and kurtosis from monthly log-returns of stock indexes for eight advanced economies, namely Canada, France, Germany, Italy, Japan, Switzerland, the United Kingdom (UK), and the United States (US) based on a century of historical data (December 1924-February 2023), using the quantile autoregressive distributed lag mixed-frequency data sampling (QADL-MIDAS) method (Ghysels et al., 2018). We must emphasize that, besides the availability of the longest possible samples of stock market data to avoid possible sample-selection-bias, the choice of the aforementioned equity markets is primarily motivated by their importance to the global economy, since they represent nearly the two-thirds of the global net wealth, and nearly half of the world output. Hence, a spillover analysis would be of pivotal importance from the perspective of the stability to the world financial system (Das et al., 2019;

Salisu et al., 2023b). Furthermore, as pointed out by Ghysels et al. (2018), the QADL-MIDAS model mixes low and high frequency data and outperforms standard autoregressive conditional heteroskedasticity (ARCH), generalized ARCH (GARCH) and quantile autoregressive (QAR) approaches in extracting risk measures. Thus, our reliance on the QADL-MIDAS model, rather than the QAR, to obtain the higher-order moments from the stock returns.

After compiling moments for each market, we analyze the connectedness of returns, volatility, skewness and kurtosis for the eight stock markets not only within the a specific-layer of the moment (as traditionally done in the literature; see, Diebold and Yilmaz (2009), BenSaïda (2019) and Choi and Yoon (2023) for reviews), but also but also across the four moments using the multi-layer approach of Wang et al. (2021), which can fully capture all possible information spillover effects between returns, volatility, skewness and kurtosis (Foglia et al., 2023). As pointed out by Wang et al. (2021), while proposing the econometric methodology of multi-layer connectedness, the complexity of the financial system makes spillover analyses based on a single-layer network involving multiple countries a sub-optimal choice, because a single measure of the financial market performance cannot capture the diversity and heterogeneity of information transmission and its interconnectedness among markets. Thus, it is necessary to use multilayer networks, which consider heterogeneous information and the multilayer structure of a complex system involving asset market moments, to understand the interaction behaviour in global stock markets. Multilayer networks, where links in each layer represent different types of connections among the same set of nodes (the eight advanced equity markets in our case), can combine various interconnectedness measures together to describe complex financial systems effectively across returns and alternative metrics of risks simultaneously. Accordingly, we use a model of multilayer information spillover networks as an extension of the original work based on a single-layer by Diebold and Yilmaz (2012, 2014), including a returns, volatility, skewness and kurtosis spillover layers, to comprehensively investigate the interconnectedness of developed stock markets. Due to the importance of returns and risk spillover analysis from the perspective of portfolio allocation and risk management (Ji et al., 2020; Gong et al., 2023; Iqbal et al., 2024), this multi-layer approach should be of paramount importance to investors, allowing them to get a complete understanding of the interconnectedness of moments across developed stock markets.

Finally, we utilize a nonparametric causality-in-quantiles framework of Jeong et al. (2012), to relate the predictability of changes in global temperature anomalies and its volatility, with the latter also derived from the QADL-MIDAS model, for the various metrics of single- and multi-layer connectedness within and across the moments, respectively. This test has the key advantage that it enables us to detect predictability across the entire conditional distribution of the connectedness measures, resulting from climate risks, while simultaneously controlling in a data-driven manner for possible misspecification due to nonlinearity usually associated with relationships involving financial data spanning long periods of time. Note that, a quantiles-based nonparametric predictive approach, rather than conditional mean-based methods (as in, for example, Diks and Panchenko (2005, 2006)), ensures that we do not end up missing possible causal influence at certain parts of the conditional distribution of the indexes of connectedness.

The contributions of our study are in multiple fronts, being the first of its kind to: (a) estimate robust metrics of volatility, skewness and kurtosis using QADL-MIDAS models involving over a century of data, which, in turn, is the longest available, on the evolution of returns of important stock markets thus controlling for possible sample-dependent bias arising from the choice of specific sample periods; (b) provide an analysis of multi-layer spillovers across returns, volatility, skewness and kurtosis 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 spillover across alternative metrics of stock market performance; and (c) evaluate the predictability of the entire conditional distribution of spillover measures using a nonparametric causality-in-quantiles framework based on the information content of proxies of climate risks, which are well-established drivers of the variability of asset market movements, with the predictions likely to be invaluable for investors to gauging the future risk profile of equity markets, and hence, assist in optimal portfolio allocation in the face of global adverse shocks.

The remainder of the paper is organized as follows: Section 2 discusses the data. Section 3 lays out the QADL-MIDAS, multi-layer connectedness, and nonparametric causality-in-quantiles models. Section 4 presents the results of the multi-layer connectedness analysis and the associated predictive exercise in relation to the changes in global temperature anomalies and its volatility. Finally, Section 5 concludes.

2. Data

The log-returns of stock market indexes used in this study cover an extensive period, spanning the period December 1924 to February 2023 at a monthly frequency and are obtained from the Global Financial Database[1]. This extended time-series dataset allows us to analyse and capture various historical events, including major financial and economic crises, such as the 1929 US financial crash, the 1973 OPEC oil crisis, the Asian crisis of 1997-1998, the global financial crisis of 2008, the 2009

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

European sovereign debt crisis, the COVID-19 pandemic of 2020, and the recent Russian-Ukrainian conflict. These extreme events have significantly impacted financial markets, increasing market volatility and making the description of the risks-returns transmission analysis a central research issue. The dataset consists of the market indices of eight advanced economies, which include the G7: Canada (CA; S&P TSX 300 Composite Index), France (FR; CAC All-Tradable Index), Germany (DE; 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) and Switzerland (CH; All Share Stock Index).

As far as climate risks are concerned, global land and ocean temperature anomalies (relative to 1901-2000) over the corresponding period, derived from the National Oceanic and Atmospheric Administration of the National Centers for Environmental Information[2]. We compute year-on-year changes in the median world temperature anomalies to ensure that we avoid seasonal patterns in the data. The QADL-MIDAS, discussed in detail in the next section, is fitted to log-returns to obtain our measures of volatility, skewness and kurtosis, while the same model is used to obtain the corresponding volatility of year-on-year changes in temperature anomalies.

Table 1 shows the list of financial markets and summary statistics of our stock returns data, with the non-Gaussian distributions, as confirmed by the Jarque-Bera (JB) test-statistic, confirming the need to look beyond the first moment, while analysing spillovers.

Table 1: Summary statistics

	Mean	Variance	Skewness	Ex.Kurtosis	JB
Stock Returns (RET)					
CA	0.422	21.643	-1.152	5.960	2003.998***
FR	0.598	30.527	-0.242	1.824	174.722***
DE	0.504	25.24	-0.397	4.270	926.035***
IT	0.519	50.818	0.807	5.794	1775.359***
JP	0.583	36.205	0.566	7.298	2676.796***
UK	0.419	21.932	-0.256	9.299	4256.988***
US	0.511	19.667	-0.600	12.051	7199.268***
CH	0.363	18.743	-0.541	5.328	1450.698***

Note: The Table shows the summary statistics for log-returns. The Jarque–Bera (JB) statistic tests the null hypothesis of normal distribution. *** indicates rejection of the null hypothesis at the 1% level of significance.

[2] https://www.ncei.noaa.gov/access/monitoring/climate-at-a-glance/global/time-series.

3. Methodology

To estimate the multilayer information spillover network between stock market returns (RET), inter-quartile range (IQR) capturing volatility, skewness (SKEW) and kurtosis (KURT), we applied the model proposed in Wang et al. (2021). Based on a Granger causality test, the approach is able to capture the static and dynamic spillover effect on a multilayer network. The empirical design is carried out in five steps. Firstly, we employ the QADL-MIDAS to extract the relevant stock market measures, namely our four layers of the network. Secondly, we compute the informational spillover effect. Thirdly, we build the multilayer network, and fourthly, we calculate the single and multi-layer network measures. Finally, the nonparametric causality-in-quantiles model is used to predict the entire conditional distribution of the various metrics of within and across layer connectedness due to climate risks.

3.1. QADL-MIDAS model

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

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

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

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

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

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

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

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

and skewness (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:

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

When the distribution is symmetric, the two distances are similar and skewness is zero, while when $\hat{q}_{1-\tau,t|t-h} - \hat{q}_{0.50,t|t-h}$ is larger (smaller) the distribution is skewed to the right (left). The standardization makes the measure unit-free and between -1 and 1. Finally, kurtosis (KURT) as a measure of the existence of outliers in the dataset, at τ = 0.01, can be estimated as:

$$KURT^{\tau}_{t|t-h} = \frac{(\hat{q}_{1-\tau,t|t-h} - \hat{q}_{\tau|t-h})}{\hat{q}_{0.75,t|t-h} - \hat{q}_{0.25,t|t-h}} \tag{6}$$

Note that, the volatility of the year-on-year changes in temperature anomalies are also derived using the IQR, specified in equation (4).

3.2. Multi-layer connectedness

We now turn our attention to the methodological background of multi-layer connectedness in a step-by-step manner. First, we estimate the information spillover and build the multilayer network. Second, we compute the connectedness measures from a single- and multilayer network perspective.

3.2.1. Spillover and network framework

The multilayer information spillover network is computing following Wang et al. (2021), i.e., based on a Granger causality test in mean. To compute the spillover from financial market 2 to financial market 1 (and vice versa), we test the following null hypotheses:

$$\begin{cases} H_0: E\left(RET_{1,t} \middle| I_{1,t-1}\right) = E\left(RET_{1,t} \middle| I_{t-1}\right) \\ H_A: E\left(RET_{1,t} \middle| I_{1,t-1}\right) \neq E\left(RET_{1,t} \middle| I_{t-1}\right) \end{cases},$$

$$\begin{cases} H_0: E\left(\mathrm{IQR}_{1,t} \middle| I_{1,t-1}\right) = E\left(\mathrm{IQR}_{1,t} \middle| I_{t-1}\right) \\ H_A: E\left(\mathrm{IQR}_{1,t} \middle| I_{1,t-1}\right) \neq E\left(\mathrm{IQR}_{1,t} \middle| I_{t-1}\right) \end{cases},$$

$$\begin{cases} H_0: E\left(\mathrm{SKEW}_{1,t} \middle| I_{1,t-1}\right) = E\left(\mathrm{SKEW}_{1,t} \middle| I_{t-1}\right) \\ H_A: E\left(\mathrm{SKEW}_{1,t} \middle| I_{1,t-1}\right) \neq E\left(\mathrm{SKEW}_{1,t} \middle| I_{t-1}\right) \end{cases}, \tag{7}$$

$$\begin{cases} H_0: E\left(\mathrm{KURT} \middle| I_{1,t-1}\right) = E\left(\mathrm{KURT}_{1,t} \middle| I_{t-1}\right) \\ H_A: E\left(\mathrm{KURT}_{1,t} \middle| I_{1,t-1}\right) \neq E\left(\mathrm{KURT}_{1,t} \middle| I_{t-1}\right) \end{cases},$$

where *RET, IQR, SKEW and KURT* refer to the measures of financial stock market performance, while I_{t-1} is the information set. If the null hypothesis of the Granger causality in mean is true, it implies that there is no spillover effect from the financial market 2 to market 1 at a given significance level (in our case, = 0:05). On the contrary, there is a spillover effect from the financial market 2 to market 1.

Following Hong et al., (2009), we built a Q statistic, to merge the information spillover in a unified framework as follows:

$$Q = T\sum_{j=1}^{T-1}\left[k^2(j/M)/\widehat{\rho^2}(j) - C_T(M)\right]/\left(2D_T(M)\right)^{1/2} \tag{8}$$

where $C_T(M)$ and $D_T(M)$ stand for the centering and standardization constants, respectively, *M* denotes the effective lag truncation order and $k(\cdot)$ is the Daniel kernel function as suggested by Hong et al. (2009).

3.2.2. The multi-layer network framework

Following Wang et al., (2021), we define the multilayer information spillover network as $\Omega = \{G^{[1]}, G^{[2]}, \dots, G^{[L]}\}$, with *N* nodes and *L* layers. $G^{[\alpha]} = G\left(V, A^{[\alpha]}\right)$ is layer α of the multilayer information spillover network, $V = \{1,2,\dots,N\}$ is a set of nodes, while $A^{[\alpha]}$ is a set of edges on layer α. The multilayer network is composed by four layers (*L = 4*), namely stock returns, IQR volatility, skewness index and kurtosis measure, respectively. The binary connection matrix is defined as

$$A^{[\alpha]} = a_{i,j\ \ N\times N}^{[\alpha]} \tag{9}$$

where $a_{i,j}^{[\alpha]} = \begin{cases} 1, & \text{if i} \neq \text{ j and i has a corresponding spillover effect on j on layer a} \\ & 0, \text{ otherwise} \end{cases}$

Thus, the multilayer information spillover network is a 4-dimensional $N \times N$ adjacency matrix. In order, to investigate the dynamic features of a multilayer information network, we approach the sample interval using rolling windows estimation. Following Balcilar and Usman (2021) we use a 60-month (5-year) rolling sample on 12-step horizons.

3.2.3. Network measures

To analyse the network's topological features, we calculate three connectivity measures. In particular, we compute the single-layer index (the degree index) and two multilayer indexes, the overlap measure and the participation coefficient.

3.2.4. Single-layer measure: the degree index

This measure captures the number of edges on the layer, i.e., the higher the degree of a layer, the closer the connection between the layer variables. We can define the degree index as:

$$a^{[\alpha]} = \sum_{i,j=1;i\neq j}^{N} a_{ij}^{[\alpha]} \tag{10}$$

where $a_{ij}^{[\alpha]}$ is the edge from financial market *i* to financial market *j* on layer α.

3.2.5. Multi-layer measures: overlap index

The overlap index, as defined by Musmeci et al. (2017), quantifies the number of overlaps associated with each edge (financial markets) within our network. This metric provides insights into the similarity and homogeneity of edge structures across each layer, delineated by the respective layers they represent - stock market returns (RET), inter-quartile range (IQR) volatility, skewness (SKEW) and kurtosis (KURT). The overlap index is defined as follows:

$$O = \frac{1}{K} \sum_{i=1}^{N} \sum_{j=1,i\neq j}^{N} \sum_{a=1}^{L} a_{ij}^{[\alpha]} \tag{11}$$

To identify the markets exerting significant influence on spillover transmission, we compute the degree of overlap, identifying central nodes within the network, hence:

$$o_i = \sum_{a=1}^{L} \sum_{i=1}^{N} \sum_{j=1,i\neq j}^{N} a_{ij}^{[\alpha]} \tag{12}$$

With our network comprising four layers, the overlap index ranges from 1 to 4, reflecting the extent of connectivity among financial markets. In other words, it measures the similarity (homogeneity) of the edge structures of each layer. The degree of overlap defines the total number of overlaps between layers to which financial markets belong. A value near 1 signifies that an edge exists solely within one layer, whereas a value nearing 4 indicates a high degree of similarity in connectivity across layers.

3.2.6. *Multi-layer measures: participation coefficient measure*

We calculate the participation coefficient index to gauge the node distribution across layers. This index, ranging from 0 to 1, delineates the extent to which a financial market serves as a hub within one layer relative to others. A value close to zero suggests that the node's connections are predominantly confined to one layer, while a value near 1 indicates a more uniform distribution of connections across layers. Higher coefficient values signify a greater uniformity in the direct connections between network layers. The participation coefficient is given by:

$$P_i = \frac{L}{L-1}\left[1 - \sum_{\alpha=1}^{L}\left(\frac{k_i^{[\alpha]}}{o_i}\right)^2\right] \tag{13}$$

where $k_i^{[\alpha]}$ is the degree of node i on layer α.

3.3. *Nonparametric causality-in-quantiles test*

In this sub-section, we briefly present the methodology for testing nonlinear causality based on the framework of Jeong et al. (2012). Let y_t denote the specific spillover measure and x_t either the year-on-year changes in temperature anomalies or its IQR-based volatility, which we call climate risks 1 or climate risks 2, i.e., CR1 or CR2. Further, let $Y_{t-1} \equiv (y_{t-1}, \dots, y_{t-p})$, $X_{t-1} \equiv (x_{t-1}, \dots, x_{t-p})$, $Z_t = (X_t, Y_t)$, and $F_{y_t|\cdot}(y_t|\,\bullet)$ denote the conditional distribution of y_t given $\bullet$. Defining $Q_\theta(Z_{t-1}) \equiv Q_\theta(y_t|Z_{t-1})$ and $Q_\theta(Y_{t-1}) \equiv Q_\theta(y_t|Y_{t-1})$, we have $F_{y_t|Z_{t-1}}\{Q_\theta(Z_{t-1})|Z_{t-1}\} = \theta$ with probability one. The (non)causality in the θ-th quantile hypotheses to be tested are:

$$H_0\colon\; P\left\{F_{y_t|Z_{t-1}}\{Q_\theta(Y_{t-1})|Z_{t-1}\} = \theta\right\} = 1 \tag{14}$$

$$H_1\colon\; P\left\{F_{y_t|Z_{t-1}}\{Q_\theta(Y_{t-1})|Z_{t-1}\} = \theta\right\} < 1 \tag{15}$$

Jeong et al. (2012) show that the feasible kernel-based (standard normal) test statistic has the following format:

$$\hat{J}_T = \frac{1}{T(T-1)h^{2p}} \sum_{t=p+1}^{T} \sum_{s=p+1, s\neq t}^{T} K\left(\frac{Z_{t-1} - Z_{s-1}}{h}\right)\hat{\varepsilon}_t\hat{\varepsilon}_s \tag{16}$$

where $K(\bullet)$ is the kernel function with bandwidth h, T is the sample size, p is the lag order, and $\hat{\varepsilon}_t = \mathbf{1}\{y_t \le \hat{Q}_\theta(Y_{t-1})\} - \theta$ is the regression error, where $\hat{Q}_\theta(Y_{t-1})$ is an estimate of the θ-th conditional quantile and $\mathbf{1}\{\bullet\}$ is the indicator function. The *Nadarya-Watson* kernel estimator of $\hat{Q}_\theta(Y_{t-1})$ is given by

$$\hat{Q}_\theta(Y_{t-1}) = \frac{\sum_{s=p+1, s\neq t}^{T} L\left(\frac{Y_{t-1} - Y_{s-1}}{h}\right)\,\mathbf{1}\{y_s \le y_t\}}{\sum_{s=p+1, s\neq t}^{T} L\left(\frac{Y_{t-1} - Y_{s-1}}{h}\right)} \tag{17}$$

with $L(\bullet)$ denoting the kernel function.

The empirical implementation of causality testing via quantiles entails specifying three key parameters: the bandwidth (h), the lag order (p), and the kernel types for $K(\cdot)$ and $L(\cdot)$. We use a lag order of one based on the Schwarz Information Criterion (SIC). We determine h by the leave-one-out least-squares cross validation. Finally, for $K(\cdot)$ and $L(\cdot)$, we use Gaussian kernels.

4. Empirical findings

In this section, we will first present the discussion of the multi-layer spillover and then relate the alternative measures of within and across layer connectedness involving returns, volatility, skewness and kurtosis with climate risks via a nonparametric causality-in-quantiles framework.

4.1. Global-level investigation

Examining the dynamics of global connection degree offers important insights into the behaviour of layers, shedding light on the topological characteristics of the four layers under examination. In Figure 1, we plot the dynamic evolution of global connection density degrees across stock market returns (RET), inter-quartile range (IQR) volatility, skewness (SKEW), and kurtosis (KURT) from 1929 to 2023.

Several important findings emerge from Figure 1, and Table 2. First, we can see how the measures capture different dimensions of financial market connectedness. For example, we can note significantly higher degree values in the returns layer (RET). This suggests a heightened degree of connectivity among financial markets concerning stock returns. On the other hand, the SKEW layer manifests lower levels of connectedness, indicating lesser connectivity of markets during low-probability events. The differing levels of connectedness in these layers suggest distinct market responses to varying types of risk, as highlighted in the literature (Finta et al., 2020; Bouri et al., 2021). In fact, we can note that financial markets exhibit significant integration in the IQR volatility and kurtosis layers.

Second, graphic evidence shows that spillovers vary over time and respond to crisis events differently depending on the layer considered.

The trend in the RET layer highlights several crucial phases in global economic and geopolitical history. Each peak reflects significant events that impacted global markets and shaped the dynamics of financial and investment markets. The first peak shows the 1929 crisis. This crisis witnessed plummeting stock prices, widespread bank failures, and high unemployment (Galbraith, 2009). This period marked the onset of a prolonged global recession with severe consequences for financial markets and investor confidence. The second peak, in the 1950s and 1960s, coincides with the escalation of the Cold War and the Korean War. These geopolitical events increased international tensions and significantly impacted financial markets (Ohaninan, 1997). The third peak shows the 1973-1974 oil crisis. In this period, there was a surge in oil prices and the emergence of stagflation. This posed significant challenges for global financial markets, leading to declining stock prices and influencing both inflation and economic growth. The fourth peak, in 1990, coincides with the geopolitical risk turmoil due to the Gulf War (1990-91). The fifth peak, during the dot-com bubble's collapse in the early 2000s, highlighted the risks of excessive speculation in financial markets, which resulted in significant losses for investors (Basse et al., 2021). The sixth peak coincides with the global financial crisis 2008 and the subsequent European sovereign debt crisis, reflecting the ensuing economic and financial turmoil. Finally, the COVID-19 pandemic (2020) is another recent event with a significant impact on the RET layer.

While the RET layer provides significant insights into broad historical trends, the IQR layer offers a more granular perspective on financial market dynamics during pivotal events. By delving into the IQR layer, we can gain a deeper understanding of how markets respond to economic and financial crises, as well as systemic risks. A prime example is the period surrounding World War II (1939-1945). The IQR layer effectively captures the substantial fluctuations in stock markets worldwide. The geopolitical tensions associated with the war and its aftermath significantly impacted investor uncertainty, leading to volatile stock prices. This case underlines the significant impact of geopolitical events on financial markets, which the IQR layer captures with greater detail compared to the RET layer. For example, the Global Financial Crisis (2007-2009) and the European Debt Crisis (2010-2014) exposed deep-seated vulnerabilities in the financial system, leading to unprecedented market turmoil. The IQR layer excels at capturing this period of heightened volatility and uncertainty. The collapse of major financial institutions, the housing market crash, and the proliferation of toxic assets are all reflected in the broader range of market movements captured by the IQR layer. Additionally, complex financial products like mortgage-backed securities and credit default swaps amplified market volatility and systemic risks, further emphasizing the value of the IQR layer in revealing such dynamics. Finally, the IQR layer remains relevant in the contemporary context. Heightened geopolitical tensions, such as the ongoing Russia-Ukraine conflict, have significant implications for financial markets. The IQR layer reflects increased market volatility and risk aversion driven by these conflicts.

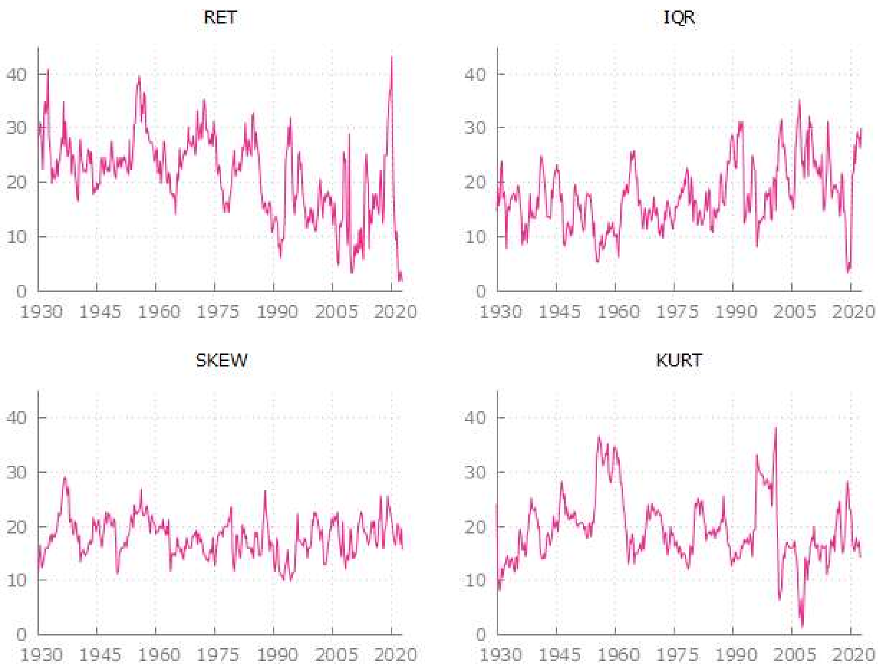

Figure 1: Degree connectedness for each layer

Table 2: Summary statistics of degree of connectedness index

Layer	Mean	S.D.	Min	Max
RET	21.4	7.88	1.000	44.0
IQR	17.5	6.23	3.00	37.0
SKEW	18.0	3.60	9.00	31.0
KURT	19.3	6.26	0.000	42.0

Note: S.D. stands for standard deviation; Min and Max corresponds to minimum and maximum, respectively.

While the IQR volatility spillovers offer a valuable starting point, analysing spillovers in the SKEW and KURT layers can help gain a deeper understanding of financial market dynamics. These layers help to reveal how extreme events and market anomalies influence market behaviour over time.

Unlike volatility, skewness spillovers exhibit a smoother pattern, reflecting subtle shifts in market sentiment and risk preferences. It is interesting to note that connections within the IQR volatility layer are consistently prevalent compared to the skewness (SKEW) layer across different periods. This suggests a heightened degree of interconnectedness among financial markets concerning volatility risk relative to low-probability event risks. The IQR layer consistently exhibits greater connectivity, reflecting the significant transmission of volatility-related information and risk across markets during both normal and crisis periods. These results corroborate the analysis of He and Hamore (2021). The authors investigate the volatility and skewness spillovers for four developed markets (the United States, the United Kingdom, Japan, and Hong Kong) and four emerging markets (Mainland China, South Korea, Thailand, and India) from 1995-2019. Their results show how the total skewness spillover is far smaller than the total volatility.

In contrast, the KURT layer exhibits distinct peaks associated with historical events and financial market crises. These peaks coincide with pivotal moments like the Cold War, the Korean War, Black Monday (1987), the Asian Financial Crisis (1997-1998), and the Argentine great depression (1998-2002). Each event represents a period of heightened uncertainty, systemic risk, and extreme market conditions reflected in elevated kurtosis spillovers. For example, Black Monday's sudden and severe crash generated significant market dislocation, reflected in the peak kurtosis spillover, highlighting the event's extreme nature. The Asian Financial Crisis and the Argentine great depression expose vulnerabilities in emerging markets and the potential for contagion across global financial systems. Peaks in kurtosis spillovers during these crises reflect the heightened tail risk and extreme market conditions, underlining the systemic implications of financial instability.

Overall, the analysis at the layer level underscores the importance of adopting a multidimensional approach to information spillover assessment, considering various financial market layer components and their respective impacts on market dynamics. The results show the interrelationship of return and risk indicators across markets, particularly during significant crisis events. Hence, distinguish spillover indices at each layer serve as a crucial tool for monitoring and understanding market conditions and risk dynamics (Bouri et al., 2021). For example, as we can observe, focusing solely on the connectivity dynamics of returns may overlook valuable information. Each layer captures different dimensions of information that, when considered together, can lead to a deeper understanding of spillover effects across financial markets.

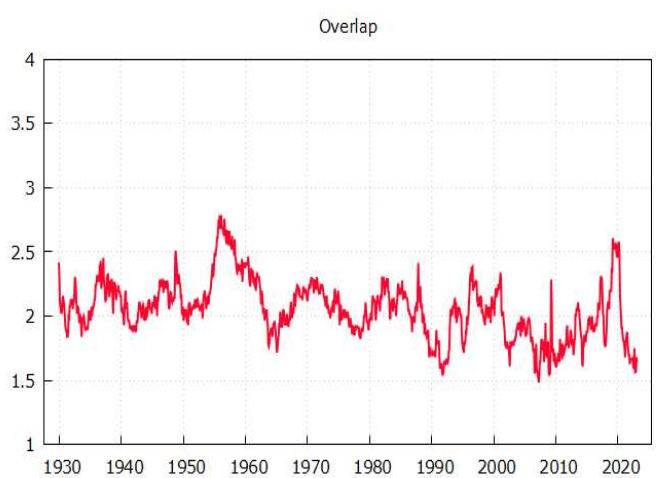

Figure 2: The evolution of overlap index

In Figure 2, we report the dynamic average edge overlap within multilayer information spillover networks. The index exhibits variations, with values ranging from 1.5 to 2.7, with a mean close to 2. This indicates that each layer offers crucial and complementary information, facilitating a more comprehensive understanding of information spillover transmission between markets. This significant overlap between layers signifies that no single layer holds all the crucial information. Instead, each layer captures distinct aspects of information flow, encompassing factors like volatility, skewness, and kurtosis. Hence, the finding underscores the complementary nature of the information provided by each layer. By considering all layers together, we can achieve a more comprehensive understanding of how information spills over between financial markets. In fact, an edge in multilayer information spillover networks always appears in less than four layers. It is interesting to note that the behaviour of the index mirrors market conditions, with an increase during financial turmoil signifying heightened overlap and interaction among layers and a decrease during stability indicating reduced overlap and interaction.

To further understand the multilayer network features, we follow Wang et al., (2023), and analyse cross-layer spillover measurements to gain insight into within network influence. Figure 3 depicts the cross-spillover layer measures. As we observe, spillovers are transmitted within the same layer. Across all four layers, cross-spillover dynamics within the same layer range from 60% to 80%. This suggests a significant level of internal transmission within each layer, indicating that spillovers tend to propagate primarily within their respective layers.

However, upon closer examination, we observe variations in the composition of cross-spillover dynamics across layers. For instance, the analysis highlights notable differences in spillover patterns between the return and other layers. Specifically, we observe that spillovers from the return layer (RET), particularly into the inter-quartile range (IQR) volatility layer, range from 20% to 30%. This finding suggests a strong and consistent link between the return layer (RET) and the IQR volatility layer, indicating that movements in stock returns considerably impact volatility dynamics within the financial markets (Guo and Whitelaw, 2006).

Moreover, we observe distinct patterns of spillovers between the skewness (SKEW) and the kurtosis (KURT) layers. The figure shows that the SKEW layer exhibits approximately 20-25% spillovers into the KURT layer and vice versa. This reciprocal spillover relationship suggests a close interconnection between the 2 layers, indicating that changes in skewness (i.e., asymmetry of return distributions) can influence kurtosis (i.e., the fatness of tails) and vice versa.

By examining cross-layer spillover dynamics over different time periods, we can unveil the evolution of interconnectivity between layers in response to changing market conditions and external events (such as financial and economic crises). The patterns of cross-layer spillovers highlight the complex nature of spillover transmission and the importance of considering multiple layers of information to gain a comprehensive understanding market dynamics.

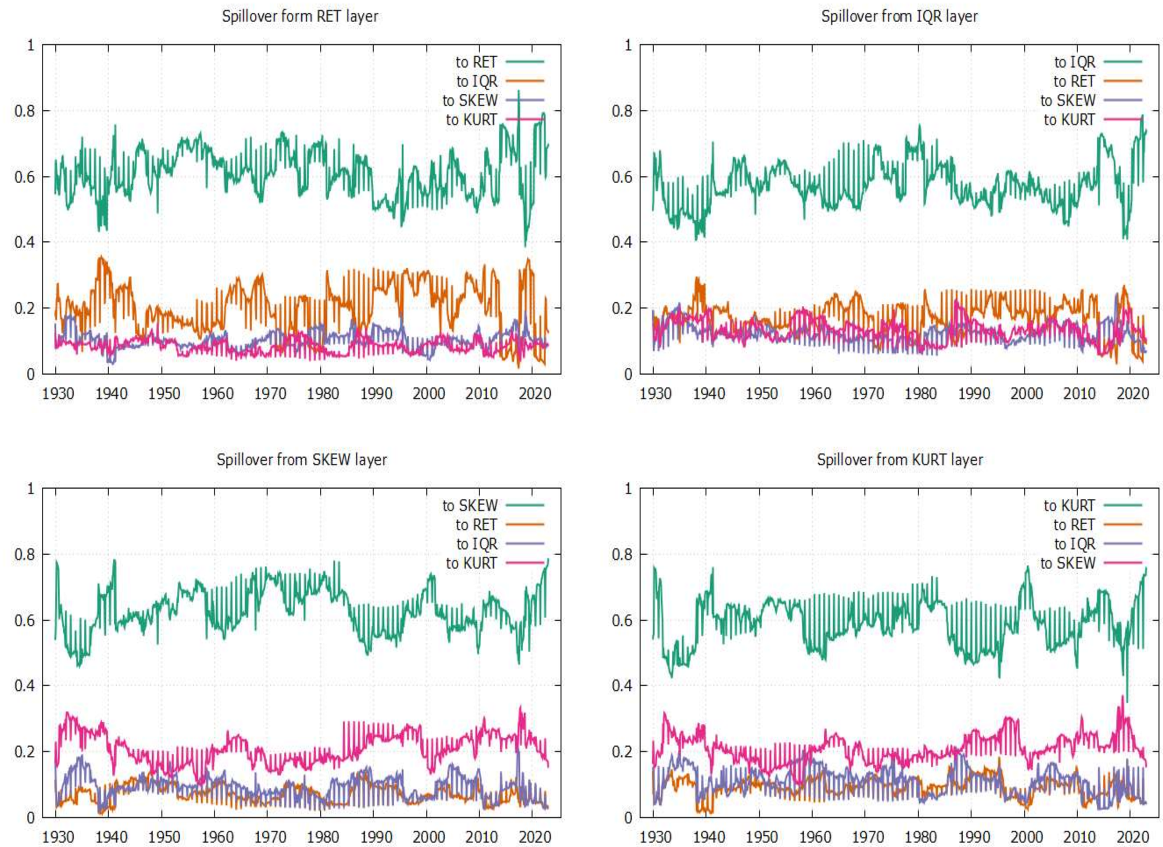

Figure 3: The dynamic of cross-spillover

4.2. Financial markets overview

In this sub-section, we investigate each financial market's role in the spillover information dynamics according to the four layers. For this purpose, we calculate two multilayer network measure, i.e., the overlapping and participation coefficient indexes, as plotted in Figure 4.

The dynamic fluctuations in the overlap degree offer evidence of the evolving roles played by individual markets across different economic periods, potentially reflecting the influence of distinct financial and macroeconomic conditions. The colour scale ranges from lighter colour, indicating values close to zero, to darker, representing high values of the degree index. The overlapping dynamics track major events occurring during this period, which were historically triggered by significant economic events, recessions, financial crises, and health crises. The indices underscore the highly interconnected nature of the global financial system, where shocks in one part of the world can swiftly propagate to affect markets globally. In fact, during periods of heightened economic uncertainty or crisis, we observe darker shades indicating increased overlap, signifying a convergence of risk transmission channels across countries. This convergence underscores the interconnectedness of financial markets, where shocks in one countries can swiftly propagate to affect others, amplifying systemic risks.

These high levels of financial market overlap may stem from two reasons: (i) the strong interconnection of countries within a specific layer, and; (ii) the overlapping effect of each layer. We can note how the US consistently exhibits the highest level of overlap degree measure. This aligns with its central role in influencing global risk levels due to its centrality within the international financial system. Given its economic significance and extensive network of financial linkages, developments in the US economy often reverberate across global markets, influencing risk perceptions and investor behaviour worldwide (Finta et al., 2020; Gong et al., 2023).

The right-side of Figure 4 reports the participation coefficient. According to this, we can further investigate the distribution of connections between financial markets across layers. The multiple participation coefficient, which ranges from 0 to 1, reflects the level of spillover connection among the network's layers. A coefficient of 0 indicates that the direct spillover connection of the considered financial market exists only in one of the four layers, while a coefficient of 1 suggests a more evenly distributed spillover connection across all four layers. During times of stability, we observe more uniform distributions, indicating balanced spillover connections across different layers. However, during periods of heightened financial stress, such as economic downturns or financial crises, participation coefficients tend to converge towards unity, reflecting a more concentrated and interconnected network of spillover channels. Analysing financial markets through a multilayer network lens is crucial. By considering the interconnectedness between different information channels (return, volatility, skewness and kurtosis), we can avoid underestimating the potential for spillover amplification during periods of stability. This comprehensive understanding is essential for safeguarding the global economic and financial system.

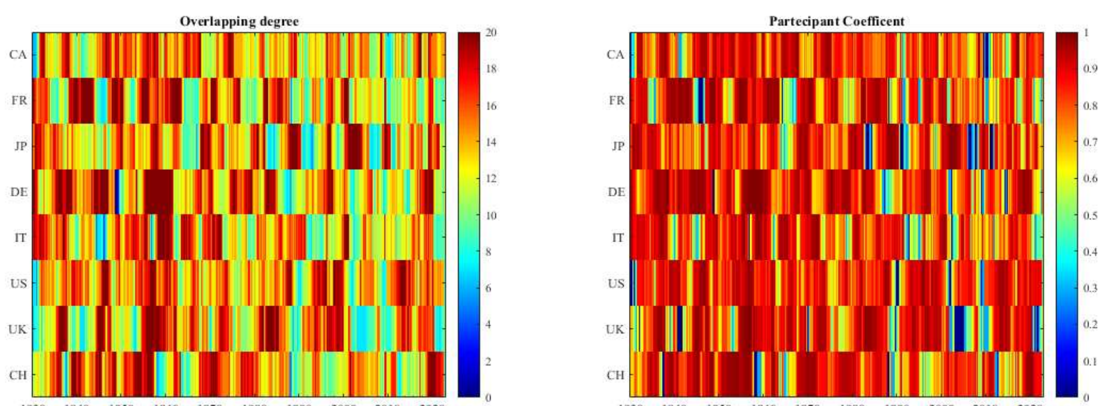

Figure 4: Multilayer information spillovers measures

4.3. *Predictability of spillover measures due to climate risks*

Having depicted the evidence that there is not only significant within- but across-layer spillovers involving returns, volatility, skewness and kurtosis of the eight advanced equity markets, we now evaluate if climate risks can predict the entire conditional distribution of the spillovers using a quantiles-based nonparametric causality test. As we consider the entire conditional distribution, we are able to identify the state or regime characterizing the degree of the spillover that is caused by climate risks, and hence provide invaluable information for investors in terms of portfolio allocation decisions requiring the input on evolution of various moments of equity prices. In this regard, we look at *CR1* and *CR2* on the total connectedness indexes of returns, volatility, skewness and kurtosis, depicted by TCI_RET, TCI_IQR, TCI_SKEW and TCI_KURT. Then we investigate the causal impact on the total within-layer spillover of returns, volatility, skewness and kurtosis, which we call RET-RET, IQR-IQR, SKEW-SKEW, and KURT-KURT. Finally, we also predict the cross-layer spillover involving the four underlying moments of stock prices, which results in a total of additional 12 indicators, with the names capturing the obvious across-strata spillovers, namely: RET-IQR, RET-SKEW, RET-KURT, IQR-RET, IQR-SKEW, IQR-KURT, SKEW-RET, SKEW-IQR, SKEW-KURT, KURT-RET, KURT-IQR, and KURT-SKEW.

As can be seen from Table 3, the two metrics of climate risks associated with level and variability of changes in temperature anomalies consistently predict the various spillover indicators over their respective entire conditional distributions, as suggested from the significant (primarily at the 1% level) standard normal test-statistics of the nonparametric causality-in-quantiles test. Interestingly, the inverted u-shaped pattern over the quantile ranges of 0.10 to 0.90, suggests that the causal effect is particularly strong around the median, which corresponds to the normal degree of spillovers. Though the effect tends to taper down around the extreme-ends, and at times statistical significance is lost, for TCI_IQR and IQR-IQR, predictability due to climate risks for the various conditional states of the spillover measures still exists in an overwhelming manner. Thus, we are able to confirm our hypothesis, that global shocks involving climate change tends to affect the various performance metrics of the eight stock markets, causing spillovers within and across the markets associated with returns, volatility, skewness and kurtosis.[3] This suggests that climate risks, serving as proxies for

[3] Realizing the possibility of omitted variable bias affecting our causality results in a bivariate set-up, we filtered each of the spillover indicators by regressing them on West Texas Intermediate (WTI) oil returns, its IQR, as well as the ratio of gold-to-silver prices and geopolitical risks, to recover the residuals from these regressions, and re-running the quantile causality tests. Oil returns, its volatility and the gold-to-silver ratio are basically capturing metrics of the sate of global fundamentals, worldwide uncertainty and sentiment, respectively, as discussed in detail by Salisu et al. (2022). The WTI oil price data is obtained from the Global Financial Data, while, gold and silver prices are sourced from Macrotrends: https://www.macrotrends.net/. The newspapers-based measure of geopolitical risks developed by Caladara and Iacoviello (2022), serves as an alternative metric of rare disaster risks, and is available for download from:

disaster risks, have the power to predict the transmission of various aspects of risk and return within the system of the G7 plus Switzerland stock markets in a robust manner. Given that our causality model is nonparametric in its nature to control for nonlinearity, they provide robust information on the entire conditional distribution of the metrics of spillovers.[4]

https://www.matteoiacoviello.com/gpr.htm. As can be seen from Table A1 in the Appendix, the predictive results are qualitatively similar to the unfiltered data, thus confirming the robustness of our findings to additional controls.

[4] Although reliable predictive inference is derived based on the nonparametric causality-in-quantiles test, it would also be interesting to estimate the sign of the effects of climate risks on the various metrics of multi-layer spillovers at various quantiles. However, in a nonparametric framework, this is not straightforward, as we need to employ the first-order partial derivatives. Estimation of the partial derivatives for nonparametric models can experience complications because these methods exhibit slow convergence rates, which can depend on the dimensionality and smoothness of the underlying conditional expectation function. Hence, the reader is referred to Figure A1 to derive tentative conclusions in this regard based on the quantiles-on-quantiles (QQ) approach of Sim and Zhou (2015). The technical details of the QQ method have been presented in Appendix B. As can be seen from Figure A2, the quantiles of CR1 and CR2, especially the upper ones, generally tends to be positively related to the conditional distribution of the multi-layer spillover indexes, in line with expectations, that "bad news" in form of climate risks is associated with stronger stock market comovements (Longin and Solnik. 1995, 2001).

Table 3. Nonparametric causality-in-quantiles test results from climate risks to metrics of spillovers

		Quantile								
Dependent Variable	Predictor	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
TCI_RET	CR1	1.9488*	2.6726***	4.4284***	4.8371***	4.2167***	3.8422***	3.4600***	2.2671**	1.6986*
	CR2	1.6810*	2.4840**	3.5668***	3.8264***	3.9164***	3.4461***	3.3249***	2.6811***	1.8770*
TCI_IQR	CR1	1,6425	2.5001**	4.3415***	3.3756***	7.4417***	3.5394***	3.8999***	2.9241***	1,5838
	CR2	1.7098*	3.0144***	5.3008***	3.6549***	6.2164***	2.8818***	4.3641***	2.7318***	1,4425
TCI_SKEW	CR1	4.7979***	7.1857***	7.8232***	12.2869***	9.8962***	7.4770***	6.8521***	4.9092***	4.3765***
	CR2	5.3225***	7.7358***	8.4830***	13.9337***	11.4671***	9.0396***	8.4672***	5.8026***	5.0734***
TCI_KURT	CR1	2.5319**	3.3972***	4.9280***	16.0273***	12.5277***	6.0584***	3.0516***	3.8783***	2.5670**
	CR2	2.6157***	3.7167***	6.2343***	15.0602***	13.1412***	5.7116***	3.0006***	4.3674***	2.0879**
RET-IQR	CR1	3.5139***	4.1197***	4.5097***	4.4022***	4.4220***	4.1599***	4.0393***	3.4275***	2.6746***
	CR2	3.5257***	4.0648***	4.4322***	4.9085***	4.8747***	5.3956***	4.5150***	4.2063***	2.9563***
RET-SKEW	CR1	1.8631*	3.1191***	3.0480***	3.2717***	3.1777***	2.8826***	2.8703***	3.0791***	1.7268*
	CR2	2.2483**	3.0872***	3.6707***	2.9293***	2.7154***	2.6333***	3.3329***	3.2493***	1.7659*
RET-KURT	CR1	3.5411***	4.0941***	4.2828***	4.9509***	5.4173***	5.3454***	4.9947***	4.2186***	3.0558***
	CR2	3.2263***	3.4567***	4.0561***	5.1601***	5.1618***	4.2565***	4.0609***	3.7406***	2.4443**
IQR-RET	CR1	5.1000***	5.8015***	4.4822***	4.2567***	3.8912***	3.9477***	4.0997***	3.1466***	2.2029**
	CR2	5.3835***	6.2393***	5.5365***	5.8188***	4.9075***	4.4753***	4.4872***	3.4857***	2.2821**
IQR-SKEW	CR1	2.0385**	3.0102***	3.3893***	4.3994***	5.3295***	5.5178***	6.0158***	6.5390***	5.5490***
	CR2	2.0732**	2.9003***	3.2618***	4.4631***	4.7555***	5.1629***	6.0584***	6.7725***	5.8662***
IQR-KURT	CR1	2.7062***	2.8356***	3.6455***	3.7734***	3.6154***	4.1416***	3.6413***	3.2142***	2.6647***
	CR2	2.2834**	2.6555***	3.5146***	3.7276***	3.6769***	3.7827***	4.5948***	3.6114***	2.6218***
SKEW-RET	CR1	3.7892***	4.5754***	4.9023***	5.6401***	5.4640***	5.3930***	5.1658***	4.7956***	3.7199***
	CR2	4.3389***	5.2765***	5.4772***	5.7961***	5.6600***	6.1441***	5.8743***	5.3150***	3.6589***
SKEW-IQR	CR1	2.7171***	3.0344***	3.8068***	4.0603***	3.6168***	3.5604***	3.6235***	5.0780***	4.0771***
	CR2	2.5803***	2.8090***	3.1527***	2.9464***	3.5884***	3.9071***	4.2307***	5.6453***	4.4528***
SKEW-KURT	CR1	3.5175***	4.8876***	5.4536***	5.4423***	5.9455***	5.2499***	4.1446***	3.2739***	2.2212**
	CR2	3.4864***	4.6507***	5.2041***	5.2851***	5.3706***	5.0045***	3.7064***	2.9337***	2.3702**
KURT-RET	CR1	2.9320***	3.1936***	4.1050***	3.6284***	4.2022***	4.6889***	5.1084***	6.2973***	5.8719***

	CR2	2.7631***	2.7612***	3.4228***	3.7231***	3.7956***	3.9728***	5.0936***	7.3491***	5.4260***
KURT-IQR	CR1	4.8182***	4.3085***	4.9920***	5.3925***	5.3584***	4.9674***	5.5257***	5.6894***	4.8397***
	CR2	4.8214***	4.3225***	5.1770***	5.6291***	5.5569***	5.7739***	5.2486***	5.9354***	4.8641***
KURT-SKEW	CR1	2.6574***	3.1989***	3.6153***	3.5397***	3.9158***	4.4413***	3.7180***	3.7086***	3.8261***
	CR2	2.3529**	3.5111***	4.3280***	4.3944***	4.2959***	4.3436***	4.0555***	3.6646***	3.5870***

Note: Entries report the standard normal test statistic for the hypothesis that there is no Granger causality for a particular quantile running from a specific climate risks predictor to a particular spillover metric; ***, ** and * indicates rejection of the null hypothesis at 1% (Critical value: 2.5750), 5% (Critical value: 1.96), and 10% (Critical value: 1.645) level of significance, respectively. The total connectedness indexes of returns (RET), volatility (inter quantile range, i.e., IQR), skewness (SKEW) and kurtosis (KURT) is depicted by TCI_RET, TCI_IQR, TCI_SKEW and TCI_KURT, respectively; Total within-layer spillover of RET, IQR, SKEW and KURT is called: RET-RET, IQR-IQR, SKEW-SKEW, and KURT-KURT, respectively; The cross-layer spillover involving RET, IQR, SKEW and KURT are: RET-IQR, RET-SKEW, RET-KURT, IQR-RET, IQR-SKEW, IQR-KURT, SKEW-RET, SKEW-IQR, SKEW-KURT, KURT-RET, KURT-IQR, and KURT-SKEW. CR1 and CR2 are climate risks due to year on-year changes in global temperature anomalies and its volatility (i.e., IQR) of the same, respectively.

5. Conclusions

In this paper, we conduct a comprehensive analysis on the transmission of returns and measures of risk (volatility, skewness and kurtosis) across the G7 plus Switzerland stock markets, approached using a QADL-MIDAS model, over the period December 1924 to February 2023, corresponding to the entire financial history of the markets under examination. Using the multi-layer spillover approach, we evaluate the risks and returns spillover effects between stock markets for each measure in one-and four-layer analyses. By allowing for not only within-layer but also cross-layer spillovers, we describe in better detail the transmission mechanism of returns and risks across the stock markets.

Our empirical findings suggest that the US stock market tends to transmit return and risk measures to the other markets, with a higher degree observed during turbulent periods. This extends the evidence from the less comprehensive but typical within-layer analyses often used in the existing literature to show the intensity and occurrence of returns and risks spillover effects. Therefore, our main analysis points to the significance of considering all four moments of stock prices when studying the spillover effect across stock markets. Accordingly, investors and policymakers concerned with the systemic risks transmission among advanced stock markets should not overlook the individual layers or, importantly, the significant cross-layer spillovers, when examining information transmission dynamics. Otherwise, an important part of the returns and risks transmission would be missed, possibly making any investment and risk management decision or policy formulation incomplete and suboptimal. This evidence has also implications for portfolio allocation and risk inference as limiting the optimization analysis to the first and second moments of stock returns without considering skewness and kurtosis or the interaction between the four measures 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 returns, volatility, skewness and kurtosis is required for the sake of completeness.

In a different strand of research, we evaluate the role of rare disaster risks, captured by changes in global temperature anomalies and its volatility, in predicting the conditional distribution of layer-based returns and risks spillovers. We conclude that climate risks drive the patterns of returns and risks connectedness. This new evidence has direct investment and policy implications, as it provides a structured approach to link spillovers of moments with disaster risks associated with climate change and global warming. 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 climate risks and accordingly formulate preventive policies to make stock markets more resilient to climate change and improve their stability.

Future research strands could include the examination of a broader sample of financial markets or regions, especially involving emerging countries, which are known to be more impacted by climate risks.

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APPENDIX:

Table A1. Nonparametric causality-in-quantiles test results from climate risks to filtered metrics of spillovers

		Quantile								
Dependent Variable	Predictor	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
TCI_RET	CR1	1,1883	1.7383*	1.7709*	2.8347***	3.2897***	2.3301**	2.4800**	1.7683*	1,0635
	CR2	1,1425	1,4457	2.1038**	2.4502**	3.1783***	2.5067**	1.9477*	1.9631**	1,2008
TCI_IQR	CR1	1.8046*	2.2261**	2.6158***	2.8617***	3.4995***	3.4770***	3.2348***	2.5408**	1.9131*
	CR2	1,5023	2.3352**	2.8545***	2.8934***	3.9860***	3.6641***	3.1429***	3.3989***	2.0676**
TCI_SKEW	CR1	5.2793***	7.4174***	8.7810***	9.0485***	9.1041***	8.7176***	7.8905***	6.8970***	5.0471***
	CR2	5.3433***	7.5250***	8.6359***	9.5185***	9.6096***	9.7988***	9.2342***	7.6921***	5.3501***
TCI_KURT	CR1	2.0985**	2.4082**	2.9188***	2.6687***	2.8691***	3.0774***	2.5835***	2.4747**	1.7889*
	CR2	1.9760**	3.0685***	3.3677***	3.6991***	3.4021***	3.7774***	3.2900***	3.1627***	2.0860**
RET-IQR	CR1	3.1173***	4.3631***	5.5057***	5.5416***	6.0212***	6.0685***	5.0265***	4.1467***	3.1012***
	CR2	3.2608***	4.0419***	4.1791***	4.7415***	4.5156***	4.5891***	3.8285***	3.5399***	2.3031**
RET-SKEW	CR1	1,3293	1.8955*	1.9140*	2.0080**	2.1276**	2.7139***	2.6420***	3.1418***	2.5798***
	CR2	2.2959**	2.9380***	2.8742***	2.5209**	2.0631**	2.5600**	3.0280***	3.4563***	2.4786**
RET-KURT	CR1	2.8079***	2.7109***	3.1731***	3.0342***	3.1352***	3.1977***	3.3732***	3.2585***	2.5833***
	CR2	2.4881**	2.2949**	2.2314**	3.0035***	3.1551***	2.8149***	3.6282***	2.9296***	2.4074**
IQR-RET	CR1	4.3883***	5.8951***	5.0263***	4.2549***	3.8998***	3.5298***	3.4032***	3.0702***	2.2281**
	CR2	4.9705***	6.1921***	6.1108***	5.9167***	4.7262***	4.4492***	4.2857***	3.5693***	2.4976**
IQR-SKEW	CR1	2.0677**	2.9458***	2.8643***	3.7991***	4.1211***	4.3131***	5.0281***	5.8681***	5.0760***
	CR2	2.1885**	2.6189***	2.8760***	4.2256***	5.4895***	5.4588***	6.1070***	7.1640***	5.7428***
IQR-KURT	CR1	2.4151**	2.4139**	3.6007***	3.5412***	3.2867***	3.4623***	3.6904***	3.0588***	2.5454**
	CR2	2.1497**	2.4640**	3.5225***	3.3493***	3.4419***	3.8291***	4.0836***	3.6769***	2.4655**
SKEW-RET	CR1	3.2961***	3.5481***	4.0238***	3.3676***	3.6674***	3.3330***	3.8302***	3.3319***	3.9117***
	CR2	3.8665***	3.5529***	3.6318***	3.2970***	4.3011***	3.9549***	3.8462***	3.4349***	3.5315***
SKEW-IQR	CR1	3.0284***	3.7921***	4.4064***	4.3688***	4.2593***	4.0585***	4.1018***	6.2528***	4.1120***
	CR2	3.0249***	4.0450***	3.7889***	4.4497***	4.6462***	4.7138***	4.9095***	6.3299***	4.5175***
SKEW-KURT	CR1	2.8288***	2.7418***	3.0729***	2.8910***	3.2159***	2.8434***	2.8435***	2.4479**	1,5204
	CR2	2.4924**	2.6087***	2.7055***	2.9599***	3.0690***	2.9920***	2.6149***	1.9902**	1,336

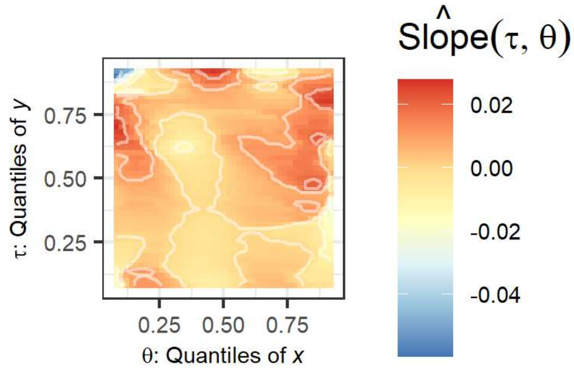
KURT-RET	CR1	3.1692***	3.7916***	3.7972***	4.1422***	3.8069***	3.2475***	4.0060***	5.4051***	5.3537***
	CR2	2.6216***	3.3356***	3.6598***	3.7664***	3.7848***	3.6034***	4.8096***	6.1844***	5.0436***
KURT-IQR	CR1	3.3737***	3.3185***	3.8129***	3.8275***	4.3643***	4.2111***	3.6901***	4.0247***	3.8794***
	CR2	3.0798***	3.3255***	3.9290***	4.3188***	5.2142***	4.4834***	4.4458***	5.0470***	4.3226***
KURT-SKEW	CR1	2.7346***	3.3950***	3.6090***	3.7781***	3.3367***	3.2700***	3.5793***	3.1732***	3.2892***
	CR2	2.5885***	2.8921***	2.7919***	2.8811***	3.3223***	4.3073***	4.7272***	3.7095***	3.4392***

Note: Entries report the standard normal test statistic for the hypothesis that there is no Granger causality for a particular quantile running from a specific climate risks predictor to a particular filtered spillover metric, obtained from running a regression of the spillover index on oil returns, its volatility (inter quantile range, i.e., IQR), gold to silver ratio, and geopolitical risks, and recovering the residuals; ***, ** and * indicates rejection of the null hypothesis at 1% (Critical value: 2.5750), 5% (Critical value: 1.96), and 10% (Critical value: 1.645) levels of significance, respectively. The total connectedness indexes of returns (RET), volatility (IQR), skewness (SKEW) and kurtosis (KURT) is given by depicted by TCI_RET, TCI_IQR, TCI_SKEW and TCI_KURT, respectively; Total within-layer spillover of RET, IQR, SKEW and KURT is called: RET-RET, IQR-IQR, SKEW-SKEW, and KURT-KURT, respectively; The cross-layer spillover involving RET, IQR, SKEW and KURT are: RET-IQR, RET-SKEW, RET-KURT, IQR-RET, IQR-SKEW, IQR-KURT, SKEW-RET, SKEW-IQR, SKEW-KURT, KURT-RET, KURT-IQR, and KURT-SKEW. CR1 and CR2 are climate risks due year on-year changes in global temperature anomalies and its volatility (i.e., IQR) of the same, respectively.

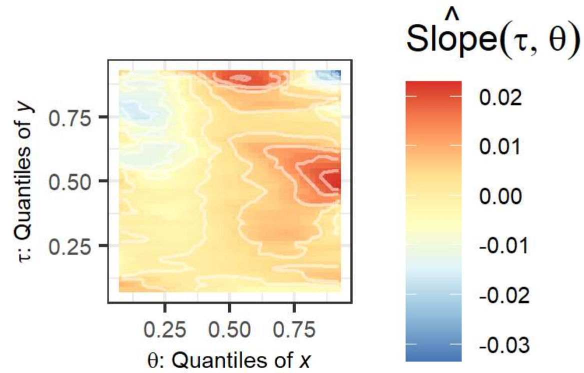
Figure A1. Quantile-on-quantile results of the effect of climate risks on multi-layer spillover indexes

A1.1. RET-RET

(a) CR1

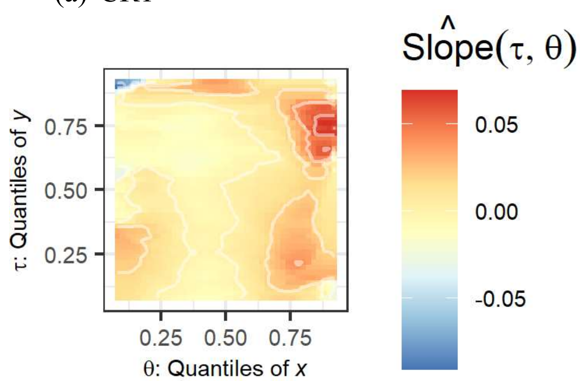


(b) CR2

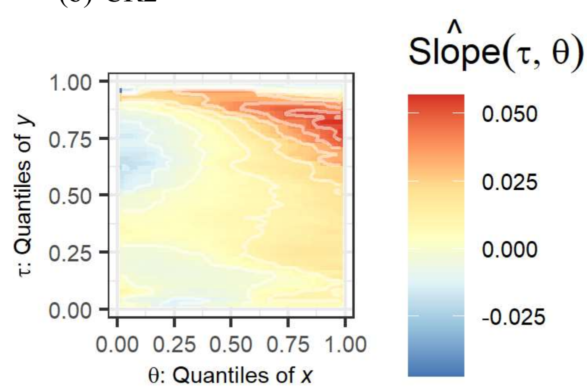


A1.2. IQR-IQR

(a) CR1

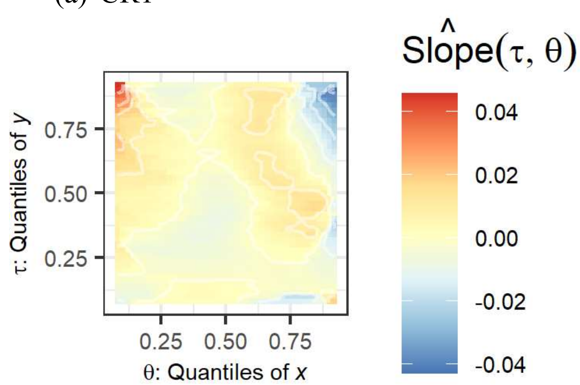


(b) CR2

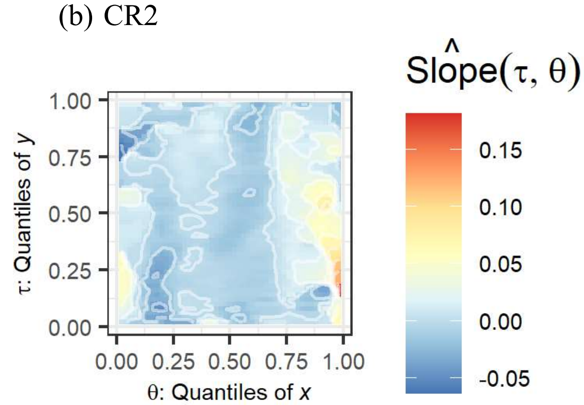


A1.3. SKEW-SKEW

(a) CR1

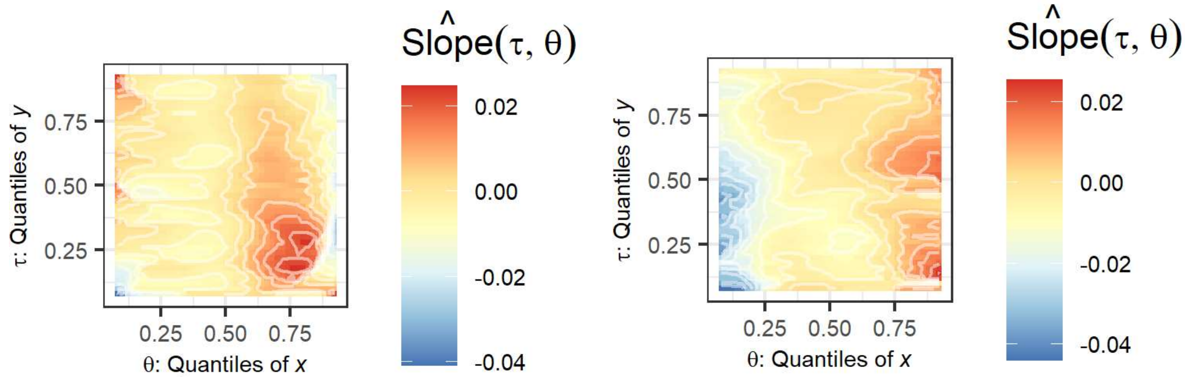


(b) CR2



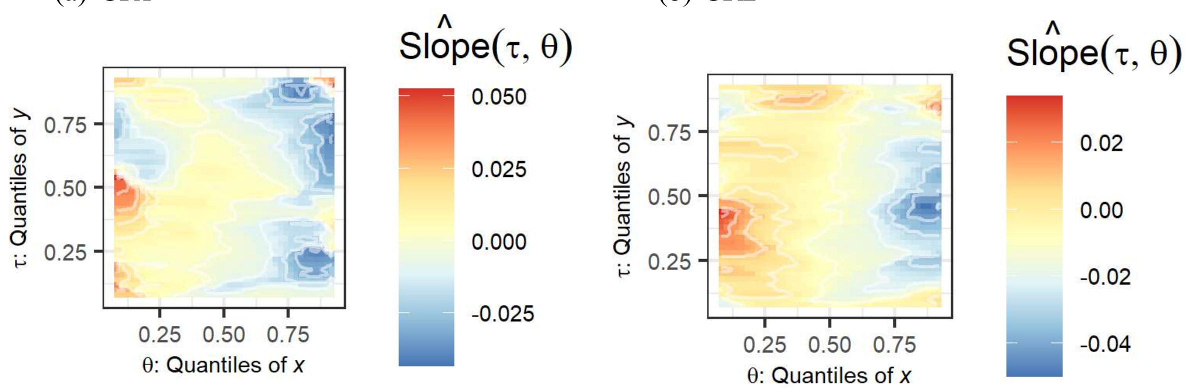
A1.4. KURT-KURT

(a) CR1 (b) CR2



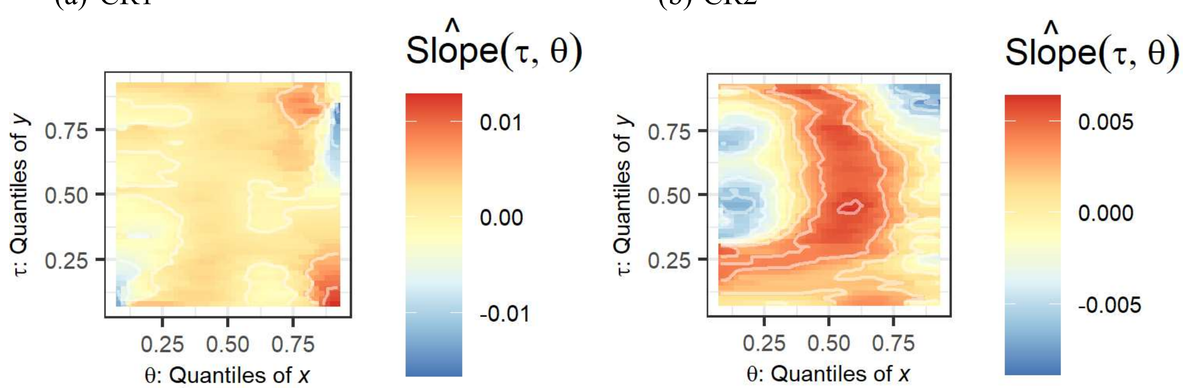
A1.5. RET-IQR

(a) CR1 (b) CR2



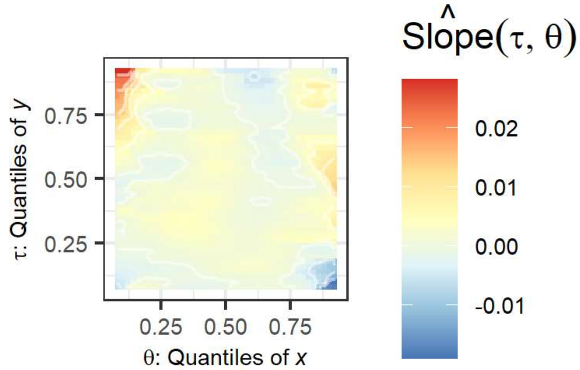
A1.6. RET-SKEW

(a) CR1 (b) CR2

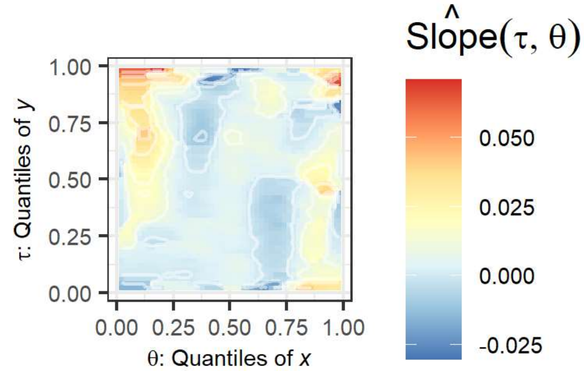


A1.7. RET-KURT

(a) CR1

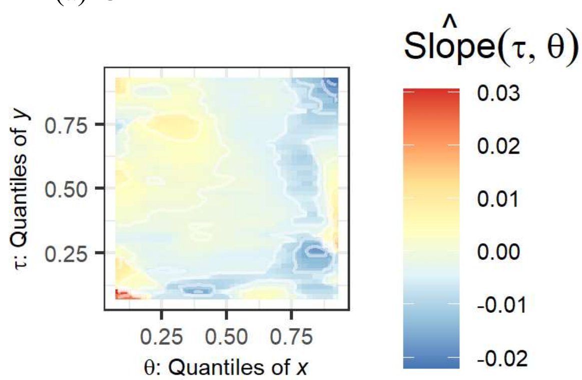


(b) CR2

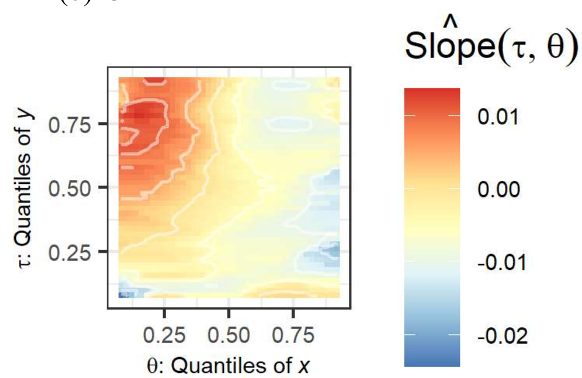


A1.8. IQR-RET

(a) CR1

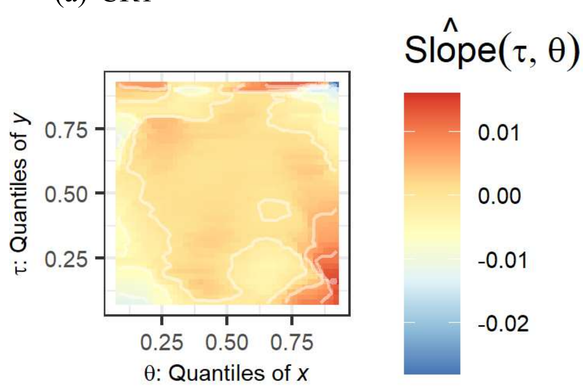


(b) CR2

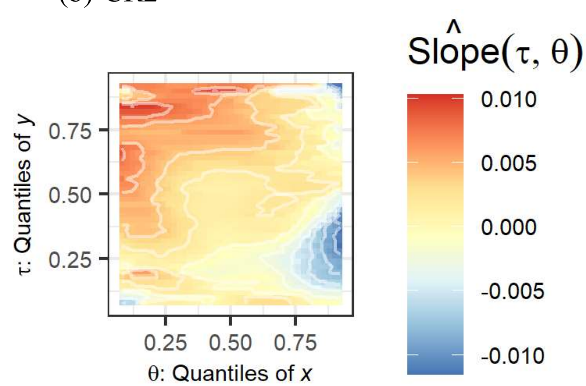


A1.9. IQR-SKEW

(a) CR1

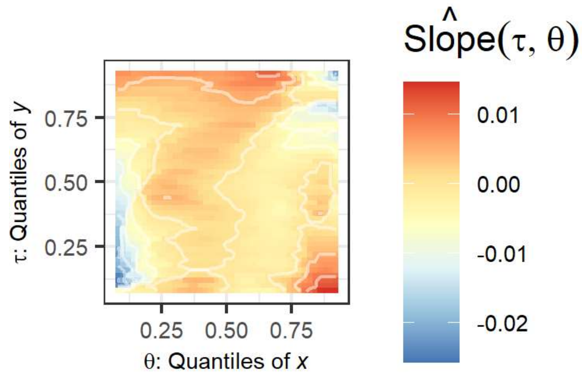


(b) CR2

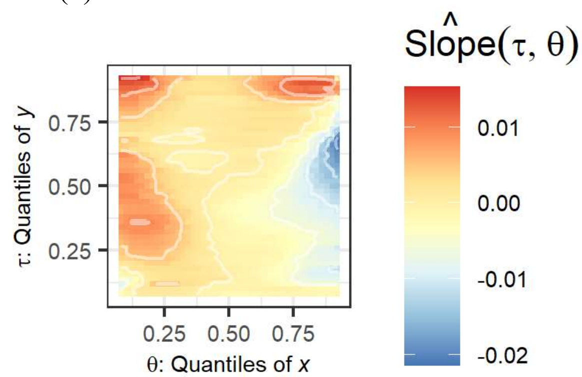


A1.10. IQR-KURT

(a) CR1

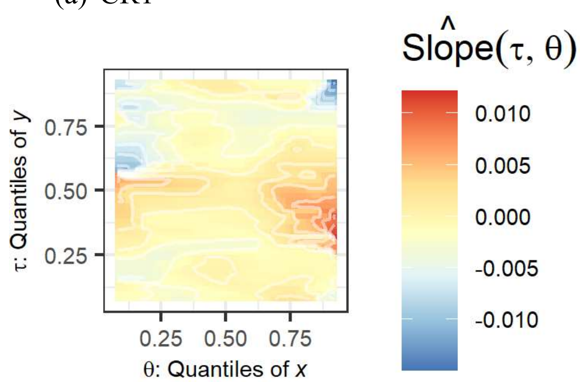


(b) CR2

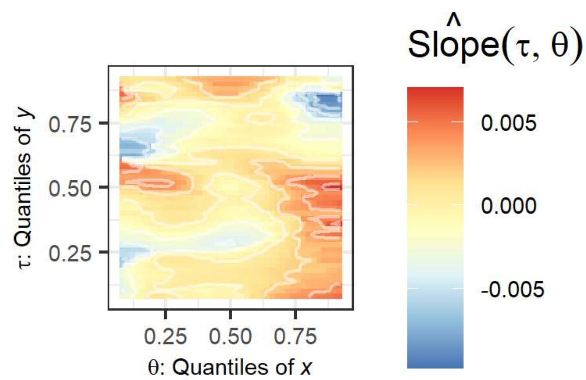


A1.11. SKEW-RET

(a) CR1

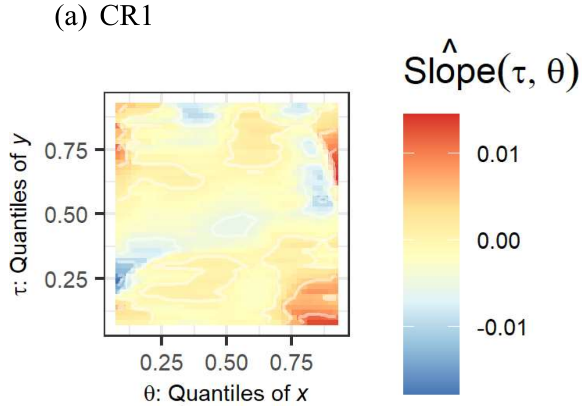


(b) CR2

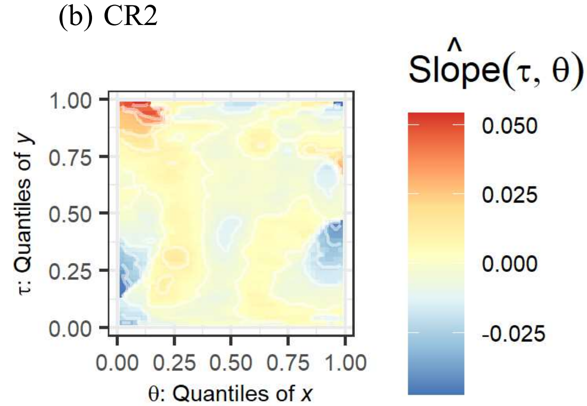


A1.12. SKEW-IQR

(a) CR1

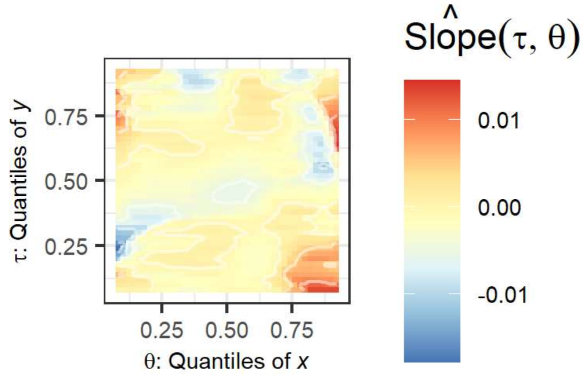


(b) CR2

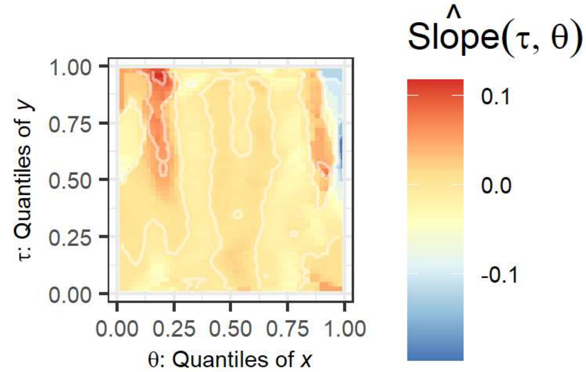


A1.13. SKEW-KURT

(a) CR1

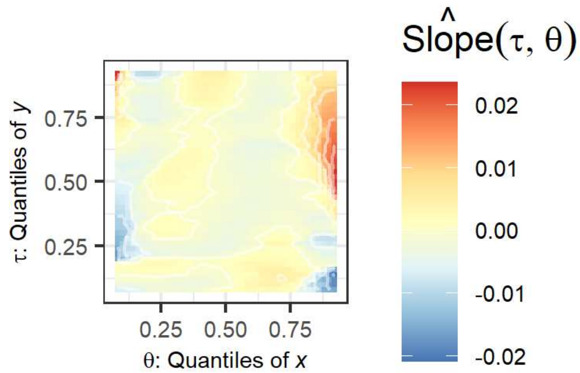


(b) CR2

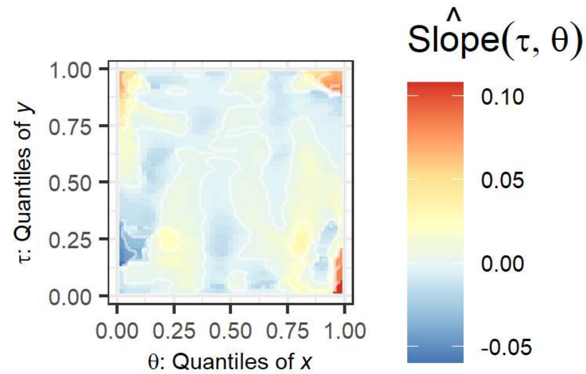


A1.14. KURT-RET

(a) CR1

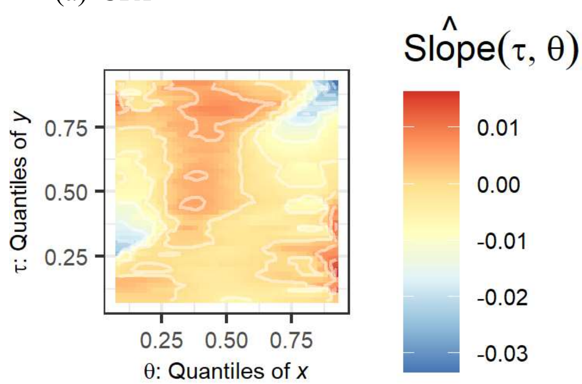


(b) CR2

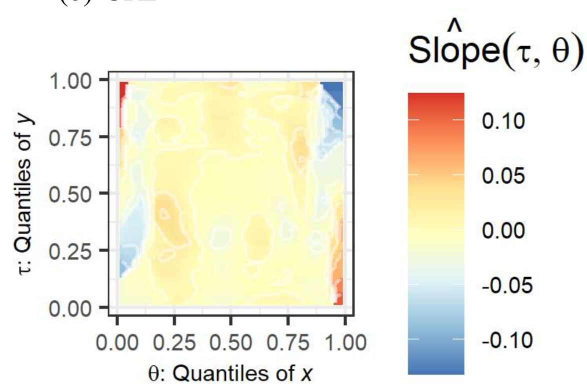


A1.15. KURT-IQR

(a) CR1

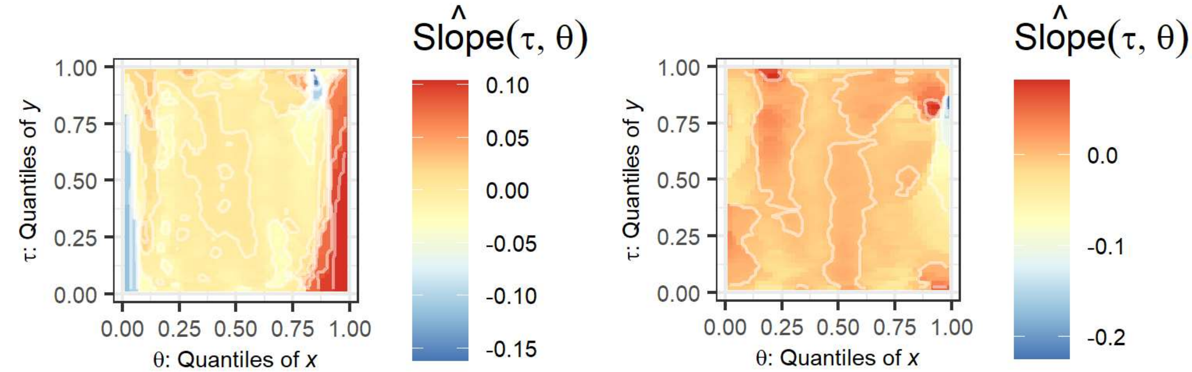


(b) CR2



A1.16. KURT-SKEW

(a) CR1 (b) CR2



Note: *y* corresponds to various indexes of multi-layer spillovers (RET-RET, IQR-IQR, SKEW-SKEW, and KURT-KURT, RET-IQR, RET-SKEW, RET-KURT, IQR-RET, IQR-SKEW, IQR-KURT, SKEW-RET, SKEW-IQR, SKEW-KURT, KURT-RET, KURT-IQR, and KURT-SKEW), and; *x* to climate risks (CR1 and CR2).

Appendix B: Quantile-on-quantile (QQ) regression

We study the impact of the climate risks variables (CR1 and CR2), denoted by x for the 12 indicators of multi-layer spillovers, namely: RET-IQR, RET-SKEW, RET-KURT, IQR-RET, IQR-SKEW, IQR-KURT, SKEW-RET, SKEW-IQR, SKEW-KURT, KURT-RET, KURT-IQR, and KURT-SKEW, captured by y using a quantile-on-quantile (QQ) regression model. This method is chosen, as it allows the for the change in x, conditional on its current state, to have varied influences on y, where a standard quantile regression simply estimates the heterogeneous response of y to x at various points of the conditional distribution of y.

For the ease of estimation, we choose the single equation regression method of Sim and Zhou (2015) for estimating QQ models, over the triangular system of equations-based approach of Ma and Koenker (2006).

Let θ superscript denote the quantile of the y and x under consideration. We first postulate a model for the θ-quantile of y as a function of the x (note this is for the temporaneous relationship). We have:

$$y_t = \beta^{\theta} x_t + \varepsilon_t^{\theta} \ , \tag{B1}$$

where ε_t^{θ} is an error term that has a zero θ -quantile.

As we do not have a prior on how the y and x changes are interlinked, we allow the relationship function $\beta^{\theta}(x_t)$ to be unknown. To examine this linkage between the θ-quantile of y and τ-quantile of x, denoted by x^{τ}, we linearize the function $\beta^{\theta}(x_t)$ by taking a first-order Taylor expansion of β^{θ} (.) around x^{τ}, which yields the following:

$$\beta^{\theta}(x_t) \approx \beta^{\theta}(x^{\tau}) + \beta^{\theta\prime}(x^{\tau})(x_t - x^{\tau}) \tag{B2}$$

Based on Sim and Zhou's (2015) study, we can redefine $\beta^{\theta}(x^{\tau})$ and $\beta^{\theta\prime}(x^{\tau})$, respectively, as $\beta_0(\theta, \tau)$ and $\beta_1(\theta, \tau)$. Then, equation (9) can be re-written as follows:

$$\beta^{\theta}(x_t) \approx \beta_0(\theta, \tau) + \beta_1(\theta, \tau)(x_t - x^{\tau}) \tag{B3}$$

Ultimately, we substitute equation (B3) into equation (B1) to obtain the following:

$$y_t = \beta_0(\theta, \tau) + \beta_1(\theta, \tau)(x_t - x^{\tau}) + \varepsilon_t^{\theta} \tag{B4}$$

Unlike a standard conditional quantile function, the expression

$$\beta_0(\theta, \tau) + \beta_1(\theta, \tau)(x_t - x^{\tau}) \tag{B5}$$

captures the relationship between the θ-quantile of the y and τ-quantile of x, given that $\beta_0$and β_1 are doubly indexed in θ and τ. That is, this expression can capture the overall dependence structure between the y and x through the dependence between their respective distributions.

To estimate (B4), we solve for:

$$\min_{\beta_0 \beta_1} \sum_{i=1}^{n} \rho_\theta \left[y_t - \beta_0 - \beta_1 (x_t - x\hat{}\tau) \right] K \left(\frac{F_n(x_t) - \tau}{h} \right) \tag{B6}$$

to obtain the estimates $\hat{\beta}_0(\theta, \tau)$ and $\hat{\beta}_1(\theta, \tau)$, where the function ρ_θ is the tilted absolute value function that provides the θ-conditional quantile of y_t as the solution. Because we are interested in the effect exerted locally by the τ-quantile of x, we employ a Gaussian kernel $K(.)$ to weight the observations in the neighbourhood of x^τ, based on bandwidth h (=0.05, following Sim and Zhou (2015)). The weights are inversely related to the distance of x_t from x^τ, or more conveniently, the distance of the empirical distribution function

$$F_n(x_t) = \frac{1}{n} \sum_{k=1}^{n} I(x_k < x_t) \tag{B7}$$

from τ, where τ is the value of the distribution function that corresponds with x^τ.